Fachbereich Wirtschaftswissenschaft

# Regional clusters: Really the place to be?

A multidimensional investigation of firm performance within clusters

Kumulative Dissertation
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## List of Abbreviations

| | |
|---|---|
| cf. | See for instance |
| Ed. | Editor |
| Eds. | Editors |
| e.g. | For example |
| et al. | And others |
| etc. | And so forth |
| EU | European Union |
| f. | And the following (page) |
| IPC | International Patent Classification |
| IPRs | Intellectual property rights |
| MAUP | Modifiable Area Unit Problem |
| MBV | Market-based view |
| NACE | Nomenclature statistique des activités économiques dans la Communauté européenne; Statistical classification of economic activities in the European Community |
| No. | Number |
| NUTS | Nomenclature of territorial units for statistics |
| OLS | Ordinary Least Squares |
| p. | Page |
| PhD | Philosophiae doctor; Doctor |
| pp. | Pages |
| RBV | Resource-based view |
| Rel. | Relative(ly) |
| Rev. | Revised version |
| RV | Relational view |
| R&D | Research and Development |
| SMEs | Small and medium-sized enterprises |
| SSRN | Social Science Research Network |
| Vol. | Volume |

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# I. Framework Paper

## 1. Introduction

The ongoing globalization, spurred by significant improvements in the information and communication as well as transportation infrastructure, has remarkably shaped modern societies all over the world (De Martino et al., 2006; Enright, 2000; Klumbies, 2015). For instance, nowadays people communicate worldwide without time delays via email or video chats, they travel fast to other continents and use the internet for doing business 24 hours a day, seven days a week. For companies, it would therefore be quite logical to relocate their business activities to those regions in the world where production costs are the lowest, so that the corresponding profits can be maximized (Porter, 1998; Steffen, 2012). However, in today´s ever increasing globalized economies, the co-location of firms from similar industries in regional clusters is indeed still an essential economic reality (Brown et al., 2007; Nathan and Overman, 2013). Examples for such clusters can be found around the globe and in all industries, such as the ceramic tile and fashion clusters in north-east Italy, the software cluster in Bangalore (India) as well as the automotive cluster in south-western Germany (McCann and Folta, 2008; Šarić, 2012; Schilirò, 2017; Steffen, 2012). Throughout the European Union (EU), regional clusters for instance employ nearly 40% of the European workforce and account for 55% of European wages (European Union, 2016; Festing et al., 2012).

Consequently, researchers and policy makers alike have developed a keen interest in regional clusters, resulting in a large number of publications (e.g. Lazzeretti et al., 2014) and funding measures (e.g. Zenker et al., 2019). Regarding the latter, Germany for instance has a particularly long history of national cluster programs (Fornahl et al., 2015; Lehmann and Menter, 2018), starting with the "BioRegio-Wettbewerb" in 1996 and continuing with the recently announced program of "Zukunftscluster", being part of the High-Tech Strategy 2025 (BMBF, 2018; EFI, 2015; Presse- und Informationsamt der Bundesregierung, 2019). The popularity of the concept is thereby primarily driven by the assumed benefits of the co-location of firms from similar industries in regional clusters, promoting supposedly, among others, the productivity (e.g. Borowiecki 2013), the innovativeness (e.g. Baptista and Swann, 1998) as well as the employment of firms (e.g. Wennberg and Lindqvist, 2010).

However, as indicated by Martin and Sunley (2003): "(…) the mere popularity of a construct is by no means a guarantee of its profundity." (Martin and Sunley, 2003, p. 7). Besides the lack of standardized methodologies and cluster definitions, one of the main research challenges for the cluster concept is overcoming the still prevalent assumption that all firms profit equally and in the same manner from being located in a cluster (Frenken et al., 2015; Grashof, 2020b). Even though it is a fascinating idea, particularly for politicians, that by settling in a cluster companies can automatically gain competitive advantages, it is a quite unrealistic one (Grashof, 2020b; Klumbies, 2015). Indeed, despite its popularity, the corresponding empirical results regarding the firm-specific cluster effect are so far highly contradictive, ranging from positive to mixed and even to negative performance effects (Grashof and Fornahl, 2020; Grashof, 2020a). The relationship between clusters and firm performance therefore appears to be more complex than many, including Michael Porter, have assumed (Grashof, 2020a; Grashof, 2020b). However, this complexity has not been widely taken into account in the scientific literature. This can also be seen in figure 1, which is based on a content analysis of the keywords used by the 168 articles considered in Grashof and Fornahl (2020) as well as Grashof (2020a).[1]

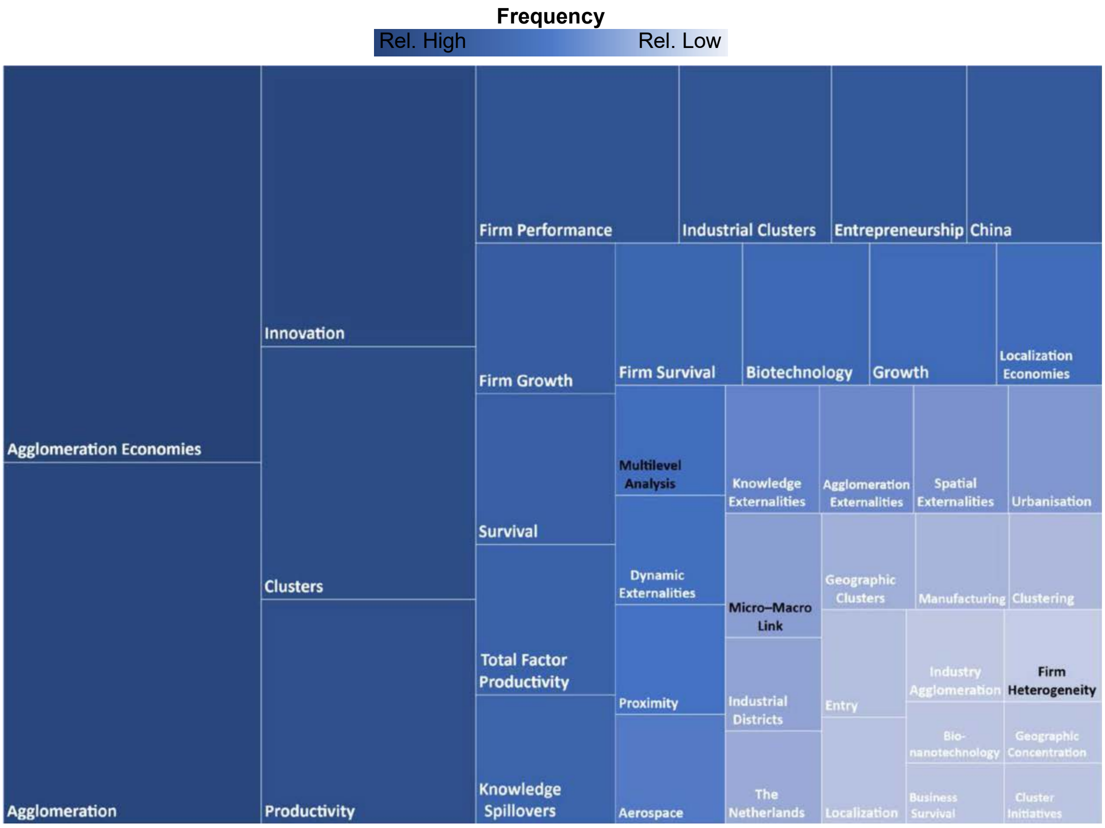


**Figure 1:** Top 40 keywords of the cluster literature focussing on firms (until 2016)

[1] As such, only empirical studies that investigate the firm-specific cluster effects are considered. For the exact procedure of the literature collection, please see Grashof and Fornahl (2020).

In general, it can be shown that not surprisingly broad keywords such as "Agglomeration Economies" and "Clusters" shape the overall picture. Nevertheless, there are also more specific keywords such as "Knowledge Spillovers" and "Entrepreneurship" that are relatively frequently employed in the corresponding research field of interest, particularly in comparison with keywords that are related with firms' heterogeneity in clusters. In this context, only three keywords can be identified that actually deal with the heterogeneity in clusters, namely "Multilevel Analysis" (four times mentioned), "Micro-Macro Link" (four times mentioned) and "Firm Heterogeneity" (three times mentioned). Together they only account for 1.6% of all keywords, while "Entrepreneurship" by itself has almost the same share. Thus, it can be stated that firms' performance differentials within clusters and the corresponding contextual determinants have so far only marginally been investigated. At the same time, this comparatively small and under-researched thematic field can be characterized as a relatively new and emerging field, since almost three quarters of the underlying studies have been published in the recent period between 2012 and 2016. However, this lack of knowledge about contextual influences challenges previous scientific as well as policy implications in the cluster context. Without properly understanding the concrete conditions through which the assumed advantages of clusters can be realized, it is meaningless to debate whether firms gain or lose from localization economies (e.g. debate about urbanization and localization economies)[2]. Based on previous research, which widely ignores the specific context by assuming equal gains, it is thus still quite difficult to evaluate the concrete consequences of being located in a cluster (Schiele, 2008). For policy makers, which are already commonly supporting cluster initiatives, this knowledge gap is also of particular relevance, as "[i]n an economy where the agglomeration of activities does not generate any benefits, a policy that attempts to generate such agglomerations does not make any sense." (Maier and Trippl, 2012, p. 14).

As such, from a research and practical point of view, it remains to be answered: *To what extent it is strategically reasonable for a single company to be located in a cluster?*

By answering the overall research question, this dissertation pursues the aim of enriching the previous research on firm performance in regional clusters, particularly

[2] For a comprehensive overview of this debate, please see Beaudry and Schiffauerova (2009).

with respect to firm innovativeness. Based on the derived theoretical and empirical insights, it also strives to provide practical guidance for company managers and in particular for politicians about the conditions necessary to gain from the cluster environment, so that they can effectively evaluate where more efforts need to be invested in order to improve the present situation.

Theoretically, the reasons for the co-location of firms in regional clusters have already been formulated in the last century. Apart from exogenous factors such as the unique physical conditions of particular areas (e.g. climate conditions and availability of natural resources), Marshall (1920) additionally posited that firms endogenously create externalities due to their location decisions. These externalities form the basis for all later developed theoretical conceptualizations of regional clusters (Lazzeretti et al., 2014; Marshall, 1920; Palazuelos, 2005; Šarić, 2012). These externalities include four different types: the access to specialized inputs, the access to a common specialized labour market, the access to knowledge spillovers and by reducing the consumer search costs the access to greater demand (Marshall, 1920; McCann and Folta, 2008). Regarding the first type, it has been established that, on the one hand, the constant demand for specialized inputs within clusters attracts input suppliers in larger numbers, since it reduces the market risk and facilitates the bearing of fixed costs for specialized machinery necessary for the production of intermediary inputs. On the other hand, final good producers can in turn gain from the access to lower cost and/or better-quality inputs from specialized suppliers located within the same cluster (Krugman, 1991a; Marshall, 1920; McCann and Folta, 2008; Palazuelos, 2005). The identical reasoning also holds true for the access to the specialized labour market within clusters. By providing a pooled market for skills, the spatial clustering of economic activities offers a variety of employment opportunities, benefiting both the employers as well as the employees (Krugman, 1991a; Marshall, 1920). The pooling of specialized employers and employees in close geographical distance reduces the risk of becoming unemployed as well as of not finding the most adequate job candidate (David and Rosenbloom, 1990; Krugman, 1991a). Additionally, it improves the overall matching process between both sides, since companies and workers alike do not have to search on the national or even international labour market (Amend and Herbst, 2008; Otto and Fornahl, 2010). Furthermore, the improved matching process is also beneficial for a pronounced labour mobility within clusters, which, due to the corresponding person-embedded human capital, has been shown to be crucial for inter-firm knowledge diffusion (Erikson and Lindgren, 2009; Otto and Fornahl, 2010). This latter aspect is related with the third type of externalities: knowledge spillovers. It has been indicated that geographic proximity can encourage the transfer of knowledge in general and in particular the interchange of tacit knowledge (Daft and Lengel, 1986; Jaffe et al., 1993). While the exchange of general information can potentially occur regardless of firms' location, although in a more inefficient way, the transfer of tacit knowledge indeed requires face-to-face contacts which are more frequently available in regional clusters (Daft and Lengel, 1986; McCann and Folta, 2008). These contacts can for instance occur through participating in social meetings or in local industry events (Almeida and Kogut, 1999; McCann and Folta, 2008; Saxenian, 1990). Apart from the three previously mentioned supply-side advantages, firms located within clusters can also potentially gain from an increased demand by easing the consumer search process due to the geographically concentrated supply within clusters (McCann and Folta, 2008; Marshall, 1920). This demand-side advantage will be particularly salient when product heterogeneity is high (e.g. Fischer and Harrington, 1996) and when the corresponding product traits require a visual inspection by the consumers (e.g. Stahl, 1982).

Building on these insights, later theoretical streams further developed the cluster concept by additionally emphasizing specific characteristics of the regional agglomeration of firms from similar industries.[3] In general, they can be grouped into socio-economic and economic perspectives (Šarić, 2012). The former focuses mainly on the social and institutional dimensions of clusters. In this context, researchers, particularly Italians, have highlighted that firms profit from the thick institutional context, including common values, norms and trust, which promotes especially informal relationships (Becattini, 1990; Bekele and Jackson, 2006; Piore and Sabel, 1984; Šarić, 2012). Nevertheless, as indicated in the comprehensive descriptive meta-analysis provided in Grashof and Fornahl (2020), this social dimension is not regarded as a central element of a cluster, but instead it is just a special component of specific forms of clusters such as industrial districts in Italy. The underlying cluster conceptualization of this dissertation is therefore more in line with the economic perspective, concentrating especially on the externalities highlighted by Marshall (1920). Apart from Marshall, one of the most popular contributors of this theoretical stream is Michael Porter (Bekele and Jackson, 2006; Šarić, 2012). In his cluster concept, he stressed the competitiveness aspect of clusters, indicating that the competition within clusters created by co-locating with rivalries can, for example, provide a competitive advantage, and he framed his concept as a business strategy

[3] However, most of these characteristics have already been implicitly as well as explicitly mentioned by Marshall (1920).

with the so-called "diamond-model" at its heart (Porter, 1990; Porter, 1998; Porter, 2000; Steffen, 2012). Due to its focus on competitiveness and its quite broad applicability, Porter´s cluster concept has been appealing to company managers, politicians and academics alike (Martin and Sunley, 2003; Steffen, 2012). This is also reflected in the high citation counts of Michael Porter's pioneering cluster article published in 1998, amounting to 2,641 citations up to now.[4]

Despite these long-term efforts, the cluster concept is, however, still just at the beginning of its development. While the underlying reasons for clustering have continuously been further developed, it is unclear to what extent they depend on the specific context. As indicated in figure 1, only recently have isolated papers been published that address this research gap (e.g. Knoben et al., 2015). However, even though these contributions go in the right direction, they do not go far enough.

(1.) They commonly consider only contextual influences from one level of analysis (often the firm-level). Potential interaction effects with contextual variables from different levels of analysis are therefore ignored, thereby limiting the informative value.

(2.) Furthermore, the analysed contextual variables are normally not related with the concrete externalities. As such, a differentiated understanding about the relevance of contextual variables for each externality is missing, which again prevents a significant development of the cluster concept.

(3.) Moreover, they typically concentrate their research only on one performance indicator, providing only a limited picture about the effects of regional clusters, since the underlying externalities as well as the corresponding contextual variables have different influences on different performance indicators (Grashof and Fornahl, 2020; Grashof, 2020a).

All three aspects therefore drive the research design of this dissertation, which will be presented in the following. Table 1 thereby provides a visualized summary.

[4] The corresponding information is based on the literature database Web of Science (last retrieved from 21.04.2020).

**Table 1:** Thematic classification of the core papers of this cumulative dissertation

| | | Paper I | Paper II | Paper III | Paper IV | Paper V |
|---|---|---|---|---|---|---|
| **Mechanisms** | *Knowledge Spillovers* | | | ● | | |
| | *Specialized inputs* | | | | | |
| | *Specialized labour* | | | | ● | |
| | *Access to greater demand* | | | | | |
| | *Overall* | ● | ● | | | ● |
| **Level of analysis** | *Firm (Micro)* | ● | ● | ● | ● | ● |
| | *Cluster (Meso)* | ● | ● | ● | ● | ● |
| | *Market and Industry (Macro)* | ● | ● | ● | ● | ● |
| | *Nation (Macro)* | | ● | | | ● |
| **Performance indicator** | Innovativeness | ● | ● | ● | ● | |
| | Productivity | ● | ● | | | |
| | Survival | ● | ● | | | |
| | Employment growth | ● | ● | | | |
| | Overall | | | | | ● |

In order to be able to answer the overall research question of this dissertation adequately, it is necessary to address related research questions beforehand. As a consequence of its popularity, the cluster term has experienced a large proliferation, resulting in conceptual misunderstandings (Brown et al., 2007; Martin and Sunley, 2003; Šarić, 2012). Given the research focus of this dissertation on firm-specific effects, it is therefore necessary to address in a first step the following sub-research question:

**Sub-research question 1:** *How can the term cluster be adequately defined for the purpose of a firm-specific analysis?*

By conducting a profound systematic literature overview about the various cluster definitions, the first core paper of this dissertation, Grashof and Fornahl (2020), synthesizes in this context the central elements of a cluster definition. Based on these results, an adequate working definition for the further analyses within this dissertation is derived.

As already indicated, the empirical evidence about the firm-specific cluster effect is characterized by a relatively high inconsistency, preventing general conclusions (Grashof and Fornahl, 2020a). Frenken et al. (2015) therefore urges research to reconcile these contradictory empirical findings in order to shed more light on the alleged effects of clusters on firm performance. Hence, in a second step the following sub-research question needs to be answered:

**Sub-research question 2:** *Does being located in a cluster influence firm success?*

By applying a descriptive meta-analysis of 168 empirical studies based on four different performance variables, Grashof and Fornahl (2020) find indeed first evidence for a rather significant positive firm-specific cluster effect. However, at the same time the results point towards the importance of contextual variables in understanding the relationship between clusters and firm success.

Nonetheless, as also illustrated in figure 1, in previous cluster literature, due to the still prevalent assumption of homogeneity between firms located within clusters, contextual variables such as firm-level characteristics (e.g. the firm´s resources and capabilities) have been widely ignored (Porter, 1998; Šarić, 2012; Tallman et al., 2004). There are of course a few important exceptions (e.g. Hervas-Oliver et al., 2018; Knoben et al., 2015; Rigby and Brown, 2015). Nevertheless, these relatively recent articles again come to quite ambiguous results, thereby emphasizing the need to comprehensively consider the influence of contextual variables from different levels of analysis (Grashof, 2020b). Responding to this need, in a third step this dissertation investigates the following sub-research question:

**Sub-research question 3:** *To what extent does the (innovative) performance in clusters relate to specific firm-level, cluster-level and industry-/market-level conditions?*

The results of the second core paper, Grashof (2020a), extend the previous analysis of Grashof and Fornahl (2020) by applying a meta-analysis that particularly focuses on the direct and interactive effects of contextual variables on four different performance variables. As shown in table 1, both core papers therefore address the limited focus on single levels of analysis and performance indicators, characterizing the current research on regional clusters. While the second core paper considers tertiary data[5] and four different performance variables, the third and fourth core papers concentrate on firm innovativeness based on secondary data. By investigating the specific conditions through which companies can gain particularly from the cluster environment, with a concrete focus on the two Marshallian externalities of knowledge spillovers (cf. Grashof, 2020b) and the specialized labour pool (cf. Grashof, 2020c), the analysis of the underlying sub-research question can in this context be deepened. In other words, compared with the previous two core papers, the third and fourth core papers follow a narrower analysis, focussing on one specific externality (knowledge spillovers and specialized labour pool) and one performance indicator (innovativeness). As such, they address multilevel conditions and the respective relationship with the concrete externalities that have both been ignored in previous literature.

While the empirical results of the previous three core papers clearly constitute direct and interacting effects from various contextual variables from different levels of analysis on firm (innovative) performance, this multilevel heterogeneity within clusters has, however, not been adequately considered in the design of cluster policies (Brakman and van Marrewijk, 2013; Ebbekink and Lagendijk, 2013; Nathan and Overman, 2013). Consequently, in spite of the widespread implementation of cluster policies underpinned by large financial state expenses, the effectiveness of these policies is still rather questionable (Brenner and Schlump, 2011; Lehmann and Menter, 2018; Vicente, 2014). The last step of this dissertation is therefore dedicated to the rather pragmatical aim of answering the following sub-research question:

**Sub-research question 4:** *How can policy effectively promote the performance of firms in clusters?*

By integrating the various rationales for policy interventions with a systematic

[5] With the term meta-analysis, Glass (1976) differentiated between primary, secondary and tertiary data. The latter one is derived from a large collection and integration of published empirical findings (Glass, 1976; Wagner and Weiß, 2014).

overview about moderating variables[6] influencing firm performance in clusters, Grashof (2020d) conceptualizes a targeted (problem-oriented) cluster policy framework. Based on this framework, it is further elaborated that cluster policy should move beyond one-size-fits-all as well as off-the-rack approaches and instead actively identify as well as address problems within clusters in order to effectively foster the performance of firms in clusters. The last core paper of this cumulative dissertation is therefore more dedicated to the missing consideration of the context in current policy approaches (see table 1).

Apart from these research questions that are addressed by the five core papers of this cumulative dissertation, there are additional research questions investigated during the preparation of this doctoral thesis. These side papers, even though not at the centre of this dissertation, will also be presented during this framework paper, since they belong to the overall scientific achievement and, even more importantly, they contribute to broadening and supplementing the research of the general dissertation. For example, they extend the analysis of firm innovativeness by investigating the effect of clusters on the creation of radical innovations (cf. Grashof et al., 2019). Additionally, they deepen the analysis conducted in the third core paper of the influence of basic research by examining whether and under which conditions research institute- or university-industry collaborations are beneficial for radical innovations in German firms (cf. Arant et al., 2019). Moreover, they provide the starting point for the first core paper by conducting a detailed overview of the effects inside and outside clusters (cf. Fornahl et al., 2018).

## 2. Procedure and structure of the dissertation

The concrete research context of the five core papers and the three side papers of this cumulative dissertation is illustrated in figure 2. In general, the five core papers of this cumulative dissertation are grouped into three consecutive thematic modules. The first thematic module deals with a literature-based analysis of the firm-specific cluster effect. It consists of a descriptive meta-analysis (Grashof and Fornahl, 2020) and a statistically oriented meta-analysis (Grashof, 2020a). Both core papers constitute a stepwise development, since the rather descriptive analysis in Grashof and Fornahl (2020) provides the basis for the further and more detailed meta-analytical investigation in Grashof (2020a).

[6] Moderating variables and contextual variables are here used as synonyms, describing a variable that affects the relationship between clusters and firm performance.

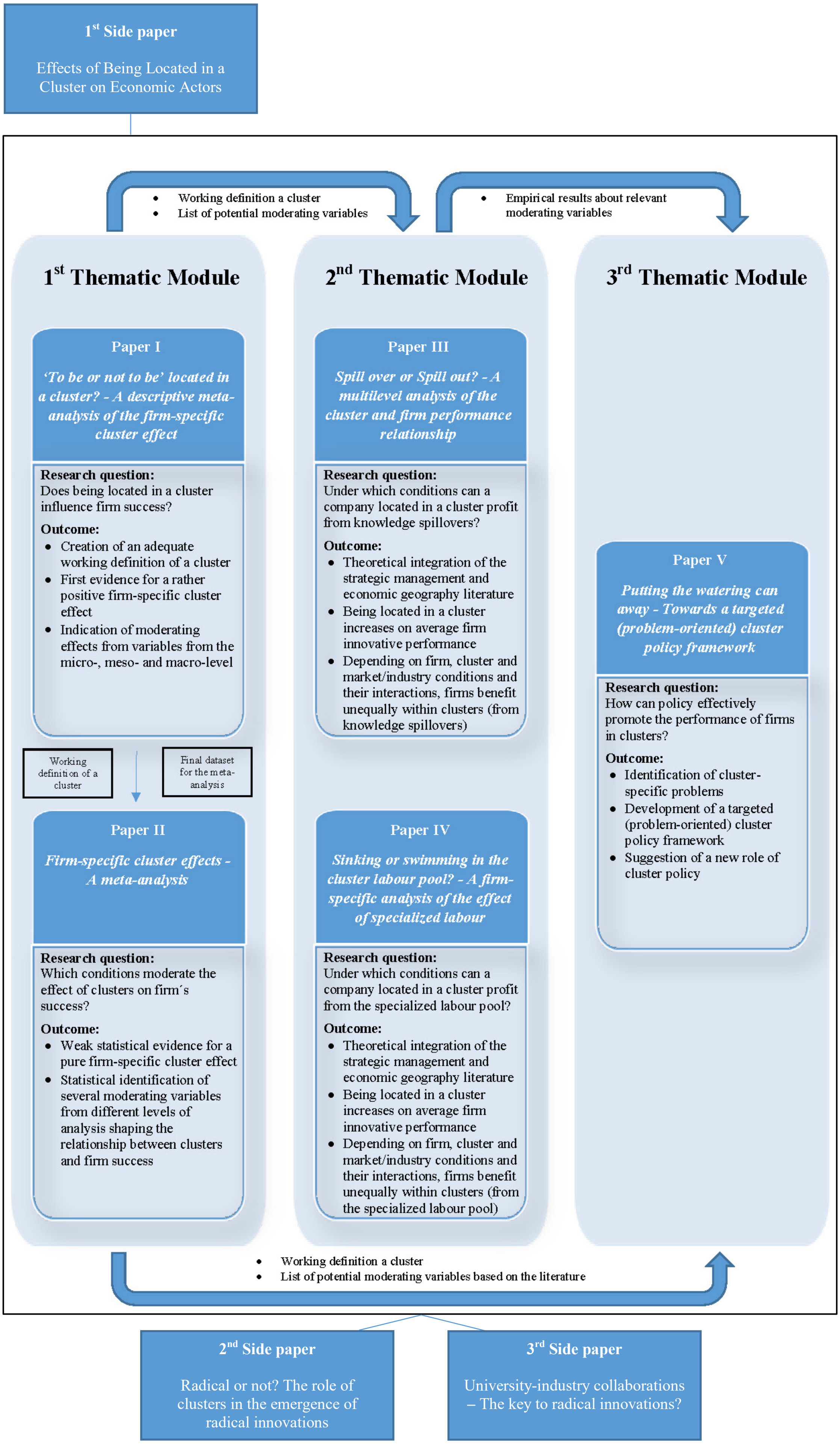


**Figure 2:** Overall structure of the dissertation

As indicated in figure 2, particularly the derived working definition of a cluster as well as the final dataset of matching empirical studies are relevant results that are immediately taken up in Grashof (2020a). By finding first evidence for the moderating influence of contextual variables on the relationship between clusters and firm success, the rather descriptive results of Grashof and Fornahl (2020) additionally show the substantive necessity of diving deeper into the role of these multilevel contextual variables, thereby providing a reasonable explanation for the further analysis in Grashof (2020a).

Taken together, the first thematic module has crucial implications for the two papers in the second thematic module, focussing on secondary data analyses of multilevel conditions shaping the firm´s innovative performance within clusters. Apart from the appropriate working definition of a cluster, the results of the first thematic module offer a systematic list of potential moderating variables from different levels of analysis that have been empirically shown to influence the effect of clusters on firms' success. While this list is rather general, not differentiating between the corresponding externalities nor the performance indicators, it is still a useful orientation for the theoretical and empirical design of Grashof (2020b) and Grashof (2020c), concentrating on specific externalities (knowledge spillovers and specialized labour pool) and performance indicators (firm innovativeness). In particular, the detected relevance of a mix of different moderating variables has motivated the further research of the direct as well as interactive influence of these variables on firm innovative performance with a specific focus on the corresponding externalities, which is at the centre of interest of the second thematic module.

Lastly, the findings of both thematic modules are decisive for the preparation of the fifth core paper, constituting the third thematic module. Besides the underlying cluster definition derived in Grashof and Fornahl (2020), the literature-based findings from the first thematic module as well as the empirical results based on secondary data from the second thematic module are applied in Grashof (2020d). For the corresponding development of the targeted (problem-oriented) cluster policy framework in Grashof (2020d), the findings from both modules regarding multilevel conditions influencing firm performance in clusters are used and integrated with the comprehensively identified general rationales of policy interventions. As a result, six cluster-specific problems from different levels of analysis can be determined, which, in combination with the respective policy interventions, form the suggested cluster policy framework.

A comprehensive overview of the publication status of both the core and the side papers as well as the share that the author had in creating the respective papers of this cumulative dissertation are shown in table 2.

**Table 2:** Publication status and declaration of own contribution

| Paper | Share by the author | Type of participation | Status |
|---|---|---|---|
| 1st Core paper: Grashof and Fornahl (2020) | 95% | • Introduction<br>• Theoretical foundation<br>• Methodology development<br>• Creation of the dataset<br>• Analysis of the data<br>• Interpretation of the results | • Published in Working Papers on Innovation and Space<br>• Revised and resubmitted to Annals of Regional Science (24.01.2020) |
| 2nd Core paper: Grashof (2020a) | 100% | • Single authorship | • Published in Papers in Regional Science |
| 3rd Core paper: Grashof (2020b) | 100% | • Single authorship | • Published in Papers in Evolutionary Economic Geography<br>• Submitted to Industry and Innovation (07.02.2020) |
| 4th Core paper: Grashof (2020c) | 100% | • Single authorship | • Published in Jena Economic Research Papers<br>• Submitted to Journal of Management (10.04.2020) |
| 5th Core paper: Grashof (2020d) | 100% | • Single authorship | • Published in Papers in Innovation Studies<br>• Submitted to Research Policy (20.12.2019) |
| 1st Side paper: Fornahl et al. (2018) | 45% | • Introduction<br>• Theoretical foundation<br>• Literature review<br>• Conclusion | • Published Monography |
| 2nd Side paper: Grashof et al. (2019) | 45% | • Introduction<br>• Theoretical foundation<br>• Creation of the dataset<br>• Analysis of the data<br>• Interpretation of the results | • Published in European Planning Studies |
| 3rd Side paper: Arant et al. (2019) | 30% | • Methodology development<br>• Creation of the dataset<br>• Analysis of the data<br>• Interpretation of the results | • Published in Review of Regional Research |

In general, it can be seen that all papers are published. In the case of the core papers, four articles are published in working paper series[7] and one article is already published in a journal. From the three side papers, two are published in a journal and one in a monography. While all of the side papers are written in collaboration, all but one of the core papers are written in single authorship. The concrete content and the main contributions of each paper, including the three side papers, are concisely summarized and interpreted in the following.

### 2.1. First thematic module

The underlying motivation of the two core papers of the first thematic module arises from the tension between the already substantial financial support of cluster activities and the still contradictory scientific results about the firm-specific cluster effect (EFI, 2015; Malmberg and Maskell, 2002; Martin and Sunley, 2003). Despite the relatively long cluster research tradition, creating thousands of scientific journal papers (Lazzeretti et al., 2014), the concrete reasons for these inconclusive results have not been comprehensively investigated yet (Frenken et al., 2015), thereby preventing general conclusions about the firm-specific cluster effect. Consequently, by reconciling previous empirical findings, the first thematic module of this cumulative dissertation primarily aims to address the following two research questions:

- Grashof and Fornahl (2020): *Does being located in a cluster influence firm success?*
- Grashof (2020a): *Which conditions moderate the effect of clusters on firm´s success?*

In order to answer these research questions, a meta-analytical approach is conducted. In general, a meta-analysis can be defined as the "(…) analysis of analyses." (Glass, 1976, p. 3), meaning that it statistically synthesizes empirical evidence from multiple studies examining a common research question (Eisend, 2004; Florax et al., 2002; Quintana, 2015; Wagner and Weiß, 2014). Compared with traditional narrative reviews, although sometimes used as synonyms, it offers several advantages (Cooper and Hedges, 2009; Wagner and Weiß, 2014). The underlying statistical nature and the explicit selection criteria of meta-analyses form in this context one of the main advantages, because hereby a potential subjective bias is minimized and the transparency as well as reproducibility is strengthened.

[7] At the same time, three of these articles are also submitted to journals and one is already revised and resubmitted.

Conversely, in the case of traditional narrative reviews, the related procedure is often rather insufficiently standardized. Instead it is quite common that the reviewer subjectively selects which articles to include and what weights to attach to the corresponding results (Fang, 2015; Melo et al., 2009; Stanley and Jarrell, 1989; Wagner and Weiß, 2014). By applying a meta-analytical approach, it is therefore on the one hand possible to reconcile the contradictory empirical results as well as to investigate the cluster effect on firm success. On the other hand, it is feasible to likewise examine the respective moderating effects. However, as always there are of course some general limitations to this methodical approach. Meta-analyses are primarily based on empirical results, so that theoretical contributions cannot be explicitly considered. Furthermore, the appropriate integration of the empirical results requires that there also exist a sufficiently high number of different research articles. If there are too few studies to integrate and statistically analyse, a meta-analysis makes indeed no sense (Eisend, 2004; Valentine et al., 2010). In light of the relatively large sample size within Grashof and Fornahl (2020) and Grashof (2020a), this limitation is not seen as a major concern. Another concern, however, is the uniformity problem, also called the "apples and oranges" problem, of a meta-analysis. This concern stems from the fact that empirical studies can be integrated within a meta-analysis, although they are incomparable, e.g. in terms of the employed method and the operationalization of the used variables. Some researchers, especially from medicine, therefore apply a rather strict approach and only analyse perfect replications (Borenstein et al., 2009; Eisend, 2004; Florax et al., 2002). However, according to Glass et al. (1981), such a strict procedure is senseless, because, except for the standard error, identical studies will derive similar empirical results, making a statistical integration of these results unnecessary. Additionally, the methodological stringency comes at the expense of a smaller sample size of the meta-analysis. As such, perfect replications are rather scarce in the behavioural and social sciences (Eisend, 2004). In line with these disciplines, empirical studies that are similar but not identical, for example regarding their methodological approach, are here integrated and the possible resulting heterogeneity is explained by moderating variables, thereby following the argument by Smith et al. (1980): "Indeed the approach does mix apples and oranges, as one necessarily would do in studying fruit." (Smith et al., 1980, p. 47).

While a meta-analysis has already become a standard method in various disciplines such as medicine, in the case of economics it has only recently been applied (Borenstein et al., 2009; Melo et al., 2009). To the author´s knowledge, there is only one article that applied a meta-analytical approach to reconcile and thereby understand the contradictory empirical results concerning the firm-specific cluster effect (cf. Fang, 2015). Nevertheless, both core papers of the first thematic module differ remarkably from Fang (2015), since they exclusively focus on firm-level effects, their scope of considered performance variables and literature are more extensive and they are both based on a more precise selection process (Grashof and Fornahl, 2020; Grashof, 2020a). In view of the heterogeneity in the empirical design of the considered studies (e.g. the measurement of the dependent/independent variables) a meta-regression cannot be correctly conducted (De Groot et al., 2007; De Groot et al., 2016; Eisend, 2004). Based on the available standardized information about the statistical significance, both papers of the first thematic module rely however on other more adequate meta-analytical approaches.[8]

The first core paper of this cumulative dissertation, "'To be or not to be' located in a cluster? – A descriptive meta-analysis of the firm-specific cluster effect"[9], investigates the alleged effect of clusters on firm performance by conducting a descriptive meta-analysis. Before that, the ongoing theoretical discussion about cluster (dis-)advantages as well as an adequate working definition of a cluster is elaborated. The latter aspect is particularly important for a correct implementation of a meta-analysis, because it is necessary that all considered empirical studies have the same underlying cluster understanding so that a possible bias from other networklike effects can be avoided. Due to a missing common definition, a comparative empirical approach, being explicitly inductive, is applied. By conducting a profound literature overview about cluster definitions used in the literature, several similarities can be identified and are summarized in the following four central elements: Spatial connection, thematic connection, interdependencies as well as complementary institutions and trust. Since the latter element is only mentioned in a comparatively small number of definitions, complementary institutions and trust are not further considered within the following working definition of a cluster:

> "Clusters are defined as a geographical concentration of closely interconnected horizontal, vertical and lateral actors, such as universities, from the same industry that are related to each other in terms of common resource and knowledge base, technologies and/or product-market." (Grashof and Fornahl, 2020, p. 10f.).

[8] For a good overview see in this context for example De Groot et al. (2007).

[9] The complete article can be found in the second chapter of this cumulative dissertation (on page 58 and following).

After establishing an adequate working definition of a cluster, the dataset for the descriptive meta-analysis is constructed. For this purpose, four different publication databases (Web of Science, Google Scholar, Ebsco, SSRN) are used, thereby avoiding a potential database bias and contributing to a comprehensive literature collection, including working papers. The actual search strategy relies on keyword combinations of (1.) “cluster” or “agglomeration”[10] and (2.) one of the four performance variables that are used for the measurement of firm success (innovativeness, productivity, survival and employment growth) and (3.) “firm” or “company”. This search strategy is conducted for all years and all document types. The resulting broad collection of literature is then step by step further processed within an extensive selection and exclusion process. The corresponding inclusion criteria are thereby as follows: (1.) Studies need to be empirical. (2.) The cluster understanding of the selected studies must correspond to the three identified key characteristics of a cluster. (3.) Relative cluster measures have to be at least based on the national average. (4.) Empirical studies using working wages or earnings at the establishment level as measures for firm productivity are excluded, because a rise in productivity does not directly imply a wage increase. (5.) The analytical focus has to be on the firm-level. At the end, the final dataset consists of 168 empirical studies. More or less half of these studies, apart from those using employment growth as the corresponding performance indicator, were published between 2012 and 2016. Hence, it can be shown that the firm-specific perspective has indeed only recently gained some attention in the empirical analysis of cluster effects, thereby confirming the postulated research direction of this dissertation. For detecting the estimated direction of cluster effects on the four considered performance variables and for avoiding a possible overvaluation of studies containing several regressions, a study-level vote counting is conducted (De Groot et al., 2007; Fang, 2015). For this purpose, all available estimates in each paper are grouped into seven classes: positive (always referring to significant positive effects), insignificant, negative (always referring to significant negative effects), positive & insignificant, negative & insignificant, negative & positive as well as negative, positive & insignificant. Despite the existing criticism of the vote counting method (e.g. missing consideration of the sample size and the actual effect size), in light of the relatively broad research question and the available information, the chosen methodological approach is argued to adequately serve the purpose of the first core paper of this dissertation

[10] Agglomeration has been quite often used as a synonym for clusters (e.g. Delgado et al., 2010; Martin et al., 2011; McCann and Folta, 2011).

(De Groot et al., 2007; Hedges and Olkin, 1980; Stanley, 2001).

On the one hand, the results of the study-level vote counting indicate a tendency towards a rather significant positive cluster effect on firm success. But on the other hand, the results in general appear to be rather mixed, particularly between the four performance variables, providing first hints for the influence of moderating variables. By re-grouping the vote-counting into significant positive, insignificant and significant negative estimation results[11], these tendencies are further solidified. Nearly 40% of the considered empirical studies find evidence at least once for a positive cluster effect on firm performance. Nevertheless, this picture changes when the corresponding performance variables are investigated separately. While the effects on employment growth and survival are most frequently found to be insignificant, in the cases of innovativeness and productivity, significant positive estimation results are most often reported. These differences are explained by the two-sided effect of the high competition within clusters, promoting firms' innovativeness and productivity but hampering firms' employment growth and survival through, for instance, labour poaching (Audia and Rider, 2010; McCann and Folta, 2008; Porter, 1998; Sorenson and Audia, 2000). Another reasonable explanation is the unequal consideration of contextual variables, which is further investigated by focussing on the model level.[12] Thereby it can be shown that there is relatively little evidence for a pure firm-specific cluster effect, meaning that being located in a cluster, at least in most cases, does not automatically lead to a positive or a negative effect on firm performance. Instead, it can be stated descriptively that several variables from the micro- (firm-level), meso- (cluster-level) and macro-level (market-/industry-level) directly or interactively moderate the relationship between clusters and firm performance. The specific industry constitutes one of the most prominent contextual variables. By grouping the different industries into low-technologies, medium-low-technologies, medium-high-technologies and high-technologies, it can be pointed out that a negative firm-specific cluster effect is more frequently occurring in low-tech industries than in high-tech industries. Additionally, within the aggregated industry groups a relatively high inter-industry variation can be found, emphasizing the need to further consider the specific industry characteristics, such as the pace of market and technology evolution, in future empirical studies.[13] Moreover, by studying the interaction effect between geographical distance and the industry context, it can be determined that

[11] For example, a study that previously reported positive and insignificant effects will be consequently counted twice. One time for a positive and a second time for an insignificant effect.

[12] Consequently, the corresponding number of observations exceeds the number of considered empirical studies, because one study may include several empirical models.

[13] This identified need is empirically addressed within Grashof (2020b) and Grashof (2020c).

high geographical distance is in high-tech and low-tech industries rather inhibitory for a positive firm-specific cluster effect, while low and medium distance are more frequently beneficial for companies in high-tech industries. All in all, it can be resumed that the first core paper of this dissertation makes a first important contribution to closing the still prevalent research gap concerning the effect of clusters on firms performance by reconciling the contradictory empirical findings and descriptively investigating potential contextual influences from three different levels of analysis. Particularly the latter aspect, indicating that there exist firm performance differentials within clusters, marks the starting point for the further empirical analysis of the underlying contextual influences conducted in the second thematic module of this dissertation.

Since the underlying results of Grashof and Fornahl (2020) are only descriptive, they are however first taken up and methodologically extended in the second core paper of this dissertation in order to provide a more detailed statistical analysis of potential moderating variables. The second core paper of this dissertation, “Firm-specific cluster effects – A meta-analysis”[14], therefore examines the concrete conditions that moderate the effect of clusters on firm success by applying a meta-analysis. As already indicated at the beginning of this section, the heterogeneity in the empirical design of the considered empirical studies makes a meta-regression of the “true” effect size inappropriate in this context (De Groot et al., 2016; Eisend, 2004). Nevertheless, the available information about the significance level offers the opportunity to investigate statistically the determinants of significant positive and negative estimation results of being located in a cluster (e.g. De Groot et al., 2007). The corresponding empirical investigation consists of bivariate correlation analyses and of logistic regressions. The underlying full sample consists of 2,201 statistical models from 168 empirical studies.

By conducting a bivariate correlation analysis according to Pearson, the weak evidence for a pure direct firm-specific cluster effect previously identified in Grashof and Fornahl (2020) is further reinforced. Across all four performance variables, no significant correlation between a pure cluster effect, meaning the direct effect in absence of moderating influences, and the positive, insignificant and negative estimation results, can be determined. Hence, it can be shown that the relationship between clusters and firm performance is more complex than conventionally assumed. Consequently, the determinants of a positive firm-specific cluster effect,

[14] The complete article can be found in the third chapter of this cumulative dissertation (on page 105 and following).

measured by a dummy variable indicating a significant positive estimation result on the cluster measure, are examined in greater detail by conducting a logistic regression.[15] The relatively high number of missing values in some cases requires separate regression analyses. Since in the corresponding cases over 50% of the data is missing, the standard procedure of an imputation of the missing data is not valid in this context, as it may introduce or increase bias (Lee et al., 2016; McNeish, 2017). In total, six different regression models are analysed. In the baseline model, variables, not explicitly considered within the original studies, are investigated. The corresponding results indicate for instance that, compared with survival as the baseline variable, the performance variables employment growth, productivity and innovativeness assert a significant positive influence on the probability of identifying a positive firm-specific cluster effect. As such, previously derived (policy) implications that are only based on one performance variable have to be reinterpreted in a more cautious way, as they are not generalizable for different performance variables. It can therefore be concluded that future research should preferably consider different performance variables in order to gain a more comprehensive understanding about the relationship between clusters and firm performance.[16] An additional variable that has normally not been explicitly considered in the original studies refers to the country of investigation. In this context, two distinctive patterns can be identified. On the one hand, in the Western European countries of Germany and the Netherlands, the probability for a positive firm-specific cluster effect is significantly reduced. On the other hand, in the Anglo-Saxon countries of the United Kingdom and the USA, evidence for a rather beneficial influence on the probability of determining a positive firm-specific cluster effect is found.[17] Based on the concept of ‘varieties of capitalism’ (e.g. Hall and Soskice, 2001), this pattern is explained by highlighting that the Anglo-Saxon countries, being rather competition-driven economies, are a more favourable ground for clusters, because they are more flexible and adaptive than coordinated market economies, such as Germany (Asheim, 2007; Cooke, 2001; Sternberg et al., 2010). In addition, it is argued that potential policy failures (e.g. Bach and Matt, 2005; Hudson et al., 2019) are more likely to happen in coordinated market economies, since in these economies the state forms an essential force. The same reasoning also applies to the similar dualistic pattern detected in Japan and China. Furthermore, the quality of the used methods of the underlying empirical studies is

[15] The corresponding results are controlled by separate bivariate correlation analyses.

[16] The side paper of this dissertation, Grashof et al. (2019), focussing on an alternative measure for firm innovative performance, namely radical innovations, goes in that direction.

[17] While being insignificant in the case of a positive firm-specific cluster effect, the influence of the USA as the country of investigation becomes significantly negative in the case of a negative firm-specific cluster effect.

also investigated in the baseline model. The corresponding results show that the use of high quality methods, such as panel-regressions and multilevel analyses, significantly reduces the probability of asserting a negative firm-specific cluster effect while also significantly increasing the likelihood of determining a positive cluster effect on firm performance. In light of the influence of the chosen methods, it is therefore suggested, if possible, to utilize a mix of different methodological approaches. Apart from these three variables not explicitly considered in the original studies, other moderating variables from three different levels of analysis are identified and thoroughly analysed. On the firm-level (micro-level), evidence is found that small and medium-sized enterprises (SMEs) have a significant higher probability to realize a positive cluster effect than large companies. The results therefore point towards the argument that the complex internal structure and the related inflexibility prevents large firms from integrating the resources available within the corresponding cluster environment, thereby hampering potential gains (e.g. Knoben et al., 2015; McCann and Folta, 2011; Miller and Chen, 1994). By using the same industry classification as in Grashof and Fornahl (2020), on the industry-level (macro-level)[18], it is detected that firms in high-tech industries have a higher likelihood for a positive performance effect in clusters than low-tech firms. This reinforces in turn the previous descriptive findings of the first core paper of this dissertation and can be explained with the specific characteristics of high-tech industries in terms of their knowledge intensity as well as their related need of qualified labour (e.g. Brenner and Mühlig, 2013; Cooke, 2002; Tödtling et al., 2006). Surprisingly, this finding does not hold true for firms in medium-high-tech and medium-low-tech industries, as in both industries it is less likely, compared with low-tech industries, to realize a positive firm-specific cluster effect. The different requirements of these industries are in this context presented as reasonable explanations. It is argued that both forms of medium-high-tech industries are stuck in the middle, because they compete against high-tech industries for the most adequate talents while firms from low-tech industries can simply free-ride by using the available knowledge or technology and adapt it to their concrete market niche (e.g. Rammer, 2011). Moreover, interacting effects[19] between the moderating variables have been additionally tested. In the case of the industry context, the interaction effect together with the geographical distance of firms is examined. It can be shown that low distance particularly contributes to the realization of a positive

[18] Due to the lack of variance, no further statistical analysis could be performed for the cluster-level (meso-level).

[19] In this context, an interaction effect between firm size and industry means for example that the interaction term between firm size and the corresponding measurement for regional clusters in one specific industry setting asserts an influence on one of the four considered performance variables.

firm-specific cluster effect in high-tech and not so much in low-tech industries. Conversely, high distance has a negative, but insignificant, influence in high-tech industries on the chance of achieving such an effect. Due to their knowledge intensity, firms in high-tech industries profit particularly from the geographically close concentration, as they also rely on tacit knowledge that is most efficiently exchanged through face-to-face contacts being more pronounced in close geographic proximity (Cooke, 2002; Daft and Lengel, 1986; Tödtling et al., 2006). Another interesting interaction effect can be identified between a company's headquarters location and the industry context. Evidence is found that the likelihood for a positive firm-specific cluster effect is significantly higher in low-tech industries when a firm´s headquarters is locally and not remotely situated. The already mentioned relevance of local embeddedness (e.g. Meyer et al., 2011; Mudambi and Swift, 2012) can thus be emphasized, because it is likely that the engagement in cluster activities is more pronounced for firms having their headquarters established locally.
In total, it can be resumed that the second core paper of this dissertation constitutes a reasonable and useful extension of Grashof and Fornahl (2020), because it provides a more statistically oriented analysis of the determinants of a positive firm-specific cluster effect. The corresponding empirical results of the underlying meta-analysis indicate in more detail that there exist several moderating variables from three different levels of analysis that directly or interactively shape the relationship between clusters and firm performance. The second core paper therefore contributes to a better understanding of the so far contradictory empirical results concerning the firm-specific cluster effect and thereby enriches the current discussion about the conditions through which firms profit differently from the cluster environment.

In general, future research can build on the results of both papers in the first thematic module of this dissertation, as they provide a systematic and comprehensive overview about potential moderating variables that need to be considered when analysing research questions concerning regional clusters. Thus, they are instrumental in bringing forth the underlying foundation of the cluster concept, which appears to be particularly crucial in light of the already widespread implementation of this concept (Frenken et al., 2015; Martin and Sunley, 2003).

### 2.2. Second thematic module

Since the underlying results of Grashof and Fornahl (2020) as well as Grashof (2020a) are rather broad (see also table 1), they are taken one step further in the second thematic module of this dissertation by using them to inform secondary data analyses, which focus on specific externalities (knowledge spillovers and specialized labour pool) as well as on one concrete performance indicator (innovativeness). The underlying motivation for Grashof (2020b) and Grashof (2020c), constituting the second thematic module of this dissertation, is rooted in the missing systematic consideration of contextual variables that may moderate firm performance within clusters (e.g. Frenken et al., 2015). Despite the still prevalent assumption of equal gains in clusters (e.g. Porter, 1998), the results of the first thematic module as well as of studies dealing with firm performance differentials in general (e.g. Dyer and Singh, 1998; Van Oort et al., 2012; Vega-Jurado et al., 2008) clearly emphasize the need to comprehensively analyse the influence of multilevel variables on firm performance within clusters. Especially the results of the first thematic module provide evidence that so far there are only few studies that consider potential moderating variables from different levels of analysis[20]. Instead, at most only individual factors, such as firm size or cluster size, have been investigated. As a consequence, it remains unclear, particularly in light of possible interactions between the different levels of analysis, under which conditions companies can profit from being located in a cluster. Frenken et al. (2015) therefore assert correctly in this context that

> “(…) the main research challenge at the interface of industrial dynamics and economic geography is therefore no longer to look for evidence of localization economies by simply associating indicators of industrial dynamics with indicators of clustering, but rather to ask the question which type of firms profit from clustering and under what conditions?” (Frenken et al., 2015, p. 20).

Moreover, the results of the first thematic module, providing an overview across several externalities and performance indicators, additionally show the need to focus on specific externalities and performance indicators in this context, since the corresponding role of contextual influences is likely to vary according to the regarded externalities and performance indicators. In line with the invocation of Frenken et al. (2015) and following an “interactionist approach” suggested by Beugelsdijk (2007), the two papers of the second thematic module of this dissertation therefore strive to advance the currently limited understanding about contextual factors influencing the

[20] The content analysis of the keywords carried out at the beginning of this framework paper points in the same direction.

firm´s innovative performance[21] within clusters, by answering the following research questions (belonging to the third sub-research question of this cumulative dissertation):

- Grashof (2020b): *Under which conditions can a company located in a cluster profit from knowledge spillovers?*
- Grashof (2020c): *Under which conditions can a company located in a cluster profit from the specialized labour pool?*

In order to answer these research questions, in a first step it is necessary to arrive at a better theoretical understanding of these factors (Frenken et al., 2015). Apart from using the insights of the first thematic module of this dissertation, theoretical streams from the strategic management and the economic geography literature are therefore synthesized, thereby conceptualizing potential moderating variables from three different levels of analysis: micro-level (firm-level conditions), meso-level (cluster-level conditions) and macro-level (market-/industry-level conditions). The resource-based view (RBV) is one of the most well-known theoretical perspectives in the research field of strategic management (Newbert, 2007; Šarić, 2012; Steffen, 2012). The emergence of the RBV can be attributed to the economist Edith Penrose, who recognized in her pioneering work from 1959 the importance of internal resources for the competitive position of a company (Newbert, 2007; Penrose, 1959; Wernerfelt, 1984). The later contribution of Barney (1991) is, however, considered as the first comprehensive theoretical framework of the resource-based view (Barney, 1991; Newbert, 2007). Based on previous arguments by among others Penrose (1959) and Wernerfelt (1984), he formulates two essential assumptions:

(1.) Resources are distributed heterogeneously between companies.
(2.) Resources are perfectly immobile.

Both assumptions lead to the existence of different resource endowments and to its persistency over time. From this asymmetry arises ultimately the possibility of achieving a resource-based competitive advantage. In the RBV, the realization of competitive advantages is therefore related to the resources a firm owns and how

[21] Since firm innovativeness is one of the most frequently used performance indicators (e.g. Bell, 2005; Hervas-Oliver et al., 2018; McCann and Folta, 2011) and due to data constraints, both core papers focus on the innovative performance of firms within clusters.

these resources[22] are utilized (Barney, 1991; Newbert, 2007; Steffen, 2012). Nevertheless, this does not mean that any given resource holds the potential to contribute to a firm´s competitive advantage. Instead it depends on the attributes of firms' resources, namely whether they are valuable, rare, non-substitutable and imitable (Barney, 1991; Šarić, 2012; Steffen, 2012). Resources are valuable if they allow a company to develop and implement strategies that improve its efficiency and effectiveness. Furthermore, regarding the corresponding product or service resulting from these strategies, it is crucial to note that it is the market that ultimately determines the value of these strategies. Firms can for instance allocate resources to create a superior product but fail to generate a competitive advantage if this product does not convince customers to purchase it (Barney, 1991; Barney and Clark, 2007; Šarić, 2012). The value of firms' resources is a necessary but not sufficient condition for a competitive advantage. Valuable resources that are possessed by a relatively large number[23] of competing firms cannot be a source of competitive advantage for any of them, because there are no differences in terms of their resource endowments. This would in turn create a competitive parity. Consequently, firm resources need also to be rare (Barney, 1991; Šarić, 2012). In addition, it can be stated that a competitive advantage can only be long-lived if it is likewise non-substitutable and imitable (Barney, 1991; Newbert, 2007; Šarić, 2012). The former one refers to the existence of strategically equivalent strong resources that can be used separately to implement the same strategies. This can be particularly the case in industries with a fast pace of technology evolution, facing the continuous replacement of previously established technologies through more efficient disruptive technologies (Barney, 1991; Collis, 1994; Šarić, 2012). The criteria of imitable resources involves the argument that in order to obtain a rather sustained competitive advantage, competitors should not be able to easily imitate the underlying critical resources (Barney, 1991; Šarić, 2012). In general, there are three reasons for such an imitability: (1.) The unique historical conditions for the resource creation, such as the accumulated knowledge stock of a firm or a firm´s organizational culture. Due to its path dependency and its time consumption, such resources are quite difficult to imitate (Barney, 1991; Dierickx and Cool, 1989; Šarić, 2012). (2.) Causal ambiguity concerning the way in which a resource or a resource

[22] In line with the widely used definition by Barney (1991), resources are here defined as "(…) all assets, capabilities, organizational processes, firm attributes, information, knowledge, etc. controlled by a firm that enable the firm to conceive of and implement strategies that improve its efficiency and effectiveness." (Barney, 1991, p. 101).

[23] It is however quite difficult to assess how rare a valuable resource must be in order to generate a competitive advantage. Barney (1991) therefore defines a resource as valuable as long as the number of companies owning it is less than the number of firms needed for the creation of a perfectly competitive market.

bundle contributes to a competitive advantage. Consequently, potential imitators cannot identify exactly which resources actually represent the underlying cause for the competitive advantage (Barney, 1991; Rumelt, 1984; Šarić, 2012; Starbuck, 1992). (3.) Social complexity of resources means that complementary resource bundles consisting of tangible (e.g. machines) and intangible resources (e.g. expert knowledge) create a barrier to imitation due to their pronounced pattern of interaction (Barney, 1991; Šarić, 2012).

Originally rather static, the RBV has subsequently developed into a dynamic concept emphasizing more the underlying dynamic capabilities of firms (e.g. Teece et al., 1997) that are necessary to effectively exploit the possessed resources (Newbert, 2007). Moreover, more nuanced advancements of the RBV, such as the knowledge-based view concentrating particularly on the firm´s knowledge, have been additionally developed (e.g. Grant, 1996a).[24]

Apart from its sometimes broad and inconsistent terminology (Steffen, 2012), the RBV has also been criticized for its assumption of ownership and control, being embedded in most applied resource definitions. Such a conceptualisation is argued to be inadequate for an evaluation of a firm´s competitive advantage, particularly in view of the increasing prevalence of inter-firm alliances in today´s business world (Lavie, 2006). In response to this criticism, an extension of the RBV called the relational view (RV) has been developed. The RV focuses on network resources which are jointly used in a partnership amongst firms and on the corresponding relational rents derived out of these collaborations (Dyer and Singh, 1998; Gulati, 1999; Lavie, 2006; Steffen, 2012). According to one of the pioneers of this theoretical approach, Dyer and Singh (1998), relational rents are defined as: "(…) supernormal profit jointly generated in an exchange relationship that cannot be generated by either firm in isolation and can only be created through the joint idiosyncratic contributions of the specific alliance partners." (Dyer and Singh, 1998, p. 662). This typology has been taken up and further differentiated by Lavie (2006). He distinguishes between four types of rents extracted by a focal firm in an alliance:

(1.) Internal rents which are private benefits that are exclusively enjoyed by the focal firm. These rents are based on non-shared focal firm resources as well as shared resources.

(2.) Appropriated relational rents follow basically the same notion as originally

[24] Since both approaches can be seen as slight advancements of the RBV that basically follow the same core logic, they will not be discussed in detail here (Barney and Clark, 2007; Šarić, 2012).

proposed by Dyer and Singh (1998) and refer to the common gains for the corresponding alliance partners through combination, exchange and co-development of resources.

(3.) Inbound spillover rents can arise out of both the shared and non-shared resources of the alliance partner. Apart from the access to shared resources, alliances also provide unintended opportunities to appropriate non-shared resources of the partner.

(4.) Outbound spillover rents go in the opposite direction. As in the case of the partner, the non-shared resources of the focal firm can also face unintended leakages that benefit exclusively the alliance partner.

Since the RV constitutes an extension of the RBV, its main assumptions remain basically the same (e.g. heterogeneity and immobility of resources). However, due to its relational focus, further assumptions are added stemming from transaction cost theory (e.g. Coase, 1937;  Coase, 1984; Williamson, 1975; Williamson, 1985), which primarily deals with make or buy decisions (e.g. should a firm outsource some activities or keep them in-house?) (Steffen, 2012). In line with the transaction cost theory, transactions between actors are influenced by their bounded rationality and their opportunistic behaviour. In other words, normally firms do not have full information, thus preventing the best rational decision. Moreover, since firms pursue a rent-seeking behaviour, they behave opportunistically in order to maximize their rents (Lavie, 2006; Steffen, 2012; Williamson, 1996). As a consequence of these two additional assumptions, effective governance mechanisms (safeguards) reducing transaction costs, are key for the creation of relational rents (Dyer and Singh, 1998; Mody, 1993). Additionally, it has been argued that the scope of the alliance partners' investments in relation-specific assets (e.g. common communication platform or production facility) is also an essential determinant of the corresponding relational rents (Duschek, 2004; Dyer and Singh, 1998; Lavie, 2006; Steffen, 2012). Another way of generating relational rents is the implementation of well-functioning interfirm knowledge-sharing routines permitting the transfer, recombination or creation of specialized knowledge (Duschek, 2004; Dyer and Singh, 1998; Grant, 1996b). Lastly, through an efficient use of the complementary resource endowments of the alliance partners, relational rents can additionally be achieved (Dyer and Singh, 1998; Lavie, 2006).

A related research stream is the social network theory, which particularly emphasizes the structural dimensions of the overall cooperation network (Lavie, 2006; Wasserman and Faust, 1994). Important contributions in this context include for instance the measure of embeddedness (e.g. Granovetter, 1985; Uzzi, 1996), the notion of structural holes (e.g. Burt, 1992) and several centrality measures (e.g. Bonacich, 1972; Freeman, 1979). Various types of networks (Kudic, 2015), such as alliance (e.g. Koka and Presscott, 2008; Phelps, 2010), knowledge (e.g. Saviotti, 2011) and innovation networks (e.g. Cantner and Graf, 2011), have been investigated over the years. Nevertheless, the underlying assumption that the network structures influence the firm´s actions and performance remains thereby the same (e.g. Ahuja, 2000; Powell et al., 1996). One central argument in this context refers to the transfer of knowledge. It has for instance been emphasized that depending on the network position, firms may have more or less access to the corresponding knowledge flows within the network. As such, differences in network positions can contribute to explaining the heterogeneity in firm performance (Bell, 2005; Ferriani and MacMillan, 2017; Zaheer and Bell, 2005).

The last theoretical stream that is used for the derivation of potentially influential contextual variables is the market-based view (MBV), which is mainly driven by Porter´s contributions (Porter, 1980; Steffen, 2012).[25] In contrast to the RBV, the market-based view takes an “outside-in” perspective. A competitive advantage is therefore not determined by the firm´s internal resources as suggested in the RBV but by external factors such as the market environment. As such, within the MBV, firms are regarded as being homogenous (Porter, 1980; Porter, 1985; Steffen, 2012). However, despite their differences, it has been argued that both theoretical perspectives complement each other and cannot be viewed in isolation (Freiling, 2001; Steffen, 2012). In order to achieve the aim of a comprehensive analysis of moderating influences of firm performance within clusters, firms’ resources and the market/industry environment are thus taken into consideration.

The previously described theoretical perspectives underpin in general the conceptualisation of potential moderating variables from three different levels of analysis. Based on Marshall´s pioneering contribution, these variables are however conceptualized with a specific focus on knowledge spillovers (cf. Grashof, 2020b) and on specialized labour pools in clusters (cf. Grashof, 2020c). In view of the conceptualisation of multilevel variables, for the empirical investigation, focussing on

[25] Porter (1980) developed in this context the so-called five forces-framework in order to analyse the market/industry structure which is, according to his framework, influenced by the threat of new entrants, the bargaining power of buyers and suppliers, the threat of substitutes as well as the rivalry among competitors.

the German context, both core papers therefore use and integrate various data sources, ranging from firm-level data (Stifterverband) to data about subsidized R&D collaborations (Germany subsidy catalogue) to patent data (PATSTAT database). For the cluster identification, the actor-based approach by Brenner (2017) is applied, calculating a cluster index for each company on the community level ("Gemeineebene"). This approach offers two main advantages. It avoids the Modifiable Area Unit Problem (MAUP), as, unlike in the case of frequently used regional specialization quotients, it is free of predefined borders. Moreover, by considering the geographical distance to all other firms from the same industry as a weight, it prevents a potential overvaluation of one large company (Brenner, 2017; Scholl and Brenner, 2016). As an adequate cluster threshold, the widely used procedure of the European Cluster Observatory is applied, suggesting a value of two (European Cluster Observatory, 2018; European Commission, 2008).

The third core paper of this cumulative dissertation, "Spill over or Spill out? – A multilevel analysis of the cluster and firm performance relationship"[26], thereby investigates the conditions through which firms can gain from being located in clusters based on a dataset of 11,889 firms in Germany, including 1,391 firms that are located within a cluster. Since year-to-year variability, being omnipresent in micro-level data, may introduce potential measurement errors, an OLS regression of the across panels´ averages (the between estimator approach) is employed to analyse the data (Cameron and Trivedi, 2005; Gould, 2019; Rigby and Brown, 2015; Stern, 2010). Furthermore, due to the hierarchical nature of the underlying database, a cluster correction of the standard errors is likewise considered in the applied empirical approach (McNeish, 2014; Moulton, 1990). Consequently, several empirical findings can be made. Besides providing evidence that being located in a cluster increases on average firm innovative performance, it can also be shown that companies indeed profit unequally from the cluster environment. Firms with a medium level of innovation capabilities and knowledge similarity with the cluster knowledge stock profit for instance the most from the available knowledge spillovers within the corresponding cluster environment. On the firm-level, it can be further determined that in general the number of firm cluster external relationships does not have a significant influence by itself on firm innovative performance in clusters. But it does have a relevant influence when the geographical position within the cluster is also taken into consideration. This result can be explained with the statistically higher

[26] The complete article can be found in the fourth chapter of this cumulative dissertation (on page 142 and following).

number of firm cluster internal relationships within the centre of a cluster. As such, the risk for an innovation-hampering lock-in situation is higher in the centre than in the periphery of a cluster. Cluster external relations are thus particularly important for firms located in the cluster core, as they offer a crucial channel for new knowledge complementing the cluster internal knowledge and thereby minimizing the risk of a lock-in situation. On the cluster-level, it can additionally be ascertained that the stock of alliances is a significant driver for firm innovative performance within clusters. Compared with an alliance-poor cluster, it therefore appears to be much easier in alliance-rich clusters to come in contact with different kinds of partners coming from inside and outside of the corresponding clusters. Moreover, on the macro-level, evidence can be found for the particular relevance of basic research for firm innovative performance within clusters.[27] Due to its protection against potential threats by competitors in terms of new unexpected technological developments, conducting basic research is argued to be especially crucial in the competitive environment within clusters (e.g. Czarnitzki and Thorwarth, 2012; Rosenberg, 1990). Furthermore, while not finding a statistically significant direct effect of the pace of technology evolution, relevant moderation effects can however be asserted when examining the interaction with variables from different levels of analysis. For example, it can be shown that in industries characterized by a fast pace of technology evolution, companies need to own sufficiently high innovation capabilities in order to access and integrate the corresponding frequently changing new knowledge. Additionally, evidence is provided for the moderating influence on the relationship between firm cluster external relations and firm innovative performance. As a consequence of the fast pace of technology evolution, the access to external knowledge sources becomes of particular importance for firm innovativeness, because it secures that the current knowledge stock of a firm does not become obsolete in the near future. The third core paper of this dissertation therefore contributes to a more elaborated understanding of firms' heterogeneous benefits within clusters by determining the direct as well as interactive influence of contextual variables with a specific focus on the Marshallian externality of knowledge spillovers.

These insights are further complemented by the fourth core paper of this cumulative dissertation, "Sinking or swimming in the cluster labour pool? – A firm-specific analysis of the effect of specialized labour"[28], which studies the conditions through

[27] As already indicated in the first section of this framework paper, these findings are taken up and further developed within the third side paper of this cumulative dissertation (cf. Arant et al., 2019).

[28] The complete article can be found in the fifth chapter of this cumulative dissertation (on page 181 and following).

which firms can gain from being located in a cluster with a specific focus on the specialized labour pool. Therefore, by applying the same methodological approach as in Grashof (2020b), a multilevel database is analysed consisting of 11,500 firms in Germany from which 1,396 are located within a cluster. The corresponding empirical results are thereby in general in line with the findings of Grashof (2020b), indicating that on the one hand being located in a cluster increases on average firm innovativeness, but on the other hand firms gain heterogeneously from the cluster environment. In this context, multilevel conditions that are necessary to profit particularly from the specialized labour pool in clusters have been identified. On the firm-level, it is shown that the firm´s human resource capabilities are significantly promoting the firm´s innovative performance within clusters, since they are necessary to identify, acquire and train the best talents from the specialized labour pool. In addition, it is also beneficial for firms to have a human resource stock with similar skills compared to the overall cluster. By minimizing the probability of mismatches between employers and employees, a high degree of overlap is proven to significantly enhance firm innovative performance in clusters. Furthermore, evidence for a significant positive influence of gender diversity within the firm´s stock of R&D employees can be found. Gender diversity therefore acts as a fountain for new diverse ideas and capabilities. The same holds true for the cluster-level, where the diversity of the overall labour pool within clusters has been shown to significantly promote firm innovativeness. In addition to this, by detecting a small, however, very significant influence of the stock of human resources of the cluster on firm innovative performance, evidence is also provided for the principal rationale of the economies of agglomeration (e.g. Arthur, 1990). Besides the pure size of the labour pool, it can additionally be shown that the matching capacities of the labour pool are significant determinants of firm innovative performance within clusters. Clusters with a relatively well functioning labour pool, with regard to matching labour supply and demand, therefore constitute a more beneficial environment for innovations than clusters with a rather poorly functioning labour pool. In contrast, a rather inhibitory influence can be determined for the quality of the labour pool within clusters, indicating that the role of high-level scientific degrees (e.g. PhD or a habilitation) should not be overstressed compared with lower university degrees. Apart from the direct effects, these cluster-level variables also interact with firm-specific variables. For instance, while a high quality of the labour pool within clusters has in general a significant negative influence on firm innovativeness in clusters, it becomes beneficial when firms own sufficiently high human resource capabilities. In other words, firms need to possess these capabilities in order to be capable of fully exploiting the opportunities of such a high quality labour pool within clusters. Evidence is additionally found that high human resource capabilities become detrimental to firm innovative performance in clusters with a large labour pool. By having a high supply of specialized labour, it is easier for firms to find the right job candidate in such clusters and consequently it would be more efficient for them to assign their limited resources to other areas such as R&D material resources. Furthermore, in this context it can likewise be stated that firms located in the centre of the cluster core profit significant more from such a large stock of human resources of the cluster. The higher visibility of the central firms located in the cluster core is here for seen as a plausible explanation (e.g. Ferriani and MacMillan, 2017), because these firms can attract the most talented candidates much more easily and thereby profit particularly from a large labour pool within clusters. In line with the results of Grashof (2020b), it can be shown that especially these central firms located in the cluster core need to have a sufficiently pronounced human capital exchange intensity. While the human capital exchange intensity does not assert a significant direct influence on firm innovative performance in clusters, due to a potential lock-in situation it becomes of significant importance when firms are located within the geographical centre of a cluster. Regarding the market-/industry-level, it can be additionally stated that a fast pace of technology evolution promotes firm innovative performance within clusters, because on the one hand it offers extensive opportunities for innovations and on the other hand it puts firms under pressure to constantly innovate. Nevertheless, at the same time it can be determined that the innovative performance of firms is inhibited when firms are confronted with a rapid technology and market evolution, resulting in a high market risk. As a consequence of such a high market risk, it is plausible that human resource decisions, commonly including large sunk costs (e.g. Ernst and Viegelahn, 2014; Schaal, 2017), are postponed or even rejected, reducing in turn the potential gains from the specialized labour pool in clusters. Hence, to sum up, the fourth core paper of this cumulative dissertation also enriches the recent debate about firm performance differentials within clusters by systematically analysing contextual conditions influencing firm innovative performance within clusters. With its specific focus on the specialized labour pool, which is often not extensively considered in the literature (e.g. Klumbies, 2015), the fourth core paper not only supplements the findings of Grashof (2020b), but it also has a practical value, particularly in times of an increasing shortage of skilled labour (e.g. Bossler et al., 2017; IAB, 2017).

All in all, it can be resumed that the systematically derived insights of the two core papers of the second thematic module of this dissertation can be used by future scientific studies as a starting point for further investigations of firm-specific cluster effects. As such, by examining the direct as well as interactive effect of contextual variables from three different levels of analysis with a focus on specific externalities, both core papers contribute to the theoretical and empirical development of the cluster concept. Apart from further advancing the scientific discourse about regional clusters, both core papers are additionally useful for policy makers, as they provide a first comprehensive guideline for the identification of potential problems within clusters that policy can concretely address to improve the overall performance within clusters.

### 2.3. Third thematic module

At this point, the third thematic module of this dissertation also sets in, concentrating on the role of policy in promoting firm performance in clusters. As already indicated, the cluster concept has become quite popular among policy makers. Driven by the desire to replicate success stories such as Silicon Valley, cluster policies are nowadays a standard approach for national and regional administrations to improve the overall economic performance (Brenner and Schlump, 2011; Ebbekink and Lagendijk, 2013; Lehmann and Menter, 2018).[29] Nevertheless, their effectiveness still remains rather questionable, although large amounts of money have already been invested in the widespread application of these policies (Brenner and Schlump, 2011; Lehmann and Menter, 2018; Vicente, 2014; Zenker et al., 2019). Consequently, the third thematic module of this dissertation aims to address the following research question:

- Grashof (2020d): *How can policy effectively promote the performance of firms in clusters?*

The missing focus on concrete problems is argued to be one crucial reason for the rather unsatisfactory role of policy (Brakman and van Marrewijk, 2013; Nathan and Overman, 2013). Instead, cluster policies have been highly standardized, by widely ignoring the previously determined heterogeneity within clusters (see the first and second thematic module of this dissertation). As such, nowadays nearly all cluster policies concentrate their measures on stimulating R&D collaborations and networks development, which can be effective for some cases, but not for all (Ebbekink and Lagendijk, 2013; Vicente, 2014; Zenker et al., 2019). To move cluster policy beyond

[29] In general, cluster policies can be defined as "(…) a wider set of specific government policy interventions aiming at strengthening existing clusters or facilitating the emergence of new ones." (European Commission, 2008, p. 31).

these one-size-fits-all approaches, it must be elaborated, especially from the firm perspective, what specific problems exist within clusters and how policy can effectively address them (Auer and Tödtling, 2017; Wolman and Hincapie, 2015). The fifth core paper of this cumulative dissertation, “Putting the watering can away – Towards a targeted (problem-oriented) cluster policy framework”[30], therefore aims to contribute to closing this research gap by developing a targeted (problem-oriented) cluster policy framework that comprises context-specific problems and the corresponding targeted policy measures. In order to do so, in a first step the different understandings of policies in the cluster context, emphasizing the basic rationales of policy interventions, are systematically reviewed. Contrary to Porter (2000), the fifth core paper of this dissertation has thereby taken the principal understanding that cluster policy is not an independent policy approach, but instead it is based on the same rationales as standard industrial and innovation policy (e.g. Uyarra and Ramlogan, 2012). Thus, cluster policies are here seen as policies that are designed for the specific needs within clusters. In general, three different rationales for policy interventions can be determined: (1.) Market failures rationale referring to the fact that due to market imperfections (e.g. uncertainty and lack of appropriability), investments in knowledge production are below the socially desired level (e.g. Arrow, 1962; Martin and Scott, 2000; Nelson, 1959). (2.) The systems of innovation approach instead focuses on the interaction between interrelated actors (e.g. firms and universities) and the institutional framework (Laranja et al., 2008; Woolthuis et al., 2005). Potential mismatches, also called system failures, inhibit in this context the creation as well as diffusion of innovations and make policy interventions necessary (Konstantynova and Wilson, 2014; Laranja et al., 2008; Uyarra and Ramlogan, 2012). (3.) While both previous approaches aim to generate innovations in the most efficient way, the ‘new mission oriented’ (Cantner and Vannuccini, 2018) approach primarily deals with the directionality of innovation activities.[31] Since not all innovation happens where it would be socially desirable, the underlying rationale for policy interventions is to set the direction of change (Foray, 2018; Wanzenböck and Frenken, 2018; Weber and Rohracher, 2012). Nevertheless, in the cluster context, policy has only devoted efforts to solve the market failures and network failures (belonging to the group of system failures) (Vicente, 2014; Zenker et al., 2019). Consequently, it can again be argued that the current policy measures are not appropriately related towards the actual problems within clusters. Based on the

[30] The complete article can be found in the sixth chapter of this cumulative dissertation (on page 223 and following).

[31] In addition to these directionality failures, Weber and Rohracher (2012) also emphasize in this context three other transformational systems failures (demand articulation failure, policy coordination failure and reflexivity failure).

previously described review of the general rationales of policy as well as on the results of the first and second thematic modules of this dissertation concerning moderating variables, the cluster-specific problems are thus elaborated. In total, six relevant cluster-specific problems that policy can target on different levels of analysis can thereby be identified.

(1.) **Resource and capability problems** refer to an inadequate level of resources and capabilities on the firm- as well as cluster-level hampering firm performance. It is suggested that instruments targeting the development of financial (e.g. direct support to firm R&D and innovation) as well as/or non-financial resources and capabilities (e.g. policies for training and skills) are both useful to address this problem on the firm-level. On the cluster-level, policy can primarily tackle this problem by regulating and funding the regional educational system.

(2.) **Connectivity and network problems** deal with the functioning of the overall network and the knowledge exchange between the various actors located within and outside regional clusters. In order to increase knowledge collaborations on the micro-level, cooperative R&D funding can be applied for instance. By aiming more at shaping the overall network structure of clusters, the suggested policy measures are rather indirectly on the cluster-level (e.g. influencing the network assortativity within clusters).

(3.) Since in both previous cases the particular direction has been ignored, potential **matching problems** can occur. In standard direct R&D support measures, it has been disregarded which type of competences is actually supported, resulting eventually in a matching problem between the firm´s knowledge stock and the corresponding cluster knowledge stock. The same holds true for cooperative R&D funding measures where the matching between the knowledge profiles of all partners is not taken explicitly into consideration. In order to optimize the matching on the firm-level, it is therefore proposed that so-called directed policies should be used in the form of directed policies to build up the resources and capabilities or directed selection measures of R&D partners to support collaboration and network development. Moreover, in order to address matching problems on the cluster-level, such as an inadequate matching between labour supply and demand within clusters, policies focussing on the regional labour market (e.g. establishment of cluster skill centres) should be implemented.

(4.) Related to this are **diversity problems**, referring to an inadequate level of diversity, for example with respect to knowledge bases, on the firm- and cluster-level. These problems can lead to a lock-in situation, thereby reducing the innovative performance of firms and/or clusters. By fostering in particular interdisciplinary collaborative R&D projects, it is however argued that policy can reinforce creativity and finally prevent such a lock-in situation on the firm-level. For the cluster-level, it is propounded that policies for the regional labour market (e.g. migration policies), entrepreneurship policies (e.g. attraction and funding of start-ups) as well as the regulation, organisation and funding of the regional educational system (e.g. promoted establishment of new related research institutes) are effective approaches to strengthening the overall diversity within clusters.

(5.) **Market and industry problems** comprise missing R&D infrastructure on the cluster-level as well as industry and market particularities (e.g. high market risk) leading to under investments in R&D and skill formation. Even though policy can hardly directly influence these problems, it can create safeguards that reduce the underlying uncertainty and market risk. In this context, a mixed policy measure, combining public procurement policy with technology foresight and standardisation, is suggested.

(6.) **Institutional problems**, being more systemic, constitute the last of the cluster-specific problems. To effectively address these problems, national and regional policy have to implement regulation and framework policies, including for example the establishment and enforcement of reliable labour laws, intellectual property rights (IPRs) and commercial property policies. The lack of such regulations and framework policies can also be attributed to a deeper institutional problem, referring to missing state capacities. By pursuing the promotion of specialized skills and expertise in public administration (e.g. through appropriately adjusted recruitment processes) as well as the implementation of policy learning measures (e.g. benchmarks and best practices), it is argued that this rather deep-seated institutional problem can be addressed effectively.

Since several problems can exist at the same time (on different levels of analysis) and also interact with each other, it is not sufficient to concentrate exclusively on one problem on one level of analysis (e.g. regional specificities). Instead it is necessary to comprehensively consider cluster-specific problems from different levels of analysis so that more targeted and adaptive cluster policies can be realized. Depending on their impact and their complexity, three stylized types of cluster policies can consequently be conceptualized. While one-size-fits-all cluster policies are quite easy to implement, as they simply rely on best practices, their impact is, if at all, minimal. Off-the-rack cluster policies instead are more complex, but also have a potentially higher impact, because they focus on single problems and thereby move beyond the idea of ideal policy measures. Nevertheless, as already indicated these kinds of cluster policies can only be an intermediate step towards truly tailor-made cluster policies which are based upon a comprehensive analysis of potential cluster-specific problems from different levels of analysis and a related customization of their respective policy measures. Based on the derived results in Grashof (2020d), it is therefore claimed that a new rather active role of cluster policy is needed to foster firm performance in clusters effectively. Similar to privately owned firms, the state should actively make strategic investment decisions about the concrete funding of clustered firms depending on an objective identification of serious cluster-specific problems requiring a state intervention. The suggested cluster policy framework is a promising tool in this context. After this active identification process, it is argued that the corresponding actors should be included in the design of the concrete policy measures in order to also utilize their practice-oriented knowledge (e.g. Ebbekink and Lagendijk, 2013; Foray, 2015). In the end, to ensure the overall quality, these pre-selected actors should compete in a targeted proposal contest. Despite requiring sufficient state capacities, this new role of cluster policy would result in a more targeted (problem-oriented) funding, as the state aligns its measures in accordance with the real needs in terms of existing serious cluster-specific problems.

In total, it can therefore be resumed that the fifth core paper of this dissertation contributes to the ongoing scientific discussion about policies in the cluster context by deriving a targeted (problem-oriented) cluster policy framework and conceptualising a new active role of cluster policy. It thereby differs from other policy-oriented studies, since the developed cluster policy framework is not only based on theoretical elaborations, but additionally it is grounded on a comprehensive empirical foundation. Consequently, it also provides a high pragmatic value for policy makers, who can appropriate the insights of the proposed cluster policy framework in order to realize tailor-made cluster policies that consider the concrete needs and the heterogeneity within the cluster context. The fifth core paper of this dissertation thus makes a highly valuable contribution to overcome commonly used but rather ineffective one-size-fits-all as well as off-the-rack cluster policies.

### 2.4. Side papers

As already indicated, besides these five core papers, additional side papers broadening the previous findings have also been prepared during this dissertation. The first side paper, “Effects of Being Located in a Cluster on Economic Actors”[32], co-authored by Dirk Fornahl and Cathrin Söllner, provides a detailed literature-based overview of the effects inside and outside clusters. In line with Grashof and Fornahl (2020) as well as Grashof (2020a), the underlying motivation of the first side paper therefore also relates to the so far unclear empirical results regarding the effects of clusters. However, the corresponding analytical focus and procedure differs from the two core papers by conducting a detailed literature review of the cluster internal and external effects on innovativeness, productivity, employment growth and wages, entrepreneurship, survival probability and growth of start-ups as well as resilience. In general, evidence for a positive influence of clusters on various dependent variables for firms inside clusters and for the entire region in which clusters are embedded can be determined. Nevertheless, at the same time it can also be shown that the cluster effect is far more complex than a simple direct effect. Instead, the effects of clusters have to be analysed against the background of the respective contextual compilation with which the clusters are confronted. Thus, this paper marks a first step towards a more comprehensive understanding of the cluster effects which is directly taken up and further expanded in the first thematic module of this dissertation.

The second side paper, “Radical or not? The role of clusters in the emergence of radical innovations”[33], co-authored by Kolja Hesse and Dirk Fornahl, is an additional extension of the core papers of this dissertation. In particular, it supplements the analysis of firm innovativeness conducted in Grashof (2020b) and Grashof (2020c) by examining the effect of clusters on the emergence of radical innovations.[34] Due to their outstanding opportunities in creating new markets and securing long-term economic growth, radical innovations have in recent years gained much attention by company managers as well as policy makers. However, the corresponding role of regional clusters remains thereby unclear. Instead, previous empirical studies, investigating the firm-specific cluster effects, primarily focus on firm innovativeness in general. In theory, two opposing effects of regional clusters on the emergence of radical innovations can be established. On the one hand, the creation of radical new ideas can be promoted by the cross-fertilization of knowledge in clusters and

[32] The complete article can be found in the appendix A.1. (on page 267 and following).

[33] The complete article can be found in the appendix A.2. (on page 282 and following).

[34] In both core papers, proxies for radical innovations have already been used as robustness checks; however, they only roughly capture radical innovations and are therefore not as precise as in Grashof et al. (2019), where radical innovations are measured by new combinations of previously unconnected technology domains (based on IPC classes at the four-digit level).

especially from the exchange of tacit knowledge. On the other hand, it is also reasonable that due to a rather uniform thinking, firms located within clusters become sluggish towards potential (technological) changes, thereby hampering the emergence of radical innovations. By applying a quantitative approach, based on data about 8,404 German companies active in patenting between 2012 and 2014, an empirical validation of the role of clusters can be made. The corresponding results indicate that clusters provide in general an encouraging environment for radical innovations. However, in addition evidence is found that these kinds of innovations especially occur in the periphery of a cluster, where firms tend to be more open to the exchange of cluster external knowledge and therefore are less likely to face a lock-in situation. In this context, it can also be shown that the number of relationships with other firms is up to a certain degree indeed beneficial for the creation of radical innovations. Moreover, it is determined that firms located in clusters can exploit the fast technology evolution in industries to come up with rather radical innovations, while firms outside clusters cannot do so. In sum, it can therefore be resumed that the second side paper not only provides evidence for the significant positive influence of clusters on the emergence of radical innovations, but it additionally emphasizes in line with Grashof (2020b) and Grashof (2020c), the moderating effect of contextual variables, such as the firm´s geographical location in clusters. It thereby enriches the scientific literature about firm-specific cluster effects.

In the third side paper, "University-industry collaborations – The key to radical innovations?"[35], co-authored by William Arant, Dirk Fornahl, Kolja Hesse and Cathrin Söllner, the previous dataset created in Grashof et al. (2019) is extended by R&D collaborations with universities, research institutes and other firms. It thereby deepens the investigation of Grashof (2020b) regarding the influence of basic research on firm innovative performance. The underlying motivation of this paper refers to the still missing empirical insights about the role of university-industry collaboration for the emergence of rather radical innovations. While the relevance of public research institutions in promoting innovations in general has commonly been recognized, it remains indeed unclear whether and even more importantly under which conditions university-industry collaborations contribute to the creation of radical innovations in German firms. The corresponding results of the applied logistic regression models contribute to closing this still prevalent research gap. It can be shown that having more university-industry collaborations increases in general the

[35] The complete article can be found in the appendix A.3. (on page 312 and following).

probability for the creation of radical innovations. However, this influence is not significantly different from collaborations with research institutes nor from collaborations with other firms. As such, it can be stated that the number of collaborations in general significantly promotes the emergence of radical innovations on the firm-level. Nevertheless, in addition evidence is found that particularly a greater number of collaborations with geographically distant universities, providing a different perspective on the same underlying (research) problem, increases the likelihood of generating radical innovations. In this context, it can likewise be demonstrated that collaborating with highly cognitively distant universities does not significantly enhance the probability to create radical innovations, while it does in the case of research institutes. With regard to university-industry collaborations, it thus appears to be easier to cross-fertilize ideas when they are cognitively related over longer distances than to assimilate ideas stemming from geographically close partners that have, however, completely different knowledge bases. In total, it can therefore be summarized that it is beneficial for firms, in terms of creating radical innovations, to collaborate with scientific partners and with other firms. For policy makers this implies that collaborative R&D measures are also a promising approach to support the emergence of rather radical innovations. The geographical distance should thereby, however, additionally be considered, in the way that particularly the collaboration with geographically distant partners is fostered, as collaborations with nearby organisations might take place even without funding.

## 3. Conclusion

The co-location of firms from the same industry in regional clusters can be observed worldwide, despite increasing globalization. Consequently, researchers from different disciplines have investigated this ongoing economic phenomenon of regional clusters. Although it is a relatively well-established research field, consisting of thousands of different scientific articles, important research questions still remain to be answered. One of the most fundamental questions in this context, namely to what extent it is actually reasonable for a single firm to be located in a cluster, is investigated within this cumulative dissertation, encompassing five core papers and three side papers. By synthesizing different theoretical streams and by employing tertiary as well as secondary data, this cumulative dissertation takes a crucial step towards a more comprehensive understanding of firm-specific cluster effects, thereby overcoming the still prevalent assumption of homogeneity.

The corresponding core findings can be summarized in figure 3, illustrating the conceptualization of a cluster advantage, meaning a competitive advantage that results from a firm´s location in a cluster. The exogenous and endogenous factors theorized by Marshall (1920) are the starting point in this context, since they form the origin of the sources for a potential cluster advantage.

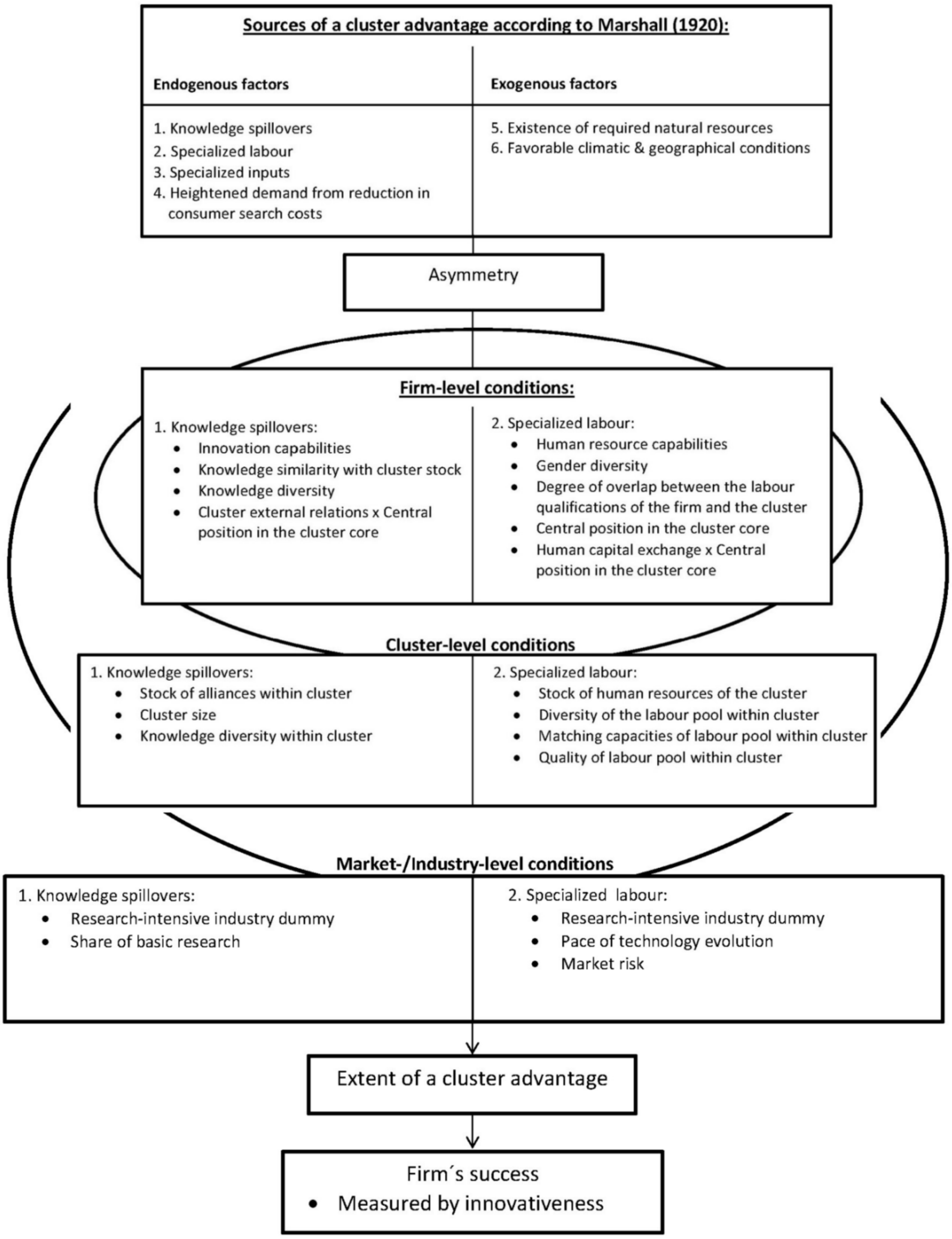


**Figure 3:** Conceptualization of a cluster advantage

Contrary to other studies, it is here however argued that firms located within clusters do not automatically gain from the endogenously created externalities, but instead it depends on several (interacting) conditions from the firm-level, cluster-level, and market-/industry-level (cf. Grashof and Fornahl, 2020; Grashof, 2020a). In other words, the relationship between clusters and firm performance is far more complex than conventionally assumed.

For an adequate analysis of these conditions it is necessary to bear in mind that their influence should be examined against the background of different externalities and performance indicators. Due to the limited scope of this work, these multilevel conditions are only further investigated for firm innovativeness as well as with a concrete focus on the two Marshallian externalities of knowledge spillovers (cf. Grashof, 2020b) and the specialized labour pool (cf. Grashof, 2020c). In addition to the determination of direct and sometimes interacting moderating effects for each single level of analysis, it can likewise be shown that there exist strong interdependencies between the three levels of analysis. For instance, it is revealed that firms in industries characterized by a fast pace of technology evolution need particularly cluster external relations in order to prevent their current knowledge stock from becoming obsolete in the near future (Grashof, 2020b). Hence, the extent to which firms can realize a cluster advantage cannot be attributed to one independent condition but to a variety of complex interacting conditions.

In this context, it is additionally necessary to consider also the complementarity as well as the contrast between these conditions across the different externalities. On the one hand, there are contextual conditions with strong complementarities, such as innovation capabilities (referring to knowledge spillovers) and human resource capabilities (referring to specialized labour). Investments in one of these conditions are likely to also enhance the other capability. On the other hand, the contextual conditions might also be contrasting. For instance, this is the case for the firm´s knowledge similarity with the cluster stock (referring to knowledge spillovers) and the degree of overlap between the labour qualifications of the firms and the cluster (referring to specialized labour). While a high degree of overlap between the firm´s human resources and the corresponding cluster is argued to be beneficial for firm innovativeness, as the potential of mismatches is minimized (Grashof, 2020c), in the case of knowledge spillovers too much similarity (as well as too much dissimilarity) between the firm´s knowledge stock and the overall stock of knowledge within the corresponding cluster is found to be least beneficial for firm innovativeness (Grashof, 2020b). In other words, in the case of the specialized labour pool, firms should own a human resource stock with similar skills compared to the overall cluster. However, this implies that the corresponding person-embedded knowledge is also quite similar, which would in turn be rather suboptimal in the case of knowledge spillovers.

For the realization of a cluster advantage, it is consequently necessary to pursue a unified approach where the multilevel conditions and their respective interactions are considered, also across the externalities. By doing so, in the end the potential firm-specific gains in terms of innovativeness can be maximized.

In general, the findings of this cumulative dissertation contribute to a more systematic in-depth understanding of the previously rather inconclusive evidence regarding the firm-specific cluster effects, by examining the separate and interactive influence of contextual variables from three different levels of analysis with broad (cf. first thematic module) and specific perspectives (cf. second thematic module). As such, it provides a comprehensive starting point for future studies dealing with firm-specific cluster effects and it thereby further advances the underlying foundation of the cluster concept.

Besides its scientific contribution, this cumulative dissertation has also rather practical implications. For company managers it offers a practical guidance about the conditions necessary to gain from the cluster environment, so that, on the one hand, expensive ill-reflected location decisions, promoted by the prevailing idea of automatically derived gains from being located in a cluster, can be prevented. Moreover, on the other hand, managers of companies that are already located within clusters can effectively evaluate where more efforts need to be invested in order to maximize the potential profits from being located in their corresponding cluster.

Furthermore, the developed targeted (problem-oriented) cluster policy framework not only enriches the ongoing scientific discussion about policies in the cluster context but additionally provides a high pragmatic value for policy makers. By comprising six relevant cluster-specific problems that can occur on different levels of analysis and the corresponding targeted policy measures to address them, the derived cluster policy framework helps policy makers to assess relevant problems as well as to design and implement adequate policy measures. Thus, this cumulative dissertation ultimately also contributes to the realization of more targeted and adaptive policies for clusters that can effectively foster firm performance in clusters, thereby responding to the common need in most European countries for higher efficiency in public funding (e.g. Kitson et al., 2011; Vicente, 2014).

Besides these contributions, there are, however, some limitations to this cumulative dissertation. First of all, the empirical analysis conducted in the second thematic module primarily relies on firm-level data provided by the Stifterverband. Even though it is an extensive database, it captures only all R&D-active firms in Germany, which limits the derived conclusions to this (important) group. Moreover, although the applied actor-based cluster identification approach offers several advantages (e.g. Brenner, 2017; Scholl and Brenner, 2016), it has also one major limitation. It is only based on three-digit NACE Rev. 2 industries. As such, similar to other studies (e.g. Hervas-Oliver et al., 2018), clusters are here only identified by firms from the same industry. Consequently, other closely related industries are not considered as belonging to the same cluster, which may lead to an underestimation of the actual size of the clusters (Brachert et al., 2011). By considering related industry linkages, future studies may in this context also focus more on the complexity of clusters (e.g. Delgado et al., 2016). Potential problems of endogeneity constitute another methodological limitation, since the empirical results of the second thematic module are based on cross-sectional averages over time. While data constraints, e.g. in terms of inconsistent answers to the Stifterverband survey over time, impose this empirical approach on the second thematic module of this dissertation, future studies may have access to other data sources that allow panel-regressions.

Apart from addressing these rather methodologically-driven limitations in future studies, the thoroughly developed findings of this cumulative dissertation also show thematically shortcomings that can potentially open up new avenues for future research. Based on table 1, it can be stated that the analysis of the second thematic module only considers firm innovativeness, although the results of the first thematic module indicate that the firm-specific cluster effect varies between different performance indicators. Thus, future studies should address this research gap by investigating alternative performance indicators, such as employment growth. Similarly, it appears to be promising for future research to investigate the here suggested cluster policy framework against the background of specific performance indicators, thereby contributing to the development of more targeted and output-oriented cluster policy approaches.

Besides the thematically shortcomings regarding the performance indicators, table 1 also shows that within this cumulative dissertation, the contextual variables are only further investigated for two specific externalities, namely knowledge spillovers and specialized labour. For further research projects, it is therefore proposed to examine the contextual variables in the context of the remaining localization externalities (specialized inputs and greater demand). The findings of this cumulative dissertation can additionally be used to support the disentanglement of the firm-specific cluster effect into its underlying externalities. Due to data constraints, these externalities could not directly be measured here, but instead similar to other studies (e.g. McCann and Folta, 2011), it is implicitly assumed that the applied cluster index and the corresponding contextual variables capture the concrete externalities. The procedure by Rigby and Brown (2015) can, however, serve as an example for the explicit measurement of the specific externalities, even though, following Krugman (1991b), they also argue that knowledge spillovers cannot adequately be measured in a direct way (e.g. through patents). For future research it is therefore quite promising to further develop the measurement of the specific externalities in order to disentangle the firm-specific cluster effect into its components and thereby investigate in more detail the reasons behind firm performance differentials in clusters.

Moreover, even though this cumulative dissertation already follows a relatively broad approach by considering three different levels of analysis, there are of course more levels of analysis (e.g. national-level) and more relevant contextual variables that shape the relationship between clusters and firm performance. In connection with this, the developed cluster policy framework can likewise be potentially extended. One promising aspect in this context is the dynamic evolution across the cluster life cycle (e.g. Menzel and Fornahl, 2010) and its potential influence on the sustainability of firm performance in clusters. While data constraints, particularly regarding the very detailed geographical level that is required for the cluster index by Brenner (2017), have prevented such an analysis in this dissertation, future studies may be able to investigate the dynamic influence across the cluster life cycle. In this context, it seems to be especially promising to examine possible changes of the contextual variables identified here. It is for instance reasonable to assume that, e.g. due to changes in the heterogeneity of accessable knowledge, the influence of the firm´s innovation capabilities on the firm´s innovative performance varies between the emergence and the sustainment or even decline phase of a cluster. Furthermore, while this dissertation follows a relatively broad approach, in order to take a unified perspective, for future studies it may be additionally promising to analyse selected contextual influences more in detail. Building on the derived results of this dissertation, the influence of the firm´s cluster position appears for instance to be an interesting aspect that should be further examined especially with regard to different gradations and their potential interaction effects with other contextual variables. For this purpose, quantile regression techniques seem to be particularly appropriate (e.g. Grillitsch and Nilsson, 2019; Koenker and Bassett, 1978).

Lastly, while this dissertation primarily relies on tertiary and secondary data, the usage of primary data should also be considered in future research, since some research questions may require rather qualitative data. The concrete network structure within the clusters is one exemplary case in this context. Even though the employed data about subsidized R&D collaborations, derived from the German subsidy catalogue ("Förderkatalog"), can be used to determine cluster internal and external relationships, during this dissertation it became apparent that it offers too limited information for the appropriate analysis of the more detailed network structures within the considered regional clusters. For these and related cases, primary data therefore appears to be of particular relevance. Building on the contributions of this dissertation, subsequent research, preferably from various disciplines, can thus further extend our underlying understanding about firm-specific cluster effects and thereby move from "(…) a sort of academic and policy fashion item." (Martin and Sunley, 2003, p. 6) towards a highly practical, well-grounded and elaborated concept.

All in all, it can therefore be concluded that apart from opening up promising research avenues, this cumulative dissertation provides highly valuable insights about the extent to which it is actually strategically reasonable for a single company to be located in a cluster. By statistically determining the (interacting) influence of multilevel variables on firm (innovative) performance in clusters, it can be shown that the location in clusters is not a panacea for all corresponding firms, but instead it depends on the right mix of ingredients whether a firm can more or less benefit from the respective cluster environment. Consequently, company managers as well as policy makers cannot simply wait for automatically derived gains from the cluster environment. Instead, they have to take matters in their own hands and adapt their strategy to the corresponding context in order to really make the cluster what everyone expects from it: The place to be.

## Bibliography


Ahuja, G. (2000): Collaboration Networks, Structural Holes, and Innovation: A Longitudinal Study, *Administrative Science Quarterly*, Vol. 45, No. 3, pp. 425-455.

Almeida, P., & Kogut, B. (1999): Localization of Knowledge and the Mobility of Engineers in Regional Networks, *Management Science*, Vol. 45, Issue 7, pp. 905-1024.

Amend, E., & Herbst, P. (2008): Labor market pooling and human capital investment decisions, *IAB Discussion Paper*, No. 4/2008.

Arant, W., Fornahl, D., Grashof, N., Hesse, K., & Söllner, C. (2019): University-industry collaborations—The key to radical innovations?, *Review of Regional Research*, Vol. 39, Issue 2, pp. 119-141.

Arrow, K. J. (1962): Economic welfare and the allocation of resources for invention, in: Nelson, R. R. (Ed.): The Rate and Direction of Inventive Activity: Economic and Social Factors, Princeton University Press, Princeton, NJ, pp. 609-626.

Arthur, W. B. (1990): 'Silicon Valley' locational clusters: when do increasing returns imply monopoly?, *Mathematical Social Sciences*, Vol. 19, Issue 3, pp. 235-251.

Asheim, B. (2007): DIFFERENTIATED KNOWLEDGE BASES AND VARIETIES OF REGIONAL INNOVATION SYSTEMS, *Innovation*, Vol. 20, Issue 3, pp. 223-241.

Audia, P. G., & Rider, C. I. (2010): Close, but not the same: Locally headquartered organizations and agglomeration economies in a declining industry, *Research Policy*, Vol. 39, Issue 3, pp. 360-374.

Auer, A., & Tödtling, F. (2017): Are policies supporting cluster development? A comparative firm-level analysis, in: Fornahl, D., & Hassink, R. (Eds.): The Life Cycle of Clusters - A Policy Perspective, Edward Elgar Publishing, Cheltenham, UK, pp. 203-221.

Baptista, R., & Swann, P. (1998): Do firms in cluster innovate more?, *Research Policy*, Vol. 27, Issue 5, pp. 525-540.

Bach, L., & Matt, M. (2005): From Economic Foundations to S&T Policy Tools: a Comparative Analysis of the Dominant Paradigms, in: Llerena, P., & Matt, M. (Eds.): Innovation Policy in a Knowledge-based Economy: Theory and Practice, Heidelberg: Springer, pp. 17-46.

Barney, J. B. (1991): Firm Resources and Sustained Competitive Advantage, *Journal of Management*, Vol. 17, No. 1, pp. 99-120.

Barney, J. B., & Clark, D. N. (2007): Resource-based theory: Creating and sustaining competitive advantage, Oxford University Press, Oxford.

Beaudry, C., & Schiffauerova, A. (2009): Who's right, Marshall or Jacobs? The localization versus urbanization debate, *Research Policy*, Vol. 38, Issue 2, pp. 318-337.

Becattini, G. (1990): The Marshallian industrial district as a socio-economic notion, in: Pyke, F., Becattini, G., & Sengenberger, W. (Eds.): Industrial Districts and Inter-Firm Co-operation in Italy, International Institute for Labour Studies, Geneva, Switzerland.

Bekele, G., & Jackson, R. (2006): Theoretical Perspectives on Industry Clusters, Research Paper 2006-05, Regional Research Institute, West Virginia University.

Bell, G. G. (2005): Clusters, networks, and firm innovativeness, *Strategic Management Journal*, Vol. 26, Issue 3, pp. 287-295.

Beugelsdijk, S. (2007): The Regional Environment and a Firm's Innovative Performance: A Plea for a Multilevel Interactionist Approach, *Economic Geography*, Vol. 83, Issue 2, pp. 181-199.

BMBF (2018): Forschung und Innovation für die Menschen - Die Hightech-Strategie 2025, Bundesministerium für Bildung und Forschung (BMBF).

Bonacich, P. (1972): Factoring and weighting approaches to status scores and clique identification, *The Journal of Mathematical Sociology*, Vol. 2, Issue 1, pp. 113-120.

Borenstein, M., Hedges, L. V., Higgins, J. P., & Rothstein, H. R. (2009): Introduction to Meta-analysis, John Wiley & Sons, Chichester, England.

Borowiecki, K. J. (2013): Geographic clustering and productivity: An instrumental variable approach for classical composers, *Journal of Urban Economics*, Vol. 73, Issue 1, pp. 94-110.

Bossler, M., Dietrich, H., Gartner, H., Hummel, M., Klinger, S., Kubis, A., Weber, E., & Wolter, S. (2017): Zur Lage und Entwicklung auf dem Arbeitsmarkt in Deutschland, IAB Stellungnahme, 4/2017, ISSN: 2195-5980.

Brachert, M., Titze, M., & Kubis, A. (2011): Identifying industrial clusters from a multidimensional perspective: Methodical aspects with an application to Germany, *Papers in Regional Science*, Vol. 90, Issue 2, pp. 419-439.

Brakman, S., & van Marrewijk, C. (2013): Reflections on cluster policies, *Cambridge Journal of Regions, Economy and Society*, Vol. 6, Issue 2, pp. 217-231.

Brenner, T. (2017): Identification of Clusters – An Actor-based Approach, *Working Papers on Innovation and Space*, No. 02.17.

Brenner, T., & Mühlig, A. (2013): Factors and Mechanisms Causing the Emergence of Local Industrial Clusters: A Summary of 159 Cases, *Regional Studies*, Vol. 47, Issue 4, pp. 480-507.

Brenner, T., & Schlump, C. (2011): Policy Measures and their Effects in the Different Phases of the Cluster Life Cycle, *Regional Studies*, Vol. 45, Issue 10, pp. 1363-1386.

Brown, K., Burgees, J., Festing, M., Royer, S., & Steffen, C. (2007): The Value Adding Web – A Conceptual Framework of Competitive Advantage Realisation in Clusters, *ESCP-EAP Working Paper*, No. 27, ISSN: 1619-7658.

Burt, R. S. (1992): Structural holes: The social structure of competition, Harvard University Press, Cambridge, MA.

Cameron, A. C., & Trivedi, P. K. (2005): Microeconometrics - Methods and Applications, Cambridge University Press, NY, USA.

Cantner, U., & Graf, H. (2011): Innovation Networks: Formation, Performance and Dynamics, in: Antonelli, C. (Ed.): Handbook on the Economic Complexity of Technological Change, Edward Elgar, Cheltenham, UK, pp. 366-394.

Cantner, U., & Vannuccini, S. (2018): Elements of a Schumpeterian catalytic research and innovation policy. *Industrial and Corporate Change*, Vol. 27, Issue 5, pp. 833-850.

Coase, R. H. (1937): The nature of the firm, *Economica*, Vol. 4, Issue 16, pp. 386-405.

Coase, R. H. (1984): The new institutional economics, *Journal of Institutional and*

*Theoretical Economics*, Bd. 140, H. 1, pp. 229-231.

Collis, D. J. (1994): Research Note: How Valuable Are Organizational Capabilities?, *Strategic Management Journal*, Vol. 15, pp. 143-152.

Cooke, P. (2001): Regional innovation systems, clusters, and the knowledge economy, *Industrial and Corporate Change*, Vol. 10, Issue 4, pp. 945-974.

Cooke, P. (2002): Knowledge Economies: Clusters, Learning and Co-operative Advantage, Routledge, London.

Cooper, H., & Hedges, L. V. (2009): Research Synthesis as a Scientific Process, in: Cooper, H., Hedges, L. V., & Valentine, J. C. (Eds.): The Handbook of Research Synthesis and Meta-Analysis, Russell Sage Foundation, New York, 2nd Edition, pp. 3-18.

Czarnitzki, D., & Thorwarth, S. (2012): Productivity effects of basic research in low-tech and high-tech industries, *Research Policy*, Vol. 41, Issue 9, pp. 1555-1564.

Daft, R. L., & Lengel, R. H. (1986): Organizational information requirements, media richness and structural design, *Management Science*, Vol. 32, No. 5, pp. 554-571.

David, P. A., & Rosenbloom, J. L. (1990): Marshallian factor market externalities and the dynamics of industrial localization, *Journal of Urban Economics*, Vol. 28, No. 3, pp. 349-370.

De Groot, H. L., Poot, J., & Smit, M. J. (2007): Agglomeration, Innovation and Regional Development: Theoretical Perspectives and Meta-Analysis, *Tinbergen Institute Discussion Paper*, No. 07-079/3.

De Groot, H. L., Poot, J., & Smit, M. J. (2016): WHICH AGGLOMERATION EXTERNALITIES MATTER MOST AND WHY?, J*ournal of Economic Surveys*, Vol. 30, Issue 4, pp. 756-782.

De Martino, R., Hardy Reid, D. M., & Zygliodopoulos, S. C. (2006): Balancing localization and globalization:exploring the impact of firm internationalization on a regional cluster, *Entrepreneurship & Regional Development*, Vol. 18, Issue 1, pp. 1-24.

Delgado, M., Porter, M. E., & Stern, S. (2010): Clusters and entrepreneurship, *Journal of Economic Geography*, Vol. 10, Issue 4, pp. 495-518.

Delgado, M., Porter, M. E., & Stern, S. (2016): Defining clusters of related industries, *Journal of Economic Geography*, Vol. 16, Issue 1, pp. 1-38.

Dierickx, I., & Cool, K. (1989): Asset Stock Accumulation and Sustainability of Competitive Advantage, *Management Science*, Vol. 35, No. 12, pp. 1415-1524.

Duschek, S. (2004): Inter-firm resources and sustained competitive advantage, *Management Revue*, Vol. 15, Issue 1, pp. 53-73.

Dyer, J. H., & Singh, H. (1998): The Relational View: Cooperative Strategy and Sources of Interorganizational Competitive Advantage, *The Academy of Management Review*, Vol. 23, No. 4, pp. 660-679.

Ebbekink, M., & Lagendijk, A. (2013): What's Next in Researching Cluster Policy: Place-Based Governance for Effective Cluster Policy, *European Planning Studies*, Vol. 21, Issue 5, pp. 735-753.

EFI (2015): Gutachten zu Forschung, Innovation und Technologischer Leistungsfähigkeit Deutschlands, Expertenkommission Forschung und Innovation.

Eisend, M. (2004): Metaanalyse - Einführung und kritische Auseinandersetzung, B*etriebswirtschaftliche Reihe*, No. 2004/8, Freie Universität Berlin.

Enright, M. J. (2000): The Globalization of Competition and the Localization of Competitive Advantage: Policies towards Regional Clustering, in: Hood, N., & Young, S. (Eds): The Globalization of Multinational Enterprise Activity and Economic Development, Palgrave Macmillan, pp. 303-331.

Erikson, R., & Lindgren, U. (2009): Localized mobility clusters: impacts of labour market externalities on firm performance, *Journal of Economic Geography*, Vol. 9, Issue 1, pp. 33-53.

Ernst, E., & Viegelahn, C. (2014): Hiring uncertainty: a new labour market indicator, ILO Working Paper, available under https://ssrn.com/abstract=2411299, last retrieved 07.04.2020.

European Cluster Observatory (2018): Methodology - Indicators, available under http://www.clusterobservatory.eu/index.html#!view=aboutobservatory;url=/about-observatory/methodology/indicators/, last retrieved: 04.10.2018.

European Commission (2008): The concept of clusters and cluster policies and their role for competitiveness and innovation: Main statistical results and lessons learned, *Europe INNOVA / PRO INNO Europe paper*, No. 9.

European Union (2016): Smart Guide to Cluster Policy, Guidebook Series: How to support SME Policy from Structural Funds, doi:10.2873/729624.

Fang, L. (2015): Do Clusters Encourage Innovation? A Meta-analysis, *Journal of Planning Literature*, Vol. 30, No. 3, pp. 239-260.

Ferriani, S., & MacMillan, I. (2017): Performance gains and losses from network centrality in cluster located firms: a longitudinal study, *Innovation*, Vol. 19, Issue 3, pp. 307-334.

Festing, M., Royer, S., & Steffen, C. (2012): Unternehmenscluster schaffen Wettbewerbsvorteile - Eine Analyse des Uhrenclusters in Glashütte, *Zeitschrift Führung + Organisation*, Vol. 81, No. 4, pp. 264-272.

Fischer, J. H., & Harrington, J. E. (1996): Product Variety and Firm Agglomeration, *The RAND Journal of Economics*, Vol. 27, No. 2, pp. 281-309.

Florax, R. J., de Groot, H. L., & De Mooij, R. A. (2002): Meta-Analysis, *Tinbergen Institute Discussion Paper*, No. 2002-041/3.

Foray, D. (2015): Smart Specialisation: Opportunities and Challenges for Regional Innovation Policy, Routledge, London & New York.

Foray, D. (2018): Smart specialisation strategies and industrial modernisation in European regions—theory and practice, *Cambridge Journal of Economics*, Vol. 42, Issue 6, pp. 1505-1520.

Fornahl, D., Heimer, T., Campen, A., Talmon-Gros, L., & Treperman, J. (2015): Cluster als Paradigma der Innovationspolitik - Eine erfolgreiche Anwendung von Theorie in der politischen Praxis?, Studien zum deutschen Innovationssystem, No. 13-2015.

Freeman, L. C. (1979): Centrality in social networks: Conceptual clarification, *Social Networks*, Vol. 1, pp. 215-239.

Freiling, J. (2001): Resource-based View und ökonomische Theorie - Grundlagen und Positionierung des Ressourcenansatzes, Deutscher Universitäts-Verlag, Gabler Edition, Wiesbaden.

Frenken, K., Cefis, E., & Stam, E. (2015): Industrial dynamics and clusters: a survey, *Regional Studies*, Vol. 49, Issue 1, pp. 10-27.

Glass, G. V. (1976): Primary, Secondary, and Meta-Analysis of Research, *Educational Researcher*, Vol. 5, No. 10, pp. 3-8.

Glass, G. V., McGaw, B., & Smith, M. L. (1981): Meta-analysis in Social Research, Sage, Beverly Hills, CA.

Gould, W. (2019): Between estimators, available under https://www.stata.com/support/faqs/statistics/between-estimator/, last retrieved: 09.01.2019.

Granovetter, M. (1985): Economic Action and Social Structure: The Problem of Embeddedness, *American Journal of Sociology*, Vol. 91, No. 3, pp. 481-510.

Grant, R. M. (1996a): Toward a knowledge-based theory of the firm, *Strategic Management Journal*, Vol. 17, Issue S2, pp. 109-122.

Grant, R. M. (1996b): Prospering in Dynamically-Competitive Environments: Organizational Capability as Knowledge Integration, *Organization Science*, Vol. 7, No. 4, pp. 375-387.

Grashof, N. (2020a): Firm-specific cluster effects - A meta-analysis, *Papers in Regional Science*, doi: 10.1111/pirs.12526.

Grashof, N. (2020b): Spill over or Spill out? - A multilevel analysis of the cluster and firm performance relationship, *Papers in Evolutionary Economic Geography*, No. 20.13.

Grashof, N. (2020c): Sinking or swimming in the cluster labour pool? - A firm-specific analysis of the effect of specialized labour, *Jena Economic Research Papers*, No. 2020 - 006.

Grashof, N. (2020d): Putting the watering can away - Towards a targeted (problem-oriented) cluster policy framework, *Papers in Innovation Studies*, No. 2020/04.

Grashof, N., & Fornahl, D. (2020): 'To be or not to be' located in a cluster? - A descriptive meta-analysis of the firm-specific cluster effect, *Working Papers on Innovation and Space*, No. 01.20.

Grashof, N., Hesse, K., & Fornahl, D. (2019): Radical or not? The role of clusters in the emergence of radical innovations, *European Planning Studies*, Vol. 27, Issue 10, pp. 1904-1923.

Grillitsch, M., & Nilsson, M. (2019): Knowledge externalities and firm heterogeneity: Effects on high and low growth firms, *Papers in Regional Science*, Vol. 98, Issue 1, pp. 93-114.

Gulati, R. (1999): Network Location and Learning: The Influence of Network Resources and Firm Capabilities on Alliance Formation, *Strategic Management Journal*, Vol. 20, Issue 5, pp. 397-420.

Hall, P. A., & David, S. (2001): An introduction to varieties of capitalism, in: Hall, P. A., & Soskice, D. (Eds.): Varieties of Capitalism: The Institutional Foundations of Comparative Advantage, Oxford University Press, Oxford, pp. 1-68.

Hedges, L. V., & Olkin, I. (1980): Vote-counting methods in research synthesis, *Psychological Bulletin*, Vol. 88, No. 2, pp. 359-369.

Hervas-Oliver, J.-L., Sempere-Ripoll, F., Alvarado, R. R., & Estelles-Miguel, S. (2018): Agglomerations and firm performance: who benefits and how much?, *Regional Studies*, Vol. 52, Issue 3, pp. 338-349.

Hudson, B., Hunter, D., & Peckham, S. (2019): Policy failure and the policy-implementation gap: can policy support programs help?, *Policy Design and Practice*, Vol. 2, No. 1, pp. 1-14.

IAB (2017): IAB Stellenerhebung, available under https://www.iab.de/de/befragungen/stellenangebot/aktuelle-ergebnisse.aspx, last retrieved: 23.11.2018.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993): Geographic localization of knowledge spillovers as evidenced by patent citations, *Quarterly Journal of Economics*, Vol. 108, No. 3, pp. 577-598.

Kitson, M., Martin, R., & Tyler, P. (2011): The geographies of austerity, *Cambridge Journal of Regions, Economy and Society*, Vol. 4, Issue 3, pp. 289-302.

Klumbies, I. (2015): Cluster Location: Is this the Place to be? - An Investigation on the Influence of Cluster Affiliation on Firm Performance and Human Resources, Dissertation, Jacobs University, Bremen.

Knoben, J., Arikan, A. T., Van Oort, F., & Raspe, O. (2015): Agglomeration and firm performance: One firm's medicine is another firm's poison, *Environment and Planning A*, Vol. 48, No. 1, pp. 1-22.

Koenker, R., & Bassett, G. J. (1978): Regression Quantiles, *Econometrica*, Vol. 46, No. 1, pp. 33-50.

Koka, B. R., & Prescott, J. E. (2008): Designing alliance networks: the influence of network position, environmental change, and strategy on firm performance, *Strategic Management Journal*, Vol. 29, Issue 6, pp. 639-661.

Konstantynova, A., & Wilson, J. (2014): Comparing Cluster Policies: An Analytical Framework, *Orkestra Working Paper Series in Territorial Competitiveness*, No. 2014-R01.

Krugman, P. (1991a): Geography and trade, MIT Press, Cambridge, MA.

Krugman, P. (1991b): Increasing returns and economic geography, *Journal of Political Economy*, Vol. 99, No. 3, pp. 483-499.

Kudic, M. (2015): Innovation Networks in the German Laser Industry - Evolutionary Change, Strategic Positioning, and Firm Innovativeness, Springer International Publishing, Switzerland.

Laranja, M., Uyarra, E., & Flanagan, K. (2008): Policies for science, technology and innovation: Translating rationales into regional policies in a multi-level setting, *Research Policy*, Vol. 37, Issue 5, pp. 823-835.

Lavie, D. (2006): The Competitive Advantage of Interconnected Firms: An Extension of the Resource-Based View, *The Academy of Management Review*, Vol. 31, No. 3, pp. 638-658.

Lazzeretti, L., Sedita, S. R., & Caloffi, A. (2014): Founders and disseminators of cluster research, *Journal of Economic Geography*, Vol. 14, Issue 1, pp. 21-43.

Lee, K. J., Roberts, G., Doyle, L. W., Anderson, P. J., & Carlin, J. B. (2016): Multiple imputation for missing data in a longitudinal cohort study: a tutorial based on a detailed case study involving imputation of missing outcome data, *International Journal of Social Research Methodology*, Vol. 19, No. 5, pp. 575-591.

Lehmann, E. E., & Menter, M. (2018): Public cluster policy and performance, *The Journal of Technology Transfer*, Vol. 43, Issue 3, pp. 558-592.

Maier, G., & Trippl, M. (2012): The Pitfalls and Booby Traps of Cluster Policy, S*RE - Discussion Papers*, No. 2012/01,WU Vienna University of Economics and Business.

Malmberg, A., & Maskell, P. (2002): The elusive concept of localization economies: towards a knowledge-based theory of spatial clustering, *Environment and Planning A*, Vol. 34, No. 3, pp. 429-449.

Marshall, A. (1920): Principles of economics, Macmillan, London, 8th Edition.

Martin, P., Mayer, T., & Mayneris, F. (2011): Public support to clusters: A firm level study of French "Local Productive Systems", *Regional Science and Urban Economics*, Vol. 41, Issue: 2, pp. 108-123.

Martin, R., & Sunley, P. (2003): Deconstructing clusters: chaotic concept or policy panacea?, *Journal of Economic Geography*, Vol. 3, Issue 1, pp. 5-35.

Martin, S., & Scott, J. T. (2000): The nature of innovation market failure and the design of public support for private innovation, *Research Policy*, Vol. 29, Issues 4–5, pp. 437-447.

McCann, B. T., & Folta, T. B. (2008): Location Matters: Where We Have Been and Where We Might Go in Agglomeration Research, *Journal of Management*, Vol. 34, Issue 3, pp. 532-565.

McCann, B. T., & Folta, T. B. (2011): Performance differentials within geographic clusters, *Journal of Business Venturing*, Vol. 26, Issue 1, pp. 104-123.

McNeish, D. M. (2014): Analyzing Clustered Data with OLS Regression: The Effect of a Hierarchical Data Structure, *Multiple Linear Regression Viewpoints*, Vol. 40, No. 1, pp. 11-16.

McNeish, D. (2017): Missing data methods for arbitrary missingness with small samples, *Journal of Applied Statistics*, Vol. 44, No. 1, pp. 24-39.

Melo, P. C., Graham, D. J., & Noland, R. B. (2009): A meta-analysis of estimates of urban agglomeration economies, *Regional Science and Urban Economics*, Vol. 39, Issue 3, pp. 332-342.

Menzel, M.-P., & Fornahl, D. (2010): Cluster life cycles—dimensions and rationales of cluster evolution, *Industrial and Corporate Change*, Vol, 19, Issue 1, pp. 205-238.

Meyer, K. E., Mudambi, R., & Narula, R. (2011): Multinational Enterprises and Local Contexts: The Opportunities and Challenges of Multiple Embeddedness, *Journal of Management Studies*, Vol. 48, Issue 2, pp. 235-252.

Miller, D., & Chen, M.-J. (1994): Sources and Consequences of Competitive Inertia: A Study of the U.S. Airline Industry, *Administrative Science Quarterly*, Vol. 39, No. 1, pp. 1-23.

Mody, A. (1993): Learning through alliances, *Journal of Economic Behavior & Organization*, Vol. 20, Issue 2, pp. 151-170.

Moulton, B. R. (1990): An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units, *The Review of Economics and Statistics*, Vol. 72, No. 2, pp. 334-338.

Mudambi, R., & Swift, T. (2012): Multinational Enterprises and the Geographical Clustering of Innovation, *Industry and Innovation*, Vol. 19, Issue 1, pp. 1-21.

Nathan, M., & Overman, H. (2013): Agglomeration, clusters, and industrial policy, *Oxford Review of Economic Policy*, Vol. 29, Issue 2, pp. 383-404.

Nelson, R. R. (1959): The Simple Economics of Basic Scientific-Research, *Journal of Political Economy*, Vol. 67, No. 3, pp. 297-306.

Newbert, S. L. (2007): Empirical research on the resource-based view of the firm: an assessment and suggestions for future research, *Strategic Management Journal*, Vol. 28, Issue 2, S. 121-146.

Otto, A., & Fornahl, D. (2010): Origins of human capital in clusters: Regional, industrial and academic transitions in media clusters in Germany, in: Fornahl, D., Henn, S.,Menzel, M.-P. (Eds.): Emerging Clusters: Theoretical, Empirical and Political Perspectives on the Initial Stage of Cluster Evolution, Edward Elgar, Cheltenham, UK, pp. 99-139.

Palazuelos, M. (2005): Clusters: Myth or Realistic Ambition for Policy-makers?, *Local Economy*, Vol. 20, Issue 2, pp. 131-140.

Penrose, E. (1959): The Theory of the Growth of the Firm, Oxford University Press, Oxford, 4th Edition.

Phelps, C. C. (2010): A Longitudinal Study of the Influence of Alliance Network Structure and Composition on Firm Exploratory Innovation, *Academy of Management Journal*, Vol. 53, No. 4, pp. 890-913.

Piore, M. J., & Sabel, C. F. (1984): The Second Industrial Divide: Possibilities for Prosperity, Basic Books, New York.

Porter, M. E. (1980): Competitive Strategy: Techniques for Analyzing Industries and Competitors, Free Press, New York.

Porter, M. E. (1985): The Competitive Advantage: Creating and Sustaining Superior Performance, Free Press, New York.

Porter, M. E. (1990): The Competitive Advantage of Nations, Macmillan, London.

Porter, M. E. (1998): Clusters and the New Economics of Competitiveness, *Harvard Business Review*, Vol. 76, Issue 6, pp. 77-90.

Porter, M. E. (2000): Location, Competition, and Economic Development: Local Clusters in a Global Economy, *Economic Development Quarterly*, Vol. 14, Issue 1, pp. 15-34.

Powell, W. W., Koput, K. W., & Smith-Doerr, L. (1996): Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology, *Administrative Science Quarterly*, Vol. 41, No. 1, pp. 116-145.

Presse- und Informationsamt der Bundesregierung (2019): Startschuss für Zukunftscluster - Regionale Innovationsnetzwerke stärken, available under https://www.bundesregierung.de/breg-de/aktuelles/zukunftscluster-1659402, last retrieved: 08.11.2019.

Quintana, D. (2015): From pre-registration to publication: a non-technical primer for conducting a meta-analysis to synthesize correlational data, *Frontiers in Psychology*, Vol. 6, Article 1549, pp. 1-9.

Rammer, C. (2011): Bedeutung von Spitzentechnologien, FuE-Intensität und nicht forschungsintensiven Industrien für Innovationen und Innovationsförderung in Deutschland, *ZEW Dokumentation*, No. 11-01, ISSN: 1611-681X.

Rigby, D. L., & Brown, M. W. (2015): Who Benefits from Agglomeration?, *Regional Studies*, Vol. 49, Issue 1, pp. 28-43.

Rosenberg, N. (1990): Why do firms do basic research (with their own money)?, *Research Policy*, Vol. 19, Issue 2, pp. 165-174.

Rumelt, R. P. (1984): Towards a strategic theory of the firm, in: Lamb, R. B. (Ed.): Competitive Strategic Management, Prentice-Hall, Englewood Cliffs, N.J., pp. 556-570.

Šarić, S. (2012): Competitive Advantages through Clusters - An Empirical Study with Evidence from China, Strategisches Kompetenz-Management, Springer Fachmedien, Wiesbaden.

Saviotti, P. P. (2011): Knowledge, Complexity and Networks, in: Antonelli, Cristiano (Ed.): Handbook on the Economic Complexity of Technological Change, Edward Elgar, Cheltenham, UK, pp. 141-180.

Saxenian, A. (1990): Regional Networks and the Resurgence of Silicon Valley, *California Management Review*, Vol. 33, Issue 1, pp. 89-113.

Schaal, E. (2017): Uncertainty and Unemployment, *Econometrica*, Vol. 85, Issue 6, pp. 1675-1721.

Schiele, H. (2008): Location, location: the geography of industry clusters, *Journal of Business Strategy*, Vol. 29, No. 3, pp. 29-36.

Schilirò, D. (2017): Italian industrial districts: theories, profiles and competitiveness, *MPRA Paper*, No. 86729, available under https://mpra.ub.uni-muenchen.de/86729/.

Scholl, T., & Brenner, T. (2016): Detecting Spatial Clustering Using a Firm-Level Cluster Index, *Regional Studies*, Vol. 50, Issue 6, pp. 1054-1068.

Smith, M. L., Glass, G. V., & Miller, T. I. (1980): The Benefits of Psychotherapy, John Hopkins University Press, Baltimore, MD.

Sorenson, O., & Audia, P. G. (2000): The Social Structure of Entrepreneurial Activity: Geographic Concentration of Footwear Production in the United States, 1940–1989, *American Journal of Sociology*, Vol. 106, No. 2, pp. 424-462.

Stahl, K. (1982): Differentiated Products, Consumer Search, and Locational Oligopoly, *The Journal of Industrial Economics*, Vol. 31, No. 1/2, pp. 97-113.

Stanley, T. D. (2001): Wheat From Chaff: Meta-Analysis As Quantitative Literature Review, *Journal of Economic Perspective*, Vol. 15, No. 3, pp. 131-150.

Stanley, T. D., & Jarrell, S. B. (1989): Meta-Regression Analysis: A Quantitative Method of Literature Surveys, *Journal of Economic Surveys*, Vol. 3, Issue 2, pp. 161-170.

Starbuck, W. H. (1992): Learning By Knowledge-Intensive Firms, *Journal of Management Studies*, Vol. 29, Issue 6, pp. 713-740.

Steffen, C. (2012): How Firms Profit from Acting in Networked Environments: Realising Competitive Advantages in Business Clusters. A Resource-oriented Case Study Analysis of the German and Swiss Watch Industry, Schriftenreihe: Internationale Personal- und Strategieforschung, Rainer Hamp Verlag, München & Mering.

Stern, D. I. (2010): Between estimates of the emissions-income elasticity, *Ecological Economics*, Vol. 69, Issue 11, pp. 2173-2182.

Sternberg, R., Kiese, M., & Stockinger, D. (2010): Cluster policies in the US and Germany: varieties of capitalism perspective on two high-tech states, *Environment and Planning C: Government and Policy*, Vol. 28, Issue 6, pp. 1063-1082.

Tallman, S., Jenkins, M., Henry, N., & Pinch, S. (2004): Knowledge, Clusters, and Competitive Advantage, *The Academy of Management Review*, Vol. 29, No. 2, pp. 258-271.

Täube, F. A. (2005): The geography of technology entrepreneurship: an exploratory study of the Indian IT industry, available under http://www.econ.mpg.de/files/2006/workshops/india_workshop/papers/Taeube.pdf, last retrieved: 04.01.2019.

Teece, D. J., Pisano, G., & Shuen, A. (1997): Dynamic Capabilities and Strategic Management, *Strategic Management Journal*, Vol. 18, Issue 7, pp. 509-533.

Tödtling, F., Lehner, P., & Trippl, M. (2006): Innovation in Knowledge Intensive Industries: The Nature and Geography of Knowledge Links, *European Planning Studies*, Vol. 14, Issue 8, pp. 1035-1058.

Uyarra, E., & Ramlogan, R. (2012): The Effects of Cluster Policy on Innovation, *Nesta Working Paper*, No. 12/05.

Uzzi, B. (1996): The Sources and Consequences of Embeddedness for the Economic Performance of Organizations: The Network Effect, *American Sociological Review*, Vol. 61, No. 4, pp. 674-698.

Valentine, J. C., Pigott, T. D., & Rothstein, H. R. (2010): How Many Studies Do You Need? A Primer on Statistical Power for Meta-Analysis, *Journal of Educational and Behavioral Statistics*, Vol. 35, No. 2, pp. 215-247.

Van Oort, F. G., Burger, M. J., Knoben, J., & Raspe, O. (2012): Multilevel Approaches and the Firm-Agglomeration Ambiguity in Economic Growth Studies, *Journal of Economic* Surveys, Vol. 26, Issue 3, pp. 468-491.

Vega-Jurado, J., Gutiérrez-Gracia, A., Fernández-de-Lucio, I., & Manjarrés-Henríquez, L. (2008): The effect of external and internal factors on firms' product innovation, *Research Policy*, Vol. 37, Issue 4, pp. 616-632.

Vicente, J. (2014): Don't throw the baby out with the bath water. Network failures and policy challenges for cluster long run dynamics, *Papers in Evolutionary Economic Geography*, No. 14.20.

Wagner, M., & Weiß, B. (2014): Meta-Analyse, in: Baur, N., & Blasius, J. (Eds.): Handbuch Methoden der empirischen Sozialforschung, Springer Fachmedien, Wiesbaden, pp. 1117-1126.

Wanzenböck, I., & Frenken, K. (2018): The subsidiarity principle: Turning challenge-oriented innovation policy on its head, *Papers in Evolutionary Economic Geography*, No. 18.06.

Wasserman, S., & Faust, K. (1994): Social network analysis: Methods and applications, Cambridge University Press, Cambridge.

Weber, K. M., & Rohracher, H. (2012): Legitimizing research, technology and innovation policies for transformative change: Combining insights from innovation systems and multi-level perspective in a comprehensive 'failures' framework, *Research Policy*, Vol. 41, Issue 6, pp. 1037-1047.

Wennberg, K., & Lindqvist, G. (2010): The effect of clusters on the survival and performance of new firms, *Small Business Economics*, Vol. 34, Issue 3, pp. 221-241.

Wernerfelt, B. (1984): A resource-based view of the firm, *Strategic Management Journal*, Vol. 5, Issue 2, pp. 171-180.

Williamson, O. E. (1975): Markets and Hierarchies: Analysis and Antitrust Implications: A Study in the Economics of Internal Organization, Free Press, New York.

Williamson, O. E. (1985): The economic institutions of capitalism: Firms, markets, relational contracting, Free Press, New York.

Williamson, O. E. (1996): Transaktionskostenökonomie, in: Dietl, H., Erlei, C., Erlei, M., & Leschke, M. (Eds.): Ökonomische Theorie der Institutionen, LIT-Verlag, Hamburg, 2nd Edition.

Wolman, H., & Hincapie, D. (2015): Clusters and Cluster-Based Development Policy, *Economic Development Policy*, Vol. 29, Issue 2, pp. 135-149.

Woolthuis, R. K., Lankhuizen, M., & Gilsing, V. (2005): A system failure framework for innovation policy design, *Technovation*, Vol. 25, Issue 6, pp. 609-619.

Zaheer, A., & Bell, G. G. (2005): BENEFITING FROM NETWORK POSITION: FIRM CAPABILITIES, STRUCTURAL HOLES, AND PERFORMANCE, *Strategic Management Journal*, Vol. 26, Issue 9, pp. 809-825.

Zenker, A., Delponte, L., Mayán, N. D., Wintjes, R., Amichetti, C., Carneiro, J., Meyborg, M., Notten, A., Schnabl, E., & Stahlecker, T. (2019): Cluster programmes in Europe and beyond, European Observatory for Clusters and Industrial Change, available under https://www.clustercollaboration.eu/eu-initiatives/european-cluster-observatory, last retrieved: 17.07.2019.

# II. Paper I: ‘To be or not to be’ located in a cluster? – A descriptive meta-analysis of the firm-specific cluster effect

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**Abstract:** In the 21st century clusters can be observed in most developed economies. However, the scientific results regarding the effect of clusters on firm performance are highly contradictive. This inconsistency in the empirical results makes it difficult to infer general conclusions about the firm-specific cluster effect, referring to the effect from being located in a cluster on firm performance, e.g. derived through the externalities within clusters. Therefore, this paper aims to reconcile the contradictory empirical findings. It investigates whether the still prevalent assumption that clusters are a beneficial location for firms is unconditionally true or whether doubts about the alleged positive effect of clusters on firm performance are justified. By conducting a descriptive meta-analysis of the empirical literature, based on four different performance variables from four separate publication databases, the study investigates the actual effect direction as well as possible moderating influences. We find evidence for a rather positive firm-specific cluster effect. However, we identify several variables from the micro-, meso- and macro-level that directly or interactively moderate the relationship between clusters and firm success. The corresponding results demonstrate, for example, that a negative firm-specific cluster effect occurs more frequently in low-tech industries than in high-tech industries. ‘To be or not to be’ located in a cluster is therefore not the question, but it rather depends on the specific conditions.

**Keywords:** meta-analysis, cluster effect, firm performance
**JEL Classification:** L25, O31, O32, R1

[36] In the interest of consistency, the following version differs slightly from the design of the published article.

## 1. Introduction

The co-location in regional clusters[37] is an economic reality that characterizes most developed economies in the 21st century. According to the European Cluster Observatory, just within the European Union (EU) there are 2,000 statistically relevant clusters that employ nearly 40% of the European workforce (Brown et al., 2007; Festing et al., 2012; Nathan and Overman, 2013). In view of conspicuous examples, such as Silicon Valley, the concept has become popular among politicians who are motivated to foster cluster initiatives in order to write a similar success story for their region. Therefore, many cluster initiatives receive financial support from national governments, the EU, and other public institutions. For example, since 2005 the German government has launched several programs with a total volume of 1.391 billion € to foster clusters in Germany (EFI, 2015; Festing et al., 2012).

Given the already substantial financial support of cluster activities, it is reasonable to assume that scientists have identified a consistent positive cluster effect on the success of companies within a cluster. However, the scientific results about the firm-specific cluster effect are indeed highly contradictive (Malmberg and Maskell, 2002; Martin and Sunley, 2003). While authors such as Borowiecki (2013) as well as Basant et al. (2011) find evidence that companies located in clusters have a higher productivity than companies outside clusters, other researchers come to different results, ranging from negative performance effects (Pouder and St. John, 1996) to rather mixed effects (Knoben et al., 2015).

This inconsistency in the empirical results prevents general conclusions about the firm-specific cluster effect[38], particularly with regard to the actual effect direction (Fang, 2015). According to Frenken et al. (2015), one of the main challenges for future research lies in reconciling the contradictory empirical findings and thereby working towards closing the research gap on the alleged effect of clusters on firm performance. We respond to this call by integrating previous empirical results, thereby answering the following research question: Does being located in a cluster influence firm success? More specifically, we investigate whether the still prevalent assumption in the scientific literature and among policy-makers that clusters are a beneficial location for firms is unconditionally true or whether doubts about the alleged positive effect of clusters on firm performance are reasonable.

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[37] The corresponding working definition for a cluster is presented in section 2.1.

[38] Referring to the effect from being located in a cluster on firm performance (e.g. derived through the existing localization externalities within clusters such as knowledge spillovers).

In order to answer this research question adequately, we conduct a descriptive meta-analysis of the empirical literature on the firm-specific cluster effect. A descriptive meta-analysis is an appropriate methodical approach in this context, because it is a meaningful way of combining empirical studies with contradicting results (Fang, 2015). Yet, up to now, studies have employed a meta-analysis procedure only on the regional level (e.g. De Groot et al., 2007; Melo et al., 2009) and not in the context of firm-specific cluster effects. One important exception is the recent work by Fang (2015). However, this article differs from Fang (2015) in several important ways, for example its explicit focus on the firm-level, its scope of considered performance variables, its extensive literature collection based on four publication databases, as well as a more precise selection process that controls for, among others, a similar cluster understanding across the considered studies. As such, this article follows a clearer and more comprehensive approach to investigate the effect of being located in a cluster on firm success. By providing an answer to the underlying research question through reconciling the contradictory empirical results, the paper not only provides a comprehensive overview that enriches the understanding about the alleged effect of clusters and serves as a crucial stepping stone to closing a still ubiquitous research gap, but also fulfils a practical demand by informing companies as well as policy-makers so they can gauge the concrete firm-specific effects of cluster initiatives.

The remainder of this paper is structured as follows: The second section introduces the theoretical background, highlighting the theoretical debate about cluster (dis-)advantages and establishing an adequate working definition of a cluster by reviewing the corresponding literature. The third section describes the applied methodical approach and data. Thereafter, the fourth section presents the empirical results. The paper will end with some concluding remarks, including limitations to this study as well as promising future research directions.

## 2. Theoretical background

In order to develop a useful working definition for the term cluster to analyse the contradictory empirical results regarding the firm-specific cluster effect, a literature overview about the various cluster definitions is undertaken to identify possible similarities. Furthermore, the ongoing theoretical discussion about cluster advantages and disadvantages is described.

### 2.1. Defining clusters

Although the term cluster is a very widespread and prevalent theme in economics at least since the two scientific papers of Porter (1990 and 1998), there are still fundamental differences in its definition as well as understanding (Brown et al., 2007; Malmberg and Maskell, 2002; Martin and Sunley, 2003). Even Michael Porter applies different kinds of definitions in his numerous articles about the cluster topic. As a consequence of the unclear definitional delimitation, the term has experienced a large proliferation and thereby has lost some of its explanatory power (Brown et al., 2007; Martin and Sunley, 2003; Šarić, 2012; Sedita et al., 2012). For a correct implementation of a meta-analysis this definitional inconsistency implies a serious problem, as it is required that the considered empirical studies have the same underlying understanding of what is meant by cluster when they analyse the firm-specific cluster effects. It is therefore essential to establish an adequate working definition of a cluster which serves as the baseline for the definitions of the empirical studies derived from the literature review.

Given the absence of a more or less mandatory definition, in line with Fornahl et al. (2015) a comparative empirical approach is applied that is explicitly inductive. Thus, this study does not intend to open 'pandora´s box' of a theoretical discussion about a new (conceptual) cluster definition, instead a rather pragmatic approach is chosen. By conducting a profound literature overview about the various cluster definitions used in empirical as well as theoretical studies, several similarities could be identified. In general, these similarities can be summarized in the following four central elements:

(1) The spatial connection constitutes one of the most important elements of a cluster definition. It includes the sub-dimensions of (spatial) proximity as well as concentration. The latter one refers to a critical mass of actors which is a fundamental condition for the functioning of clusters (e.g. Brenner, 2004). However, in most cases, this critical mass is not determined in detail (Fornahl et al., 2015). Additionally, it is also still unclear and highly debated which spatial scale is most appropriated to cover the proximity dimension (Asheim et al., 2006; Martin and Sunley, 2003). In this context, empirical studies make use of different kind of levels of analysis, ranging from Nuts I, II or III to whole labour market regions (Fornahl et al., 2015). Besides these predefined areal units, some empirical studies also consider directly the geographical

distance to the cluster in order to increase the geographic precision of their analysis (e.g. Bagley, 2019a; Duranton and Overman, 2005; Maine et al., 2010; Rosenthal and Strange, 2008). Among others, Maine et al. (2010) indicate in this context that a firm´s geographical distance to a cluster is negatively related with its corresponding growth performance. In general, it can therefore be resumed that spatial proximity is widely acknowledged as a crucial dimension of clusters (Fornahl et al., 2015; Martin and Sunley, 2003).

(2) The thematic connection covers the following three sub-dimensions: similar/complementary industries, value chain and specialization. These three sub-dimensions encompass similar value-chain activities of the firms within a cluster and their possible specialization. In accordance with the Marshall-Arrow-Romer (MAR) framework, arguing that the co-location of firms in a single industry fosters firm performance due to externalities[39], clusters are often associated with the specialization around on specific industry (Marshall, 1920; Maine et al., 2010). However, based on Jacobs (1969) it has been indicated that a single metropolitan area may contain several specialized clusters which may benefit from inter-industry related knowledge flows (Maine et al., 2010). Recently, contributions from the evolutionary economic geography (EEG) thinking school have moved beyond the localization versus urbanization debate and suggested in this context that related economic activities should also be considered as part of the regional specialization (Grillitsch et al., 2018; Kemeny and Storper, 2015; Neffke et al., 2011; Potter and Watts, 2014). Likewise in the case of spatial proximity it is therefore indeed rather complex for empirical studies to define potential thematically boundaries, especially in changing (e.g. new or diversifying) clusters (Boschma and Frenken, 2011a; Fornahl et al., 2015).

(3) The element of interdependencies deals with the interconnectedness of various actors within a cluster and the resulting externalities, which are defined as the “net benefits to being in a location together with other firms increase with the number of firms in the location.” (Arthur, 1990, p.

[39] Apart from these externalities, Klepper proposed an alternative, although not mutually exclusive, explanation for the clustering of industries referring to spinoff dynamics (Boschma, 2015; Klepper, 2007a; Klepper, 2010).

237). The corresponding sub-dimension of co-location advantages thereby depicts the general existence of a firm-specific advantage, while knowledge/technology spillovers, cooperation and competition deal more with the mechanisms of clustering. Whether externalities arise from specialization, diversification or related variety has however not been put into concrete terms (Fornahl et al., 2015). At the same time, there exist several cluster mechanisms, such as spinoff formation (e.g. Klepper, 2007a, 2007b) or labour mobility (e.g. Angel, 1991), that cause the emergence of a cluster and the corresponding co-location advantages (Benner, 2009).

(4) Complementary institutions and trust consists of formal/institutional relationships and establishments as well as informal exchange/trust. The first sub-dimension summarizes the role of institutions, such as universities or regional development agencies. The second sub-dimension is contrarily concerned with the informal exchange and its significance for cognitive proximity as well as trust.

The results of the literature overview, building on 25 identified cluster definitions, are illustrated in figure 1. It can be shown that especially the spatial connection, the thematic connection and the interdependencies are seen as central elements of a cluster definition. In contrast, complementary institutions and trust are only mentioned in a relatively small number of definitions. One explanation may be that not all clusters are built on informal relationships, social capital and trust, but just some specific forms of a cluster such as industrial districts in Italy (Fornahl et al., 2015). Complementary institutions and trust are therefore not further considered as key characteristics of a cluster.

Consequently, based on the results of the literature overview the following working definition for a cluster can be derived: 'Clusters are defined as a geographical concentration of closely interconnected horizontal, vertical and lateral actors, such as universities, from the same industry[40] that are related to each other in terms of a common resource and knowledge base, technologies and/or product-market.'

[40] The same industry can thereby encompass narrowly defined industries (e.g. based on single industry codes) and/or broader industry classifications, such as the automotive industry, consisting of closely related sub-industry groups.

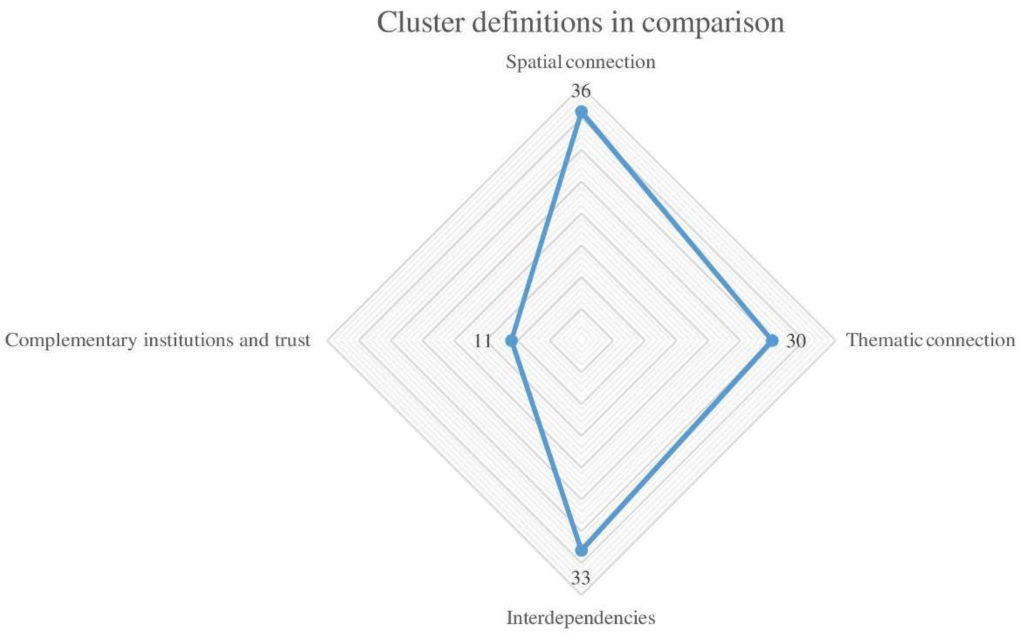


**Figure 1:** Cluster definitions in comparison (own figure based on Fornahl et al., 2015)[41]

The here derived working definition for a cluster is therefore very close to Marshall´s understanding and more in line with economic perspectives focussing particularly on the externalities highlighted by Marshall (1920), such as Porter´s competitiveness school, than with socio-economic perspectives, e.g. Innovative Milieu literature stream (Šarić, 2012). In light of our focus on firm performance, it is argued that such a theoretical classification is particularly appropriate (e.g. McCann and Folta, 2008). It therefore differs on the one hand from the conceptualization of pure agglomerations where firms are not necessary linked nor related to each other (Šarić, 2012). On the other hand, it is also conceptually distinct from Jacob´s externalities (Jacobs, 1969) and the further distinction in related and unrelated variety (Frenken et al., 2007), stressing the economic blessings of diversified regional industrial structures promoting the creation of new (rather radical) ideas and protecting against industry-specific shocks (Boschma and Iammarino, 2009; Frenken, et al., 2007; Jacobs, 1969). Even though this theoretical stream should be mentioned when dealing with clusters, in line with the results of Lazzeretti et al. (2014) it is argued that it does not constitute the core of the cluster understanding. Nevertheless, it is crucial to bear in mind that the here derived working definition is generalized in the way that it appropriately captures the definitional core elements of a good functioning cluster in the sustaining phase of the cluster life cycle. As such, across the cluster life cycle

[41] For a detailed list and classification of the considered cluster definitions please see appendix 1.

(e.g. Menzel and Fornahl, 2010) other elements (e.g. the spatial concentration in the emerging phase) may, however, become more important.

### 2.2. Cluster advantages and disadvantages

Similar to the definitional confusion, the theoretical discussion about cluster advantages and disadvantages is also characterized by a certain inconsistency. In this section, the most prominent arguments will therefore be presented.

Marshall (1920) was among the first to consider the benefits that firms can gain from being located in close proximity to similar firms. He presented four crucial types of localization externalities: access to specialized labour, access to specialized inputs, access to knowledge spillovers and access to greater demand by reducing the consumer search costs (Marshall, 1920; McCann and Folta, 2008).[42]

Specialized labour refers to individuals that make industry-specific investments in their human capital (McCann and Folta, 2008). Krugman (1991) highlighted, in this context, that clusters create a common market pool for workers with specialized skills, benefiting both the workers as well as the hiring firms. On the one hand, a spatial concentration of similar types of firms reduces the risk for specialized workers able to attain work from multiple employers. On the other hand, this reduced risk also benefits employers by minimizing the risk premium as well as search cost components of workers` wages (David and Rosenbloom, 1990, Krugman, 1991). Furthermore, it is also argued that specialized workers may be more willing to invest in industry-specific human capital when they believe that they have a greater ability to appropriate the benefits (Rotemberg and Saloner, 2000). This is, however, a condition more likely to occur when there exist multiple companies pursuing the services of similar workers (McCann and Folta, 2011). In general, it has been indicated that the pooling of specialized employers and employees in close geographical distance also improves the overall matching process between both sides (Amend and Herbst, 2008; Otto and Fornahl, 2010). This results in a pronounced labour mobility within clusters, being crucial for the inter-firm knowledge diffusion, fostering firm performance, due to the person-embedded knowledge (Erikson and Lindgren, 2009; Otto and Fornahl, 2010). A somehow special case refers in this context to spinoffs, which have been shown to exploit their knowledge of local employees, resulting in a higher probability of hiring employees from the

[42] Besides these externalities he also noted that the unique physical conditions of particular areas, such as limited natural resources, are the chief cause for the localization of industries.

entrepreneur´s prior employer as well as from other nearby firms from the same industry (Carias and Klepper, 2010). While this entails a knowledge transfer from the incumbent firm to the spinoff (Bagley, 2019b), it has also been demonstrated that the previous employer gains from this process, due to enduring social relationships with their former employees, contributing to sustained flows of knowledge (Agrawal et al., 2006).

Related to this is the access to knowledge spillovers. It is argued that geographic proximity can facilitate the transfer of knowledge in general (Jaffe et al., 1993) and specifically the transfer of tacit knowledge because it increases the likelihood of face-to-face contacts which is an efficient medium for the transfer of such knowledge (Daft and Lengel, 1986). As such, the eased knowledge diffusion within clusters, particularly the tacit one, can in turn promote collective learning processes and innovation activities of the corresponding firms (Audretsch and Feldman, 2003; Rigby and Brown, 2015; Terstriep and Lüthje, 2018).[43]

Many of the same reasons that firms in clusters have improved access to specialized labour hold also true for the improved access to specialized inputs in general. Due to its demand for specialized inputs, a cluster attracts input suppliers in larger numbers, which in turn provides access to services that firms could otherwise not afford individually (Feldman, 1994; Marshall, 1920; McCann and Folta, 2008).

Apart from the previous mentioned supply-side advantages, companies in clusters can also gain from an access to greater demand. The underlying idea is that geographical concentration facilitates the search and evaluation of the variety of options available from multiple firms. By reducing the corresponding consumer costs, the probability that consumers will purchase in specialized agglomerations in comparison with more isolated locations is increased (McCann and Folta, 2008).

Another argument put forward for the benefits of clusters refers to the competition created by collocating with rivalries. The competition exposes firms to great pressure and in the end motivates them to innovate in order to stay competitive (Harrison et al., 1996; Porter, 1998).

[43] Recently, evidence has been found that due to the pronounced knowledge diffusion within clusters, especially regarding tacit knowledge, clusters promote the creation of radical innovations (Grashof et al., 2019), which can open up completely new markets and industries (Castaldi et al., 2015; Verhoeven et al., 2016).

Furthermore, it has been highlighted that companies located within clusters can additionally profit from a common reputation (Molina-Morales and Martínez-Fernández, 2004; Wu et al., 2010), an information and communication ecology (Bathelt et al., 2004; Beaudry and Breschi, 2003) as well as infrastructure benefits (Kuah, 2002).

Although much of the discussion so far has focused almost exclusively on the advantages of clusters, there are also some authors highlighting potential disadvantages as a cluster grows larger and ages (Boschma and Frenken, 2011b; McCann and Folta, 2008). The previously positive aspect of competition can become a negative one with a size increase of the cluster. The higher density of similar actors can lead to increased competition for input factors, which may result in scarcity of these factors as well as significantly price increases (Fang, 2015; McCann and Folta, 2008).[44] In the case of human resources, such a fierce competition can lead to labour poaching, entailing costs for the corresponding firm. On the one hand, competitors can gain access to the firm´s own knowledge embodied in its employees, thereby increasing their relative competitive advantage over other firms. On the other hand, firms can prevent this and retain their human capital by raising their personnel expenses (e.g. paying higher wages or gratifications). Consequently, in both cases firms are negatively affected (Combes and Duranton, 2006; Otto and Fornahl, 2010). Additionally, an increasing density can also lead to what some authors called congestion costs. These costs are typically expressed in outcomes such as increased traffic and transportation costs within a certain region (McCann and Folta, 2008). Another possible disadvantage refers to negative knowledge spillovers or in other words knowledge leakages that may discourage a firm to further innovate within a cluster, as other firms can actually free-ride on their knowledge (Fang 2015; Shaver and Flyer 2000). Furthermore, over time companies in clusters may face a certain inertia regarding market and technology changes. In this context, Pouder and St. John (1996) argued that the performance decline over time can be explained with the convergent mental models of managers within the corresponding region. This kind of uniform thinking, a sort of group thinking behaviour, reinforces old behaviours and old ways of thinking. As a consequence, it prevents the recognition and adoption of new technological trends and new ideas in general (Martin and Sunley, 2003; McCann and Folta, 2008; Porter, 2000; Pouder and St. John, 1996). Additionally, there are some authors suggesting that a simple reliance

[44] The concrete geographical distance has also be found to matter in this context (e.g. De Silva and McComb, 2012).

on local face-to-face contacts and tacit knowledge makes local networks of industry especially vulnerable to lock-in situations which in turn enforce again the inertia of companies within clusters (Boschma, 2005; Martin and Sunley, 2003).

Summing up the theoretical discussion, it can be stated that clusters are supposed to comprise several advantages as well as disadvantages to the firms depending on the specific context, such as the firm´s absorptive capacity and cluster size (Frenken et al., 2015; McCann and Folta, 2008).

## 3. Data and Methodology

This rather mixed picture is also reflected in the empirical results. In order to reconcile the conflicting empirical results of the firm-specific cluster effect a descriptive meta-analysis will be conducted. In general, a meta-analysis statistically integrates empirical results from different studies investigating a common research question (Florax, et al., 2002; Quintana, 2015; Wagner and Weiß, 2014). It can therefore be defined as the "(…) analysis of analyses." (Glass, 1976, p. 3). There exist indeed many reasons for applying meta-analysis as an appropriate alternative methodical approach to the traditional narrative review. One of the most important reasons refers to the proceeding of narrative reviews which is often insufficient standardized and therefore difficult, if at all, verifiable. It is quite common that the reviewer subjectively chooses which studies to include in his review and what weights to attach to the results of these studies. Contrarily, by its statistical nature meta-analysis can minimize subject bias and offer a great transparency as well as reproducibility (Fang, 2015; Melo et al., 2009; Stanley and Jarrell, 1989; Wagner and Weiß, 2014). Thus, it is supposed that a meta-analysis is an appropriate methodical approach to answer the underlying research question, whether being located in a cluster does influence firm success. In general, the meta-analysis method can be divided into two broad categories: descriptive meta-analysis and meta-regression (addressing sampling error or addressing both sampling error as well as other artefacts). In light of the available information and the relatively broad research question of this paper it is acceptable to apply a descriptive meta-analysis. This method offers the possibility of not only analysing the cluster effect on firm success, but also the corresponding moderating variables (Hunter and Schmidt, 2004; Wagner and Weiß, 2014).

For the measurement of firm success, four different performance variables are taken into consideration: innovativeness, productivity, survival and employment growth. By considering four different performance variables, the effect of being located in a cluster on firm success can be analysed from a broader perspective. It is argued that the selected four performance variables capture most frequently and adequately firm success (Globerman et al., 2005; Sleutjes et al., 2012).[45]

The first step of the publication-based meta-analysis refers to collecting relevant data through a literature review. The empirical studies used in the meta-analysis are first of all collected from three different publication databases, namely Web of Science, Google Scholar as well as Ebsco. The application of various publication databases is crucial in order to avoid a possible database bias, meaning that one database may favour a specific kind of literature, and hence in the end contributes to a more meaningful literature collection. The search strategy is based on keyword combinations of 'cluster' or 'agglomeration'[46] (which is quite often used as a synonym[47]) and one of the four performance variables and 'firm' or 'company'. The last two keywords are necessary to exclude empirical studies focusing only on the regional performance level. For the literature collection, only the 200 most relevant articles for each search query are considered.[48] Moreover, the search is conducted for all years and for all document types, as at the beginning a preferably comprehensive literature collection should be achieved. Since the above procedure returns mainly published articles, which may lead to a publication bias, it is explicitly necessary to include further working papers to mitigate this bias. The four combinations of keywords are therefore additionally used for a search query in the Social Science Research Network (SSRN). This publication database is especially convenient, as it implies an internal review process, even though it mainly deals with working papers (Elsevier Inc, 2017). Hence, by choosing SSRN the quality of the data is ensured. Because the main purpose of this publication database is to include recent but not already published articles, only the results for the years 2014 until

[45] Nevertheless, other performance variables, such as wages, may also be interesting to consider in future meta-analysis due to among other reasons the relatively high number of empirical studies (e.g. Andersson et al., 2016; Wennberg and Lindqvist, 2010).

[46] However, as highlighted later in the inclusion criteria, the three identified key characteristics of clusters (spatial connection, thematic connection and interdependencies) have to be fulfilled by the collected studies in order to be included in the final sample. This guarantees a similar conceptual cluster understanding, while ignoring the definitional inconsistency characterising this particular research field.

[47] See for example Delgado et al. (2010), Martin et al. (2011) or McCann and Folta (2011).

[48] The sorting by relevance is provided by the corresponding publication database and is based on the frequency of the search terms that appear in each record (in the title, abstract and keywords). As such, it is argued that only the most suitable (with respect to the research focus of this paper) articles are considered.

2016 are considered.[49] Furthermore, in some instances relevant empirical studies from different search queries were also taken into consideration. For example, this would be the case if some results from the search query of innovation are also relevant for the performance variable productivity.

After this very broad collection of literature, specific results are sorted out by applying inclusion criteria. The inclusion criteria are as follows: first, the studies need to be empirical. Even though the findings of theoretical papers are briefly summarized in the theoretical discussion, they are not included in the overall meta-analysis. Second, to ensure that all selected studies have the same cluster understanding, the three identified key characteristics (spatial connection, thematic connection and interdependencies) have to be considered. As a consequence, studies focusing only on networks, industrial parks or urbanization are not included in the final sample. Third, relative cluster measures[50], such as relative specialization indicators, have to be at least based on the national average in the corresponding industry and not on the regional average. In absence of this condition one can hardly speak about a cluster, because on a county or city level a high specialization in a specific industry can be achieved quite easily. Fourth, the worker wages as well as the earnings at the establishment level are not seen as adequate measures for firm productivity. In contrast to traditional economic thinking it is argued that a rise in productivity does not automatically imply a wage increase.[51] Empirical studies making use of these or similar measures are therefore not incorporated in the final sample. Last, the analytical focus of the empirical studies needs to be on the firm-level and not on the regional level. Although already integrated in the search queries, in some cases this condition is not fulfilled. By knowing the essential meaning of the selection process for the overall meta-analysis, in case of doubt a second opinion is recognized.

Figure 2 depicts the concrete selection and exclusion process of the considered studies. In total 2,201 studies are collected that match the already mentioned search queries. After excluding duplicate studies and studies without author, only 1,944 results are considered in the first review process. In this first review process the title and the abstract are read in order to analyse whether the studies fulfil the inclusion criteria. Consequently, 1,465 studies are sorted out, mainly due to their content

[49] The authors acknowledge that it is of course possible that older working papers may not, as assumed, convert itself in a journal article. Nevertheless, it is not illusory to assume that ‘good’ working papers are likely to be published in journals.

[50] For a detailed overview about different cluster measures see for example Brenner (2017).

[51] For a comprehensive overview about this issue please see Van Biesebroeck (2015).

which often deals with a cluster analysis or with the regional level. Subsequently, two more detailed reviews are implemented. In these more detailed reviews especially the statistical part is analysed. At the end, the final meta-analysis considers a population of 168 empirical studies.[52] This corresponds to 8.6% of the adapted population (studies without author and duplications excluded).

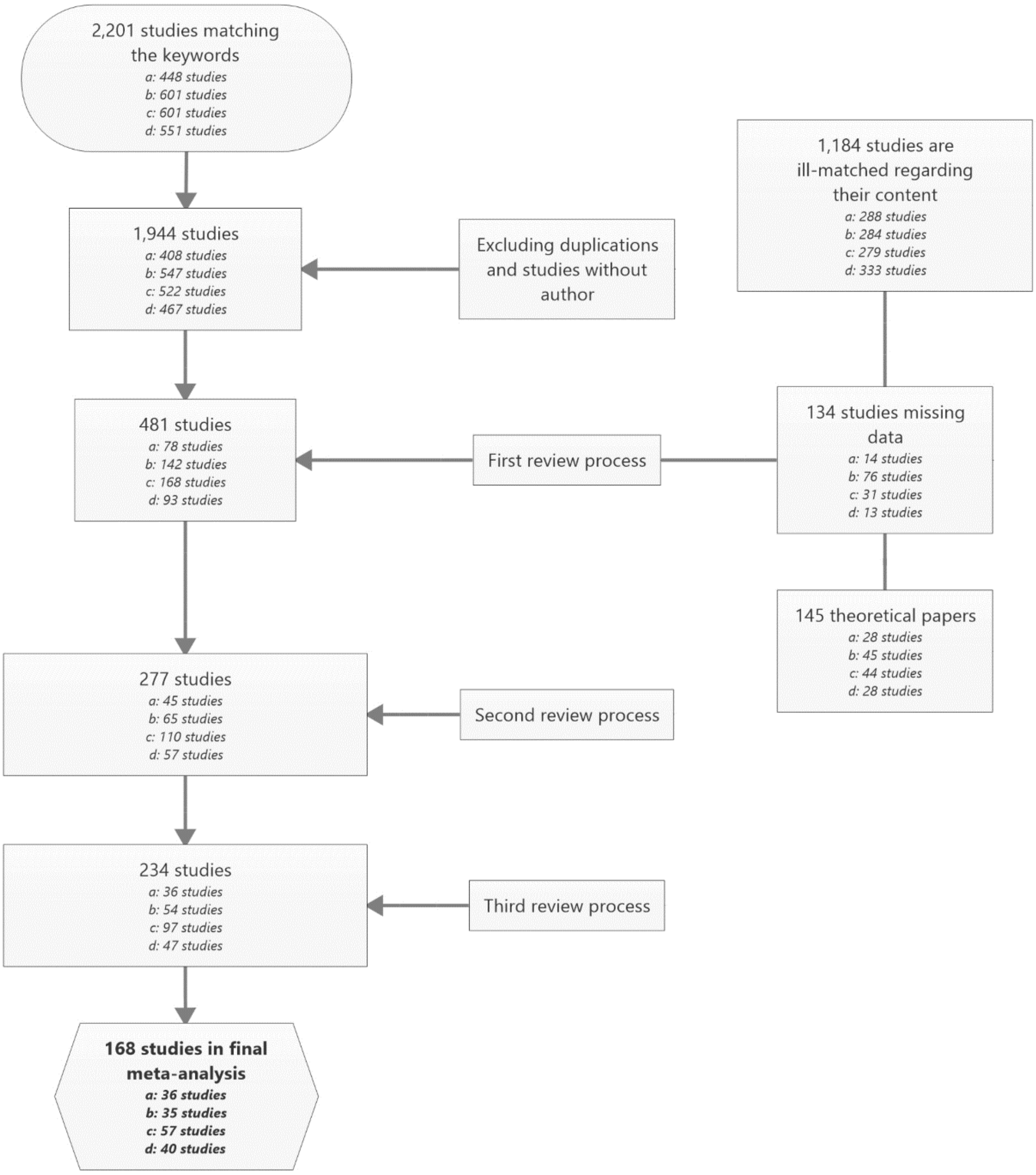


**Figure 2:** Selection and exclusion process of the considered empirical studies (own illustration)

Note: *a*: Employment growth; *b*: Innovativeness; *c*: Productivity; *d*: Survival

[52] A detailed overview about the considered empirical studies is illustrated in appendix 2.

In general, it can be stated that up to now relatively few papers have applied such a meta-analysis in the context of a firm-specific cluster effect. One important exception refers to the recent work of Li Fang (2015) which provides a meta-analysis for relevant empirical studies on the relationship of clusters and the innovativeness of firms and regions. Yet, this scientific work differs from Li Fang (2015) in four mayor aspects. First, instead of mixing firm-level and regional-level oriented studies, this article explicitly focuses on the firm-level. Consequently, the derived results are not biased by the regional effect of clusters and therefore provide more specific insights about the cluster effect on firms. Second, the meta-analysis here considers not only one performance variable, like innovativeness, but four different performance variables. By taking four different performance variables into account, the influence of the settlement in a cluster on firm success can be detected from a broader and more differentiated perspective. Furthermore, the literature collection of this meta-analysis is more extensive because the search is based on four different publication databases in total. Additionally, during the selection and exclusion process it is controlled whether the underlying cluster definitions of the empirical studies match with the three main elements of a cluster definition, shown in the previous section. Even though the strict definitional compliance is one of the principal reasons for the relatively large exclusion of articles, it is essential for a meaningful meta-analysis, as the firm-specific cluster effect does not get distorted by other network like effects. In other words, the true firm-specific cluster effect can be detected.

## 4. Empirical results

Before investigating this potential effect, it is, however, first of all interesting to have a closer look at the empirical studies of the final sample. Figure 3 illustrates the years of publication of the sample. At first glance, it becomes obvious that most of the studies in the final sample are relatively new. The oldest empirical record dates back to the year 1998. So, from the introduction of the term cluster by Michael Porter (1990) it took eight more years for an empirical study to test the relationship between clusters and firm performance. One explanation for this delay refers to the theoretical discussion and deepening of the concept. It is quite conventional that a new concept is first of all theoretical discussed within the research community. In this concrete case, it is additionally reasonable to suggest that the first empirical articles mainly focused on the regional level. Indeed, while widely been ignored for quite a long time, only in recent years researchers have shifted their focus of analysis on the firm-specific perspective (Brown et al., 2007; Šarić, 2012; Steffen, 2012). Apart from employment growth, more or less half of the empirical studies of the analysed performance indicators were published in the last five years (2012-2016). In more concrete terms, 46% of the empirical studies dealing with the cluster effect on firm innovativeness and even 65% of studies concerning the effect on firm survival were published in this period of time. Regarding the firm-specific cluster effect on employment growth at least 28% of the empirical studies were published in the last five years.

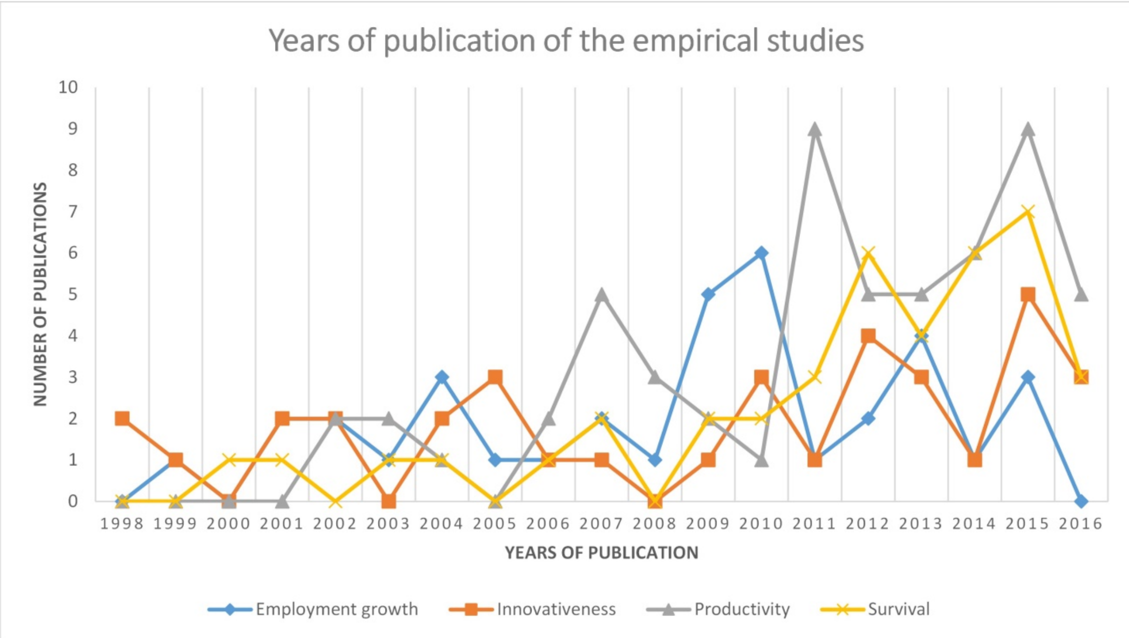


**Figure 3:** Years of publication of the empirical studies (own illustration)

Having a closer look at the specific journals one can state that the most frequent used journals come from the regional science. However, journals from the field of economics and management are also prevalent. Thus, it can be stated that the relationship between clusters and firm performance has received the attention from a multidisciplinary audience.[53]

Moreover, even though the considered studies in the final sample have analysed the firm-specific cluster effect in the context of various countries worldwide (in total 29 different countries), it can be observed that in most cases, except for productivity, the USA have been the most highly investigated country setting. Partially this can be explained by the fact that due to Michael Porters contributions (1990 and 1998) the roots of the cluster concept lay in the USA. Nevertheless, on a more aggregated level it can be stated that on average half of all considered studies base their empirical analysis in a European country, whereas countries from North America

[53] For a detailed list of the journal distribution of the sample please see appendix 3.

(USA, Canada, Mexico) account on average only for a quarter of all studies in the final sample. Despite some core countries of investigation (e.g. USA, Netherlands, Italy), it can therefore be argued that the final sample of this study appears to be quite diverse in this context.[54]

In order to detect the estimated direction of cluster effects on the four considered performance variables, a vote counting method is applied (De Groot et al., 2007; Fang, 2015). Since one study may use several regression models to measure, for example, different kinds of characteristics of the cluster, it can also identify several effects. To treat studies equally, a study-level vote counting is conducted, meaning that all findings regarding the effect direction of clusters on firms performance are for each study summarized. This is necessary in order to avoid a possible overvaluation of studies containing several regressions (Fang, 2015). All the available estimates of each study are therefore grouped into seven classes:

- Sig. positive: Referring to significant positive cluster effects on firm performance.
- Insignificant: Referring to insignificant cluster effects on firm performance.
- Sig. negative: Referring to significant negative cluster effects on firm performance.
- Sig. positive and insignificant: Referring to significant positive and insignificant cluster effects on firm performance.[55]
- Sig. negative and insignificant: Referring to significant negative and insignificant cluster effects on firm performance.
- Sig. negative and sig. positive: Referring to significant negative and significant positive cluster effects on firm performance.
- Sig. negative, sig. positive and insignificant: Referring to significant negative, significant positive and insignificant cluster effects on firm performance.

However, at this point it is essential to highlight that the vote counting method has also been criticized, because the corresponding results are rather imprecise in comparison to the fixed effects model for example. The imprecision refers to the fact that the sample size of each study as well as the actual effect size are not

[54] For a detailed illustration of the countries of investigation please see appendix 4.

[55] In other words, studies belong to this class if they find significant positive and insignificant results regarding the influence of clusters on firm performance.

considered at all (Hedges and Olkin, 1980; Stanley, 2001). Nevertheless, as already mentioned at the beginning of the previous chapter, in light of the relatively broad research question as well as the available information the vote counting method offers a suitable way of approaching the firm-specific cluster effect. As a consequence, it is suggested that vote counting serves the purpose to get first insights about this effect (Wagner and Weiß, 2014).[56]

The results of the study-level vote counting for all four performance variables are presented in figure 4.

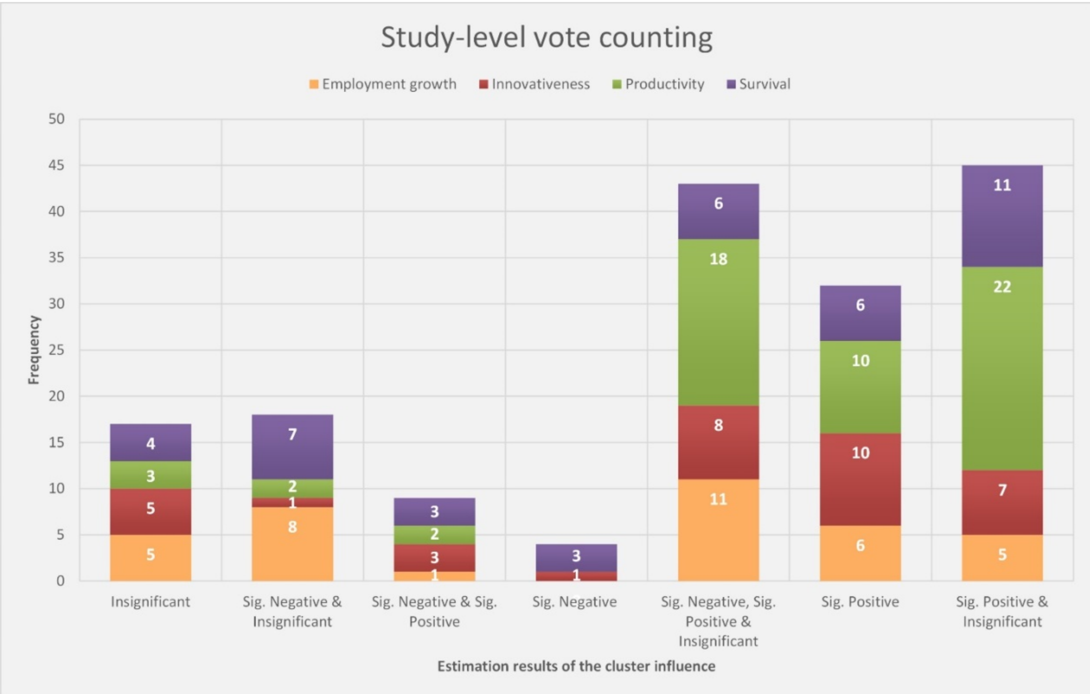


**Figure 4:** Study-level vote counting (own illustration)

What is striking the most are indeed the mixed empirical results for all four variables, indicating that there exist possible moderators, such as the industry context, shaping the relationship between cluster and firm performance. Interestingly, this holds also true for the results within the same underlying study. As such, 25.6% of the considered empirical studies determine at the same time sig. negative and sig. positive as well as insignificant firm-specific cluster effects. However, what can be further observed is that the majority of studies report either a sig. positive or a sig. positive and insignificant cluster effect. In total, 45.8% of the considered empirical studies note either one of these two directions. Contrary, only 22 studies (13.1%)

[56] In the context of the localization and urbanization debate such an approach has for instance been applied by Beaudry and Schiffauerova (2009).

find empirical support for a pure sig. negative or a sig. negative and insignificant effect. Thus, a tendency towards a rather sig. positive cluster effect on firm success can be asserted. Nevertheless, having a closer look at the four different performance variables some variation between the results can be found. While the empirical studies dealing with the innovativeness and the productivity of a firm find nearly no evidence for a rather sig. negative cluster effect, the results for the variables of employment growth and survival more frequently indicate to a sig. negative effect. Even though that there also exist evidence for a sig. positive firm-specific cluster effect in these both cases, the results appear to be more negative than for innovativeness as well as productivity. In more concrete terms, 22.2% of the empirical studies dealing with employment growth and even 25% of the studies dealing with survival report a pure sig. negative or a sig. negative and insignificant effect. In comparison, in the case of innovativeness and productivity only 5.7% of the considered empirical studies respectively 3.5% assert similar effects. This can on the one hand be explained with differences in the consideration and importance of moderating variables, which are also highlighted later in table 1. In general, it seems to be plausible that the realization of employment growth and survival depends on different and supposedly more on the specific context than innovativeness and productivity. On the other hand, the results may also indicate towards the two-sided effect of the high competition within clusters. While the high competition between similar firms fosters their innovativeness and productivity, it hampers their employment growth and survival through e.g. labour poaching (Audia and Rider, 2010; McCann and Folta, 2008; Porter, 1998; Sorenson and Audia, 2000).

These tendencies can be solidified by re-grouping the vote counting into positive, insignificant and negative estimation results.[57] As a consequence, a study that previously reported sig. positive and insignificant effects will now appear twice, meaning that in the end it is counted one time for a sig. positive and a second time for an insignificant effect. The results of this re-organization of the data are outlined in figure 5. By analysing the re-grouped data for the four different performance variables, it becomes obvious that nearly 40% of the considered empirical studies report at least once a positive cluster effect on firm performance. In contrast to this, only 23% of the studies find evidence for a negative effect. Thus, it can be stated that in general most studies indeed identify a rather positive firm-specific cluster effect.

[57] Positive and negative estimation results refer in both cases to significant results.

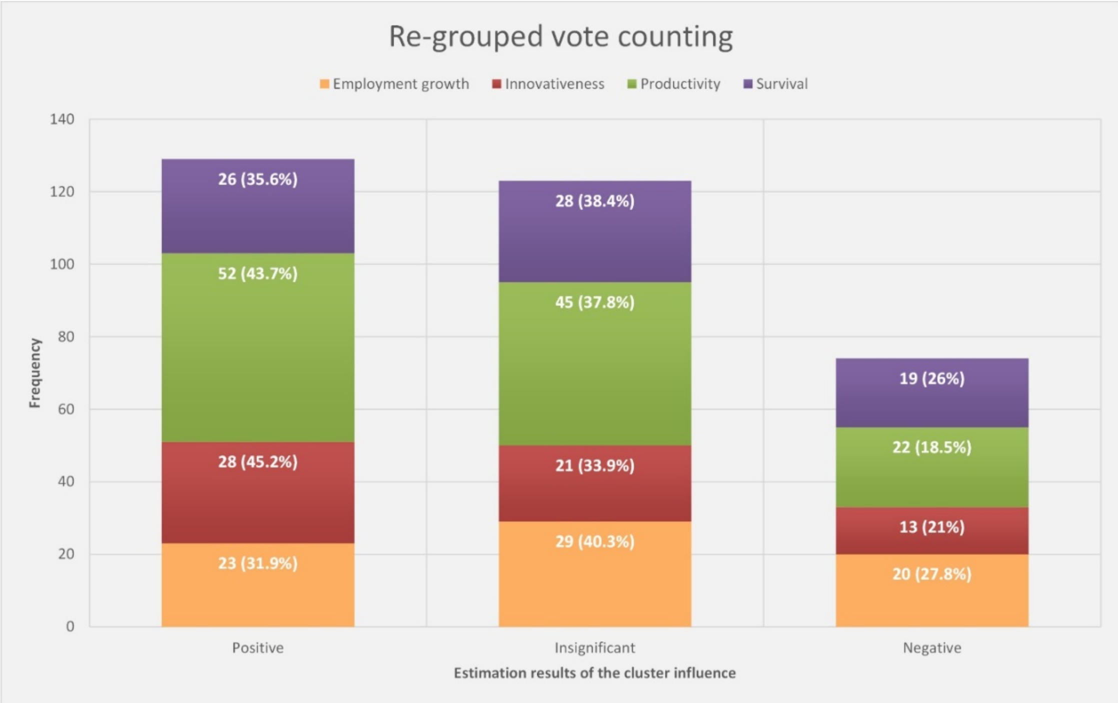


**Figure 5:** Re-grouped vote counting (own illustration)

Although, as already described before, there exists some variation between the four performance variables. In the cases of employment growth and survival the most dominant estimation results refer to an insignificant effect, whereas empirical studies dealing with innovativeness as well as productivity most frequently report a positive effect. One plausible explanation for these differences refers to the unequal consideration of different moderating variables. Even though there are moderating variables, such as the industry, that are considered across all four performance variables, some variables, such as a firm´s internal knowledge base, are only recognized in relatively few cases. Table 1 depicts the results for these and additional moderating variables.[58] Although all moderating variables have been collected, for a better visualisation table 1 presents only a selection of them. Since the focus lies on moderating variables, the actual level of analysis is thereby on the model level and not on the study level anymore. Consequently, the number of observations exceeds the number of considered empirical studies, because one study may potentially include several empirical models. In total, out of the 168 empirical studies 2,201 statistical models have been considered.

[58] Moderating variables encompass in this context interaction effects between the applied cluster measure and a contextual variable (e.g. firm size) as well as investigations of the cluster effect in subsamples (e.g. different industry settings), also implying a potential moderating effect.

**Table 1:** Moderating effects across all four performance variables (own illustration)

| **Estimation results** | **Employment growth** | | | **Innovativeness** | | | **Productivity** | | | **Survival** | | | **Total** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Moderation effects** | **+** | **±** | **-** | **+** | **±** | **-** | **+** | **±** | **-** | **+** | **±** | **-** | **+** | **±** | **-** |
| Pure | 17 (4.7%) | 10 (2.4%) | 10 (5.6%) | 11 (12.5%) | 15 (16.9%) | 11 (28.9%) | 36 (10.6%) | 50 (17.2%) | 5 (6.7%) | 11 (10.9%) | 3 (2%) | 0 | ***75 (8.4%)*** | ***78 (8.2%)*** | ***26 (7.5%)*** |
| ***Micro-level*** | | | | | | | | | | | | | ***28 (3.1%)*** | ***39 (4.1%)*** | ***16 (4.6%)*** |
| Firm size | 0 | 0 | 2 (1.1%) | | | | 10 (2.9%) | 12 (4.1%) | 7 (9.3%) | 1 (1%) | 0 | 0 | 11 (1.2%) | 12 (1.3%) | 9 (2.6%) |
| Firm age | 10 (2.8%) | 0 | 1 (0.6%) | | | | 1 (0.3%) | 6 (2.1%) | 0 | | | | 11 (1.2%) | 6 (0.6%) | 1 (0.3%) |
| Firm´s ownership | | | | 1 (1.1%) | 3 (3.4%) | 4 (10.5%) | 2 (0.6%) | 12 (4.1%) | 2 (2.7%) | | | | 3 (0.3%) | 15 (1.6%) | 6 (1.7%) |
| Internal knowledge base | | | | | | | 0 | 2 (0.7%) | 0 | | | | 0 | 2 (0.2%) | 0 |
| Firm´s organisational structure | | | | 3 (3.4%) | 3 (3.4%) | 0 | 1 (0.3%) | 1 (0.3%) | 0 | | | | 3 (0.3%) | 4 (0.4%) | 0 |
| ***Meso-level*** | | | | | | | | | | | | | ***8 (0.9%)*** | ***5 (0.5%)*** | ***14 (4%)*** |
| Cluster size | | | | 0 | 0 | 3 (7.9%) | 7 (2.1%) | 2 (0.7%) | 9 (12%) | | | | 7 (0.8%) | 2 (0.2%) | 12 (3.4%) |
| Sector of specialization | 1 (0.3%) | 1 (0.2%) | 1 (0.6%) | | | | | | | 0 | 2 (1.3%) | 1 (1.8%) | 1 (0.1%) | 3 (0.3%) | 2 (0.6%) |
| ***Macro-level*** | | | | | | | | | | | | | ***571 (64.2%)*** | ***533 (56.2%)*** | ***195 (56%)*** |
| Industry | 202 (56.1%) | 280 (67.3%) | 119 (66.9%) | 59 (67.0%) | 66 (74.2%) | 7 (18.4%) | 257 (75.4%) | 150 (51.5%) | 37 (49.3%) | 51 (50.5%) | 37 (24.3%) | 31 (54.4%) | 569 (64%) | 533 (56.2%) | 194 (55.7%) |
| Spatial regimes | | | | 2 (2.3%) | 0 | 1 (2.6%) | | | | | | | 2 (0.2%) | 0 | 1 (0.3%) |
| ***Interaction effects*** | | | | | | | | | | | | | ***207 (23.3%)*** | ***293 (30.9%)*** | ***97 (27.9%)*** |
| *Micro-level x Macro-level* | | | | | | | | | | | | | | | |
| Firm size x industry | 24 (6.7%) | 14 (3.4%) | 3 (1.7%) | 0 | 0 | 1 (2.6%) | 8 (2.3%) | 10 (3.4%) | 9 (12%) | 2 (2%) | 1 (0.7%) | 1 (1.8%) | 34 (3.8%) | 25 (2.6%) | 14 (4%) |
| Firm age x industry | 0 | 3 (0.7%) | 0 | | | | 0 | 0 | 3 (4%) | 1 (1%) | 3 (2%) | 0 | 1 (0.1%) | 6 (0.6%) | 3 (0.9%) |
| Firm´s ownership x industry | | | | | | | 3 (0.9%) | 5 (1.7%) | 0 | 1 (1%) | 5 (3.3%) | 0 | 4 (0.4%) | 10 (1.1%) | 0 |
| Knowledge intensity x industry | 0 | 3 (0.7%) | 1 (0.6%) | | | | | | | | | | 0 | 3 (0.3%) | 1 (0.3%) |
| Firm´s innovation capabilities x industry | | | | 10 (11.4%) | 1 (1.1%) | 10 (26.3%) | | | | | | | 10 (1.1%) | 1 (0.1%) | 10 (2.9%) |
| Subsidiary-status x industry | 8 (2.2%) | 6 (1.4%) | 0 | | | | 1 (0.3%) | 3 (1%) | 0 | 0 | 2 (1.3%) | 0 | 9 (1%) | 11 (1.2%) | 0 |
| Headquarter location x industry | 2 (0.6%) | 1 (0.2%) | 1 (0.6%) | | | | | | | 4 (4%) | 17 (11.2%) | 7 (12.3%) | 6 (0.7%) | 18 (1.9%) | 8 (2.3%) |
| Geographical distance x industry | 83 (23.1%) | 77 (18.5%) | 28 (15.7%) | | | | 12 (3.5%) | 17 (5.8%) | 0 | 23 (22.8%) | 71 (46.7%) | 8 (14%) | 118 (13.3%) | 165 (17.4%) | 36 (10.3%) |
| Geographical location x industry | 9 (2.5%) | 7 (1.7%) | 0 | | | | | | | | | | 9 (1%) | 7 (0.7%) | 0 |
| Plant type x size x industry | | | | | | | 3 (0.9%) | 20 (6.9%) | 0 | | | | 3 (0.3%) | 20 (2.1%) | 0 |
| *Meso-level x Macro-level* | | | | | | | | | | | | | | | |
| Cluster life cycle x industry | | | | | | | | | | 3 (3%) | 4 (2.6%) | 0 | 3 (0.3%) | 4 (0.4%) | 0 |
| Cluster size x industry | | | | 1 (1.1%) | 0 | 0 | 0 | 1 (0.3%) | 3 (4%) | 2 (2%) | 0 | 2 (3.5%) | 3 (0.3%) | 1 (0.1%) | 5 (1.4%) |
| Degree of specialization x industry | 0 | 11 (2.6%) | 3 (1.7%) | | | | | | | 2 (2%) | 2 (1.3%) | 6 (10.5%) | 2 (0.2%) | 13 (1.4%) | 9 (2.6%) |
| Sector of specialization x industry | 0 | 0 | 6 (3.4%) | | | | | | | 0 | 5 (3.3%) | 1 (1.8%) | 0 | 5 (0.5%) | 7 (2%) |
| Value chain of the cluster x industry | | | | 1 (1.1%) | 1 (1.1%) | 1 (2.6%) | | | | | | | 1 (0.1%) | 1 (0.1%) | 1 (0.3%) |
| *Macro-level x Macro-level* | | | | | | | | | | | | | | | |
| Spatial regimes x industry | 4 (1.1%) | 3 (0.7%) | 3 (1.7%) | | | | | | | | | | 4 (0.4%) | 3 (0.3%) | 3 (0.9%) |

Note: + Positive significant cluster effect; ± Insignificant cluster effect; - Negative significant cluster effect

By analysing the moderating effects, shown within the considered empirical studies, it is interesting to note that there exists relatively few evidence for a pure firm-specific cluster effect, meaning a direct and generic cluster effect on firm performance in absence of potential moderating variables. Thus, being located in a cluster does not, at least in most cases, automatically lead to a positive or a negative firm-specific cluster effect. Instead several variables from the micro-, meso- and macro-level directly or interactively moderate the relationship between clusters and firm performance. In other words, it is a rather complicated relationship which is influenced by a mix of different moderating variables. However, the specific industry is one of the most important moderating effects. Nearly across all four performance variables around 50% of the positive, insignificant and negative firm-specific cluster effects can be explained by the corresponding industry.

By grouping the different industries according to the classification of Eurostat (Eurostat, 2014; Eurostat, 2017) and the OECD (OECD, 2011) into low-technologies, medium-low-technologies, medium-high-technologies and high-technologies further interesting results can be derived in this context, which are presented in table 2.

**Table 2:** Moderation effects according to the industry group (own illustration)

| **Estimation results** | **Industry effect** | | |
|---|---|---|---|
| **Moderation effect** | **+** | **±** | **-** |
| Industry | 405 | 395 | 160 |
| Low-tech | 170 (42%) | 147 (37.2%) | 91 (56.9%) |
| Mid-low-tech | 23 (5.7%) | 46 (11.6%) | 17 (10.6%) |
| Mid-high-tech | 26 (6.5%) | 52 (13.2%) | 20 (12.5%) |
| High-tech | 186 (45.9%) | 150 (38%) | 32 (20%) |

Note: + Positive significant cluster effect; ± Insignificant cluster effect; - Negative significant cluster effect

Across all four performance variables it can be shown that a negative firm-specific cluster effect can be especially asserted in low-tech industries and not so much in high-tech industries. Indeed 56.9% of the negative firm-specific cluster effects can be traced back towards low-tech industries, whereas for high-tech industries this share decreases to only 20%. Additionally, the results also point out that there exists a relatively high inter-industry variation (within the aggregated industry groups), indicating that the specific industry characteristics, such as pace of market and technology evolution, are highly important and therefore should be considered in more detail in future empirical studies.

Moreover, as can be seen in table 1, in comparison with the macro-level, mainly consisting of the industry variable, are the variables of the micro- and meso-level only investigated in a relatively small number of empirical studies. Instead interaction effects appear to be more important in this context, as 23.3% of the positive, 30.9% of the insignificant and 27.9% of the negative firm-specific cluster effects can be traced back towards different interaction effects.[59] Especially to highlight is the moderating effect of the geographical distance together with the industry context. This interaction effect is of particular importance for employment growth as well as survival. Having a closer look at the concrete categories of this interaction effect some interesting patterns can be observed, which are illustrated in table 3.

**Table 3:** Interaction effect of distance and industry (own illustration)

| **Estimation results** | **Distance and industry effect** | | |
|---|---|---|---|
| **Moderation effect** | **+** | **±** | **-** |
| Distance x industry | 100 | 152 | 36 |
| High distance x High-tech | 19 (19%) | 50 (32.9%) | 9 (25%) |
| High distance x Low-tech | 0 | 10 (6.6%) | 7 (19.4%) |
| Medium distance x High-tech | 33 (33%) | 51 (33.6%) | 4 (11.1%) |
| Medium distance x Low-tech | 10 (10%) | 17 (11.2%) | 5 (13.9%) |
| Low distance x High-tech | 28 (28%) | 21 (13.8%) | 7 (19.4%) |
| Low distance x Low-tech | 10 (10%) | 3 (2%) | 4 (11.1%) |

Notes: Low distance refers to >1 mile; Medium distance refers to 1-10 miles; High distance refers to 10-25 miles
+ Positive significant cluster effect; ± Insignificant cluster effect; - Negative significant cluster effect

For high-tech industries, it appears that a medium geographical distance between the corresponding actors contributes most frequently towards a positive firm-specific cluster effect. In more concrete terms, 33% of the asserted significant positive effects of the interaction between geographical distance and industry can be traced back to a medium distance and a high-tech industry. Although, in this context, it has to be stated that evidence is also found for an insignificant effect for this interaction term (33.6%), indicating towards an inter-industry variation likewise in the case of the sole moderating effect of the industry variable. Despite the inter-industry variation, it can be however seen that in high-tech as well as low-tech industries high geographical distance more frequently leads to an insignificant or even negative performance effect. Thus, it can be argued that high geographical distance is in general rather inhibitory for a positive firm-specific cluster effect in the context of both high-tech and

[59] In this context, an interaction effect between e.g. firm age and industry means that the interaction term between firm age and the corresponding cluster measure in one particular industry setting has a certain influence on one of the four considered performance variables.

low-tech industries. Regarding low geographical distance the results become more mixed, especially for low-tech industries. Whereas the results for high-tech industries indicate towards a rather positive moderating effect (28%), in the case of low-tech industries there exists nearly equally evidence for a positive (10%) as well as negative (11.1%) effect. Consequently, it can be asserted that low and medium geographical distance are more frequently beneficial for companies in high-tech industries, while high geographical distance is rather detrimental for both industry groups.

In light of the results derived from the vote counting and the analysis of the moderating effects, in total it can be resumed that on the one hand there indeed exist evidence for a rather positive firm-specific cluster effect. But on the other hand, the results remarkably differ in this context between the four considered performance variables. While the results are quite clear in the case of innovativeness and productivity, they are highly equivocal with regard to employment growth and survival. Additionally, strong moderating variables from different levels of analysis, shaping the relationship between clusters and firm performance, can also be asserted, thereby indicating that there exist firm performance differentials within clusters.

## 5. Conclusion

Even though cluster initiatives have received substantial financial support from national governments, the EU and other public institutions, it is still unclear whether being in a cluster really influences firm success (EFI, 2015; Frenken et al., 2015; Martin and Sunley, 2003). By conducting a meta-analysis of the empirical literature that investigates the firm-specific cluster effect, our paper reconciles the so far rather contradictory empirical results, thereby enriching the understanding about the alleged effect of clusters on firm performance. The descriptive analysis of the selected sample indicates that most empirical studies find evidence for the existence of a positive cluster effect on firm success. But at the same time, we also show that the empirical results are rather mixed. This pattern can be explained by moderating influences of a mix of different variables from different levels of analysis. The industry context provides a particularly crucial moderating effect. The corresponding results point out that a negative firm-specific cluster effect occurs more frequently in low-tech industries than in high-tech industries.

Moreover, the derived results, especially the moderating effects, emphasize that future empirical studies about the firm-specific cluster effect have to account for different moderating variables in order to investigate the relationship between clusters and firm success in more detail. It is argued that multilevel analysis methods are for this context especially suitable (Burger et al., 2012). In view of the variation between the four considered performance variables, it is additionally promising for future studies to make use of several outcome measures in order to get a more detailed picture about the effects of regional clusters. This also includes rather alternative socio-economic indicators, focusing for example more on environmental pollution or social cohesion, which remain to be properly investigated in the cluster context.
However, there is also one current limitation to this paper. The presented results are only descriptive in nature. The descriptive meta-analysis can only be the first step for a more detailed meta-regression, as the actual magnitude of the effect still needs to be investigated (Koricheva and Gurevitch, 2013). In this context, it is essential to take the diversity of applied methods into consideration. Furthermore, it would be interesting to analyse whether there exist national differences between the estimation results of the considered empirical studies.

Nevertheless, all in all it can be resumed that this paper makes a first step towards reconciling the contradictory empirical findings and thereby serving as a valuable stepping stone to closing the research gap concerning the alleged effect of clusters on firm performance. Or to say it with Shakespeare ‘to be or not to be’ located in a cluster is not the question, it rather depends on the specific conditions.

## References


Agrawal, A., Cockburn, I., & McHale, J. (2006): Gone but Not Forgotten: Knowledge Flows, Mobility, and Enduring Social Relationships, *Journal of Economic Geography*, Vol. 6, Issue 5, pp. 571-591.

Amend, E., & Herbst, P. (2008): Labor market pooling and human capital investment decisions, *IAB Discussion Paper*, No. 4/2008.

Andersson, M., Klaesson, J., & Larsson, J. P. (2016): How Local are Spatial Density Externalities? Neighbourhood Effects in Agglomeration Economies, *Regional Studies*, Vol. 50, Issue 6, pp. 1082-1095.

Angel, D. P. (1991): High-Technology Agglomeration and the Labor Market: The Case of Silicon Valley, *Environment and Planning A*, Vol. 23, Issue 10, pp. 1501-1516.

Arthur, W. B. (1990): 'Silicon Valley' locational clusters: when do increasing returns imply monopoly?, *Mathematical Social Sciences*, Vol. 19, Issue 3, pp. 235-251.

Asheim, B., Cooke, P., & Martin, R. (2006): The rise of the cluster concept in regional analysis and policy: a critical assessment, in: Asheim, B., Cooke, P., & Martin, R. (Eds.): Clusters and Regional Development: Critical Reflections and Explorations, Routledge, London, pp. 1-19.

Audia, P. G., & Rider, C. I. (2010): Close, but not the same: Locally headquartered organizations and agglomeration economies in a declining industry, *Research Policy*, Vol. 39, Issue 3, pp. 360-374.

Audretsch, D. B., & Feldman, M. (2004): Knowledge spillovers and the geography of innovation, in: Henderson, J. V., & Thisse, J. F. (Eds.): Handbook of Urban and Regional Economics, Vol. 4, Elsevier, Amsterdam, pp. 2713-2739.

Bagley, M. J. O. (2019a): Networks, geography and the survival of the firm, *Journal of Evolutionary Economics*, Vol. 29, pp. 1173-1209.

Bagley, M. J. O. (2019b): Small worlds, inheritance networks and industrial clusters, *Industry and Innovation*, Vol. 26, Issue 7, pp. 741-768.

Basant, R., Chandra, P., & Upadhyayula, R. (2011): Knowledge Flows and Capability Building in the Indian IT Sector: A Comparative Analysis of Cluster and Non-Cluster Locations, IIMA working paper, Indian Institute of Management Bangalore.

Bathelt, H., Malmberg, A., & Maskell, P. (2004): Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation, *Progress in Human Geography*, Vol. 28, Issue 1, pp. 31-56.

Beaudry, C., & Breschi, S. (2003): Are firms in clusters really more innovative?, *Economics of Innovation and New Technology*, Vol. 12, No. 4, pp. 325-342.

Beaudry, C., & Schiffauerova, A. (2009): Who's right, Marshall or Jacobs? The localization versus urbanization debate, *Research Policy*, Vol. 38, Issue 2, pp. 318-337.

Benner, M. (2009): What do we know about clusters? In search of effective cluster policies, *SPACES online*, Vol. 7, Issue 2009-04, Toronto and Heidelberg, www.spaces-online.com.

Borowiecki, K. J. (2013): Geographic clustering and productivity: An instrumental variable approach for classical composers, *Journal of Urban Economics*, Vol. 73, Issue 1, pp. 94-110.

Boschma, R. (2005): Proximity and Innovation: A Critical Assessment, *Regional Studies*, Vol. 39, Issue 1, pp. 61-74.

Boschma, R., & Iammarino, S. (2009): Related Variety, Trade Linkages, and Regional Growth in Italy, *Economic Geography*, Vol. 85, Issue 3, pp. 289-311.

Boschma, R., & Frenken, K. (2011a): The emerging empirics of evolutionary economic geography, *Journal of Economic Geography*, Vol. 11, Issue 2, pp. 295-307.

Boschma, R., & Frenken, K. (2011b): Technological relatedness and regional branching, in: Bathelt, H., Feldman, M. P., & Kogler, D. F. (Eds.): Dynamic Geographies of Knowledge Creation and Innovation, Taylor & Francis/Routledge, London, pp. 64-81.

Boschma, R. (2015): Do spinoff dynamics or agglomeration externalities drive industry clustering? A reappraisal of Steven Klepper's work, *Industrial and Corporate Change*, Vol. 24, Issue 4, pp. 859-873.

Brenner, T. (2004): Local Industrial Clusters: Existence, Emergence and Evolution, Routledge, London/New York.

Brenner, T. (2017): Identification of Clusters - An Actor-based Approach, *Working Papers on Innovation and Space*, No. 02.17.

Brown, K., Burgees, J., Festing, M., Royer, S., & Steffen, C. (2007): The Value Adding Web – A Conceptual Framework of Competitive Advantage Realisation in Clusters, *ESCP-EAP Working Paper*, No. 27, ISSN: 1619-7658.

Burger, M. J., Knoben, J., Raspe, O., & Van Oort, F. G. (2012): Multilevel Approaches and the Firm-Agglomeration Ambiguity in Economic Growth Studies, *Tinbergen Institute Discussion Paper,* No. 014/3.

Carias, C., & Klepper, S. (2010): Entrepreneurship, the Initial Labor Force, and the Location of New Firms, Paper presented at the International Schumpeter Society Conference, Aalborg, June 21-24.

Castaldi, C., Frenken, K., & Los, B. (2015): Related variety, unrelated variety and technological breakthroughs: An analysis of US state-level patenting, *Regional Studies*, Vol. 49, Issue 5, pp. 767-781.

Combes, P.-P., & Duranton, G. (2006): Labour pooling, labour poaching, and spatial clustering, *Regional Science and Urban Economics*, Vol. 36, Issue 1, pp. 1-28.

Daft, R. L., & Lengel, R. H. (1986): Organizational information requirements, media richness and structural design, *Management Science*, Vol. 32, No. 5, pp. 554-571.

David, P. A., & Rosenbloom, J. L. (1990): Marshallian factor market externalities and the dynamics of industrial localization, *Journal of Urban Economics*, Vol. 28, No. 3, pp. 349-370.

De Groot, H. L., Poot, J., & Smit, M. J. (2007): Agglomeration, Innovation and Regional Development: Theoretical Perspectives and Meta-Analysis, *Tinbergen Institute Discussion Paper*, No. 07-079/3.

Delgado, M., Porter, M. E., & Stern, S. (2010): Clusters and entrepreneurship, *Journal of Economic Geography*, Vol. 10, Issue 4, pp. 495-518.

De Silva, D. G., & McComb, R. P. (2012): Geographic concentration and high tech firm survival, *Regional Science and Urban Economics*, Vol. 42, Issue 4, pp. 691-701.

Duranton, G., & Overman, H. G. (2005): Testing for Localization Using Micro-Geographic Data, *The Review of Economic Studies*, Vol. 72, Issue 4, pp. 1077-1106.

EFI (2015): Gutachten zu Forschung, Innovation und Technologischer Leistungsfähigkeit Deutschlands, Expertenkommission Forschung und Innovation.

Elsevier Inc (2017): SSRN - Frequently Asked Questions, available under https://www.ssrn.com/en/index.cfm/ssrn-faq/, last retrieved: 24.05.2017.

Erikson, R., & Lindgren, U. (2009): Localized mobility clusters: impacts of labour market externalities on firm performance, *Journal of Economic Geography*, Vol. 9, Issue 1, pp. 33-53.

Eurostat (2014): Aggregations of manufacturing based on NACE Rev. 2, available under http://statistica.regione.emilia-romagna.it/allegati/factbook_2014/eurostat-high-tech-aggregation-of-manufacturing-and-services-nace-rev-2, last retrieved: 24.05.2017.

Eurostat (2017): Glossary: High-tech classification of manufacturing industries, available under http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:High-tech_classification_of_manufacturing_industries, last retrieved: 23.05.2017.

Fang, L. (2015): Do Clusters Encourage Innovation? A Meta-analysis, *Journal of Planning Literature*, Vol. 30, No. 3, pp. 239-260.

Feldman, M. P. (1994): The Geography of Innovation, Kluwer Academic Publishers, Dordrecht.

Festing, M., Royer, S., & Steffen, C. (2012): Unternehmenscluster schaffen Wettbewerbsvorteile - Eine Analyse des Uhrenclusters in Glashütte, *Zeitschrift Führung + Organisation*, Vol. 81, No. 4, pp. 264-272.

Florax, R. J., de Groot, H. L., & De Mooij, R. A. (2002): Meta-Analysis, *Tinbergen Institute Discussion Paper*, No. 2002-041/3.

Fornahl, D., Heimer, T., Campen, A., & Talmon-Gros, L. (2015): Cluster als Paradigma der Innovationspolitik - Eine erfolgreiche Anwendung von Theorie in der politischen Praxis?, Studien zum deutschen Innovationssystem, No. 13-2015.

Frenken, K., Van Oort, F., & Verburg, T. (2007): Related variety, unrelated variety and regional economic growth, *Regional Studies*, Vol. 41, Issue 5, pp. 685-697.

Frenken, K., Cefis, E., & Stam, E. (2015): Industrial Dynamics and Clusters: A Survey. *Regional Studies*, Vol. 49, Issue 1, pp. 10-27.

Glass, G. V. (1976): Primary, Secondary, and Meta-Analysis of Research, *Educational Researcher*, Vol. 5, No. 10, pp. 3-8.

Globerman, S., Shapiro, D., & Vining, A. (2005): Clusters and intercluster spillovers: their influence on the growth and survival of Canadian information technology firms, *Industrial and Corporate Change*, Vol. 14, Issue 1, pp. 27-60.

Grashof, N., Hesse, K., & Fornahl, D. (2019): Radical or not? The role of clusters in the emergence of radical innovations, *European Planning Studies*, Vol. 27, Issue 10, pp. 1904-1923.

Grillitsch, M., Asheim, B., & Trippl, M. (2018): Unrelated knowledge combinations: the unexplored potential for regional industrial path development, *Cambridge Journal of Regions, Economy and Society*, Vol. 11, Issue 2, pp. 257-274.

Harrison, B., Kelley, M. R., & Gant, J. (1996): Innovative Firm Behavior and Local Milieu: Exploring the Intersection of Agglomeration, Firm Effects, and Technological Change, *Economic Geography*, Vol. 72, Issue 3, pp. 233-258.

Hedges, L. V., & Olkin, I. (1980): Vote-counting methods in research synthesis, *Psychological Bulletin*, Vol. 88, No. 2, pp. 359-369.

Hunter, J. E., & Schmidt, F. L. (1980): Methods of Meta-Analysis - Correcting Error and Bias in Research Findings, Sage Publications, Thousand Oaks, CA, Second Edition.

Jacobs, J. (1969): The economy of cities, Vintage, New York.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993): Geographic localization of knowledge spillovers as evidenced by patent citations, *Quarterly Journal of Economics*, Vol. 108, No. 3, pp. 577-598.

Kemeny, T., & Storper, M. (2015): Is Specialization Good for Regional Economic Development?, *Regional Studies*, Vol. 49, Issue 6, pp. 1003-1018.

Klepper, S. (2007a): Disagreements, Spinoffs and the Evolution of Detroit as the Capital of the U.S. Automobile Industry, *Management Science*, Vol. 53, Issue 4, pp. 616-631.

Klepper, S. (2007b): The evolution of geographic structures in new industries, in: Frenken, K. (Ed.): Applied Evolutionary Economics and Economic Geography, Edward Elgar, Cheltenham, UK, pp. 69-92.

Klepper, S. (2010): The origin and growth of industry clusters: the making of Silicon Valley and Detroit, *Journal of Urban Economics*, Vol. 67, Issue 1, pp. 15-32.

Knoben, J., Arikan, A. T., Van Oort, F., & Raspe, O. (2015): Agglomeration and firm performance: One firm's medicine is another firm's poison, *Environment and Planning A*, Vol. 48, No. 1, pp. 1-22.

Koricheva, J., & Gurevitch, J. (2013): Place of Meta-analysis among Other Methods of Research Synthesis, in: Koricheva, J., Gurevitch, J, & Mengersen, K. (Eds.): Handbook of Meta-analysis in Ecology and Evolution, Princeton University Press, Princeton, pp. 3-13.

Krugman, P. (1991): Geography and trade, MIT Press, Cambridge, MA.

Kuah, A. T. (2002): Cluster Theory and Practice: Advantages for the Small Business Locating in a Vibrant Cluster, *Journal of Research in Marketing and Entrepreneurship*, Vol. 4, No. 3, pp. 206-228.

Lazzeretti, L., Sedita, S. R., & Caloffi, A. (2014): Founders and disseminators of cluster research, *Journal of Economic Geography*, Vol. 14, Issue 1, pp. 21-43.

Maine, E. M., Shapiro, D. M., & Vining, A. R. (2010): The role of clustering in the growth of new technology-based firms, *Small Business Economics*, Vol. 34, pp. 127-146.

Malmberg, A., & Maskell, P. (2002): The elusive concept of localization economies: towards a knowledge-based theory of spatial clustering, *Environment and Planning A*, Vol. 34, No. 3, pp. 429-449.

Marshall, A. (1920): Principles of economics, Macmillan, London, 8th Edition.

Martin, P., Mayer, T., & Mayneris, F. (2011): Public support to clusters: A firm level study of French "Local Productive Systems", *Regional Science and Urban Economics*, Vol. 41, Issue 2, pp. 108-123.

Martin, R., & Sunley, P. (2003): Deconstructing clusters: chaotic concept or policy panacea?, *Journal of Economic Geography*, Vol. 3, Issue 1, pp. 5-35.

McCann, B. T., & Folta, T. B. (2008): Location Matters: Where We Have Been and Where We Might Go in Agglomeration Research, *Journal of Management*, Vol. 34, Issue 3, pp. 532-565.

McCann, B. T., & Folta, T. B. (2011): Performance differentials within geographic clusters, *Journal of Business Venturing*, Vol. 26, Issue 1, pp. 104-123.

Melo, P. C., Graham, D. J., & Noland, R. B. (2009): A meta-analysis of estimates of urban agglomeration economies, *Regional Science and Urban Economics*, Vol. 39, Issue 3, pp. 332-342.

Menzel, M.-P., & Fornahl, D. (2010): Cluster life cycles—dimensions and rationales of cluster evolution, *Industrial and Corporate Change*, Vol. 19, Issue 1, pp. 205-238.

Molina-Morales, F. X., & Martínez-Fernández, M. T. (2004): How much difference is there between industrial district firms? A net value creation approach, *Research Policy*, Vol. 33, Issue 3, pp. 473-486.

Nathan, M., & Overman, H. (2013): Agglomeration, clusters, and industrial policy, *Oxford Review of Economic Policy*, Vol. 29, Issue 2, pp. 383-404.

Neffke, F., Henning, M., Boschma, R., Lundquist, K. J., & Olander, L. O. (2011): The dynamics of agglomeration externalities along the life cycle of industries, *Regional Studies*, Vol. 45, Issue 1, pp. 49-65.

OECD (2011): ISIC REV. 3 TECHNOLOGY INTENSITY DEFINITION - Classification of manufacturing industries into categories based on R&D intensities, OECD Directorate for Science, Technology and Industry.

Otto, A., & Fornahl, D. (2010): Origins of human capital in clusters: Regional, industrial and academic transitions in media clusters in Germany, in: Fornahl, D., Henn, S., & Menzel, M.-P. (Eds.): Emerging Clusters: Theoretical, Empirical and Political Perspectives on the Initial Stage of Cluster Evolution, Edward Elgar, Cheltenham, UK, pp. 99-139.

Porter, M. E. (1990): The competitive advantage of nations, Macmillan, London.

Porter, M. E. (1998): Clusters and the New Economics of Competitiveness, *Harvard Business Review*, Vol. 76, Issue 6, pp. 77-90.

Porter, M. E. (2000): Location, Competition, and Economic Development: Local Clusters in a Global Economy, *Economic Development Quarterly*, Vol. 14, Issue 1, pp. 15-34.

Potter, A., & Watts, H. D. (2014): Revisiting Marshall's Agglomeration Economies: Technological Relatedness and the Evolution of the Sheffield Metals Cluster, *Regional Studies*, Vol. 48, Issue 4, pp. 603-623.

Pouder, R., & St. John, C. H. (1996): Hot Spots and Blind Spots: Geographical Clusters of Firms and Innovation, *The Academy of Management Review*, Vol. 21, No. 4, pp. 1192-1225.

Quintana, D. (2015): From pre-registration to publication: a non-technical primer for conducting a meta-analysis to synthesize correlational data, *Frontiers in Psychology*, Vol. 6, Article 1549, pp. 1-9.

Rigby, D. L., & Brown, M. W. (2015): Who Benefits from Agglomeration?, *Regional Studies*, Vol. 49, Issue 1, pp. 28-43.

Rosenthal, S. S., & Strange, W. C. (2008): The attenuation of human capital spillovers, *Journal of Urban Economics*, Vol. 64, Issue 2, pp. 373-389.

Rotemberg, J. J., & Saloner, G. (2000): Competition and human capital accumulation: a theory of interregional specialization and trade, *Regional Science and Urban Economics*, Vol. 30, Issue 4, pp. 373-404.

Šarić, S. (2012): Competitive Advantages through Clusters - An Empirical Study with Evidence from China, Strategisches Kompetenz-Management, Springer Fachmedien, Wiesbaden.

Sedita, S. R., Lazzeretti, L., & Caloffi, A. (2012): The birth and the rise of the cluster concept, Paper presented at the DRUID 2012, CBS, Copenhagen.

Shaver, J. M., & Flyer, F. (2000): Agglomeration economies, firm heterogeneity, and foreign direct investment in the United States, *Strategic Management Journal*, Vol. 21, Issue 12, pp. 1175-1193.

Sleutjes, B., Van Oort, F., & Schutjens, V. (2012): A PLACE FOR AREA-BASED POLICY? THE SURVIVAL AND GROWTH OF LOCAL FIRMS IN DUTCH RESIDENTIAL NEIGHBORHOODS, *Journal of Urban Affairs*, Vol. 34, Issue 5, pp. 533-558.

Sorenson, O., & Audia, P. G. (2000): The Social Structure of Entrepreneurial Activity: Geographic Concentration of Footwear Production in the United States, 1940–1989, *American Journal of Sociology*, Vol. 106, No. 2, pp. 424-462.

Stanley, T. D. (2001): Wheat From Chaff: Meta-Analysis As Quantitative Literature Review, *Journal of Economic Perspective*, Vol. 15, No. 3, pp. 131-150.

Stanley, T. D., & Jarrell, S. B. (1989): Meta-Regression Analysis: A Quantitative Method of Literature Surveys, *Journal of Economic Surveys*, Vol. 3, Issue 2, pp. 161-170.

Steffen, C. (2012): How Firms Profit from Acting in Networked Environments: Realising Competitive Advantages in Business Clusters. A Resource-oriented Case Study Analysis of the German and Swiss Watch Industry, Schriftenreihe: Internationale Personal- und Strategieforschung, Rainer Hamp Verlag, München & Mering.

Terstriep, J., & Lüthje, C. (2018): Innovation, knowledge and relations – on the role of clusters for firms' innovativeness, *European Planning Studies*, Vol. 26, Issue 11, pp. 2167-2199.

Van Biesebroeck, J. (2015): How tight is the link between wages and productivity? A survey of the literature, *Conditions of Work and Employment Series*, No. 54, International Labor Organization, Geneva.

Verhoeven, D., Bakker, J., & Veugelers, R. (2016): Measuring technological novelty with patent-based indicators, *Research Policy*, Vol. 45, Issue 3, pp. 707-723.

Wagner, M., & Weiß, B. (2014): Meta-Analyse, in: Baur, N., & Blasius, J. (Eds.): Handbuch Methoden der empirischen Sozialforschung, Springer Fachmedien, Wiesbaden, pp. 1117-1126.

Wennberg, K., & Lindqvist G. (2010): The effect of clusters on the survival and performance of new firms, *Small Business Economics*, Vol. 34, Issue 3, pp. 221-241.

Wu, X., Geng, S., Li, J., & Zhang, W. (2010): Shared Resources and Competitive Advantage in Clustered Firms: The Missing Link, *European Planning Studies*, Vol. 18, Issue 9, pp. 1391-1410.

## Appendix

# Cluster definitions

| Author | Definition | Dimensions | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Interconnectedness/ Exchange relations[1] | | | | | | |
| | | (Spatial) proximity | Concentration | Similar/ complementary industries | Value chain | Specialization | | Co-Location advantages | Knowledge / Technology spillovers | Cooperation | Competition | Formal/institutional relationships | Informal exchange/trust |
| **Enright (1996: 191)** | "A regional cluster is an industrial cluster in which member firms are in close proximity to each other." | x | | | | | | | | | | | |
| **Baptista and Swann (1998: 525)** | "A geographical cluster is defined here as a strong collection of related companies located in a small geographical area, sometimes centred on a strong part of a country's science base." | x | x | | | | | x | x | | | | |
| **Rosenfeld (1997:4)** | "A 'cluster' is very simply used to represent concentrations of firms that are able to produce synergy because of their geographic proximity and interdependence, even though their scale of employment may not by pronounced or prominent." | x | x | | | | x | | | | | | |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Feser (1998: 26)** | “Economic clusters are not just related and supporting industries and institutions, but rather related and supporting institutions that are more competitive by virtue of their relationships.” | | | x | | | x | | | | | | |
| **Porter (1998: 78)** | “Clusters are geographic concentrations of interconnected companies and institutions in a particular field.” | x | x | x | | | x | | | | | | |
| **Porter (2000: 15)** | “Clusters are geographic concentrations of interconnected companies, specialized suppliers, service providers, firms in related industries, and associated institutions (e.g., universities, standards agencies, trade associations) in a particular field that compete but also cooperate.” | x | x | x | | x | | | | x | x | x | |
| **Porter (2003: 562)** | “We define a cluster as a geographically proximate group of interconnected companies, suppliers, service providers and associated institutions in a particular field, linked by externalities of various types.” | x | x | x | | | | x | | | | x | |
| **Swann et al. (1998: 1)** | “A cluster means a large group of firms in related industries at a particular location.” | x | x | x | | | | | | | | | |
| **Bresnahan, Gambardella and Saxenian (2001: 836)** | “We define a regional cluster simply as a spatial and sectoral concentration of firms; and we measure success by the ability of the cluster as a whole to grow, typically through the expansion of entrepreneurial start-ups.” | | x | x | | | | | | | | | |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Simmie and Sennett (1999: 51)** | "We define an innovative cluster as a large number of inter-connected industrial and/or service companies having a high degree of collaboration, typically through a supply chain, and operating under the same market conditions." | | x | x | x | | | | | x | | | |
| **Crouch and Farrell (2001: 163)** | "The more general concept of ''cluster'' suggests something looser: a tendency for firms in similar types of business to locate close together, though without having a particularly important presence in an area." | x | | x | | | | | | | | | |
| **Van den Berg et al. (2001: 187)** | "The popular term cluster is most closely related to this local or regional dimension of networks (...) Most definitions share the notion of clusters as localised networks of specialized organisations, whose production processes are closely linked through the exchange of goods, services and/or knowledge." | x | x | | x | x | | | x | | | | |
| **Ketels (2003:3f.)** | "Clusters are groups of companies and institutions co-located in a specific geographic region and linked by interdependencies in providing a related group of products and/or services. Because of the proximity among them – both in terms of geography and of activities – cluster constituents enjoy the economic benefits of several types of positive | x | x | x | | x | | x | x | x | x | x | |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **European Commission (2003: 16)** | "Clusters are groups of independent companies and associated institutions that are:<br>• Collaborating and competing;<br>• Geographically concentrated in one or several regions, even though the cluster may have global extensions;<br>• Specialised in a particular field, linked by common technologies and skills;<br>• Either science-based or traditional;<br>• Clusters can be either institutionalised (they have a proper cluster manager) or non-institutionalised." | **x** | **x** | **x** | | **x** | | | **x** | **x** | **x** | **x** | **x** |
| **Cooke (2002: 121)** | "Clusters are geographically proximate firms in vertical and horizontal relationships, involving a localized enterprise support infrastructure with shared developmental vision for business growth, based on competition and cooperation in a specific market field." | **x** | | **x** | | **x** | | **x** | | **x** | **x** | **x** | **(x)** |
| **Stimson et al. (2002: 203)** | There are three significant attributes associated with contemporary notions of industry clusters:<br>a) Shared end-markets (…)<br>b) Strong buyer-supplier linkages (…)<br>c) Shared technology and know-how (…) | | | **x** | **x** | | | **(x)** | **x** | | **(x)** | | |
| **Hill and Brennan (2000)** | "We define a competitive industrial cluster as a geographic concentration of competitive firms or establishments in the same industry that either have close buy-sell relationships with other industries in the region, use common technologies, or share a specialized labor pool that provides firms with a competitive advantage over the same industry in other places." | | **x** | **x** | | | | **x** | **x** | **x** | | | |

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| **Fromhold-Eisbebith and Eisebith (2005: 1251)** | "We conceive a cluster as a regional agglomeration of sector or value chain related firms and other organizations (like universities, R&D centers, public agencies) which derive economic advantages from co-location and collaboration" | **x** | **x** | **x** | **x** | | | | | **x** | | **x** | |
| **World Bank (2009: 1)** | "An industrial cluster is an agglomeration of companies, suppliers, service providers, and associated institutions in a particular field. Often included are financial providers, educational institutions, and various levels of government. These entities are linked by externalities and complementarities of different types and are usually located near each other." | **x** | **x** | **x** | | | | **x** | | | | **x** | |
| **Waits (2000: 37)** | "These industry clusters are geographical concentrations of competitive firms in related industries that do business with each other and that share needs for common talent, technology, and infrastructure." | | **x** | **x** | | | | | **x** | **x** | | **(x)** | |
| **Pietrobelli and Barrera (2002: 542)** | "(…)a cluster is defined as a group of enterprises spatially close, and specialized in the development of a similar or the same product." | **x** | **x** | **x** | | **x** | | | | | | | |
| **Bell (2005: 287)** | "Industry clusters—groups of geographically proximate firms in the same industry—are a striking feature of the geography of economic activity(…)." | **x** | **x** | **x** | | | | | | | | | |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Maskell and Kebir (2006: 1)** | "Clusters may be defined as non-random geographical agglomerations of firms with similar or closely complementary capabilities." | | **x** | **x** | | | x | | | | | | |
| **Christensen et al. (2012: 14)** | "Clusters are networks of interacting companies, R&D institutions, universities and other relevant stakeholders whose activities result in the generation of new knowledge which translates into new products and services as well as innovations in processes, organisations and markets." | | | | | | | | x | | | | |
| **Dalum et al. (2002: 7)** | "A regional cluster is a geographically concentrated group of firms and related organisations active in similar or closely connected technologies. The firms are interconnected by formation of specialized local labour markets and institutional set-ups." | **x** | **x** | **x** | | | x | | | | | **x** | |
| **Sum** | N=25 | **17** | **19** | **20** | **4** | **6** | **5** | **6 (1)** | **8** | **8** | **4 (1)** | **8 (1)** | **1 (1)** |

**X**= explicitly mentioned; **(x)** = implicitly mentioned;

[1] Column 6: Interconnectedness/Exchange relations are mentioned, however missing concretization according to the following dimensions

**Appendix 1:** List and classification of different cluster definitions (own illustration based on Fornahl et al., 2015)

| Authors | Title of Publication | Year of Publication | Performance Variable | Database |
|---|---|---|---|---|
| Schimke, A; Teichert, N; Ott, I | Impact of local knowledge endowment on employment growth in nanotechnology | 2013 | Employment growth | Webofscience |
| Fingleton, B; Igliori, DC; Moore, B | Employment growth of small high-technology firms and the role of horizontal clustering: Evidence from computing services and R&D in Great Britain, 1991-2000 | 2004 | Employment growth | Webofscience |
| Boshuizen, J; Geurts, P; Van der Veen, A | REGIONAL SOCIAL NETWORKS AS CONDUITS FOR KNOWLEDGE SPILLOVERS: EXPLAINING PERFORMANCE OF HIGH-TECH FIRMS | 2009 | Employment growth | Webofscience |
| van Oort, FG; Burger, MJ; Knoben, J; Raspe, O | MULTILEVEL APPROACHES AND THE FIRM-AGGLOMERATION AMBIGUITY IN ECONOMIC GROWTH STUDIES | 2012 | Employment growth | Webofscience |
| Escobar-Mendez, A | Employment growth in manufacturing industry in Mexico | 2011 | Employment growth | Webofscience |
| Gabe, TM | Establishment growth in small cities and towns | 2004 | Employment growth | Webofscience |
| Micucci, G; Di Giacinto, V | The Producer Service Sector in Italy: Long-term Growth and its Local Determinants | 2009 | Employment growth | Webofscience |
| Vor, Friso de; Groot, Henri L. F. de | Agglomeration externalities and localized employment growth: the performance of industrial sites in Amsterdam | 2010 | Employment growth | Google Scholar |
| van Soest, Daan P.; Gerking, Shelby; van Oort, Frank G. | Spatial impacts of agglomeration externalities | 2006 | Employment growth | Google Scholar |
| van Soest, Daan P.; Gerking, Shelby D.; van Oort, Frank G. | Knowledge externalities, agglomeration economies, and employment growth in Dutch cities | 2002 | Employment growth | Google Scholar |
| Rosenthal, Stuart S.; Strange, William C. | Geography, industrial organization, and agglomeration | 2003 | Employment growth | Google Scholar |
| Gabe, Todd M.; Kraybill, David S. | The effect of state economic development incentives on employment growth of establishments | 2002 | Employment growth | Google Scholar |
| Delgado, Mercedes; Porter, Michael E.; Stern, Scott | Clusters and entrepreneurship | 2010 | Employment growth | Google Scholar |
| Beaudry, Catherine; Swann, Peter | Growth in industrial clusters: A bird’s eye view of the United Kingdom | 2001 | Employment growth | Google Scholar |
| Wennberg, Karl; Lindqvist, Göran | The effect of clusters on the survival and performance of new firms | 2010 | Employment growth | Google Scholar |
| van Oort, Frank G. | Spatial and sectoral composition effects of agglomeration economies in the Netherlands | 2007 | Employment growth | Google Scholar |
| Paci, Raffaele; Usai, Stefano | Agglomeration economies, spatial dependence and local industry growth | 2008 | Employment growth | Google Scholar |
| Duschl, Matthias; Scholl, Tobias; Brenner, Thomas; Luxen, Dennis; Raschke, Falk | Industry-specific firm growth and agglomeration | 2015 | Employment growth | Google Scholar |
| Blasio, Guido de; Di Addario, Sabrina | Do workers benefit from industrial agglomeration? | 2005 | Employment growth | Google Scholar |
| Bishop, Paul; Gripaios, Peter | Spatial externalities, relatedness and sector employment growth in Great Britain | 2010 | Employment growth | Google Scholar |
| Baptista, Rui; Swann, G. PeterM | A comparison of clustering dynamics in the US and UK computer industries | 1999 | Employment growth | Google Scholar |

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|---|---|---|---|---|
| Yamada, Eri; Kawakami, Tetsu | Assessing dynamic externalities from a cluster perspective: the case of the motor metropolis in Japan | 2015 | Employment growth | Ebsco |
| MARTINEZ, JOSE; MCPHERSON, MICHAEL A.; MOLINA, DAVID J.; ROUS, JEFFREY J. | Geography and microenterprises: clustering, networking, and knowledge spillovers | 2013 | Employment growth | Ebsco |
| Bonte, Werner | Innovation and Employment Growth in Industrial Clusters: Evidence from Aeronautical Firms in Germany | 2004 | Employment growth | Ebsco |
| Beaudry, Catherine; Swann, G. M. Peter | Firm Growth in Industrial Clusters of the United Kingdom | 2009 | Employment growth | Ebsco |
| Beaudry, Catherine | Entry-Growth and Patenting in Industrial Clusters: A Study of the Aerospace Industry in the UK | 2001 | Employment growth | Ebsco |
| Shuai, Xiaobing | Will Specialization Continue Forever? A Case Study of Interactions between Industry Specialization and Diversity | 2013 | Employment growth | Ebsco |
| Kowalewski, Julia | Inter-industrial Relations and Sectoral Employment Development in German Regions | 2013 | Employment growth | Ebsco |
| George Deltas, Dakshina G. De Silva, Robert P. McComb | Industrial Agglomeration and Spatial Persistence of Employment in Software Publishing | 2015 | Employment growth | SSRN |
| van Oort, Frank G.; Stam, Erik | 14. Agglomeration economies and firm growth: testing for spatial externalities in the Dutch ICT industry | 2010 | Employment growth | Google Scholar |
| Lindqvist, Göran | Disentangling clusters: agglomeration and proximity effects | 2009 | Employment growth | Google Scholar |
| Kunkle, Gary Monroe | Cluster requiem and the rise of cumulative growth theory | 2009 | Employment growth | Google Scholar |
| van Geenhuizen, Marina; Reyes-Gonzalez, Leonardo | Does a clustered location matter for high-technology companies' performance? The case of biotechnology in the Netherlands | 2007 | Employment growth | Webofscience |
| Sleutjes, B; Van Oort, F; Schutjens, V | A PLACE FOR AREA- BASED POLICY? THE SURVIVAL AND GROWTH OF LOCAL FIRMS IN DUTCH RESIDENTIAL NEIGHBORHOODS | 2012 | Employment growth | Webofscience |
| Audia, PG; Rider, CI | Close, but not the same: Locally headquartered organizations and agglomeration economies in a declining industry | 2010 | Employment growth | Webofscience |
| Deltas, George; Silva, Dakshina G. de; McComb, Robert P. | Agglomeration Spillovers and Industry Dynamics: Firm Entry, Growth, and Exit in the Software Publishing Industry | 2014 | Employment growth | Google Scholar |
| Gjelsvik, Martin; Haus-Reve, Silje | Capabilities for innovation in a globalizing world: to be or not to be in clusters | 2015 | Innovativeness | Webofscience |
| Jose Ruiz-Ortega, Maria; Parra-Requena, Gloria; Manuel Garcia-Villaverde, Pedro | Do Territorial Agglomerations Still Provide Competitive Advantages? A Study of Social Capital, Innovation, and Knowledge | 2016 | Innovativeness | Webofscience |
| Smit, Martijn J.; Abreu, Maria A.; de Groot, Henri L. F. | Micro-evidence on the determinants of innovation in the Netherlands: The relative importance of absorptive capacity and agglomeration externalities | 2015 | Innovativeness | Webofscience |
| Huang, Kuo-Feng; Yu, Chwo-Ming Joseph; Seetoo, Dah-Hsian | Firm innovation in policy-driven parks and spontaneous clusters: the smaller firm the better? | 2012 | Innovativeness | Webofscience |
| De Beule, Filip; Van Beveren, Ilke | DOES FIRM AGGLOMERATION DRIVE PRODUCT INNOVATION AND RENEWAL? AN APPLICATION FOR BELGIUM | 2012 | Innovativeness | Webofscience |
| Ozer, Muammer; Zhang, Wen | The effects of geographic and network ties on exploitative and exploratory product innovation | 2015 | Innovativeness | Webofscience |
| He, Zheng; Rayman-Bacchus, Lez | Cluster network and innovation under transitional economies An empirical study of the Shaxi garment cluster | 2010 | Innovativeness | Webofscience |

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|---|---|---|---|---|
| Boasson, V; MacPherson, A | The role of geographic location in the financial and innovation performance of publicly traded pharmaceutical companies: empirical evidence from the United States | 2001 | Innovativeness | Webofscience |
| Shefer, D; Frenkel, A | Local milieu and innovations: Some empirical results | 1998 | Innovativeness | Webofscience |
| van Geenhuizen, Marina; Reyes-Gonzalez, Leonardo | Does a clustered location matter for high-technology companies' performance? The case of biotechnology in the Netherlands | 2007 | Innovativeness | Webofscience |
| Bell, GG | Clusters, networks, and firm innovativeness | 2005 | Innovativeness | Webofscience |
| Zhang, Hongyong | How does agglomeration promote the product innovation of Chinese firms? | 2015 | Innovativeness | Webofscience |
| Folta, TB; Cooper, AC; Baik, Y | Geographic cluster size and firm performance | 2006 | Innovativeness | Webofscience |
| MacPherson, A; Boasson, V | Patent activity and financial performance of publicly traded companies in the US pharmaceutical industry: The role of local economic conditions | 2004 | Innovativeness | Webofscience |
| Whittington, Kjersten Bunker; Owen-Smith, Jason; Powell, Walter W. | Networks, Propinquity, and Innovation in Knowledge-intensive Industries | 2009 | Innovativeness | Webofscience |
| Fang, Jianguo; Guo, Huiwu | Electronic information industry, clustering and growth: empirical study of the Chinese enterprises | 2013 | Innovativeness | Webofscience |
| Lo, Hsuan; Chung, Hsien-Jui | The Impact of Complementary Agglomeration and Multi-unit Systems on New Product Introduction | 2010 | Innovativeness | Webofscience |
| Antonietti, Roberto; Cainelli, Giulio | The role of spatial agglomeration in a structural model of innovation, productivity and export: a firm-level analysis | 2011 | Innovativeness | Webofscience |
| Zhang, Peng; He, Canfei; Sun, Yifei | Agglomeration economies and firm R&D efforts: an analysis of China's electronics and telecommunications industries | 2014 | Innovativeness | Webofscience |
| Quintana-Garcia, C; Benavides-Velasco, CA | Agglomeration economies and vertical alliances: the route to product innovation in biotechnology firms | 2005 | Innovativeness | Webofscience |
| Galliano, Danielle; Magrini, Marie-Benoit; Triboulet, Pierre | Marshall's versus Jacobs' Externalities in Firm Innovation Performance: The Case of French Industry | 2015 | Innovativeness | Webofscience |
| van Oort, Frank | Innovation and agglomeration economies in the Netherlands | 2002 | Innovativeness | Google Scholar |
| Propris, Lisa De | Types of innovation and inter-firm co-operation | 2002 | Innovativeness | Google Scholar |
| Molina-Morales, Francesc Xavier; Martínez-Fernández, María Teresa | Social networks: effects of social capital on firm innovation | 2010 | Innovativeness | Google Scholar |
| Feldman, Maryann P.; Audretsch, David B. | Innovation in cities:: Science-based diversity, specialization and localized competition | 1999 | Innovativeness | Google Scholar |
| Baptista, Rui; Swann, Peter | Do firms in clusters innovate more? | 1998 | Innovativeness | Google Scholar |
| Lecocq, Catherine; Leten, Bart; Kusters, Jeroen; van Looy, Bart | Do Firms Benefit from Being Present in Multiple Technology Clusters? An Assessment of the Technological Performance of Biopharmaceutical Firms | 2012 | Innovativeness | Ebsco |
| Huang, Fang; Rice, John | Does Open Innovation Work Better in Regional Clusters? | 2013 | Innovativeness | Ebsco |
| Cook, Gary A. S.; Pandit, Naresh R.; Loof, Hans; Johansson, Borje | Clustering, MNEs, and Innovation: Who Benefits and How? | 2013 | Innovativeness | Ebsco |
| Bönte, Werner | Innovation and employment growth in industrial clusters: evidence from aeronautical firms in Germany | 2004 | Innovativeness | Ebsco |

| | | | | |
|---|---|---|---|---|
| Bindroo, Vishal; Mariadoss, Babu John; Pillai, Rajani Ganesh | Customer Clusters as Sources of Innovation-Based Competitive Advantage | 2012 | Innovativeness | Ebsco |
| Prim, Alexandre Luis; Amal, Mohamed; Carvalho, Luciano | Regional Cluster, Innovation and Export Performance: An Empirical Study | 2016 | Innovativeness | Ebsco |
| Martínez-Pérez, Ángela; García-Villaverde, Pedro M.; Elche, Dioni | The mediating effect of ambidextrous knowledge strategy between social capital and innovation of cultural tourism clusters firms | 2016 | Innovativeness | Ebsco |
| Boschma, RA;Weterings, ABR | The effect of regional differences on the performance of software firms in the Netherlands | 2005 | Innovativeness | Webofscience |
| Beaudry, Catherine | Entry-Growth and Patenting in Industrial Clusters: A Study of the Aerospace Industry in the UK | 2001 | Innovativeness | Ebsco |
| Lin, HL;Li, HY;Yang, CH | Agglomeration and productivity: Firm-level evidence from China's textile industry | 2011 | Productivity | Webofscience |
| Knoben, J;Arikan, AT;van Oort, F;Raspe, O | Agglomeration and firm performance: One firm's medicine is another firm's poison | 2016 | Productivity | Webofscience |
| Hu, C;Xu, ZY;Yashiro, N | Agglomeration and productivity in China: Firm level evidence | 2015 | Productivity | Webofscience |
| Lee, Y;Chyi, YL;Lin, ES;Wu, SY | Do local industrial agglomeration and foreign direct investment to China enhance the productivity of Taiwanese firms? | 2013 | Productivity | Webofscience |
| Sanfilippo, M;Seric, A | Spillovers from agglomerations and inward FDI: a multilevel analysis on sub-Saharan African firms | 2016 | Productivity | Webofscience |
| Arimoto, Y;Nakajima, K;Okazaki, T | Sources of productivity improvement in industrial clusters: The case of the prewar Japanese silk-reeling industry | 2014 | Productivity | Webofscience |
| Yang, CH;Lin, HL;Li, HY | Influences of production and R&D agglomeration on productivity: Evidence from Chinese electronics firms | 2013 | Productivity | Webofscience |
| Nakamura, R | Contributions of local agglomeration to productivity: Stochastic frontier estimations from Japanese manufacturing firm data | 2012 | Productivity | Webofscience |
| van Oort, FG;Burger, MJ;Knoben, J;Raspe, O | MULTILEVEL APPROACHES AND THE FIRM-AGGLOMERATION AMBIGUITY IN ECONOMIC GROWTH STUDIES | 2012 | Productivity | Webofscience |
| Bekes, G;Harasztosi, P | Agglomeration premium and trading activity of firms | 2013 | Productivity | Webofscience |
| Cainelli, G | Spatial agglomeration, technological innovations, and firm productivity: Evidence from Italian industrial districts | 2008 | Productivity | Webofscience |
| Hashiguchi, Y;Tanaka, K | Agglomeration and firm-level productivity: A Bayesian spatial approach | 2015 | Productivity | Webofscience |
| Drucker, J;Feser, E | Regional industrial structure and agglomeration economies: An analysis of productivity in three manufacturing industries | 2012 | Productivity | Webofscience |
| Lall, SV;Shalizi, Z;Deichmann, U | Agglomeration economies and productivity in Indian industry | 2004 | Productivity | Webofscience |
| Martin, P;Mayer, T;Mayneris, F | Spatial concentration and plant-level productivity in France | 2011 | Productivity | Webofscience |
| Autant-Bernard, C;Guironnet, JP;Massard, N | Agglomeration and social return to R&D: Evidence from French plant productivity changes | 2011 | Productivity | Webofscience |
| Cainelli, G;Ganau, R;Iacobucci, D | Do Geographic Concentration and Vertically Related Variety Foster Firm Productivity? Micro-Evidence from Italy | 2016 | Productivity | Webofscience |
| Rigby, DL;Essletzbichler, R | Agglomeration economies and productivity differences in US cities | 2002 | Productivity | Webofscience |
| Widodo, W;Salim, R;Bloch, H | The effects of agglomeration economies on technical efficiency of manufacturing firms: evidence from Indonesia | 2015 | Productivity | Webofscience |

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|---|---|---|---|---|
| Antonietti, R;Cainelli, G | The role of spatial agglomeration in a structural model of innovation, productivity and export: a firm-level analysis | 2011 | Productivity | Webofscience |
| Tveteras, R;Battese, GE | Agglomeration externalities, productivity, and technical inefficiency | 2006 | Productivity | Webofscience |
| Andini, M;de Blasio, G;Duranton, G;Strange, WC | Marshallian labour market pooling: Evidence from Italy | 2013 | Productivity | Webofscience |
| Fazio, G;Maltese, E | Agglomeration Externalities and the Productivity of Italian Firms | 2015 | Productivity | Webofscience |
| Cainelli, G;Fracasso, A;Marzetti, GV | Spatial agglomeration and productivity in Italy: A panel smooth transition regression approach | 2015 | Productivity | Webofscience |
| Widodo, W;Salim, R;Bloch, H | Agglomeration Economies and Productivity Growth in Manufacturing Industry: Empirical Evidence from Indonesia | 2014 | Productivity | Webofscience |
| Graham, DJ | Variable returns to agglomeration and the effect of road traffic congestion | 2007 | Productivity | Webofscience |
| Fukao, K;Kravtsova, V;Nakajima, K | How important is geographical agglomeration to factory efficiency in Japan's manufacturing sector? | 2014 | Productivity | Webofscience |
| Di Giacinto, V;Gomellini, M;Micucci, G;Pagnini, M | Mapping local productivity advantages in Italy: industrial districts, cities or both? | 2014 | Productivity | Webofscience |
| Pan, ZH;Zhang, F | Urban productivity in China | 2002 | Productivity | Webofscience |
| Long, C;Zhang, XB | Cluster-based industrialization in China: Financing and performance | 2011 | Productivity | Webofscience |
| Eriksson, R;Lindgren, U | Localized mobility clusters: impacts of labour market externalities on firm performance | 2009 | Productivity | Webofscience |
| Rigby, DL;Brown, WM | Who Benefits from Agglomeration? | 2015 | Productivity | Webofscience |
| Aranguren, MJ;de la Maza, X;Parrilli, MD;Vendrell-Herrero, F;Wilson, JR | Nested Methodological Approaches for Cluster Policy Evaluation: An Application to the Basque Country | 2014 | Productivity | Webofscience |
| Graham, DJ;Kim, HY | An empirical analytical framework for agglomeration economies | 2008 | Productivity | Webofscience |
| Koo, J;Lall, S | New economic geography: Real or hype? | 2007 | Productivity | Webofscience |
| Antonietti, R;Cainelli, G | KIBS and the City: GIS Evidence from Milan | 2012 | Productivity | Webofscience |
| Siba, Eyerusalem; Söderbom, Måns; Bigsten, Arne; Gebreeyesus, Mulu | Enterprise Agglomeration, Output Prices, and Physical Productivity: Firm-Level Evidence from Ethiopia | 2012 | Productivity | Google Scholar |
| Maré, David C.; Timmons, Jason; Economic, M. | Geographic concentration and firm productivity | 2006 | Productivity | Google Scholar |
| Madsen, Erik Strøjer; Smith, Valdemar; Dilling-Hansen, Mogens | Industrial clusters, firm location and productivity | 2003 | Productivity | Google Scholar |
| Henderson, J. Vernon | Marshall's scale economies | 2003 | Productivity | Google Scholar |
| Graham, Daniel J.; Melo, Patricia S.; Jiwattanakulpaisarn, Piyapong; Noland, Robert B. | Testing for causality between productivity and agglomeration economies | 2010 | Productivity | Google Scholar |
| Graham, Daniel J. | Agglomeration, productivity and transport investment | 2007 | Productivity | Google Scholar |
| Damijan, Jože P.; Konings, Jozef | Agglomeration Economies, Globalization and Productivity: Firm Level Evidence for Slovenia | 2011 | Productivity | Google Scholar |

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|---|---|---|---|---|
| Raspe, Otto; van Oort, Frank G. | Firm heterogeneity, productivity and spatially bounded knowledge externalities | 2011 | Productivity | Google Scholar |
| Feser, Edward J. | Agglomeration, enterprise size, and productivity | 2011 | Productivity | Google Scholar |
| Drucker, Joshua M.; Feser, Edward | Regional industrial dominance, agglomeration economies, and manufacturing plant productivity | 2007 | Productivity | Google Scholar |
| Chang, Chia-Lin; Oxley, Les | Industrial agglomeration, geographic innovation and total factor productivity: The case of Taiwan | 2009 | Productivity | Google Scholar |
| Baldwin, John R.; Beckstead, Desmond; Mark Brown, W.; Rigby, David L. | Agglomeration and the geography of localization economies in Canada | 2008 | Productivity | Google Scholar |
| Thabet, Khaled | Industrial Structure and Total Factor Productivity: The Tunisian Manufacturing Sector between 1998 and 2004 | 2015 | Productivity | Ebsco |
| HAILU, GETU; DEATON, B. JAMES | AGGLOMERATION EFFECTS IN ONTARIO'S DAIRY FARMING | 2016 | Productivity | Ebsco |
| Borowiecki, Karol J. | Agglomeration economies in classical music | 2015 | Productivity | Ebsco |
| Backman, Mikaela | Human Capital in Firms and Regions: Impact on Firm Productivity | 2014 | Productivity | Ebsco |
| Antonelli, Cristiano; Scellato, Giuseppe | Complexity and Technological Change: Knowledge Interactions and Firm Level Total Factor Productivity | 2013 | Productivity | Ebsco |
| Guiso, Luigi; Schivardi, Fabiano | What Determines Entrepreneurial Clusters? | 2011 | Productivity | Ebsco |
| Becchetti, Leonardo; Panizza, Andrea de; Oropallo, Filippo | Role of Industrial District Externalities in Export and Value-added Performance: Evidence from the Population of Italian Firms | 2007 | Productivity | Ebsco |
| Anthony J. Howell | Do Marshallian Sources Drive Technological Relatedness? Implications for Firm Survival and Subsequent Success in China | 2016 | Productivity | SSRN |
| Mushtaq A. Khan, Hadia Majid, Amina Riaz, Masood Sarwar | Cluster Based Industrialization and its Effect on Firm Productivity in Pakistan | 2015 | Productivity | SSRN |
| Pe'er, A; Keil, T | Are all startups affected similarly by clusters? Agglomeration, competition, firm heterogeneity, and survival | 2013 | Survival | Webofscience |
| Wennberg, K; Lindqvist, G | The effect of clusters on the survival and performance of new firms | 2010 | Survival | Webofscience |
| Audia, PG; Rider, CI | Close, but not the same: Locally headquartered organizations and agglomeration economies in a declining industry | 2010 | Survival | Webofscience |
| Shaver, JM; Flyer, F | Agglomeration economies, firm heterogeneity, and foreign direct investment in the United States | 2000 | Survival | Webofscience |
| De Vaan, M; Boschma, R; Frenken, K | Clustering and firm performance in project-based industries: the case of the global video game industry, 1972-2007 | 2013 | Survival | Webofscience |
| Wang, L; Madhok, A; Li, SX | AGGLOMERATION AND CLUSTERING OVER THE INDUSTRY LIFE CYCLE: TOWARD A DYNAMIC MODEL OF GEOGRAPHIC CONCENTRATION | 2014 | Survival | Webofscience |
| De Silva, DG; McComb, RP | Geographic concentration and high tech firm survival | 2012 | Survival | Webofscience |
| Sasatani, D; Zhang, DW | The Pattern of Softwood Sawmill Closures in the US South: A Survival Analysis Approach | 2015 | Survival | Webofscience |
| van Oort, FG; Burger, MJ; Knoben, J; Raspe, O | MULTILEVEL APPROACHES AND THE FIRM-AGGLOMERATION AMBIGUITY IN ECONOMIC GROWTH STUDIES | 2012 | Survival | Webofscience |
| Heebels, B; Boschma, R | Performing in Dutch book publishing 1880-2008: the importance of entrepreneurial experience and the Amsterdam cluster | 2011 | Survival | Webofscience |

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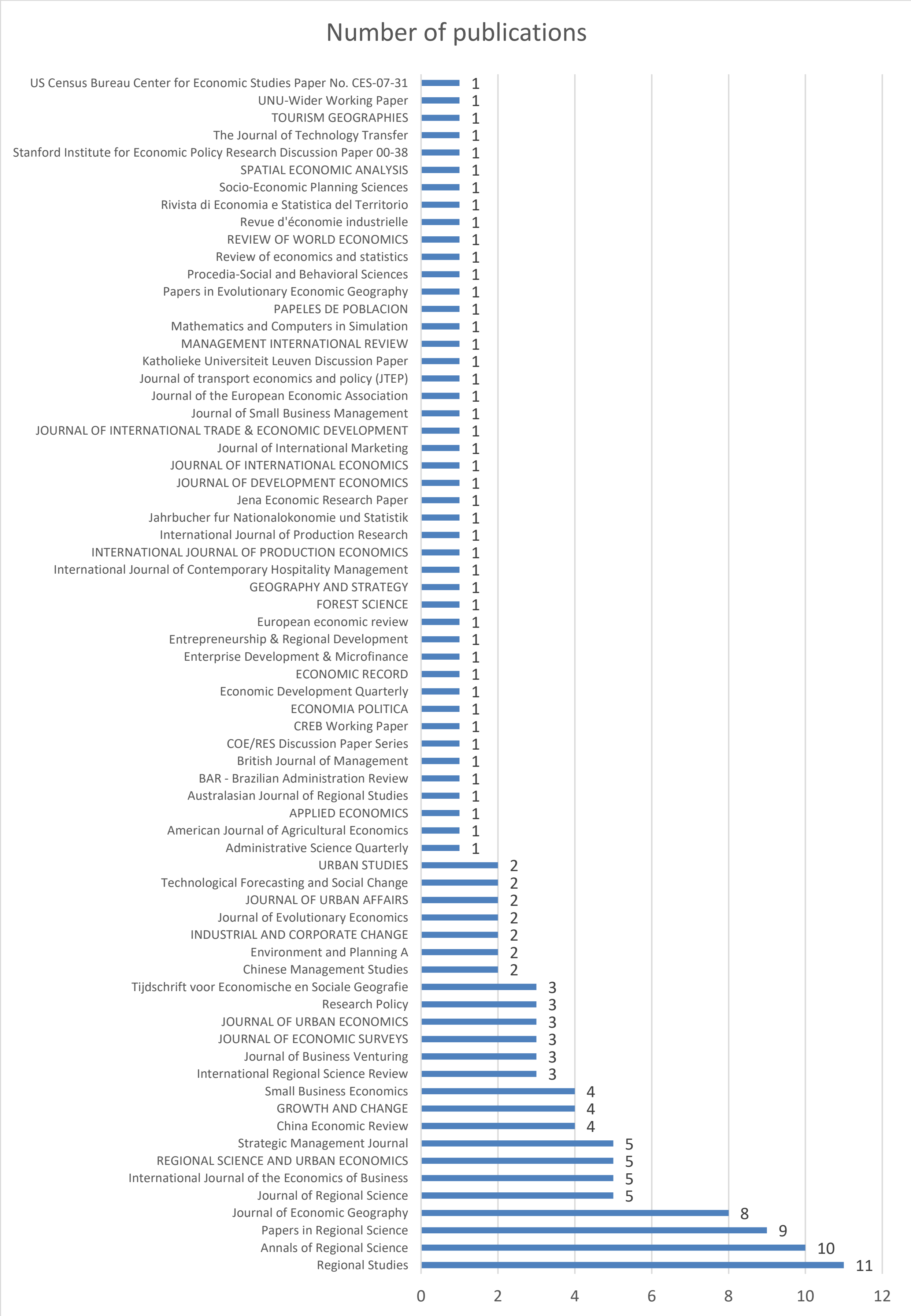
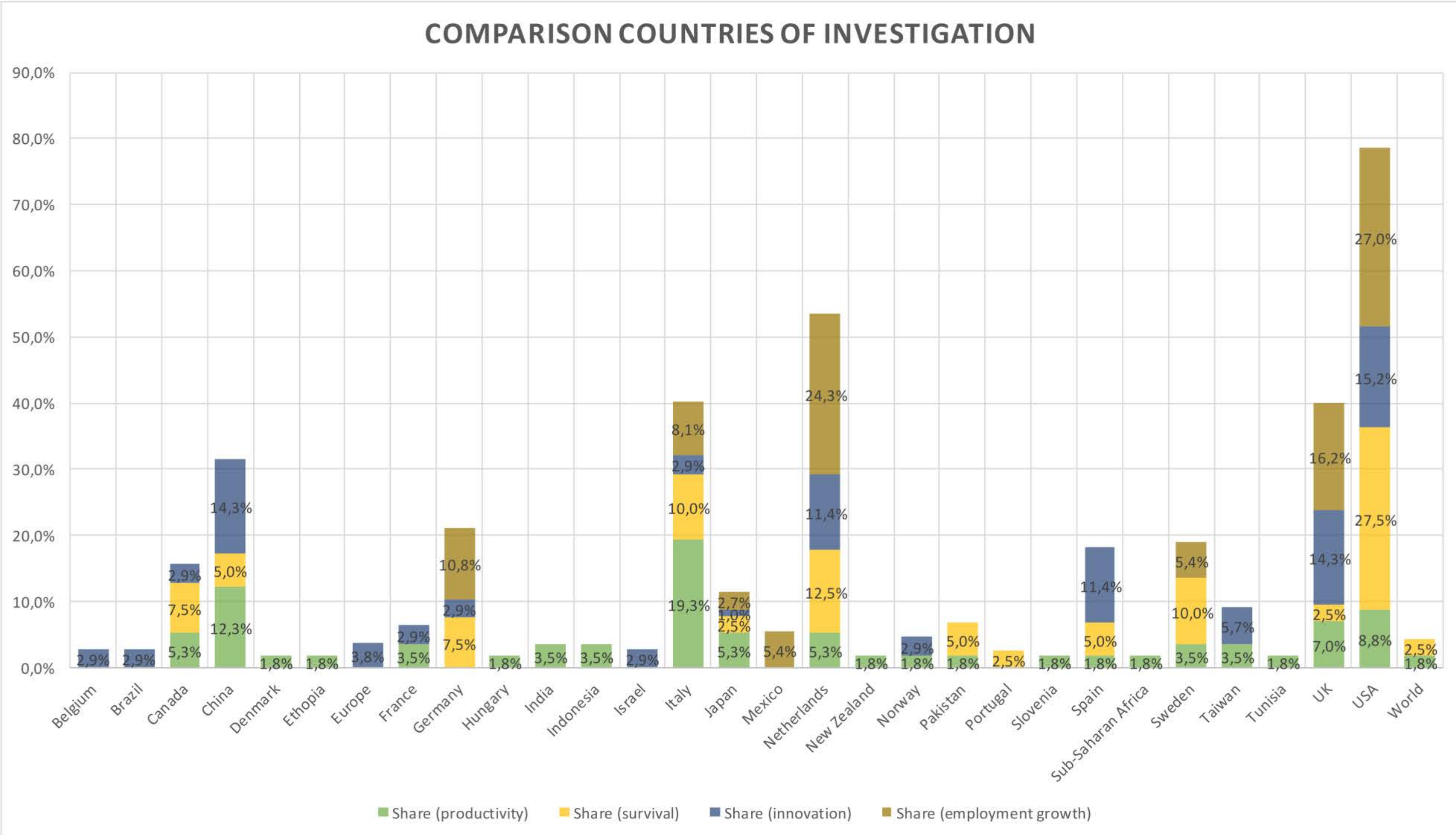
|---|---|---|---|---|
| Pe'er, A; Vertinsky, I; Keil, T | Growth and survival: The moderating effects of local agglomeration and local market structure | 2016 | Survival | Webofscience |
| Cainelli, G; Montresor, S; Vittucci Marzetti, G | Spatial agglomeration and firm exit: a spatial dynamic analysis for Italian provinces | 2014 | Survival | Webofscience |
| Renski, H | External economies of localization, urbanization and industrial diversity and new firm survival | 2011 | Survival | Webofscience |
| Jaffee, J | Law firm office location and firm survival in Silicon Valley, 1969 to 1998 | 2003 | Survival | Webofscience |
| Neffke, FMH; Henning, M; Boschma, R | The impact of aging and technological relatedness on agglomeration externalities: a survival analysis | 2012 | Survival | Webofscience |
| Brouder, P; Eriksson, RH | Staying Power: What Influences Micro-firm Survival in Tourism? | 2013 | Survival | Webofscience |
| Renski, H | Externalities or Experience? Localization Economies and Start-up Business Survival | 2015 | Survival | Webofscience |
| Burger, MJ; van Oort, FG; Raspe, O | Agglomeration and New Establishment Survival: A Mixed Hierarchical and Cross-Classified Model | 2011 | Survival | Webofscience |
| Puig, F; Gonzalez-Loureiro, M; Ghauri, PN | Internationalisation for Survival: The Case of New Ventures | 2014 | Survival | Webofscience |
| Staber, U | Spatial proximity and firm survival in a declining industrial district: The case of knitwear firms in Baden-Wurttemberg | 2001 | Survival | Webofscience |
| Sleutjes, B; Van Oort, F; Schutjens, V | A PLACE FOR AREA- BASED POLICY? THE SURVIVAL AND GROWTH OF LOCAL FIRMS IN DUTCH RESIDENTIAL NEIGHBORHOODS | 2012 | Survival | Webofscience |
| Boschma, RA; Wenting, R | The spatial evolution of the British automobile industry: Does location matter? | 2007 | Survival | Webofscience |
| Okamuro, Hiroyuki | Survival of New Firms in an Industry Agglomeration: An Empirical Analysis Using Telephone Directory of Tokyo | 2004 | Survival | Google Scholar |
| Lindqvist, Göran | Disentangling clusters: agglomeration and proximity effects | 2009 | Survival | Google Scholar |
| Kunkle, Gary Monroe | Cluster requiem and the rise of cumulative growth theory | 2009 | Survival | Google Scholar |
| Folta, Timothy B.; Cooper, Arnold C.; Baik, Yoon-suk | Geographic cluster size and firm performance | 2006 | Survival | Google Scholar |
| Ferragina, Anna Maria; Mazzotta, Fernanda | Local agglomeration economies: what impact on multinational and national Italian firms' survival? | 2014 | Survival | Google Scholar |
| Buenstorf, Guido; Guenther, Christina | No place like home? Location choice and firm survival after forced relocation in the German machine tool industry | 2007 | Survival | Google Scholar |
| Nasir, Marjan | Agglomeration and Firm Turnover | 2013 | Survival | Google Scholar |
| Moreno-Monroya, Ana I.; Arauzo-Carodb, Josep-Maria | Firm dynamics and intra-metropolitan agglomeration: an empirical analysis for Spain 2006-2012 | 2015 | Survival | Google Scholar |
| He, Canfei; Guo, Qi; Rigby, David | Industry Relatedness, Agglomeration Externalities and Firm Survival in China | 2015 | Survival | Google Scholar |
| Deltas, George; Silva, Dakshina G. de; McComb, Robert P. | Agglomeration Spillovers and Industry Dynamics: Firm Entry, Growth, and Exit in the Software Publishing Industry | 2014 | Survival | Google Scholar |
| Costa, Carla; Baptista, Rui | The Impact of Clusters on Firm Performance in the Growth and Sustainment Stages of the Cluster Lifecycle | 2015 | Survival | Google Scholar |

| | | | | |
|---|---|---|---|---|
| Cainelli, Giulio; Montresor, Sandro; Vittucci, Marzetti Giuseppe | Firms’ death rate and spatial agglomeration. Evidence on the resilience of Italian local production systems | 2012 | Survival | Google Scholar |
| Basile, Roberto; Pittiglio, Rosanna; Reganati, Filippo | Do Agglomeration Externalities Affect Firm Survival? | 2016 | Survival | Google Scholar |
| Nasir, Marjan | Effects of Agglomeration and Trade Liberalization On Firm Entry and Exit | 2012 | Survival | Google Scholar |
| Wrobel, Martin | 'One for all and all for one': Cluster, employment, and the global economic crisis. Evidence from the German mechanical engineering industry | 2015 | Survival | Ebsco |
| Weterings, Anet; Marsili, Orietta | Spatial Concentration of Industries and New Firm Exits: Does This Relationship Differ between Exits by Closure and by M&A? | 2015 | Survival | Ebsco |
| Anthony J. Howell | Do Marshallian Sources Drive Technological Relatedness? Implications for Firm Survival and Subsequent Success in China | 2016 | Survival | SSRN |
| George Deltas, Dakshina G. De Silva, Robert P. McComb | Industrial Agglomeration and Spatial Persistence of Employment in Software Publishing | 2014 | Survival | SSRN |

**Appendix 2:** Overview about the studies considered in the final sample




**Appendix 3:** Journal distribution of the final sample




**Appendix 4:** Countries of investigation of the final sample

# III. Paper II: Firm-specific cluster effects – A meta-analysis

**Author:** Nils Grashof

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**Abstract:** The aim of this paper is to investigate the alleged effect of clusters on firm performance and the moderating influence of the specific context by conducting a meta-analysis of the relevant empirical literature. Therefore four different performance variables from four separate publication databases are considered. The final sample of the meta-analysis consists of 168 empirical studies. The statistical integration of the corresponding results of these empirical studies indicate that there exist relatively weak evidence for a pure firm-specific cluster effect. Instead, it can be asserted that several variables from different levels of analysis directly or interactively moderate the relationship between clusters and firm´s success.

**Keywords:** meta-analysis, cluster effect, firm performance, moderating effects

**JEL Classification:** L25, O31, O32, R1

[60] In the interest of consistency, the following version differs slightly from the design of the published article.

## 1. Introduction

At least since Marshall´s work from 1920, the tendency of industries to cluster in some areas as well as possible economic effects of this regional clustering, have fascinated researchers from multiples disciplines alike. Spurred by the success of some clusters, as for example Silicon Valley, the concept has also become quite popular among politicians who are trying to copy the success in their region (Duranton and Overman 2005; Festing et al. 2012; Fornahl et al. 2015). Therefore, many cluster initiatives receive financial support. Since 2005 the German government, for example, has launched several programs with a total volume of 1.391 billion € to foster clusters in Germany (EFI 2015; Festing et al. 2012; Martin et al. 2011).

A typical explanation of these policies is that clusters will automatically generate economic benefits (Martin et al. 2011). However, the scientific results about the firm-specific cluster effect are indeed highly contradictive (Malmberg and Maskell 2002; Martin and Sunley 2003). While authors such as Baptista and Swann (1998) as well as Bell (2005) find evidence for a positive performance effect for companies located in clusters, other researchers come to slightly different results, ranging from negative performance effects (Pouder and St. John 1996) to rather mixed effects (Knoben et al. 2015). Given the already substantial financial support of cluster activities, it is actually quite surprising that a positive cluster effect on the success of companies within a cluster has not been consistently asserted yet. In this context, the authors Maier and Trippl (2012) comprehensively indicate that "In an economy where the agglomeration of activities does not generate any benefits, a policy that attempts to generate such agglomerations does not make any sense." (Maier and Trippl 2012, p. 14).

Recently, it has been however stressed that contextual variables, such as the industry context, moderate the cluster effect on firm´s success and should thus be explicitly addressed in future research. This in turn will deepen the understanding about the concrete conditions that shape the effect of clusters (Frenken et al. 2013; Grashof and Fornahl 2020). The aim of this paper is therefore to investigate the alleged effect of clusters on firm performance by examining potential moderating variables and answering the following research question: Which conditions moderate the effect of clusters on firm´s success?

In order to answer this research question adequately a meta-analysis of the empirical literature, dealing with the firm-specific cluster effect and possible moderating influences, is conducted. Such a meta-analysis is an appropriate methodical approach, because it is supposed to be a meaningful way of combining empirical studies with contradicting results (Fang 2015). By reconciling the contradictory empirical results, the paper does not only contribute to closing a still ubiquitous research gap concerning the moderation of firm-specific cluster effects (Frenken et al. 2013), but also has a practical meaning, because companies as well as policy-makers can evaluate better the concrete firm-specific effects of being located in a cluster. Up to now, such a meta-analysis has primarily been applied in the regional context (e.g. De Groot et al. 2007; Melo et al. 2009). One crucial exception, however, refers to the recent contribution by Fang (2015). Nevertheless, this article differs substantial from Fang (2015), as it explicitly concentrates on the firm level, its scope of considered performance variables (focusing on innovativeness, productivity, survival and employment growth) and literature is more extensive and it is based on a more precise selection process controlling, for instance, for a similar underlying cluster understanding in all selected studies. Consequently, this paper offers for the first time a comprehensive overview about the moderating influence of contextual variables from different levels of analysis on the firm-specific cluster effects.

The remainder of this paper proceeds as follows: The second section introduces the theoretical debate about cluster advantages as well as disadvantages and the respective moderating influence of the specific context by reviewing the corresponding literature. In the third section, the applied methodical approach and data is described. The final empirical results are then presented in the fourth section. The paper will end with some concluding remarks, including limitations to this paper as well as promising future research directions.

## 2. Theoretical Background – Cluster (dis-)advantages and the moderating role of the specific context

Similar to the definitional confusion (Brown et al. 2007; Malmberg and Maskell 2002; Martin and Sunley 2003), the theoretical discussion about cluster advantages and disadvantages is also characterized by a certain inconsistency. In this section, the most prominent arguments, focusing in particular on potential moderating influences, will therefore be presented.

In general, the agglomeration of economic activities can be explained by urbanization externalities (Jacobs, 1969) as well as localization externalities (Marshall, 1920). While the former one emphasizes the economic blessings of diversified regional industrial structures, promoting the creation of innovations and protecting against industry-specific shocks, the later one refers to the endogenous benefits from local specialization (McCann and Folta, 2008). As indicated by Grashof and Fornahl (2020) as well as Lazzeretti et al. (2014), urbanization externalities do not belong to the core of the common cluster understanding. Consequently, the underlying cluster understanding of this study is very close to Marshall´s notion. As already highlighted at the beginning of this article, Marshall (1920) was among the first to consider the benefits that firms can gain from being located in close proximity to similar firms. He identified four crucial types of localization externalities: access to specialized labour, access to specialized inputs, access to knowledge spillovers and access to greater demand by reducing the consumer search costs (Marshall 1920; McCann and Folta 2008).[61] Regarding the access to specialized labour Krugman (1991), for example, highlighted that clusters create a common market pool for workers with specialized skills that benefits employers and employees alike. On the one side, specialized employees reduce their risks, as they are able to attain work from multiple employers. On the other side, the local concentration of specialized workers also benefits employers in terms of minimizing the risk premium as well as search cost components of workers` wages (David and Rosenbloom 1990). Similar reasons hold also true for the improved access for firms in clusters to specialized inputs. By having a specific demand for specialized inputs, a cluster attracts a relatively high number of input suppliers, which in turn provides access to services that firms could otherwise only hardly afford individually (McCann and Folta 2008). In both cases, it has been however highlighted that the extent of these potential benefits may depend on the concrete size of the corresponding firm (e.g. Knoben et al. 2015). On the one hand, firms need to have sufficient resources in order to be able to acquire specialized labour from the common labour pool within clusters (Hatch and Dyer 2004; Knoben et al. 2015). On the other hand, there also exist evidence indicating that due to their complexity and inflexibility particularly large firms face problems of finding and integrating the available resources within clusters (Knoben et al. 2015; McCann and Folta 2011; Miller and Chen 1994). In the case of possible knowledge spillovers it is argued that geographic proximity can facilitate the transfer of knowledge in general (Jaffe et al. 1993) and specifically the transfer of tacit knowledge because it increases the probability of face-to-face contacts, which is an efficient medium for the transmission of such knowledge (Daft and Lengel 1986). Nevertheless, to actually profit from these externalities, it has been argued that firms need to own sufficient

[61] Besides these externalities, he also noted that the unique physical conditions of particular areas, such as limited natural resources, are the chief cause for the localization of industries.

absorptive capacities, referring to firm´s ability to recognize and evaluate new information from its environment as well as to process and integrate it into the corresponding innovation operations (Cohen and Levinthal 1990; Hervas-Oliver et al. 2018; McCann and Folta 2011). Besides these supply-side advantages, companies in clusters can also profit from an access to greater demand. The geographical concentration facilitates the search and evaluation of the large amount of options available from multiple firms. By reducing the corresponding consumer costs, the probability that consumers will purchase in agglomerations in comparison with more isolated locations is increased (McCann and Folta 2008). Moreover, it has been shown that companies gain from a common reputation within the cluster (Molina-Morales and Martínez-Fernández 2004; Wu et al. 2010) as well as from the available infrastructure (Kuah 2002). Another prominent argument for the benefits of clusters refers additionally to the competition created by collocating with rivalries. Due to the relatively high competition, firms are put under great pressure, which in the end motivates them to innovate in order to stay competitive (Harrison et al. 1996; Porter 1998).

Although much of the discussion so far has focused almost exclusively on the advantages of clusters, there exist also some authors emphasizing potential disadvantages as a cluster grows larger and ages (Folta et al. 2006; McCann and Folta 2008). With a size increase of the cluster for example, the previously positive aspect of competition can become a negative one. A high density of similar actors can result in an increased competition for input factors, which may lead to scarcity of these factors as well as significantly price increases (Folta et al. 2006; McCann and Folta 2008). Negative knowledge spillovers or in other words knowledge leakages are argued to be an additional possible disadvantage. Such leakages can discourage a firm to further innovate within a cluster, because other competing firms can actually free-ride on their knowledge (Fang 2015; Shaver and Flyer 2000). Furthermore, over time companies in clusters may face a certain inertia regarding market and technology changes. Pouder and St. John (1996) asserted in this context that the performance decline over time can be explained with the convergent mental models of managers within the corresponding region. By reinforcing old behaviours as well as old ways of thinking, this sort of group thinking behaviour prevents the recognition and adoption of new ideas (Martin and Sunley 2003; McCann and Folta 2008; Porter 2000; Pouder and St. John 1996). Moreover, it is suggested by some authors that a simple reliance on local face-to-face contacts and tacit knowledge makes local networks of industry especially vulnerable to lock-in situations, which in turn enforce again the inertia of companies within clusters (Boschma 2005; Martin and Sunley 2003). To avoid such a lock-in it has been emphasized that apart from local relationships it is also necessary for firms to have external linkages with more distant partners. Through these linkages, they can acquire access to an additional knowledge source that is different from the knowledge available in the corresponding regional cluster. Consequently, depending on the right balance between cluster internal and external linkages firms may gain more or less from being located in a cluster (Knoben et al. 2015; McCann and Folta 2011; Zaheer and George 2004). Similarly, the industry context can additionally moderate the firm-specific cluster effects. For example, due to a high market risk, implying relatively high uncertainty, companies will likely postpone their human resource decisions in order to avoid costly mistakes. As a consequence of these held-back investments, companies will not profit from the specialized labour pool within clusters (Ernst and Viegelahn 2014; Grashof 2019; Schaal 2017).

Thus, it can be summarized that being located in a cluster can imply several advantages as well as disadvantages to the corresponding firms.

## 3. Data and Methodology

In the empirical results this rather mixed picture is continued. To reconcile the conflicting empirical results of the firm-specific cluster effect, a meta-analysis will be conducted. According to one of the founders of this method, Gene V. Glass, a meta-analysis is defined as the "(…) analysis of analyses." (Glass 1976, p. 3). In other words, a meta-analysis refers to the statistical synthesis of evidence from multiple studies investigating a common research question (Quintana 2015; Wagner and Weiß 2014). Up to now meta-analysis has been more frequently applied in psychology and medical sciences, but only rarely in economics (Melo et al. 2009).[62] In comparison with traditional narrative reviews, meta-analysis is an appropriate alternative methodical approach, as it provides a more objective and transparent summary of the literature of one specific research field. In the case of narrative reviews, it is actually quite common that the reviewer subjectively chooses which studies to include in his review and what weights to attach to the results of these studies. In contrast to this, by its statistical nature and its explicit selection criteria meta-analysis can minimize subjective bias[63] and offers a great transparency as well as reproducibility.

[62] For important exceptions, see for example De Groot et al. 2007; Fang 2015 or Melo et al. 2009.

[63] Even though it is also not completely free from subjectivity (for instance regarding the selection of the inclusion criteria).

Furthermore, by including all relevant studies, published as well as unpublished ones, that match with the previously defined selection criteria, a meta-analysis provides not only a more objective but also a more complete overview on a given research topic than narrative reviews. In addition, it likewise offers the possibility of extracting more information from the selected studies through investigating non-sampling characteristics such as the research design (Fang 2015; Melo et al. 2009; Stanley and Jarrell 1989; Wagner and Weiß 2014). In light of the heterogeneity in the empirical design of the considered empirical studies, the “true” effect size cannot be estimated properly. A correct meta-regression of the “true” effect size of being located in a cluster can therefore not be conducted (De Groot et al. 2016; Eisend 2004). The available information offers, however, the possibility to analyse statistically the determinants of significant positive and negative estimation results of being located in a cluster (e.g. De Groot et al. 2007). Consequently, it is argued that such a methodical approach is appropriate to answer the underlying research question of this paper, whether and under which conditions being located in a cluster does influence firm´s success.

Firm´s success is here measured by four different performance variables: innovativeness, productivity, survival and employment growth. By considering four different performance variables, the effect of being located in a cluster on firm´s success as well as the corresponding moderating variables can be analysed from a broader perspective. These four performance variables have been selected, because it is argued that they capture most frequently and adequately firm´s success (Globerman et al. 2005; Sleutjes et al. 2012).[64] Although each of them has also its drawbacks[65] (e.g. employment growth and survival are not necessarily good proxies for high firm performance), in light of the varying appreciation across different stakeholders (e.g. policy-makers attach more value to employment growth) and industry/company contexts (e.g. in industrial crisis or highly competitive markets survival is seen as the most important performance variable) (Globerman et al. 2005; Richard et al. 2009; Sleutjes et al. 2012), it is argued that the common investigation of these four performance variables is appropriate. As already indicated, the empirical design, also encompassing the corresponding individual empirical measures for the four performance variables, differs across the considered studies. While employment growth is almost consistently measured by the rate of change in the number of

[64] Nevertheless, other performance variables, such as wages, may also be interesting to consider in future meta-analysis.

[65] For a comprehensive overview, see for example Giuliani et al. 2013 or Richard et al. 2009.

employees and survival by hazard rates of failure, the used indicators for innovativeness and productivity vary more. The former one is in most studies measured either by patents or by dummy variables (e.g. innovating or not).[66] The latter one is instead mostly measured by output indicators such as output per worker and total factor productivity (TFP).[67]

In general, the final dataset for the meta-analysis is based on the procedure presented in detail in Grashof and Fornahl (2020). The collection of relevant data through a literature review marks in this context the first step of the meta-analysis. For the literature collection three different publication databases are employed, namely Web of Science, Google Scholar as well as Ebsco. By applying various publication databases, a possible database bias, meaning that one database may favour a specific kind of literature, can be avoided. Hence, in the end the application of various publication databases contributes to a more meaningful literature collection. The actual search strategy is based on keyword combinations of “cluster” or “agglomeration” (which is quite often used as a synonym for clusters) and one of the four performance variables and “firm” or “company”. The latter ones are necessary to exclude empirical studies focusing only on the regional performance level. For each search query, only the 200 most relevant articles are taken into consideration. In general, the literature search process is subject to diminishing returns, meaning that after a certain point, further searching will return increasingly fewer relevant papers so that it becomes increasingly inefficient to extend the search process. Since there is no commonly accepted threshold, the search limit has to be selected based on a well thought trade-off between the rewards and the costs of further extending the search process (Koricheva et al. 2013; Kugley et al. 2017; Stevinson and Lawlor 2004). In this study, across all search queries strong diminishing returns can be identified after a threshold of 150 search results. Consequently, it is argued that the consideration of the 200 most relevant articles for each search query is reasonable.[68] Furthermore, at the beginning a preferably comprehensive literature collection should be achieved. Thus, the search is conducted for all years and for all document types. Since the above procedure returns mainly articles already published in some journals, which may lead to a publication bias, it is crucial to explicitly include further working papers in order to mitigate this bias. The already shown keyword combinations are therefore additionally used for a search query in the Social Science Research Network (SSRN).

[66] For a comprehensive review of innovation indicators please see Dziallas and Blind (2019).

[67] For a critical discussion about the measurement of productivity please see Van Biesebroeck (2015).

[68] This is particularly true in view of the comparatively high number of considered empirical studies (e.g. Melo et al. 2009), described in figure 1.

By conducting an internal review process, this publication database is especially convenient, because the quality of the corresponding data is ensured (Elsevier Inc 2017). As the main purpose of using SSRN is to include recent but not already published articles, only the results for the years 2014 until 2016 are considered.[69] Moreover, in some instances relevant empirical studies from different search queries were also taken into consideration. For example, this would be the case if some results from the search query of innovation are also relevant for the performance variable productivity.

After this very broad and comprehensive collection of literature, specific results are sorted out by applying inclusion criteria. The inclusion criteria are as follows: first, the studies need to be empirically investigating the effect of being located in a cluster on firm´s success. Although the findings of theoretical papers are briefly summarized in section two, they are not included in the overall meta-analysis. Second, it is required that all selected studies have the same underlying cluster understanding, because otherwise their results cannot really be integrated correctly. Even though the term cluster is a very widespread theme in economics, there are still fundamental differences in its definition as well as understanding, which have resulted in a large proliferation (Brown et al. 2007; Malmberg and Maskell 2002; Martin and Sunley 2003). However, for an appropriate implementation of a meta-analysis this definitional inconsistency implies a serious problem. Thus, it is essential to establish an adequate working definition of a cluster, which serves as the baseline for the definitions of the empirical studies derived from the literature collection. Building on the corresponding results of the descriptive meta-analysis in Grashof and Fornahl (2020), the following working definition for a cluster can be derived: “Clusters are defined as a geographical concentration of closely interconnected horizontal, vertical and lateral actors, such as universities, from the same industry that are related to each other in terms of a common research and knowledge base, technologies and/or product-market.” (Grashof and Fornahl 2020, p. 10f.). The identified key characteristics of a cluster, which have to be considered in the definitions of the selected empirical studies, refer in this context to the spatial connection, thematic connection and

[69] The author acknowledges that it is of course possible that older working papers may not, as assumed, convert itself in a journal article. Nevertheless, it is not illusory to assume that “good” working papers are likely to be published in journals. However, as a first robustness check all working papers, including the older ones, have been considered. As assumed most of them (around 80%) have indeed convert itself in a journal article and are therefore already included in the search results of the other three literature databases. From the remaining search results only two additional relevant empirical studies can be identified. The here later presented empirical results remain however stable and are not significantly changed by including the two additional studies in the final sample of this meta-analysis. The corresponding results can be provided upon request.

interdependencies (Grashof and Fornahl 2020). Consequently, studies focusing only on networks, industrial parks or urbanization are not included in the final sample. Third, relative cluster measures[70], such as relative specialization indicators, have to be at least based on the national average. Without fulfilling this condition, one can hardly speak about a cluster, because on a county or city level a high specialization in a specific industry can be achieved quite easily. Fourth, in contrast to traditional economic thinking, worker wages as well as earnings at the establishment level are not regarded as adequate measures for firm´s productivity, because it is argued that a rise in productivity does not automatically imply a wage increase. Thus, empirical studies making use of these or similar measures are not incorporated in the final sample. Last, the analytical focus of the empirical studies needs to be on the firm level and not on the regional level. Even though already explicitly integrated in the search queries, in some cases this condition is still not been met. As the selection process has an essential meaning for the overall meta-analysis, in case of doubt a second opinion is recognized.

The concrete selection and exclusion process of the considered empirical studies is depicted in figure 1. In total 2,201 studies are collected that match the already mentioned search queries. By excluding duplications and studies without author, only 1,944 results are considered in the first review process. Due to limited access to six articles, the corresponding authors were directly contacted. In four cases, however, they have not responded yet. As a further review process is not possible, these articles cannot be included in the final sample. In order to analyse whether the studies fulfil the inclusion criteria, in the first review process the title, the abstract as well as excerpts of the actual main text are read. As a consequence, 1,465 studies are sorted out, mainly because of their content, which often deals with a cluster analysis or with the regional level. Subsequently, two more detailed reviews are conducted. In these more detailed reviews, especially the statistical part is analysed. At the end of these review processes, the final meta-analysis considers a population of 168 empirical studies.[71] This corresponds to 8.6% of the adapted population (studies without author and duplications excluded). Since the focus of this article is particularly on the conditions shaping the effect of clusters on firm´s success, out of these 168 empirical studies, all explicitly and implicitly used moderating variables, have been selected and coded. The latter one refers to variables such as the industry context, which sometimes have not been explicitly analysed as a potential moderating variable, but

[70] For a detailed overview about different cluster measures see for example Brenner (2017).
[71] The full list of all considered articles is provided per request.

have been implicitly taken into consideration by investigating for example the firm-specific cluster effect in a particular industry setting.

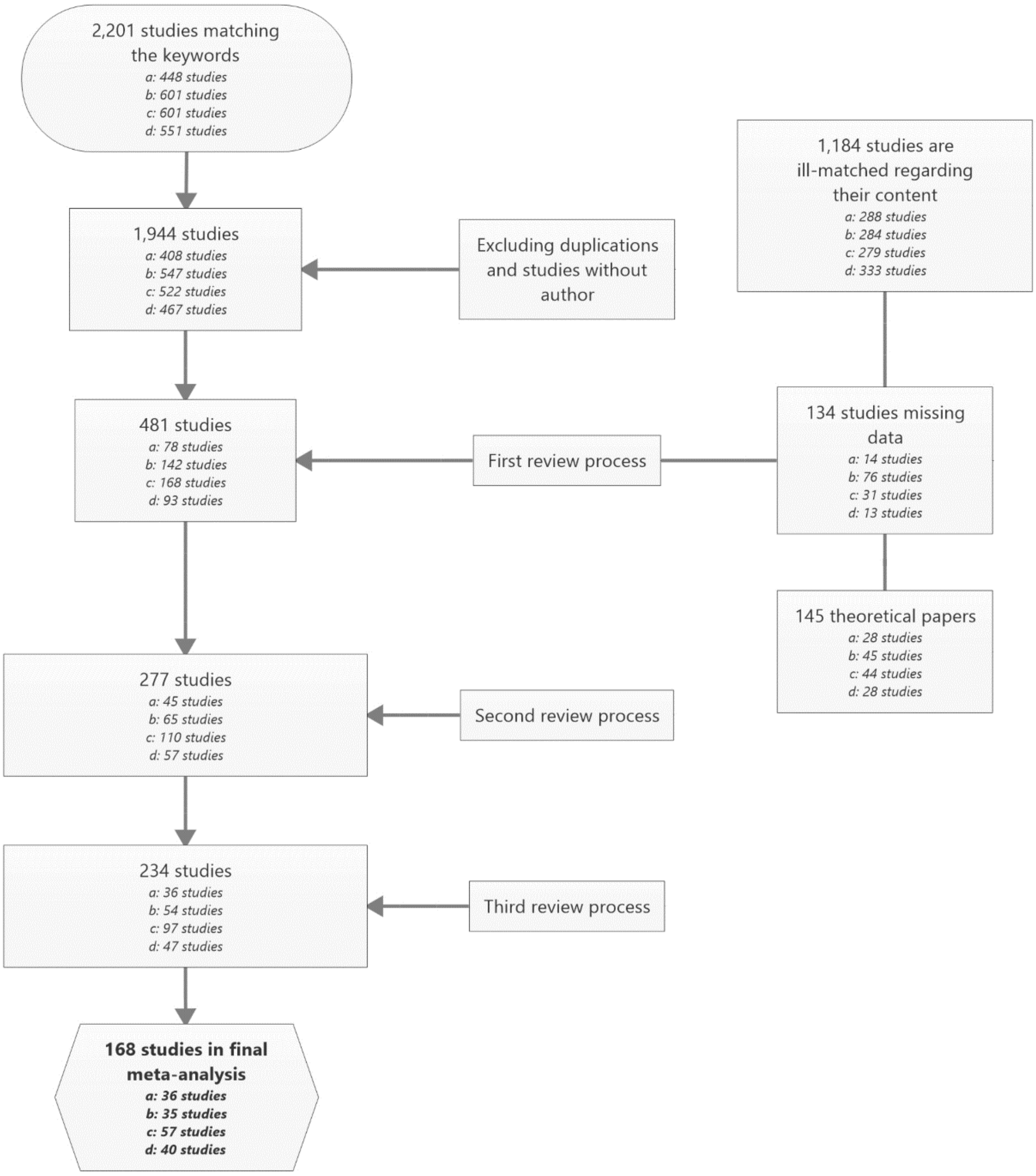


**Figure 1:** Selection and exclusion process of the considered empirical studies (Source: Grashof and Fornahl, 2020)

Note: *a*: Employment growth; *b*: Innovativeness; *c*: Productivity; *d*: Survival

Even though all moderating variables have been coded, for the sake of clarity only a selection of them are presented in this article.[72] The shown moderating variables are only those that have also been considered in at least three different empirical studies. In light of the underlying research question, the actual level of analysis is therefore on

[72] The full list of moderating variables is, however, available upon request.

the model and not on the study level. In other words, the number of observations potentially exceeds the number of considered empirical studies, as one study may include several empirical models e.g. in order to investigate different moderating influences. In total, 2,201 statistical models from the 168 empirical studies have been used to analyse the conditions under which firms can profit from being located in a cluster.

As already highlighted, up to now a meta-analysis has been only rarely applied in economics (Melo et al. 2009). In the context of a firm-specific cluster effect, even fewer papers have applied such a methodical approach. One important exception refers to the recent work of Li Fang (2015), providing a meta-analysis of the relationship of clusters and firm´s innovativeness. Nevertheless, this paper is different from Fang (2015) in four mayor aspects. First of all, even though Fang (2015) also partly investigates the cluster effect on the firm level, the main results are based on firm level and regional level oriented studies. By explicitly concentrating on the firm level, the derived results of this study are therefore not biased by regional effects of clusters, which may be quite different from the company-specific ones. Consequently, this study offers more detailed insights about the effect of clusters on firms. The second difference refers to the consideration of four different performance variables. By taking not only innovativeness, but four different performance variables into account, the influence of being located in a cluster on firm´s success can be investigated from a broader and more differentiated perspective. Likewise is the literature collection of this meta-analysis more extensive, because the actual search is based on four different publication databases. The last major difference refers to the inspection of the underlying cluster definitions of the empirical studies. As already stressed before, during the selection and exclusion process it is controlled for the match with the three main elements of a cluster definition. Although the strict definitional compliance is indeed one of the principal reasons for the relatively large exclusion of articles, it is indispensable for a meaningful meta-analysis, because the firm-specific cluster effect does not get distorted by other networklike effects. Thus, the firm-specific cluster effect and potential moderating influences can be analysed accurately.

## 4. Empirical results

To start with this analysis, the descriptive results of the pure cluster effect and all relevant moderating variables[73] across all four performance variables are presented in table 1.

**Table 1:** Pure cluster effect and moderating variables across all four performance variables (own illustration)

| **Estimation results** | **Across all four performance variables** | | |
|---|---|---|---|
| **Moderation effects** | **+** | **±** | **-** |
| Pure | ***75 (8.4%)*** | ***78 (8.2%)*** | ***26 (7.5%)*** |
| ***Micro-level*** | ***28 (3.1%)*** | ***39 (4.1%)*** | ***16 (4.6%)*** |
| Firm size | 11 (1.2%) | 12 (1.3%) | 9 (2.6%) |
| Firm age | 11 (1.2%) | 6 (0.6%) | 1 (0.3%) |
| Firm´s ownership | 3 (0.3%) | 15 (1.6%) | 6 (1.7%) |
| Internal knowledge base | 0 | 2 (0.2%) | 0 |
| Firm´s organisational structure | 3 (0.3%) | 4 (0.4%) | 0 |
| ***Meso-level*** | ***8 (0.9%)*** | ***5 (0.5%)*** | ***14 (4%)*** |
| Cluster size | 7 (0.8%) | 2 (0.2%) | 12 (3.4%) |
| Sector of specialization | 1 (0.1%) | 3 (0.3%) | 2 (0.6%) |
| ***Macro-level*** | ***571 (64.2%)*** | ***533 (56.2%)*** | ***195 (56%)*** |
| Industry | 569 (64%) | 533 (56.2%) | 194 (55.7%) |
| Spatial regimes | 2 (0.2%) | 0 | 1 (0.3%) |
| ***Interaction effects*** | ***207 (23.3%)*** | ***293 (30.9%)*** | ***97 (27.9%)*** |
| *Micro-level x Macro-level* | | | |
| Firm size x industry | 34 (3.8%) | 25 (2.6%) | 14 (4%) |
| Firm age x industry | 1 (0.1%) | 6 (0.6%) | 3 (0.9%) |
| Firm´s ownership x industry | 4 (0.4%) | 10 (1.1%) | 0 |
| Knowledge intensity x industry | 0 | 3 (0.3%) | 1 (0.3%) |
| Firm´s innovation capabilities x industry | 10 (1.1%) | 1 (0.1%) | 10 (2.9%) |
| Subsidiary-status x industry | 9 (1%) | 11 (1.2%) | 0 |
| Headquarter location x industry | 6 (0.7%) | 18 (1.9%) | 8 (2.3%) |
| Distance x industry | 118 (13.3%) | 165 (17.4%) | 36 (10.3%) |
| Geographical location x industry | 9 (1%) | 7 (0.7%) | 0 |
| Plant type x size x industry | 3 (0.3%) | 20 (2.1%) | 0 |
| *Meso-level x Macro-level* | | | |
| Cluster life cycle x industry | 3 (0.3%) | 4 (0.4%) | 0 |
| Cluster size x industry | 3 (0.3%) | 1 (0.1%) | 5 (1.4%) |
| Degree of specialization x industry | 2 (0.2%) | 13 (1.4%) | 9 (2.6%) |
| Sector of specialization x industry | 0 | 5 (0.5%) | 7 (2%) |
| Value chain of the cluster x industry | 1 (0.1%) | 1 (0.1%) | 1 (0.3%) |
| *Macro-level x Macro-level* | | | |
| Spatial regimes x industry | 4 (0.4%) | 3 (0.3%) | 3 (0.9%) |

Note: + Positive significant effect; ± Insignificant effect; - Negative significant effect

What is striking the most is the relatively weak evidence for a pure firm-specific cluster effect, meaning a direct effect of being located in a cluster on firm´s performance in absence of potential moderating variables. In the case of positive estimation results, for example, only 8.4% can be traced back towards a pure firm-

[73] As already indicated, for a simplified presentation of the results, moderating variables that are only analysed in relatively small number of empirical studies (less than 3 studies) are not illustrated.

specific cluster effect.

Regarding insignificant (8.2%) and negative (7.5%) estimation results, this share becomes even lower. By conducting a bivariate correlation analysis according to Pearson, these tendencies can be further reinforced.[74] Across all four performance variables there is no significant correlation between a pure cluster effect and the positive, insignificant as well as negative estimation results. Consequently, overall it can be asserted that being located in a cluster does not, at least in most cases, automatically lead to a positive or negative firm-specific cluster effect. This is in line with recent contributions emphasizing the need to understand the concrete conditions under which firms can gain from clusters (Frenken et al. 2013; Knoben et al. 2015). The following section will therefore particularly focus on the influence of moderating variables. A closer analysis of the results presented in table 1 reveals for example that there exist some variation between the four different performance variables. By separating the previous correlation analysis according to Pearson into the four performance variables, these variations can be depicted in table 2.

Interestingly the correlation coefficients of all four performance variables report a different direction. While the correlation between a pure cluster effect and the positive estimation results is significant positive, although small, for the performance variable survival, it is not significant for innovativeness. Contrarily, in this case a significant positive correlation with negative estimation results can be detected. In other words, empirical studies dealing with survival more frequently indicate towards a pure positive cluster effect, whereas the results of studies coping with innovativeness appear to give more evidence towards a pure negative cluster effect. Additionally, for productivity and employment growth significant positive respectively significant negative correlations with insignificant estimation results are found. Thus, it can be argued that the relationship between clusters and firm´s success also depends to some extent on the particular performance variable of interest. In view of recent cluster policy evaluation studies (e.g. Arthurs et al. 2009; Giuliani et al. 2013), stressing the importance of considering different output variables, it makes indeed sense that being located in a cluster has different implications for firm´s innovativeness, productivity, employment growth and survival.

[74] For the complete table please see appendix 1.

**Table 2:** Bivariate correlation analysis of the pure cluster effect and the estimation results for each performance variable (own illustration)

| Bivariate correlation analysis | | | | |
|---|---|---|---|---|
| | | **EstimationPositive** | **EstimationInsignificant** | **EstimationNegative** |
| **Pure Cluster Effect (Survival)** | Correlation according to Pearson | 0.212** | -0.123* | -0.099 |
| | Significance (1-sided) | 0.000 | 0.029 | 0.077 |
| | N | 318 | 318 | 318 |
| **Pure Cluster Effect (Productivity)** | Correlation according to Pearson | -0.067 | 0.104** | -0.057 |
| | Significance (1-sided) | 0.064 | 0.004 | 0.115 |
| | N | 756 | 756 | 756 |
| **Pure Cluster Effect (Innovativeness)** | Correlation according to Pearson | -0.093 | -0.015 | 0.139* |
| | Significance (1-sided) | 0.164 | 0.822 | 0.038 |
| | N | 225 | 225 | 225 |
| **Pure Cluster Effect (Employment Growth)** | Correlation according to Pearson | 0.037 | -0.071* | 0.044 |
| | Significance (1-sided) | 0.264 | 0.034 | 0.187 |
| | N | 902 | 902 | 902 |

**. The correlation is significant at the level of 0.01 (1-sided).

*. The correlation is significant at the level of 0.05 (1-sided).

Apart from the performance variables, table 1 also highlights that several variables from the micro-, meso- and macro-level directly or interactively moderate the relationship between clusters and firm´s success. In contrast to conventional wisdom, it is therefore a rather complicated relationship, which is influenced by a mix of different variables. One of the most influential variables refers to the industry context. Across all four performance variables over 50% of the positive, insignificant and negative firm-specific cluster effects can be explained by the corresponding industry. Thus, companies from specific kind of industries benefit more than others from being located in a cluster (e.g. Beaudry 2001; De Beule and Van Beveren 2012). In comparison with the macro-level, mainly consisting of the industry context, the variables of the micro- and meso-level are only investigated in a relatively small number of empirical studies. The interaction effects, however, appear to be of similar importance as the macro-level, because 23.3% of the positive, 30.9% of the insignificant and 27.9% of the negative firm-specific cluster effects can be traced back towards different interaction effects.[75] Especially to highlight is in this context the moderating effect of distance together with the industry context.

Having a closer look at the concrete influence of the most relevant moderating variables of the cluster and firm performance relationship, some interesting patterns can be observed. In order to detect the determinants of a positive firm-specific cluster effect, measured by a dummy variable indicating a significant positive estimation result of the cluster measure, a logistic regression is carried out. The applied logistic regression models have the following form:

$$\text{Logit}\ (\pi_{ij}) = \beta 0 + \beta 1\ \text{Industry setting} + \beta 2\ \text{Controls} + \varepsilon_{ij}\ ,$$

where $\pi$ is the natural log of the odds for model i from study j to derive significant positive estimation results of the cluster variable in terms of one of the four considered performance variables and $\varepsilon$ represents the corresponding error term.

In light of the available data and the primarily use of dummy variables this approach is argued to be most suitable for the further analysis (e.g. Hervas-Oliver et al. 2018; McCann and Folta 2011). As a control of the results, a bivariate correlation analysis is separately applied.[76] Due to the relatively high number of missing values in some cases, separate regression analysis are conducted. The standard procedure of an

[75] An interaction effect between firm size and industry means in this context that the interaction term between firm size and the corresponding cluster measurement, e.g. location quotient, in one particular industry setting has a particular influence on one of the four considered performance variables.
[76] For the results, please see appendix 2.

imputation of the missing data is in this context not possible, as in the corresponding cases over 50% of the data is missing. Under such conditions, an imputation may introduce or increase bias (Lee et al. 2016; McNeish 2017). Therefore, six different models are analysed. Model 1 contains the baseline model. In some cases, an estimation of the control variables of the baseline model is not possible because there are no observations or no variance. The results of the logistic regressions are presented in table 3.

**Table 3:** Logistic regression: Positive estimation results of being located in a cluster (own illustration, coefficients)

| ***EstimationPositive*** | *Model 1 n = 2093* | *Model 2 n = 887* | *Model 3 n = 295* | *Model 4 n = 30* | *Model 5 n = 23* | *Model 6 n = 41* |
|---|---|---|---|---|---|---|
| **PerformanceEmploymentGrowth** | 0.466*** | -0.240 | 2.298*** | ommitted[1] | 19.098 | ommitted[1] |
| **PerformanceProductivitiy** | 0.724*** | 0.616* | ommitted[2] | / | 15.269 | -3.187 |
| **PerformanceInnovativeness** | 0.634*** | 0.256 | / | / | / | / |
| **Germany** | -1.599*** | -1.324*** | / | / | / | / |
| **Italy** | -0.024 | -0.046 | -0.508 | / | No variance | -0.334 |
| **Japan** | 0.767** | 1.372*** | / | / | / | / |
| **Netherlands** | -1.604*** | -0.856* | / | / | No variance | 0.914 |
| **UK** | 0.443** | 1.039*** | / | / | / | / |
| **USA** | 0.186 | 0.843*** | -3.271*** | No variance | ommitted[1] | / |
| **Spain** | 0.738 | 1.220 | / | / | / | / |
| **China** | 0.273 | 2.181*** | / | / | ommitted[1] | -4.636* |
| **QualityofmethodHigh** | 0.700*** | 0.529 | 2.494*** | No variance | No variance | -2.456* |
| **IndustryHighTech** | | 0.381** | | | | |
| **IndustryMidHighTech** | | -0.847*** | | | | |
| **IndustryMidLowTech** | | -0.691** | | | | |
| **HighTech x LowDistance** | | | 0.939** | | | |
| **LowTech x LowDistance** | | | 0.689 | | | |
| **HighTech x HighDistance** | | | -0.148 | | | |
| **LowTech x HeadQuarterLocally** | | | | 1.946* | | |
| **AgeOld** | | | | | -1.836 | |
| **SizeLarge** | | | | | | -3.552*** |
| *Constant* | *-0.960**** | *-1.091**** | *0.591* | *-2.639*** | *-16.488* | *4.583*** |
| *Pseudo $R^2$* | *0.0564* | *0.1484* | *0.1163* | *0.1193* | *0.6221* | *0.3673* |

*Significance level: * p < 0.10, ** p < 0.05, *** p < 0.01*

*[1]Ommitted because it predicts success/failure perfectly*

*[2]Ommitted because of collinearity with USA*

*/ means that there are no observations*

The baseline model consists primarily of variables that are not explicitly analysed in the original studies, such as the quality of method[77] or the country of investigation. As already highlighted in the bivariate correlation analysis of the pure firm-specific cluster effect, some influence by the considered performance variable can be observed. Evidence is found that the performance variables employment growth, productivity and innovativeness appear to have a significant positive effect on the probability of identifying a positive firm-specific cluster effect in comparison with survival as the baseline variable. Consequently, when investigating the relationship between clusters and firm´s performance, future research should take different performance variables into account in order to get a broader understanding about this relationship. Because otherwise the derived conclusions and policy implications are potentially misleading in the way that they are not generalizable for different performance variables. So that conclusions that are made for example for the innovativeness of firms in clusters may be completely inadequate in terms of employment growth and/or survival.

Moreover, by applying a meta-analysis it is of particular interest whether the quality of the used methods of the considered empirical studies has a significant impact on the final results (e.g. Beaudry and Schiffauerova 2009). The application of high quality methods, such as a multilevel analysis, indeed significantly increases the probability of asserting a positive firm-specific cluster effect. Additionally, by using a negative cluster effect on firm performance as the dependent variable, a significant negative influence of high quality methods can be detected.[78] Consequently, it can be argued that a high quality of applied methods significantly decreases the probability for finding a negative firm-specific cluster effect, while it also significantly increases the likelihood for asserting a positive cluster effect on firm´s performance.

Apart from the quality of the used methods, an additional variable that is most often not been considered explicitly in the corresponding empirical studies, refers to the country of investigation.[79] In this context, two interesting patterns have to be highlighted. On the one hand, for Germany and the Netherlands a significant negative effect can be detected. Meaning that in both countries, but stronger in the Netherlands, the probability to realize a positive firm-specific cluster effect is significantly reduced. However, in other European countries, such as Italy, this effect

[77] The underlying classification is provided upon request.
[78] The logistic regression (baseline model) for the negative estimation results is depicted in appendix 3.
[79] For a detailed overview of the countries of investigation of the final sample please see appendix 4.

turns out to be insignificant. On the other hand, in the United Kingdom the probability for a positive cluster effect on firm´s performance is significantly higher than in other countries of investigation. Even though not significant in model 1[80], by analysing a negative firm-specific cluster effect as the dependent variable, a highly significant negative effect of the USA as the country of investigation can additionally be asserted.[81] Consequently, in general in the Anglo-Saxon countries and Western Europe two antithetical influences on the positive as well as negative firm-specific cluster effect can be determined. This dualism can eventually be explained by the different innovation approaches in Western Europe and in the Anglo-Saxon countries of investigation (Kickert 2005; Kiese et al. 2012). Based on the concept of 'varieties of capitalism' (e.g. Hall and Soskice 2001) Western Europe can be described as coordinated market economies (CMEs) while the Anglo-Saxon countries can be rather characterized as liberal market economies (LMEs). Consequently, in CMEs there exist rather institutionalized innovation systems, meaning that the state is interacting and an essential component of the innovation system. Contrary, in LMEs the state takes a hands-off role and only maintains an arm´s length relationship with the industry by trying to create a beneficial business environment. These rather competition-driven economies seem to be a favourable ground for clusters as they are argued to be more flexible as well as adaptive and thereby preventing a possible lock-in (Asheim 2007; Cooke 2001; Sternberg et al. 2010). Moreover, the results can also be explained by potential policy failures (e.g. Bach and Matt 2005; Hudson et al. 2019), which due to their nature, happen more frequently in coordinated market economies than in liberal market economies. Interestingly, such an opposed effect can also be constituted for Japan and China. While in Japan the probability for a positive firm-specific cluster effect is significantly increased, it is insignificant in China. However, using a negative firm-specific cluster effect as the dependent variable, in China it is significantly more likely to assert such a negative performance effect than in other countries of investigation.[82] Thus, a similar dualistic pattern, as in the case of Western Europe and the Anglo-Saxon countries, also applies to Japan and China.[83] The distinctive national innovation systems again offer a reasonable explanation for these two-sided results (Cuhls and Wieczorek 2008; Hobday 1995; Kroll et al. 2008). In Japan, the mayor driver in the national innovation system are large companies. The

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[80] The change of the estimation direction in model 3 is due to changes in the reference group only consisting of Canada, whereas in the previous two models several other countries are considered.
[81] The corresponding results are depicted in appendix 3.
[82] The corresponding results are depicted in appendix 3.
[83] The sign change of the China dummy in model 6 can be explained by the smaller number of observations compared with model 1.

state takes only the role of a mediator (Cuhls and Wieczorek 2008). Contrary, in China the state is omnipresent and the main force within the national innovation system (Kroll et al. 2008). Potential policy failures are thus more likely in China, which may explain the difference between both countries. In the final sample of this meta-analysis, some empirical studies, e.g. Van Geenhuizen and Reyes-Gonzalez (2007), also control for possible moderating effects by the corresponding region or city. Due to the relatively small number of studies performing such an investigation, an adequate integration is not possible. However, the consideration of such regional effects seems to be a promising avenue for the future research of the cluster and firm performance relationship. Because, as also Van Geenhuizen and Reyes-Gonzalez (2007) indicate, there may exist heterogeneity between the regional clusters in terms of knowledge and experience-based advantages influencing the performance of firms located in these regional clusters.

In model 2 the potential moderating effect of the industry context is considered. For the division of the industry context, the classification of Eurostat (Eurostat 2014; Eurostat 2017) and the OECD (OECD 2011) into low-technologies, medium-low-technologies, medium-high-technologies and high-technologies is employed. Regarding the moderating effect of the industry context on the firm-specific cluster effect, it can be stated that the probability for a positive firm-specific cluster effect is in high-tech industries significantly higher than in low-tech industries. In other words, firms in high-tech industries have a higher chance of realizing a positive performance effect in clusters than low-tech firms. This is quite intuitive as high-tech industries are normally quite knowledge-intensive, so that these industries particularly gain from knowledge spillovers, especially with regard to tacit knowledge (Cooke 2002; Tödtling et al. 2006). Furthermore, it has been highlighted that the supply of qualified labour is especially crucial for firms in high-tech industries (e.g. Brenner and Mühlig 2013). Since regional clusters provide access to a specialized labour pool (e.g. Krugman 1991), high-tech firms are argued to gain in particular from being located in such an environment. Surprisingly, the effect of medium-high-tech and medium-low-tech industries is significantly negative. In both industries it is therefore less likely, compared with low-tech industries, to realize a positive cluster effect. This can eventually be explained by the different requirements of these industries. While the medium-high-tech and medium-low-tech industries compete against high-tech industries for the most adequate talents of the common labour pool, low-tech industries do not need to hire an extensive number of high qualified employees. Instead they benefit from the access to knowledge spillovers from the other rather high-tech oriented industries by simply using the available knowledge or technology and adapting it to their concrete market niche (Rammer 2011). Medium-high-tech and medium-low-tech industries therefore seem to be somehow stuck in the middle.

The interaction effect of industry and distance is investigated in model 3. Low distance refers in this context to less than 1 mile, whereas high distance covers 10 to 25 miles range.[84] Several control variables from the baseline model could not be included in this case, because there were no observations. Moreover, the dummy for the performance variable productivity is omitted due to collinearity issues with the country dummy for the USA. As already highlighted, the change in the estimation direction of this country dummy can be explained by the reference group, which only consists of Canada, whereas in the previous models several other countries of investigations are incorporated within the reference group. Regarding the interaction effect of industry and distance, differences between high-tech and low-tech industries can be observed. Together with low distance only in high-tech industries, it is significantly more likely for companies to realize a positive cluster effect than in low-tech industries with high distance. In low-tech industries, low distance also increases the probability in this context, however, this is effect is not significant. Therefore, it can be argued that low distance matters especially in high-tech industries. In contrast to this, high distance in high-tech industries asserts a negative, but not significant, impact on the probability for a positive firm-specific cluster effect. In line with for example Rosenthal and Strange (2003), it can therefore in general be stated that the firm-specific gains from being located in a cluster, in terms of knowledge spillovers, are geographically concentrated. Due to their knowledge intensity, this is particularly pronounced for high-tech firms (Cooke 2002; Tödtling et al. 2006).

Regarding firm size, it can be further constituted that small and medium-sized companies (SMEs) are significantly more likely to realize a positive cluster effect than large companies.[85] Their complex internal structure and the related inflexibility thus tend to prevent large firms form finding and integrating resources that are available within the corresponding cluster (Knoben et al. 2015; McCann and Folta 2011; Miller and Chen 1994). However, it has to be highlighted that due to the available information in the considered empirical studies, it was not possible, unlike in the

[84] As a further robustness check, the classification of low distance has been regrouped and extended towards less than 10 miles. The corresponding results remain robust and can be provided upon request.

[85] The two changes in the estimation direction of the dummy variables of China and the quality of applied methods in model 6 have to be relativized in the light of the comparably small subsample, focussing specifically on a possible moderating effect by firm size.

previous case of the interaction effect of industry and distance, to define the exact borders of large firms as well as SMEs. Thus, the definition of large firms is based on the classification of the authors of the corresponding articles and can therefore vary.

The same holds true for the age of the company. The corresponding results of the logistic regression (model 5) indicate that the probability for a positive cluster effect is lower, although not significant, for old than for young companies. The results of the bivariate correlation analysis, however, indicate a significant correlation between firm´s age and a positive firm-specific cluster effect. A reasonable explanation here for is that young firms are supposed to be more flexible than old firms in re-organising and adopting new routines, which is especially a concern in dynamic environments (McCann and Folta 2008; McCann and Folta 2011).

In the light of the worldwide trends of globalization and localization (e.g. De Martino et al. 2006) it is additionally interesting to analyse whether the headquarter location of a company has a moderating influence on the positive firm-specific cluster effect. As shown in model 4, at least for low-tech industries this seems to be the case. The chance of realizing a positive firm-specific cluster effect is significantly higher in low-tech industries when firm´s headquarter is locally and not remotely settled. This result underlines to some extent the importance of local embeddedness (e.g. Meyer et al. 2011; Mudambi and Swift 2012), as it can be argued that the commitment of being engaged in cluster activities is higher for companies whose headquarter is locally settled.[86]

In view of the results derived from the bivariate correlation analysis and the logistic regression, in total it can be resumed that in general there exist relatively weak evidence for a pure firm-specific cluster effect. Instead, it can be asserted that the relationship between clusters and firm´s success is significantly shaped by several moderating variables from different levels of analysis.

## 5. Conclusion

Even though cluster initiatives have received substantial financial support from national governments, the EU and other public institutions, it is still rather unclear under which conditions being located in a cluster really influences firm´s success

[86] Due to the relatively small number of observations (n = 21), other quite interesting moderating variables such as cluster size and firm´s innovation capabilities could only be descriptively analysed. The corresponding results can, however, be provided upon request.

(Festing et al. 2012; Frenken et al. 2013; Martin and Sunley 2003). By conducting a profound meta-analysis of 168 empirical studies, dealing with the firm-specific cluster effect, a first step towards closing this research gap is accomplished.

The derived results emphasize that being located in a cluster does not, at least in most cases, lead automatically to a positive or negative performance effect. In contrast to conventional thinking, it can be shown that the relationship between clusters and firm performance is far more complex than just a simple direct effect. Indeed several variables from different levels of analysis significantly moderate the cluster effect on firm´s performance. On the micro-level, especially large firms are less likely to realize a positive firm-specific cluster effect. By using the classification of Eurostat (Eurostat 2014; Eurostat 2017) and the OECD (OECD 2011), on the macro-level it can be demonstrated that firms in high-tech industries have a higher chance for a positive performance effect in clusters than low-tech firms. However, in comparison with low-tech industries, in medium-high-tech and medium-low-tech industries it is even less likely to achieve such a performance effect. Furthermore, by analysing the interaction effect of the industry context and distance on the positive firm-specific cluster effect, it can be seen that low distance may especially contribute to a significantly increased chance of achieving such an effect, in high-tech and not so much in low-tech industries. Nevertheless, this does not mean that companies from low-tech industries per se should be located outside clusters. Because the interaction effect of low-tech industries and a locally settled headquarter indeed significantly increases the probability of realizing a positive firm-specific cluster effect. Thus, the effect of clusters on firm´s success rather depends on a mix of different moderating variables and not only on one specific feature. Future empirical studies about the firm-specific cluster effect should therefore account for a variety of moderating variables in order to investigate the relationship between clusters and firm´s success in more detail. For this purpose, it is supposed that multilevel analysis methods are especially suitable (Burger et al. 2012).

Apart from these variables, directly analysed in the corresponding empirical studies, three unconsidered variables are investigated. The results of the logistic regression indicate that, in comparison with survival as the performance variable, it is more likely to identify a positive firm-specific cluster effect if productivity, employment growth or innovativeness are chosen as the performance variables. Future research should therefore preferably consider a mix of different performance variables. Regarding the countries of investigation, two patterns can be detected. While the probability for a positive firm-specific cluster effect is significantly reduced in Germany and the Netherlands, it is significantly increased in the United Kingdom. Additionally, by using a negative firm-specific cluster effect as the dependent variable, it can be shown that in the USA the probability of asserting such a negative performance effect is significantly reduced. One possible explanation for this dualistic pattern refers to the different national innovation approaches, which differ in terms of the degree of state involvement and consequently in their probability of creating policy failures. The quality of the used methods of the considered empirical studies is also of particular interest. A high methodical quality implies a significant higher probability for a positive firm-specific cluster effect. Moreover, for the dependent variable of a negative cluster effect on firm performance, a significant negative influence can also be determined. Hence, it can be concluded that a high quality of applied methods significantly reduces the probability of finding a negative firm-specific cluster effect, while it also significantly increases the likelihood of asserting a positive cluster effect on firm´s performance. A mix of different methodical approaches is in this context supposed to be a useful way of dealing with this possible influence.

Nevertheless, there are also two limitations to this paper. Due to the relatively high heterogeneity in the empirical design of the considered empirical studies, the presented results of the meta-analysis do not account for the actual effect sizes of the corresponding empirical studies, but only for the significance and the estimation direction. Therefore, this meta-analysis can only be the first step for a more detailed meta-regression of the corresponding determinants of the relationship between clusters and firm´s performance. Furthermore, it is not controlled for the number of models applied in one study. This may lead to a possible overvaluation of studies containing multiple estimates. In order to mitigate such an overvaluation some researchers select only the "best" estimate from each study. However, in turn this can introduce an even larger bias concerning subjectivity, which is actually one of the mayor advantages over a narrative review (Melo et al. 2009). As a consequence, it is argued that the inclusion of all relevant results appears to be the most reasonable option.

All in all it can be resumed that this paper makes a first step towards reconciling the contradictory empirical findings about the alleged effect of clusters on firm´s success. Evidence is provided that clusters can indeed be a beneficial place to be located for companies. But this is not a self-evident automatism as commonly believed (Frenken et al. 2013; Martin and Sunley 2003). Instead, the positive impact of clusters on firm´s success depends on the particular circumstances of each individual firm. In fact, clusters can therefore be blessing and curse at the same time depending on the specific conditions. For policy makers this implies that they should avoid one-size-fits all policies (e.g. Tödtling and Trippl 2005), but instead design and implement policy approaches that explicitly take the specific context into account so that in the end policy efficiency can be increased.

## References

Arthurs, D., Cassidy, E., Davis, C. H., & Wolfe, D. (2009): Indicators to support innovation cluster policy, International Journal of Technology Management, Vol. 46, Nos. 3/4, pp. 263-279.

Asheim, B. (2007): DIFFERENTIATED KNOWLEDGE BASES AND VARIETIES OF REGIONAL INNOVATION SYSTEMS, *Innovation*, Vol. 20, Issue 3, pp. 223-241.

Bach, L., & Matt, M. (2005): From Economic Foundations to S&T Policy Tools: a Comparative Analysis of the Dominant Paradigms, in: Llerena, P., & Matt, M. (Eds.): Innovation Policy in a Knowledge-based Economy: Theory and Practice, Springer, Heidelberg, pp. 17-46.

Baptista, R., & Swann, P. (1998): Do firms in cluster innovate more?, *Research Policy*, Vol. 27, Issue 5, pp. 525-540.

Beaudry, C. (2001): Entry, Growth and Patenting in Industrial Clusters: A Study of the Aerospace Industry in the UK, *International Journal of the Economics of Business*, Vol. 8, Issue 3, pp. 405-436.

Beaudry, C., & Schiffauerova, A. (2009): Who's right, Marshall or Jacobs? The localization versus urbanization debate, *Research Policy*, Vol. 38, Issue 2, pp. 318-337.

Bell, G. G. (2005): Clusters, networks, and firm innovativeness, *Strategic Management Journal*, Vol. 26, Issue 3, pp. 287-295.

Boschma, R. (2005): Proximity and Innovation: A Critical Assessment, *Regional Studies*, Vol. 39, Issue 1, pp. 61-74.

Brenner, T., & Mühlig, A. (2013): Factors and Mechanisms Causing the Emergence of Local Industrial Clusters: A Summary of 159 Cases, *Regional Studies*, Vol. 47, Issue 4, pp. 480-507.

Brenner, T. (2017): Identification of Clusters - An Actor-based Approach, *Working Papers on Innovation and Space*, No. 02.17.

Brown, K., Burgees, J., Festing, M., Royer, S., & Steffen, C. (2007): The Value Adding Web – A Conceptual Framework of Competitive Advantage Realisation in Clusters, *ESCP-EAP Working Paper*, No. 27, ISSN: 1619-7658.

Burger, M. J., Knoben, J., Raspe, O., & Van Oort, F. G. (2012): Multilevel Approaches and the Firm-Agglomeration Ambiguity in Economic Growth Studies, *Tinbergen Institute Discussion Paper*, 014/3.

Cohen, W. M., & Levinthal, D. A. (1990): Absorptive Capacity: A New Perspective on Learning and Innovation, *Administrative Science Quarterly*, Vol. 35, No. 1, pp. 128-152.

Cooke, P. (2001): Regional innovation systems, clusters, and the knowledge economy, *Industrial and Corporate Change*, Vol. 10, Issue 4, pp. 945-974.

Cooke, P. (2002): Knowledge Economies: Clusters, Learning and Co-operative Advantage, Routledge, London.

Cuhls, K., & Wieczorek, I. (2008): Japan: Innovation System and Innovation Policy, in: Fraunhofer ISI, German Institute of Global and Area Studies, & Georgia Tech Program in Science, Technology and Innovation Policy (Eds.): New Challenges for Germany in the Innovation Competition, Fraunhofer ISI, Karlsruhe, pp. 45-110.

Daft, R. L., & Lengel, R. H. (1986): Organizational information requirements, media richness and structural design, *Management Science*, Vol. 32, No. 5, pp. 554-571.

David, P. A., & Rosenbloom, J. L. (1990): Marshallian factor market externalities and the dynamics of industrial localization, *Journal of Urban Economics*, Vol. 28, No. 3, pp. 349-370.

De Beule, F., & Van Beveren, I. (2012): Does Firm Agglomeration Drive Product Innovation and Renewal? An Application for Belgium, *Tijdschrift voor economische en sociale geografie*, Vol. 103, Issue 4, pp. 457-472.

De Groot, H. L., Poot, J., & Smit, M. J. (2007): Agglomeration, Innovation and Regional Development: Theoretical Perspectives and Meta-Analysis, *Tinbergen Institute Discussion Paper*, 07-079/3.

De Groot, H. L., Poot, J., & Smit, M. J. (2016): WHICH AGGLOMERATION EXTERNALITIES MATTER MOST AND WHY?, *Journal of Economic Surveys*, Vol. 30, Issue 4, pp. 756-782.

De Martino, R., Hardy Reid, D. M., & Zygliodopoulos, S. C. (2006): Balancing localization and globalization:exploring the impact of firm internationalization on a regional cluster, *Entrepreneurship & Regional Development*, Vol. 18, Issue 1, pp. 1-24.

Duranton, G., & Overman, H. G. (2005): Testing for Localization Using Micro-Geographic Data, *The Review of Economic Studies*, Vol. 72, Issue 4, pp. 1077-1106.

Dziallas, M., & Blind, K. (2019): Innovation indicators throughout the innovation process: An extensive literature analysis, *Technovation*, Vol. 80-81, pp. 3-29.

EFI (2015): Gutachten zu Forschung, Innovation und Technologischer Leistungsfähigkeit Deutschlands, Expertenkommission Forschung und Innovation.

Eisend, M. (2004): Metaanalyse - Einführung und kritische Auseinandersetzung, B*etriebswirtschaftliche Reihe*, No. 2004/8, Freie Universität Berlin.

Elsevier Inc (2017): SSRN - Frequently Asked Questions, available under https://www.ssrn.com/en/index.cfm/ssrn-faq/, last retrieved: 24.05.2017.

Ernst, E., & Viegelahn, C. (2014): Hiring uncertainty: a new labour market indicator, ILO Working Paper, available under https://ssrn.com/abstract=2411299, last retrieved 07.04.2020.

Eurostat (2014): Aggregations of manufacturing based on NACE Rev. 2, available under http://statistica.regione.emilia-romagna.it/allegati/factbook_2014/eurostat-high-tech-aggregation-of-manufacturing-and-services-nace-rev-2, last retrieved: 24.05.2017.

Eurostat (2017): Glossary: High-tech classification of manufacturing industries, available under http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:High-tech_classification_of_manufacturing_industries, last retrieved: 23.05.2017.

Fang, L. (2015): Do Clusters Encourage Innovation? A Meta-analysis, *Journal of Planning Literature*, Vol. 30, No. 3, pp. 239-260.

Festing, M., Royer, S., & Steffen, C. (2012): Unternehmenscluster schaffen Wettbewerbsvorteile - Eine Analyse des Uhrenclusters in Glashütte, *Zeitschrift Führung + Organisation*, Vol. 81, No. 4, pp. 264-272.

Folta, T. B., Cooper, A. C., & Baik, Y.-s. (2006): Geographic cluster size and firm performance. *Journal of Business Venturing*, Vol. 21, Issue 2, pp. 217-242.

Fornahl, D., Heimer, T., Campen, A., Talmon-Gros, L., & Treperman, J. (2015): Cluster als Paradigma der Innovationspolitik - Eine erfolgreiche Anwendung von Theorie in der politischen Praxis?, Studien zum deutschen Innovationssystem, No. 13-2015.

Frenken, K., Cefis, E., & Stam, E. (2013): Industrial dynamics and clusters: a survey, Tjalling C. Koopmans Research Institute, Discussion Paper Series, No. 13-11, Utrecht School of Economics.

Giuliani, E., Maffioli, A., Pacheco, M., Pietrobelli, C., & Stucchi, R. (2013): Evaluating the Impact of Cluster Development Programs, Inter-American Development Bank, Technical Note, No. IDB-TN-551.

Glass, G. V. (1976): Primary, Secondary, and Meta-Analysis of Research, *Educational Researcher*, Vol. 5, No. 10, pp. 3-8.

Globerman, S., Shapiro, D., & Vining, A. (2005): Clusters and intercluster spillovers: their influence on the growth and survival of Canadian information technology firms, *Industrial and Corporate Change*, Vol. 14, Issue 1, pp. 27-60.

Grashof, N., & Fornahl, D. (2020): 'To be or not to be' located in a cluster? - A descriptive meta-analysis of the firm-specific cluster effect, *Working Papers on Innovation and Space*, 01.20.

Grashof, N. (2019): Sinking or swimming in the cluster labour pool? A firm-specific analysis of the effect of specialized labour, Unpublished Working Paper, Presented at the annual PhD workshop at the University of Bremen.

Hall, P. A., & David, S. (2001): An introduction to varieties of capitalism, in: Hall, P. A., & Soskice, D. (Eds.): Varieties of Capitalism: The Institutional Foundations of Comparative Advantage, Oxford University Press, Oxford, pp. 1-68.

Harrison, B., Kelley, M. R., & Gant, J. (1996): Innovative Firm Behavior and Local Milieu: Exploring the Intersection of Agglomeration, Firm Effects, and Technological Change, *Economic Geography*, Vol. 72, Issue 3, pp. 233-258.

Hatch, N. W., & Dyer, J. H. (2004): Human capital and learning as a source of sustainable competitive advantage, *Strategic Management Journal*, Vol. 25, Issue 12, pp. 1155-1178.

Hervas-Oliver, J.-L., Sempere-Ripoll, F., Alvarado, R. R., & Estelles-Miguel, S. (2018): Agglomerations and firm performance: who benefits and how much?, *Regional Studies*, Vol. 52, Issue 3, pp. 338-349.

Hobday, M. (1995): Innovation in East Asia: Diversity and development, *Technovation*, Vol. 15, Issue 2, pp. 55-63.

Hudson, B., Hunter, D., & Peckham, S. (2019): Policy failure and the policy-implementation gap: can policy support programs help?, *Policy Design and Practice*, Vol. 2, Issue 1, pp. 1-14.

Jacobs, J. (1969): The economy of cities, Vintage, New York.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993): Geographic localization of knowledge spillovers as evidenced by patent citations, *Quarterly Journal of Economics*, Vol. 108, No. 3, pp. 577-598.

Kickert, W. J. M. (2005): Public Governance: the Context of Administrative Innovations in Southern Europe, in: Veenswijk, M. (Ed.): Organizing Innovation - New Approaches to Cultural Change and Intervention in Public Sector Organizations, IOS Press, Amsterdam, pp. 173-191.

Kiese, M., Sternberg, R., & Stockinger, D. (2012): Regionale Clusterpolitik in den USA und in Deutschland: Systematische Unterschiede und Lernpotenziale, in: Koschatzky, K., & Stahlecker, T. (Eds.): Clusterpolitik quo vadis? - Perspektiven der Clusterförderung, Fraunhofer Verlag (ISI-Schriftenreihe Innovationspotenziale), Karlsruhe, pp. 119-148.

Knoben, J., Arikan, A. T., Van Oort, F., & Raspe, O. (2015): Agglomeration and firm performance: One firm's medicine is another firm's poison, *Environment and Planning A*, Vol. 48, No. 1, pp. 1-22.

Koricheva, J., Gurevitch, J., & Mengersen, K. (2013): Handbook of Meta-analysis in Ecology and Evolution, Princeton University Press, Princeton.

Kroll, H., Conlé, M., & Schüller, M. (2008): China: Innovation System and Innovation Policy, in: Fraunhofer ISI, German Institute of Global and Area Studies, & Georgia Tech Program in Science, Technology and Innovation Policy (Eds.): New Challenges for Germany in the Innovation Competition, Fraunhofer ISI, Karlsruhe, pp. 169-242.

Krugman, P. (1991): Geography and trade, MIT Press, Cambridge, MA.

Kuah, A. T. (2002): Cluster Theory and Practice: Advantages for the Small Business Locating in a Vibrant Cluster, *Journal of Research in Marketing and Entrepreneurship*, Vol. 4, No. 3, pp. 206-228.

Kugley, S., Wade, A., Thomas, J., Mahood, Q., Jørgensen, A. M. K., Hammerstrøm, K., & Sathe, N. (2017): Searching for studies: a guide to information retrieval for Campbell systematic reviews, The Campbell Collaboration, Oslo, doi: 10.4073/cmg.2016.1.

Lazzeretti, L., Sedita, S. R., & Caloffi, A. (2014): Founders and disseminators of cluster research, *Journal of Economic Geography*, Vol. 14, Issue 1, pp. 21-43.

Lee, K. J., Roberts, G., Doyle, L. W., Anderson, P. J., & Carlin, J. B. (2016): Multiple imputation for missing data in a longitudinal cohort study: a tutorial based on a detailed case study involving imputation of missing outcome data, *International Journal of Social Research Methodology*, Vol. 19, No. 5, pp. 575-591.

Maier, G., & Trippl, M. (2012): The Pitfalls and Booby Traps of Cluster Policy, S*RE - Discussion Papers*, No. 2012/01,WU Vienna University of Economics and Business.

Malmberg, A., & Maskell, P. (2002): The elusive concept of localization economies: towards a knowledge-based theory of spatial clustering, *Environment and Planning A*, Vol. 34, No. 3, pp. 429-449.

Marshall, A. (1920): Principles of economics, Macmillan, London, 8th Edition.

Martin, P., Mayer, T., & Mayneris, F. (2011): Public support to clusters: A firm level study of French "Local Productive Systems", *Regional Science and Urban Economics*, Vol. 41, Issue 2, pp. 108-123.

Martin, R., & Sunley, P. (2003): Deconstructing clusters: chaotic concept or policy panacea?, *Journal of Economic Geography*, Vol. 3, Issue 1, pp. 5-35.

McCann, B. T., & Folta, T. B. (2008): Location Matters: Where We Have Been and Where We Might Go in Agglomeration Research, *Journal of Management*, Vol. 34, Issue 3, pp. 532-565.

McCann, B. T., & Folta, T. B. (2011): Performance differentials within geographic clusters, *Journal of Business Venturing*, Vol. 26, Issue 1, pp. 104-123.

McNeish, D. (2017): Missing data methods for arbitrary missingness with small samples, *Journal of Applied Statistics*, Vol. 44, No. 1, pp. 24-39.

Melo, P. C., Graham, D. J., & Noland, R. B. (2009): A meta-analysis of estimates of urban agglomeration economies, *Regional Science and Urban Economics*, Vol. 39, Issue 3, pp. 332-342.

Meyer, K. E., Mudambi, R., & Narula, R. (2011): Multinational Enterprises and Local Contexts: The Opportunities and Challenges of Multiple Embeddedness, *Journal of Management Studies*, Vol. 48, Issue 2, pp. 235-252.

Miller, D., & Chen, M.-J. (1994): Sources and Consequences of Competitive Inertia: A Study of the U.S. Airline Industry, *Administrative Science Quarterly*, Vol. 39, No. 1, pp. 1-23.

Molina-Morales, F. X., & Martínez-Fernández, M. T. (2004): How much difference is there between industrial district firms? A net value creation approach, *Research Policy*, Vol. 33, Issue 3, pp. 473-486.

Mudambi, R., & Swift, T. (2012): Multinational Enterprises and the Geographical Clustering of Innovation, *Industry and Innovation*, Vol. 19, Issue 1, pp. 1-21.

OECD (2011): ISIC REV. 3 TECHNOLOGY INTENSITY DEFINITION - Classification of manufacturing industries into categories based on R&D intensities, OECD Directorate for Science, Technology and Industry.

Porter, M. E. (1998): Clusters and the New Economics of Competitiveness, *Harvard Business Review*, Vol. 76, Issue 6, pp. 77-90.

Porter, M. E. (2000): Location, Competition, and Economic Development: Local Clusters in a Global Economy, *Economic Development Quarterly*, Vol. 14, Issue 1, pp. 15-34.

Pouder, R., & St. John, C. H. (1996): Hot Spots and Blind Spots: Geographical Clusters of Firms and Innovation, *The Academy of Management Review*, Vol. 21, No. 4, pp. 1192-1225.

Quintana, D. (2015): From pre-registration to publication: a non-technical primer for conducting a meta-analysis to synthesize correlational data, *Frontiers in Psychology*, Vol. 6, Article 1549, pp. 1-9.

Rammer, C. (2011): Bedeutung von Spitzentechnologien, FuE-Intensität und nicht forschungsintensiven Industrien für Innovationen und Innovationsförderung in Deutschland, *ZEW Dokumentation*, No. 11-01, ISSN: 1611-681X.

Richard, P. J., Devinney, T. M., Yip, G. S., & Johnson, G. (2009): Measuring Organizational Performance: Towards Methodological Best Practice, *Journal of Management*, Vol. 35, Issue 3, pp. 718-804.

Rosenthal, S. S., & Strange, W. C. (2003): Geography, Industrial Organization, and Agglomeration, *The Review of Economics and Statistics*, Vol. 85, No. 2, pp. 377-393.

Schaal, E. (2017): Uncertainty and Unemployment, *Econometrica*, Vol. 85, Issue 6, pp. 1675-1721.

Shaver, J. M., & Flyer, F. (2000): Agglomeration economies, firm heterogeneity, and foreign direct investment in the United States, *Strategic Management Journal*, Vol. 21, Issue 12, pp. 1175-1193.

Sleutjes, B., Van Oort, F., & Schutjens, V. (2012): A PLACE FOR AREA-BASED POLICY? THE SURVIVAL AND GROWTH OF LOCAL FIRMS IN DUTCH RESIDENTIAL NEIGHBORHOODS, *Journal of Urban Affairs*, Vol. 34, Issue 5, pp. 533-558.

Stanley, T. D., & Jarrell, S. B. (1989): Meta-Regression Analysis: A Quantitative Method of Literature Surveys, *Journal of Economic Surveys*, Vol. 3, Issue 2, pp. 161-170.

Sternberg, R., Kiese, M., & Stockinger, D. (2010): Cluster policies in the US and Germany: varieties of capitalism perspective on two high-tech states, *Environment and Planning C: Government and Policy*, Vol. 28, Issue 6, pp. 1063-1082.

Stevinson, C., & Lawlor, D. A. (2004): Searching multiple databases for systematic reviews: added value or diminishing returns?. *Complementary Therapies in Medicine*, Vol. 12, Issue 4, pp. 228-232.

Tödtling, F., Lehner, P., & Trippl, M. (2006): Innovation in Knowledge Intensive Industries: The Nature and Geography of Knowledge Links, *European Planning Studies*, Vol. 14, Issue 8, pp. 1035-1058.

Tödtling, F., & Trippl, M. (2005): One size fits all?: Towards a differentiated regional innovation policy approach, *Research Policy*, Vol. 34, Issue 8, pp. 1203-1219.

Van Biesebroeck, J. (2015): How tight is the link between wages and productivity? A survey of the literature, *Conditions of Work and Employment Series*, No. 54, International Labor Organization, Geneva.

Van Geenhuizen, M., & Reyes-Gonzalez, L. (2007): Does a clustered location matter for high-technology companies' performance? The case of biotechnology in the Netherlands, *Technological Forecasting and Social Change*, Vol. 74, Issue 9, pp. 1681-1696.

Wagner, M., & Weiß, B. (2014): Meta-Analyse, in: Baur, N., & Blasius, J. (Eds.): Handbuch Methoden der empirischen Sozialforschung, Springer Fachmedien, Wiesbaden, pp. 1117-1126.

Wu, X., Geng, S., Li, J., & Zhang, W. (2010): Shared Resources and Competitive Advantage in Clustered Firms: The Missing Link, *European Planning Studies*, Vol. 18, Issue 9, pp. 1391-1410.

Zaheer, A., & George, V. P. (2004): Reach Out or Reach Within? Performance Implications of Alliances and Location in Biotechnology, *Managerial and Decision Economics* Vol. 25, Issue 6-7, pp. 437-452.

## Appendix

| Bivariate correlation analysis (across all four performance variables) | | | | |
|---|---|---|---|---|
| | | EstimationPositive | EstimationInsignificant | EstimationNegative |
| **PureClusterEffect** | Correlation according to Pearson | 0.005 | 0.001 | -0.008 |
| | Significance (1-sided) | 0.815 | 0.958 | 0.696 |
| | N | 2201 | 2201 | 2201 |

**Appendix 1:** Bivariate correlation analysis of the pure cluster effect and the estimation results across all four performance variables (own illustration)



| Bivariate correlation analysis (across all four performance variables) | | | | |
|---|---|---|---|---|
| | | EstimationPositive | EstimationInsignificant | EstimationNegative |
| **IndustryHighTech** | Correlation according to Pearson | 0.133** | -0.006 | -0.169** |
| | Significance (1-sided) | 0.000 | 0.849 | 0.000 |
| | N | 960 | 960 | 960 |
| **IndustryMidHighTech** | Correlation according to Pearson | -0.107** | 0.082* | 0.034 |
| | Significance (1-sided) | 0.001 | 0.011 | 0.295 |
| | N | 960 | 960 | 960 |
| **IndustryMidLowTech** | Correlation according to Pearson | -0.098** | 0.079* | 0.026 |
| | Significance (1-sided) | 0.002 | 0.015 | 0.419 |
| | N | 960 | 960 | 960 |

| | | | | |
|---|---|---|---|---|
| **IndustryLowTech** | Correlation according to Pearson | -0.009 | -0.089** | 0.130** |
| | Significance (1-sided) | 0.779 | 0.006 | 0.000 |
| | N | 960 | 960 | 960 |
| **PerformanceEmploymentGrowth** | Correlation according to Pearson | -0.052* | -0.003 | 0.074** |
| | Significance (1-sided) | 0.016 | 0.905 | 0.001 |
| | N | 2201 | 2201 | 2201 |
| **PerformanceProductivitiy** | Correlation according to Pearson | 0.112** | -0.033 | -0.107** |
| | Significance (1-sided) | 0.000 | 0.123 | 0.000 |
| | N | 2201 | 2201 | 2201 |
| **PerformanceInnovativeness** | Correlation according to Pearson | -0.007 | -0.008 | 0.021 |
| | Significance (1-sided) | 0.730 | 0.709 | 0.328 |
| | N | 2201 | 2201 | 2201 |
| **PerformanceSurvival** | Correlation according to Pearson | -0.073** | 0.055* | 0.024 |
| | Significance (1-sided) | 0.001 | 0.010 | 0.270 |
| | N | 2201 | 2201 | 2201 |
| **SizeLarge** | Correlation according to Pearson | -0.481** | 0.373* | 0.127 |
| | Significance (1-sided) | 0.001 | 0.016 | 0.427 |
| | N | 41 | 41 | 41 |
| **SizeSME** | Correlation according to Pearson | 0.481** | -0.373* | -0.127 |
| | Significance (1-sided) | 0.001 | 0.016 | 0.427 |
| | N | 41 | 41 | 41 |
| **AgeOld** | Correlation according to Pearson | -0.589** | 0.163 | 0.572** |
| | Significance (1-sided) | 0.003 | 0.458 | 0.004 |
| | N | 23 | 23 | 23 |

| | | | | |
|---|---|---|---|---|
| **AgeYoung** | Correlation according to Pearson | 0.589** | -0.163 | -0.572** |
| | Significance (1-sided) | 0.003 | 0.458 | 0.004 |
| | N | 23 | 23 | 23 |
| **HighTechHighDistance** | Correlation according to Pearson | -0.063 | 0.083 | -0.034 |
| | Significance (1-sided) | 0.272 | 0.149 | 0.562 |
| | N | 302 | 302 | 302 |
| **HighTechLowDistance** | Correlation according to Pearson | 0.121* | -0.122* | 0.009 |
| | Significance (1-sided) | 0.036 | 0.033 | 0.883 |
| | N | 302 | 302 | 302 |
| **LowTechLowDistance** | Correlation according to Pearson | 0.106 | -0.160** | 0.087 |
| | Significance (1-sided) | 0.065 | 0.005 | 0.129 |
| | N | 302 | 302 | 302 |
| **LowTechHighDistance** | Correlation according to Pearson | -0.190** | 0.041 | 0.221** |
| | Significance (1-sided) | 0.001 | 0.473 | 0.000 |
| | N | 302 | 302 | 302 |
| **LowTechHeadquarterLocally** | Correlation according to Pearson | 0.333 | -0.605** | 0.394* |
| | Significance (1-sided) | 0.072 | 0.000 | 0.031 |
| | N | 30 | 30 | 30 |
| **LowTechHeadquarterRemotely** | Correlation according to Pearson | -0.333 | 0.605** | -0.394* |
| | Significance (1-sided) | 0.072 | 0.000 | 0.031 |
| | N | 30 | 30 | 30 |
| **Germany** | Correlation according to Pearson | -0.148** | 0.039 | 0.148** |
| | Significance (1-sided) | 0.000 | 0.070 | 0.000 |
| | N | 2155 | 2155 | 2155 |

| | | | | |
|---|---|---|---|---|
| **Italy** | Correlation according to Pearson | 0.013 | -0.031 | 0.024 |
| | Significance (1-sided) | 0.544 | 0.156 | 0.266 |
| | N | 2155 | 2155 | 2155 |
| **Japan** | Correlation according to Pearson | 0.042 | -0.007 | -0.047* |
| | Significance (1-sided) | 0.051 | 0.733 | 0.029 |
| | N | 2155 | 2155 | 2155 |
| **Netherlands** | Correlation according to Pearson | -0.146** | 0.089** | 0.077** |
| | Significance (1-sided) | 0.000 | 0.000 | 0.000 |
| | N | 2155 | 2155 | 2155 |
| **UK** | Correlation according to Pearson | 0.098** | -0.111** | 0.019 |
| | Significance (1-sided) | 0.000 | 0.000 | 0.382 |
| | N | 2155 | 2155 | 2155 |
| **USA** | Correlation according to Pearson | 0.005 | 0.094** | -0.136** |
| | Significance (1-sided) | 0.800 | 0.000 | 0.000 |
| | N | 2155 | 2155 | 2155 |

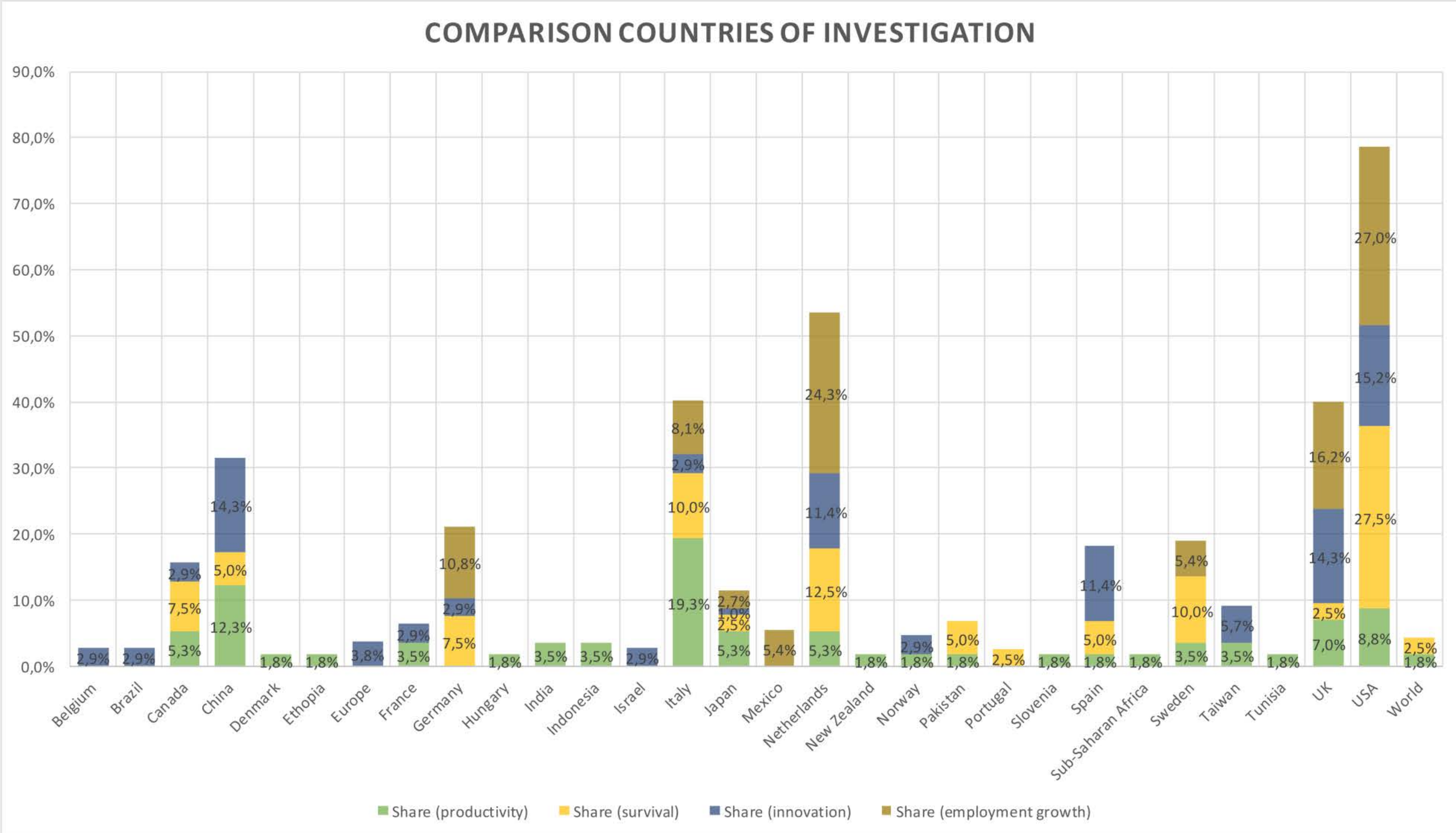
**. The correlation is significant at the level of 0.01 (1-sided).

*. The correlation is significant at the level of 0.05 (1-sided).

**Appendix 2:** Bivariate correlation analysis of moderating variables and the estimation results across all four performance variables (own illustration)

| *EstimationNegative* | *Model 1*<br>*n = 2093* |
|---|---|
| **PerformanceEmploymentGrowth** | -0.046 |
| **PerformanceProductivitiy** | -1.036*** |
| **PerformanceInnovativeness** | -0.574** |
| **Germany** | 0.602** |
| **Italy** | 0.170 |
| **Japan** | -0.566 |
| **Netherlands** | 0.523* |
| **UK** | -0.215 |
| **USA** | -1.087*** |
| **Spain** | -0.642 |
| **China** | 0.739*** |
| **QualityofmethodHigh** | -0.677** |
| *Constant* | -1.026*** |
| *Pseudo $R^2$* | 0.0695 |
| *Significance level: * p < 0.10, ** p < 0.05, *** p < 0.01* | |

**Appendix 3:** Logistic regression: Negative estimation results of being located in a cluster (own illustration, coefficients)




**Appendix 4:** Countries of investigation of the final sample (Source: Grashof and Fornahl, 2020)

# IV. Paper III: Spill over or Spill out? – A multilevel analysis of the cluster and firm performance relationship

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Published in Papers in Evolutionary Economic Geography[87] as well as submitted to Industry and Innovation

**Abstract:** Regional clusters have become an inseparable component of modern economies. Spurred by the idea that clusters unrestrictedly encourage firm innovativeness, such as in the lighthouse example of Silicon Valley, the cluster approach has particularly gained attention among policy makers who have supported the creation and development of clusters. Nevertheless, due to a lack of holistic consideration of different influencing variables, the scientific results about the effect of clusters on firm innovative performance are highly contradictive. For companies as well as policy makers, it is therefore still difficult to evaluate the concrete consequences of being located in a cluster. Consequently, the aim of this paper is to empirically investigate the conditions and mechanisms through which companies can gain from being located in clusters, focussing thereby in particular on possible knowledge spillovers. Therefore, based on an integration of the theoretical perspectives from the strategic management (e.g. resource-based view) and the economic geography literature (e.g. cluster approach), variables from three different levels of analysis (micro-level, meso-level and macro-level) are considered separately as well as interactively. By analysing a unique multilevel dataset of 11,889 companies in Germany, including 1,391 firms that are located within a cluster, evidence is found that being located in a cluster has indeed a positive impact on firm innovative performance. However, the results also indicate that firms benefit unequally within the cluster environment, depending on the specific firm, cluster and market/industry conditions.

**Keywords:** meta-analysis, cluster effect, firm performance, moderating effects
**JEL Classification:** L25, O31, O32, R1

[87] In the interest of consistency, the following version differs slightly from the design of the published article.

## 1. Introduction

The geographical concentration of economic activities forms an elementary component of today´s economic reality (Brown et al., 2007; Nathan and Overman, 2013). As such, regional clusters have gained considerable attention among scientists as well as policy makers (Martin and Sunley, 2003; Sedita et al., 2012). Inspired by early theoretical contributions about clusters and lighthouse case studies, such as Silicon Valley, the idea that clusters promote innovativeness and productivity has settled in the heads, particularly, of policy makers. By pursuing the goal of writing a similar success story for their region, policy makers at all levels of governance have implemented measures to create or support clusters (Festing et al., 2012; Martin et al., 2011; Terstriep and Lüthje, 2018). Most European countries have therefore already realized national and regional cluster programs (European Union, 2016; Zenker et al., 2019). For example, since 2005 the German national government has launched several programs with a total volume of 1.391 billion € to foster excellent clusters in Germany (EFI, 2015; Festing et al., 2012).[88]

Despite the already substantial financial support of cluster activities, an invariably positive effect of clusters on firm performance is still not conclusively proven. Instead, the scientific results about the firm-specific cluster effect are indeed highly contradictive (Malmberg and Maskell, 2002; Martin and Sunley, 2003). Some studies have found empirical evidence for a positive performance effect (Baptista and Swann, 1998; Bell, 2005), while others have also emphasized rather mixed (Knoben et al., 2015) or even negative performance effects (Pouder and St. John, 1996).

Apart from the lack of standardized methodologies and cluster definitions, this inconsistency can mainly be explained by the missing systematic consideration of potential moderating variables. Among scientists in this field, it is actually quite prevalent to assume that all companies profit equally and in the same manner from being located in a cluster (Frenken et al., 2013; Šarić, 2012; Tallman et al., 2004). Even Michael Porter assumes that “a vibrant cluster can help **any** company in **any** industry compete in the most sophisticated ways, using the most advanced, relevant skills and technologies.” (Porter, 1998, p. 86). Nevertheless, by just having a short and superficial look at the broad field of studies dealing with firm performance differentials, it becomes obvious that this idea is rather questionable (Dyer and Singh, 1998; Van Oort et al., 2012; Vega-Jurado et al., 2008). In this context, a comprehensive meta-

[88] A comprehensive overview about the financial budgets of different cluster programs in Europe is provided by Zenker et al. (2019).

analysis from 2017 of the cluster literature identified several moderating variables, such as the industry context (Grashof and Fornahl, 2020).

Frenken et al. (2013) therefore make a call to “open the black box” (Frenken et al., 2013, p. 23) about the conditions and mechanisms through which the firm-specific advantages of localization economies, including for instance the benefits of specialized labour markets, specialized inputs and knowledge spillovers (e.g. Marshall, 1920), can be realized. The aim of this paper is to respond to this call for the Marshallian component of knowledge spillovers by answering the following research question: Under which conditions can a company located in a cluster profit from knowledge spillovers?

While this firm-specific perspective has been widely ignored in the previous cluster research, there are some important exceptions (Brown et al., 2007; Grillitsch and Nilsson, 2017; Šarić, 2012; Steffen, 2012; Van Oort et al., 2012). However, these relatively recent articles again come to contradictory empirical results (Grillitsch and Nilsson, 2017; Hervas-Oliver et al., 2018). On the one hand, evidence is found that knowledge-poor firms gain the most from being located in a cluster (Rigby and Brown, 2015; Shaver and Flyer, 2000). But on the other hand, some studies highlight that knowledge-rich firms are the main beneficiaries (McCann and Folta, 2011). Consequently, it is reasonable to assume that additional moderating variables must be taken into consideration in order to analyse the relationship between clusters and firm performance in a more sophisticated way.

To do so, based on a theoretical integration of the resource-based view, the relational view, the market-based view and the cluster approach, this paper investigates three different levels of analysis (micro-level, meso-level, and macro-level) by applying an OLS regression with clustered standard errors of single cross-sectional averages over time. Therefore, varying data sources are applied, ranging from firm-level to market and industry-level data. The chosen methodical approach is appropriate as it takes the hierarchical data structure, the corresponding context dependency and the year-to-year variability being ubiquitous in micro-level data into account (McNeish, 2014; Moulton, 1990; Rigby and Brown, 2015).

By providing an answer to the underlying research question, the paper not only contributes to closing a still ubiquitous research gap but also has a pragmatic meaning, because companies as well as policy makers can evaluate better under which conditions it is more likely to realize a competitive advantage in clusters or in other words a firm-specific cluster advantage.

The remainder of this paper is structured as follows: The second section introduces the theoretical background, highlighting the theoretical debate about knowledge spillovers, establishing an adequate working definition of a cluster and elaborating the corresponding hypotheses. In the third section, the applied methodical approach and data is described in detail. Thereafter, the fourth section presents the empirical results. The paper will end with some concluding remarks, including limitations to this study as well as promising future research directions.

## 2. Theoretical foundation of the cluster and firm performance relationship

Although the term cluster is a very widespread and prevalent theme in economics, at least since the two scientific papers of Porter (1990 and 1998), there are still fundamental differences in its definition as well as understanding (Brown et al., 2007; Malmberg and Maskell, 2002; Martin and Sunley, 2003). Even Silicon Valley, which is one of the most prominent case studies in the literature, has already been defined as a regional network, industrial district, innovative milieu, agglomeration and learning region, among others (Šarić, 2012). As a consequence of the unclear definitional delimitation, the term has experienced a large proliferation and thereby has lost some of its explanatory power (Brown et al., 2007; Martin and Sunley, 2003; Šarić, 2012; Sedita et al., 2012). This study does, however, not intend to open a theoretical discussion about a new (conceptual) cluster definition. Instead, the following working definition of a cluster, derived through a comparative empirical approach in Grashof and Fornahl (2020), is used: “Clusters are defined as a geographical concentration of closely interconnected horizontal, vertical and lateral actors, such as universities, from the same industry that are related to each other in terms of a common resource and knowledge base, technologies and/or product-market.” (Grashof and Fornahl, 2020, p. 10f.). Moreover, in line with several authors (Delgado et al., 2010; Martin et al., 2011; McCann and Folta, 2011) the terms cluster and agglomeration are used interchangeably.

Marshall (1920) was actually among the first to consider the benefits that firms can gain from being located in close proximity to firms from the same industry. He presented in this context four types of agglomeration externalities: access to specialized labour, access to specialized inputs, access to knowledge spillovers and access to greater demand by reducing consumer search costs (Marshall, 1920; McCann and Folta, 2008).[89]

The focus of this paper lies on knowledge spillovers. A view held by many economists is that geographic proximity can facilitate the transfer of knowledge in general (Jaffe et al., 1993) and the transfer of tacit knowledge specifically because it increases the likelihood of face-to-face contacts, which is an efficient medium for the transfer of such knowledge (Daft and Lengel, 1986). Generally, it can be differentiated between formal linkages such as licensing, technology partnerships as well as strategic alliances and informal linkages through which the transfer of tacit knowledge can be simplified (McCann and Folta, 2011; Pouder and St. John, 1996). Apart from geographic proximity, it has been pointed out that additional types of proximity capturing cognitive, organizational, social or institutional characteristics can also foster knowledge diffusion (Boschma, 2005). However, it has been emphasized that these types of proximity are highly interrelated. In other words, there is a greater likelihood that actors which are co-located in close distance hold the same norms, share the same culture and follow the same regulations (Grillitsch and Nilsson, 2017). Even though not in the centre of the current scientific discussion, negative knowledge spillovers may also be the result of being located in close proximity to similar firms, in the sense that knowledge leakages are more likely to happen in an environment of reinforced knowledge exchange (Grillitsch and Nilsson, 2017; Shaver and Flyer, 2000). Additionally, some authors suggest that a simple reliance on local face-to-face contacts and tacit knowledge makes local networks of industry especially vulnerable to lock-in situations, which in turn enforce the inertia of companies within clusters (Boschma, 2005; Martin and Sunley, 2003). In this context, Pouder and St. John (1996) argued that the firm performance decline over time can be explained with the convergent mental models of managers within the corresponding region. As a consequence of this kind of uniform thinking, a sort of group thinking comportment, old behaviours as well as old ways of thinking are reinforced which prevent the recognition and adoption of new ideas.

While the reviewed theory about knowledge spillovers is in general rather uncontroversial in its tenor about the possible (dis-)advantages of being located in a cluster, the literature is nearly silent about the concrete conditions through which those outcomes can be realized (Frenken et al., 2013; McCann and Folta, 2011).

[89] Besides these externalities he also noted that the unique physical conditions of particular areas, such as limited natural resources, are the chief cause for the localization of industries.

### 2.1. Firm-level conditions (Micro-level)

This silence is particularly astonishing in light of the resource-based view (RBV). The resource-based view of the firm is regarded as one of the most widely accepted theoretical perspectives in the field of strategic management (Newbert, 2007; Steffen, 2012). But it has also been conceptually extended towards the regional or the cluster level (Hervas-Oliver and Albors-Garrigos, 2007; Hervas-Oliver and Albors-Garrigos, 2009). The RBV emerged from the contributions of Penrose (1959), Rubin (1973) and Wernerfelt (1984), who claimed that firms have to be seen as resource bundles. Since then the RBV has continuously been further elaborated.[90] Its focus lies on firms’ internal resource bases and how firms can utilize these resources in order to gain a competitive advantage. The strength of firms’ resources depends on their characteristics, namely whether they are valuable, rare, non-substitutable and imitable (Barney, 1991; Newbert, 2007; Steffen, 2012). In accordance with Barney (1991), resources are here defined as “all assets, capabilities, organizational processes, firm attributes, information, knowledge, etc. controlled by a firm that enable the firm to conceive of and implement strategies that improve its efficiency and effectiveness.” (Barney, 1991, p. 101). The underlying assumptions of the RBV are resource immobility and heterogeneity between companies. Both assumptions are necessary for the existence of different resource endowments and its persistency over time (Barney, 1991; Newbert, 2007). Regarding knowledge spillovers it has been argued that firms own different innovation capabilities to actually profit from these externalities (Hervas-Oliver and Albors-Garrigos, 2009; Hervas-Oliver et al., 2018; McCann and Folta, 2011). Cohen and Levinthal (1990) established in this context the term absorptive capacity[91], which describes not only a firm´s ability to recognize and evaluate new information from its environment but also its ability to process it and finally integrate it into the corresponding business innovation activities (Cohen and Levinthal, 1990).

In accordance with the core idea of the RBV, there is empirical evidence that firms with higher innovation capabilities benefit more form available knowledge spillovers. By having higher innovation capabilities, companies are better capable of accessing and integrating external knowledge (Knoben et al., 2015; McCann and Folta, 2011). Although these results are quite in line with the core idea of the RBV, they neglect to

[90] For a good overview see for example Newbert (2007). The Knowledge-based view can be additionally seen as one specific shaping of the RBV (Grant, 1996).

[91] In accordance with Hervas-Oliver et al. (2018), the terms absorptive capacity and innovation capability are used interchangeably.

some extent that strong internal innovation capabilities also implicate a higher amount of unintentional knowledge spillovers to possible competitors. These outflows of knowledge are claimed to reduce continuously a firm´s relative competitive advantage over other firms (Hervas-Oliver et al., 2017; Knoben et al., 2015; Shaver and Flyer, 2000). Thus, the following hypothesis is proposed:

**Hypothesis 1a:** The strength of the innovation capabilities of a firm has an inverted U-shaped effect on firm innovative performance in clusters such that the relationship is likely to be more positive for firms with moderately strong innovation capabilities.

In this context, it has additionally been emphasized that the capacity of firms to absorb and process new knowledge efficiently requires cognitive proximity. This means that it is essential to own a knowledge base that is close enough to the new knowledge so that the corresponding company can actually understand and evaluate the new knowledge in a resource-efficient way (Boschma, 2005; Nooteboom, 2000). While a certain level of cognitive proximity is required to gain from knowledge spillovers, too much cognitive proximity might be, however, detrimental to firm innovativeness. A high level of cognitive proximity between two actors decreases, for example, the potential of learning something radically new. Furthermore, it also increases the likelihood of a lock-in situation as well as the possibility of negative knowledge spillovers (Boschma, 2005; Fornahl et al., 2011). A moderate level of cognitive proximity is therefore likely to be most beneficial for firms (Boschma, 2005; Boschma and Frenken, 2010; Nooteboom, 2000). While the effect of cognitive proximity has been analysed extensively on the actors' level (e.g. Broekel and Boschma, 2012; Fornahl et al., 2011), the cognitive proximity between the firm´s knowledge stock and the overall stock of knowledge within the corresponding cluster has not been investigated yet. In line with the call for further investigation of this aspect by McCann and Folta (2008) as well as in accordance with Nooteboom (2000), the following hypothesis is proposed:

**Hypothesis 1b:** The cognitive proximity between the firm´s knowledge stock and the overall stock of knowledge of the corresponding cluster has an inverted U-shaped effect on firm innovative performance in clusters such that the relationship is likely to be more positive for firms with a moderate level of cognitive proximity.

In light of the increasing significance and proliferation of inter-firm alliances, an extension of the RBV called the relational view (RV) has been developed since the late 1990s (Hervas-Oliver and Albors-Garrigos, 2009; Lavie, 2006; Steffen, 2012). While the RBV has only considered those resources and capabilities that are housed within the firm, the RV focuses on inter-firm relationships and routines as valuable resources. Firms' critical resources may extend beyond firm boundaries. As a consequence, for the realization of a competitive advantage, it is not sufficient to only focus on the internal resources, but additionally it is crucial to consider relational resources (Dyer and Singh, 1998; Lavie, 2006). This relational dimension among economic actors has also been increasingly analysed by economic geographers as well as in the context of clusters (Giuliani, 2007; Wu et al., 2010). Within clusters, a firm can have various kinds of linkages. In correspondence with the relational view, it is emphasized that the extent of strategic relationships is positively associated with firm performance (Hervas-Oliver and Albors-Garrigos, 2009). Maintaining a relatively high share of local connections (within the cluster) can allow firms to extract more external knowledge from their environment, which in turn makes it more likely that firms can gain from possible knowledge spillovers. Apart from local relationships, it is additionally useful for companies to have external connections with more distant partners. Thereby, companies may acquire access to an additional knowledge base which is different from the knowledge of local partners (Knoben et al., 2015; McCann and Folta, 2011; Zaheer and George, 2004). Thus, the following hypothesis is proposed:

**Hypothesis 1c:** The number of linkages of a firm has a positive effect on firm Innovative performance in clusters.

Nevertheless, as described by Dyer and Singh (1998), relation-specific resources and capabilities, such as the ability to identify and evaluate potential complementarities, have to be devoted to each collaborative relationship in order to maximize the relational rents[92] (Dyer and Singh, 1998). The availability of these resources and capabilities is, however, limited. Consequently, the higher the share of local connections, the less relation specific resources and capabilities can be used for establishing and/or maintaining relationships with organizations outside the cluster. The absence of outside relationships can in turn lead to lock-in situations in

[92] According to Dyer and Singh (1998) relational rents are defined as: "(…) supernormal profit jointly generated in an exchange relationship that cannot be generated by either firm in isolation and can only be created through the joint idiosyncratic contributions of the specific alliance partners." (Dyer and Singh, 1998, p. 662).

which companies are unresponsive to external changes (Hervas-Oliver and Albors-Garrigos, 2009; Knoben et al., 2015). Based on these arguments, the following hypothesis is proposed:

**Hypothesis 1d:** The level of local (external) connectedness has an inverted U-shaped effect on firm innovative performance in clusters such that the relationship is likely to be more positive for firms with a moderate share of local (external) connections.

Besides the level of firm connectedness, it has been highlighted, especially in the network literature, that the firm´s network position can also influence the performance (Ferriani and MacMillan, 2017; Zaheer and Bell, 2005). Companies that are central actors within the network or the cluster are less likely than peripheral firms to miss valuable information. Moreover, by occupying a superior network position, companies are supposed to verify better the quality of the received information as well as the trustworthiness of the corresponding exchange partners. This can be crucial, as it is indicated that due to, among others, strategic reasons an exchange partner may limit the provided information (Bell, 2005; Zaheer and Bell, 2005). Thus, the following hypothesis is proposed:

**Hypothesis 1e:** The centrality of a firm´s cluster position has a positive effect on firm innovative performance in clusters.

### 2.2. Cluster-level conditions (Meso-level)

In contrast to other studies, this paper addresses the firm-specific cluster effect in a novel way, namely by analysing, in addition to the micro-level perspective, the specific cluster attributes which can also influence firm innovative performance within clusters.[93] Likewise, in the case of the differences in the resource endowments on the firm-level emphasized by the RBV (e.g. Barney, 1991), it is therefore essential to also consider the heterogeneity on the cluster-level (Hervas-Oliver and Albors-Garrigos, 2007). In this context, one very interesting point to look at is the differences in the stock of knowledge across clusters (McCann and Folta, 2008). As highlighted at the beginning of this section, knowledge spillovers are likely to happen in all clusters; however, it has been emphasized that they are likely to generate larger performance effects in clusters with a relatively high knowledge stock (Beaudry and

[93] Important exceptions in this context are Knoben et al. (2015) as well as Rigby and Brown (2015).

Breschi, 2003; Knoben et al., 2015; McCann and Folta, 2008). Thus, the following hypothesis is proposed:

**Hypothesis 2a:** The stock of knowledge of the cluster has a positive effect on firm innovative performance in clusters.

Another relevant cluster-level attribute is the stock of alliances within the cluster (McCann and Folta, 2008). Similar to hypothesis 1c and in line with the core idea of the RV highlighting the importance of relational resources (e.g. Dyer and Singh, 1998), it is expected that within alliance-rich clusters, the possibility to extract knowledge from local and external connections is enhanced. In this way, it should be much easier in an alliance-rich cluster for companies to come in contact with a larger number of different partners than in an alliance-poor cluster. Thus, the following hypothesis is proposed:

**Hypothesis 2b:** The stock of alliances of the cluster has a positive effect on firm innovative performance in clusters.

The participation and support of local organizations within the cluster, such as technical assistance centres, can additionally influence firm innovative performance. Research institutes, for example, can be instrumental in bringing different firms together to cooperate. Moreover, they are conducive for the generation and diffusion of knowledge within the corresponding cluster (Hervas-Oliver and Albors-Garrigos, 2007; Molina-Morales and Martínez-Fernández, 2004; Wu et al., 2010). Thus, the following hypothesis is proposed:

**Hypothesis 2c:** The participation and support of local research institutes have a positive effect on firm innovative performance in clusters.

### 2.3. Market-/Industry-level conditions (Macro-level)

Alongside these two different levels of analysis, the effect of the market and industry environment on firm performance has been widely acknowledged (Kohlbacher et al., 2013). One of the most prominent theoretical streams in this context is the market-based view (MBV), which is predominantly influenced by the earlier work of Michael Porter (Porter, 1980; Steffen, 2012). In line with the MBV and building on the two scientific papers of Suarez and Lanzolla (2005 and 2007), dealing with external influences on the first-mover advantage, it is supposed that the pace of technology evolution affects firm innovative performance in clusters (Suarez and Lanzolla, 2005; Suarez and Lanzolla, 2007). New product categories may experience very different paces of technology evolution. For example, while the degree of efficiency improvements over time for the computer industry is very high, it is only marginal for vacuum cleaners. The pace of technology evolution can be captured through the technology S-curve which depicts the evolution of a technology along a particular performance parameter, such as the CPU clock speed in the case of the computer industry (Cooper and Schendel, 1976; Suarez and Lanzolla, 2007). Under a rapid or radical technology evolution, it is likely that the current knowledge stock of firms as well as clusters becomes rather unsuitable or even obsolete. In addition, such a technological evolution will increase the market risk. This in turn has again a rather negative effect, as it is expected that under a high market risk, companies will exchange less knowledge as well as invest fewer resources and capabilities in new relationships, reducing the potential benefits from being located in close proximity to similar firms (Suarez and Lanzolla, 2005; Suarez and Lanzolla, 2007). Thus, the following hypothesis is proposed:

**Hypothesis 3a:** The pace of technology evolution has a negative effect on firm Innovative performance in clusters.

Furthermore, it is assumed that the extent to which a firm conducts the underlying activities of research and development (R&D), namely basic research, applied research or experimental development, can also moderate the contribution of knowledge spillovers to the realization of a firm-specific cluster advantage. In contrast to applied research and experimental development being more commercially oriented (Czarnitzki and Thorwarth, 2012), basic research is defined as "(…) experimental or theoretical work undertaken primarily to acquire new knowledge of the underlying foundation of phenomena and observable facts, without any particular application or use in view." (OECD, 2002, p. 77). In other words, basic research is never some final product, but instead it refers to new knowledge that is potentially applicable in different contexts. Conducting basic research therefore provides protection against the introduction of an innovation from an unexpected (technological) direction, as companies become better capable of understanding and monitoring potential new trends as well as possible threats by competitors (Czarnitzki and Thorwarth, 2012; Rosenberg, 1990). Since clusters seem to be a preferable environment for radical innovations (e.g. Grashof et al., 2019), potentially leading to the formation of completely new markets and industries (e.g. Cooper and

Schendel, 1976; Henderson and Clark, 1990; Verhoeven et al., 2016), this kind of protection through basic research appears to be especially important for firms located in clusters. Besides, companies may additionally benefit from first-mover advantages, as they can gain from learning experiences as well as acquire assets, such as limited natural resources, which create entry barriers for competitors (Rosenberg, 1990). This in turn creates a competitive advantage for subsequent applied research and development, which is assumed to be of particular importance in a highly competitive setting such as a cluster. Thus, the following hypothesis is proposed:

**Hypothesis 3b:** The share of basic research of overall R&D activities has a positive effect on firm innovative performance in clusters.

As already highlighted at the beginning, the overall aim of this paper is to reduce the ambiguity surrounding the cluster and firm performance relationship. Therefore, the assumed effects are not just analysed separately, but also simultaneously. By taking the firm-level, cluster-level and market-/industry-level heterogeneity simultaneously into account and focussing on the interactions between these three levels of analysis, the firm performance differentials within clusters can be explained from a broader perspective.

## 3. Data and Methodology

In order to do so, this paper employs various data sources and variables for each level of analysis.

**Micro-level**. The main database for the analysis of the innovative performance of companies within clusters is an extensive firm-level database provided by the Stifterverband. This database, which is based on a large survey taking place in a two-year rhythm, is primarily created for the use of the Federal Ministry of Education and Research in Germany. It contains innovation-related information on all identified R&D-active firms in Germany between 1995 and 2015 (Engel et al., 2016; Stifterverband, 2018). Building on this database, the dependent variable for firm innovativeness can be calculated. Innovativeness is measured by the average share of the firm´s product innovations between 1997 and 2013, including incremental as well as new to the market/firm innovations, in previous three years sales (Delgado, 2018; Steinberg et al., 2017). This indicator offers two main advantages over using patents as proxy for firm innovativeness. First, the innovative output of companies that do not patent their product innovations can also be considered. Furthermore, the share of the firm´s product innovations in sales is a market-driven indicator for innovation. Consequently, unlike in the case of patents, the true economic value of the corresponding innovation can be elaborated (Delgado, 2018; Dziallas and Blind, 2019; Kleinknecht et al., 2002). Therefore, it is argued that the share of the firm´s product innovations in sales is more appropriate to measure firm innovativeness than patents for the purpose of this study.

As already highlighted in the previous theoretical discussion, the innovation capabilities of a firm are used as an independent variable but are measured in a twofold way. Like in previous research (e.g. Knoben et al., 2015; Smit et al., 2015), the quantitative aspect of innovation capabilities is calculated by the average share of R&D employees on the total number of employees between 1997 and 2015. In line with the indication by McCann and Folta (2008) as well as Fornahl et al. (2011), the qualitative aspect of innovation capabilities is additionally considered. Therefore, the cognitive proximity as the degree of overlap between the cluster and the firm´s knowledge base is calculated. The database from the Stifterverband once again provides the basis for defining the similarity between the cluster and the corresponding company. To create an average knowledge profile for each company, the internal R&D spending for each product category based on the statistical classification of products by activity in the European Economic Community is employed for the time period between 2005 and 2013. The average of all firms knowledge profiles located in one specific cluster is used to identify the knowledge profile of the corresponding cluster. To finally measure the similarity, the Cosine index is estimated.

$$similarity = \cos(\theta) = \frac{A \times B}{\|A\|\|B\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}} \quad (1.)$$

The cosine index measures the similarity between the two vectors A (firm´s knowledge profile) and B (cluster knowledge profile) for n product categories. In total, 50 different product categories are taken into consideration. The index can take a value between zero and one, where one means perfect similarity between both knowledge profiles.

This paper utilizes data about subsidized R&D collaborations from the German subsidy catalogue (“Förderkatalog”) for the relation- and network-specific variables. The database consists of approximately more than 160,000 running or completed R&D projects subsidized by six different ministries[94] in the time span between 1960 and 2016 (Roesler and Broekel, 2017). It has been already frequently used to model knowledge networks and it provides information at an earlier stage compared to patent data (Broekel, 2015; Broekel and Graf, 2012). To gain a preferably comprehensive picture about the firm-specific relationships, the number of linkages of a firm is calculated based on all corresponding collaborative R&D projects between 2005 and 2015. For the measurement of the level of local and extra connectedness, it is essential to make use of the cluster identification (explained in detail on the next page), which serves as the frontier between both forms of connectedness. The level of local (external) connectedness is calculated by the share of cluster internal (external) relations in the total number of linkages.

Various indicators can represent the firm´s network position (Broekel and Graf, 2012; Lechner and Leyronas, 2012; Zaheer and Bell, 2005). In this article, the actor-based cluster index by Brenner (2017), which will be described in detail in the context of the cluster identification, is applied. Besides the identification of clusters, this index offers information about the position of each actor within a cluster by considering the spatial concentration and the geographical distance on the firm-level. It can therefore also be used to determine the firm´s position within a cluster. High values indicate that companies are located in the centre of a cluster, whereas low values show that they are far away from clusters (Brenner, 2017; Scholl and Brenner, 2016). For the firm´s centrality within the corresponding cluster core, a dummy variable is calculated based on the above median of the cluster index (equal to a value of 2.83).[95]

**Meso-level**. The databases from the Stifterverband as well as the “Förderkatalog” are also the basis for some of the variables on the meso-level. The stock of knowledge across clusters is measured by the average share of R&D employees of all firms of one specific cluster.

The stock of alliances within the clusters is determined in a similar way. By aggregating all firm-specific relationships in one cluster and then dividing it by the number of firms in the corresponding cluster, an indicator can be derived which

[94] More specifically, these ministries are the Federal Ministry of Education and Research (BMBF), Federal Ministry for Economic Affairs (BMWi), Federal Ministry for Environment, Nature Conservation and Nuclear Safety (BMU), Federal Ministry of Transport, Building and Urban Development (BMVBS), the Federal Ministry of Food, Agriculture (BMEL) and Consumer Protection.

[95] As a first robustness check, the cluster index has also been directly tested as a metric variable. The results thereby remain the same and can be provided upon request.

proxies adequately the stock of alliances within the clusters.

Furthermore, the participation and support of local organizations is measured by the number of research institutes within a cluster for the year 2015.[96] Hereby, the German research directory ("Research Explorer") is employed. This database contains information on over 25,000 university and non-university research institutes in Germany (Research Explorer, 2018). For the final analysis, however, only the highest organizational level of the research institutes, e.g. universities and not their working groups, are considered.

**Macro-level**. Patents, retrieved from the database PATSTAT, are used to calculate the pace of technology evolution. In order to determine a trend and to control for possible outliers, the average technological improvement in three-digit NACE Rev. 2 code industries is computed for a two-year period (2012-2013). The average technological improvement is then weighted by the size of the corresponding industry, measured by the average number of employees. Despite well-discussed drawbacks, patents are widely accepted to be an adequate proxy for the technological advances in industries (Haupt et al., 2007; McGahan and Silverman, 2001).

For the measurement of the underlying activities of R&D, the database from the Stifterverband is used, as it offers information about the share of internal R&D expenditures on basic research, applied research or experimental development. To exploit the panel structure of the database, the corresponding average share of internal R&D expenditures for the three types of activities are calculated for the time period between 2001 and 2015.

**Cluster identification**. As the main analysis focuses only on companies within clusters, it is crucial to determine these regional clusters correctly. To identify all relevant clusters in Germany, the method by Brenner (2017) is applied by calculating a cluster index for each single firm on the community level ("Gemeindeebene") based on official employment data from 2012 in three-digit NACE Rev. 2 industries.[97] In general, the actor-based cluster identification by Brenner (2017) has two main advantages over more traditional indicators such as a regional specialization quotient (e.g. Hervas-Oliver et al., 2018; Sternberg and Litzenberger, 2004). First, it

[96] Due to data constraints, the average number of research institutes within clusters could not be calculated for a longer time period.

[97] In line with other studies (e.g. Maggioni, 2002), the three-digit NACE code is argued to be the most adequate level of analysis, as it is not too broad (as the two-digit codes) nor too detailed (as the four-digit codes). It therefore fits perfectly the purpose to identify firms that are located in a cluster.

avoids the Modifiable Area Unit Problem (MAUP), because it is free of predefined borders (for an exemplary illustration see figure 1). Consequently, in contrast to all other approaches, the results of this cluster identification do not depend on the regional level that is used. As already highlighted, the corresponding cluster index can additionally be used to distinguish between the core and the periphery of a cluster. Second, it avoids a possible overvaluation of one very large company in the regional employment structure, such as Volkswagen (VW) in Wolfsburg, by considering the distance to all other firms of the same industry as a weight to the final cluster index. Therefore, large but geographical isolated firms are in this sense not part of a regional cluster. The applied distance decay function is thereby based on travel times, where 45 minutes represent the limit for close geographical distance (Brenner, 2017; Scholl and Brenner, 2016). Besides the geographical distance, the index also considers employment in absolute terms, capturing the concentration aspect of clusters, as well as in relative terms, referring to specialization. The used cluster index therefore corresponds adequately to the most central elements of cluster definitions (Grashof and Fornahl, 2020). In line with the procedure of the European Cluster Observatory, a value of 2 is applied as the corresponding cluster threshold, indicating whether a firm is located in a cluster or not (European Cluster Observatory, 2018; European Commission, 2008).

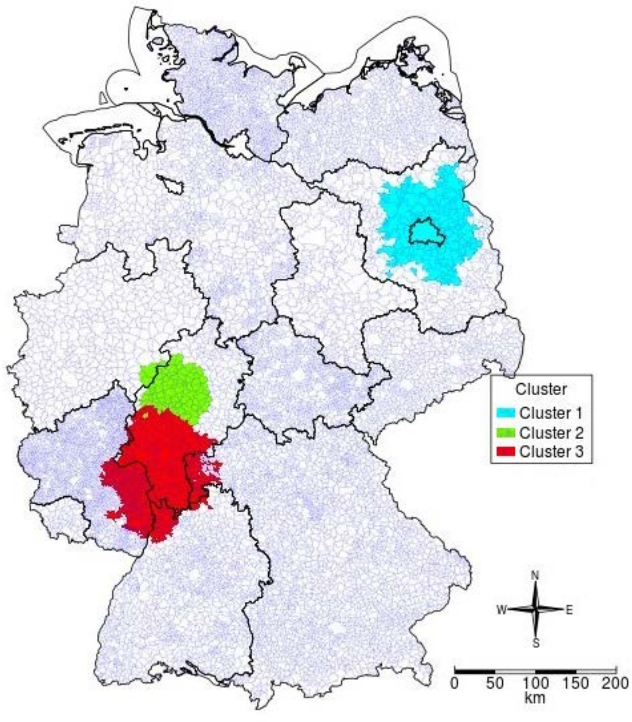


**Figure 1:** Exemplary illustration of the cluster index based on Brenner (2017) for the manufacture of basic pharmaceutical products (NACE code 211)

In addition, various control variables are included in order to account for other factors related to all three levels of analysis that might influence firm innovativeness in clusters. In line with several authors (e.g. Hervas-Oliver and Albors-Garrigos, 2009; McCann and Folta, 2011), firm age (years since foundation) and the company structure (dummy variable indicating whether firms are independent and do not belong to a corporate structure) are both included as firm control variables. Moreover, based on the spread of the internal R&D spending for the 50 different product categories, a proxy for firm's knowledge diversity is calculated which is assumed to positively influence firm innovativeness in clusters (Garcia-Vega, 2006; Miller, 2006). For the cluster level, it is additionally controlled for the cluster size, whose impact has been frequently discussed in the literature (Folta et al., 2006; McCann and Folta, 2011). In accordance with the most common approaches (McCann and Folta, 2008), cluster size is measured by the average number of employees between 2008 and 2015. Lastly, a dummy variable is included to control for research-intensive industries, which are assumed to be particularly inclined to create innovations, especially radical innovations (Tödtling et al., 2006).

To integrate the relation-specific data with the main firm-level database, it was necessary to match the company names, as a comparable identifier is missing. There are three main types of matching algorithms (Vectorial decomposition, Phonetic and Edit-distance) which all provide a similarity score between two strings by performing different string-based matching methods. As each matching algorithm has its advantages and disadvantages, four different matching algorithms[98] are applied in order to improve the overall matching quality (Raffo, 2017; Raffo and Lhuillery, 2009). In this context, the suggested name couples of all four matching algorithms were additionally checked manually by the author. The result of this detailed procedure is a unique firm-level database which combines several data sources from different levels of analysis. It contains information about 11,889 firms in Germany from which 1,391 firms are located within a cluster. As already highlighted before, most of the variables are averaged for the years 1997 to 2015 in order to reduce a possible measurement error bias created by year-to-year variability inherent in micro-level data (Rigby and Brown, 2015; Stern, 2010). By forming the average for each observation i over t = 1,…T, the following equation can be derived

[98] In more concrete terms, the Token, N-Gram, Soundex and Token Soundex algorithms were used.

(Cameron and Trivedi, 2005):[99]

$$\bar{y}_i = \alpha + \beta\bar{x}_i + (\alpha_i - \alpha + \bar{\varepsilon}_i) \qquad (2.)$$

Where $\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}$, $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{it}$ and $\bar{\varepsilon}_i = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_{it}$. The OLS regression of the across panels´ averages equals thereby the between estimator, being particularly useful to ascertain the effect of x when x changes between companies (Cameron and Trivedi, 2005; Gould, 2019). By taking the hierarchical nature of the data into account, an OLS regression with cluster correction of the standard errors is applied in the main analysis (table 3-4).[100] Such an empirical approach is more adequate than a standard OLS regression in which the corresponding standard errors are underestimated because of the nested data structure (McNeish, 2014; Moulton, 1990). It was additionally tested whether a multilevel regression would be more appropriate in this context. The corresponding results of the Likelihood-ratio test indicate however, that there is no significant improvement in comparison with an OLS regression with cluster correction. Thus, it is argued that the chosen methodical approach is valid to answer the underlying research question of this paper.

In general, the analysis can be divided into three parts. First, it is investigated whether firms located within a cluster are more innovative than firms outside clusters. Second, in line with Hervas-Oliver et al. (2018) as well as Hervas-Oliver and Albors-Garrigos (2009), the subsample of clustered companies is analysed separately to identify the conditions under which companies can gain from the cluster environment, specifically from knowledge spillovers. Third, for testing possible interaction effects and in accordance with Lee et al. (2001), the corresponding interaction terms are included one by one in order to avoid serious multicollinearity problems.

## 4. Results

Table 1 presents a pairwise correlation matrix for all independent variables.[101] In some cases the independent variables have relatively high correlations, raising a

[99] Due to some changes in the questionnaire of the Stifterverband, the dependent variable can only be averaged for the time period between 1997 and 2013. By only using the average, it is argued that the results will be unaffected. As a control and a further robustness check, the independent variables were also averaged for exactly the same time period as the dependent variable. The corresponding results of this robustness check are in line with the original results and can be provided upon request.

[100] The standard errors are clustered by regional cluster.

[101] The corresponding descriptive statistics for all main variables are presented in table 5 in the appendix.

potential concern of multicollinearity. Therefore, in all models the corresponding Variance Inflation Factors are calculated. In no case did any of the Variance Inflation Factors come close or even exceed the standard critical value of 10 (Belsley, 1991; Myers, 1990; Stevens, 2002). Thus, multicollinearity is not a significant concern. Nevertheless, to prevent any kind of multicollinearity, and thereby increasing the stability of the model estimates of the coefficients even further, in some models certain independent variables are excluded.

Table 2 includes the results regarding the existence of a cluster effect on firm innovativeness by using an OLS regression with robust standard errors. The results of model 1 and model 2 indicate that being located in a cluster asserts a significant positive effect on firm innovativeness. Consistent with previous empirical results (e.g. Baptista and Swann, 1998; Bell, 2005), it can therefore be stated that due to localization economies firms within clusters are significantly more innovative than firms outside clusters.[102]

Nevertheless, it is argued here that firms do not benefit equally and in the same manner from being located in a cluster. Consequently, table 3 tests the main formulated hypotheses regarding heterogeneous firm benefits within clusters.

[102] Following the remarks by McCann and Folta (2011), it is argued that the concern that the most innovative firms choose to locate in clusters, creating a potential selection bias, cannot be justified empirically nor theoretically. This can also be confirmed by the mean and the standard deviation of firm innovativeness within clusters, shown in table 5 in the appendix.

**Table 1:** Pairwise correlation matrix for the sample with cluster companies

| | 1. | 2. | 3. | 4. | 5. | 6. | 7. | 8. | 9. | 10. | 11. | 12. | 13. | 14. | 15. | 16. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Age | 1.000 | | | | | | | | | | | | | | | |
| 2. Independence dummy | 0.129* | 1.000 | | | | | | | | | | | | | | |
| 3. Innov. Capabilities | -0.265* | -0.037 | 1.000 | | | | | | | | | | | | | |
| 4. Number of linkages | 0.101* | 0.064* | -0.003 | 1.000 | | | | | | | | | | | | |
| 5. No. Research institutes | -0.072* | 0.034 | 0.110* | 0.029 | 1.000 | | | | | | | | | | | |
| 6. Pace of tech. evolution | -0.038 | -0.008 | 0.100* | 0.044 | -0.002 | 1.000 | | | | | | | | | | |
| 7. Research-intensive industry | -0.076* | -0.028 | 0.094* | 0.095* | -0.037 | 0.552* | 1.000 | | | | | | | | | |
| 8. Central position in cluster | -0.004 | -0.019 | -0.056* | 0.019 | -0.118* | 0.084* | 0.007 | 1.000 | | | | | | | | |
| 9. Knowledge similarity with cluster stock | 0.182* | -0.004 | -0.067* | 0.053* | -0.018 | -0.093* | -0.143* | 0.072* | 1.000 | | | | | | | |
| 10. Share basic research | -0.046 | -0.015 | 0.032 | -0.023 | -0.000 | -0.062* | -0.072* | -0.016 | -0.020 | 1.000 | | | | | | |
| 11. Share of cluster external relations | 0.025 | 0.028 | 0.011 | 0.332* | 0.084* | 0.065* | 0.047 | 0.015 | 0.044 | -0.003 | 1.000 | | | | | |
| 12. Knowledge diversity | 0.274* | 0.070* | -0.173* | 0.121* | -0.044 | 0.030 | 0.057* | 0.079* | 0.219* | -0.075* | 0.105* | 1.000 | | | | |
| 13. Stock of alliances within cluster | -0.018 | -0.015 | 0.104* | 0.595* | 0.040 | 0.156* | 0.227* | 0.032 | 0.004 | -0.034 | 0.229* | 0.050 | 1.000 | | | |
| 14. Stock of knowledge across cluster | -0.240* | 0.006 | 0.622* | 0.037 | 0.163* | 0.136* | 0.095* | -0.104* | -0.008 | 0.014 | 0.095* | -0.122* | 0.185* | 1.000 | | |
| 15. Cluster size | 0.066* | 0.007 | 0.008 | 0.673* | 0.020 | -0.012 | 0.082* | 0.012 | 0.003 | -0.008 | 0.070* | 0.049 | 0.693* | 0.013 | 1.000 | |
| 16. Knowledge diversity within cluster | 0.197* | 0.027 | -0.127* | 0.072* | -0.083* | 0.053* | 0.103* | 0.097* | -0.025 | -0.023 | 0.056* | 0.555* | 0.090* | -0.221* | 0.087* | 1.000 |

Note: $^*p < 0.05$

**Table 2:** OLS regression models with robust standard errors of single cross-section average over time for the full sample

| *Innovativeness (full sample)* | *Model 1*<br>*n = 11.530* | *Model 2*<br>*n = 11.530* |
|---|---|---|
| **Cluster dummy** | 0.642**<br>(0.324) | 0.639**<br>(0.324) |
| **Age** | -0.003<br>(0.003) | -0.003<br>(0.003) |
| **Independence dummy** | -0.393<br>(0.442) | -0.417<br>(0.442) |
| **Innovation Capabilities** | 1.907***<br>(0.410) | 1.941***<br>(0.411) |
| **Number of linkages** | 0.409***<br>(0.130) | 0.412***<br>(0.131) |
| **Number of research institutes** | -0.016***<br>(0.004) | -0.015***<br>(0.004) |
| **Pace of technology evolution** | 0.262***<br>(0.051) | 0.262***<br>(0.051) |
| **Firms knowledge diversity** | 1.159***<br>(0.036) | 1.155***<br>(0.036) |
| **Share of basic research** | -0.044*<br>(0.026) | |
| **Share of experimental development** | | 0.019<br>(0.012) |
| *Constant* | *0.687**** | *-0.434* |
| *$R^2$* | *0.1244* | *0.1245* |
| *Robust Standard errors in parentheses.*<br>*Significance level: * p < 0.10, ** p < 0.05, *** p < 0.01* | | |

Model 3 illustrates the baseline model. As assumed, the coefficients for firm's knowledge diversity, industries research-intensity and cluster size remain consistently significant positive throughout the various models. In model 4 the variables for innovation capabilities, the degree of overlap between cluster and firm knowledge base, the firm´s cluster position, the participation and support of local research institutes as well as the share of basic research are added. Regarding innovation capabilities, contrary to the full sample, there is a relatively strong positive but insignificant effect on innovativeness, indicating that more innovation capabilities do not lead to a significant higher innovative performance. By considering the above median of innovation capabilities, model 5, however, reveals that there is a threshold effect of innovation capabilities. This means that a minimum level of innovation capabilities is necessary to benefit from the cluster environment. Additionally, the results of the squared coefficient, presented in table 3 (model 8), indicate that there is indeed a curvilinear (inverted 'U'-shaped) effect on firm innovativeness.

**Table 3:** OLS regression models with clustered standard errors of single cross-section average over time for the sample with cluster companies

| ***Innovativeness (sample with cluster companies)*** | *Model 3 n =1.343* | *Model 4 n = 1.339* | *Model 5 n = 1.340* | *Model 6 n = 1.340* | *Model 7 n = 1.340* | *Squared coefficients* *Model 8 n = 1.340* | *Model 9 n = 1.340* |
|---|---|---|---|---|---|---|---|
| **Firm-level variables** | | | | | | | |
| Innovation Capabilities | | 3.466 (2.146) | | | | 11.502** (5.238) | 3.129 (2.110) |
| Innovation Capabilities above median | | | 1.505** (0.620) | 1.688*** (0.633) | | | |
| Innovation Capabilities squared | | | | | | -11.302* (6.061) | |
| Number of linkages | | | 0.504 (0.322) | | | 0.521 (0.322) | 0.521* (0.315) |
| Share of cluster external relations | | | | 0.269 (0.743) | | | |
| Knowledge similarity with cluster stock | | 1.644* (0.839) | 1.511* (0.838) | 1.620* (0.843) | | 1.415* (0.850) | 9.932*** (2.550) |
| Knowledge similarity with cluster stock squared | | | | | | | -8.324*** (2.652) |
| Central position in cluster | | 1.039 (0.638) | 0.971 (0.631) | 0.994 (0.632) | | 1.012 (0.635) | 1.138* (0.632) |
| **Cluster and industry-level variables** | | | | | | | |
| Share of basic research | | 0.185*** (0.069) | 0.182*** (0.069) | 0.181*** (0.068) | 0.139* (0.078) | 0.180** (0.071) | 0.191*** (0.070) |
| Number of research institutes | | -0.002 (0.016) | -0.002 (0.016) | -0.000 (0.016) | -0.003 (0.016) | -0.004 (0.015) | -0.002 (0.016) |
| Pace of technology evolution | | | | | 0.170 (0.137) | | |
| Stock of alliances within cluster | | | | | 10.686*** (1.697) | | |
| Stock of knowledge across cluster | | | | | -0.363 (3.186) | | |
| **Control variables** | | | | | | | |
| Age | 0.003 (0.007) | 0.006 (0.007) | 0.007 (0.007) | 0.010 (0.008) | 0.022*** (0.007) | 0.008 (0.007) | 0.006 (0.007) |
| Independence dummy | -2.193* (1.326) | -2.003 (1.301) | -2.453* (1.382) | -2.195* (1.296) | -1.312 (1.411) | -2.401* (1.377) | -2.265 (1.376) |
| Firms knowledge diversity | 1.364*** (0.101) | 1.359*** (0.105) | 1.326*** (0.103) | 1.354*** (0.103) | | 1.336*** (0.104) | 1.270*** (0.104) |
| Research-intensive industry dummy | 1.754*** (0.655) | 1.966*** (0.676) | 1.741*** (0.660) | 1.924*** (0.675) | | 1.746*** (0.665) | 1.644** (0.687) |
| Cluster size | 0.001*** (0.000) | 0.001*** (0.000) | | | | | |
| Knowledge diversity within cluster | | | | | 1.438*** (0.185) | | |
| *Constant* | *-0.181* | *-3.365**** | *-3.398**** | *-3.743**** | *-2.128*** | *-3.616**** | *-3.994**** |
| $R^2$ | *0.1575* | *0.1683* | *0.1666* | *0.1582* | *0.0926* | *0.1671* | *0.1688* |
| *Clustered standard errors in parentheses. Significance level: * p < 0.10, ** p < 0.05, *** p < 0.01* | | | | | | | |

In order to analyse this pattern in more detail, figure 2 illustrates the corresponding quadratic prediction plot. Companies in clusters with a medium level of innovation capabilities (turning point equals a value of 0.509) present a higher effect on innovativeness than firms with very low or very high innovation capabilities. In the case of very high innovation capabilities, the effect on innovativeness can even turn into a negative one, which in accordance with Shaver and Flyer (2000) can be explained with unintentional knowledge spillovers to possible competitors. Overall, the presented results are in line with very recent findings by Hervas-Oliver et al. (2018) and confirm the asymmetric benefits referred to in hypothesis 1a.

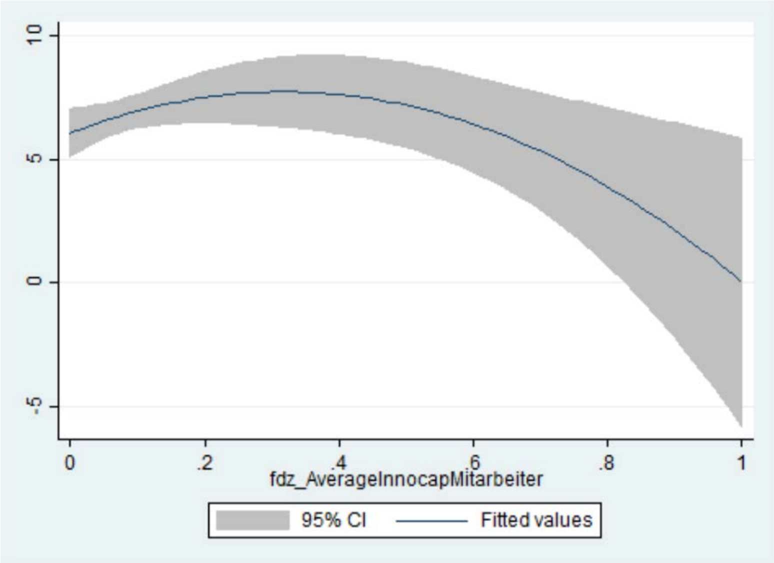


**Figure 2:** Two-way quadratic prediction plot between innovativeness and firm´s innovation capabilities

A similar pattern can be observed by analysing the more qualitative aspect of innovation capabilities, namely the degree of overlap between the firm´s and cluster´s knowledge stock. As indicated in table 3 (model 4) the effect of knowledge similarity with the cluster stock has a significant positive impact on firm innovativeness in clusters. The results of the corresponding squared coefficient, shown in table 3 (model 9), give again evidence for an inverted ‘U’-shaped effect.

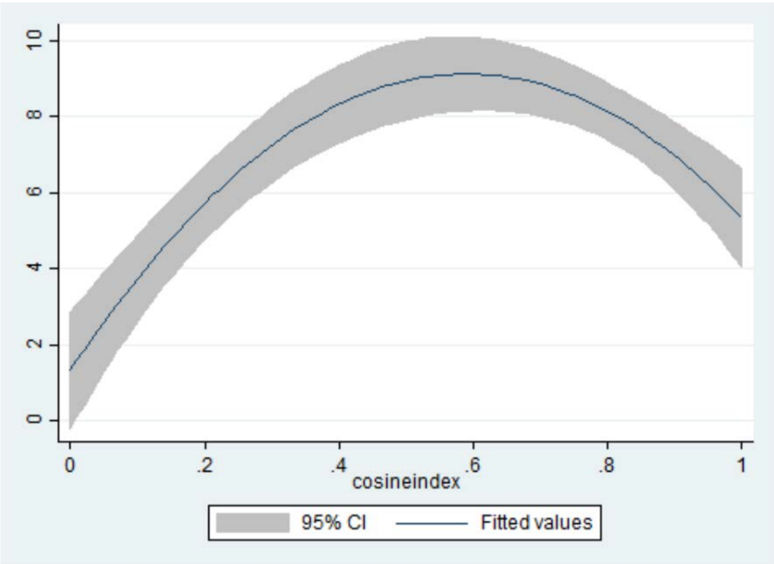


**Figure 3:** Two-way quadratic prediction plot between innovativeness and firm´s knowledge similarity with cluster stock

The non-linear relationship between the similarity of both knowledge stocks and firm innovativeness is depicted in figure 3. Especially companies in clusters with a moderate level of cognitive proximity (turning point equals a value of 0.597) profit the most. In accordance with Nooteboom (2000), it can be shown that too much proximity as well as too much distance decrease the effect on innovativeness. In the former case the predicted effect on innovativeness nearly turns to be zero. Consequently, it can be resumed that the mentioned results support the proposed assumption 1b.

In contrast to the previous two firm-level variables, the results in table 3 (model 4) reveal that the central position within clusters alone has a positive but insignificant impact on firm innovativeness. In other words, the location in the core of the cluster does not provide by itself a competitive advantage in terms of innovative performance. Therefore, the findings do not confirm the assumption 1d. This can eventually be explained with the different focus of the indicator for a firm´s central position in clusters. While other studies make use of network-specific indicators considering the concrete knowledge network within clusters (e.g. Giuliani, 2007), the cluster index applied here primarily stresses the geographical proximity between highly concentrated and specialized companies. The relations within clusters are instead considered separately in model 6.

Regarding the meso-level, it can be stated that the number of research institutes within clusters asserts a relatively small negative and insignificant effect on firm innovativeness in clusters. Hence, evidence suggests that instead of focusing primarily on the quantity of research institutes, it might be more appropriate to focus on the quality of these institutes and their collaborations with companies, as also suggested by other researchers (e.g. Agasisti et al., 2017; Barra et al., 2017; Tödtling et al., 2006).

By investigating the influence of the share of basic research on firm innovativeness in clusters, a significant positive effect is ascertained throughout all models (4-9). This means that a higher share of basic research leads to a significant higher innovative performance. This seems to be a cluster-specific effect, as in the full sample it flips to be (significantly) negative. Conducting basic research is therefore argued to be especially important for the innovative performance of companies in clusters. It provides protection against the competitive setting of clusters in which possible threats by competitors, in terms of new unexpected technological developments, may arise (Czarnitzki and Thorwarth, 2012; Grashof et al., 2019; Rosenberg, 1990). Hypothesis 3b can therefore be confirmed.

Model 5 tests the hypothesis 1b concerning the influence of the number of firm linkages on innovativeness. Contrary to the significant positive findings in the full sample, the results of the cluster sample show no significant effect of the number of linkages. In other words, in clusters the pure number of relationships, including cluster internal as well cluster external relationships, does not significantly foster firm innovativeness. Consequently, model 6 investigates the concrete impact of the share of cluster external relations further. The share of cluster external relations asserts a positive, however, statistically insignificant influence on firm innovative performance.[103] The effect of the share of cluster internal relations is respectively negative and insignificant.[104] To gain more insights about these relations, a possible interaction effect between the position within clusters and the cluster external relations is additionally analysed. The results, presented in table 4 (model 10), reveal that cluster external relations are especially important for firms located within the centre of clusters. In such a position, cluster external relations have a significant positive effect on firm innovativeness. A reasonable explanation for the difference between the centre and the periphery of a cluster can be found by comparing the cluster internal connectedness between both groups. Indeed, the mean of cluster internal relations is significantly higher in the centre than in the periphery of a cluster.[105] The risk for a lock-in situation, preventing innovations, is therefore potentially higher in the centre than in the periphery of a cluster. Thus, for companies located in the core of a cluster, it is particularly important to possess external relations. These cluster external relations provide a necessary channel for new knowledge that is different from the cluster internal knowledge. Regarding the relation-specific variables, it can therefore be resumed that the number of cluster external relationships does not significantly influence by itself firm innovative performance in clusters. Nevertheless, it becomes relevant when additionally considering the position within the cluster.

[103] As a further sensitivity test, the effect of the degree of cluster external relations instead of the share of cluster external relations is additionally investigated. The results remain thereby however the same (positive and insignificant) and can be provided upon request.

[104] To verify the results, model 6 has been replicated without the share of cluster external relations. Instead, a new dummy variable has been added, indicating whether firms own a moderate share of cluster internal (external) relations between 0.3 and 0.7. The corresponding results remain insignificant und can be provided upon request.

[105] Results can be provided upon request.

The seventh model of table 3 primarily focuses on the meso- and macro-level. The previous emphasized results for the share of basic research and the number of research institutes remain thereby unchanged. Additionally, the stock of knowledge of the cluster does not significantly influence firm innovative performance. So that the assumed generation of larger performance effects in clusters with a relatively high knowledge stock cannot be confirmed. Nevertheless, the findings of model 7 show at the same time that the stock of alliances within clusters asserts a relatively high significant positive impact on firm innovative performance. As expected, in an alliance-rich cluster the chance to extract knowledge from local and external connections seems to be enhanced, as it is much easier to come in contact with a broad variety of partners than in an alliance-poor cluster. Hypothesis 2b can therefore be supported.

Furthermore, the results of model 7 reveal that, in contrast to the full sample, the pace of technology evolution becomes insignificant. While in general asserting a significant positive impact on firm innovativeness, in clusters the pace of technology evolution seems not to have a statistically relevant stand-alone effect. Hypothesis 3a can therefore not be supported. The results of both samples however indicate that the assumption of a negative effect should be reformulated into a positive one. This means that companies primarily active in rather young industries, normally characterized by a fast technology evolution (Clark, 1985; Klepper, 1997; Neffke et al., 2011), are, at least in the full sample, more innovative than companies engaged in mature industries.

However, by investigating potential interaction terms in table 4, it can be shown that the pace of technology evolution[106] asserts statistically relevant moderation effects. The results of model 11 reveal such an effect in the context of the firm´s innovation capabilities. In industries characterized by a fast pace of technology evolution, innovation capabilities have a positive significant impact on firm innovative performance. For companies active in such industries it is therefore especially important to own sufficiently high innovation capabilities, because they allow to access and integrate new knowledge, which is frequently changing under a rapid

[106] Here calculated as a dummy variable, where 1 means that the pace of technology evolution is equal or higher than the corresponding 75$^{th}$ quantile. The 75$^{th}$ quantile has been chosen, as at the very end of the distribution (from the 90$^{th}$ quantile upwards) the number of observations for a fast technology evolution becomes too small for a further analysis. Nevertheless, in light of other contributions using for example simply the mean as a threshold (e.g. Audretsch and Feldman, 1996), it is argued that the 75$^{th}$ quantile represents a reasonable threshold for industries with a fast pace of technology evolution.

technology evolution.

**Table 4:** OLS regression models with clustered standard errors of single cross-section average over time for interaction effects (sample with cluster companies)

| ***Innovativeness (sample with cluster companies)*** | *Model 10 n = 1.340* | *Model 11 n = 1.340* | *Model 12 n = 1.340* | *Model 13 n = 1.340* |
|---|---|---|---|---|
| **Firm-level variables** | | | | |
| Innovation Capabilities | | 2.173 (2.214) | | |
| Innovation Capabilities above median | 1.580** (0.628) | | | |
| Cluster external relations | -0.177 (0.225) | | | 0.472 (0.345) |
| Knowledge similarity with cluster stock | | | 1.682** (0.818) | |
| Central position in cluster | 0.527 (0.634) | | | |
| Periphery position in cluster | | | | |
| **Cluster and industry-level variables** | | | | |
| Share of basic research | 0.174** (0.071) | 0.176** (0.069) | 0.180*** (0.067) | 0.175** (0.070) |
| Number of research institutes | -0.005 (0.016) | -0.009 (0.017) | -0.004 (0.017) | -0.006 (0.017) |
| Fast technology evolution dummy | | 0.049 (1.293) | 3.214* (1.867) | 0.742 (1.032) |
| **Interaction terms** | | | | |
| Cluster external relations x Centre | 1.125*** (0.264) | | | |
| Fast technology evolution dummy x Innovation Capabilities | | 12.583** (5.675) | | |
| Fast technology evolution dummy x Knowledge similarity with cluster stock | | | -1.802 (3.027) | |
| Fast technology evolution dummy x Cluster external relations | | | | 2.990*** (0.748) |
| **Control variables** | | | | |
| Age | 0.009 (0.007) | 0.008 (0.007) | 0.003 (0.008) | 0.003 (0.007) |
| Independence dummy | -2.175* (1.233) | -2.282* (1.239) | -2.147* (1.280) | -2.913** (1.332) |
| Firms knowledge diversity | 1.366*** (0.100) | 1.429*** (0.103) | 1.383*** (0.105) | 1.327*** (0.104) |
| Research-intensive industry dummy | 1.579** (0.652) | | | |
| *Constant* | *-2.427**** | *-1.266*** | *-1.641*** | *-0.527* |
| *$R^2$* | *0.1754* | *0.1519* | *0.1480* | *0.1693* |

*Clustered standard errors in parentheses.*
*Significance level: * p < 0.10, ** p < 0.05, *** p < 0.01*

A possible interaction effect between the pace of technology evolution and firm knowledge similarity with the cluster stock is additionally tested. Under a rapid technology evolution, it is assumed that firms need to have a larger cognitive

distance towards the cluster knowledge stock in order to be more open to new external ideas, thereby preventing a possible lock-in situation. The corresponding interaction term indeed asserts a negative, however, insignificant impact on firm innovativeness.
Finally in model 13, it is investigated whether a fast pace of technology evolution moderates the relationship between firm cluster external relations and firm innovativeness. As assumed, under a fast pace of technology evolution, firm cluster external relations assert a strong significant effect on firm innovative performance. This means that these cluster external relations are especially crucial in industries characterized by a fast pace of technology evolution. The rapid evolution requires that firms gain access towards external knowledge sources in order to secure that their current knowledge stock does not become obsolete in the near future.

Overall, evidence is found that several variables from different levels of analysis directly as well as interactively influence firm innovative performance in clusters. The derived results are, on the one hand, in line with the literature reporting a significant positive relationship between being located in a cluster and firm innovativeness (e.g. Baptista and Swann, 1998; Bell, 2005). On the other hand, the results also suggest that firms benefit unequally within the cluster environment. The results, however, differ in this context from similar studies (e.g. Hervas-Oliver et al., 2018; McCann and Folta, 2011), because variables from three different levels of analysis are seperately as well as interactively tested, thereby enriching the current discussion about contextual conditions that contribute to firms' heterogenous benefits within clusters. As a further robustness check of the presented results, all models have been calculated for an alternative dependent variable: radical innovativeness. In contrast to the main dependent variable, radical innovativeness is calculated only by the average share of the firm´s product innovations in previous three years sales (1997-2013), which are new to the market and/or new to the firm.[107] The corresponding results are in line with the findings for firm innovativeness. The relation-specific variables as well as the pace of technology evolution have been additionally tested for different time periods. In both cases no relevant changes could be detected.[108]

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[107] In light of the literature dealing with radical innovations (Dahlin and Behrens, 2005; Schoenmakers and Duysters, 2010), the author is aware of the fact that the applied indicator here is only a rough proxy for radical innovations, although it still considers the novelty of an innovation more explicitly than other frequently used innovation-related indicators, such as patent dummies (e.g. McCann and Folta, 2011).
[108] The results of all robustness checks can be provided upon request.

## 5. Discussion and conclusion

Regional clusters have become an inseparable component of modern economies. However, it is still rather unclear whether companies' innovative performance really benefits from being located in a cluster and, even more importantly, which conditions are necessary to profit particularly from the cluster environment (Festing et al., 2012; Frenken et al., 2013; Martin and Sunley, 2003). By integrating theoretical perspectives from the strategic management (e.g. RBV, RV and MBV) as well as economic geography literature (e.g. cluster approach), these essential questions are answered with a specific focus on the Marshallian externality of knowledge spillovers. The corresponding main empirical results for the three different levels of analysis (micro-level, meso-level, and macro-level) can be resumed as follows: (1.) Being located in a cluster increases on average firm innovative performance. (2.) However, firms gain unequally from the cluster environment. To profit the most from available knowledge spillovers firms need to have, for example, a medium level of innovation capabilities and knowledge similarity with the cluster stock. Besides, a high share of basic research and a pronounced stock of alliances within clusters are also beneficial conditions for firm innovativeness in clusters. Consequently, in light of the results for the stock of alliances within clusters, it can be argued that the concept of local buzz and global pipelines, proposed by Bathelt et al. (2004), can be extended with a cluster dimension. (3.) Nevertheless, evidence for interaction effects between the three levels of analysis can be found. Due to the significant higher number of cluster internal relations in the cluster centre, promoting a lock-in situation, it is crucial that firms located within the centre of a cluster possess sufficient cluster external relationships. Apart from the concrete location within clusters, the pace of technology evolution also has to be considered as a moderating variable. Under a rapid technology evolution, firms need to own sufficiently high innovation capabilities to gain from knowledge spillovers. They allow for access to and integration of new knowledge, which is frequently changing in an industry with rapid technology evolution. Moreover, this paper provides evidence is provided that the rapid evolution also requires that firms have cluster external relations through which they can access external knowledge sources in order to guarantee that the current knowledge stock does not become obsolete.

However, there are some limitations to this study which can be seen as starting points for future research. First of all, the study does not consider the dynamic evolution across the cluster life cycle (e.g. Menzel and Fornahl, 2010). Due to data availability, the corresponding cluster index could only be calculated for the year

2012. Future research may investigate several years to capture the cluster life cycle and its possible impact on the sustainability of firm innovative performance in clusters. In this context, panel-regressions are also an appropriate suggestion. The underlying data constraints of this study[109] have prevented applying such approaches. Instead the study employed an OLS regression with clustered standard errors to a single cross-section of variables average over time (between estimator). Historically, such an approach has, however, been criticized due to a concern that omitted variables, represented by the individual effects of the error term, may be correlated with the independent variables, leading to inconsistent results. Nevertheless, such a potential bias is also valid for other approaches.[110] Moreover, it only constitutes one of several possible misspecifications of such models (Baltagi, 2005; Hauk Jr. and Wacziarg, 2009; Mairesse and Sassenou, 1991; Stern, 2010). In view of the underlying research question concentrating more on the between-variation and the available data, it is therefore stated that the selected methodical approach is suitable despite its limitations in contrast to panel-regressions (Griliches and Mairesse, 1984; Hauk Jr. and Wacziarg, 2009; Kafouros, 2008). It is indeed quite common to exploit cross-sectional data in empirical studies using innovation surveys (Mairesse and Mohnen, 2010). So it may be a promising research gap for future studies to implement panel-regressions in order to investigate properly the dynamic evolution across the cluster life cycle. Furthermore, the concrete partners and their knowledge profiles are not taken into consideration in the applied relation-specific variables. For future research it may be interesting to analyse in detail whether and under which conditions the type of partners (universities, small and medium-sized enterprises etc.) and their knowledge profiles matter for firm innovativeness in clusters. Lastly, the analysis here is limited to the empirical setting within Germany. Future studies may broaden this research setting by considering countries from different economic development levels. Consequently, possible country effects could be investigated.

Nevertheless, all in all it can be resumed that the derived results about the conditions necessary to profit from knowledge spillovers contribute to closing a still ubiquitous research gap. Additionally, the results also have a pragmatic meaning for companies

[109] Since the underlying survey questions of the dependent and independent variables are only inconsistently answered over the years (e.g. Mairesse and Mohnen, 2010), a regression on a balanced panel database would result in a significant loss of observations, thereby creating a potential bias. In more concrete terms, in the underlying panel sample of this study, 50% of the firms answer only four times (between 1997 and 2015) the corresponding survey questions.

[110] The results of the omitted variables tests carried out here, however, suggest that such a bias is not a major concern in this study.

as well as policy makers, because both can evaluate better under which conditions firms' innovative performance is more likely to benefit from locating within clusters. Instead of realizing generic agglomeration and cluster policies, policy makers should establish initiatives that are customized to the specific firm, cluster and market/industry characteristics. Such a context-oriented cluster policy approach would efficiently support those firms that really need help to benefit from the cluster and thereby work towards creating a cluster environment from which all companies can gain.

## Bibliography

Agasisti, T., Barra, C., & Zotti, R. (2017): Research, knowledge transfer and innovation: the effect of Italian universities' efficiency on the local economic development 2006-2012, *Siep Working Paper,* No. 726.

Audretsch, D. B., & Feldman, M. P. (1996): Innovative Clusters and the Industry Life Cycle, *Review of Industrial Organization*, Vol. 11, Issue 2, pp. 253-273.

Baltagi, B. H. (2005): Econometric Analysis of Panel Data, John Wiley & Sons Ltd, West Sussex, England.

Baptista, R., & Swann, P. (1998): Do firms in cluster innovate more?, *Research Policy*, Vol. 27, Issue 5, pp. 525-540.

Barney, J. B. (1991): Firm Resources and Sustained Competitive Advantage, *Journal of Management*, Vol. 17, No. 1, pp. 99-120.

Barra, C., Maietta, O. W., & Zotti, R. (2017): First, Second and Third Tier Universities: Academic Excellence, Local Knowledge Spillovers and Innovation in Europe, *CSEF Working Paper*, No. 468.

Bathelt, H., Malmberg, A., & Maskell, P. (2004): Clusters and Knowledge: Local buzz, Global Pipelines and the Process of Knowledge Creation, *Progress in Human Geography*, Vol. 28, Issue 1, pp. 31-56.

Beaudry, C., & Breschi, S. (2003): Are firms in clusters really more innovative?, *Economics of Innovation and New Technology*, Vol. 12, No. 4, pp. 325-342.

Bell, G. G. (2005): Clusters, networks, and firm innovativeness, S*trategic Management Journal*, Vol. 26, Issue 3, pp. 287-295.

Belsley, D. A. (1991): Conditioning Diagnostics: Collinearity and Weak Data in Regression, Wiley, New York.

Boschma, R. (2005): Proximity and Innovation: A Critical Assessment, *Regional Studies*, Vol. 39, Issue 1, pp. 61-74.

Boschma, R., & Frenken, K. (2010): The spatial evolution of innovation networks. A proximity perspective, in: Boschma, R., & Martin, R. (Eds.): Handbook of evolutionary economic geography, Edward Elgar, Cheltenham, UK, pp. 120-138.

Brenner, T. (2017): Identification of Clusters – An Actor-based Approach, *Working Papers on Innovation and Space*, No. 02.17.

Broekel, T. (2015): The Co-evolution of Proximities – A Network Level, *Regional Studies*, Vol. 49, Issue 6, pp. 921-935.

Broekel, T., & Boschma, R. (2012): Knowledge networks in the Dutch aviation industry: the proximity paradox, *Journal of Economic Geography*, Vol. 12, Issue 2, pp. 409-433.

Broekel, T., & Graf, H. (2012): Public research intensity and the structure of German R&D networks: a comparison of 10 technologies, *Economics of Innovation and New Technology*, Vol. 21, Issue 4, pp. 345-372.

Brown, K., Burgees, J., Festing, M., Royer, S., & Steffen, C. (2007): The Value Adding Web – A Conceptual Framework of Competitive Advantage Realisation in Clusters, *ESCP-EAP Working Paper*, No. 27, ISSN: 1619-7658.

Cameron, A. C., & Trivedi, P. K. (2005): Microeconometrics - Methods and Applications, Cambridge University Press, NY, USA.

Clark, K. B. (1985): The interaction of design hierarchies and market concepts in technological evolution, *Research Policy*, Vol. 14, Issue 5, pp. 235-251.

Cohen, W. M., & Levinthal, D. A. (1990): Absorptive Capacity: A New Perspective on Learning and Innovation, *Administrative Science Quarterly*, Vol. 35, No. 1, Special Issue: Technology, pp. 128-152.

Cooper, A. C., & Schendel, D. (1976): Strategic Responses to Technological Threats, *Business Horizons*, Vol. 19, No. 1, pp. 61-69.

Czarnitzki, D., & Thorwarth, S. (2012): Productivity effects of basic research in low-tech and high-tech industries, *Research Policy*, Vol. 41, Issue 9, pp. 1555-1564.

Daft, R. L., & Lengel, R. H. (1986): Organizational information requirements, media richness and structural design, *Management Science*, Vol. 32, No. 5, pp. 554-571.

Dahlin, K. B., & Behrens, D. M. (2005): When is an invention really radical?: Defining and measuring technological radicalness, *Research Policy*, Vol. 34, Issue 5, pp. 717-737.

Delgado, M. (2018): Firms in Context: Internal and External Drivers of Success, in: Clark, G. L., Feldman, M. P., Gertler, M. S., & Wójcik, D. (Eds.): The New Oxford Handbook of Economic Geography, Oxford University Press, pp. 324-346.

Delgado, M., Porter, M. E., & Stern, S. (2010): Clusters and entrepreneurship, *Journal of Economic Geography*, Vol. 10, Issue 4, pp. 495-518.

Dyer, J. H., & Singh, H. (1998): The Relational View: Cooperative Strategy and Sources of Interorganizational Competitive Advantage, *The Academy of Management Review*, Vol. 23, No. 4, pp. 660-679.

Dziallas, M., & Blind, K. (2019): Innovation indicators throughout the innovation process: An extensive literature analysis, *Technovation*, Vol. 80-81, pp. 3-29.

EFI (2015): Gutachten zu Forschung, Innovation und Technologischer Leistungsfähigkeit Deutschlands, Expertenkommission Forschung und Innovation.

Engel, D., Rothgang, M., & Eckl, V. (2016): Systemic aspects of R&D policy subsidies for R&D collaborations and their effects on private R&D, *Industry and Innovation*, Vol. 23, Issue 2, pp. 206-222.

European Cluster Observatory (2018): Methodology - Indicators, available under http://www.clusterobservatory.eu/index.html#!view=aboutobservatory;url=/about-observatory/methodology/indicators/, last retrieved: 04.10.2018.

European Commission (2008): The concept of clusters and cluster policies and their role for competitiveness and innovation: Main statistical results and lessons learned, *Europe INNOVA / PRO INNO Europe paper*, No. 9.

European Union (2016): Smart Guide to Cluster Policy, Guidebook Series: How to support SME Policy from Structural Funds, doi:10.2873/729624.

Ferriani, S., & MacMillan, I. (2017): Performance gains and losses from network centrality in cluster located firms: a longitudinal study, *Innovation*, Vol. 19, Issue 3, pp. 307-334.

Festing, M., Royer, S., & Steffen, C. (2012): Unternehmenscluster schaffen Wettbewerbsvorteile - Eine Analyse des Uhrenclusters in Glashütte, *Zeitschrift Führung + Organisation*, Vol. 81, No. 4, pp. 264-272.

Folta, T. B., Cooper, A. C., & Baik, Y.-s. (2006): Geographic cluster size and firm performance, *Journal of Business Venturing*, Vol. 21, Issue 2, pp. 217-242.

Fornahl, D., Broekel, T., & Boschma, R. (2011): What drives patent performance of German biotech firms? The impact of R&D subsidies, knowledge networks and their location, *Papers in Regional Science*, Vol. 90, Issue 2, pp. 395-418.

Frenken, K., Cefis, E., & Stam, E. (2013): Industrial dynamics and clusters: a survey, Tjalling C. Koopmans Research Institute, Discussion Paper Series, No. 13-11, Utrecht School of Economics.

Garcia-Vega, M. (2006): Does technological diversification promote innovation? An empirical analysis for European firms, *Research Policy*, Vol. 35, Issue 2, pp. 230-246.

Giuliani, E. (2007): The selective nature of knowledge networks in clusters: evidence from the wine industry, J*ournal of Economic Geography*, Vol. 7, Issue 2, pp. 139-168.

Gould, W. (2019): Between estimators, available under: https://www.stata.com/support/faqs/statistics/between-estimator/, last retrieved: 01.11.2018.

Grant, R. M. (1996): Toward a knowledge-based theory of the firm, *Strategic Management Journal*, Vol. 17, Issue S2, pp. 109-122.

Grashof, N., & Fornahl, D. (2020): 'To be or not to be' located in a cluster? - A descriptive meta-analysis of the firm-specific cluster effect, *Working Papers on Innovation and Space*, No. 01.20.

Grashof, N., Hesse, K., & Fornahl, D. (2019): Radical or not? The role of clusters in the emergence of radical innovations, *European Planning Studies*, Vol. 27, Issue 10, pp. 1904-1923.

Griliches, Z., & Mairesse, J. (1984): Productivity and R&D at the firm level, in: Griliches, Z. (Ed.): R&D, Patents and Productivity, University of Chicago Press, pp. 339-374.

Grillitsch, M., & Nilsson, M. (2017): Knowledge externalities and firm heterogeneity: Effects on high and low growth firms, *Papers in Innovation Studies*, No. 2017/06.

Hauk Jr., W. R., & Wacziarg, R. (2009): A Monte Carlo study of growth regressions, *Journal of Economic Growth*, Vol. 14, Issue 2, pp. 103-147.

Haupt, R., Kloyer, M., & Lange, M. (2007): Patent indicators for the technology life cycle development, *Research Policy*, Vol. 36, Issue 3, pp. 387-398.

Henderson, R. M., & Clark, K. B. (1990): Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms, *Administrative Science Quarterly*, Vol. 35, No. 1, pp. 9-30.

Hervás-Oliver, J. L., & Albors-Garrigós, J. (2007): Do clusters capabilities matter? An empirical application of the resource-based view in clusters, *Entrepreneurship & Regional Development: An International Journal*, Vol. 19, Issue 2, pp. 113-136.

Hervas-Oliver, J.-L., & Albors-Garrigos, J. (2009): The role of the firm's internal and relational capabilities in clusters: when distance and embeddedness are not enough to explain innovation, *Journal of Economic Geography*, Vol. 9, Issue 2, pp. 263-283.

Hervas-Oliver, J.-L., Sempere-Ripoll, F., Alvarado, R. R., & Estelles-Miguel, S. (2018): Agglomerations and firm performance: who benefits and how much?, *Regional Studies*, Vol. 52, Issue 3, pp. 338-349.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993): Geographic localization of knowledge spillovers as evidenced by patent citations, *Quarterly Journal of*

*Economics*, Vol. 108, No. 3, pp. 577-598.

Kafouros, M. I. (2008): Industrial Innovation and Firm Performance: The Impact of Scientific Knowledge on Multinational Corporations, Edward Elgar Publishing, Cheltenham, UK.

Kleinknecht, A., Van Montfort, K., & Brouwer, E. (2002): The Non-Trivial Choice between Innovation Indicators, *Economics of Innovation and New Technology*, Vol. 11, Issue 2, pp. 109-121.

Klepper, S. (1997): Industry Life Cycles, *Industrial and Corporate Change*, Vol. 6, Issue 1, pp. 145-182.

Knoben, J., Arikan, A. T., Van Oort, F., & Raspe, O. (2015): Agglomeration and firm performance: One firm's medicine is another firm's poison, *Environment and Planning A*, Vol. 48, No. 1, pp. 1-22.

Kohlbacher, M., Weitlaner, D., Hollosi, A., Grünwald, S., & Grahsl, H.-P. (2013): Innovation in clusters: effects of absorptive capacity and environmental moderators, *Competitiveness Review: An International Business Journal*, Vol. 23, Issue 3, pp. 199-217.

Lavie, D. (2006): The Competitive Advantage of Interconnected Firms: An Extension of the Resource-Based View, *The Academy of Management Review*, Vol. 31, No. 3, pp. 638-658.

Lechner, C., & Leyronas, C. (2012): The competitive advantage of cluster firms: the priority of regional network position over extra-regional networks – a study of a French high-tech cluster, *Entrepreneurship & Regional Development*, Vol. 24, Nos. 5–6, pp. 457-473.

Lee, C., Lee, K., & Pennings, J. M. (2001): Internal Capabilities, External Networks, and Performance: A Study on Technology-Based Ventures, *Strategic Management Journal*, Vol. 22, Issue 6-7, pp. 615-640.

Maggioni, M. A. (2002): Clustering Dynamics and the Location of High-Tech-Firms, Physica-Verlag, Heidelberg/New York.

Mairesse, J., & Mohnen, P. (2010): Using Innovation Surveys for Econometric Analysis, in: Hall, B. H., & Rosenberg, N. (Eds.): Handbook of the Economics of Innovation, Vol. 2, pp. 1129-1155.

Mairesse, J., & Sassenou, M. (1991): R&D Productivity: A Survey of Econometric Studies at the Firm Level, *NBER Working Paper*, No. 3666.

Malmberg, A., & Maskell, P. (2002): The elusive concept of localization economies: towards a knowledge-based theory of spatial clustering, *Environment and Planning A*, Vol. 34, No. 3, pp. 429-449.

Marshall, A. (1920): Principles of economics, Macmillan, London, 8th Edition.

Martin, P., Mayer, T., & Mayneris, F. (2011): Public support to clusters: A firm level study of French "Local Productive Systems", *Regional Science and Urban Economics*, Vol. 41, Issue: 2, pp. 108-123.

Martin, R., & Sunley, P. (2003): Deconstructing clusters: chaotic concept or policy panacea?, *Journal of Economic Geography*, Vol. 3, Issue 1, pp. 5-35.

McCann, B. T., & Folta, T. B. (2008): Location Matters: Where We Have Been and Where We Might Go in Agglomeration Research, *Journal of Management*, Vol. 34, No. 3, pp. 532-565.

McCann, B. T., & Folta, T. B. (2011): Performance differentials within geographic clusters, *Journal of Business Venturing*, Vol. 26, Issue 1, pp. 104-123.

McGahan, A. M., & Silverman, B. S. (2001): How does innovative activity change as industries mature?, *International Journal of Industrial Organization*, Vol. 19, Issue 7, pp. 1141-1160.

McNeish, D. M. (2014): Analyzing Clustered Data with OLS Regression: The Effect of a Hierarchical Data Structure, *Multiple Linear Regression Viewpoints*, Vol. 40, No. 1, pp. 11-16.

Menzel, M.-P., & Fornahl, D. (2010): Cluster life cycles—dimensions and rationales of cluster evolution, *Industrial and Corporate Change*, Vol, 19, Issue 1, pp. 205-238.

Miller, D. J. (2006): Technological diversity, related diversification, and firm performance, *Strategic Management Journal*, Vol. 27, Issue 7, pp. 601-619.

Molina-Morales, F. X., & Martínez-Fernández, M. T. (2004): How much difference is there between industrial district firms? A net value creation approach, *Research Policy*, Vol. 33, Issue 3, pp. 473-486.

Moulton, B. R. (1990): An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units, *The Review of Economics and Statistics*, Vol. 72, No. 2, pp. 334-338.

Myers, R. H. (1990): Classical and Modern Regression with Applications, PWS-Kent, Boston, 2nd edition.

Nathan, M., & Overman, H. (2013): Agglomeration, clusters, and industrial policy, *Oxford Review of Economic Policy*, Vol. 29, Issue 2, pp. 383-404.

Neffke, F., Henning, M., Boschma, R., Lundquist, K.-J., & Olander, L.-O. (2011): The Dynamics of Agglomeration Externalities along the Life Cycle of Industries, *Regional Studies*, Vol. 45, Issue 1, pp. 49-65.

Newbert, S. L. (2007): Empirical research on the resource-based view of the firm: an assessment and suggestions for future research, *Strategic Management Journal*, Vol. 28, Issue 2, pp. 121-146.

Nooteboom, B. (2000): Learning and innovation in organizations and economies, Oxford University Press, Oxford.

OECD (2002): Frascati Manual: Proposed Standard Practice for Surveys on Research and Experimental Development, OECD Publications Service, Paris.

Penrose, E. (1959): The Theory of the Growth of the Firm, Oxford University Press, Oxford, 4th edition.

Porter, M. E. (1980): Competitive Strategy: Techniques for Analyzing Industries and Competitors, Free Press, New York.

Porter, M. E. (1990): The competitive advantage of nations, Macmillan, London.

Porter, M. E. (1998): Clusters and the New Economics of Competitiveness, *Harvard Business Review*, Vol. 76, Issue 6, pp. 77-90.

Pouder, R., & St. John, C. H. (1996): Hot Spots and Blind Spots: Geographical Clusters of Firms and Innovation, *The Academy of Management Review*, Vol. 21, No. 4, pp. 1192-1225.

Raffo, J. (2017): MATCHIT: Stata module to match two datasets based on similar text patterns.

Raffo, J., & Lhuillery, S. (2009): How to play the “Names Game”: Patent retrieval comparing different heuristics, *Research Policy*, Vol. 38, Issue 10, pp. 1617-1627.

Research Explorer (2018): Research Explorer - The German research directory, available under http://www.research-explorer.de/research_explorer.en.html?, last retrieved: 10.03.2018.

Rigby, D. L., & Brown, M. W. (2015): Who Benefits from Agglomeration?, *Regional Studies*, Vol. 49, Issue 1, pp. 28-43.

Roesler, C., & Broekel, T. (2017): The role of universities in a network of subsidized R&D collaboration: The case of the biotechnology-industry in Germany, *Review of Regional Research*, Vol. 37, Issue 2, pp. 135-160.

Rosenberg, N. (1990): Why do firms do basic research (with their own money)?, *Research Policy*, Vol. 19, Issue 2, pp. 165-174.

Rubin, P. H. (1973): The expansion of firms, *Journal of Political Economy*, Vol. 81, No. 4, pp. 936-949.

Šarić, S. (2012): Competitive Advantages through Clusters - An Empirical Study with Evidence from China, Strategisches Kompetenz-Management, Springer Fachmedien, Wiesbaden.

Schoenmakers, W., & Duysters, G. (2010): The technological origins of radical inventions, *Research Policy*, Vol. 39, Issue 8, pp. 1051-1059.

Scholl, T., & Brenner, T. (2016): Detecting Spatial Clustering Using a Firm-Level Cluster Index, *Regional Studies*, Vol. 50, Issue 6, pp. 1054-1068.

Sedita, S. R., Lazzeretti, L., & Caloffi, A. (2012). The birth and the rise of the cluster concept. Copenhagen: DRUID, 2012, CBS.

Shaver, J. M., & Flyer, F. (2000): Agglomeration economies, firm heterogeneity, and foreign direct investment in the United States, *Strategic Management Journal*, Vol. 21, Issue 12, pp. 1175-1193.

Smit, M. J., Abreu, M. A., & de Groot, H. L. (2015): Micro-evidence on the determinants of innovation in the Netherlands: The relative importance of absorptive capacity and agglomeration externalities, *Papers in Regional Science*, Vol. 94, Issue 2, pp. 249-272.

Steffen, C. (2012): How Firms Profit from Acting in Networked Environments: Realising Competitive Advantages in Business Clusters. A Resource-oriented Case Study Analysis of the German and Swiss Watch Industry, Schriftenreihe: Internationale Personal- und Strategieforschung, Rainer Hamp Verlag, München & Mering.

Steinberg, P. J., Procher, V. D., & Urbig, D. (2017): Too much or too little of R&D offshoring: The impact of captive offshoring and contract offshoring on innovation performance, *Research Policy*, Vol. 46, Issue 10, pp. 1810-1823.

Stern, D. I. (2010): Between estimates of the emissions-income elasticity, *Ecological Economics*, Vol. 69, Issue 11, pp. 2173-2182.

Sternberg, R., & Litzenberger, T. (2004): Regional clusters in Germany--their geography and their relevance for entrepreneurial activities, *European Planning Studies*, Vol. 12, Issue 6, pp. 767-791.

Stevens, J. P. (2002): Applied Multivariate Statistics for the Social Sciences, Erlbaum Hillsdale, NJ.

Stifterverband (2018): Research Data Center Wissenschaftsstatistik, available under https://www.stifterverband.org/research_data_center, last retrieved: 10.03.2018.

Suarez, F., & Lanzolla, G. (2005): The Half-Truth of First-Mover Advantage, *Harvard Business Review*, April 2005.

Suarez, F. F., & Lanzolla, G. (2007): The Role of Environmental Dynamics in Building a First Mover Advantage Theory, *Academy of Management Review*, Vol. 32, No. 2, pp. 377-392.

Terstriep, J., & Lüthje, C. (2018): Innovation, knowledge and relations – on the role of clusters for firms' innovativeness, *European Planning Studies*, Vol. 26, Issue 11, pp. 2167-2199.

Tallman, S., Jenkins, M., Henry, N., & Pinch, S. (2004): Knowledge, Clusters, and Competitive Advantage, *The Academy of Management Review*, Vol. 29, No. 2, pp. 258-271.

Tödtling, F., Lehner, P., & Trippl, M. (2006): Innovation in Knowledge Intensive Industries: The Nature and Geography of Knowledge Links, *European Planning Studies*, Vol. 14, Issue 8, pp. 1035-1058.

Van Oort, F. G., Burger, M. J., Knoben, J., & Raspe, O. (2012): Multilevel Approaches and the Firm-Agglomeration Ambiguity in Economic Growth Studies, *Journal of Economic Surveys*, Vol. 26, Issue 3, pp. 468-491.

Vega-Jurado, J., Gutiérrez-Gracia, A., Fernández-de-Lucio, I., & Manjarrés-Henríquez, L. (2008): The effect of external and internal factors on firms' product innovation, *Research Policy*, Vol. 37, Issue 4, pp. 616-632.

Verhoeven, D., Bakker, J., & Veugelers, R. (2016): Measuring technological novelty with patent-based indicators, *Research Policy*, Vol. 45, Issue 3, pp. 707-723.

Wernerfelt, B. (1984): A resource-based view of the firm, *Strategic Management Journal*, Vol. 5, Issue 2, pp. 171-180.

Wu, X., Geng, S., Li, J., & Zhang, W. (2010): Shared Resources and Competitive Advantage in Clustered Firms: The Missing Link, *European Planning Studies*, Vol. 18, Issue 9, pp. 1391-1410.

Zaheer, A., & Bell, G. G. (2005): Benefiting from network position: firm capabilities, structural holes, and performance, *Strategic Management Journal*, Vol. 26, Issue 9, pp. 809-825.

Zaheer, A., & George, V. P. (2004): Reach Out or Reach Within? Performance Implications of Alliances and Location in Biotechnology, *Managerial and Decision Economics*, Vol. 25, Issue 6-7, pp. 437-452.

Zenker, A., Delponte, L., Mayán, N. D., Wintjes, R., Amichetti, C., Carneiro, J., Meyborg, M., Notten, A., Schnabl, E., & Stahlecker, T. (2019): Cluster programmes in Europe and beyond, European Observatory for Clusters and Industrial Change, available under https://www.clustercollaboration.eu/eu-initiatives/european-cluster-observatory, last retrieved: 17.07.2019.

## Appendix

**Table 5:** Descriptive Statistics

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Innovativeness | 1391 | 6.642 | 11.991 | 0 | 80 |
| Age | 1344 | 44.763 | 41.477 | 0 | 355 |
| Independence dummy | 1391 | 0.040 | 0.195 | 0 | 1 |
| Innov. Capabilities | 1391 | 0.124 | 0.166 | 0 | 1 |
| Number of linkages | 1391 | 0.447 | 2.225 | 0 | 55.900 |
| No. Research institutes | 1391 | 4.702 | 15.213 | 0 | 85 |
| Pace of tech. evolution | 1391 | 1.708 | 2.638 | 0 | 18.399 |
| Research-intensive industry | 1391 | 0.451 | 0.498 | 0 | 1 |
| Central position in cluster | 1391 | 0.500 | 0.500 | 0 | 1 |
| Knowledge similarity with cluster stock | 1391 | 0.592 | 0.332 | 0 | 1 |
| Share basic research | 1387 | 5.845 | 5.038 | 0 | 67.828 |
| Share of cluster external relations | 1391 | 0.264 | 0.438 | 0 | 1 |
| Knowledge diversity | 1391 | 4.300 | 3.177 | 0 | 17 |
| Stock of alliances within cluster | 1391 | 0.064 | 0.186 | 0 | 4.658 |
| Stock of knowledge across cluster | 1391 | 0.114 | 0.103 | 0 | 1 |
| Clustersize | 1390 | 164.006 | 1177.277 | 1.385 | 41667.94 |
| Knowledge diversity within cluster | 1391 | 4.300 | 1.763 | 0 | 12 |

# V. Paper IV: Sinking or swimming in the cluster labour pool? – A firm-specific analysis of the effect of specialized labour

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Published in Jena Economic Research Papers[111] as well as submitted to Journal of Management

**Abstract:** Human resources are a key factor for firm success, particularly nowadays when most industrial economies face an increasing shortage of qualified labour. With their pooled labour markets, regional clusters have been shown to be a preferable location for firms in order to satisfy their demand for skilled employees. Nevertheless, in light of possible disadvantages (e.g. labour poaching) and the broad field of studies dealing with firm performance differentials, the prevalent assumption that all companies profit equally from the specialized labour pool in clusters must be questioned. Consequently, the aim of this paper is to empirically investigate the conditions and mechanisms through which companies located in clusters can gain, in terms of innovativeness, from the specialized labour pool. By synthesizing theoretical streams from the strategic management (e.g. resource-based view) and the economic geography literature (e.g. cluster approach), variables from three different levels of analysis (micro-level, meso-level and macro-level) are examined separately as well as interactively. Apart from revealing that being located in a cluster indeed increases on average firm innovativeness, one of the central findings is that firms benefit unequally within the cluster environment depending on the specific firm-level, cluster-level, industry-/market-level conditions and their respective interactions.

**Keywords:** specialized labour pool, cluster, agglomeration, firm performance differentials, innovation

**JEL Classification:** C31, J24, L22, O30, R10, R23

[111] In the interest of consistency, the following version differs slightly from the design of the published article.

## 1. Introduction

Human resources are commonly seen as a key factor for firm success (Barney and Wright, 1998; Pfeffer, 1994; Stiles and Kulvisaechana, 2003). They offer the potential to advance firms' efficiency, to exploit novel business opportunities and to prevent approaching competitive threats (Barney, 1991; Klumbies, 2015; Lepak and Snell, 2002). In light of an adverse demographic development in most industrial economies exacerbating the currently increasing shortage of qualified labour, particularly nowadays human resources have become even more important for profitable and sustainable firm performance. In Germany for example 31.4% of the establishments reported problems in finding sufficient applicants (Bossler et al., 2017; IAB, 2017; Martinez-Fernandez and Weyman, 2012). To satisfy their demand for skilled employees, it has been theoretically as well as empirically shown that companies tend to locate in agglomerations or clusters[112] providing a pooled labour market (Combes and Duranton, 2006; Ellison et al., 2010; Overman and Puga, 2010). The economist Alfred Marshall asserted, already in the year 1920, that "(…) a localized industry gains a great advantage from the fact that it offers a constant market for skill." (Marshall, 1920, p. 271). Subsequent scientific contributions additionally highlighted in this context that clusters create a common market pool for workers with specialized skills that offers advantages in terms of risk reduction and efficiency gains in the job search process for both the workers as well as the hiring firms (David and Rosenbloom, 1990; Krugman, 1991).

So far, most of the studies dealing with the externality of labour pooling and firm performance, however, do not consider the specific context. Instead, it is actually quite prevalent to assume that all companies profit equally and in the same manner from being located in a cluster (Frenken et al., 2013; Šarić, 2012; Tallman et al., 2004). Nevertheless, there is indeed also evidence for possible disadvantages from the clustered labour pool referring to high competition between companies for new employees and labour poaching which is part of this high competition (Combes and Duranton, 2006; Otto and Fornahl, 2010). In view of these potential negative effects and the broad field of studies dealing with firm performance differentials (Dyer and Singh, 1998; Van Oort et al., 2012; Vega-Jurado et al., 2008) it becomes obvious that the idea of equal gains for all companies located in a cluster is rather questionable.

Frenken et al. (2013) therefore make a call to investigate the conditions and

[112] In line with several authors (Delgado et al., 2010; Martin et al., 2011; McCann and Folta, 2011), the terms cluster and agglomeration are used interchangeably.

mechanisms through which the firm-specific advantages of localization economies can be realized. The analysis should thereby sepeartely consider the three main components of localization economies, referring to specialized labour markets, specialized inputs and knowledge spillovers. Consequently, the aim of this paper is to respond to this call for the Marshallian component of specialized labour by answering the following research question: Under which conditions can a company located in a cluster profit from the specialized labour pool?

The theoretical conceptualization of potential contextual variables is thereby based on an integration of the theoretical perspectives from the strategic management (e.g. resource-based view, relational view and market-based view) and the economic geography literature (e.g. cluster approach). As a result and in contrast to recent studies examining the firm performance heterogeneity within clusters only for one level of analysis, in this paper three different levels of analysis (micro-level, meso-level and macro-level) are therefore separately as well as interactively investigated by applying a OLS regression with clustered standard errors of single cross-section average over time, equalling the between estimator. Hence, for the empirical analysis, varying data sources are integrated, ranging from firm-level to market and industry-level data. The corresponding unique multilevel dataset consists of 11,500 companies in Germany. The selected methodical approach is in this context appropriate because it considers the hierarchical data structure, the context dependency and the year-to-year variability inherent to micro-level data (McNeish, 2014; Moulton, 1990; Rigby and Brown, 2015).

By examining the separate as well as interactive influence of variables from three different levels of analysis, the paper enriches the current discussion about firm performance differentials within clusters (e.g. Hervas-Oliver et al., 2018), because it offers a more systematic and comprehensive analysis of the contextual conditions shaping firm performance within clusters. Besides contributing to closing a still ubiquitous research gap, the paper also offers a rather pragmatic value, especially in times of an increasing shortage in skilled labour, because companies as well as policy makers can evaluate better under which conditions the potential advantages of the specialized labour pool in clusters are more likely to be realized.

The remainder of this paper is organized as follows: The second section presents the theoretical background, highlighting the current debate about specialized labour and elaborating the corresponding hypotheses for each level of analysis.[113] In the third section, the applied methodical approach, the multilevel sources of the data and the corresponding variables are discussed in detail. The empirical results are thereafter presented in the fourth section. The paper will end with some concluding remarks, including limitations to this study as well as promising areas for future research.

## 2. Theoretical background of the labour pool in clusters and firm performance

Despite the popularity and widespread application of the cluster term in various disciplines, there still remains definitional and conceptual dissension about clusters, resulting in a loss of explanatory power (Brown et al., 2007; Malmberg and Maskell, 2002; Martin and Sunley, 2003; Šarić, 2012). Having a clear understanding about the main definitional elements is therefore the first step to analyse adequately the firm-specific cluster effect. Instead of theoretically elaborating a new (conceptual) cluster definition, this study exploits, however, the following working definition, derived through a comparative empirical approach in Grashof and Fornahl (2020): "Clusters are defined as a geographical concentration of closely interconnected horizontal, vertical and lateral actors, such as universities, from the same industry that are related to each other in terms of a common resource and knowledge base, technologies and/or product-market." (Grashof and Fornahl, 2020, p. 10f.).

Marshall (1920) made one of the pioneering contributions that consider the benefits that firms can gain from being located in close proximity to similar firms. He emphasized in this context four types of agglomeration externalities: access to specialized labour, access to specialized inputs, access to knowledge spillovers and access to greater demand by reducing consumer search costs (Marshall, 1920; McCann and Folta, 2008).[114]

The paper will specifically focus on the access to specialized labour. It has been emphasized that clusters create a common market pool for specialized workers that provides benefits for both the employers as well as the employees (Krugman, 1991; Marshall, 1920). The reduction of risk is one of these two-sided benefits. For

[113] The first group of hypotheses therefore covers the micro-level, while the second refers to the meso-level and the third group of hypotheses deals with the macro-level.

[114] Besides these externalities he also noted that the unique physical conditions of particular areas, such as limited natural resources, are the chief cause for the localization of industries.

employees, the spatial concentration of similar thematic firms reduces the risk of becoming unemployed, as they are able to attain work from multiple employers. At the same time, employers can minimize their risk of not finding and hiring the right job candidates (David and Rosenbloom, 1990; Krugman, 1991). Furthermore, the pooling of specialized employers and employees in close geographical distance facilitates the search and screening process for both sides. In absence of such a pooled specialized labour market, companies and workers alike have to search on the national or even international labour market, resulting in relatively high search costs and in potentially lower matching qualities (Amend and Herbst, 2008; Otto and Fornahl, 2010). With their pooled labour markets, clusters therefore help to alleviate the typical hold-up problem. Specialized workers are more willing to make industry-specific investments in their human capital when they believe that they can appropriate the corresponding benefits, which is particularly the case in a highly competitive setting such as a cluster (Almazan et al., 2007; Amend and Herbst, 2008; Rotemberg and Saloner, 2000).

Despite these advantages, there also exist possible disadvantages of being located in a pooled specialized labour market. Companies located in clusters are confronted with fierce competition in the recruitment of new talented employees. One extreme form of this competition refers to labour poaching, meaning that current employees are hired by competing firms. The associated costs of this poaching are twofold. First, due to the efficient matching process resulting in an alleviated mobility of employees, competitors can have access to the firm´s own knowledge embodied in its employees by recruiting them. In this way, competing firms can increase their relative competitive advantage over other firms. Second, to avoid such a loss of knowledge, companies may be more inclined to pay higher wages. Thereby, they can indeed retain their current human capital, but this comes at the cost of higher personnel expenses. In general, it can therefore be resumed that companies can realize advantages as well as disadvantages from the pooled labour market in clusters (Combes and Duranton, 2006; Otto and Fornahl, 2010).

While the reviewed theory about the specialized labour pool within clusters and its potential (dis-)advantages is relatively well elaborated, the literature is, however, nearly silent about the concrete conditions and mechanisms through which those outcomes can be realized (Frenken et al., 2013; McCann and Folta, 2011). In light of the resource-based view (RBV), this silence is particularly surprising. The resource-based view of the firm is one of the most widely accepted theoretical perspectives in the field of strategic management (Newbert, 2007; Steffen, 2012), but it has also been applied in the cluster context (Hervas-Oliver and Albors-Garrigos, 2007; Hervas-Oliver and Albors-Garrigos, 2009). Originally emerged from the contributions of Penrose (1959), Rubin (1973) and Wernerfelt (1984), the RBV has since then continuously been advanced, highlighting for example the importance of dynamic capabilities to actually utilize the available resource bundles (Teece et al., 1997) as well as focussing on specific resources such as knowledge (Grant, 1996).[115] The core idea of the RBV deals with the firm´s internal resource base and how firms can make use of these resources in order to gain a competitive advantage. It is further assumed that resources are immobile and unequally distributed between companies. Both assumptions are necessary for the existence of different resource endowments and its persistency over time. The strength of firms' resources is given by their characteristics, namely whether they are valuable, rare, non-substitutable and imitable (Barney, 1991; Newbert, 2007; Steffen, 2012). In line with Barney (1991), resources are here defined as "(…) all assets, capabilities, organizational processes, firm attributes, information, knowledge, etc. controlled by a firm that enable the firm to conceive of and implement strategies that improve its efficiency and effectiveness." (Barney, 1991, p. 101).[116]

In the literature firms' human resources and their corresponding human capital have been regarded as central determinants for firm competitive advantage and have therefore been frequently analysed (De Saá-Pérez and García-Falcón, 2002; Newbert, 2007). Even though some evidence is found for a positive effect, also on firm innovative performance (e.g. Bornay-Barrachina et al., 2017; Cabello-Medina et al., 2011), the results are in general not as consistent as one would assume (Newbert, 2007). One plausible explanation here for refers to the missing consideration of associated variables with human capital (Bornay-Barrachina et al., 2017; Newbert, 2007). Building on the RBV and its supplement theoretical perspective of dynamic capabilities, it has been highlighted in this context that companies need to own the necessary human resource capabilities to realize a competitive advantage (Hatch and Dyer, 2004; Newbert, 2007; Snell et al., 1996). Companies that are able to identify, acquire and train the most adequate talents are argued to own a significant competitive advantage (De Saá-Pérez and García-Falcón, 2002; Hatch and Dyer, 2004). While the role of human resource capabilities

[115] For a good overview see for example Newbert (2007).

[116] Although a clear definition of resources has not been developed yet, the definition by Barney (1991) has become a standard definition that has been commonly used (Hervas-Oliver et al., 2014; Steffen, 2012).

for firm performance has been in general theoretically as well as empirically investigated, it has not been examined yet in the cluster environment. Nevertheless, in view of the previous theoretical and empirical contributions, it can be assumed that human resource capabilities are essential for firms to gain from the specialized labour pool in clusters. It is indeed plausible that firms lacking sufficient human resource capabilities are not able to profit so much from the specialized labour pool within clusters, because they are not capable of finding the most adequate candidates and, even more important in a competitive environment such as a cluster, they cannot hire and/or hold the best fitting labour forces. Thus, the following hypothesis is proposed:

**Hypothesis 1a:** The human resource capabilities of a firm have a positive effect on firm innovative performance in clusters.

Moreover, the ongoing changes in the labour market (e.g. demographic change and migration), which are sometimes also politically fostered, such as in the case of women´s increased labour participation, result in a more heterogeneous workers' landscape. Besides the mentioned human resource capabilities, firms therefore have also to consider the diversity of their human resources (Garnero et al., 2014; Parrotta et al., 2014). The diversity of human resources offers, however, advantages as well as disadvantages. On the one hand, diversity in terms of culture, age and gender can provide diverse ideas, problem-solving abilities and new attitudes, which in turn stimulate innovations. But on the other hand, increasing employee diversity may lead to communication problems or personal conflicts. The associated costs can potentially offset the gains from a diverse stock of employees (Østergaard et al., 2011; Parrotta et al., 2014; Schneider and Eckl, 2016). Consequently, it has been highlighted by some authors that the specific context must be taken into consideration when analysing the potential impact of employee diversity on firm performance (Dwyer et al., 2003; Garnero et al., 2014).

As mentioned briefly above, one of the main aspects of diversity, also from a policy perspective, refers to gender equality (Kladroba and Eckl, 2019). While the relationship between gender diversity and firm innovativeness has recently gained some attention (Horbach and Jacob, 2017; Østergaard et al., 2011; Schneider and Eckl, 2016), the specific environment of clusters remains yet to be properly examined. In light of the importance of (informal) linkages for accessing the available knowledge within clusters highlighted in the cluster approach (e.g. Balland et al., 2016; Ferriani and MacMillan, 2017) and the gender-segregated socialization patterns (e.g. Gray and James, 2007; Ruiz-Jiménez et al., 2016), it can however be argued that gender diversity provides access to a broader knowledge network, thereby promoting potential benefits from knowledge spillovers. Moreover, since gender diversity is ultimately associated with a more heterogeneous firm knowledge base, it is likely that such firms are more open to new ideas and develop higher absorptive capacities (e.g. Østergaard et al., 2011), which have been shown to influence firm innovative performance within clusters (Grashof, 2018; Hervas-Oliver et al., 2018). Thus, the following hypothesis is proposed:

**Hypothesis 1b:** The gender diversity of the firm´s human resource stock has a positive effect on firm innovative performance in clusters.

As already indicated in the previous theoretical discussion, the specialized labour pool within clusters makes the search and screening process for employers as well as employees more efficient. Nevertheless, in the literature it is also suggested that this is particularly the case when the corresponding skills of the employees located in a cluster are similar to the underlying core activities of the clustered firms (Amend and Herbst, 2008; Otto and Fornahl, 2010). Building on these theoretical insights, it can be further assumed that it is beneficial for firms to own a human resource stock with similar skills compared to the overall cluster. It is supposed that such a high degree of overlap minimizes the potential of mismatches, thereby contributing in the end to firm innovativeness. Thus, the following hypothesis is proposed:

**Hypothesis 1c:** The degree of overlap between the overall labour qualifications within the cluster and the labour qualifications of the firm has a positive effect on firm innovative performance in clusters.

The labour market pooling within clusters additionally encourages intensive employee mobility. Since knowledge is embedded in people, such a pronounced mobility of specialized workers is argued to be a crucial mechanism for knowledge diffusion among firms, providing new ideas as well as competences and thereby fostering firm innovative performance (Boschma et al., 2009; Erikson and Lindgren, 2009; Otto and Fornahl, 2010). For example, in their large empirical analysis of almost 257,000 workplaces in Sweden, Erikson and Lindgren (2009) found that localized labour market-induced externalities via job mobility significantly influence firm performance (Erikson and Lindgren, 2009). Labour mobility is especially important in this context for the dissemination of tacit knowledge, such as experiences and routines that cannot be easily codified in the form of texts or documents (Almeida and Kogut, 1999; Bienkowska et al., 2011; Erikson and Lindgren, 2009; Power and Lundmark, 2004). Moreover, new employees can likewise expand the overall network by bringing along previously established business and personal contacts (Bienkowska et al., 2011; Zellner and Fornahl, 2002). Besides these advantages, the mobility of labour is also argued to be associated with potential costs such as labour poaching that results in a knowledge drain (Combes and Duranton, 2006; Otto and Fornahl, 2010). The same reasoning can also be expected for the temporary exchange of human resources in the form of out-going expatriates and in-going inpatriates, which are quite prevalent measures in contemporary human resource management (Fang et al., 2010; Harzing et al., 2016; Reiche, 2006). However, despite its popularity, the concrete influence of the corresponding human capital exchange intensity still remains rather unclear in the competitive environment of clusters. Nevertheless, in line with the extension of the RBV, the relational view (RV), concentrating on relational resources that go beyond firm boundaries (Dyer and Singh, 1998; Lavie, 2006), and the cluster approach, stressing the importance of labour mobility, it is assumed that the exchange of human capital is an essential channel for inter-firm knowledge transfers, and in the end, for firm innovative performance. Thus, the following hypothesis is proposed:

**Hypothesis 1d:** The human capital exchange intensity has a positive effect on firm innovative performance in clusters.

For the recruitment of the best talents it is additionally essential for companies to be visible for potential applicants. Particularly in a highly competitive setting of similar firms, such as in clusters, it is plausible that the visibility, acting as a differentiation signal, plays a crucial role in attracting the most talented workers from the specialized labour pool (Cable and Turban, 2003; Molina-Morales and Martínez-Fernández, 2004; Williamson et al., 2010). The network literature highlights that apart from information benefits (Bell, 2005; Zaheer and Bell, 2005), firms located in the centre can also profit from a higher visibility and from status gains (Ferriani and MacMillan, 2017). Consequently, it can be assumed that the firm´s centrality within the corresponding cluster may determine to some extent the potential of gaining from the specialized labour pool within clusters. Thus, the following hypothesis is proposed:

**Hypothesis 1e:** The centrality of a firm´s cluster position has a positive effect on firm innovative performance in clusters.

Contrary to most studies dealing with clusters and firm performance[117], it is postulated here that apart from firm-specific conditions, it also necessary to consider the specific cluster attributes, which can likewise be quite heterogeneous (McCann and Folta, 2008). One important attribute in this context refers to the stock of human resources of the cluster. With an increase of specialized workers in the pooled labour market in clusters, it is likely that the matching as well as search processes of the corresponding firms become even more efficient due to the higher supply of specialized labour (Folta et al., 2006; McCann and Folta, 2008). Nevertheless, evidence for potential congestion costs (e.g. fierce competition) has also been found (Folta et al., 2006; Zucker et al., 1998). In line with the principal rationale of the economies of agglomeration (e.g. Arthur, 1990), it is however assumed that the stock of human resources of the cluster asserts a positive impact on firm innovative performance. Thus, the following hypothesis is proposed:

**Hypothesis 2a:** The stock of human resources of the cluster has a positive effect on firm innovative performance in clusters.

Apart from the quantity of the pooled labour market in clusters, the corresponding quality should be considered additionally. On the firm-level, it has already been shown that the quality of the human resources, measured for example by the educational degrees, constitutes a significant determinant of firm innovativeness (Cabello-Medina et al., 2011; Huiban and Bouhsina, 1998; Vinding, 2006). Regarding clusters, however, it has been implicitly assumed that the quality of the labour pool is homogenously distributed among all clusters and that therefore the access to it is one of the main advantages of being located in clusters (e.g. Oakey and Cooper, 1989). In line with the theoretical elaborations by McCann and Folta (2008), this work assumes that clusters vary in the quality of their respective labour pools. Consequently, firms located in clusters with a relatively high quality of the labour pool are presumed to provide a more beneficial environment for innovations than clusters with a rather low quality of the labour pool. Thus, the following hypothesis is proposed:

[117] Knoben et al. (2015) as well as Rigby and Brown (2015) are important exceptions in this context.

**Hypothesis 2b:** The quality of the labour pool within the cluster has a positive effect on firm innovative performance in clusters

Furthermore, the gender diversity within clusters is related to the quality of the pooled labour market. Even though gender diversity has primarily been investigated on the micro-level (Dwyer et al., 2003; Täube, 2005), it can be argued that specialized labour pools within clusters characterized by a high gender diversity can potentially offer a high quality of human capital, as the localized pool of different experiences and ideas becomes broader (Horbach and Jacob, 2017; Schneider and Eckl, 2016). As a result, the innovativeness of the corresponding firms is expected to be fostered. Thus, the following hypothesis is proposed:

**Hypothesis 2c:** The gender diversity of the labour pool within the cluster has a positive effect on firm innovative performance in clusters.

Similar to the quality of the labour pool, it has also been implicitly assumed that the matching process is equally efficient in all clusters. It has indeed been verified that the specialized labour pool within clusters makes the matching process between employers and employees more efficient (Amend and Herbst, 2008; Otto and Fornahl, 2010). Nevertheless, in light of its structural differences, it is reasonable to assume that the labour pools within clusters may vary in their matching capacities. Thus, the following hypothesis is proposed:

**Hypothesis 2d:** The matching capacities of the labour pool within the cluster have a positive effect on firm innovative performance in clusters.

However, in accordance with the market-based view (MBV), it is claimed that apart from the firm-specific and the cluster-specific conditions, it is additionally crucial to consider the concrete market and industry environment, whose impact on firm performance has been widely acknowledged (Kohlbacher et al., 2013). The core idea of the MBV is that firm success is primarily determined by the external environment, such as the specific market conditions (Porter, 1980; Steffen, 2012). Building on this prominent theoretical stream and on the two scientific papers of Suarez and Lanzolla (2005 and 2007), it is assumed that the pace of technology evolution influences firm innovative performance in clusters. The pace of technology evolution is typically captured through a technology S-curve, depicting the technological improvements over time along a particular performance parameter, such as the CPU clock speed in the case of the computer industry (Cooper and Schendel, 1976; Suarez and Lanzolla, 2007). Under a rapid technology evolution, it is likely that the knowledge and competencies embodied in the human resources become rather unsuitable or even obsolete. The corresponding advantage from the access to specialized labour within clusters is therefore assumed to diminish under these circumstances (Filippetti and Guy, 2016; Suarez and Lanzolla, 2005; Suarez and Lanzolla, 2007). Incumbent employees may additionally have strong incentives to prevent any mayor shifts in companies' strategic direction due to their own personal career interests which are at risk if the required competence profile dramatically changes. Such a behaviour can of course result in a lock-in situation, thereby hampering firm innovative performance (Sørensen and Stuart, 2000). Thus, the following hypothesis is proposed:

**Hypothesis 3a:** The pace of technology evolution has a negative effect on firm innovative performance in clusters.

Moreover, the pace of market evolution, varying as much as the pace of technology evolution, is also assumed to influence firm innovativeness in clusters. In a fast-growing market, measured for example in sales or household penetration, it becomes more attractive for employees to specialize themselves in the corresponding industry. Consequently, the supply of specialized labour in the particular industry increases, leading to a decreased advantage derived from the previously rather unique access to specialized labour in clusters, as the supply increases in total, also outside of clusters (Suarez and Lanzolla, 2005; Suarez and Lanzolla, 2007). Regarding the employers, it can be further argued that a fast-growing market not only attracts more labour, but also more competitors, potentially even from indirectly related industries. The resulting fierce competition may then come at the cost of innovative new ideas (Kohlbacher et al., 2013). Thus, the following hypothesis is proposed:

**Hypothesis 3b:** The pace of market evolution has a negative effect on firm innovative performance in clusters.

Lastly, the market risk is additionally suggested to have a significant impact on firm innovativeness in clusters. Under a high market risk, implying high uncertainty, it is likely that human resource decisions, frequently entailing large sunk costs (e.g. search and training costs) which are often partially irreversible (e.g. long-term labour contracts), are postponed in order to avoid costly mistakes (Ernst and Viegelahn, 2014; Schaal, 2017). Due to the held-back investments in the search and the hiring of new employees, companies will consequently not profit from the specialized labour pool within clusters. The similar reasoning can also be applied to the human capital-related investment decision of the employees. The investment in industry-specific skills is a rather major and long-term oriented decision, since the corresponding knowledge is limited in its applicability. Hence, in a risky market environment, employees may also postpone their industry-specific investment decisions in order to prevent mistakes in their career advancements (Filippetti and Guy, 2016). As a consequence of this wait-and-see behaviour, the overall quality of the specialized labour pool within clusters may in turn be negatively affected. Thus, the following hypothesis is proposed:

**Hypothesis 3c:** The market risk has a negative effect on firm innovative performance in clusters.

As already indicated, apart from simply analysing separately the direct effects of these assumed influential variables, interaction effects between them are likewise investigated. By focussing on the interactions between the firm-level, cluster-level and industry-/market-level, and thereby following a suggested 'interactionist approach' (e.g. Beugelsdijk, 2007), the firm performance differentials within clusters can be explained from an even broader perspective.

## 3. Data and Methodology

For the empirical investigation of the multilevel conditions necessary to profit, in terms of innovative performance, from the specialized labour within clusters, various data sources and variables are taken into consideration. The main database for the analysis is an extensive firm-level database provided by the Stifterverband. This database is based on a large representative survey, taking place in a two-year rhythm ("full survey"), of all designated R&D-active firms in Germany between 1995 and 2015. The Stifterverband primarily collects this comprehensive innovation-related information in the survey for the Federal Ministry of Education and Research in Germany (Engel et al., 2016; Schneider and Eckl, 2016; Stifterverband, 2018).[118] Building on this database, the dependent variable for firm innovativeness can be calculated as the average share of the firm´s product innovations between 1997 and

[118] For a good overview about the concrete advantages of this database (e.g. detailed information) compared to accounting data, see for example Schmid et al. (2014).

2013, including incremental as well as new to the market/firm innovations, in previous three years sales (Delgado, 2018; Steinberg et al., 2017). Due to the lagged nature of the underlying survey question as well as the clear distinction between innovation outputs and inputs in the overall survey design, it is argued that reverse causality is not a major concern in this study (Hervas-Oliver et al., 2018).[119] In comparison with patents, which are frequently used as proxies for firm innovativeness, this indicator offers two main advantages. First, the innovative output of companies that do not patent their product innovations is here also considered. Second, the share of the firm´s product innovations in sales is a market-driven indicator, so that unlike in the case of patents, the true economic value of the corresponding innovation can be elaborated (Delgado, 2018; Dziallas and Blind, 2019; Kleinknecht et al., 2002). It is therefore argued that the share of the firm´s product innovations in sales is, compared to patents, the more appropriate dependent variable for the purpose of this study.

The database provided by the Stifterverband is additionally used to determine several independent variables. In line with the previously presented theoretical insights (e.g. De Saá-Pérez and García-Falcón, 2002; Hatch and Dyer, 2004), the human resource capabilities are measured by dividing the average R&D personnel expenses from 1997 to 2013 (including legal personnel costs as well as pension grants, gratifications and training costs) by the average internal R&D expenditures. The derived indicator, representing the average share of R&D personnel expenses in the total internal R&D expenditures, is believed to capture adequately the most important aspects of human resource capabilities. Furthermore, the gender diversity can also be calculated by employing the Stiftverband database. In accordance with other relevant studies in this field (Drach-Zahavy and Somech, 2001; Lorenzo et al., 2017; McGuirk and Jordan, 2012), the Gini-Simpson index, also known as the Blau index, is used based on the average share of male and female R&D employees (1997-2013). The index is defined as

$$D_i = 1 - \sum_i p_i^2 \qquad (1.)$$

in which p is the proportion of the total population in each gender category (female and male). The Gini-Simpson index $D_i$ ranges thereby from zero (no diversity) to one

[119] As a first robustness check, an explicit time lag structure has been additionally implemented in the corresponding empirical models by calculating the dependent variable only for the years 1999-2013, while changing the previous reference period of the independent variables to 1997-2011. The corresponding results thereby remain basically the same and can be provided upon request.

(maximum diversity). If the entire R&D workforce is for example male, then $D_i$ equals zero. A higher value of $D_i$ therefore means more diversity or, in other words, a greater spread across the two considered categories (McGuirk and Jordan, 2012). In order to calculate the gender diversity of the labour pool within clusters, the estimated firm diversity is aggregated on the corresponding cluster-level and then divided by the number of firms in the cluster. Moreover, for the measurement of the stock of human resources of the cluster, the average number of firms' employees within the corresponding cluster (between 2008 and 2013) is calculated.

The information about human resources collected in the standard survey since 1995 has however been extended in the year 2013. With its special focus on human capital, this extended part of the survey contains even more information about additional characteristics of R&D personnel (e.g. professional qualifications and the exchange of scientific R&D personnel) (Schneider and Eckl, 2016). It therefore creates the basis for further independent variables such as the degree of overlap between the overall labour qualifications within the cluster and the labour qualifications of the firms. Based on the share of different qualification subjects (e.g. engineering as well as medicine and health services), labour qualification profiles for the firms and the clusters are first of all estimated. The labour qualification profiles of the clusters are constituted by the average labour qualification profiles of all firms located in the corresponding clusters. In order to finally measure the degree of overlap, the cosine index is calculated.

$$similarity = \cos(\theta) = \frac{A \times B}{\|A\|\|B\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}} \qquad (2.)$$

The cosine index determines the similarity between the two vectors A (firm´s labour qualification profile) and B (cluster labour qualification profile) for n qualification categories. In this case, seven different labour qualification categories are considered. The final index can take a value between zero and one, where one means perfect similarity or in other terms a perfect degree of overlap between both labour qualification profiles. The extra information from the extended survey of the Stifterverband is additionally used to estimate the human capital exchange intensity. Here for, the sum of the shares of the scientific R&D expatriates and inpatriates in the total number of scientific R&D personnel is calculated. Moreover, the data from the extended Stifterverband survey from 2013 is also utilized for estimating the matching capacities of the labour pool within clusters, as it offers information about the coverage of the staffing needs. In particular, the matching capacity of the labour pool is proxied by the share of clustered companies that expect to cover their need for scientific R&D employees in the next three years. In line with other contributions (e.g. Erikson and Lindgren, 2009), the average share of R&D employees with a PhD or a habilitation is additionally calculated for each cluster as a proxy for the quality of the labour pool within the corresponding clusters.

Apart from the Stifterverband database, further data sources are employed. Patents, retrieved from the European database PATSTAT, are for example used to estimate the pace of technology evolution of the corresponding industry. Despite well-discussed drawbacks (e.g. Griliches, 1990), patents have been frequently applied as proxies for industry-specific technological advances (Audretsch and Feldman, 1996; Haupt et al., 2007; McGahan and Silverman, 2001). The average technological improvement (measured by the weighted number of patents) in three-digit NACE Rev. 2 code industries is computed for a two-year period (2012-2013) in order to control for possible outliers. By subsequently dividing the average technological improvement by the size of the corresponding industry, measured in terms of the average number of employees, the final indicator for the pace of technology evolution is also weighted by the industry size. Furthermore, based on data about industry revenue provided by the German Federal Statistical Office, the pace of market evolution can be determined. Similar to the volatility index (e.g. Dreyer and Grønhaug, 2004), the pace of market evolution is here calculated by the rate of change (between 2012 and 2013) of the revenue in three-digit NACE Rev. 2 code industries.[120] As indicated in the literature (e.g. Suarez and Lanzolla, 2007), both the pace of technology and market evolution additionally affect the overall market risk. Consequently, market risk is estimated by the interaction term between the pace of technology and market evolution.

Since the empirical analysis is primarily concentrated on companies within clusters, it is essential to determine these regional clusters adequately. For the identification of all relevant clusters in Germany, this paper therefore applies the method of Brenner (2017). Based on official IAB[121] employment data from 2012 in three-digit NACE Rev. 2 code industries, a cluster index for each single company on the community

[120] As a further robustness check, both variables have also been tested for a different time period (between 2011 and 2013). Thereby, the corresponding empirical results remain stable.
[121] The Institute for Employment Research (IAB) is the research unit of the Federal Employment Agency in Germany. For more information please see https://www.iab.de/en/ueberblick.aspx.

level ("Gemeindeebene") is calculated accordingly. In comparison with more traditional cluster indicators, the actor-based approach by Brenner (2017) offers two main advantages. First, the Modifiable Area Unit Problem (MAUP) can be avoided, because the cluster identification by Brenner (2017) is free of predefined borders. Contrary to other approaches, the unit of analysis are individual actors and their exact geographical location. Consequently, the applied cluster identification does not depend on the regional level. Second, by using a distance decay function based on travel times[122] to consider the geographical distance to all other firms of the same industry as a weight to the final cluster index, a possible overvaluation of one very large company can be avoided (Brenner, 2017; Scholl and Brenner, 2016). Apart from the geographical distance, the cluster index used here additionally considers employment in absolute and relative terms. Thus, it accounts explicitly for geographical proximity, regional concentration and specialization being the most central elements of cluster definitions (Grashof and Fornahl, 2020). Following the procedure of the European Cluster Observatory, a value of 2 is employed as the corresponding cluster threshold, indicating whether a firm is located in a cluster or not (European Cluster Observatory, 2018; European Commission, 2008). Since the applied cluster index captures the geographical distance as well as the spatial concentration on the firm-level, it is additionally useful for identifying the firm´s position within a cluster. High values of the actor-based cluster index illustrate thereby that firms are located in the centre of a cluster, whereas low values indicate that they are far away from clusters (Brenner, 2017). Based on the cluster index of all companies located in clusters, the above median[123], representing a value of 2.86, is calculated in order to create a dummy variable for the firm´s centrality within the corresponding cluster.

Further control variables have additionally been included to account for other factors that might influence firm innovative performance in clusters. To control for firm-specific influences, firm age (years since foundation), firm size (measured by the average number of employees between 2008 and 2013) as well as the company structure (dummy variable illustrating whether firms are independent and do not belong to a corporate structure) are added. Moreover, at the cluster-level, based on the number of unemployed workers on the community level ("Gemeindeebene"), the

[122] In line with the literature, 45 minutes are seen here as an adequate limit for close geographical distance (Brenner, 2017; Scholl and Brenner, 2016).

[123] The median value has been chosen rather arbitrarily. However, other frequently applied thresholds, such as the mean and the 75$^{th}$ quantile, have also been tested. The corresponding results thereby remain quite robust and can be provided upon request.

aggregated unemployment in each cluster is computed for the year 2013. By employing the German research directory ("Research Explorer"), containing comprehensive information on over 25,000 university and non-university research institutes in Germany, the number of research institutes within each cluster is additionally calculated (Research Explorer, 2018). Lastly, to control for further industry-specific influences, a dummy variable is included capturing the research-intensity of industries, as it is assumed that particularly research-intensive industries tend to create innovations, especially radical innovations (Grashof et al., 2019; Tödtling et al., 2006).

Due to data protection regulations[124], all external data sources (e.g. cluster index and patent data) could however not be directly matched with the main database provided by the Stifterverband.[125] Instead as an intermediate step, all external data sources had to be matched with the AMADEUS[126] database offered by Bureau van Djik (BvD). Therefore, four different matching algorithms (Token, N-Gram, Soundex and Token-Soundex) were applied, each providing a similarity score between two strings (in this case company names). By using four different matching algorithms, potential weaknesses of each single algorithm can be offset, thereby improving the overall matching quality (Raffo, 2017; Raffo and Lhuillery, 2009). Additionally, the derived name couples of all four matching algorithms were also checked manually by the author to further ensure the quality of the matches. With the unique firm identifier (BvD ID), included in both datasets, the final merged data set could then be achieved.

This unique firm-level database, combining several data sources, finally consists of 11,500 firms in Germany, of which 1,396 firms are located within a cluster. In line with previous contributions (e.g. Beaudry and Breschi, 2003; Rigby and Brown, 2015) and in order to reduce a potential measurement error bias created by year-to-year variability being ubiquitous in micro-level data (Rigby and Brown, 2015; Stern, 2010), the average values of the dependent as well as independent variables are used in an OLS regression. The OLS regression of the across panels´ averages is thereby actually the same as the between estimator, which is particularly useful to determine the effect of x when x changes between companies (Cameron and

[124] For further information on this issue please review the terms of use available under https://www.stifterverband.org/fdz.

[125] This is, however, a rather typical problem when using individual firm data (e.g. Mairesse and Mohnen, 2010).

[126] Indeed, a combination between AMADEUS and ORBIS databases is used in order to cover preferably all listed firms in Germany.

Trivedi, 2005; Gould, 2019). By averaging each observation i over t = 1,…T, the following equation can be obtained (Cameron and Trivedi, 2005):

$$\bar{y}_i = \alpha + \beta\bar{x}_i + (\alpha_i - \alpha + \bar{\varepsilon}_i) \quad (3.)$$

Where $\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}$, $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{it}$ and $\bar{\varepsilon}_i = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_{it}$.

In view of the hierarchical nature of the final database, an OLS regression with cluster correction of the standard errors is conducted. This methodical approach is more adequate in this context than a standard OLS regression, whose standard errors would be underestimated due to the given nested data structure (McNeish, 2014; Moulton, 1990). A multilevel regression would be another reasonable option (Cheah, 2009; Rabe-Hesketh and Skrondal, 2012). However, Likelihood-ratio tests indicated no significant statistical improvements compared with an OLS regression with cluster correction. Thus, it can be stated that the selected methodical approach is adequate to answer the underlying research question of this paper.

## 4. Empirical results and discussion

The descriptive statistics for all main variables of the cluster sample are presented in table 1. The observations for four variables are much lower than for the rest of the variables. This can be explained by the limited data availability for these four variables in the representative extended database from 2013 provided by the Stifterverband (Schneider and Eckl, 2016). Despite the unavoidable lower number of observations, the corresponding analyses are appropriate[127], especially in light of missing alternative datasets.

By further examining the correlations between the independent variables, some cases could be identified which might potentially suffer from multicollinearity.[128] Therefore, the Variance Inflation Factor is estimated for each model. However, the results indicate that indeed in no case any of the Variance Inflation Factors come close or even exceed the standard critical value of 10 (Belsley, 1991; Myers, 1990; Stevens, 2002). Consequently, it can be stated that multicollinearity is not a

[127] The corresponding empirical models in table 3 exceed the minimum number of observations (between 10 and 20 observations per covariate) suggested by Harrell (2001).

[128] The corresponding pairwise correlation matrix for all independent variables of the cluster sample is presented in table 5 in the appendix.

significant concern in this study.[129]

**Table 1:** Descriptive statistics of all main variables

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Innovativeness | 1396 | 8.256 | 14.490 | 0 | 100 |
| Age | 1373 | 45.600 | 41.632 | 0 | 355 |
| Independence dummy | 1396 | 0.035 | 0.184 | 0 | 1 |
| Human resource capabilities | 1389 | 0.665 | 0.113 | 0.106 | 1 |
| Gender diversity | 1396 | 0.397 | 0.171 | 0 | 1 |
| Centre position in cluster | 1396 | 0.500 | 0.500 | 0 | 1 |
| Human capital exchange intensity | 166 | 0.171 | 0.971 | 0 | 11.538 |
| Firm size | 1396 | 1297.389 | 15562.18 | 0 | 460388 |
| Degree of overlap | 208 | 0.820 | 0.296 | 0 | 1 |
| Stock of alliances within cluster | 1391 | 0.064 | 0.186 | 0 | 4.658 |
| Diversity of the labour pool within cluster | 1396 | 0.397 | 0.103 | 0 | 1 |
| Stock of human resources of the cluster | 1396 | 159.980 | 1101.207 | 1.375 | 38728.05 |
| Matching capacities of labour pool within cluster | 206 | 0.209 | 0.226 | 0 | 1 |
| Quality of labour pool within cluster | 149 | 14.022 | 11.330 | 0 | 50 |
| Unemployment in cluster | 1386 | 1373.387 | 2681.416 | 4 | 31288.57 |
| No. Research institutes | 1396 | 4.580 | 14.721 | 0 | 85 |
| Pace of tech. evolution | 1396 | 1.723 | 2.683 | 0 | 18.399 |
| Pace of market evolution | 1295 | 1.010 | 0.043 | 0.626 | 1.190 |
| Market risk | 1295 | 1.801 | 2.854 | 0 | 20.793 |
| Research-intensive industry | 1396 | 0.452 | 0.498 | 0 | 1 |

Moreover, in the context of empirical studies dealing with clusters, one frequently stressed concern is the existence of a selection bias, meaning that especially above-average innovative companies are located within clusters. Nevertheless, following the argumentation by McCann and Folta (2011), such a positive selection effect cannot be theoretically nor empirically justified. For example, Shaver and Flyer (2000) present evidence for an adverse selection, indicating that due to knowledge spillovers, benefiting more rather weak innovative companies than the strong ones, very innovative companies have high incentives to avoid co-location in clusters. Furthermore, for the main empirical analysis, concentrating on explaining the

[129] Nevertheless, in some models certain independent variables are excluded in order to prevent any kind of multicollinearity, thereby further increasing the stability of the model estimates of the coefficients in the end.

heterogeneity within clusters in terms of firm innovative performance, such a bias is argued to be rather irrelevant.[130]

Before starting with the main analysis, based on the full sample and by using an OLS regression with robust standard errors, it is checked whether a cluster effect on firm innovativeness can really be found. In line with previous empirical findings (e.g. Baptista and Swann, 1998; Bell, 2005; Grashof, 2018), the corresponding results indeed show that being located in a cluster has a significant positive influence on firm innovativeness.[131] Nevertheless, it is assumed here that this positive influence of clusters is not equally distributed among firms. In accordance with Hervas-Oliver et al. (2018), the subsample of clustered firms is therefore analysed in order to identify the specific conditions under which firms can gain from the cluster environment, in particular from the specialized labour pool (see table 2 and table 3). Table 2 tests some of the main formulated hypotheses. Model 1 represents the baseline model. Except for firm age, being only significant in the baseline model, all other control variables remain the same throughout all models. In model 2, human resource capabilities, gender diversity and the centre position in the cluster core are additionally added. As assumed, for all three firm-specific variables, a significant positive effect on firm innovativeness in clusters can be asserted. This means that firms need to own sufficient human resource capabilities in order to identify, acquire and train the best talents from the specialized labour pool within clusters. Moreover, the results also provide evidence for a stimulating influence from gender diversity within the firm´s stock of R&D employees, which can be seen as a fountain for new diverse ideas and capabilities. Furthermore, due to a potentially higher visibility and status gains, the location in the core of the cluster also significantly fosters firm innovative performance. In model 3, two supplementary cluster-level variables are included. Regarding the stock of human resources of the cluster a small, however, very significant impact can be determined, indicating that the higher supply of specialized labour in clusters makes the matching and search processes of firms more efficient. Therefore, empirical evidence is provided for the principal rationale of the economies of agglomeration (e.g. Arthur, 1990). Similarly, for the diversity of the labour pool within clusters, a positive influence on firm innovative performance can likewise be detected. Thus, the gender diversity is not only on the firm-level an influential contextual variable, but also on the cluster-level.

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[130] As shown by the standard deviation in table 1 as well as in figure 1 in the appendix, the innovative performance of firms located in clusters is indeed characterised by relatively high differences.

[131] The results are presented in table 6 in the appendix.

**Table 2:** OLS regression with clustered standard errors of single cross-section average over time (sample with cluster companies)

| ***Innovativeness (sample with cluster companies)*** | *Model 1 n = 1.363* | *Model 2 n = 1.356* | *Model 3 n = 1.356* | *Model 4 n = 1.262* | *Model 5 n = 1.262* |
|---|---|---|---|---|---|
| **Firm-level variables** | | | | | |
| Gender diversity | | 10.949*** (2.869) | | | |
| Human resource capabilities | | 11.084** (4.384) | 11.152** (4.347) | 10.330** (4.709) | 10.172** (4.743) |
| Centre position in cluster | | 1.917** (0.872) | 1.942** (0.861) | 1.455* (0.850) | 1.537* (0.846) |
| **Cluster-level variables** | | | | | |
| Stock of human resources of the cluster | | | 0.001*** (0.000) | 0.002*** (0.000) | 0.002*** (0.000) |
| Diversity of the labour pool within cluster | | | 8.894** (4.325) | 8.966** (4.094) | 9.809** (4.075) |
| **Market-/Industry-level variables** | | | | | |
| Pace of technology evolution | | | | 0.547*** (0.206) | 5.558** (2.178) |
| Pace of market evolution | | | | -1.037 (8.337) | 8.435 (7.604) |
| Market risk | | | | | -4.830** (2.045) |
| **Control variables** | | | | | |
| Age | 0.015* (0.009) | 0.006 (0.008) | 0.014 (0.008) | 0.007 (0.008) | 0.007 (0.008) |
| Independence dummy | -1.552 (1.724) | -1.832 (1.769) | -1.613 (1.687) | -0.901 (1.590) | -1.067 (1.537) |
| Number of research institutes in cluster | -0.002 (0.023) | -0.007 (0.023) | -0.004 (0.023) | -0.013 (0.023) | -0.017 (0.024) |
| Unemployment in cluster | -0.000 (0.000) | -0.000 (0.000) | -0.000 (0.000) | -0.000 (0.000) | -0.000 (0.000) |
| Research-intensive industry dummy | 3.084*** (0.906) | 3.428*** (0.854) | 3.285*** (0.877) | | |
| Firm size | 0.000* (0.000) | 0.000* (0.000) | | | |
| *Constant* | *6.236**** | *-6.065** | *-5.755** | *-3.396* | *-13.478* |
| $R^2$ | *0.0237* | *0.0491* | *0.0411* | *0.0420* | *0.0468* |

*Clustered standard errors in parentheses.*
*Significance level: * p < 0.10, ** p < 0.05, *** p < 0.01*

Model 4 introduces the pace of technology and market evolution. Contrary to hypothesis 3a, the pace of technology evolution asserts a significant positive impact on firm innovative performance in clusters. Hence, evidence is found that under a rapid technology evolution, firms rather promote product innovations in order to potentially avoid an erosion of their existing competitive advantage. The fast-changing technology developments offer in this context a relatively high opportunity of creating these new product innovations, as existing value chains are reshaped

(Zhou et al., 2005). Regarding the pace of market evolution, however, no significant influence on firm innovativeness in clusters can be ascertained, so that hypothesis 3b cannot be confirmed. In model 5, the market risk, being an interaction term between both paces, is additionally analysed. As assumed, the market risk asserts a negative impact on firm innovativeness, meaning that a high market risk significantly reduces the innovativeness of clustered firms. One plausible explanation here for is that the human resource decisions, frequently containing large sunk costs (Ernst and Viegelahn, 2014; Schaal, 2017), are likely to be postponed, which in turn decreases potential gains derived from the specialized labour pool in clusters.

In light of the unavoidable smaller number of observations related with the extended Stifterverband survey from 2013, the corresponding results are presented separately in table 3.[132] Model 6 in table 3 shows the results for the degree of overlap between the overall labour qualifications within the clusters and the labour qualifications of the corresponding firms. In accordance with hypothesis 1c, evidence is found that a high degree of overlap between both labour qualification profiles significantly increases firm innovative performance.[133] Hence, for firms it is beneficial to possess a human resource stock with similar skills compared to the overall cluster. Moreover, model 7 contains the human capital exchange intensity. The corresponding results suggest a positive, however, insignificant impact of the human capital exchange intensity on firm innovativeness in clusters. Hypothesis 1d can therefore not be confirmed. In model 8, the influence of the matching capacities of the labour pool within clusters is additionally analysed. It can be shown in this context that the matching capacities of the labour pool have a significant positive effect on firm innovativeness.[134] In other words, clusters with a relatively well functioning labour pool, in terms of matching labour supply and demand, offer a more beneficial environment for firm innovative performance than clusters with a rather poorly functioning labour pool. Hypothesis 2d can therefore be confirmed. The last model of table 3 investigates the relationship between firm innovativeness in clusters and the quality of the labour pool within clusters. Contrary to hypothesis 2c, the quality of the labour pool within clusters has

[132] The results have been verified by using single year values for the dependent variable (from 2013 or 2015) as well as short-term averages (from 2011 to 2013). The corresponding results can be provided upon request.
[133] The existence of a potential inverted u-shaped pattern has also been tested. However, no evidence is found for such a pattern.
[134] The coefficient becomes even more significant ($p = 0.034$), when it is only analysed together with the control variables. The corresponding results can be provided upon request.

a significant negative influence on firm innovativeness in clusters.[135] Being located in a cluster with a relatively high share of scientific R&D employees with a PhD or a habilitation is therefore rather inhibitory to firm innovativeness compared with lower degrees such as a Master or Bachelor. Therefore, evidence is provided that the role of scientific degrees should not be overemphasized as in general clusters with lower university degrees offer a more conducive context for firm innovativeness. In light of previous studies (e.g. Vinding, 2006), the results are at first sight quite surprising.

**Table 3:** OLS regression with clustered standard errors of single cross-section average over time (sample with cluster companies based on the extended survey focussing on HR)

| ***Innovativeness (sample with cluster companies)*** | *Model 6 n = 205* | *Model 7 n = 163* | *Model 8 n = 162* | *Model 9 n = 121* |
|---|---|---|---|---|
| **Firm-level variables** | | | | |
| Degree of overlap | 15.879*** (4.092) | 17.360*** (4.384) | | |
| Human capital exchange intensity | | 3.745 (3.311) | 3.542 (3.260) | 3.895 (3.441) |
| **Cluster-level variables** | | | | |
| Matching capacities of labour pool within cluster | | | 10.501* (6.226) | |
| Quality of labour pool within cluster | | | | -0.241* (0.139) |
| **Control variables** | | | | |
| Age | -0.035 (0.028) | -0.055* (0.029) | -0.070** (0.031) | -0.066** (0.032) |
| Independence dummy | -8.840** (3.837) | -8.022** (4.035) | -11.559*** (4.119) | -8.775* (4.967) |
| Number of research institutes in cluster | -0.016 (0.094) | -0.042 (0.096) | -0.066 (0.097) | -0.047 (0.103) |
| Unemployment in cluster | -0.001** (0.000) | -0.001*** (0.000) | -0.001** (0.000) | -0.001** (0.000) |
| Research-intensive industry dummy | 7.418** (2.839) | 6.674** (3.155) | 5.256** (3.075) | 4.916 (3.385) |
| *Constant* | *10.876*** | *11.458*** | *25.232**** | *30.201**** |
| $R^2$ | *0.1021* | *0.1282* | *0.0896* | *0.1073* |
| *Clustered standard errors in parentheses. Significance level: * p < 0.10, ** p < 0.05, *** p < 0.01* | | | | |

But, by analysing the specific operationalization of other variables used in this context, it becomes obvious that most studies group all university degrees as being

[135] Similar to the matching capacities, the significance of the coefficient of the quality of the labour pool within clusters even increases (p = 0.047) when it is only examined together with the control variables. The corresponding results can be provided upon request.

the highest qualification level (López-Bazo and Motellón, 2018; Pfeifer and Wagner, 2014; Vinding, 2006). By comparing this rather large group with other groups, such as those having a high-school diploma, these studies come to the conclusion that a high share of qualified employees asserts a significant positive impact on firm innovativeness. However, in view of an increasing qualification trend in Germany (Baethge and Wolter, 2015), resulting in more and more university graduates, and the underlying focus on R&D-active firms, this study takes a different approach, separating between the various university degrees (e.g. Bachelor, Master as well as PhD and habilitation).

Apart from the direct effects of the firm-level, cluster-level and industry-level variables, it is assumed that there exist potential interaction effects between the three levels of analysis. Consequently, several interaction effects have additionally been investigated. The most interesting results are presented in table 4. In line with Lee et al. (2001), the corresponding interaction terms are added one by one in order to prevent multicollinearity problems. Model 10 tests whether the stock of human resources of the cluster moderates the effect of firm's human resource capabilities. The underlying assumption is that in clusters with a large labour pool, it is not necessary for firms to strengthen their human resource capabilities, as it is easier for them to find and acquire the right candidate due to the higher supply of specialized labour. As indicated by the corresponding significant negative interaction term, evidence is indeed found that high human resource capabilities are not beneficial in clusters with a large labour pool. Instead, companies should rather increase their R&D expenditures in other areas, such as R&D material resources, in order to avoid an inefficient distribution of their limited resources towards high human resource capabilities. Furthermore, in model 11 it is tested whether the effect of human resource capabilities on firm innovativeness differs between the centre and the periphery positions in clusters. It is reasonable to assume that due to a lower visibility especially in the periphery of a cluster, human resource capabilities are required to find and acquire the most adequate talents. The corresponding empirical results indeed show a negative, however, insignificant interaction effect between the human resource capabilities and the centre position in clusters. Consequently, no statistically significant differences can be found in this context.

Nevertheless, by investigating the interaction effect between the stock of human resources of the cluster and the position in clusters, statistically significant results can be determined. The results, presented in model 12, indicate that particularly companies located in the core of the cluster can gain from a large stock of human resources of the cluster.

**Table 4:** OLS regression with clustered standard errors of single cross-section average over time for interaction effects (sample with cluster companies)

| ***Innovativeness (sample with cluster companies)*** | *Model 10 n = 1.356* | *Model 11 n = 1.356* | *Model 12 n = 1.356* | *Model 13 n = 163* | *Model 14 n = 146* |
|---|---|---|---|---|---|
| **Firm-level variables** | | | | | |
| Human resource capabilities | 12.291*** (4.402) | 15.856*** (5.679) | 11.468*** (4.368) | | -29.577 (27.850) |
| Gender diversity | | 10.902*** (2.856) | 9.951*** (2.898) | | |
| Centre position in cluster | | 8.250 (5.532) | 1.513* (0.894) | -0.930 (5.532) | -1.170 (3.713) |
| Human capital exchange intensity | | | | -15.318 (6.309) | |
| **Cluster-level variables** | | | | | |
| Stock of human resources of the cluster | 0.008*** (0.001) | | -0.001 (0.001) | | |
| Diversity of the labour pool within cluster | 11.098** (4.327) | | | | |
| Quality of labour pool within cluster | | | | | -1.668** (0.754) |
| **Interaction terms** | | | | | |
| Stock of human resources of the cluster x Human resource capabilities | -0.014*** (0.003) | | | | |
| Human resource capabilities x Centre | | -9.713 (8.327) | | | |
| Stock of human resources of the cluster x Centre | | | 0.003*** (0.001) | | |
| Human capital exchange x Centre | | | | 21.988*** (7.328) | |
| Quality of labour pool within cluster x Human resource capabilities | | | | | 2.189** (1.088) |
| **Control variables** | | | | | |
| Age | 0.014 (0.009) | 0.005 (0.008) | 0.004 (0.009) | -0.063** (0.030) | -0.060* (0.032) |
| Independence dummy | -1.634 (1.684) | -1.737 (1.775) | -1.604 (1.691) | -9.556 (5.748) | -6.949 (5.866) |
| Firm size | | 0.000* (0.000) | | -0.000 (0.000) | 0.000 (0.000) |
| Number of research institutes in cluster | -0.007 (0.024) | -0.008 (0.024) | -0.006 (0.025) | -0.058 (0.096) | -0.010 (0.105) |
| Unemployment in cluster | -0.000 (0.000) | -0.000 (0.000) | -0.000 (0.000) | -0.001*** (0.000) | -0.000 (0.000) |
| Research-intensive industry dummy | 3.637*** (0.900) | 3.473*** (0.844) | | 4.292 (3.059) | 7.297** (2.931) |
| *Constant* | *-6.250** | *-9.232*** | *-4.030* | *28.522**** | *47.019*** |
| $R^2$ | *0.0417* | *0.0503* | *0.0424* | *0.0984* | *0.1050* |

*Clustered standard errors in parentheses.*
*Significance level: * p < 0.10, ** p < 0.05, *** p < 0.01*

One plausible explanation here for is that central companies located in the cluster core can, due to their higher visibility, attract much easier the most talented candidates from the large labour pool compared with companies located in the periphery of a cluster. The thirteenth model tests the potential interaction effect of the human capital exchange and the centre position in the cluster core. Evidence is found for a significant positive interaction effect on firm innovativeness in clusters, meaning that especially in the centre of a cluster, firms need to have a sufficiently large human capital exchange intensity. Since these central firms possess a more intensive internal connection (Grashof, 2018), such a sufficiently large human capital exchange intensity seems to be necessary to avoid a potential lock-in situation. Similar to the results of Boschma et al. (2009), focussing on labour mobility and plant performance, it can hence be asserted that the human capital exchange per se does not have a significant influence on firm innovativeness, but it rather depends on the concrete circumstances whether such an exchange is beneficial for firm innovativeness.[136]

The last model of table 4 investigates a potential interaction effect between the quality of the labour pool within clusters and the human resource capabilities of a firm. The results show that the corresponding interaction term has a significant positive influence on firm innovative performance in clusters. Thus, it can be argued that, while in general asserting a negative effect, when owning sufficiently high human resource capabilities, firms can indeed benefit from a high quality of the labour pool within clusters, as they are capable of fully exploiting such an environment.

## 5. Conclusion

All in all, the results indicate that, on the one hand, in accordance with Baptista and Swann (1998), being located in a cluster increases on average firm innovativeness. But on the other hand, companies located in regional clusters do not gain equally and in the same manner from the specialized labour pool in clusters. Instead there exist several conditions, from different levels of analysis, that are necessary to profit from the specialized labour pool.

On the firm-level, it has been shown that particularly the gender diversity, human resource capabilities, the centre position in the cluster core as well as the degree of

[136] Boschma et al. (2009) suggested considering the types of skills that flow into a plant and/or company in this context. Due to data constraints this has not been possible with the applied database. However, future studies may further concentrate on this issue.

overlap between the labour qualifications within the cluster and the labour qualifications of the firms are significant determinants of firm innovative performance in clusters. For managers it is therefore essential to consider these four firm-specific variables so that they can evaluate and adapt better their current situation in order to realize the potential advantages of the specialized labour pool in clusters. In addition, they should also take possible interaction effects into account. For example, even though the human capital exchange intensity by itself asserts no significant impact, it does in the case of a centre position in clusters. For companies located in the cluster core, it is thus beneficial to possess a relatively high human capital exchange intensity in order to avoid a possible lock-in situation, which is more likely in the cluster core due to its pronounced internal linkages (Grashof, 2018).

Although not directly influenced by companies, the cluster-level should also be taken into account. Despite the direct positive effect of the stock of human resources of the cluster, the diversity of the labour pool within clusters and the matching capacities of the labour pool within clusters as well as the direct negative effect of the quality of the labour pool within clusters, they also interact with firm-specific variables. For example, in clusters with a large labour pool, it is suggested that it is not efficient for firms to strengthen their human resource capabilities, as it is easier for them to acquire the right candidates due to the relatively high supply of specialized labour. Moreover, evidence is found that especially companies located in the centre of the cluster can gain from such a large labour pool due to their higher visibility, easing the attraction of the most talented candidates. Additionally, firms particularly need to have sufficiently large human resource capabilities in a high quality labour pool in order to be capable of exploiting the existing opportunities of such a high quality labour pool in clusters.

Lastly, variables from the market-/industry-level have also been shown to be relevant determinants of firm innovative performance in clusters. Surprisingly, the pace of technology evolution, with its increasing technological pressure to innovate and its extensive opportunities for innovations, creates a promoting context for firm innovativeness in clusters. Nevertheless, in a situation characterized by a rapid technology and market evolution, the innovativeness of firms is inhibited. Such a high market risk is argued to delay or even reject human resource decisions, decreasing in turn the potential gains from the specialized labour pool in clusters.

For policy makers it also seems to be important to take the derived results into account so that the recent criticism about the one-size-fits-all orientation of most cluster policies, focussing primarily on collaborative incentives, can be effectively addressed (Uyarra and Ramlogan, 2017; Tödtling and Trippl, 2005; Vicente, 2014). As proposed by Auer and Tödtling (2017), cluster policies should rather focus on the concrete conditions and needs within clusters in order to improve the efficiency of such measures. In this context, the results of this paper can serve as a first profound guideline for the identification of potential problems and needs that policy can concretely target so that more companies can gain from the specific cluster environment, which in turn increases the overall performance within clusters due to interrelations and knowledge spillovers (McCann and Folta, 2008; Shaver and Flyer, 2000).

In spite of these interesting and extensive results, there exist, however, some limitations to this study. Due to data constraints[137], especially regarding the calculation of the cluster index for several years, the study applied an OLS regression with clustered standard errors to a single cross-section of variables average over time (between estimator). Historically, such an approach has been criticized due to a concern that omitted variables, represented by the individual effects, may be correlated with the independent variables. In other words, this would mean that there exists a correlation between the error term and the explanatory variables that leads to inconsistent estimates. However, such a potential bias also holds true for other approaches.[138] Additionally, such a bias constitutes only one of several possible misspecifications of such models (Baltagi, 2005; Hauk Jr. and Wacziarg, 2009; Mairesse and Sassenou, 1991; Stern, 2010). In light of the underlying research question focusing more on the between-variation as well as the available data, it is thus argued that the chosen methodical approach is appropriate despite its limitations in contrast to panel-regressions (Griliches and Mairesse, 1984; Hauk Jr. and Wacziarg, 2009; Kafouros, 2008).[139] Nonetheless, for future studies it may be promising to fully exploit panel-data so that dynamic effects can also be investigated. This holds particularly true for the dynamic evolution across the cluster life cycle (e.g. Menzel and Fornahl, 2010) and potential impacts on the sustainability of firm innovative performance in clusters. Since detailed information about the employees (e.g. from which company they come) is missing within the used

[137] A regression on a balanced panel data set would result in a significant loss of observations, as the underlying questions of the dependent as well as independent variables are only inconsistently answered over the years (50% of the firms respond only four times during the period under investigation). For further information on this issue, see also Mairesse and Mohnen (2010).

[138] The results of the omitted variable tests performed here, however, indicate that such a bias is not a mayor concern in this study.

[139] It is indeed very common for empirical studies using innovation surveys to predominantly exploit cross-sectional data, instead of panel-data (Mairesse and Mohnen, 2010).

database, for subsequent studies it may also be interesting to utilize a linked employer-employee dataset (e.g. provided by the IAB in Germany[140]) with which questions related to the labour movements within regional clusters can be addressed specifically. Additionally, the empirical setting of this study is limited to Germany, eliminating the risk of unobserved effects by country-specific differences in the corresponding institutational environments (López-Bazo and Motellón, 2018). Nevertheless, future research may expand the analysis by taking countries from diverse economic development levels into account so that potential country-specific effects can also be investigated.

However, despite these limitations, it can be resumed that the empirical results contribute to closing a still ubiquitous research gap regarding firm performance differentials in clusters. Contrary to the prevalent assumption of equal gains within clusters, it can be shown that depending on multilevel conditions and their interplay, firms profit differently from the specialized labour pool in clusters. Furthermore, the findings provide a practical value especially for managers as well as policy makers, because they can better evaluate under which conditions it is more likely to realize the potential advantages of the specialized labour pool in clusters and where more efforts have to be invested in order to improve the present situation.

[140] For further information on this dataset please review the corresponding IAB website available under https://fdz.iab.de/en/Integrated_Establishment_and_Individual_Data/LIAB.aspx.

## Bibliography


Almazan, A., De Motta, A., & Titman, S. (2007): Firm Location and the Creation and Utilization of Human Capital, *The Review of Economic Studies*, Vol. 74, No. 4, pp. 1305-1327.

Almeida, P., & Kogut, B. (1999): Localization of Knowledge and the Mobility of Engineers in Regional Networks, *Management Science*, Vol. 45, Issue 7, pp. 905-1024.

Amend, E., & Herbst, P. (2008): Labor market pooling and human capital investment decisions, *IAB Discussion Paper*, No. 4/2008.

Arthur, W. B. (1990): 'Silicon Valley' locational clusters: when do increasing returns imply monopoly?, *Mathematical Social Sciences*, Vol. 19, Issue 3, pp. 235-251.

Audretsch, D. B., & Feldman, M. P. (1996): Innovative Clusters and the Industry Life Cycle, *Review of Industrial Organization*, Vol. 11, Issue 2, pp. 253-273.

Auer, A., & Tödtling, F. (2017): Are policies supporting cluster development? A comparative firm-level analysis, in: Fornahl, D., & Hassink, R. (Eds.): The Life Cycle of Clusters - A Policy Perspective, Edward Elgar Publishing, Cheltenham, UK, pp. 203-221.

Baethge, M., & Wolter, A. (2015): The German skill formation model in transition: from dual system of VET to higher education?, *Journal for Labour Market Research*, Vol. 48, Issue 2, pp. 97-112.

Balland, P.-A., Belso-Martínez, J. A., & Morrison, A. (2016): The Dynamics of Technical and Business Knowledge Networks in Industrial Clusters: Embeddedness, Status, or Proximity?, *Economic Geography*, Vol. 92, Issue 1, pp. 35-60.

Baltagi, B. H. (2005): Econometric Analysis of Panel Data, John Wiley & Sons Ltd, West Sussex, England.

Baptista, R., & Swann, P. (1998): Do firms in cluster innovate more?, *Research Policy*, Vol. 27, Issue 5, pp. 525-540.

Barney, J. B. (1991): Firm Resources and Sustained Competitive Advantage, *Journal of Management*, Vol. 17, No. 1, pp. 99-120.

Barney, J. B., & Wright, P. M. (1998): On becoming a strategic partner: The role of human resources in gaining competitive advantage, *Human Resource Management*, Vol. 37, Issue 1, pp. 31-46.

Beaudry, C., & Breschi, S. (2003): Are firms in clusters really more innovative?, *Economics of Innovation and New Technology*, Vol. 12, No. 4, pp. 325-342.

Bell, G. G. (2005): Clusters, networks, and firm innovativeness, *Strategic Management Journal*, Vol. 26, Issue 3, pp. 287-295.

Belsley, D. A. (1991): Conditioning Diagnostics: Collinearity and Weak Data in Regression, Wiley, New York.

Beugelsdijk, S. (2007): The Regional Environment and a Firm's Innovative Performance: A Plea for a Multilevel Interactionist Approach, *Economic Geography*, Vol. 83, Issue 2, pp. 181-199.

Bienkowska, D., Lundmark, M., & Malmberg, A. (2011): Brain circulation and flexible adjustment: labour mobility as a cluster advantage, G*eografiska Annaler: Series B, Human Geography*, Vol. 93, Issue 1, pp. 21-39.

Bornay-Barrachina, M., López-Cabrales, A., & Valle-Cabrera, R. (2017): How do employment relationships enhance firm innovation? The role of human and social capital, *International Journal of Human Resource Management*, Vol. 28, No. 9, pp. 1363-1391.

Boschma, R., Eriksson, R., & Lindgren, U. (2009): How does labour mobility affect the performance of plants? The importance of relatedness and geographical proximity, *Journal of Economic Geography*, Vol. 9, Issue 2, pp. 169-190.

Bossler, M., Dietrich, H., Gartner, H., Hummel, M., Klinger, S., Kubis, A., Weber, E., & Wolter, S. (2017): Zur Lage und Entwicklung auf dem Arbeitsmarkt in Deutschland, IAB Stellungnahme, 4/2017, ISSN: 2195-5980.

Brenner, T. (2017): Identification of Clusters – An Actor-based Approach, *Working Papers on Innovation and Space*, No. 02.17.

Brown, K., Burgees, J., Festing, M., Royer, S., & Steffen, C. (2007): The Value Adding Web – A Conceptual Framework of Competitive Advantage Realisation in Clusters, *ESCP-EAP Working Paper*, No. 27, ISSN: 1619-7658.

Cabello-Medina, C., López-Cabrales, Á., & Valle-Cabrera, R. (2011): Leveraging the innovative performance of human capital through HRM and social capital in Spanish firms, *International Journal of Human Resource Management*, Vol. 22, Issue 4, pp. 807-828.

Cable, D. M., & Turban, D. B. (2003): The Value of Organizational Reputation in the Recruitment Context: A Brand-Equity Perspective, *Journal of Applied Social Psychology*, Vol. 33, Issue 11, pp. 2244-2266.

Cameron, A. C., & Trivedi, P. K. (2005): Microeconometrics - Methods and Applications, Cambridge University Press, NY, USA.

Cheah, B. C. (2009): Clustering Standard Errors or Modeling Multilevel Data?, available under: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.169.6644&rep=rep1&type=pdf, last retrieved: 09.01.2019.

Combes, P.-P., & Duranton, G. (2006): Labour pooling, labour poaching, and spatial clustering, *Regional Science and Urban Economics*, Vol. 36, Issue 1, pp. 1-28.

Cooper, A. C., & Schendel, D. (1976): Strategic Responses to Technological Threats, *Business Horizons*, Vol. 19, No. 1, pp. 61-69.

David, P. A., & Rosenbloom, J. L. (1990): Marshallian factor market externalities and the dynamics of industrial localization, *Journal of Urban Economics*, Vol. 28, No. 3, pp. 349-370.

De Saá-Pérez, P., & García-Falcón, M. (2002): A resource-based view of human resource management and organizational capabilities development, *International Journal of Human Resource Management*, Vol. 13, Issue 1, pp. 123-140.

Delgado, M. (2018): Firms in Context: Internal and External Drivers of Success, in: Clark, G. L., Feldman, M. P., Gertler, M. S., & Wójcik, D. (Eds.): The New Oxford Handbook of Economic Geography, Oxford University Press, pp. 324-346.

Delgado, M., Porter, M. E., & Stern, S. (2010): Clusters and entrepreneurship, *Journal of Economic Geography*, Vol. 10, Issue 4, pp. 495-518.

Drach-Zahavy, A., & Somech, A. (2001): Understanding Team Innovation: The Role of Team Processes and Structures, *Group Dynamics: Theory, Research, and Practice*, Vol. 5, No. 2, pp. 111-123.

Dreyer, B., & Grønhaug, K. (2004): Uncertainty, flexibility, and sustained competitive advantage, *Journal of Business Research*, Vol. 57, Issue 5, pp. 484-494.

Dwyer, S., Richard, O. C., & Chadwick, K. (2003): Gender diversity in management and firm performance: the influence of growth orientation and organizational culture, *Journal of Business Research*, Vol. 56, Issue 12, pp. 1009-1019.

Dyer, J. H., & Singh, H. (1998): The Relational View: Cooperative Strategy and Sources of Interorganizational Competitive Advantage, *The Academy of Management Review*, Vol. 23, No. 4, pp. 660-679.

Dziallas, M., & Blind, K. (2019): Innovation indicators throughout the innovation process: An extensive literature analysis, *Technovation*, Vol. 80-81, pp. 3-29.

Ellison, G., Glaeser, E. L., & Kerr, W. R. (2010): What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns, *American Economic Review*, Vol. 100, No. 3, pp. 1195-1213.

Engel, D., Rothgang, M., & Eckl, V. (2016): Systemic aspects of R&D policy subsidies for R&D collaborations and their effects on private R&D, *Industry and Innovation*, Vol. 23, Issue 2, pp. 206-222.

Erikson, R., & Lindgren, U. (2009): Localized mobility clusters: impacts of labour market externalities on firm performance, *Journal of Economic Geography*, Vol. 9, Issue 1, pp. 33-53.

Ernst, E., & Viegelahn, C. (2014): Hiring uncertainty: a new labour market indicator, ILO Working Paper, available under https://ssrn.com/abstract=2411299, last retrieved 07.04.2020.

European Cluster Observatory (2018): Methodology - Indicators, available under: http://www.clusterobservatory.eu/index.html#!view=aboutobservatory;url=/about-observatory/methodology/indicators/, last retrieved: 04.10.2018.

European Commission (2008): The concept of clusters and cluster policies and their role for competitiveness and innovation: Main statistical results and lessons learned, *Europe INNOVA / PRO INNO Europe paper*, No. 9.

Fang, Y., Jiang, G.-L. F., Makino, S., & Beamish, P. W. (2010): Multinational Firm Knowledge, Use of Expatriates, and Foreign Subsidiary Performance, *Journal of Management Studies*, Vol. 47, Issue 1, pp. 27-54.

Ferriani, S., & MacMillan, I. (2017): Performance gains and losses from network centrality in cluster located firms: a longitudinal study, *Innovation*, Vol. 19, Issue 3, pp. 307-334.

Filippetti, A., & Guy, F. (2016): Risk-taking, skill diversity, and the quality of human capital: how insurance affects innovation, *Papers in Evolutionary Economic Geography*, No. 16.25.

Folta, T. B., Cooper, A. C., & Baik, Y.-s. (2006): Geographic cluster size and firm performance, *Journal of Business Venturing*, Vol. 21, Issue 2, pp. 217-242.

Frenken, K., Cefis, E., & Stam, E. (2013): Industrial dynamics and clusters: a survey, Tjalling C. Koopmans Research Institute, Discussion Paper Series, No. 13-11, Utrecht School of Economics.

Garnero, A., Kampelmann, S., & Rycx, F. (2014): The Heterogeneous Effects of Workforce Diversity on Productivity, Wages, and Profits, *Industrial Relations*, Vol. 53, Issue 3, pp. 430-477.

Gould, W. (2019): Between estimators, available under: https://www.stata.com/support/faqs/statistics/between-estimator/, last retrieved: 09.01.2019.

Grant, R. M. (1996): Toward a knowledge-based theory of the firm, *Strategic Management Journal*, Vol. 17, Issue S2, pp. 109-122.

Grashof, N., & Fornahl, D. (2020): 'To be or not to be' located in a cluster? - A descriptive meta-analysis of the firm-specific cluster effect, *Working Papers on Innovation and Space*, No. 01.20.

Grashof, N. (2018): Spill over or Spill out? - A multilevel analysis of the cluster and firm performance relationship, Working Paper.

Grashof, N., Hesse, K., & Fornahl, D. (2019): Radical or not? The role of clusters in the emergence of radical innovations, *European Planning Studies*, Vol. 27, Issue 10, pp. 1904-1923.

Gray, M., & James, A. (2007): Connecting gender and economic competitiveness: lessons from Cambridge's high-tech regional economy, *Environment and Planning A*, Vol. 39, Issue 2, pp. 417-436.

Griliches, Z. (1990): Patent Statistics as Economic Indicators: A survey, *Journal of Economic Literature*, Vol. 28, No. 4, pp. 1661-1707.

Griliches, Z., & Mairesse, J. (1984): Productivity and R&D at the firm level, in: Griliches, Z. (Ed.): R&D, Patents and Productivity, University of Chicago Press, pp. 339-374.

Harrell, F. E. (2001): Regression Modeling Strategies: With Applications to Linear Models, Logistic Regression, and Survival Analysis, Springer-Verlag, New York.

Hatch, N. W., & Dyer, J. H. (2004): Human capital and learning as a source of sustainable competitive advantage, *Strategic Management Journal*, Vol. 25, Issue 12, pp. 1155-1178.

Harzing, A.-W., Pudelko, M., & B., S. R. (2016): The Bridging Role of Expatriates and Inpatriates in Knowledge Transfer in Multinational Corporations, *Human Resource Management*, Vol. 55, Issue 4, pp. 679-695.

Hauk Jr., W. R., & Wacziarg, R. (2009): A Monte Carlo study of growth regressions, *Journal of Economic Growth*, Vol. 14, Issue 2, pp. 103-147.

Haupt, R., Kloyer, M., & Lange, M. (2007): Patent indicators for the technology life cycle development, *Research Policy*, Vol. 36, Issue 3, pp. 387-398.

Hervas-Oliver, J. L., & Albors-Garrigos, J. (2007): Do clusters capabilities matter? An empirical application of the resource-based view in clusters, *Entrepreneurship & Regional Development*, Vol. 19, Issue 2, pp. 113-136.

Hervas-Oliver, J.-L., & Albors-Garrigos, J. (2009): The role of the firm’s internal and relational capabilities in clusters: when distance and embeddedness are not enough to explain innovation, *Journal of Economic Geography*, Vol. 9, Issue 2, pp. 263-283.

Hervas-Oliver, J.-L., Sempere-Ripoll, F., & Boronat-Moll, C. (2014): Process innovation strategy in SMEs, organizational innovation and performance: a misleading debate?, *Small Business Economics*, Vol. 43, Issue 4, pp. 873-886.

Hervas-Oliver, J.-L., Sempere-Ripoll, F., Alvarado, R. R., & Estelles-Miguel, S. (2018): Agglomerations and firm performance: who benefits and how much?, *Regional Studies*, Vol. 52, Issue 3, pp. 338-349.

Horbach, J., & Jacob, J. (2017): The relevance of personal characteristics and gender diversity for (eco) - innovation activities at the firm-level - Results from a linked employer-employee database in Germany, *IAB Discussion Paper*, No. 11/2017.

Huiban, J.-P., & Bouhsina, Z. (1998): Innovation and the Quality of Labour Factor: An empirical investigation in the French food industry, *Small Business Economics*, Vol. 10, Issue 4, pp. 389-400.

IAB (2017): IAB Stellenerhebung, available under: https://www.iab.de/de/befragungen/stellenangebot/aktuelle-ergebnisse.aspx, last retrieved: 23.11.2018.

Kabaila, P., Mainzer, R., & Farchione, D. (2015): The impact of a Hausman pretest, applied to panel data, on the coverage probability of confidence intervals, Working Paper, Cornell University.

Kafouros, M. I. (2008): Industrial Innovation and Firm Performance: The Impact of Scientific Knowledge on Multinational Corporations, Edward Elgar Publishing, Cheltenham, UK.

Kladroba, A., & Eckl, V. (2019): Diversity in den FuE-Abteilungen der Unternehmen: Empirische Evidenz und Ausblick, in: Hermeier, B., Heupel, T., & Fichtner-Rosada, S. (Eds.): Arbeitswelten der Zukunft, Springer Fachmedien, Wiesbaden, pp. 23-35.

Kleinknecht, A., Van Montfort, K., & Brouwer, E. (2002): The Non-Trivial Choice between Innovation Indicators, *Economics of Innovation and New Technology*, Vol. 11, Issue 2, pp. 109-121.

Klumbies, I. (2015): Cluster Location: Is this the Place to be? - An Investigation on the Influence of Cluster Affiliation on Firm Performance and Human Resources, Dissertation, Jacobs University, Bremen.

Knoben, J., Arikan, A. T., Van Oort, F., & Raspe, O. (2015): Agglomeration and firm performance: One firm's medicine is another firm's poison, *Environment and Planning A*, Vol. 48, No. 1, pp. 1-22.

Kohlbacher, M., Weitlaner, D., Hollosi, A., Grünwald, S., & Grahsl, H.-P. (2013): Innovation in clusters: effects of absorptive capacity and environmental moderators, *Competitiveness Review: An International Business Journal*, Vol. 23, Issue 3, pp. 199-217.

Krugman, P. (1991): Geography and trade, MIT Press, Cambridge, MA.

Lavie, D. (2006): The Competitive Advantage of Interconnected Firms: An Extension of the Resource-Based View, *The Academy of Management Review*, Vol. 31, No. 3, pp. 638-658.

Lee, C., Lee, K., & Pennings, J. M. (2001): Internal Capabilities, External Networks, and Performance: A Study on Technology-Based Ventures, *Strategic Management Journal*, Vol. 22, Issue 6-7, pp. 615-640.

Lepak, D. P., & Snell, S. A. (2002): Examining the Human Resource Architecture: The Relationships Among Human Capital, Employment, and Human Resource Configurations, *Journal of Management*, Vol. 28, Issue 4, pp. 517-543.

López-Bazo, E., & Motellón, E. (2018): Innovation, heterogeneous firms and the region: evidence from Spain, *Regional Studies*, Vol. 52, Issue 5, pp. 673-687.

Lorenzo, R., Voigt, N., Schetelig, K., Zawadzki, A., Welpe, I., & Brosi, P. (2017): The Mix That Matters - Innovation Through Diversity, Boston Consulting Group and Technical University of Munich (TUM).

Mairesse, J., & Mohnen, P. (2010): Using Innovation Surveys for Econometric Analysis, in: Hall, B. H., & Rosenberg, N. (Eds.): Handbook of the Economics of Innovation, Vol. 2, pp. 1129-1155.

Mairesse, J., & Sassenou, M. (1991): R&D Productivity: A Survey of Econometric

Studies at the Firm Level, *NBER Working Paper*, No. 3666.

Malmberg, A., & Maskell, P. (2002): The elusive concept of localization economies: towards a knowledge-based theory of spatial clustering, *Environment and Planning A*, Vol. 34, No. 3, pp. 429-449.

Marshall, A. (1920): Principles of economics, Macmillan, London, 8th Edition.

Martin, P., Mayer, T., & Mayneris, F. (2011): Public support to clusters: A firm level study of French “Local Productive Systems”, *Regional Science and Urban Economics*, Vol. 41, Issue 2, pp. 108-123.

Martin, R., & Sunley, P. (2003): Deconstructing clusters: chaotic concept or policy panacea?, *Journal of Economic Geography*, Vol. 3, Issue 1, pp. 5-35.

Martinez-Fernandez, C., & Weyman, T. (2012): THE CROSSROADS OF DEMOGRAPHIC CHANGE AND LOCAL DEVELOPMENT, in: Martinez-Fernandez, C., Kubo, N., Noya, A., & Weyman, T. (Eds.): Demographic Change and Local Development - Shrinkage, Regeneration and Social Dynamics, OECD Publishing, Paris, pp. 15-36.

McCann, B. T., & Folta, T. B. (2008): Location Matters: Where We Have Been and Where We Might Go in Agglomeration Research, *Journal of Management*, Vol. 34, No. 3, pp. 532-565.

McCann, B. T., & Folta, T. B. (2011): Performance differentials within geographic clusters, *Journal of Business Venturing*, Vol. 26, Issue 1, pp. 104-123.

McGahan, A. M., & Silverman, B. S. (2001): How does innovative activity change as industries mature?, *International Journal of Industrial Organization*, Vol. 19, Issue 7, pp. 1141-1160.

McGuirk, H., & Jordan, D. (2012): Local Labour Market Diversity and Business Innovation: Evidence from Irish Manufacturing, *European Planning Studies*, Vol. 20, Issue 12, pp. 1945-1960.

McNeish, D. M. (2014): Analyzing Clustered Data with OLS Regression: The Effect of a Hierarchical Data Structure, *Multiple Linear Regression Viewpoints*, Vol. 40, No. 1, pp. 11-16.

Menzel, M.-P., & Fornahl, D. (2010): Cluster life cycles—dimensions and rationales of cluster evolution, *Industrial and Corporate Change*, Vol, 19, Issue 1, pp. 205-238.

Molina-Morales, F. X., & Martínez-Fernández, M. T. (2004): How much difference is there between industrial district firms? A net value creation approach, *Research Policy*, Vol. 33, Issue 3, pp. 473-486.

Moulton, B. R. (1990): An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units, *The Review of Economics and Statistics*, Vol. 72, No. 2, pp. 334-338.

Myers, R. H. (1990): Classical and Modern Regression with Applications, PWS-Kent, Boston, 2nd edition.

Newbert, S. L. (2007): Empirical research on the resource-based view of the firm: an assessment and suggestions for future research, *Strategic Management Journal*, Vol. 28, Issue 2, pp. 121-146.

Oakey, R. P., & Cooper, S. Y. (1989): High Technology Industry, Agglomeration and the Potential for Peripherally Sited Small Firms, *Regional Studies*, Vol. 23, Issue 4, pp. 347-360.

Østergaard, C. R., Timmermans, B., & Kristinsson, K. (2011): Does a different view create something new? The effect of employee diversity on innovation, *Research Policy*, Vol. 40, Issue 3, pp. 500-509.

Otto, A., & Fornahl, D. (2010): Origins of human capital in clusters: Regional, industrial and academic transitions in media clusters in Germany, in: Fornahl, D., Henn, S., & Menzel, M.-P. (Eds.): Emerging Clusters: Theoretical, Empirical and Political Perspectives on the Initial Stage of Cluster Evolution, Edward Elgar, Cheltenham, UK, pp. 99-139.

Overman, H. G., & Puga, D. (2010): Labour pooling as a source of agglomeration: An empirical investigation, in: Glaeser, Edward L. (Ed.): Agglomeration economics, University of Chicago Press, Chicago, IL, pp. 133-150.

Parrotta, P., Pozzoli, D., & Pytlikova, M. (2014): The nexus between labor diversity and firm's innovation, *Journal of Population Economics*, Vol. 27, Issue 2, pp. 303-364.

Penrose, E. (1959): The Theory of the Growth of the Firm, Oxford University Press, Oxford, 4th edition.

Pfeffer, J. (1994): Competitive Advantage Through People, *California Management Review*, Vol. 36, No. 2, pp. 9-28.

Pfeifer, C., & Wagner, J. (2014): Is innovative firm behavior correlated with age and gender composition of the workforce? Evidence from a new type of data for German enterprises, *Journal for Labour Market Research*, Vol. 47, Issue 3, pp. 223-231.

Porter, M. E. (1980): Competitive Strategy: Techniques for Analyzing Industries and Competitors, Free Press, New York.

Rabe-Hesketh, S., & Skrondal, A. (2012): Multilevel and longitudinal modeling using Stata, Stata Press, College Station, TX.

Raffo, J. (2017): MATCHIT: Stata module to match two datasets based on similar text patterns.

Raffo, J., & Lhuillery, S. (2009): How to play the "Names Game": Patent retrieval comparing different heuristics, *Research Policy*, Vol. 38, Issue 10, pp. 1617-1627.

Reiche, B. S. (2006): The inpatriate experience in multinational corporations: an exploratory case study in Germany, *The International Journal of Human Resource Management*, Vol. 17, Issue 9, pp. 1572-1590.

Research Explorer (2018): Research Explorer - The German research directory, available under: http://www.research-explorer.de/research_explorer.en.html?: last retrieved: 10.03.2018.

Rigby, D. L., & Brown, M. W. (2015): Who Benefits from Agglomeration?, *Regional Studies*, Vol. 49, Issue 1, pp. 28-43.

Rotemberg, J. J., & Saloner, G. (2000): Competition and human capital accumulation: a theory of interregional specialization and trade, *Regional Science and Urban Economics*, Vol. 30, Issue 4, pp. 373-404.

Rubin, P. H. (1973): The expansion of firms, *Journal of Political Economy*, Vol. 81, No. 4, pp. 936-949.

Ruiz-Jiménez, J. A., Fuentes-Fuentes, M. M., & Ruiz-Arroyo, M. (2016): Knowledge Combination Capability and Innovation: The Effects of Gender Diversity on Top Management Teams in Technology-Based Firms, *Journal of Business Ethics*, Vol. 135, Issue 3, pp. 503-515.

Šarić, S. (2012): Competitive Advantages through Clusters - An Empirical Study with Evidence from China, Strategisches Kompetenz-Management, Springer Fachmedien, Wiesbaden.

Schaal, E. (2017): Uncertainty and Unemployment, *Econometrica*, Vol. 85, Issue 6, pp. 1675-1721.

Schmid, T., Achleitner, A.-K., Ampenberger, M., & Kaserer, C. (2014): Family firms and R&D behavior – New evidence from a large-scale survey, *Research Policy*, Vol. 43, Issue 1, pp. 233-244.

Schneider, J., & Eckl, V. (2016): The difference makes a difference: Team diversity and innovative capacity, OECD workshop: "Developing novel approaches to measure human capital and innovation".

Scholl, T., & Brenner, T. (2016): Detecting Spatial Clustering Using a Firm-Level Cluster Index, *Regional Studies*, Vol. 50, Issue 6, pp. 1054-1068.

Shaver, J. M., & Flyer, F. (2000): Agglomeration economies, firm heterogeneity, and foreign direct investment in the United States, *Strategic Management Journal*, Vol. 21, Issue 12, pp. 1175-1193.

Snell, S. A., Youndt, M. A., & Wright, P. M. (1996): Establishing a framework for research in strategic human resource management: Merging resource theory and organisational learning, in: Ferris, G. R. (Ed.): Research in personnel and human resources management, JAI Press, Greenwich, CT, pp. 61-90.

Sørensen, J. B., & Stuart, T. E. (2000): Aging, Obsolescence, and Organizational Innovation, *Administrative Science Quarterly*, Vol. 45, No. 1, pp. 81-112.

Steffen, C. (2012): How Firms Profit from Acting in Networked Environments: Realising Competitive Advantages in Business Clusters. A Resource-oriented Case Study Analysis of the German and Swiss Watch Industry, Schriftenreihe: Internationale Personal- und Strategieforschung, Rainer Hamp Verlag, München & Mering.

Steinberg, P. J., Procher, V. D., & Urbig, D. (2017): Too much or too little of R&D offshoring: The impact of captive offshoring and contract offshoring on innovation performance, *Research Policy*, Vol. 46, Issue 10, pp. 1810-1823.

Stern, D. I. (2010): Between estimates of the emissions-income elasticity, *Ecological Economics*, Vol. 69, Issue 11, pp. 2173-2182.

Stevens, J. P. (2002): Applied Multivariate Statistics for the Social Sciences, Erlbaum, Hillsdale, NJ.

Stifterverband (2018): Research Data Center Wissenschaftsstatistik, available under: https://www.stifterverband.org/research_data_center: last retrieved: 10.03.2018.

Stiles, P., & Kulvisaechana, S. (2003): Human capital and performance: A literature review, University of Cambridge.

Suarez, F. F., & Lanzolla, G. (2007): The Role of Environmental Dynamics in Building a First Mover Advantage Theory, *Academy of Management Review*, Vol. 32, No. 2, pp. 377-392.

Suarez, F., & Lanzolla, G. (2005): The Half-Truth of First-Mover Advantage, *Harvard Business Review*, April 2005.

Tallman, S., Jenkins, M., Henry, N., & Pinch, S. (2004): Knowledge, Clusters, and Competitive Advantage, *The Academy of Management Review*, Vol. 29, No. 2, pp. 258-271.

Täube, F. A. (2005): The geography of technology entrepreneurship: an exploratory study of the Indian IT industry, available under: http://www.econ.mpg.de/files/2006/workshops/india_workshop/papers/Taeube.pdf, last retrieved: 04.01.2019.

Teece, D. J., Pisano, G., & Shuen, A. (1997): Dynamic Capabilities and Strategic Management, *Strategic Management Journal*, Vol. 18, Issue 7, pp. 509-533.

Tödtling, F., & Trippl, M. (2005): One size fits all?: Towards a differentiated regional innovation policy approach, *Research Policy*, Vol. 34, Issue 8, pp. 1203-1219.

Tödtling, F., Lehner, P., & Trippl, M. (2006): Innovation in Knowledge Intensive Industries: The Nature and Geography of Knowledge Links, *European Planning Studies*, Vol. 14, Issue 8, pp. 1035-1058.

Uyarra, E., & Ramlogan, R. (2017): Cluster policy in an evolutionary world? Rationales, instruments and policy learning, in: Fornahl, D., & Hassink, R. (Eds.): The Life Cycle of Clusters - A Policy Perspective, Edward Elgar Publishing, Cheltenham, UK, pp. 35-55.

Van Oort, F. G., Burger, M. J., Knoben, J., & Raspe, O. (2012): Multilevel Approaches and the Firm-Agglomeration Ambiguity in Economic Growth Studies, *Journal of Economic Surveys*, Vol. 26, Issue 3, pp. 468-491.

Vega-Jurado, J., Gutiérrez-Gracia, A., Fernández-de-Lucio, I., & Manjarrés-Henríquez, L. (2008): The effect of external and internal factors on firms' product innovation, *Research Policy*, Vol. 37, Issue 4, pp. 616-632.

Vicente, J. (2014): "Don't throw the baby out with the bath water" Network failures and policy challenges for cluster long run dynamics, *Papers in Evolutionary Economic Geography*, No. 14.20.

Vinding, A. L. (2006): Absorptive capacity and innovative performance: A human capital approach, *Economics of Innovation and New Technology*, Vol. 15, Issue 4-5, pp. 507-517.

Wernerfelt, B. (1984): A resource-based view of the firm, *Strategic Management Journal*, Vol. 5, Issue 2, pp. 171-180.

Williamson, I. O., King Jr., J. E., Lepak, D., & Sarma, A. (2010): Firm reputation, recruitment web sites, and attracting applicants, *Human Resource Management*, Vol. 49, No. 4, pp. 669-687.

Zaheer, A., & Bell, G. G. (2005): Benefiting from network position: firm capabilities, structural holes, and performance, *Strategic Management Journal*, Vol. 26, Issue 9, pp. 809-825.

Zellner, C., & Fornahl, D. (2002): Scientific knowledge and implications for its diffusion, *Journal of Knowledge Management*, Vol. 6, No. 2, pp. 190-198.

Zhou, K. Z., Yim, C. K., & Tse, D. K. (2005): The Effects of Strategic Orientations on Technology- and Market-Based Breakthrough Innovations, *Journal of Marketing*, Vol. 69, No. 2, pp. 42-60.

Zucker, L. G., Darby, M. R., & Armstrong, J. (1998): GEOGRAPHICALLY LOCALIZED KNOWLEDGE: SPILLOVERS OR MARKETS?, *Economic Inquiry*, Vol. 36, Issue 1, pp. 65-86.

# Appendix

**Table 5:** Pairwise correlation matrix for the sample with cluster companies

| | 1. | 2. | 3. | 4. | 5. | 6. | 7. | 8. | 9. | 10. | 11. | 12. | 13. | 14. | 15. | 16. | 17. | 18. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Age | 1.000 | | | | | | | | | | | | | | | | | |
| 2. Independence dummy | 0.104* | 1.000 | | | | | | | | | | | | | | | | |
| 3. HR capabilities | 0.003 | 0.011 | 1.000 | | | | | | | | | | | | | | | |
| 4. Human capital exchange | -0.035 | -0.007 | -0.054 | 1.000 | | | | | | | | | | | | | | |
| 5. No. Research institutes | -0.055* | -0.006 | 0.091* | -0.026 | 1.000 | | | | | | | | | | | | | |
| 6. Pace of tech. evolution | -0.046 | -0.002 | 0.093* | 0.019 | 0.027 | 1.000 | | | | | | | | | | | | |
| 7. Pace of market evolution | -0.035 | 0.004 | 0.043 | 0.008 | 0.082* | 0.134* | 1.000 | | | | | | | | | | | |
| 8. Market risk | -0.044 | -0.005 | 0.093* | 0.128 | 0.028 | 0.997* | 0.161* | 1.000 | | | | | | | | | | |
| 9. Research-intensive industry | -0.079* | -0.009 | 0.034 | -0.073 | -0.008 | 0.548* | 0.042 | 0.514* | 1.000 | | | | | | | | | |
| 10. Centre position in cluster | -0.033 | -0.020 | -0.024 | -0.043 | -0.122* | 0.076* | -0.001 | 0.078* | -0.010 | 1.000 | | | | | | | | |
| 11. Degree of overlap | -0.132 | -0.102 | 0.086 | 0.044 | -0.030 | -0.124 | -0.124 | -0.129 | -0.205* | -0.074 | 1.000 | | | | | | | |
| 12. Gender diversity | 0.213* | 0.050 | -0.039 | -0.128 | 0.070* | -0.130* | 0.020 | -0.122* | -0.136* | 0.032 | -0.176* | 1.000 | | | | | | |
| 13. Matching capacities of labour pool | 0.168* | 0.094 | -0.033 | 0.071 | 0.034 | -0.048 | -0.071 | -0.034 | -0.183* | -0.044 | 0.180* | 0.068 | 1.000 | | | | | |
| 14. Stock of HR of the cluster | 0.066* | 0.008 | -0.073* | 0.001 | 0.022 | -0.014 | 0.000 | -0.016 | 0.085* | 0.018 | -0.060 | 0.055* | 0.023 | 1.000 | | | | |
| 15. Diversity of the labour pool | 0.137* | 0.049 | -0.073* | -0.084 | 0.080* | -0.215* | 0.033 | -0.200* | -0.226* | 0.055* | -0.154* | 0.604* | 0.136 | 0.091* | 1.000 | | | |
| 16. Firm size | 0.119* | 0.023 | -0.067* | -0.011 | 0.017 | -0.006 | 0.002 | -0.008 | 0.058* | 0.016 | -0.228* | 0.079* | 0.002 | 0.807* | 0.067* | 1.000 | | |
| 17. Unemployment in cluster | -0.011 | 0.002 | -0.020 | -0.042 | 0.041 | 0.006 | -0.092* | 0.011 | -0.064* | 0.008 | 0.052 | 0.035 | 0.114 | 0.029 | 0.058* | 0.018 | 1.000 | |
| 18. Quality of labour pool | 0.008 | 0.117 | -0.079 | 0.117 | 0.026 | -0.152 | 0.129 | -0.138 | -0.063 | -0.093 | -0.103 | 0.030 | -0.018 | 0.147 | 0.179* | 0.244* | 0.047 | 1.000 |

Note: $^*p < 0.05$

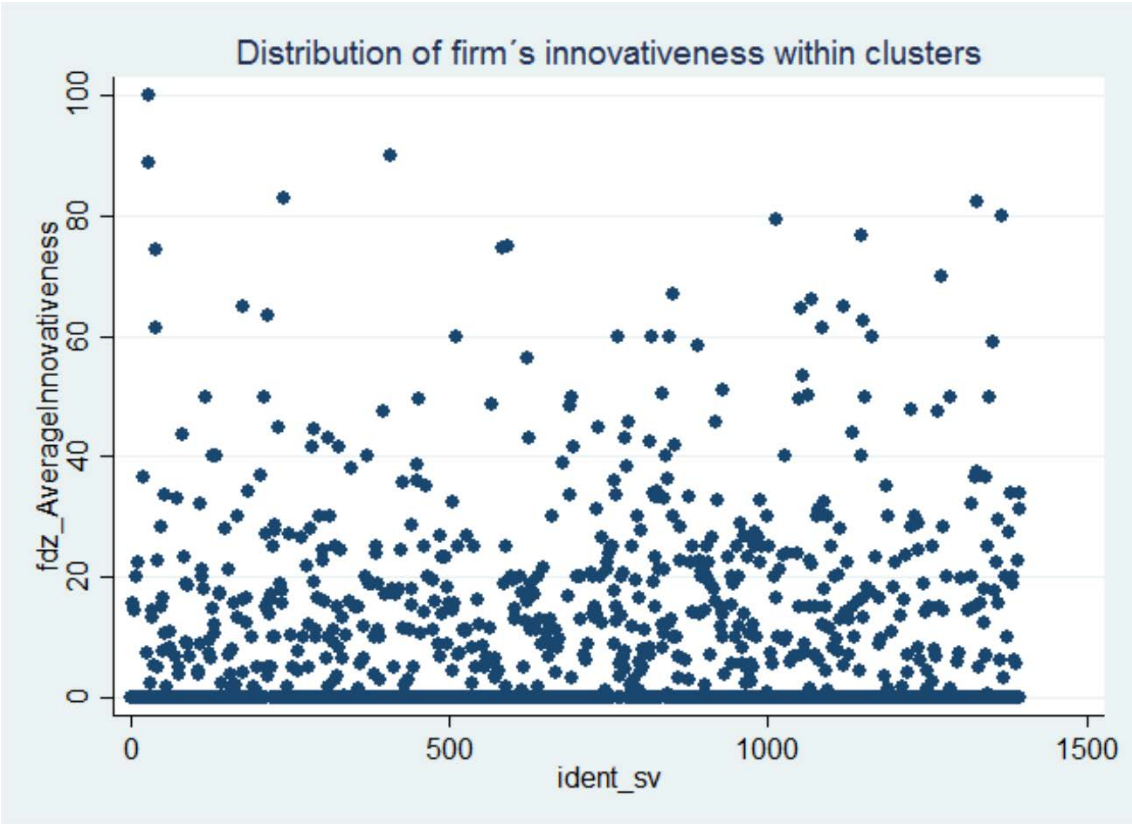


**Figure 1:** Variance of the innovativeness (sample with cluster companies)

Note: fdz_AverageInnovativeness: Firm innovativeness; ident_sv: Firm specific identifier

**Table 6:** OLS regression models with robust standard errors of single cross-section average over time (full sample)

| ***Innovativeness (full sample)*** | *Model 1* *n = 11.228* |
|---|---|
| **Cluster dummy** | 0.822** (0.418) |
| **Age** | 0.004 (0.004) |
| **Independence dummy** | 0.076 (0.661) |
| **Human resource capabilities** | 16.626*** (1.527) |
| **Gender diversity** | 7.001*** (1.089) |
| **Number of research institutes** | -0.032*** (0.006) |
| **Pace of technology evolution** | 0.531*** (0.074) |
| **Firm size** | 0.000 (0.000) |
| *Constant* | *-7.312**** |
| $R^2$ | *0.0317* |

*Robust Standard errors in parentheses.*
*Significance level: * p < 0.10, ** p < 0.05, *** p < 0.01*

# VI. Paper V: Putting the watering can away – Towards a targeted (problem-oriented) cluster policy framework

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Published in Papers in Innovation Studies[141] as well as submitted to Research Policy

**Abstract:** In view of the undisputed promising effects of regional clusters and spurred by lighthouse examples such as Silicon Valley, cluster policies have been popular in many countries worldwide. However, in recent years the complaints have become louder about the actual economic relevance and efficiency of such regional innovation policies. In particular, the high degree of standardization in the so far applied cluster policies, focusing primarily on collaborative incentives to strengthen the relational density in clusters, have been criticized as being rather ineffective and costly to society. In order to solve this one-size-fits-all problem, it has been proposed that cluster policies should instead focus on the concrete conditions and needs within regional clusters. The aim of this paper is to respond to this call by considering firm-, cluster- and market-/industry-specific particularities. Based on an extensive systematic literature review and own empirical results about the relationship between clusters and firms' performances, an overview about relevant conditions is elaborated. Such an overview makes it possible to identify potential problems, e.g. in terms of missing absorptive capacities, which cluster policy can purposefully address. For each identified problem, a potential targeted (problem-oriented) policy intervention is therefore suggested. The corresponding result of this procedure is a policy-framework that offers an increased practical value in terms of bringing forth specific adaptive cluster policies rather than one-size-fits-all policies and thereby contributing to a more sophisticated understanding of the design of cluster policies.

**Keywords:** innovation policy, cluster policy, cluster effect, firm performance
**JEL Classification:** L52, L53, O25, O38, R5, R10

[141] In the interest of consistency, the following version differs slightly from the design of the published article.

## 1. Introduction

Regional clusters constitute an indispensable part of today´s economies. For example, just within the European Union (EU), regional clusters employ nearly 40% of the European workforce and account for 55% of European wages. The co-location of similar firms in regional clusters is therefore an economic phenomenon that can be observed all over the world (Brown et al., 2007; European Union, 2016; Festing et al., 2012; Nathan and Overman, 2013). Consequently, clusters and their multi-dimensional impacts have become a core topic in a variety of scientific disciplines (Grashof and Fornahl, 2020; Sedita et al., 2012; Vicente, 2014). Encouraged by lighthouse examples, such as Silicon Valley, also policy makers discovered the cluster concept. Nowadays, cluster policies have become a standard approach for national and regional authorities to improve economic performance (Brenner and Schlump, 2011; Ebbekink and Lagendijk, 2013; Lehmann and Menter, 2018). Since 2005 the German government has launched, for example, several funding programs with a total volume of 1.391 billion € to foster excellent clusters in Germany (EFI, 2015).

Despite the widespread application and the relatively high financial support allocated to cluster policies, the effectiveness of these policies is still rather questionable (Brenner and Schlump, 2011; Lehmann and Menter, 2018; Vicente, 2014). In his meta-survey of more than 750 clusters, Van der Linde (2003), for example, concludes that there is little evidence for a positive effect of cluster policy. Instead, cluster policy measures are much more important determinants in uncompetitive clusters. One reason for the rather unsatisfactory role of policy is the missing focus on concrete problems (Brakman and van Marrewijk, 2013; Nathan and Overman, 2013). Nowadays nearly all cluster policies, such as the Pôles de compétitivité initiative in France[142], focus for instance on fostering research and development (R&D) collaborations and networks development, which can of course be a crucial way of improving innovativeness within clusters (Uyarra and Ramlogan, 2012; Vicente, 2014; Zenker et al., 2019). Yet often this is not the main problem policy should address. Instead of just increasing the number of R&D linkages, it may be more effective to address the partner selection in order to connect the right partners with each other. As such, in general the so-far applied cluster policy is therefore rather characterized by trial-and-error as well as incremental change than by comprehensively understanding what kind of problem actually needs to be solved. A focus on the

[142] For a good overview, see for instance Fontagné et al. (2013) as well as Barmeyer and Krüth (2012).

specific context, for example differences on the firm- and/or cluster-level, has not been successfully implemented up to now. However, by ignoring these particularities, policies run the risk of simply copying already successful strategies (Brenner and Schlump, 2011; Ebbekink and Lagendijk, 2013). Furthermore, without analysing and understanding the concrete problems within clusters, the outcome of these policy measures will remain unpredictable. Since there may exist several problems at the same time, the limited focus on just one prominent problem (e.g. market failures) is likely to lead to unintended side effects due to potential interdependencies between the different problems (Ketels, 2009; Nathan and Overman, 2013; Wolfe and Gertler, 2004). Recently, research in the context of innovation systems has therefore highlighted that the comprehensive assessment of the concrete problems and their activity-related causes constitutes the basis for an adequate innovation policy (Borrás and Edquist, 2013). However, it still remains rather unclear, especially in the context of firms, what specific problems exist within clusters and how policy can effectively address them (Auer and Tödtling, 2017; Wolman and Hincapie, 2015). Consequently, the aim of this paper is to contribute to closing this research gap by answering the following research question: How can policy effectively promote the performance of firms in clusters?

In order to answer this research question, the rich literature about potential failures in innovation systems is thus applied to the firm-level, which is likely influenced by the setting of the corresponding innovation system (Borrás and Edquist, 2013). Based on an extensive systematic literature review of the potential failures in innovation systems and own empirical results about moderating variables explaining firm performance differentials within clusters, a targeted (problem-oriented) policy framework is developed. This framework comprises several context-specific problems and the corresponding targeted measures that policy can use in order to purposefully address the problems within clusters and thereby promote the overall performance.

Therefore, this study not only contributes to the current scientific discussion about policies in the cluster context but also provides a pragmatic value in terms of bringing forth specific adaptive policies for clusters rather than one-size-fits-all cluster policies (Burfitt and MacNeill, 2008; Tödtling and Trippl, 2005; Wolfe and Gertler, 2004). Contrary to other policy-oriented papers (e.g. Benner, 2012), the policy framework suggested here has its roots in a comprehensive empirical basis instead of only relying on theoretical elaborations. Thus, it contributes to a more sophisticated understanding of the design of policies for clusters that can effectively foster firm performance in clusters. This seems to be of particular relevance in light of the current austerity in most European countries that demands a higher efficiency in public funding (Kitson et al., 2011; Vicente, 2014).

The remainder of this paper is organized as follows: The second section encompasses a status-quo-analysis of the different understandings of policies in the cluster context, highlighting the general rationales of policy interventions. In the third section, the influence of moderating variables from different levels of analysis on firm performance in clusters is discussed based on own empirical results (e.g. Grashof, 2019) as well as on empirical results from the literature. The fourth section integrates the findings from the previous two sections into a policy framework. The paper will end with some concluding remarks concerning the role of the state in fostering firm performance in clusters as well as promising areas for future research.

## 2. From cluster policy to policies for clusters – A status-quo-analysis

Even though cluster policies comprise a relatively broad tool-box of different measures (e.g. Andersson et al., 2004; Uyarra and Ramlogan, 2012), in accordance with the European Commission they can be defined as: "(…) a wider set of specific government policy interventions aiming at strengthening existing clusters or facilitating the emergence of new ones." (European Commission, 2008, p. 31). As highlighted by Brenner and Mühlig (2013), it is crucial to distinguish between these two general aims, as the corresponding mechanisms that cause the emergence and the efficiency of regional clusters can be quite different. While the former refers to the prerequisites, triggering-events and self-augmenting processes (e.g. Brenner and Mühlig, 2013), this paper explicitly focuses on the aim of strengthening existing clusters. In this context, various target-levels, ranging from direct firm support to framework policies, are conceivable. Consequently, this paper takes a different view about cluster policy than Porter (2000), who argues that cluster policy is an independent policy approach that should replace traditional firm- and industry-oriented policies. Typically, policies to promote clusters are indeed based on the same rationales as standard industrial and innovation policy (Uyarra and Ramlogan, 2012), so that in this paper cluster policies are viewed as policies for clusters, meaning that they are designed for the specific needs within clusters.

One of the main reasons for policy interventions, also in the context of clusters, is to correct market failures (Andersson et al., 2004). The core idea of the market failures rationale goes back to Nelson (1959) and Arrow (1962), who state that investments in the creation of knowledge, viewed as the most important source of innovation, are below the socially desired level due to market imperfections such as uncertainty and information asymmetries, lack of appropriability and indivisibilities (Beck et al., 2014; Edler and Fagerberg, 2017; Martin and Scott, 2000). In clusters, especially the existence of externalities as well as spillovers, can be potential forces behind a reduction of market efficiency (Konstantynova and Wilson, 2014; Uyarra and Ramlogan, 2012). The benefits of generating knowledge will not only be exploited by the knowledge generator, but also by other actors. Since the knowledge generating firm cannot appropriate all of the potential benefits alone, there exists a disincentive to invest in knowledge production, as private returns are lower than public returns, resulting in market failure (Edler et al., 2016; Edler and Fagerberg, 2017; Laranja et al., 2008). The close proximity to similar firms can even enforce this inefficiency within clusters (Beaudry and Breschi, 2003; Shaver and Flyer, 2000). As a result of such market failure, it has been argued that the state must intervene in order to reach the market equilibrium and optimal level of knowledge and innovation generation (Edler et al., 2016; Laranja et al., 2008). The following three policy instruments have commonly been applied in this context (Edler and Fagerberg, 2017):

(1) Since basic research is particularly confronted with high uncertainty and with returns in the long-run, private firms have relatively small incentives to invest in basic research, even though it would be desirable for society as a whole. To address this market failure, the state needs to invest in the production of knowledge in public organisations such as universities and other public research institutions.

(2) Another frequently applied policy instrument is financial support for private firms through direct subsidies for R&D or through the tax system. These direct as well as indirect support measures may incentivize firms to undertake more R&D than they would have otherwise. However, the empirical evidence of this additionality effect is quite inconsistent (e.g. Cunningham et al., 2016; Larédo et al., 2016).

(3) Lastly, in order to tackle the lack of appropriability of the created knowledge, improving the intellectual property rights can be regarded as another useful policy instrument.

Despite its ongoing popularity and relevance among policy makers, the simple reliance on the market failures rationale has also been criticized (Edler and Fagerberg, 2017; Laranja et al., 2008). For example, it has been called into question whether governments are really always equally capable of identifying and fixing a market failure (e.g. limited state capacity). In some cases, it may indeed come to policy failures that will even worsen the initial situation. The evaluation of the socially optimal level of R&D investments constitutes in this context one exemplary challenge for policy makers (Berglof and Cable, 2018; Edler and Fagerberg, 2017). In general, it appears that market failures are commonly used as justification for policy interventions, although policy makers seldom really assess their concrete manifestations (Dalitz and Toner, 2016; Laranja et al., 2008).

Apart from the focus on the market equilibrium, there is another rather evolutionary rational for policy interventions that follows a systems of innovation approach (SI) (Edler et al., 2016; Konstantynova and Wilson, 2014; Schot and Steinmueller, 2018). In the SI approach, innovations are conceptualized as a non-linear process in which different actors, such as firms and universities, interact with each other as well as with the institutional framework. Hence, this approach explicitly focuses on institutions (formal as well as informal ones) and networks of interactions, both being regarded as the key features for innovation activities (Laranja et al., 2008; Woolthuis et al., 2005). System failures are therefore the result of a mismatch between these interrelated actors and institutions (Andersson et al., 2004; Metcalfe, 1995; Uyarra and Ramlogan, 2012). In this context, policy interventions, promoting the collective learning and coordinating the relationships of the system with its components, are justified as a solution to system failures that inhibit the creation and diffusion of innovations (Konstantynova and Wilson, 2014; Laranja et al., 2008). For regional clusters, being a local innovation system in itself, it is for example crucial, particularly in the emergence phase (e.g. Brenner and Schlump, 2011), that there exist a sufficient level of networking between the various cluster actors and that the corresponding knowledge exchange is well functioning (Andersson et al., 2004; Piquero and Vicente, 2019; Uyarra and Ramlogan, 2012). However, system failures can take many different forms (Laranja et al., 2008). A comprehensive and frequently applied categorization of system failures is provided by Woolthuis et al. (2005):

(1) Infrastructural failures refer to an insufficient supply of physical infrastructure that actors need to effectively function (e.g. ICT infrastructure and reliable energy supply) as well as of the science and technology infrastructure.
(2) Institutional failures can be differentiated in hard and soft institutional failures. Hard institutional failures refer to failures that exist in the formal institutions (e.g. in the general legal system), whereas soft institutional failures describe failures within the informal institutions (e.g. in the political culture and the social values).

(3) Network failures are normally concerned with a lack of sufficient interactions. However, they also comprise too many interactions between an already established group of partners, which can potentially result in lock-in situations. Consequently, in both cases a network failure exists that hampers the innovation activities.
(4) Capabilities failures, which are also addressed within the market failure rationale (e.g. underinvestment in research), deal with a lack of capabilities and resources of firms that prevent the adaptation to new changing (technological) circumstances. Smith (2000) additionally highlighted in this context that the inability to effectively manage a transition can also apply to complete (social) systems.

Nevertheless, recently the SI approach has been criticized for its notion of policy, referring only to fixing system failures and focussing exclusively on generating economic growth (Alkemade et al., 2011; Dodgson et al., 2011; Lindner, et al., 2016; Mazzucato, 2016). In light of the Grand Societal Challenges, such as climate change, it has been postulated that the state has to act as an entrepreneur by creating new markets and thereby setting the direction of change (Cantner and Vannuccini, 2018; Mazzucato, 2016; Weber and Rohracher, 2012). The basic rationale for policy interventions therefore refers here to addressing directionality failures[143], meaning that innovations do not necessarily happen where it would be socially desirable (Foray, 2018; Weber and Rohracher, 2012). Hence, the focus of these 'new mission oriented' (Cantner and Vannuccini, 2018) approaches lies more on the directionality of innovation activities, whereas the system failure as well as the market failure framework only highlight the necessity to generate innovations as efficiently and effectively as possible by reducing market and/or system imperfections (Wanzenböck and Frenken, 2018; Weber and Rohracher, 2012). As a result, in the system failure framework the direction of the innovation is for instance at best implicitly driven by potent actors within the system, often very large incumbent firms, who are not primarily interested in achieving societal missions but rather in improving their performance (Alkemade et al., 2011; Wanzenböck and Frenken, 2018).

Despite these varieties of rationales, each highlighting specific problems, in the case of clusters, policy has primarily focused on addressing market failures (through R&D subsidies and the provision of an adequate infrastructure) as well as network failures

[143] Apart from directionality failures, Weber and Rohracher (2012) indicate three additional transformational system failures, namely demand articulation failure, policy coordination failure and reflexivity failure.

(through cooperative R&D subsidies).[144] Other problems, for example related to the directionality failure, have so far not been taken into consideration (Vicente, 2014; Zenker et al., 2019). As such, it seems that the selection of policy instruments has not been appropriately related to the actual problems within clusters, even though it is one of the most crucial elements for a functioning innovation policy (Borrás and Edquist, 2013; Edquist, 2011). Instead the application of cluster policies is characterized by copying standardized measures, such as collaborative R&D subsidies, as well as by institutional path-dependencies (Ebbekink and Lagendijk, 2013; Uyarra and Ramlogan, 2012). The latter one also refers to the feature of picking winners, meaning that policy tends to support the same applicants over and over again due to differences in their resources and knowledge (Aschhoff, 2009; Umlauf, 2016). The specific context is therefore not really considered in the corresponding cluster policy design. If at all, only specific particularities, such as firm size, are explicitly taken into consideration (e.g. the national funding program KMU-NetC[145] and regional funding program RegioWIN[146] in Germany). However, the rather complex and often interacting effects from several contextual variables from the firm-, cluster-, and market-/industry-level of analysis remain to be recognized and properly integrated in the design of cluster policies (Brenner and Schlump, 2011; Ebbekink and Lagendijk, 2013).

## 3. Firm performance heterogeneity in clusters

Despite the still prevalent assumption of equal gains for all companies located in clusters (Frenken et al., 2015; Tallman et al., 2004), recently is has been theoretically as well as empirically stressed that there are several conditions from different levels of analysis that directly or interactively moderate the performance of companies located in clusters (Grashof, 2018; Hervas-Oliver et al., 2018; Knoben et al., 2015). Auer and Tödtling (2017) therefore propose that cluster policies should change their focus towards these influential conditions within clusters, so that the concrete needs and requirements of the firms located within clusters are taken explicitly into consideration. Based on a systematic literature review of studies dealing with firm

[144] The focus is thereby, however, primarily limited to increasing the number of collaborations. Other kinds of network failures, referring for instance to connecting the right partners with each other, are in general ignored.

[145] In this program, the Federal Ministry of Education and Research in Germany supports research and development projects of SMEs in high performance networks and clusters (BMBF, 2019b).

[146] RegioWIN is an important program element of the EFRE strategy of the state of Baden-Württemberg for the funding period between 2014 and 2020. The program supports in a two-step approach the participatory evaluation of development potentials of regional innovation systems resulting in a smart specialisation strategy and also the corresponding practical implementation of selected lighthouse projects (Ministerium für Finanzen und Wirtschaft Baden-Württemberg, 2013).

performance differentials within clusters and own empirical investigations, this section elaborates a comprehensive overview about relevant multilevel conditions influencing firm performance within clusters. The corresponding results are presented in table 1.

**Table 1:** Overview of moderating variables influencing firm performance within clusters

| Group of indicators | Exemplary indicators | Level of analysis | Exemplary references |
|---|---|---|---|
| **Collaboration and network** | | | |
| | Number of linkages | Firm-level | Grashof, 2018; Hervas-Oliver and Albors-Garrigos, 2009 |
| | External openness | Firm-level | Giuliani, 2013; Zaheer and George, 2004 |
| | Centrality within the cluster | Firm-level | Bell, 2005; Ferriani and MacMillan, 2017; Giuliani, 2007 |
| | Stock of alliances within cluster | Cluster-level | Grashof, 2018 |
| **Resources and capabilities** | | | |
| | Innovation capabilities[147] | Firm-level | Hervas-Oliver et al., 2018; Knoben et al., 2015 |
| | Human resource capabilities | Firm-level | Grashof, 2019 |
| | Age | Firm-level | McCann and Folta, 2011 |
| | Size | Firm-level | Hervas-Oliver et al., 2018; Knoben et al., 2015 |
| | Degree of Internationalization | Firm-level | De Martino et al., 2006; Rigby and Brown, 2015 |
| | Quality of labour pool within cluster | Cluster-level | Grashof, 2019 |
| | Cluster size | Cluster-level | Folta et al., 2006; McCann and Folta, 2011 |
| **Relatedness** | | | |
| | Knowledge similarity with cluster stock | Firm-level | Grashof, 2018 |
| | Degree of overlap between the labour qualifications of the firm and the cluster | Firm-level | Grashof, 2019 |
| | Knowledge similarity with leading firms | Firm-level | Hesse, 2020 |
| **Diversity** | | | |
| | Gender diversity | Firm-level | Grashof, 2019 |
| | Knowledge diversity | Firm-level | Grashof, 2018 |
| | Gender diversity of the labour pool within cluster | Cluster-level | Grashof, 2019 |
| | Knowledge diversity within cluster | Cluster-level | Grashof, 2018 |
| | Related variety of clusters | Cluster-level | Boschma et al., 2012; Hundt et al., 2019; Porter, 2003 |
| **Market and industry context** | | | |
| | Pace of technology evolution | Market-/Industry-level | Grashof, 2018; Grashof, 2019; Suarez and Lanzolla, 2007 |
| | Market risk | Market-/Industry-level | Kohlbacher et al., 2013; Schaal, 2017 |
| | Research-intensive industry | Market-/Industry-level | Grashof et al., 2019 |
| **Institutional context** | | | |
| | Institutional quality | Institutional-level | Barasa et al., 2017; Saxenian, 1994 |
| | Number of local institutions | Institutional-level | Belso-Martinez and Molina-Morales, 2013; Hervas-Oliver and Albors-Garrigos, 2007; Wu et al., 2010 |

[147] In line with Hervas-Oliver et al. (2018) the terms absorptive capacity and innovation capability are used interchangeably.

It can be seen that there are several contextual variables from four different levels of analysis: firm-level, cluster-level, market-/industry-level and institutional-level. Consequently, depending on different contextual compilations, firm performance within clusters will be particularly promoted or hampered. As such, for high firm performance it is not sufficient that a cluster is well functioning, for example regarding the quality and matching capacities of the corresponding labour pool. But additionally it is likewise necessary that firms meet the firm-specific requirements for gaining from the cluster environment (e.g. owning an adequate level of absorptive capacities) and that the market/industry as well as institutional environment is conducive for the performance of firms within clusters. While only selected indicators, such as the firm´s external openness and innovation capabilities, can be directly targeted by funding measures, for the design of efficient policy interventions it is in general crucial that all factors from all levels are comprehensively considered (Auer and Tödtling, 2017; Grashof, 2019; Knoben et al., 2015).

In total, the indicators can be organized into six different groups. The first group comprises collaboration and network related indicators, primarily on the firm-level, such as the firm´s centrality within clusters as well as the cluster external connectedness of firms located within clusters (Bell, 2005; Giuliani, 2013; Hervas-Oliver and Albors-Garrigos, 2009). However, it also refers to the cluster-level, because recently it has been highlighted that the stock of alliances within clusters promotes firm innovativeness due to an enhanced possibility of extracting knowledge from a number of different actors (Grashof, 2018; McCann and Folta, 2008).
The second group of influential moderating variables deals with resources and capabilities. It has been emphasized by several authors (e.g. Hervas-Oliver et al., 2018; Knoben et al., 2015) that firms' internal resources and capabilities are essential determinants of their performance within clusters. Some of the most prominent indicators in this context are the innovation capabilities of a firm, which describe the firm´s ability to recognize, evaluate, process and integrate new knowledge from its environment (Cohen and Levinthal, 1990; Grashof, 2018). In the cluster context, these capabilities are essential, because otherwise companies are not capable of exploiting available knowledge spillovers within clusters (Knoben et al., 2015; McCann and Folta, 2011). Apart from the innovation capabilities, additional indicators more related to the overall firm structure, such as firm size and age, play also an influential role, since they represent the firm´s ability to coordinate its internal groups and the knowledge transfer between them (Hervas-Oliver and Albors-Garrigos, 2009; Knoben et al., 2015; McCann and Folta, 2011). Moreover, the resources and

capabilities of the clusters, for example measured by the cluster size, have also been shown to influence firm performance within clusters (Folta et al., 2006). The group of indicators dealing with resources and capabilities is therefore also related to both levels of analysis.

The next group of influential moderating variables deals more with the relatedness between these two levels of analysis. The relatedness between companies and the corresponding clusters, e.g. in terms of the similarity between the firm´s knowledge stock and the overall stock of knowledge of the corresponding cluster, has only recently been investigated. However, in general the empirical results of this group indicate that firms and clusters are not isolated from each other, but instead it is important for firm innovativeness that there exist a moderate level of similarity and relatedness between clustered firms and the corresponding clusters (Grashof, 2018; Grashof, 2019). Recently, it has been additionally emphasized that the discussion about firm similarity needs to be enriched by considering the corresponding firm type, since it may be more important to have a relatively high similarity to leading firms than to lagging firms (Hesse, 2020).

Similar to the group of indicators dealing with resources and capabilities, the fourth group, being concerned with diversity, is also related to both levels of analysis. On the firm-level, evidence is found that, for example, gender diversity asserts a stimulating impact on firm innovative performance by providing a fountain for new diverse ideas and capabilities (Grashof, 2019). Similarly on the cluster-level, it has been shown that specialized labour pools within clusters characterized by a high gender diversity are particularly beneficial for firm innovative performance within clusters, as they provide a wider basis for different experiences and ideas (Grashof, 2019). Apart from gender diversity, it has been additionally emphasized that firms located in clusters of related industries particularly profit from co-locating, because they have more possibilities to recombine their existing knowledge base with new and diverse knowledge from firms from related industry contexts (Boschma et al., 2012; Hundt et al., 2019; Porter, 2003).

Besides the previous groups of moderating variables, there are also empirical studies highlighting the relevance of the market and industry context (e.g. Kohlbacher, 2013). For example, it has been shown that the innovativeness of companies located within clusters is significantly hampered by a high market risk, which implies high uncertainty. As a result of this risky market environment, employers as well as employees postpone their human capital related investments, thereby offsetting the potential positive effects of the specialized labour pool within clusters (Grashof, 2019).

Lastly, the institutional context, e.g. the number of local institutions within clusters such as research institutes, has been proven to be important for firm performance within clusters (Belso-Martinez and Molina-Morales, 2013; Hervas-Oliver and Albors-Garrigos, 2007; Wu et al., 2010).

Consequently, in principle it can be resumed that there are six groups of moderating variables that shape the performance of firms located within clusters on four different levels of analysis. With regard to policy, this work therefore argues that understanding firm performance heterogeneity within clusters and the corresponding moderating influences is a meaningful step towards implementing more targeted (problem-oriented) cluster policies.

## 4. Targeted (problem-oriented) cluster policy framework

Targeted (problem-oriented) cluster policies have, however, not easily been developed and implemented, as they require a basic understanding of the concrete problems within clusters that policy should address (Brakman and van Marrewijk, 2013; Fornahl et al., 2015). Based on the general rationales of policy presented in section two, and the previously highlighted contextual influences on firm performance within clusters, it is possible to derive the cluster-specific problems that should be the driver of cluster policy interventions. Table 2 introduces six relevant cluster-specific problems that policy can target on different levels. In line with the classification provided by Peneder (2017), the types of policy approaches are separated according to the corresponding level of intervention between enterprise policies (addressing individual firms), structural policies (aiming at specific industries and clusters) and framework policies (dealing with regulations, institutions and infrastructure).

The first problem within clusters refers to connectivity and network problems. Based on the network failure rationale, stressing the importance of a well-functioning network and knowledge exchange between the various actors located within as well as outside clusters, the target of cluster policy is to strengthen and to balance the internal and external connectedness on the firm- and/or cluster-level (Andersson et al., 2004; Piquero and Vicente, 2019; Uyarra and Ramlogan, 2012). For example, Vicente (2014) highlights the importance of the connectedness between cluster core and periphery organizations (disassortativity of the cluster network), since it brings new rather disruptive ideas from the periphery into the cluster core, thereby preventing a potential lock-in of the cluster. In other words, such ties-oriented policies are argued to reinforce clusters capacity to keep their explorative capabilities as well as their mass-market exploitation abilities (Vicente, 2014).

**Table 2:** Identification of cluster-specific problems

| *Problems* | *Type of policy approach* | *Target* | *Failures* |
|---|---|---|---|
| ***Connectivity and network problems*** | • Enterprise policy<br>• Structural policy | • Strengthening and balancing the internal and external connectedness on the firm- and/or cluster-level | Network failure |
| ***Resource and capability problems*** | • Enterprise policy<br>• Structural policy | • Building of resources and capabilities on the firm- and/or cluster-level | Market failure/Capability failure |
| ***Matching problems*** | • Enterprise policy<br>• Structural policy | • Optimizing the matching between firms and/or firms and clusters | Directionality failure (in terms of partner selection and competence development) |
| ***Diversity problems*** | • Enterprise policy<br>• Structural policy | • Fostering the diversity on the firm- and/or cluster-level | Capability failure |
| ***Market and industry problems*** | • Structural policy | • Supporting the functioning/development of market and industries | Market failure |
| ***Institutional problems*** | • Framework policy | • Provision of a stable, reliable and fruitful regional and macroeconomic environment | Institutional failure |

Furthermore, the resource and capability problems constitute another reason for cluster policy interventions. As already highlighted in table 1, sufficient resources (e.g. financial resources) and capabilities (e.g. innovation capabilities) on the firm-level as well as on the cluster-level are necessary conditions for firm performance within clusters. Companies and/or clusters that lack an adequate level of resources and capabilities should therefore be supported by the state. This intervention is a classic example for the market failures rationale, arguing that due to market imperfections (e.g. lack of appropriability), there is a disincentive to invest in knowledge creation (Edler et al., 2016; Laranja et al., 2008). Apart from this neoclassical rationale, a policy intervention can also be explained from a (structural) system failures view. In this approach, the capabilities failure particularly highlights that the lack of resources and capabilities makes firms unable to adapt to new and changing circumstances, resulting in a lock-in situation (Smith, 2000; Weber and Rohracher, 2012; Woolthuis et al., 2005).

As already indicated in section two, resource- and network-related problems have been most frequently addressed by cluster policies (Konstantynova and Wilson, 2014; Vicente, 2014; Zenker et al., 2019). Nevertheless, in both cases the particular direction of the competence and resource development as well as of the partner selection has commonly been ignored. Based on the underlying notion of the 'new mission oriented' (Cantner and Vannuccini, 2018) approaches, the rather neutral logics of policy interventions, meaning that no pre-determinations are made, can likewise potentially create problems in the cluster context, namely matching problems (Foray, 2018). While the 'new mission oriented' approaches primarily refer to setting a new (technological) direction (Cantner and Vannuccini, 2018; Weber and Rohracher, 2012), for example towards sustainable energy, this paper instead pursues a not mutually exclusive focus on the direction of the partner selection and competence development. Regarding the latter one, which is motivated by resource and capabilities problems, it can be constituted that cluster policies tend to particularly support the knowledge creation of SMEs which often lack sufficient resources to invest in R&D (e.g. KMU-NetC program in Germany).[148] However, it has to be highlighted that not every SME is also identical in terms of its real needs and its existing knowledge base (Schulze-Krogh, 2018; Wapshott and Mallett, 2018). In current policies addressing this problem, the concrete direction of the funding measures, referring to the question of which type of competences (on the firm- and/or cluster-level) is actually supported, has not been adequately considered yet (Borrás and Edquist, 2015; Weber and Rohracher, 2012). As presented in the literature overview of moderating variables showing the importance of a balanced level of similarity between the firm´s knowledge stock and the corresponding cluster knowledge stock (e.g. Grashof, 2018), it can consequently come to a matching problem between firms and the respective clusters. Furthermore, with regard to the connectivity and network problems, it can indeed be observed that current cluster policies frequently aim at constructing and expanding already established relationships (Crespo et al., 2016; Vicente, 2014). Nevertheless, less attention is payed to the concrete partners of these fostered relationships and their corresponding knowledge profiles. In other words, the direction of the funding measures (in terms of the partner selection) is again not explicitly taken into consideration even though previous empirical results have stressed the importance of the partner as well as network structure on firm innovative performance within clusters (Beck et al., 2014; Dohse et al., 2018; Fornahl et al., 2011; Vicente, 2014). For example, it has been emphasized that R&D cooperation contributes the most to firms' innovative performance when the cognitive proximity between the partners is moderate, so that an effective knowledge interchange as well as new ideas through recombination can

[148] For a comprehensive European-wide overview of this aspect also see Zenker et al. (2019).

be achieved (Fornahl et al., 2011; Sampson, 2007). Cluster policies should therefore aim at optimizing the matching between firms and/or firms and the corresponding clusters.

A related problem refers to diversity problems, which can occur on the firm-level as well as on the cluster-level. The diversity, for example with respect to the firm or cluster knowledge, has been shown to be a relevant determinant of firm innovative performance (Grashof, 2018). In absence of an adequate level of diversity, firms as well as clusters run the risk of being unable to adapt to new changes, e.g. technological shifts, and thereby becoming locked-in in a particular path (Dohse et al., 2018; Garcia-Vega, 2006; Garnero et al., 2014). Consequently, cluster policies should aim at fostering the diversity up to a certain degree, so that due to more diverse ideas and approaches, the performance of firms within clusters can be stimulated. The previous described target of optimizing the matching can be overlapping in this context, as it may likewise lead to a more diversified firm and/or cluster structure.

Moreover, on a more aggregated level, market and industry problems can be identified, requiring cluster policy actions. While market and industry problems also comprise missing R&D infrastructure on the cluster-level (e.g. resource and capabilities problem), it captures additionally the industry and market-specific particularities, such as a high market risk, which potentially results in under investments in R&D and skill formation (Czarnitzki and Toole, 2007; Jones and Grimshaw, 2016; Nathan and Overman, 2013; Suarez and Lanzolla, 2007). Even though policy can hardly directly influence the market risk, created for example through a fast pace of technology and market evolution, it can provide safeguards such as technical standards that reduce the market risk (Blind et al., 2017). Policy should therefore track the target of supporting the functioning and development of market and industries.

The last cluster-specific problem refers to institutional problems that are more systemic in nature. As highlighted in section three, the local institutions as well as the general quality of institutions are of great importance for firm performance. In the literature it has therefore been highlighted that one of the most central tasks of national policy is to establish a stable, reliable and fruitful macroeconomic environment (Peneder, 2017; Smith, 2000). For instance, without established and enforced intellectual property rights, companies cannot properly appropriate their gains from being an innovator and consequently reduce their innovation efforts (Edler and Fagerberg, 2017; Woolthuis et al., 2005). Notwithstanding the importance of national-wide institutions, regional institutions are also attributed a decisive influence on firms' and regions' performance (Barasa et al., 2017; Rodríguez-Pose and Di Cataldo, 2015). Although the overall target is basically similar, the focus of national and regional policy is different. While national policy is primarily concerned with the macroeconomic environment, regional institutions have a more meso-oriented perspective concentranting on the regional (socio-)economic landscape by e.g. regulating learning processes and facilitating the knowledge diffusion between actors in the corresponding regional innovation system (Barasa et al., 2017; Cooke et al., 1998; Rodríguez-Pose and Di Cataldo, 2015). The overall quality of these regional institutions varies thereby, as for instance indicated by the European Quality of Government Index (European Commission, 2019a; Rodríguez-Pose and Di Cataldo, 2015). Nevertheless, in the end the linkage between both the macro- and regional institutional framework has been argued to be of paramount importance for firm innovative performance (e.g. Asheim and Coenen, 2006; Barasa et al., 2017; Cooke et al., 1998) as well as for a successful economic-wide transition by avoiding a policy coordination failure (e.g. Weber and Rohracher, 2012). Related to institutional quality differences, influencing the effectiveness of the overall regulation policies, are variations in the underlying experiences, state capacities[149] and (financial) resource endowments of national as well as regional institutions (Borrás, 2011; Cooke et al., 1998; Farole et al., 2011). Without having a sufficient level of state capacities, for example with regard to the individual competences of the bureucrats, policy actors cannot address existing public problems effectively (Wu et al., 2015; Peters, 2015).

In general, it is crucial at this point to recognize that simply solving one of the identified cluster-specific problems may not necessarily improve the overall outcome, as several problems can exist at the same time and can also interact with each other (Andersson et al., 2004; Nathan and Overman, 2013). A pronounced market and industry problem will likely intensify resource and capability problems, because, in a fast developing industry context, it is even more important than usual to possess an adequate level of resources and capabilities, such as innovation capabilities, in order to successfully master the fast changing environment (Grashof, 2018). Additionally, the connectivity and network problems can likewise interact with market and industry problems. Under a rapid technology evolution, it has been empirically shown that cluster external linkages become of particular importance, as they provide access to

[149] State or policy capacity is here defined "(…) as the set of skills and resources—or competences and capabilities—necessary to perform policy functions." (Wu et al., 2015, p. 166).

new knowledge sources that can limit the prevalent risk of a lock-in situation (Grashof, 2018). Thus, it is not sufficient to consider exclusively regional specificities (e.g. Tödtling and Trippl, 2005), but it is necessary to take a holistic perspective which additionally includes for instance firm characteristics as well as the market and industry conditions. By using the distinction made by Borrás and Tsagdis (2008), it is therefore argued that cluster policies should in general follow a rather broad approach in order to address several problems at different levels of analysis, for example by applying policy mixes.

Based on the derived cluster-specific problems presented in table 2 and the comprehensive taxonomy of innovation policy instruments developed by Edler and Fagerberg (2017), the following section elaborates a cluster policy framework that provides precise policy intervention options for each identified cluster-specific problem. The cluster policy framework, illustrated in table 3, therefore contributes to the realization of a more targeted (problem-oriented) cluster policy. As highlighted before, some cluster-specific problems can occur on different levels of analysis, ranging from the firm-level to the institutional-level. The corresponding policy instruments may consequently vary for the same cluster-specific problem dependening on the concrete level of analysis. Such a customization based on the level of analysis is a crucial step for more targeted cluster policies (Auer and Tödtling, 2017; Burfitt and MacNeill, 2008).

Resource and capability problems, being relevant on the firm- and the cluster-level, demonstrate a prime example of the multilevel character of some previously determined cluster-specific problems. On the firm-level, it can be differentiated between instruments focussing more on the strengthening of private R&D spending (e.g. direct support to firm R&D and innovation) and instruments targeting more the development of rather non-financial resources and capabilities (e.g. policies for training and skills) (Edler et al., 2016). One example for the latter are continuous vocational trainings which have been shown, depending on the concrete training arrangements, to matter for firms performance (Borrás and Edquist, 2015; CEDEFOP, 2011). Regarding the public support of R&D in the private sector it can be constituted that it has been a very popular approach in most OECD countries (EFI, 2018; Torregrosa-Hetland et al., 2019; Veugelers, 2015). As indicated in section two, in this context there are direct (normally project funding)[150] as well as indirect (particularly tax-based R&D funding) support measures that both should incentivize firms to undertake more R&D than they otherwise would have done.

**Table 3:** Cluster policy framework

| Problems | Level of analysis | Policy measures |
|---|---|---|
| **Resource and capability problems** | Firm-level | • Policies for training and skills<br>○ e.g. continuous vocational trainings<br>• Direct support to firm R&D and innovation |
| | Cluster-level | • Policies for training and skills<br>○ e.g. regulation and funding of the regional educational system |
| **Connectivity and network problems** | Firm-level | • Direct policies to support collaboration and network development |
| | Cluster-level | • Indirect policies to support collaboration and network development |
| **Matching problems** | Firm-level | • Directed policies<br>○ Directed policies to build up the resources and capabilities<br>○ Directed selection of partners to support collaboration and network development |
| | Cluster-level | • Policies for the regional labour market<br>○ e.g. establishment of cluster skill centres |
| **Diversity problems** | Firm-level | • Policies for interdisciplinarity<br>○ e.g. fostering of interdisciplinary collaborative R&D projects |
| | Cluster-level | • Policies for the regional labour market<br>• Regulation, organization and funding of the regional educational system<br>• Entrepreneurship policies |
| **Market and industry problems** | Market- and industry-level | • Public procurement policy in combination with technology foresight and standards. |
| **Institutional problems** | Institutional-level | • Regulation and framework policies<br>○ e.g. labour law, health and safety regulation, IPR, commercial property policies, etc.<br>• Policies for developing state capacity<br>○ Promotion of specialized skills and expertise in public administration<br>○ Policy learning measures (e.g. benchmarks, best practices) |

[150] Other direct support measures refer in this context for example to innovation vouchers, which are often connected with R&D expenditures, as well as advisory services (e.g. Flanagan et al., 2011; McCann and Ortega-Argilés, 2013).

Both forms of state funding have their advantages and disadvantages (e.g. EFI, 2017; Mohnen, 2018). In line with Mohnen (2018), the choice between both options is therefore rather based on the question of whether the state aims at the neutrality of funding (fiscal incentives) or to actively decide which projects shall be supported (project funding). However, in light of the underlying idea of an active (problem-oriented) cluster policy approach, the use of fiscal incentives for R&D, avoiding any kind of contextual differentiation, is argued to be unsuitable in this context.

On the cluster-level, some of the most prominent policy measures to address the potential resource and capability problems within clusters are policies for training and skills. In particular they deal with the regulation and funding of the regional educational system. In order to tackle resources and capability problems on the cluster-level, the state can influence the supply of specifically needed human capital by fostering and shaping the educational landscape in the corresponding region (Borrás and Edquist, 2015).[151] Nevertheless, despite a positive bias towards high-qualified labour (e.g. 'skill biased technological change'), the balance between the different levels of skills has to be considered in this context (Borrás and Edquist, 2015; Jones and Grimshaw, 2016). This is the case because a pure focus on high-skilled human capital may create a deficit in the supply of technical and intermediate skill-levels which are also crucial for the innovativeness and productivity of firms (Herrmann and Peine, 2011; Jones and Grimshaw, 2016; Keep and Mayhew, 2004).

Connectivity and network problems can likewise occur on the firm-level and/or cluster-level. Thus, the corresponding policy measures also differ in their concrete alignment. Cooperative R&D funding has become a prominent tool to increase knowledge collaborations and thereby address the problem of too limited knowledge exchange that inhibits the exploitation of complementary knowledge sources (Piquero and Vicente, 2019; Vicente, 2014; Weber and Rohracher, 2012). For a long time, policy makers have focused in this context primarily on promoting interactions between regional actors (Dohse et al., 2018). A too strong reliance on cluster internal relationships can, however, lead to a lock-in situation due to a missing inflow of new external ideas and perspectives (Boschma 2005, Martin and Sunley 2003). It has therefore been highlighted that the access to cluster external knowledge sources is crucial for firm performance (Giuliani, 2013; Knoben et al., 2015). Recently, also policy makers have recognized the need to additionally support external linkages in

[151] Depending on the national constitution, the responsibility for the education system may be borne by national or regional policy (Edler and Kuhlmann, 2008; Windzio et al., 2005).

order to balance the internal and external connectedness of firms. For example, the funding program Zwanzig20, endowed with 500 million €, not only formed ten regional thematic networks in Eastern Germany, but additionally supported the interregional and interdisciplinary cooperation with relevant actors from Western Germany (BMBF, 2019c). Moreover, regarding international linkages, the German Federal Government has launched (in 2009) and in 2017 updated a comprehensive strategy to foster the internationalization of science and research (Deutscher Bundestag, 2017; Dohse et al., 2018). The same logic basically also applies to the cluster-level, although the corresponding policy measures are more indirect targeting of the overall network structure within clusters. Nevertheless, in general the existence of connectivity and network problems on the cluster-level has mainly been ignored by policy makers up to now (Crespo et al., 2016; Dohse et al., 2018; Piquero and Vicente, 2019). One important and pioneering exception is the large-scale funding measure of the Federal Ministry of Education and Research in Germany (BMBF) called "Internationalisation of Leading-Edge Clusters, Forward-Looking Projects and Comparable Networks" (InterSpiN). Equipped with more than 100 million €, this new policy instrument supports thirty-two selected clusters and networks in Germany to develop cooperation with international partners in the area of R&D (BMBF, 2019a; Dohse et al., 2018). Apart from fostering existing or new international linkages, Vicente (2014) also highlights that ties-oriented policies may be another option to influence the network structure within clusters. The idea of this policy measure is to support the connectedness between organizations from the cluster core and periphery, which is argued to be crucial to avoid a potential lock-in of the cluster (Crespo et al., 2016; Vicente, 2014). Both exemplary approaches can therefore effectively shape the overall network structure of clusters and thereby solve prevalent connectivity and network problems on the cluster-level.

The matching problems that have largely been ignored up to now can also occur on the firm- and/or cluster-level. To address these cluster-specific problems on the firm-level, so-called directed policies can be implemented.[152] Directed policies can tackle the matching problems in two different ways. First, policy makers can implement directed policies to build up the resources and capabilities of the organizations located within clusters. As already highlighted, in current R&D funding schemes the concrete direction, referring to the type of competences, is not appropriately considered. In order to maximize the firm-specific gains from being located in a

[152] Deviating from the original idea of Edler and Boon (2018), directed policies refer here only to shaping the particular direction of the competence and resource development as well as of the partner selection.

cluster, it has been indicated that, for example, the firm´s knowledge stock should have a balanced level of similarity with the corresponding cluster knowledge stock (Grashof, 2018). If there is a potential mismatch, policy makers should therefore promote the development or reinforcement of specific competences of the organizations located within clusters, e.g. via direct R&D funding. Second, in the cooperative R&D funding, the selection of the partners should be considered in order to support the collaboration and network development in the end. In more concrete terms, the firm-specific knowledge profiles of the cooperation partners should be recognized in the corresponding cooperative R&D measures. For example, this can be done by establishing a new kind of cooperative R&D funding scheme that exclusively aims to connect actors that show a medium similarity in terms of their knowledge profiles. On the cluster-level, the matching problems refer to the labour market pool in clusters (e.g. Duranton, 2011; Grashof, 2019). The matching between labour supply and demand within regional clusters can be improved by applying policies focussing in particular on the regional labour market. One measure in this context is for instance the establishment of cluster skill centres. By knowing the specific job requirements of the clustered firms, the cluster skill centres can improve the skills of the regional labour force in a way that they fit better with the requests of the corresponding employers. Additionally, these cluster skill centres do not need to be physical, but they can also be virtual centres that might co-organize and develop the curricula of regional technical schools and universities so that the abilities of graduates match appropriately with the labour needs within the regional cluster (Andersson et al., 2004; Pietrobelli and Rabellotti, 2006; Rosenfeld, 2002).

Apart from matching problems, an inadequate level of diversity can likewise constitute a problem on the firm-level as well as on the cluster-level. In this context, policies for interdisciplinarity can offer a promising solution. By explicitly requiring an interdisciplinary cooperation, funding programs can particularly foster interdisciplinary collaborative R&D projects. Such collaborative arrangements have the potential to reinforce creativity and to open up completely new and original mindsets, preventing a possible lock-in situation (Alves et al., 2007; Meyer-Krahmer, 2001; Van Rijnsoever et al., 2015). A rather structural oriented policy approach refers to the regulation, organization and funding of the regional educational system. Policy makers, in particular the regional ones, can for example promote the settlement of new research institutes that are related but at the same time provide additional insights for the corresponding regional cluster. Especially broad and parent topics, such as artificial intelligence (AI) or other general purpose technologies[153], seem to be promising in this context. For instance, the German Research Centre for Artificial Intelligence, a non-profit multi-stakeholder research institute, runs seven different research departments located all over Germany (Accenture, 2017; DFKI, 2019; Schiller, 2011). Promoting the establishment of such institutes in regional clusters offers for example the chance to strengthen the knowledge diversity within clusters. However, in their establishment measures, policy should find an appropriate balance between basic and applied research (Henard and McFadyen, 2005; Jones and Grimshaw, 2016; Oosterlinck et al., 2002). In this context, the attraction and funding of start-ups can be an additional way of tackling potential diversity problems. Since these companies are particularly prone to new and often radical ideas, they can enrich the overall knowledge diversity within clusters (Andersson et al., 2004; Audretsch, 2004; Ortega-Argilés and Voigt, 2009). Another option is to address possible diversity problems through migration policies. Obviously, the scope of actions of this approach is dependent upon national regulations, which can vary between open and restrictive ones. Nevertheless, within this range regional policy makers can pursue strategies to particularly attract foreign labour forces (e.g. through exchange programs), which can bring new diverse ideas into the regional cluster (Borrás and Edquist, 2015; Jones, 2012; Niebuhr, 2010).

In the case of market- and industry problems, the main task for policy makers is to reduce the underlying uncertainties. Several measures have already proven to effectively minimize the uncertainty in markets, thereby promoting the performance of firms (Boon and Edler, 2018; Borrás and Edquist, 2013; Harper, 2016). One example refers to formal standards, differing significantly from legal regulations enacted by the government and not by a multi-actors consortium (standardization bodies) (Blind et al., 2017). Instead of just using one instrument, it is suggested here to apply a mix of different approaches in order to reduce the uncertainty. In a first step, multilevel actors, including the state, shall identify new technological trajectories. The process of technology foresight can in this context consist of several activities such as scenario workshops, consensus building and trend analysis (Georghiou and Harper, 2011; Harper, 2016). Based on the gathered information from various perspectives about emerging technological opportunities, standards can be developed by the corresponding standardization bodies in a second step. These standards will not only reduce the risk associated with new technologies and markets but also serve as a

[153] For a good overview of general purpose technologies, please see Bresnahan and Trajtenberg (1995) as well as Lipsey et al. (2005).

first cornerstone for future technological leadership (Blind, 2016; Blind et al., 2017; DIN, 2000). Since these standards will not necessarily ensure the marketization of innovations, the last step of the suggested mixed policy measure also comprises public procurement policies. The idea of these demand-oriented policies is that the state places an order for a product or process that does not yet exist in order to further incentivize companies to really bring the innovations into the market (Borrás and Edquist, 2013; Uyarra, 2016). The suggested mixed policy measure can be seen as a reasonable development of the already proposed combinations of technology foresight and public procurement (e.g. Georghiou et al., 2014; Harper, 2016; Vecchiato and Roveda, 2014) as well as standardization and public procurement (e.g. Blind et al., 2019; Georghiou et al., 2014; Rainville, 2017).

For the last problem concerning the institutional framework conditions, national policy can implement regulation and framework policies. For example, these policies include the establishment of labour laws, health and safety regulations as well as IPRs (Peneder, 2017; Smith, 2000; Woolthuis et al., 2005). In absence of such regulations, the national economy is likely to face serious economic problems (Acemoglu and Robinson, 2010; Acemoglu et al., 2005; Rodrik et al., 2004). Depending on the legal responsibilities, in addition to national policy, also regional policy can realize region-specific regulations for instance with regard to commercial property policies and education (Cooke et al., 1998). The absence of such regulations can, however, also be the result of a deeper institutional problem, namely a lack of state capacities. Even if an extensive collection of information and data is available, policy makers and the respective public administration have to understand, evaluate and apply them to their specific circumstances in order to implement effective policies in the end (Borrás, 2011). Similar to the firm-level, policies for training and skills on the institutional level can be employed to address this problem. The latter aspect refers to the educational background and careers of the employees within the public administration. In this context, it has been emphasized that a missing focus on specialization in the recruitment process and the subsequent careers generates in total less policy expertise within public administrations. Thus, in the recruitment process and the further internal career paths of the employees, the availability of specialized skills and knowledge should be considered more in order to increase the overall state capacities. One example here for can be found in the American civil service, where recruitment is directed towards hiring specialists which then normally remain in the same department, thereby further strengthening their specialized background (Peters, 2015). Although the specialization of skills and knowledge provides advantages, it also implies the danger of a lock-in situation. It is therefore also necessary to realize training measures resulting in a policy learning process which can be defined as a process of "(…) adjusting understandings and beliefs related to public policy." (Moyson et al., 2017, p. 162). In other words, these measures aim to gain access to new knowledge, for example, coming from other countries' experiences. This transnational policy learning can be achieved through benchmarks, best practices[154], expert workshops, program evaluations and interactive online policy learning platforms (Borrás, 2011). One promising example regarding the latter measure is the "Policy Learning Platform"[155] established under the Interreg Europe program. Similar to other online platforms, it collects information and best practices of all Interreg projects as well as it provides news about (networking) events and expert contributions. A unique feature of this particular platform is the direct contact with international experts that answer questions from e.g. local authorities in European regions (Interreg Europe, 2019). By combining the promotion of specialized skills and expertise in public administration with the suggested training measures, this paper argues that the deeper institutional problem of lacking state capacities can be addressed effectively.

In total, the derived targeted (problem-oriented) cluster policy framework contributes to the implementation of more tailor-made cluster policies. As indicated in figure 1, cluster policies can be grouped into three stylized types depending on their impact and their complexity. One-size-fits-all cluster policies are on the hand quite easy to implement, as they are based on simply copying best practices which worked in other contexts regardless of the real existing problems. However, on the other hand, due to their lack of focus on concrete problems, their impact is, if at all, marginal. Consequently, it has been argued by e.g. Tödtling and Trippl (2005) that there is no ideal model for innovation policy but instead regional characteristics need to be considered. Based on this argument, so-called off-the-rack cluster policies concentrating on specific regions (e.g. Land(auf)Schwung[156]), industries (e.g.

[154] In the context of the European Union, the approach of best practices has been further developed and integrated into the "Open Method of Coordination", where experts from ministries and other institutions meet in order to exchange best practices and produce policy manuals which are widely shared throughout Europe (Borrás and Radaelli, 2010; European Commission, 2019b).

[155] For more information please see https://www.interregeurope.eu/policylearning/what-is-policy-learning-platform/.

[156] Within the model project Land(auf)Schwung the Federal Ministry of Food and Agriculture (BMEL) invests more than 32 million € in the economic development of structurally weak rural regions in Germany. For more information please visit https://www.bmel.de/DE/Laendliche-Raeume/BULE/land-auf-schwung/las_node.html.

BioRegio[157]) or firms (e.g. KMU-NetC), have been implemented. These kinds of cluster policies represent an important improvement in terms of their impact but also require more efforts in coordinating and organising from policy makers.

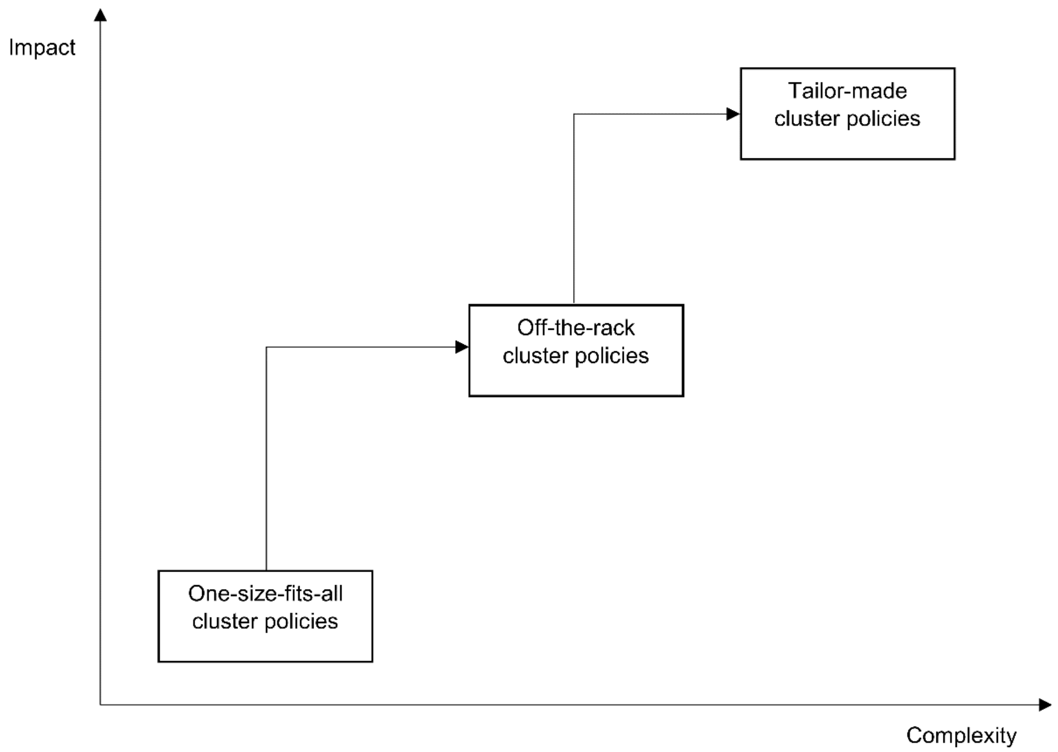



**Figure 1:** Evolution of stylized types of cluster policies

Although they go in the right direction, they constitute only an intermediate step towards truly tailor-made cluster policies. By comprehensively considering cluster-specific problems from different levels of analysis (e.g. firm-level, cluster-level, market-/industry-level), more targeted and adaptive policies can be realized, thereby improving their overall impact. For policy makers it is, however, quite complicated to execute these kinds of cluster policies, since they require for instance sufficient resources and capabilities for a multilevel assessment of relevant cluster-specific problems. Furthermore, since several problems can occur at the same time and with different manifestations, the corresponding design of policy measures is not always straightforward but may become quite complex and diverse (Andersson et al., 2004).[158] In some cases, it may therefore be more reasonable not to simply combine the different policy measures presented in table 3 but to design and implement new ones that particularly consider the multilevel dimensions as well as the potential

[157] BioRegio was a funding initiative of the Federal Ministry of Education and Research (BMBF) from 1997 to 2005 which aimed at strengthening the use of biotechnology in Germany and improving the economic implementation of the results of biotechnological research. For more information about BioRegio please see Dohse (2000).

[158] A detailed illustration of four stylized forms of tailor-made cluster policies can be found in appendix 1.

interaction between the problems. For example, under a high pace of technology evolution, implying high uncertainty (creating market and industry problems), it may be more appropriate to deal with resource and capability problems through technical services and advice instead of direct R&D funding or policies for training and skills (Jones and Grimshaw, 2016). In general, technical services and advice include similar elements as direct R&D funding as well as policies for training and skills, but they additionally offer an external perspective. The main aim of technical services and advice is to improve the (technological) knowledge and skills of a firm by providing external guidance by experts. These external advisory services are argued to be especially suitable in a highly uncertain market environment, because they can reduce the risk of misleading investments in capabilities that may become outdated due to fast technological changes (Shapira and Youtie, 2016). As such, in the case of tailor-made cluster policies, the risk of committing policy failures and distortions is relatively high.

Nevertheless, contrary to the other types of cluster policy, tailor-made cluster policies are based upon a comprehensive analysis of potential cluster-specific problems from different levels of analysis and a related customization of their corresponding policy measures. They therefore meet the need for more targeted cluster policies and move beyond one-size-fits-all as well as off-the-rack cluster policies.

## 5. Conclusion

Despite the widespread application of cluster policies, their effectiveness is still rather questionable (Lehmann and Menter, 2018; Van der Linde, 2003). One reason for this is that the existing multilevel heterogeneity within clusters has not been properly considered yet in the design of cluster policies (Brakman and van Marrewijk, 2013; Nathan and Overman, 2013). Instead, by ignoring these particularities, cluster policies are characterized by highly standardized measures that may work for some cases but not for all (Ebbekink and Lagendijk, 2013; Zenker et al., 2019). Following recent calls (e.g. Auer and Tödtling, 2017; Wolman and Hincapie, 2015), the aim of this paper has therefore been to investigate the specific problems within clusters and how policy can effectively address them. The derived cluster policy framework, comprised of six context-specific problems and the corresponding targeted policy measures, not only contributes to the current scientific discussion about policies in the cluster context, but also offers a high pragmatic value in bringing forth specific adaptive policies for clusters rather than one-size-fits-all cluster policies (Burfitt and MacNeill, 2008; Wolfe and Gertler, 2004).

All in all, this paper claims that cluster policy should actively identify and address problems within clusters. Instead of passively waiting for the best project proposals, resulting in a path-dependent picking winners tendency (Eickelpasch and Fritsch, 2005; Umlauf, 2016; Vicente, 2014), similar to private owned companies the state should actively make strategic investment decisions about the concrete funding of clustered firms. This suggested new role of cluster policy follows a three-step approach.

First, the strategic investment decisions require an objective analytical tool to evaluate and identify potential investment cases (serious cluster-specific problems) (Borrás and Edquist, 2016; Ebbekink and Lagendijk, 2013; Passas et al., 2006). Even though not perfect, for example the dynamic development over the cluster life cycle (e.g. Menzel and Fornahl, 2010) is not explicitly considered, the cluster policy framework suggested here is argued to be an appropriate option in this context.[159]

Second, after actively identifying cluster-specific problems that require state intervention, the corresponding actors should be included. In line with the idea of the entrepreneurial discovery process (Foray, 2015; Foray et al., 2011), the concrete policy measure should be designed in consultation with the respective actors, as they have a more detailed and practice-oriented knowledge, e.g. about potential R&D cooperation partners, than the state (Ebbekink and Lagendijk, 2013). However, in this context the state should not be naïve but instead always be aware of the prevalent rent-seeking behaviour of firms (Boschma, 2014; Lado et al., 1997; Rumelt, 1984).

Lastly, since the widely used proposal contests also offer advantages, in particular as their competitive component ensures the overall quality of the submitted concepts, such a contest constitutes the final step of the proposed approach (Eickelpasch and Fritsch, 2005). Nevertheless, the proposal contests that are suggested here are more targeted than the common ones in the way that only the pre-selected actors, that really need policy support, can apply.

One of the main advantages of this procedure is that the current problem of picking-winners can be solved (e.g. Eickelpasch and Fritsch, 2005; Vicente, 2014), as the state pre-selects actors based on an objective assessment of the real needs. In other words, large companies, such as Siemens, owning sufficient resources to apply for several funding opportunities although they actually do not need the funding, will not

[159] However, for future research it may be promising to develop the suggested cluster policy framework further so that the differences over the cluster life cycle are taken explicitly into consideration (e.g. Brenner and Schlump, 2011; Elola et al., 2017).

continue to be the only winners of these proposal contests. Instead, due to the active engagement of the state in assessing relevant cluster-specific problems, those firms that normally would not apply for funding because of resource constraints, although they actually would need support, have the chance to receive suitable policy support. Hence, in the end more targeted (problem-oriented) funding can be realized, which is likely to lead to a higher efficiency of the corresponding measures. Moreover, the overall quality can also be ensured by considering the competition element of current proposal contests.

Nevertheless, this active role of cluster policy requires sufficient state capacities in order to conduct the necessary assessment of cluster-specific problems and to implement the corresponding policy measures successfully (Berglof and Cable, 2018; Grande, 2001). In light of the increasing complexity of economic issues binding state capacities and financial austerity reducing existing capacities, countries have limited state capacities which can of course be an obstacle in carrying out the suggested cluster policy approach (Grande, 2001; Lobao et al., 2018). One currently discussed option in this context is outsourcing some task to innovation agencies. Although there are good examples such as Vinnova in Sweden or the Defense Advanced Research Projects Agency (DARPA) in the USA, due to their political independence, such institutional arrangements are quite controversial, particularly with regard to their legitimacy (Breznitz et al., 2018; Grande, 2001; Kattel and Mazucatto, 2018; Mazzucato, 2018). However, in general the data that is needed to identify the cluster-specific problems is indeed quite often already available (e.g. Borrás and Edquist, 2013), so that the bureaucrats just have to properly combine and analyse it. With the so-called “Regionale Informationssystem Online” (RISO), an online system for the analysis of regional innovation systems has already been established in Germany, making the data analysis even more convenient. The RISO system combines the information from various administrative data sources, e.g. the German Federal Statistics Office and the Stifterverband[160], and offers analytical as well as graphical tools to directly evaluate the data within the system (DLR, 2011). Such an integrative database can eventually facilitate the analysis and identification of cluster-specific problems. In the future, increasing digitalization, in particular the developments in AI, will likely support the administrative processes, so that the actual data analysis for instance may be completely automatically executed. Thereby, restrictions from limited state capacities can be resolved. Nevertheless, the exact possibilities as well as

[160] The Stifterverband conducts, primarily for the Federal Ministry of Education and Research, the official R&D survey of the research-based German business and enterprise sector (Schneider and Eckl, 2016; Stifterverband, 2018).

limitations of the implementation of AI in the administrative innovation policy context must be properly elaborated in future research. Furthermore, since this study primarily focuses on policies in the cluster context, it is suggested that future research should further develop and adapt the derived cluster policy framework to the broader category of regional policies.

In total, it can therefore be concluded that cluster policy should put the watering can away and move towards a more active and targeted (problem-oriented) approach that takes the specific needs as well as the heterogeneity within the cluster context into account. In other words, cluster policy should ultimately pursue the rationale that inequality has to be treated in an unequal way.

## Bibliography

Accenture (2017): Embracing Artificial Intelligence: Enabling Strong and Inclusive AI driven Economic Growth, available under https://www.accenture.com/_acnmedia/accenture/next-gen-5/event-g20-yea-summit/pdfs/accenture-intelligent-economy.pdf, last retrieved: 29.07.2019.

Acemoglu, D., & Robinson, J. A. (2010): The Role of Institutions in Growth and Development, *Review of Economics and Institutions*, Vol. 1, No. 2, doi: 10.5202/rei.v1i2.14.

Acemoglu, D., Johnson, S., & Robinson, J. A. (2005): *I*nstitutions as a Fundamental Cause of Long-Run Growth, *Handbook of Economic Growth*, Vol. 1, Part A, pp. 385-472.

Alkemade, F., Hekkert, M. P., & Negro, S. O. (2011): Transition policy and innovation policy: Friends or foes?, *Environmental Innovation and Societal Transitions*, Vol. 1, Issue 1, pp. 125-129.

Alves, J., Marques, M. J., Saur, I., & Marques, P. (2007): Creativity and Innovation through Multidisciplinary and Multisectoral Cooperation, *Creativity and Innovation Management*, Vol. 16, No. 1, pp. 27-34.

Andersson, T., Serger, S. S., & Sörvik, J. (2004): Cluster Policies Whitebook, International Organisation for Knowledge Economy and Enterprise Development (IKED).

Arrow, K. J. (1962): Economic welfare and the allocation of resources for invention, in: Nelson, R. R. (Ed.): The Rate and Direction of Inventive Activity: Economic and Social Factors, Princeton University Press, Princeton, NJ, pp. 609-626.

Aschhoff, B. (2009): Who Gets the Money? The Dynamics of R&D Project Subsidies in Germany, *ZEW Discussion Paper*, No. 08-018, available under ftp://ftp.zew.de/pub/zew-docs/dp/dp08018.pdf, last retrieved: 24.07.2019.

Asheim, B. T., & Coenen, L. (2006): Contextualising Regional Innovation Systems in a Globalising Learning Economy: On Knowledge Bases and Institutional Frameworks, *The Journal of Technology Transfer*, Vol. 31, Issue 1, pp. 163-173.

Audretsch, D. B. (2004): Sustaining Innovation and Growth: Public Policy Support for Entrepreneurship, *Industry and Innovation*, Vol. 11, Issue 3, pp. 167-191.

Auer, A., & Tödtling, F. (2017): Are policies supporting cluster development? A comparative firm-level analysis, in: Fornahl, D., & Hassink, R. (Eds.): The Life Cycle of Clusters - A Policy Perspective, Edward Elgar Publishing, Cheltenham, UK, pp. 203-221.

Barasa, L., Knoben, J., Vermeulen, P., Kimuyu, P., & Kinyanjui, B. (2017): Institutions, resources and innovation in East Africa: A firm level approach, *Research Policy*, Vol. 46, Issue 1, pp. 280-291.

Barmeyer, C., & Krüth, K. (2012): The pôles de compétitivité – regional innovation clusters with a French touch, in: Heidenreich, M. (Ed.): Innovation and Institutional Embeddedness of Multinational Companies, Edward Elgar Publishing, Cheltenham, UK, pp. 271-294.

Beaudry, C., & Breschi, S. (2003): Are firms in clusters really more innovative?, *Economics of Innovation and New Technology*, Vol. 12, No. 4, pp. 325-342.

Beck, M., Lopes-Bento, C., & Schenker-Wickia, A. (2014): Radical or Incremental: Where Does R&D Policy Hit ?, *ZEW Discussion Paper*, No. 14-106, available under http://ftp.zew.de/pub/zew-docs/dp/dp14106.pdf, last retrieved: 12.04.2019.

Bell, G. G. (2005): Clusters, networks, and firm innovativeness, *Strategic Management Journal*, Vol. 26, Issue 3, pp. 287-295.

Belso-Martinez, J. A., & Molina-Morales, F. X. (2013): Non-Linear Relationships of Internal and External Resources on a Firm's Innovation: The Case of the Spanish Vinalopó Footwear Cluster, *Growth and Change*, Vol. 44, Issue 3, pp. 494-521.

Benner, M. (2012): Cluster policy: Principles and a toolbox, *SPACES online*, Vol. 10, Issue 2012-01, Toronto and Heidelberg.

Berglof, E., & Cable, V. (2018): Back in Business: Industrial Policy for Emerging Economies in the New Globalization, *ADB Economics Working Paper Series*, No. 537, doi: 10.22617/WPS189236-2.

Blind, K., Petersen, S. S., & Riillo, C. A. (2017): The impact of standards and regulation on innovation in uncertain markets, *Research Policy*, Vol. 46, Issue 1, pp. 249-264.

Blind, K., Pohlisch, J., & Rainville, A. (2019): Innovation and standardization as drivers of companies' success in public procurement: an empirical analysis, *The Journal of Technology Transfer*, doi: 10.1007/s10961-019-09716-1.

BMBF (2019a): Clusters - Networks - International, Bundesministerium für Bildung und Forschung, available under https://www.bmbf.de/en/internationalisation-of-leading-edge-clusters-forward-looking-projects-and-comparable-1416.html, last retrieved: 27.07.2019.

BMBF (2019b): KMU-NetC, Bundesministerium für Bildung und Forschung, available under https://www.bmbf.de/de/kmu-netc-3244.html, last retrieved: 19.07.2019.

BMBF (2019c): Zwanzig20 – Partnerschaft für Innovation, Bundesministerium für Bildung und Forschung, available under https://www.innovation-strukturwandel.de/de/zwanzig20---das-programm-1780.html, last retrieved: 05.12.2019.

Boon, W., & Edler, J. (2018): Demand, challenges, and innovation. Making sense of new trends in innovation policy, *Science and Public Policy*, Vol. 45, Issue 4, pp. 435-447.

Borrás, S. (2011): Policy learning and organizational capacities in innovation policies, *Science and Public Policy*, Vol. 38, Issue 9, pp. 725-734.

Borrás, S., & Edquist, C. (2013): The choice of innovation policy instruments, *Technological Forecasting and Social Change*, Vol. 80, Issue 8, pp. 1513-1522.

Borrás, S., & Edquist, C. (2015): Education, training and skills in innovation policy, *Science and Public Policy*, Vol. 42, Issue 2, pp. 215-227.

Borrás, S., & Edquist, C. (2016): Conceptual Underpinnings for Innovation Policy Design: Indicators and Instruments in Context, Paper presented at OECD Blue Sky Forum on Science and Innovation Indicators, Ghent, Belgium.

Borrás, S., & Radaelli, C. M. (2010): Recalibrating the Open Method of Coordination: Towards Diverse and More Effective Usages, *Sieps Report*, No. 2010:7, Svenska institutet för europapolitiska studier, Stockholm.

Borrás, S., & Tsagdis, D. (2008): Cluster Policies in Europe - Firms, Institutions, and Governance, Edward Elgar Publishing, Cheltenham, UK.

Boschma, R. (2005): Proximity and Innovation: A Critical Assessment, *Regional*

*Studies*, Vol. 39, Issue 1, pp. 61-74.

Boschma, R. (2014): Constructing Regional Advantage and Smart Specialization: Comparison of Two European Policy Concepts, *Scienze Regionali, Italian Journal of Regional Science*, Vol. 13, No. 1, pp. 51-68.

Boschma, R., Minondo, A., & Navarro, M. (2012): Related variety and regional growth in Spain, *Papers in Regional Science*, Vol. 91, Issue 2, pp. 241-256.

Brakman, S., & van Marrewijk, C. (2013): Reflections on cluster policies, *Cambridge Journal of Regions, Economy and Society*, Vol. 6, Issue 2, pp. 217-231.

Brenner, T., & Mühlig, A. (2013): Factors and Mechanisms Causing the Emergence of Local Industrial Clusters: A Summary of 159 Cases, *Regional Studies*, Vol. 47, Issue 4, pp. 480-507.

Brenner, T., & Schlump, C. (2011): Policy Measures and their Effects in the Different Phases of the Cluster Life Cycle, *Regional Studies*, Vol. 45, Issue 10, pp. 1363-1386.

Breznitz, D., Ornston, D., & Samford, S. (2018): Mission critical: the ends, means, and design of innovation agencies, *Industrial and Corporate Change*, Vol. 27, No. 5, pp. 883-896.

Brown, K., Burgees, J., Festing, M., Royer, S., & Steffen, C. (2007): The Value Adding Web – A Conceptual Framework of Competitive Advantage Realisation in Clusters, *ESCP-EAP Working Paper*, No. 27, ISSN: 1619-7658.

Burfitt, A., & MacNeill, S. (2008): The Challenges of Pursuing Cluster Policy in the Congested State, *International Journal of Urban and Regional Research*, Vol. 32, Issue 2, pp. 492-505.

Cantner, U., & Vannuccini, S. (2018): Elements of a Schumpeterian catalytic research and innovation policy, *Industrial and Corporate Change*, Vol. 27, Issue 5, pp. 833-850.

CEDEFOP (2011): The impact of vocational education and training on company performance, *CEDEFOP Research paper*, No. 19, European Centre for the Development of Vocational Training, Publications Office of the European Union, Luxembourg, doi:10.2801/37083.

Cohen, W. M., & Levinthal, D. A. (1990): Absorptive Capacity: A New Perspective on Learning and Innovation, *Administrative Science Quarterly*, Vol. 35, No. 1, Special Issue: Technology, pp. 128-152.

Cooke, P., Uranga, M. G., & Etxebarria, G. (1998): Regional systems of innovation: an evolutionary perspective, *Environment and Planning A*, Vol. 30, Issue 9, pp. 1563-1584.

Crespo, J., Vicente, J., & Amblard, F. (2016): Micro-behaviors and structural properties of knowledge networks: toward a 'one size fits one' cluster policy, *Economics of Innovation and New Technology*, Vol. 25, Issue 6, pp. 533-552.

Cunningham, P., Gök, A., & Larédo, P. (2016): The impact of direct support to R&D and innovation in firms, in: Edler, J., Cunningham, P., Gök, A., & Shapira, P. (Eds.): Handbook of Innovation Policy Impact, Edward Elgar Publishing, Cheltenham, UK, pp. 54-107.

Czarnitzki, D., & Toole, A. A. (2007): Business R&D and the Interplay of R&D Subsidies and Product Market Uncertainty, *Review of Industrial Organization*, Vol. 31, Issue 3, pp. 169-181.

Dalitz, R., & Toner, P. (2016): Systems failure, market failure, or something else? The case of skills development in Australian innovation policy, *Innovation and Development*, Vol. 6, No. 1, pp. 51-66.

De Martino, R., Hardy Reid, D. M., & Zygliodopoulos, S. C. (2006): Balancing localization and globalization:exploring the impact of firm internationalization on a regional cluster, *Entrepreneurship & Regional Development*, Vol. 18, Issue 1, pp. 1-24.

Deutscher Bundestag (2017): Strategie der Bundesregierung zur Internationalisierung von Bildung, Wissenschaft und Forschung, Bundestagsdrucksache 18/11100, Berlin.

DFKI (2019): Competence Centers, German Research Center for Artificial Intelligence (DFKI), available under https://www.dfki.de/en/web/research/competence-centers/, last retrieved from: 29.07.2019.

DLR (2011): Geschäftsbericht 2010 - Im Dienst von Forschung und Wissenschaft, Deutsches Zentrum für Luft- und Raumfahrt e. V., Projektträger im DLR, available under https://www.dlr.de/pt/PortalData/45/Resources/a_dokumente/service/GB_2010_web.pdf, last retrieved: 17.07.2019.

Dodgson, M., Hughes, A., Foster, J., & Metcalfe, S. (2011): Systems thinking, market failure, and the development of innovation policy: The case of Australia, *Research Policy*, Vol. 40, Issue 9, pp. 1145-1156.

Dohse, D. (2000): Technology policy and the regions — the case of the BioRegio contest, *Research Policy*, Vol. 29, Issue 9, pp. 1111-1133.

Dohse, D., Fornahl, D., & Vehrke, J. (2018): Fostering place-based innovation and internationalization – the new turn in German technology policy, *European Planning Studies*, Vol. 26, Issue 6, pp. 1137-1159.

Duranton, G. (2011): California Dreamin': The Feeble Case for Cluster Policies, *Review of Economic Analysis*, Vol. 3, No. 1, pp. 3-45.

Ebbekink, M., & Lagendijk, A. (2013): What's Next in Researching Cluster Policy: Place-Based Governance for Effective Cluster Policy, *European Planning Studies*, Vol. 21, Issue 5, pp. 735-753.

Edler, J., & Boon, W. P. (2018): 'The next generation of innovation policy: Directionality and the role of demand-oriented instruments'—Introduction to the special section, *Science and Public Policy*, Vol. 45, Issue 4, pp. 433-434.

Edler, J., & Fagerberg, J. (2017): Innovation policy: what, why, and how, *Oxford Review of Economic Policy*, Vol. 33, Issue 1, pp. 2-23.

Edler, J., & Kuhlmann, S. (2008): Coordination within fragmentation: governance in knowledge policy in the German federal system, *Science and Public Policy*, Vol. 35, Issue 4, pp. 265-276.

Edler, J., Gök, A., Cunningham, P., & Shapira, P. (2016): Introduction: Making sense of innovation policy, in: Edler, J., Cunningham, P., Gök, A., & Shapira, P. (Eds.): Handbook of Innovation Policy Impact, Edward Elgar Publishing, Cheltenham, UK, pp. 1-17.

Edquist, C. (2011): Design of innovation policy through diagnostic analysis: identification of systemic problems (or failures), *Industrial and Corporate Change*, Vol. 20, Issue 6, pp. 1725-1753.

EFI (2015): Gutachten zu Forschung, Innovation und Technologischer Leistungsfähigkeit Deutschlands, Expertenkommission Forschung und Innovation.

EFI (2017): Gutachten zu Forschung, Innovation und Technologischer Leistungsfähigkeit Deutschlands, Expertenkommission Forschung und Innovation.

EFI (2018): Gutachten zu Forschung, Innovation und Technologischer Leistungsfähigkeit Deutschlands, Expertenkommission Forschung und Innovation.

Eickelpasch, A., & Fritsch, M. (2005): Contests for cooperation—A new approach in German innovation policy, *Research Policy*, Vol. 34, Issue 8, pp. 1269-1282.

Elola, A., Valdaliso, J. M., Franco, S., & López, S. M. (2017): Public policies and cluster life cycles: insights from the Basque country experience, *European Planning Studies*, Vol. 25, Issue 3, pp. 539-556.

European Commission (2008): The concept of clusters and cluster policies and their role for competitiveness and innovation: Main statistical results and lessons learned, *Europe INNOVA / PRO INNO Europe paper*, No. 9.

European Commission (2019a): European Quality of Government Index 2017, available under https://ec.europa.eu/regional_policy/en/information/maps/quality_of_governance#1, last retrieved: 02.12.2019.

European Commission (2019b): European cooperation: the Open Method of Coordination, available under https://ec.europa.eu/culture/policy/strategic-framework/european-coop_en, last retrieved: 04.12.2019.

European Union (2016): Smart Guide to Cluster Policy, Guidebook Series: How to support SME Policy from Structural Funds, doi:10.2873/729624.

Farole, T., Rodríguez-Pose, A., & Storper, M. (2011): Cohesion Policy in the European Union: Growth, Geography, Institutions, *Journal of Common Market Studies*, Vol. 49, Issue 5, pp. 1089-1111.

Ferriani, S., & MacMillan, I. (2017): Performance gains and losses from network centrality in cluster located firms: a longitudinal study, *Innovation*, Vol. 19, Issue 3, pp. 307-334.

Festing, M., Royer, S., & Steffen, C. (2012): Unternehmenscluster schaffen Wettbewerbsvorteile - Eine Analyse des Uhrenclusters in Glashütte, *Zeitschrift Führung + Organisation*, Vol. 81, No. 4, pp. 264-272.

Flanagan, K., Uyarra, E., & Laranja, M. (2011): Reconceptualising the ‘policy mix’ for innovation, *Research Policy*, Vol. 40, Issue 5, pp. 702-713.

Folta, T. B., Cooper, A. C., & Baik, Y.-s. (2006): Geographic cluster size and firm performance, *Journal of Business Venturing*, Vol. 21, Issue 2, pp. 217-242.

Fontagné, L., Koenig, P., Mayneris, F., & Ponce, S. (2013): Cluster Policies and Firm Selection: Evidence from France, *Journal of Regional Science*, Vol. 53, Issue 5, pp. 897-922.

Foray, D. (2015): Smart Specialisation: Opportunities and Challenges for Regional Innovation Policy, Routledge, London & New York.

Foray, D. (2018): Smart specialisation strategies and industrial modernisation in European regions—theory and practice, *Cambridge Journal of Economics*, Vol. 42, Issue 6, pp. 1505-1520.

Foray, D., David, P. A., & Hall, B. H. (2011): Smart Specialisation: From academic idea to political instrument, the surprising career of a concept and the difficulties involved in its implementation, *MTEI Working Paper*, No. 2011.001, École

Polytechnique Fédérale de Lausanne.

Fornahl, D., Broekel, T., & Boschma, R. (2011): What drives patent performance of German biotech firms? The impact of R&D subsidies, knowledge networks and their location, *Papers in Regional Science*, Vol. 90, Issue 2, pp. 395-418.

Fornahl, D., Heimer, T., Campen, A., Talmon-Gros, L., & Treperman, J. (2015): Cluster als Paradigma der Innovationspolitik - Eine erfolgreiche Anwendung von Theorie in der politischen Praxis?, Studien zum deutschen Innovationssystem, No. 13-2015.

Frenken, K., Cefis, E., & Stam, E. (2015): Industrial dynamics and clusters: a survey, *Regional Studies*, Vol. 49, Issue 1, pp. 10-27.

Garcia-Vega, M. (2006): Does technological diversification promote innovation? An empirical analysis for European firms, *Research Policy*, Vol. 35, Issue 2, pp. 230-246.

Garnero, A., Kampelmann, S., & Rycx, F. (2014): The Heterogeneous Effects of Workforce Diversity on Productivity, Wages, and Profits, *Industrial Relations*, Vol. 53, Issue 3, pp. 430-477.

Georghiou, L., & Harper, J. C. (2011): From priority-setting to articulation of demand: Foresight for research and innovation policy and strategy, *Futures*, Vol. 43, Issue 3, pp. 243-251.

Georghiou, L., Edler, J., Uyarra, E., & Yeow, J. (2014): Policy instruments for public procurement of innovation: Choice, design and assessment, *Technological Forecasting and Social Change*, Vol. 86, pp. 1-12.

Giuliani, E. (2007): The selective nature of knowledge networks in clusters: evidence from the wine industry, *Journal of Economic Geography*, Vol. 7, Issue 2, pp. 139-168.

Giuliani, E. (2013): Clusters, networks and firms' product success: an empirical study, *Management Decision*, Vol. 51, Issue 6, pp. 1135-1160.

Grande, E. (2001): The erosion of state capacity and the European innovation policy dilemma: A comparison of German and EU information technology policies, *Research Policy*, Vol. 30, Issue 6, pp. 905-921.

Grashof, N. (2018): Spill over or Spill out? - A multilevel analysis of the cluster and firm performance relationship, Working Paper.

Grashof, N. (2019): Sinking or swimming in the cluster labour pool? - A firm-specific analysis of the effect of specialized labour, Working Paper.

Grashof, N., & Fornahl, D. (2020): 'To be or not to be' located in a cluster? - A descriptive meta-analysis of the firm-specific cluster effect, *Working Papers on Innovation and Space*, No. 01.20.

Grashof, N., Hesse, K., & Fornahl, D. (2019): Radical or not? The role of clusters in the emergence of radical innovations, *European Planning Studies*, Vol. 27, Issue 10, pp. 1904-1923.

Harper, J. C. (2016): The impact of technology foresight on innovation and innovation policy, in: Edler, J., Cunningham, P., Gök, A., & Shapira, P. (Eds.): Handbook of Innovation Policy Impact, Edward Elgar Publishing, Cheltenham, UK, pp. 483-504.

Henard, D. H., & McFadyen, M. A. (2005): The Complementary Roles of Applied and Basic Research: A Knowledge-Based Perspective, *Journal of Product Innovation Management*, Vol. 22, Issue 6, pp. 503-514.

Herrmann, A. M., & Peine, A. (2011): When ‘national innovation system’ meet ‘varieties of capitalism’ arguments on labour qualifications: On the skill types and scientific knowledge needed for radical and incremental product innovations, *Research Policy*, Vol. 40, Issue 5, pp. 687-701.

Hervas-Oliver, J. L., & Albors-Garrigos, J. (2007): Do clusters capabilities matter? An empirical application of the resource-based view in clusters, *Entrepreneurship & Regional Development*, Vol. 19, Issue 2, pp. 113-136.

Hervas-Oliver, J.-L., & Albors-Garrigos, J. (2009): The role of the firm’s internal and relational capabilities in clusters: when distance and embeddedness are not enough to explain innovation, *Journal of Economic Geography*, Vol. 9, Issue 2, pp. 263-283.

Hervas-Oliver, J.-L., Sempere-Ripoll, F., Alvarado, R. R., & Estelles-Miguel, S. (2018): Agglomerations and firm performance: who benefits and how much?, *Regional Studies*, Vol. 52, Issue 3, pp. 338-349.

Hesse, K. (2020). Related to whom? The impact of organisational and regional capabilities on radical breakthroughs, *Bremen Papers on Economics & Innovation*, No. 2005.

Hundt, C., Holtermann, L., Steeger, J., & Bersch, J. (2019): Cluster externalities, firm capabilities, and the recessionary shock: How the macro-to-micro-transition shapes firm performance during stable times and times of crisis, *Papers in Evolutionary Economic Geography*, No. 19.07.

Interreg Europe (2019): What is the Policy Learning Platform?, available under https://www.interregeurope.eu/policylearning/what-is-policy-learning-platform/, last retrieved: 04.12.2019.

Jones, B. (2012): Innovation and human resources: Migration policies and employment protection policies, in: NESTA Compendium of Evidence on the Effectiveness of Innovation Policy Intervention, Manchester Institute of Innovation Research, University of Manchester.

Jones, B., & Grimshaw, D. (2016): The impact of skill formation policies on innovation, in: Edler, J., Cunningham, P., Gök, A., & Shapira, P. (Eds.): Handbook of Innovation Policy Impact, Edward Elgar Publishing, Cheltenham, UK, pp. 108-128.

Kattel, R., & Mazzucato, M. (2018): Mission-oriented innovation policy and dynamic capabilities in the public sector, *Industrial and Corporate Change*, Vol. 27, Issue 5, pp. 787-801.

Keep, E., & Mayhew, K. (2004): The Economic and Distributional Implications of Current Policies on Higher Education, *Oxford Review of Economic Policy*, Vol. 20, Issue 2, pp. 298-314.

Ketels, C. (2009): Clusters, Cluster Policy, and Swedish Competitiveness in the Global Economy, Expert report No. 30 to Sweden’s Globalisation Council.

Kitson, M., Martin, R., & Tyler, P. (2011): The geographies of austerity, *Cambridge Journal of Regions, Economy and Society*, Vol. 4, Issue 3, pp. 289-302.

Knoben, J., Arikan, A. T., Van Oort, F., & Raspe, O. (2015): Agglomeration and firm performance: One firm’s medicine is another firm’s poison, *Environment and Planning A*, Vol. 48, No. 1, pp. 1-22.

Kohlbacher, M., Weitlaner, D., Hollosi, A., Grünwald, S., & Grahsl, H.-P. (2013): Innovation in clusters: effects of absorptive capacity and environmental moderators, *Competitiveness Review: An International Business Journal*, Vol.

23, Issue 3, pp. 199-217.

Konstantynova, A., & Wilson, J. (2014): Comparing Cluster Policies: An Analytical Framework, *Orkestra Working Paper Series in Territorial Competitiveness*, No. 2014-R01.

Lado, A. A., Boyd, N. G., & Hanlon, S. C. (1997): Competition, Cooperation, and the Search for Economic Rents: A Syncretic Model, *The Academy of Management Review*, Vol. 22, No. 1, pp. 110-141.

Laranja, M., Uyarra, E., & Flanagan, K. (2008): Policies for science, technology and innovation: Translating rationales into regional policies in a multi-level setting, *Research Policy*, Vol. 37, Issue 5, pp. 823-835.

Larédo, P., Köhler, C., & Rammer, C. (2016): The impact of fiscal incentives for R&D, in: Edler, J., Cunningham, P., Gök, A., & Shapira, P. (Eds.): Handbook of Innovation Policy Impact, Edward Elgar Publishing, Cheltenham, UK, pp. 18-53.

Lehmann, E. E., & Menter, M. (2018): Public cluster policy and performance, *The Journal of Technology Transfer*, Vol. 43, Issue 3, pp. 558-592.

Lindner, R., Daimer, S., Beckert, B., Heyen, N., Koehler, J., Teufel, B., Warnke, P., & Wydra, S. (2016): Addressing directionality: Orientation failure and the systems of innovation heuristic. Towards reflexive governance, *Fraunhofer ISI Discussion Papers - Innovation Systems and Policy Analysis*, No. 52, Fraunhofer ISI, Karlsruhe.

Lobao, L., Gray, M., Cox, K., & Kitson, M. (2018): The shrinking state? Understanding the assault on the public sector, *Cambridge Journal of Regions, Economy and Society*, Volume 11, Issue 3, pp. 389-408.

Martin, R., & Sunley, P. (2003): Deconstructing clusters: chaotic concept or policy panacea?, *Journal of Economic Geography*, Vol. 3, Issue 1, pp. 5-35.

Martin, S., & Scott, J. T. (2000): The nature of innovation market failure and the design of public support for private innovation, *Research Policy*, Vol. 29, Issues 4-5, pp. 437-447.

Mazzucato, M. (2016): From market fixing to market-creating: a new framework for innovation policy, *Industry and Innovation*, Vol. 23, Issue 2, pp. 140-156.

Mazzucato, M. (2018): Mission-oriented innovation policies: challenges and opportunities, *Industrial and Corporate Change*, Vol. 27, Issue 5, pp. 803-815.

McCann, B. T., & Folta, T. B. (2008): Location Matters: Where We Have Been and Where We Might Go in Agglomeration Research, *Journal of Management*, Vol. 34, No. 3, pp. 532-565.

McCann, B. T., & Folta, T. B. (2011): Performance differentials within geographic clusters, *Journal of Business Venturing*, Vol. 26, Issue 1, pp. 104-123.

McCann, P., & Ortega-Argilés, R. (2013): Modern regional innovation policy, *Cambridge Journal of Regions, Economy and Society*, Vol. 6, Issue 2, pp. 187-216.

Menzel, M.-P., & Fornahl, D. (2010): Cluster life cycles—dimensions and rationales of cluster evolution, *Industrial and Corporate Change*, Vol, 19, Issue 1, pp. 205-238.

Metcalfe, S. (1995): The Economic Foundations of Technology Policy: Equilibrium and Evolutionary Perspectives, in: Stoneman, P. (Ed.): Handbook of the Economics of Innovation and Technological Change, Blackwell, Oxford, pp. 409-512.

Meyer-Krahmer, F. (2001): The German Innovation System, in: Larédo, P., & Mustar,

P. (Eds.): Research and Innovation Policies in the New Global Economy - An International Comparative Analysis, Edward Elgar Publishing, Cheltenham, UK, pp. 205-252.

Ministerium für Finanzen und Wirtschaft Baden-Württemberg (2013): Regionale Wettbewerbsfähigkeit durch Innovation und Nachhaltigkeit - RegioWIN, Wettbewerbsaufruf, available under https://efre-bw.de/wp-content/uploads/2015/05/Foerderaufruf-RegioWIN_MFW.pdf#, last retrieved: 14.12.2019.

Mohnen, P. (2018): Effectiveness of direct and indirect R&D support, in: Niosi, J. (Ed.): Innovation Systems, Policy and Management, Cambridge University Press, Cambridge, pp. 53-78, doi: 10.1017/9781108529525.004.

Moyson, S., Scholten, P., & Weible, C. M. (2017): Policy learning and policy change: theorizing their relations from different perspectives, *Policy and Society*, Vol. 36, Issue 2, pp. 161-177.

Nathan, M., & Overman, H. (2013): Agglomeration, clusters, and industrial policy, *Oxford Review of Economic Policy*, Vol. 29, Issue 2, pp. 383-404.

Nelson, R. R. (1959): The Simple Economics of Basic Scientific-Research, *Journal of Political Economy*, Vol. 67, No. 3, pp. 297-306.

Niebuhr, A. (2010): Migration and innovation: Does cultural diversity matter for regional R&D activity?, *Papers in Regional Science*, Vol. 89, Issue 3, pp. 563-585.

Oosterlinck, A., Debackere, K., & Cielen, G. (2002): Balancing basic and applied research. In a time of economic changes and stagnating support from the government, universities have to restructure and reshape their mission, *EMBO Reports*, Vol. 3, Issue 1, pp. 2-5.

Ortega-Argilés, R., & Voigt, P. (2009): Business R&D in SMEs, *IPTS Working Papers on Corporate R&D and Innovation*, No. 07/2009. Sevilla, Spain: IPTS/Joint Research Centre of the European Commission.

Passas, I., Sefertzi, E., Komninos, N., Guth, M., Villarejo, E. P., Bermejo, J. A., Halvorsen, K., Krogh, A. C., Komendantova, M., & Egerund, M. L. (2006): Stratinc: A regional policy blueprint highlighting the uses of strategic intelligence in cluster policy, available under http://eprints.rclis.org/8783/1/blueprintanglais.pdf, last retrieved: 29.07.2019.

Peneder, M. (2017): Competitiveness and industrial policy: from rationalities of failure towards the ability to evolve, *Cambridge Journal of Economics*, Vol. 41, Issue 3, pp. 829-858.

Peters, B. G. (2015): Policy capacity in public administration, *Policy and Society*, Vol. 34, Issue 3-4, pp. 219-228.

Pietrobelli, C., & Rabellotti, R. (2006): Supporting Enterprise Upgrading in Clusters and Value Chains in Latin America, in: Pietrobelli, C., & Rabellotti, R. (Eds.): Upgrading to Compete - Global Value Chains, Clusters, and SMEs in Latin America, Inter-American Development Bank, Washington, pp. 299-330.

Piquero, D. L., & Vicente, J. (2019): The visible hand of cluster policy makers: An analysis of Aerospace Valley (2006-2015) using a place-based network methodology, *Research Policy*, Vol. 48, Issue 3, pp. 830-842.

Porter, M. E. (2000): Location, Competition, and Economic Development: Local Clusters in a Global Economy, *Economic Development Quarterly*, Vol. 14, Issue 1, pp. 15-34.

Porter, M. E. (2003): The Economic Performance of Regions, *Regional Studies*, Vol.

37, Issue 6-7, pp. 549-578.

Rainville, A. (2017): Standards in green public procurement – A framework to enhance innovation, *Journal of Cleaner Production*, Vol. 167, pp. 1029-1037.

Rigby, D. L., & Brown, M. W. (2015): Who Benefits from Agglomeration?, *Regional Studies*, Vol. 49, Issue 1, pp. 28-43.

Rodríguez-Pose, A., & Di Cataldo, M. (2015): Quality of government and innovative performance in the regions of Europe, *Journal of Economic Geography*, Vol. 15, Issue 4, pp. 673-706.

Rodrik, D., Arvind, S., & Trebbi, F. (2004): Institutions Rule: The Primacy of Institutions Over Geography and Integration in Economic Development, *Journal of Economic Growth*, Vol. 9, Issue 2, pp. 131-165.

Rosenfeld, S. A. (2002): Creating Smart Systems: A guide to cluster strategies in less favoured, Report to the Regional Innovation Strategies, European Union.

Rumelt, R. P. (1984): Towards a Strategic Theory of the Firm, in: Lamb, R. B. (Ed.): Competitive Strategic Management, Prentice-Hall, Englewood Cliffs, N.J.

Sampson, R. C. (2007): R&D Alliances and Firm Performance: The Impact of Technological Diversity and Alliance Organization on Innovation, *The Academy of Management Journal*, Vol. 50, No. 2, pp. 364-386.

Saxenian, A. (1994): Regional Advantage: Culture and Competition in Silicon Valley and Route 128, Harvard University Press, Cambridge, MA.

Schaal, E. (2017): Uncertainty and Unemployment, *Econometrica*, Vol. 85, Issue 6, pp. 1675-1721.

Schiller, D. (2011): Institutions and practice in cross-sector research collaboration: conceptual considerations with empirical illustrations from the German science sector, *Science and Public Policy*, Vol. 38, Issue 2, pp. 109-121.

Schneider, J., & Eckl, V. (2016): The difference makes a difference: Team diversity and innovative capacity, OECD workshop: "Developing novel approaches to measure human capital and innovation".

Schot, J., & Steinmueller, W. E. (2018): Three frames for innovation policy: R&D, systems of innovation and transformative change, *Research Policy*, Vol. 47, Issue 9, pp. 1554-1567.

Schulze-Krogh, A. C. (2018): Firms' Absorptive Capacity for Research-Based Collaboration—an Analysis of a Norwegian R&D Brokering Policy Program, *Science and Public Policy*, Vol. 45, Issue 4, pp. 533-542.

Sedita, S. R., Lazzeretti, L., & Caloffi, A. (2012): The birth and the rise of the cluster concept, DRUID, 2012, CBS, Copenhagen.

Shapira, P., & Youtie, J. (2016): The impact of technology and innovation advisory services, in: Edler, J., Cunningham, P., Gök, A., & Shapira, P. (Eds.): Handbook of Innovation Policy Impact, Edward Elgar Publishing, Cheltenham, UK, pp. 161-195.

Shaver, J. M., & Flyer, F. (2000): Agglomeration economies, firm heterogeneity, and foreign direct investment in the United States, *Strategic Management Journal*, Vol. 21, Issue 12, pp. 1175-1193.

Smith, K. (2000): Innovation as a Systemic Phenomenon: Rethinking the Role of Policy, *Enterprise and Innovation Management Studies*, Vol. 1, Issue 1, pp. 73-102.

Stifterverband. (2018): RESEARCH DATA CENTER WISSENSCHAFTSSTATISTIK, available under https://www.stifterverband.org/research_data_center, last retrieved: 10.03.2018.

Suarez, F. F., & Lanzolla, G. (2007): The Role of Environmental Dynamics in Building a First Mover Advantage Theory, *Academy of Management Review*, Vol. 32, No. 2, pp. 377-392.

Tallman, S., Jenkins, M., Henry, N., & Pinch, S. (2004): Knowledge, Clusters, and Competitive Advantage, *The Academy of Management Review*, Vol. 29, No. 2, pp. 258-271.

Tödtling, F., & Trippl, M. (2005). One size fits all?: Towards a differentiated regional innovation policy approach, *Research Policy*, Vol. 34, Issue 8, pp. 1203-1219.

Torregrosa-Hetland, S., Pelkonen, A., Oksanen, J., & Kander, A. (2019): The prevalence of publicly stimulated innovations –A comparison of Finland and Sweden, 1970–2013, *Research Policy*, Vol. 48, Issue 6, pp. 1373-1384.

Umlauf, F. (2016): Structure and dynamics of policy induced networks in systems of innovation, Dissertation, University of Bremen.

Uyarra, E. (2016): The impact of public procurement of innovation, in: Edler, J., Cunningham, P., Gök, A., & Shapira, P. (Eds.): Handbook of Innovation Policy Impact, Edward Elgar Publishing, Cheltenham, UK, pp. 355-381.

Uyarra, E., & Ramlogan, R. (2012): The Effects of Cluster Policy on Innovation, *Nesta Working Paper*, No. 12/05.

Van der Linde, C. (2003): The Demography of Clusters—Findings from the Cluster Meta-Study, in: Bröcker, J., Dohse, D., & Soltwedel, R. (Eds.): Innovation Clusters and Interregional Competition, Springer Verlag, Berlin.

Van Rijnsoever, F. J., Van den Berg, J., Koch, J., & Hekkert, M. P. (2015): Smart innovation policy: How network position and project composition affect the diversity of an emerging technology, *Research Policy*, Vol. 44, Issue 5, pp. 1094-1107.

Vecchiato, R., & Roveda, C. (2014): Foresight for public procurement and regional innovation policy: The case of Lombardy, *Research Policy*, Vol. 43, Issue 2, pp. 438-450.

Veugelers, R. (2015): Mixing and matching research and innovation policies in EU countries, *Bruegel Working Paper*, No. 2015/16, Bruegel, Brussels.

Vicente, J. (2014): Don't throw the baby out with the bath water. Network failures and policy challenges for cluster long run dynamics, *Papers in Evolutionary Economic Geography*, No. 14.20.

Wanzenböck, I., & Frenken, K. (2018): The subsidiarity principle: Turning challenge-oriented innovation policy on its head, *Papers in Evolutionary Economic Geography*, No. 18.06.

Wapshott, R., & Mallett, O. (2018): Small and medium-sized enterprise policy: Designed to fail?, *Environment and Planning C: Politics and Space*, Vol. 36, Issue 4, pp. 750-772.

Weber, K. M., & Rohracher, H. (2012): Legitimizing research, technology and innovation policies for transformative change: Combining insights from innovation systems and multi-level perspective in a comprehensive 'failures' framework, *Research Policy*, Vol. 41, Issue 6, pp. 1037-1047.

Windzio, M., Sackmann, R., & Martens, K. (2005): Types of governance in education: a quantitative analysis, *TranState working papers*, No. 25, SfB 597 - Staatlichkeit im Wandel, Bremen.

Wolfe, D. A., & Gertler, M. S. (2004): Clusters from the Inside and Out: Local Dynamics and Global Linkages, *Urban Studies*, Vol. 41, Issue 5-6, pp. 1071-1093.

Wolman, H., & Hincapie, D. (2015): Clusters and Cluster-Based Development Policy, *Economic Development Policy*, Vol. 29, Issue 2, pp. 135-149.

Woolthuis, R. K., Lankhuizen, M., & Gilsing, V. (2005): A system failure framework for innovation policy design, *Technovation*, Vol. 25, Issue 6, pp. 609-619.

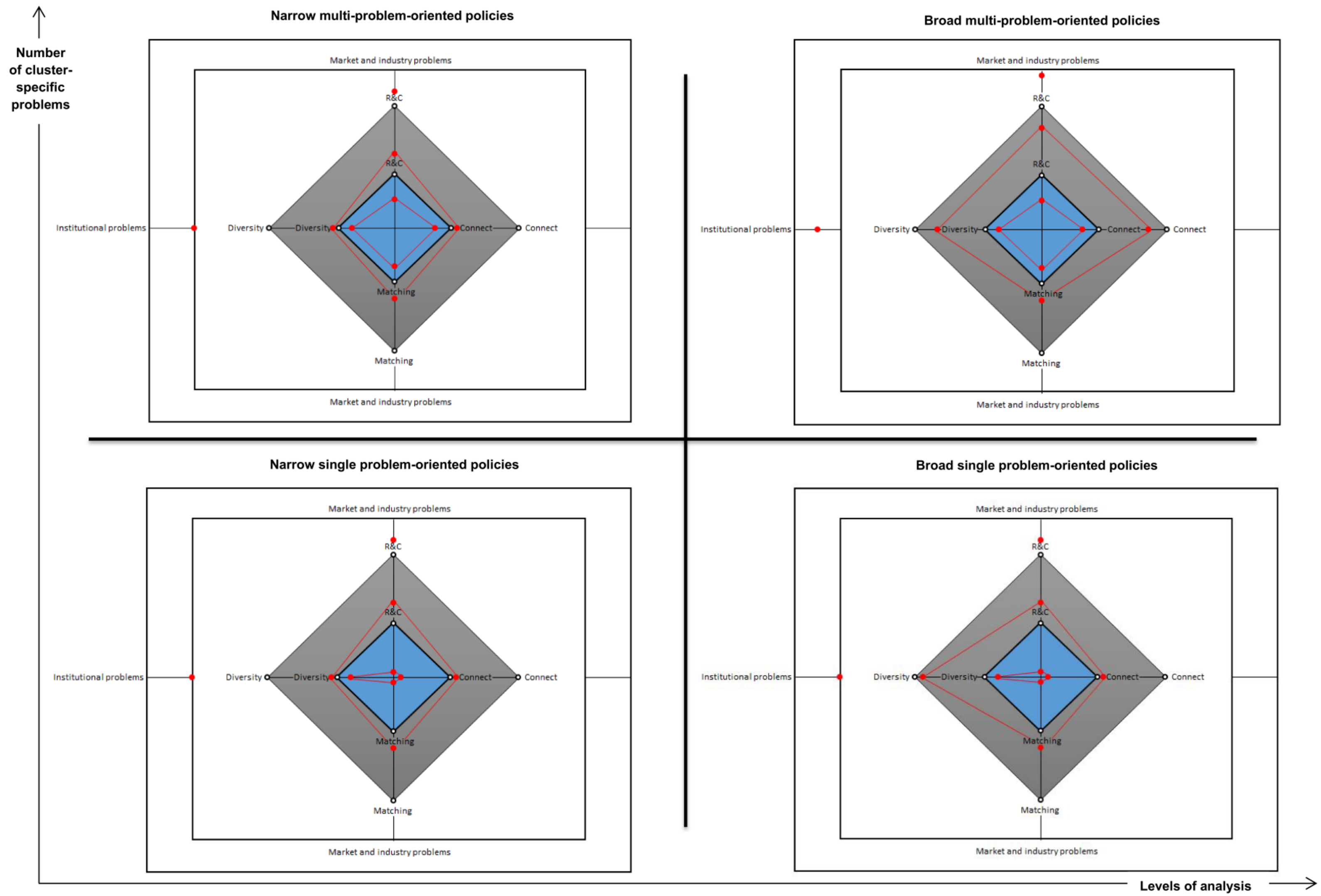
Wu, X., Geng, S., Li, J., & Zhang, W. (2010): Shared Resources and Competitive Advantage in Clustered Firms: The Missing Link, *European Planning Studies*, Vol. 18, Issue 9, pp. 1391-1410.

Wu, X., Ramesh, M., & Howlett, M. (2015): Policy capacity: A conceptual framework for understanding policy competences and capabilities, *Policy and Society*, Vol. 34, Issues 3-4, pp. 165-171.

Zaheer, A., & George, V. P. (2004): Reach Out or Reach Within? Performance Implications of Alliances and Location in Biotechnology, *Managerial and Decision Economics*, Vol. 25, Issue 6-7, pp. 437-452.

Zenker, A., Delponte, L., Mayán, N. D., Wintjes, R., Amichetti, C., Carneiro, J., Meyborg, M., Notten, A., Schnabl, E., & Stahlecker, T. (2019): Cluster programmes in Europe and beyond, European Observatory for Clusters and Industrial Change, available under https://www.clustercollaboration.eu/eu-initiatives/european-cluster-observatory, last retrieved: 17.07.2019.

# Appendix




**Appendix 1:** Four stylized forms of tailor-made cluster policies

Based on the presented cluster policy framework and the distinction made by Borrás and Tsagdis (2008), the following four forms of tailor-made cluster policies can be derived:

(1.) *Narrow single problem-oriented policies*. This type of policies refers to the simplest case. Namely, when there only exists one problem at one level of analysis. By applying the provided cluster policy framework, politicians can directly apply the most adequate measure to address the corresponding problem. The complexity and the coordination effort are therefore quite low.

(2.) *Broad single problem-oriented policies*. Although it is again just one relevant problem existing, due to the multilevel character of this problem the second stylized policy type is more complex than the first one. It requires the state to think of and implement measures that effectively work at different levels of analysis, e.g. firm-level and cluster-level.

(3.) *Narrow multi-problem-oriented policies*. This type is characterized by a relatively high coordination effort, as several problems are existing, even though just at one level of analysis. Since several problems have to be addressed, policy makers need to coordinate their measures in order to avoid unintended side effects and to increase the overall efficiency (Ketels, 2009; Nathan and Overman, 2013).

(4.) *Broad multi-problem-oriented policies*. The last type of cluster policies is the most complex one and requires the highest coordination effort, because it addresses several problems at different levels of analysis.

# Appendix of the cumulative dissertation

The appendix of this cumulative dissertation includes the published versions of the three side papers (see section **A.**), the author biography (see section **B.**) as well as the statutory declaration (see section **C.**).

## A. Side Papers

The published versions of the three side papers of this cumulative dissertation, which broaden the previous findings of the five core papers, are listed in the following sections.

The first side paper, “Effects of Being Located in a Cluster on Economic Actors” (Fornahl et al., 2018), is published in the book “Agglomeration and Firm Performance” edited by Fiorenza Belussi and Jose-Luis Hervas-Oliver (see section **A.1.**).

The second side paper, “Radical or not? The role of clusters in the emergence of radical innovations” (Grashof et al., 2019), is published in the journal ‘Papers in Regional Science’ (see section **A.2.**).

The third side paper, “University-industry collaborations – The key to radical innovations?” (Arant et al., 2019), is published in the journal ‘Review of Regional Research’ (see section **A.3.**).

### A.1. Effects of Being Located in a Cluster on Economic Actors

**Authors:** Dirk Fornahl, Nils Grashof, Cathrin Söllner

**Share by the author of the dissertation in the publication:** 45%

**Type of participation:**

- Introduction
- Theoretical foundation
- Literature Review
- Conclusion

# Effects of Being Located in a Cluster on Economic Actors

**Dirk Fornahl, Nils Grashof, and Cathrin Söllner**

**Abstract** The greatest assets of clusters are their positive external effects or knowledge spillovers generated through the colocation of firms of the same or similar industries. These externalities can have a positive influence on various performance indicators, not only for firms inside clusters but for the entire region in which clusters are embedded as well. However, several empirical studies show that these positive results do not always manifest themselves. Moderating effects such as industry- or country-specific as well as cluster- and firm-specific characteristics play important roles. Therefore, the goal of this chapter is to provide an overview on the effects both inside and outside of clusters identified in empirical studies, thereby investigating the following indicators: innovativeness, productivity, employment growth and wage level, entrepreneurship, survival probability and growth of start-ups as well as resilience.

**Keywords** Cluster effect · Firm performance · Regional development · Externalities

## 1 Introduction

Examining modern economies without considering clusters seems absurd in the twenty-first century. According to the European Cluster Observatory, within the European Union (EU), 2000 statistically relevant clusters employ nearly 40% of the European workforce. In light of the success of some clusters, for example, Silicon Valley, economic policymakers are motivated to foster cluster initiatives in order to write a similar success story for their region (Brown et al. 2007; Festing et al. 2012).

A vast amount of scientific literature underpins the widespread application of the cluster concept.[1] Since the work of Marshall (1890), several researchers from varying disciplines have analysed the cluster phenomenon and its positive economic

[1]For a detailed overview, see, for example, McCann and Folta (2008) and Sedita et al. (2012).

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effects on regional development as well as on firm performance (McCann and Folta 2008; Lee 2009). However, although the cluster concept is popular amongst scientists and politicians, until now there are no clear results regarding the effects of a cluster. Indeed, several empirical studies deal with the effects of a cluster by analysing various dependent variables such as productivity or innovativeness, but they reach highly contrary conclusions (Fornahl et al. 2015; Hervas-Oliver and Sempere-Ripoll 2014; Knoben et al. 2016).

Given the already high financial support of cluster activities by national governments, the EU and other public institutions, it is astonishing that the empirical results regarding cluster effects remain so unclear (Brown et al. 2007; EFI 2015; Martin et al. 2008). Before fostering cluster initiatives, it is reasonable to first analyse in detail whether a positive cluster effect can be empirically identified or, as Maier and Trippl (2012) state: "In an economy where the agglomeration of activities does not generate any benefits, a policy that attempts to generate such agglomerations does not make any sense" (Maier and Trippl 2012, p. 14).

Therefore, the aim of this chapter is to provide a detailed overview and a systematic discussion of the effects inside and outside clusters, concentrating on clusters that have been analysed in quantitative studies.[2] In terms of the effects, we focus on the innovativeness, productivity, employment growth and wage level, entrepreneurship, survival probability and growth of start-ups and finally resilience. The discussion will consider various types of moderating variables in order to offer some explanations for the conflicting empirical results.

Although the term cluster is a widespread and prevalent theme in economics, there are still fundamental differences in its definition as well as in understanding. As a consequence of the unclear definitional delimitation, the term has proliferated considerably (Brown et al. 2007; Martin and Sunley 2003; Sedita et al. 2012). Thus, it is essential that the considered empirical studies are all based on a similar cluster understanding. Building on Porter (2000) this chapter defines clusters as "(. . .) geographic concentrations of interconnected companies, specialized suppliers, service providers, firms in related industries, and associated institutions (e.g., universities, standards agencies, trade associations) in a particular field that compete but also cooperate" (Porter 2000, p. 15). Not all empirical studies considered here employ this definition directly. However, a paper can only be selected if it also mentions the three central elements of Porter's cluster definition, namely, the spatial connection, the sectoral connection as well as interdependencies. In this sense and in line with several authors (Delgado et al. 2010; McCann and Folta 2011), the terms cluster and agglomeration are used interchangeably.

The chapter ends with a short conclusion highlighting promising areas for further investigation.

[2]The authors however recognize that there also is a vast amount of case studies dealing with the effects of being located in a cluster (e.g. Saxenian 1994).

## 2 Effects Inside and Outside Clusters

There are several mechanisms which create cluster externalities and therefore have a positive influence on innovativeness, productivity and other dependent variables (Fornahl et al. 2015). The following section will investigate whether the effects of the postulated mechanisms on central outcome variables can be empirically identified.

### *2.1 Effects of Clusters on Innovativeness*

Starting with innovativeness, it is generally argued that clusters are an important source of innovativeness (OECD 2009). Several empirical studies show that companies localized in a cluster experience higher innovation rates than those outside clusters (Baptista and Swann 1998; Bell 2005). Likewise, regions with clusters demonstrate higher innovation rates than those without clusters (Delgado et al. 2012; Porter 2003; Spencer et al. 2010). In this context particularly the labour mobility, knowledge spillovers and the relatively high degree of competition within clusters are potential reasons for a positive impact on innovativeness (Fornahl et al. 2015).

Nevertheless, at this point it must be highlighted that the degree of the effects varies considerably amongst the empirical studies (Fang 2015; Fornahl et al. 2015; Lee 2009). Two important factors involve the age and size of the cluster as indicators for the phase of the cluster life cycle. In their empirical study, Audretsch and Feldman (1996) compare the propensity for innovative activities in 210 different industries, taking the specific phase of the life cycle into account. Their results show that geographically concentrated companies experience above average innovation rates during the early stage of the industry. However, during the mature and declining stages, the opposite is true. In the latter stages, companies outside clusters tend to be more innovative than companies within clusters. The authors conclude that the positive agglomeration effects during the early stages are replaced by congestion effects during the latter stages of the industry life cycle (Audretsch and Feldman 1996).

In addition to this, Folta et al. (2006) highlight the importance of the cluster size. Indeed, they assert a positive relationship between cluster size and innovativeness, but they emphasize at the same time that after exceeding a specific cluster size (in their case 65 companies), this positive effect diminishes due to diseconomies of agglomeration.

The cluster-innovation relationship is therefore more complex than just a simple locational effect. In other words, clustering per se is not sufficient for a higher innovative performance. Instead there are several moderating effects which influence this relationship in one way or another (Beaudry and Breschi 2003; Fang 2015; Lee 2009).

Beaudry and Breschi (2003) find that a company is more likely to innovate if it is located in a region where a large knowledge stock exists and where the concentration of innovative companies from the same industry is high. On the contrary, the strong presence of non-innovative companies from the same industry implies intense disadvantages for the innovativeness (Beaudry and Breschi 2003). The work of Hervas-Oliver and Sempere-Ripoll (2014) goes one step further. They analysed a large dataset of 6697 companies across 23 industries. On the one hand, they show that a location in an agglomeration, here defined in line with Porter's cluster definition (2000), indeed has a positive influence on a firm's absorptive capacity (the firm's ability to scan, evaluate and integrate external knowledge) and in general on innovativeness. On the other hand, however, they emphasize that not all companies benefit equally from being located in an agglomeration. Instead, whether a company can profit more or less from being located within an agglomeration depends on the firm-specific innovation capabilities. Knowledge-rich companies contribute the most to agglomeration externalities but gain the least. Conversely, the least innovative companies gain the most from agglomeration externalities. They explain this asymmetric distribution through involuntary knowledge spillovers by the knowledge-rich companies (Hervas-Oliver and Sempere-Ripoll 2014). Both results are in line with the theoretical argument of an adverse selection within clusters, meaning that "good" companies have no incentive to enter a cluster (Shaver and Flyer 2000). Nevertheless, there are several studies which show that these "good" companies, in terms of adequate resources and capabilities, are the ones which may be able to extract more from the externalities present in an agglomeration. Thus, in the end it is also reasonable to assume that these "good" companies might be able to gain more knowledge than they lose due to knowledge spillovers (Expósito-Langa et al. 2015; Hervas-Oliver and Albors-Garrigos 2009; McCann and Folta 2008).

The empirical studies mentioned above make clear that being located in a cluster does not automatically imply a positive effect on the firm's innovativeness. Instead it can perhaps be a potential source for negative externalities. In order to analyse the cluster-innovation relationship in a suitable way, it is essential to consider industry-/country-specific, cluster-specific and firm-specific characteristics which may moderate the cluster effect on innovativeness (Fang 2015; Fornahl et al. 2015; Lee 2009).

## 2.2 *Effects of Clusters on Productivity*

In addition to innovativeness, clusters' effects on productivity are of significant scientific interest. In general, it has been argued that clusters have a positive influence on firm's productivity, amongst others, due to intense cooperation between companies within clusters (Borowiecki 2013; Cainelli 2008; OECD 2009). The authors Borowiecki (2013), Basant et al. (2011) and Ketels and Protsiv (2013) prove that companies located in clusters have a higher productivity than companies outside clusters.

Despite these and other studies which show a direct effect, evidence for a moderating effect by other variables exists as well. In their recent paper, Knoben et al. (2016) analyse the agglomeration-productivity relationship by controlling for heterogeneity on the agglomeration level (level of urbanization, level of specialization, level of knowledge intensity) and on the firm level (firm size, the strength of a firm's internal knowledge base, the level of local connectedness). Differing from what other studies implicitly or explicitly have assumed, they show that there are important differences between the types of companies that benefit from particular types of agglomeration dimensions. They find evidence that the firm size is an inverted U-shaped moderator of the agglomeration-productivity relationship. On the one hand, relatively small companies tend to lack the necessary capabilities to internalize external resources. On the other hand, relatively large companies show certain inertia. This means that due to the increasing complexity of these companies, their openness to their environment, as well as their flexibility, is reduced consequently preventing them from effectively integrating external resources into their existing resource stock. Furthermore, they point out that, apart from the firm size, the level of local connectedness is also an inverted U-shaped moderator. In general, the source of the benefit of collaborating with other companies in the same region refers to the fact that geographical proximity facilitates face-to-face interactions which in turn foster the exchange of tacit knowledge. As such, having a relatively high share of local connections allows companies to better extract resources from their environment. Yet companies also need relationships with distant partners. Missing external linkages can lead to a (technological) lock-in or inertia. The higher the level of local connectedness, the fewer resources can be spent by a company in order to connect with companies outside the cluster. Therefore, in both cases a moderated level supports a positive relationship between agglomeration and productivity. In their sample, this relationship, however, turns out to be negative for many companies, as they are not capable of realizing the possible advantages of an agglomeration and simultaneously suffer from disadvantages such as diseconomies of agglomeration, crowding effects and increased local competition (Knoben et al. 2016).

Rigby and Brown (2015) reach a slightly different conclusion. Similar to the work of Knoben et al. (2016), they control for various firm-level characteristics. However, even though they also recognize differences in the degree of the effect, virtually all companies gain productivity benefits (Rigby and Brown 2015). For example, the benefits are larger for small and young businesses which are positively affected by numbers of firms in their own industry within a 5 km radius, whereas older firms gain the most from having upstream suppliers nearby.

Martin et al. (2008) detect similar results, finding evidence for a positive, although weak, effect on productivity. They highlight that the size of clusters is an important variable which moderates the effect on productivity. After exceeding a particular size, the productivity gains from being located in a cluster diminish (Martin et al. 2008).

In the end, it is obvious that several variables moderate the cluster-productivity relationship. It can be argued that clusters can have a rather positive as well as a rather negative effect on productivity. As Knoben et al. (2016) describe it: "One firm's medicine may indeed be another firm's poison" (Knoben et al. 2016, p. 148).

## 2.3 Effects of Clusters on Employment Growth and Wage Level

Several studies have shown that clusters have a positive effect on employment growth and the average wage level—not only inside the cluster itself but in the broader industrial environment (e.g. firms that are connected through value creation linkages) or even the region as well (OECD 2009; Wennberg and Lindqvist 2010; Spencer et al. 2010). Several factors can be identified which contribute to these effects. These elements include the clustering intensity, the reduction of costs due to geographical proximity (e.g. for the production or the exchange of products, services, knowledge) or the specialized infrastructure (e.g. training institutions) (Wrobel 2015; Delgado et al. 2012).

A variety of case studies of different countries and industries offer a wide range of empirical evidence as to how the positive influence of a cluster on employment numbers depends on several variables and thus cannot be generalized. Mcdonald et al. (2007) examined clusters in the United Kingdom and demonstrated that employment growth tends to be more significant in established clusters.

Additionally, affiliation to a particular industry seems to have a significant influence, as Spencer et al. (2010) showed in their study of 300 industries in Canada. In this case, with the exception of the manufacturing branch, employment growth on average is higher in firms within clusters compared to firms in non-cluster locations. Another important factor is the local environment of a cluster. Being embedded in an environment close to a (big) city correlates with a higher rate of employment growth. Nevertheless, it must be emphasized that in addition to being located close to population hot spots, the industrial landscape of a region should not be neglected (Spencer et al. 2010). Finally, an increasing specialization level of a cluster is positively associated with employment growth, whereas industry specialization has a rather negative impact (Delgado et al. 2012). Mcdonald et al. (2007) came to a similar conclusion, finding that the depth of a cluster does not have a significant influence on the employment growth inside clusters.

Taking a closer look at the wage level inside clusters, one finds similar results to those obtained for employment growth, amongst other things due to the fact that both effects depend on the overall economic performance of the cluster. For the most part, there is empirical evidence showing that the average wage level is distinctly higher in cluster-integrated firms than for those outside of it (Porter 2003; Spencer et al. 2010). Additionally, it is prudent to always consider these effects in combination, as, e.g., employment growth on its own does not allow for any conclusions about the quality of the created jobs (Wennberg and Lindqvist 2010).

As for employment growth, an established cluster, thereby embedded and linked closely to local players, has a positive impact on wages (Ketels and Protsiv 2013).

Similar are the findings regarding the influence of the industry, showing that in most industries, the wage level was significantly higher in firms inside the cluster than outside. The exception was the agricultural sector, where the income was 9.5% lower on average in cluster-internal firms. The significance of the local characteristics shows a corresponding positive effect on mean salary as well as on employment growth, the effect in urban areas being higher (Spencer et al. 2010). However, other correlating factors, such as the cost of living or regionally differing house prices, should not be neglected, as they might urge firms to pay higher salaries (Porter 2003; Wennberg and Lindqvist 2010). As far as the environment of the cluster is concerned, being situated close to an urban area has a positive effect on mean salary, similar to the effect on employment growth. Finally, being embedded in a strong cluster generates a higher wage level on average in a cluster than when a firm is simply part of an agglomerated industry (Wennberg and Lindqvist 2010; Ketels and Protsiv 2013).

Apart from the described (positive) effects on firms inside the cluster, reciprocal influences between clusters and the economic performance of their geographical surroundings can also be observed. Thus, Delgado et al. (2012) show in their study of US clusters for the years 1990–2005, in which they combined various data sources, the positive impact of clusters on regional performance that revealed itself, amongst other things, in the creation of jobs and higher salaries. Spencer et al. (2010) identify a positive correlation of cluster employment and regional employment growth in their study as well and an even stronger positive correlation between cluster employment and regional wage level. Finally, Ketels and Protsiv (2013) show the connection between (strong) clusters and the mean income, thereby concluding from this that clusters foster regional productivity and consequently can help to improve a region's competitive position. Conversely, of course the region can influence clusters as well, shown above in the example of the local factor environment.

It can be concluded that being located in a cluster has a rather positive influence on employment and on the average wage level, both on firms inside and outside clusters (but located in the same area). Still there are many variables, which moderate this influence and, thus, lead to varying degrees of impacts in different regions, industries or environments.

## *2.4 Effects of Clusters on Entrepreneurship, Survival Probability and Growth of Start-Ups*

There has been a great deal of research showing how clusters positively influence entrepreneurship and particularly start-up activities (Delgado et al. 2010), though the key reasons for these connections have not been identified yet. The reasons that have been presented thus far that explain this positive impact cover a broad field of variables. Apart from the expected higher probability of finding an idea in a cluster, it is anticipated that the motivation to start a new business is higher if one is surrounded by entrepreneurial role models. Moreover, in a cluster one has a basic general support by the existing institutions and a pool of specialized human capital and infrastructures are available. Finally, research identifies geographically concentrated demand of certain products and services as a favourable factor for entrepreneurship and its development (Cooper and Folta 2000; Fornahl 2003; Fornahl and Menzel 2003; Fornahl and Sorenson 2008; OECD 2009).

One of the main variables moderating the cluster's effects on entrepreneurship is the industry. In his study of industries located in the Appalachian region, Feser (2008) underlines its importance, showing that particularly technology-intensive clusters (e.g. information or communication technology or software) exert a strongly positive effect. The OECD study (2009) identified similar results for the Grenoble cluster in France, showing that highly innovative clusters lead to a great number of spin-offs. Still, one must be careful generalizing these findings, as a missing entrepreneurial culture, the lack of knowledge exchange between industry and research or a deficient amount of risk capital in a cluster can restrain the opportunities for founding numbers. Stuart and Sorenson (2003) studied biotechnological clusters in the USA, finding that clusters foster spin-offs, especially when the industry is older and, consequently, there are more and bigger firms present. However, they simultaneously show that when many firms are already settled, this inhibits the performance of the start-ups thereby measured by the probability to go public and raise funds. This leads to the survival probability of start-ups, which—if following Wennberg and Lindqvist (2010)—is significantly positively influenced if they are located in an industrial cluster. Reasons for this include the high productivity and the strong regional network of the cluster as well as the local demand (Borowiecki 2013; Frenken et al. 2013; Wennberg and Lindqvist 2010). Moreover, start-ups in clusters profit from knowledge spillover between the local actors. These can help start-ups to increase their innovativeness. Additionally, a cluster's already settled clientele can be exploited quickly through networking and cooperation (Delgado et al. 2010; Frenken et al. 2013; Wrobel 2015). However, Sorenson and Audia (2000) present a counterexample, revealing a higher failure rate of start-ups in the shoe manufacturing industry if they were located geographically close to a dense concentration of other manufacturers. Amongst other things, this was caused by a high level of competition for local resources. The results of the influence on growth are more heterogeneous because different factors are analysed depending on the stage of cluster development, ranging from a clearly positive impact to a rather negative one (Stuart and Sorenson 2003; Wennberg and Lindqvist 2010). Again, different cluster externalities vary in their (positive) impact. For example, the greater the cluster's specialization, the higher the growth rate of start-up activities (Delgado et al. 2010).

Studies investigating entrepreneurial activities in the geographic area surrounding a cluster are rather scarce. Delgado et al. (2010) find evidence that strong clusters support the start-up scene in their regional surroundings as well as in related co-located clusters, leading to an increasing number of new firms. Especially important here are the interregional knowledge and technical spillovers, differing in extent and type, which reduce costs and risks of starting a new business.

To sum up, it can be noted that clusters have rather positive effects on entrepreneurship, which however can vary depending on the industry, the innovativeness, the entrepreneurial culture in a cluster as well as the presence of big companies. On the one hand, there is some evidence in the literature that, apart from fostering the founding of new firms, clusters foster their survival and growth due to strong regional networks, an established clientele or internal cluster spillovers. On the other hand, being located in a cluster can have negative impacts on the growth of new firms, as they, e.g., immediately face competition.

## *2.5 Effects of Clusters on Firms Surviving*

Firms surviving is another factor that is influenced by clusters. As to how a region's economy resists, responds to or recovers from a shock depends on a wide range of aspects. These range from the general regional economic structure; the institutional, cultural, entrepreneurial and innovative atmosphere; and the governance and the political settings in which the cluster is embedded to the internal and external linkages of the single firms (Martin 2011). According to Martin (2011) four dimensions of resilience can be observed in the event of a recessional shock: resistance, recovery, reorientation and renewal. While the last three phases are influenced by a combination of the above-mentioned variables, how a cluster resists in the beginning is determined particularly by the variety or diversity of the economic structure. This is the case because the various branches are likely to respond differently to external changes. Still, diversity alone does not assure a high resistance, as the connectedness and the number and strength of (in-)direct ties amongst the different sectors can vary significantly. Taking a more evolutionary perspective, Simmie and Martin (2010) applied the adaptive cycle to a regional economic system. The model consists of four phases that are all influenced by the following aspects, varying in their extent and determined by their respective historical development:

1. The totality of the usable resources of the system (competences of the firms and their employees, the hard and soft infrastructure and the overall institutional framework of the economic structure)
2. The internal network (traded and untraded interdependencies, including various factors such as trust, knowledge spillovers, labour mobility or supply inputs)
3. Resilience (how reactive a cluster can be influenced by all levels of the cluster environment: the readiness of workers to adapt, the innovative and entrepreneurial capabilities of the firms, the accessibility of financial support and the capability of the institutional framework to adapt and innovate)

Also taking an evolutionary perspective, Boschma (2015) considered time as a key factor and, consequently, emphasized the role of the historic development of networks as well as the institutional and industrial structures.

Wrobel (2015) examined the German mechanical engineering industry and found that firms in clusters are more resilient than non-cluster firms. However, this finding is based only on his investigation of employment trends. Still, his results are congruent with the results of Cainelli et al. (2012), who investigated manufacturing sectors in various Italian provinces over a 12-year period. They found evidence that industry specialization, urbanization economies and a certain (un)related variety have a positive impact on resilience. A higher industry specialization leads to stronger Marshallian externalities, which, again, affect productivity and thereby reduce firms' exit rates. However, this positive effect changes into a negative one once a certain point has been reached. Urbanization economies as a part of agglomeration economies are expressed in the density of a province's population, thus supporting firms in overcoming crisis through institutional leverages. Finally, (un) related variety is seen as an enhancing factor for knowledge spillovers, leading to increased longevity. Additionally, Delgado et al. (2015) found evidence that stronger clusters are more resilient and their firms recover faster after a recession period, irrespective of the amount of larger firms in the cluster.

Still, there are other sources that show cluster firms to be less resilient than others in certain circumstances. One example is Martin et al. (2014), who examined French clusters, revealing that firms in competitiveness clusters[3] are more afflicted by recessions than outside firms due to the fact that cluster firms depend more on the performance of the leading firms.

Regarding how the resilience of a cluster influences or is influenced by the region in which it is embedded, or the industries to which single cluster firms are linked, there is still little quantitative evidence. However, qualitative studies recognize some interdependencies between clusters and their wider surroundings that affect their resilience and which are based on knowledge exchange processes (Boschma 2015). Likewise, Martin (2011) names the external openness as a factor that reinforces the resilience capacity of firms inside a cluster.

Considering all of the issues described above, one can conclude that resilience is positively influenced by clusters, though one always must consider moderating factors such as the phase of the cluster life cycle, the general regional economic structure and the framing political settings.

## 3 Conclusion

After providing a detailed overview and systematic discussion about the effects inside and outside of clusters, there is indeed evidence for a positive cluster effect on various dependent variables, for example, productivity. Nevertheless, it also becomes clear that the cluster effect is far more complex than simply a direct effect. There are several moderating variables, some of which are listed in Table 1, which influence the effect of clusters in one way or another. Moreover, one must consider that a cluster is a complex system in which the various elements are interconnected and hence cannot be interpreted as isolated influencing factors. Additionally, clusters themselves may be embedded not only in the regional environment but in larger networks as well, these thus influencing the interdependencies mentioned above once again (e.g. Fang 2015; Litzel 2017).

[3] Clusters that benefited from the public support "poles de competitivité", which started in 2005 (Martin et al. 2014).

**Table 1** Cluster effects and their moderating variables (own compilation)

| Effect | Source | Results of empirical studies | Influenced by |
|---|---|---|---|
| Innovativeness | Audretsch and Feldman (1996) | Heterogeneous results | • Stage of the industry life cycle |
| | Beaudry and Breschi (2003) | Heterogeneous results | • Knowledge stock of the cluster/region<br>• Presence of innovative companies from the same industry |
| Productivity | Knoben et al. (2016) | Heterogeneous results | • Level of urbanization<br>• Level of specialization<br>• Level of knowledge intensity<br>• Firm size<br>• Level of local connectedness |
| | Martin et al. (2008) | Positive although weak effect | • Cluster size |
| Employment growth and wage level | Delgado et al. (2012) | Employment growth: positive effect | • Clustering intensity<br>• Industry |
| | Ketels and Protsiv (2013) | Wage level: positive effect | • Environment<br>• Level of specialization |
| Entrepreneurship, survival probability and growth of start-ups | Delgado et al. (2010) | Entrepreneurship: positive effect | • Level of specialization<br>• Industry<br>• Degree of innovativeness<br>• Age of the cluster |
| | Wennberg and Lindqvist (2010) | Survival probability: positive effect | • Productivity level |
| | Wennberg and Lindqvist (2010), Stuart and Sorenson (2003) | Growth: very heterogeneous results | • Local competition<br>• Pool of skilled workers<br>• Age of the cluster<br>• Cluster density |
| Resilience | Delgado et al. (2015) | Positive effect | • Industry<br>• Cluster strength<br>• Level of specialization |
| | Cainelli et al. (2012) | Positive effect | • Industry specialization (to a certain degree)<br>• Urbanization economies<br>• (Un)related variety |

However, more work is necessary before the precise mechanisms of the described effects of clusters can be completely understood. In this sense, particularly the potential for adverse selection in clusters and the related question of whether "good" firms benefit relatively less from clusters than "poor" firms are very interesting areas for future scientific contributions. Furthermore, the effects that clusters exert on their surroundings, which can be very significant as, e.g., shown in the example of employment growth, have been neglected in the majority of the case studies and therefore provide a significant research gap ripe for investigation.

## References


Audretsch, D. B., & Feldman, M. P. (1996). Innovative clusters and the industry life cycle. *Review of Industrial Organization, 11*(2), 253–273.

Baptista, R., & Swann, P. (1998). Do firms in cluster innovate more? *Research Policy, 27*(5), 525–540.

Basant, R., Chandra, P., & Upadhyayula, R. (2011). *Knowledge flows and capability building in the Indian IT sector: A comparative analysis of cluster and non-cluster locations*. Indian Institute of Management Banglador, Working Paper No. 2011-10-02

Beaudry, C., & Breschi, S. (2003). Are firms in clusters really more innovative? *Economics of Innovation and New Technology, 12*(4), 325–342.

Bell, G. G. (2005). Clusters, networks, and firm innovativeness. *Strategic Management Journal, 26*(3), 287–295.

Borowiecki, K. J. (2013). Geographic clustering and productivity: An instrumental variable approach for classical composers. *Journal of Urban Economics, 73*(1), 94–110.

Boschma, R. (2015). Towards an evolutionary perspective on regional resilience. *Regional Studies, 49*(5), 733–751.

Brown, K., Burgees J., Festing M., Royer S., & Steffen, C. (2007). *The value adding web – A conceptual framework of competitive advantage realisation in clusters*. WP n. 27 Berlin. ESCt-EAP Euröpish Wirtshaft Hochschule Berlin.

Cainelli, G. (2008). Spatial agglomeration, technological innovations, and firm productivity: Evidence from Italian industrial districts. *Growth and Change, 39*(3), 414–435.

Cainelli, G., Montresor, S., & Vittucci Marzetti, G. (2012). Firms' death rate and spatial agglomeration. Evidence on the resilience of Italian local production systems. *Rivista di Economica e statistica del territorio*, 101–126.

Cooper, A., & Folta, T. (2000). Entrepreneurship and hightechnology clusters. In D. L. Sexton & H. Landström (Eds.), *The Blackwell handbook of entrepreneurship* (pp. 348–367). Malden: Blackwell Business.

Delgado, M., Porter, M. E., & Stern, S. (2010). *Clusters and entrepreneurship*. CES Research Paper No. 10-31, Center for Economic Studies (CES), US Census Bureau.

Delgado, M., Porter, M. E., & Stern, S. (2012). *Clusters, convergence, and economic performance*. NBER Working Paper series, Working Paper 18250.

Delgado, M., Porter M. E., & Stern, S. (2015). *Clusters and the great recession*. DRUID 2015, Rome.

EFI. (2015). *Gutachten zu Forschung, Innovation und Technologischer Leistungsfähigkeit Deutschlands*. Expertenkommission Forschung und Innovation.

Expósito-Langa, M., Molina-Morales, F. X., & Tomás-Miquel, J.-V. (2015). Innovation in clusters: Exploration capacity, networking intensity and external resources. *Journal of Organizational Change Management, 28*(1), 26–42.

Fang, L. (2015). Do clusters encourage innovation? A meta-analysis. *Journal of Planning Literature, 30*(3), 239–260.

Feser, E. (2008). On building clusters versus leveraging synergies in the design of innovation policy for developing economies. In U. Blien & G. Maier (Eds.), *The economics of regional clusters: Networks, technology and policy* (pp. 191–213). Northampton, MA: Edward Elgar.

Festing, M., Royer, S., & Steffen, C. (2012). Unternehmenscluster schaffen Wettbewerbsvorteile - Eine Analyse des Uhrenclusters in Glashütte. *Zeitschrift Führung + Organisation, 81*(4), 264–272.

Folta, T. B., Cooper, A. C., & Baik, Y.-s. (2006). Geographic cluster size and firm performance. *Journal of Business Venturing, 21*(2), 217–242.

Fornahl, D. (2003). Entrepreneurial activities in a regional context. In D. Fornahl & T. Brenner (Eds.), *Cooperation, networks and institutions in regional innovation systems* (pp. 38–57). Northampton, MA: Edward Elgar.

Fornahl, D., Heimer, T., Campen, A., Talmon-Gros, L., & Treperman, J. (2015). Cluster als Paradigma der Innovationspolitik - Eine erfolgreiche Anwendung von Theorie in der politischen Praxis? *Studien zum deutschen Innovationssystem Nr*, 13–2015.

Fornahl, D., & Menzel, M.-P. (2003). *Co-development of firm foundings and regional clusters. Diskussionspapiere der Wirtschaftswissenschaftlichen Fakultät der Universität Hannover*. Hannover: Universität Hannover, Wirtschaftswissenschaftliche Fakultät.

Fornahl, D., & Sorenson, O. (2008). Geographic clustering in biotechnology: Social networks and firm foundings. In T. Brenner & H. Patzelt (Eds.), *Handbook of bioentrepreneurship* (pp. 35–51). New York: Springer.

Frenken, K., Cefis E. and Stam E. (2013). *Industrial dynamics and clusters: A survey.* Tjalling C. Koopmans Research Institute, Discussion Papers Series nr: 13-11.

Hervas-Oliver, J.-L., & Albors-Garrigos, J. (2009). The role of the firm's internal and relational capabilities in clusters: When distance and embeddedness are not enough to explain innovation. *Journal of Econonmic Geography, 9*(2), 263–283.

Hervas-Oliver, J-L. and Sempere-Ripoll F. (2014). Agglomerations and firm performance: How does it work, who benefits and how much?. INGENIO (CSIC-UPV) Working Paper Series 2014-11.

Ketels, C., & Protsiv, S. (2013). *Clusters and the new growth path for Europe*. Work Package 301: MS47 "Research paper on the role of clusters for the new growth path", Working Paper no. 14.

Knoben, J., Arikan, A. T., Van Oort, F., & Raspe, O. (2016). Agglomeration and firm performance: One firm's medicine is another firm's poison. *Environment and Planning A, 48*(1), 132–153.

Lee, C.-Y. (2009). Do firms in clusters invest in R&D more intensively? Theory and evidence from multi-country data. *Research Policy, 38*(7), 1159–1171.

Litzel, N. (2017). Does embeddedness in clusters enhance firm survival and growth? An establishment-level analysis using CORIS data. *Regional Studies, 51*(4), 563–574.

Maier, G., & Trippl, M. (2012). *Pitfalls and booby traps of cluster policy. SRE-Discussion Papers 2012/01*. Vienna: WU Vienna University of Economics and Business.

Marshall, A. (1890). *Principles of economics* (8th ed.). London: Macmillan.

Martin, R. (2011). Regional economic resilience, hysteresis and recessionary shocks. *Journal of Economic Geography, 12*(1), 1–32.

Martin, P., Mayer, T., & Mayneris, F. (2008). *Spatial concentration and plant-level productivity in France*. Discussion Paper No. DP6858. London: Centre for Economic Policy Research (CEPR).

Martin, P., Mayer, T., & Mayneris, F. (2014). *Are clusters more resilient in crises? Evidence from French exporters in 2008-2009*. Presented at the conference "The Factory Free Economy: What next for the 21st century" 2013.

Martin, R., & Sunley, P. (2003). Deconstructing clusters: Chaotic concept or policy panacea? *Journal of Economic Geography, 3*(1), 5–35.

McCann, B. T., & Folta, T. B. (2008). Location matters: Where we have been and where we might go in agglomeration research. *Journal of Management, 34*(3), 532–565.

McCann, B. T., & Folta, T. B. (2011). Performance differentials within geographic clusters. *Journal of Business Venturing, 26*(1), 104–123.

Mcdonald, F., Huang, Q., Tsagdis, D., & Tüselmann, H. J. (2007). Is there evidence to support porter-type cluster policies? *Regional Studies, 41*(1), 33–49.

OECD. (2009). *Clusters, innovation and entrepreneurship*. Paris: Organisation for Economic Co-operation and Development.

Porter, M. E. (2000). Location, competition, and economic development: Local clusters in a global economy. *Economic Development Quarterly, 14*(1), 15–34.

Porter, M. E. (2003). The economic performance of regions. *Regional Studies, 37*(6-7), 549–578.

Rigby, D. L., & Brown, M. W. (2015). Who benefits from agglomeration? *Regional Studies, 49*(1), 28–43.

Saxenian, A. (1994). *Regional advantage: Culture and competition in Silicon Valley and Route 128*. Harvard: Harvard University Press.

Sedita, S. R., Lazzeretti, L., & Caloffi, A. (2012). *The birth and the rise of the cluster concept. DRUID 2012*. CBS: Copenhagen.

Shaver, J. M., & Flyer, F. (2000). Agglomeration economies, firm heterogeneity, and foreign direct investment in the United States. *Strategic Management Journal, 21*(12), 1175–1193.

Simmie, J., & Martin, R. (2010). The economic resilience of regions: Towards an evolutionary approach. *Cambridge Journal of Regions, Economy and Society, 3*(1), 27–43.

Sorenson, O., & Audia, P. G. (2000). The social structure of entrepreneurial activity: Geographic concentration of footwear production in the United States, 1940–1989. *American Journal of Sociology, 106*(2), 424–462.

Spencer, G. M., Vinodrai, T., Gertler, M. S., & Wolfe, D. A. (2010). Do clusters make a difference? Defining and assessing their economic performance. *Regional Studies, 44*(6), 697–715.

Stuart, T., & Sorenson, O. (2003). The geography of opportunity: Spatial heterogeneity in founding rates and the performance of biotechnology firms. *Research Policy, 32*(2), 229–253.

Wennberg, K., & Lindqvist, G. (2010). The effect of clusters on the survival and performance of new firms. *Small Business Economics, 34*(3), 221–241.

Wrobel, M. (2015). 'One for all and all for one': Cluster, employment, and the global economic crisis. Evidence from the German mechanical engineering industry. *Papers in Regional Science, 94*(2), 273–294.

### A.2. Radical or not? The role of clusters in the emergence of radical innovations

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# Radical or not? The role of clusters in the emergence of radical innovations

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**ABSTRACT**
Recently, radical innovations have received increasing attention in order to achieve long-term economic success. Regional clusters, being frequently used as an innovation policy instrument, have been shown to have the potential to support innovations in general. However, it remains unclear whether clusters are really a beneficial environment for the generation of radical innovations. This study aims to shed light on the specific role clusters can play in radical innovation processes. In order to do this, we apply a quantitative approach on the firm-level and combine several data sources (e.g. AMADEUS, PATSTAT, German subsidy catalogue). Our results show that clusters indeed provide a suitable environment for radical innovations. Furthermore, we find that radical innovations rather occur in the periphery of the cluster, where actors tend to be more open to the exchange of external knowledge. This happens in general through linkages with other actors, which we also find to be beneficial for the emergence of radical innovations up to a certain degree. Our findings implicate that policy makers should continue to support clusters and further develop funding schemes. Moreover, managers should be open to collaborations with other actors for the cross-fertilization of knowledge to promote radical innovations.

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## 1. Introduction

Innovations are commonly accepted to be a key factor for economic growth (e.g. Rosenberg, 2004; Verspagen, 2006). Recently, especially the outstanding opportunities arising from rather radical innovations have been highlighted (Castaldi, Frenken, & Los, 2015). These kinds of innovations combine knowledge pieces that have not been combined before and consequently create something radically new (Fleming, 2001; Nerkar, 2003; Weitzman, 1998). If successful, they can open up completely new markets and industries as well as provide the basis for a long-lasting competitive advantage (Castaldi et al., 2015; Henderson & Clark, 1990; Verhoeven, Bakker, & Veugelers, 2016). From a firm's perspective, they are desirable to enhance their competitiveness (Zhang, Wei, Yang, & Zhu, 2018). Policy makers have also recognized this great economic potential of radical innovations. For instance, in 2019 the German government will establish a public agency for the promotion of radical innovations in Germany (BMBF, 2018).

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An already prevalent instrument of innovation policy are regional clusters (Brown, Burgees, Festing, Royer, & Steffen, 2007; Cantner, Graf, & Rothgang, 2018; EFI, 2015; Festing, Royer, & Steffen, 2012), which have been shown to foster the innovativeness of firms (Baptista & Swann, 1998; Bell, 2005). Nevertheless, there also exist contradictory evidence about the effect of clusters on firm's innovativeness (e.g. Pouder & St. John, 1996). It therefore still remains unclear whether clusters are a beneficial environment for innovations in general (Martin & Sunley, 2003) and the generation of radical innovations in particular (Hervás-Oliver, Albors-Garrigos, Estelles-Miguel, & Boronat-Moll, 2018a). In theory, there exist two opposing streams of reasoning in this context. On the one hand, the relatively fast and eased diffusion of knowledge (e.g. via labour mobility), particularly of tacit knowledge, can challenge current thinking, which may result in radical new ideas (Braunerhjelm, Ding, & Thulin, 2017; Mascitelli, 2000; Otto & Fornahl, 2010). On the other hand, firms located within clusters may also be confronted with an inertia regarding potential changes due to uniform thinking and a lack of new challenging external ideas (Boschma, 2005; Martin & Sunley, 2003; Pouder & St. John, 1996). In order to contribute to a clarification, the following research question shall be answered: Does being located in a cluster increase the likelihood to create radical innovations?

By answering this research question in a quantitative way, our study makes a so far pioneering step towards explaining empirically the relationship between clusters and radical innovations. Besides contributing to close a research gap, this paper also has a rather practical meaning for companies as well as policy makers. It does not only show evidence that being located in a cluster can contribute to the emergence of radical innovations, but also deals with the corresponding conditions necessary to generate radical innovations in clusters.

The remainder of this paper is structured in the following way: The subsequent chapter deals with the theoretical background on radical innovations and clusters and combines both strands of literature. Moreover, we embed our hypothesis based on an extensive literature review. In the third section, we describe our data and methodology. After that, the paper turns to the empirical analysis. First, we present some descriptive statistics on our sample and then, we discuss our econometrical results. Finally, the study draws conclusions from our results and points out possible future research endeavours.

## 2. Theory and hypotheses

During the last decades, it has become common sense that innovations are a core factor for economic growth (Cortright, 2001; Rosenberg, 2004; Verspagen, 2006). In addition, scholars have found evidence that new knowledge, which is transformed into innovations, builds on already existing knowledge pieces. For instance, Weitzman (1998) stated that existing knowledge is recombined in a new way to form new artefacts. Hence, innovative search processes have a cumulative nature (Arthur, 2007; Basalla, 1988).

We can distinguish between two types of new knowledge creation, namely incremental and radical innovations. Most innovations rely on well-defined knowledge pieces, which are recombined repeatedly and hence represent small improvements. These incremental innovations develop mostly alongside well-known knowledge trajectories (Dosi, 1982). On the other hand, search processes that are radical in nature combine knowledge pieces that have not been combined before (Fleming, 2001; Nerkar, 2003; Weitzman, 1998). New combinations then emerge when inventors discover a new purpose for their existing knowledge or they fuse together some external expertise with their own mindset (Desrochers, 2001). A good example is, for instance, the new combination of the technological fields automotive, sensor-based safety systems, communication and high-resolution mapping which are combined for the first time in the self-driving car (Boschma, 2017). Radical innovations are more likely to fail and are accompanied with higher uncertainty in terms of their economic impact in the future (Strumsky & Lobo, 2015). However, if successful, these innovations can bring about a paradigm shift and thus radical change (Dosi, 1982; Verhoeven et al., 2016). This radical change can lead to the formation of new markets and entire industries thereby disrupting old ones (e.g. Henderson & Clark, 1990; Tushman & Anderson, 1986). Radical innovations can introduce a new set of performance features or have a higher functional quality and improve performance significantly (Bers, Dismukes, Miller, & Dubrovensky, 2009). Also, they may reduce cost compared to existing products and may alter the characteristics of the market, such as consumer expectations (Nagy, Schuessler, & Dubinsky, 2016). Hence, radical innovations can help to build a strong competitive advantage (Castaldi et al., 2015) and serve as the basis for future sustainable economic growth (Ahuja & Morris Lampert, 2001; Arthur, 2007).

Scientific literature has used several methodologies to analyse radical innovations empirically mainly based on indicators using forward (e.g. Albert, Avery, Narin, & McAllister, 1991 Trajtenberg, 1990;) and backward (e.g. Rosenkopf & Nerkar, 2001) citations on patents. Recently, approaches following the theoretical concept of recombinant innovation particularly focus on technology classes provided in patent documents to study the nature of radical innovations (e.g. Fleming, 2007; Strumsky & Lobo, 2015; Verhoeven et al., 2016). Our study follows this notion and defines radical innovations as the result of search processes that combine unconnected knowledge domains for the first time (Fleming, 2001, 2007; Rizzo, Barbieri, Ramaciotti, & Iannantuono, 2018). Thus, we focus especially on the emergence of radical innovations, instead of its diffusion. The high degree of radicalness is indicated by the new combination of knowledge. Despite the fact that we cannot predict if these new combinations will have a major impact in the future, we term them 'radical' since they introduce totally novel knowledge combinations (Rizzo et al., 2018; Verhoeven et al., 2016). In line with, e.g. Dahlin and Behrens (2005), we argue that radical innovations have two dimensions (emergence and impact) which are worth inspecting.[1]

In the context of regional clusters, however, the concept of radical innovations has been under-researched (Hervás-Oliver et al., 2018a). This holds especially true for quantitative empirical studies. In light of the popularity and widespread application of the cluster concept, also in terms of policy funding measures, this research gap is particularly astonishing (Brown et al., 2007; EFI, 2015; Martin & Sunley, 2003). In line with Grashof and Fornahl (2017), clusters are here defined as: '[ … ] a geographical concentration of closely interconnected horizontal, vertical and lateral actors, such as universities, from the same industry that are related to each other in terms of a common resource and knowledge base, technologies and/or product-market' (Grashof & Fornahl, 2017, p. 4).[2] It has been emphasized that clusters can be a preferable environment for fostering firm's innovativeness (Baptista & Swann, 1998; Bell, 2005; Porter, 1998). Although, recently it has been argued that this rather positive relationship between clusters and firm performance also depends on the specific context (e.g. firm and cluster characteristics). Thus, contextual variables, such as cluster size and the industry characteristics, should additionally be considered when investigating firm-specific cluster effects (Frenken, Cefis, & Stam, 2013; Knoben, Arikan, Van Oort, & Raspe, 2015; Rigby & Brown, 2015).

In his pioneering contribution, Marshall (1920) considers the firm-specific advantages of being located in close proximity to similar firms.[3] He emphasized in this context four types of externalities: access to specialized labour, access to specialized inputs, access to knowledge spillovers and access to greater demand by reducing the consumer search costs (Marshall, 1920; McCann & Folta, 2008). Besides promoting innovations in general, these externalities within clusters can likewise provide a fertile ground for the creation of radical innovations in particular. As presented in several case studies dealing with the Silicon Valley (e.g. Brown & Duguid, 2000; Casper, 2007; Saxenian, 1994), the existence of a pooled specialized labour market is beneficial for the emergence of radically new ideas. The pooling of specialized employers and employees in geographical proximity simplifies the search process and strengthens the overall matching quality, leading to an alleviated mobility of employees. The extensive labour mobility is in turn considered to further facilitate localized spillovers of embodied tacit knowledge. The faster diffusion of such knowledge within clusters is essential for collective learning processes and innovation activities of the corresponding firms (Amend & Herbst, 2008; Otto & Fornahl, 2010). This holds particularly true for rather radical innovation activities, as the new knowledge incorporated in local human resources can challenge established processes and ways of thinking, originating potentially radical new insights (Bekkers & Freitas, 2008; Braunerhjelm et al., 2017; Zucker, Darby, & Torero, 2002). In addition to the knowledge diffusion via labour mobility, more generally it has been argued that geographic proximity within clusters can facilitate the transfer of common knowledge (Jaffe, Trajtenberg, & Henderson, 1993) and particularly the dissemination of tacit knowledge due to the higher likelihood of face-to-face contacts, being an efficient medium for the transfer of such knowledge (Daft & Lengel, 1986). This eased knowledge diffusion within clusters, especially the tacit one, is indeed a powerful source for the creation of radical innovations (Audretsch, 1998; Mascitelli, 2000). Glaeser, Kallal, Scheinkman, and Shleifer (1992) connoted in this context that '[ … ] intellectual breakthroughs must cross hallways and streets more easily than oceans and continents' (Glaeser et al., 1992, p. 1127). By analysing the geographic concentration of superstar patents across U.S. states, Castaldi and Los (2012) empirically confirm this observation. They find evidence that the regional clustering of these superstar patents is much higher than for non-superstar patents. Therefore, companies tend to locate in very specific geographic places for the development of technological breakthroughs, whereas standard innovations seem to happen in many more places (Castaldi et al., 2015; Castaldi & Los, 2012).

Nevertheless, it has also been suggested that over time firms located within clusters may face an inertia regarding market and technology changes, hampering radical innovations. For example, Pouder and St. John (1996) explain the firm performance decline over time with the convergent mental models of managers within the corresponding region, which reinforces old ways of thinking and thereby preventing the recognition of new ideas. Moreover, the exclusive reliance on local face-to-face contacts and tacit knowledge can make local networks especially vulnerable to lock-in situations, enforcing again the inertia of firms located in clusters (Boschma, 2005; Martin & Sunley, 2003). Consequently, it still remains rather unclear whether a cluster can contribute to the creation of radical innovations. Nevertheless, building on the previous theoretical literature contributions, the following hypothesis is proposed:

**Hypothesis 1:** Being located in a cluster has a positive effect on the emergence of radical innovations in firms.

However, as already indicated, it is reasonable to assume that these potential benefits are not equally distributed (Frenken et al., 2013; Martin, 2009). The established and leading firms in clusters are for example argued to organize the overall knowledge network in a way that guarantees their central position within the corresponding clusters. They only share the specific knowledge, which is necessary to maintain their leading role, with other clustered companies. This directed knowledge exchange may be beneficial for these central actors, but it prevents the recognition of new ideas and thereby promoting an inertia (Hervás-Oliver et al., 2018a; Munari, Sobrero, & Malipiero, 2012). Thus, the following hypothesis is proposed:

**Hypothesis 2:** A firm's central position in the cluster core has a negative effect on the emergence of radical innovations in this firm.

Besides the position within clusters it may also be crucial for firms to have a sufficiently large number of relationships. The increasing significance and proliferation of inter-firm alliances has promoted the development of the relational view (RV). The main idea of the RV is that internal resources (e.g. financial resources) are not sufficient for the realization of a competitive advantage, but additionally it is essential to consider relational resources, such as inter-firm relationships and routines (Dyer & Singh, 1998; Lavie, 2006; Steffen, 2012). This relational dimension has also been investigated in the context of clusters (Giuliani, 2007; Hervás-Oliver & Albors-Garrigos, 2009). In line with the relational view, it has been highlighted that the number of relationships is positively associated with firm's innovative performance by facilitating local and external knowledge-sharing as well as interactive learning processes (Hervás-Oliver & Albors-Garrigos, 2009; Zaheer & George, 2004). Regarding radical innovations, it can therefore be assumed that by providing access to new knowledge from the local and external environment the number of strategic relationships can mitigate the potential of a lock-in situation within clusters and thereby promote the creation of radical innovations. Nevertheless, it has also been highlighted that after a certain threshold the related costs may outweigh the benefits from collaborating. Engaging in numerous collaborations goes at the cost of intensive coordination expenditures as well as free-riding and unintended knowledge spillovers (Hottenrott & Lopes-Bento, 2016; Kesteloot & Veugelers, 1995). Too many relationships are therefore assumed to hinder the creation of radical innovations. Consequently, the following hypothesis is proposed:

**Hypothesis 3:** The number of relationships to other organisations asserts an inverted u-shape effect on the emergence of radical innovations in firms, such that a moderate level of relationships is likely to be most beneficial.

Furthermore, the effect of the market and industry environment on firm's innovative performance has been widely acknowledged (Kohlbacher, Weitlaner, Hollosi, Grünwald, & Grahsl, 2013). Building on the theoretical insights proposed by Suarez and Lanzolla

(2005, 2007), dealing with external influences on the first-mover advantage, it is supposed that the pace of technology evolution also affects firm's innovative performance. The pace of technology is captured by technology S curves, depicting the evolution of a technology or the corresponding industry along a particular performance parameter, such as the CPU clock speed in the computer industry. The technology evolution can vary significantly across different industries. While the development of efficiency improvements in the computer industry has been very high, it has only been marginal in the case of the vacuum cleaner industry (Cooper & Schendel, 1976; Suarez & Lanzolla, 2007). In general, it is likely that under a rapid technology evolution firm's current knowledge stock becomes rather unsuitable or even obsolete. The creation of radical innovations is therefore potentially hampered (Suarez & Lanzolla, 2005; Suarez & Lanzolla, 2007). Nevertheless, in clusters a different outcome can be expected. The specific cluster environment, fostering interactions and knowledge spillovers, protects the knowledge stock of the corresponding firms from being outdated. Firms located within clusters are therefore assumed to rather benefit from the new opportunities arising from the fast technology evolution than suffering from its negative accompaniments. Thus, the following hypothesis is proposed:

**Hypothesis 4:** Firms located in a cluster have advantages in terms of producing radical innovations if the pace of technology evolution of industries is high.

Lastly, the size of the cluster is frequently discussed in the literature as an influential variable for firm's innovativeness (Folta, Cooper, & Baik, 2006; McCann & Folta, 2011). It has been asserted in this context that cluster size has an inverted u-shape effect on firm's innovative performance. Meaning that the marginal firm-specific benefits decline as the cluster grows, providing evidence for size-based negative externalities (Folta et al., 2006; McCann & Folta, 2008). On the one hand, clusters with several different actors provide access to more heterogeneous knowledge than smaller clusters, which is argued to be beneficial for the creation of radically new ideas (Menzel & Fornahl, 2010). On the other hand, at some point a size increase can convert the previously positive aspect of competition into a negative one. The higher density of similar firms encourages the competition within clusters, leading to scarcity of crucial input factors, such as human resources, and significantly higher costs (Folta et al., 2006; McCann & Folta, 2008). Particularly, the lack of adequate input factors can be an enormous obstacle for the development of radical innovations. Thus, the following hypothesis is proposed:

**Hypothesis 5:** The size of the cluster has a reversed u-shape relation to the emergence of radical innovations in firms.

## 3. Data and methodology

To construct our final dataset, we employed several databases. The basic database for the empirical analysis providing detailed firm-specific information is the AMADEUS database offered by Bureau van Djik (BvD). It contains extensive firm-level data such as year of establishment, whether the firm is independent and employment data.

For the identification of all relevant clusters in Germany we apply the method by Brenner (2017). Therefore, we calculate a cluster index for each single company on the community level ('Gemeindeebene') based on official IAB employment data from 2012 in three-digit NACE Rev. 2[4] industries. Generally, this actor-based cluster identification offers two main advantages in comparison with more traditional indicators. First, the calculated indicator is free of predefined borders, so that the corresponding cluster identification does not depend on the regional level. Second, the applied index avoids a possible overvaluation of very large companies by using a distance decay function based on travel times (Brenner, 2017).[5] The applied cluster index additionally considers employment in absolute and relative terms. Thus, it accounts for the most central elements of cluster definitions, namely geographical proximity, regional concentration and specialization (Grashof & Fornahl, 2017). The corresponding cluster threshold, indicating whether a company is located in a cluster, has a value of two. It thereby follows the procedure of the European Cluster Observatory (European Cluster Observatory, 2018; European Communities, 2008).[6]

Furthermore, we use patent data retrieved from the European database PATSTAT, to identify radical innovations. We approximate the emergence of radical innovations by new combinations of formerly unconnected technology domains (new dyads). First, we identify all technology combinations proxied by IPC classes mentioned on patents in the years 2012–2014 in Germany. Then, we construct a dataset with all existing IPC combinations between 1983 and one year before the focal year. Subsequently, we compare both datasets to identify new combinations. Hence, a new combination is radical in the sense that it is completely new to Germany (since 1983).[7] Our analysis of IPC combinations is carried out at the four-digit level. This aggregation level is used to have a sufficiently large number of patents in the classes and a maximal number of technologies.

Moreover, patents are used to determine the pace of technology evolution of the corresponding industries (Audretsch & Feldman, 1996; McGahan & Silverman, 2001). By computing the average technological improvement (measured by the weighted number of patents) in three-digit NACE Rev. 2 code industries for a three-year period (2011–2013) it is controlled for possible outlier years. To also consider the industry size, the average technological improvement is then weighted by the size of the corresponding industry, which is measured by the average number of employees.

For the determination of the number of relationships data on subsidized R&D collaborations from the German subsidy catalogue ('Förderkatalog') is used. The German subsidy catalogue comprises approximately more than 160,000 running or already finished R&D projects financed by six different national ministries in the time period between 1960 and 2016 (Roesler & Broekel, 2017). It has been commonly used to capture cooperative relations in knowledge networks and it offers information at an earlier stage than patent data which is why the German subsidy catalogue fits adequately the purpose of this study (Broekel, 2015; Broekel & Graf, 2012). Due to the existing time lag between patents (see the main dependent variable) and received national subsidies, the unweighted number of firm linkages is computed based on all corresponding collaborative R&D projects between 2008 and 2010 (Fornahl, Broekel, & Boschma, 2011).

Regarding a firm's cluster position, various measures have been used (Broekel & Graf, 2012; Lechner & Leyronas, 2012). However, here the already presented cluster index by Brenner (2017) is applied. Apart from the identification of clusters, it also offers information about the position of each company within the corresponding cluster by taking the spatial concentration (in terms of employment) and the geographical distance on the firm-level into account. Hence, the cluster index is also applicable to determine whether a firm is located in the core or periphery of the cluster. Rather low values indicate that companies are located in the periphery, whereas high values emphasize that they are in the centre of the corresponding cluster (Brenner, 2017; Scholl & Brenner, 2016). For the calculation of the cluster size the employment data included in the AMADEUS database is used. In line with most common approaches (McCann & Folta, 2008), cluster size is here computed by the average number of employees within the corresponding cluster between 2012 and 2014.

Additionally, several control variables have been considered. To control for firm-specific influences, firm's age (years since foundation) as well as firm's corporate structure are added. Regarding the corporate structure, based on the AMADEUS database an independence dummy is calculated that indicates whether the corresponding firm is independent and does not belong to a corporate structure. Moreover, on the regional level it is controlled for the regional knowledge base, measured by the weighted number of patents in each administrative community ('Gemeindeebene'). Based on the German research directory ('Research Explorer'), containing information on over 25,000 university and non-university research institutes in Germany, the number of research institutes is additionally calculated on the community level (Research Explorer, 2018). Last, in order to correctly identify research-intensive industries, official data from the German Federal Statistics Office is additionally employed. Based on the corresponding NACE codes, a dummy variable is created that indicated whether an industry is rather research-intensive or not.

For the combination of the different datasets it is required to match the corresponding names of the companies listed in the comprehensive AMADEUS database with the applicants in the patent data and with the grant recipients (executive company) in the German subsidy catalogue, as a comparable identifier is missing.[8] The result of this matching process is a unique firm-level database.

Since our main dependent variable is binary, in line with other contributions (e.g. Hervás-Oliver, Sempere-Ripoll, Alvarado, & Estelles-Miguel, 2018b; McCann & Folta, 2011) we applied logistic regression to test our hypotheses. The logistic regression model has the following form:

$$\begin{aligned}\text{Logit}\,(\pi_i) = \beta 0 + \beta 1\text{ Cluster dummy} + \beta 2\text{ Central position} + \beta 3\text{ Relationships}\\ + \beta 4\text{ Technology evolution} + \beta 5\text{ Cluster size} + \beta 6\text{Controls}_i + \varepsilon_i\end{aligned}$$

where $\pi$ is the natural log of the odds for company $i$ to introduce a radical innovation (between 2012 and 2014) and $\varepsilon$ represents the corresponding error term.

## 4. Empirical results and discussion

As can be seen in Table 1, our sample consists of 8404 organizations active in patenting between 2012 and 2014 in Germany. A total number of 365 firms have filed at least one new combination and are considered as radically innovating firms. This represents almost 5% of the total sample, which means that the vast majority of organizations engage in incremental innovating processes. Moreover, 1028 organizations of our sample, corresponding to more than a tenth of all firms, are located in a cluster.

**Table 1.** Radical innovations and clusters 2012–2014 (own illustration).

| | Variable | |
|---|---|---|
| | Radical innovation dummy | Cluster dummy |
| 0 | 8039 (95.66%) | 7376 (87.77%) |
| 1 | 365 (4.34%) | 1028 (12.23%) |
| Total | 8404 (100%) | 8404 (100%) |

Furthermore, we calculated the number of radical innovations per organization based on patent data. Shared patents with more than one applicant where assigned equally to all partners resulting in a variable indicating the number of (radical) patents weighted by the number of co-applicants (Fornahl et al., 2011). The top three firms with the highest number of new combinations are BASF SE (Ludwigshafen), Daimler AG (Stuttgart) and Rehau AG (Hof). The top three industry sectors in terms of new combination amount are manufacture of machinery and equipment (C28), manufacture of chemicals and chemical products (C20) and manufacture of rubber and plastic products (C22). Knowledge-intensive business services also play an important role (e.g. M71, M72).[9] We used the share of radical innovations to analyse the geographical distribution of radical innovations between 2012 and 2014. Based on the firm's address (retrieved from AMADEUS), we assigned all patents to 141 labour market regions as defined by Kosfeld and Werner (2012). We used this definition so that commuter and urban-periphery structures are

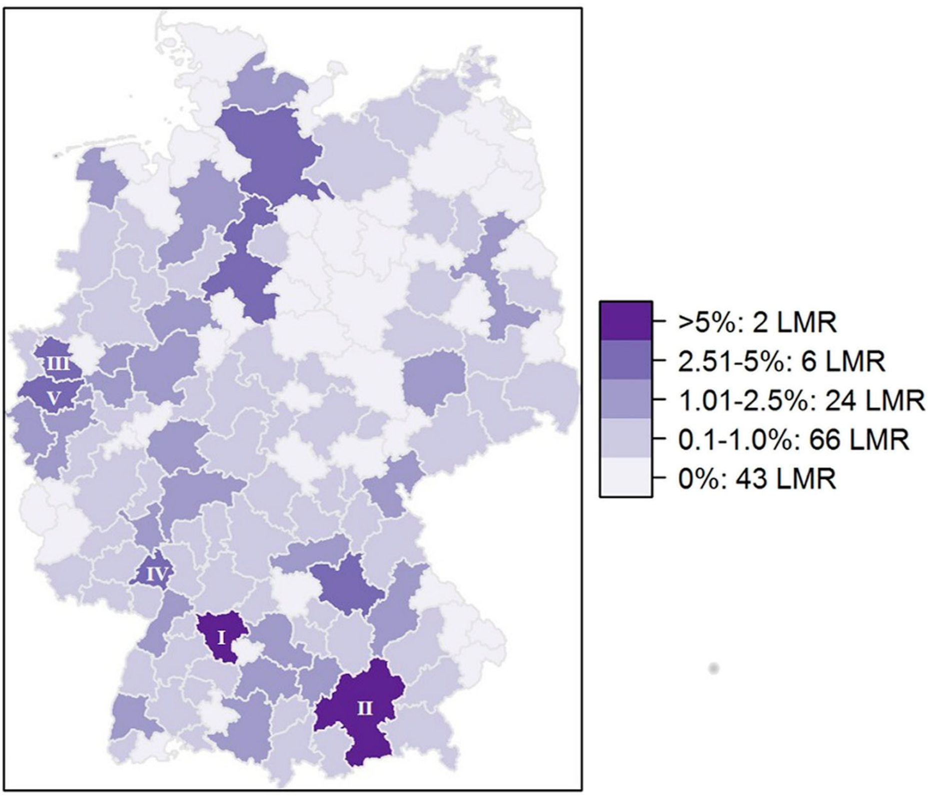


**Figure 1.** Share of radical innovations in labour market regions 2012–2014 (own illustration).

unlikely to bias the results. As seen in Figure 1, there have not been any radical innovations in one third of the labour market regions. However, the majority of regions (66) at least have a share between 0 and 1%. Overall, the distribution shows that Southern and Western German regions tend to be stronger in radical innovation processes, whereas most regions without radical innovations belong to Eastern Germany. Stuttgart (I) and Munich (II), located in Southern Germany, have the highest share in terms of radical innovations. This is a straightforward observation since both labour market regions are among the economically strongest in the country. The regions include successful firms like Bosch, Daimler and Siemens and are home of some of the most prestigious universities and research institutions like the technical university in Munich and the Fraunhofer Society, Europe's largest application-oriented research organization. The regions Essen (III), Ludwigshafen (IV; South-West) and Dusseldorf (V), lying in the western part of the country, are among the top five regarding the share of radical innovations. Hence, the results show a strong core–periphery disparity, since all these regions include a major city. By contrast, radical innovations are absent mainly in peripheral regions e.g. in Mecklenburg-Western Pomerania, Saxony and Lower Saxony.[10]

To test our main hypotheses, we apply several logistic regression models on the firm-level (see Table 2). For this, we use our full sample of 8404 organizations. In Models 1–4 our dependent variable is a dummy indicating whether a firm is radically innovating (1) or not (0). By investigating the pairwise correlation matrix shown in Appendix 1, one can see that none of our key independent variables are highly and significantly correlated, except for the cluster index and the cluster dummy, which is as expected.

In all models, we find evidence that being located in a cluster indeed has a positive and significant influence on the emergence of radical innovations in firms. This holds true for both indicators, namely the cluster dummy (Model 1, 2, 4) and the cluster index (Model 3 and 4). Hence, we can accept our hypothesis 1. In model 1, the average marginal effect of the cluster dummy is 0.024, which means that being in a cluster increases the probability to produce radical innovations by 2.04 percentage points. The cluster index in model 3 has an average marginal effect of 0.0032, which means that one unit increase in the cluster index

**Table 2.** Logistic regression results (own illustration).

| Radical innovation dummy<br>*n* = 8404 | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Cluster dummy | 0.432*** | 0.225 | | 0.46* |
| Cluster index | | | 0.079*** | 0.302** |
| Cluster size | | | 0.0005* | 0.0005** |
| Cluster size squared | | | −1.9e-08 | −1.5e-08 |
| Pace of technology evolution | −0.075* | −0.136** | −0.061 | −0.062 |
| Number of Linkages | 0.064*** | 0.063*** | 0.062*** | 0.061*** |
| Number of Linkages squared | −0.0002** | −0.0002** | −0.0002** | −0.0002** |
| Research-intensive industry dummy | 0.527*** | 0.615*** | 0.485*** | 0.48*** |
| Number of Research Institutes | 0.003 | 0.003 | 0.003 | 0.003 |
| Regional knowledge base | 0.0001* | 0.0001* | 0.00008 | 0.00008 |
| Independence dummy | 0.341 | 0.394 | 0.302 | 0.302 |
| Age | 0.004** | 0.004** | 0.004*** | 0.004*** |
| Cluster dummy*Pace of technology evolution | | 0.132** | | |
| Cluster dummy*cluster index | | | | −0.254* |
| *Constant* | *−3. 459**** | *−3.436**** | *−3.525**** | *−3.77**** |
| *Pseudo* $R^2$ | *0.021* | *0.022* | *0.027* | *0.028* |

Significance level: *$p < .10$, **$p < .05$, ***$p < .01$.

and hence, being located in a cluster, increases the probability to produce radical innovations by 0.32 percentage points.

One common concern in this context refers to the existence of a selection bias, meaning that the empirical results become biased as particularly firms with above-average performance choose to locate in clusters. However, in line with the argumentation by McCann and Folta (2011), it is here argued that there are neither theoretically nor empirically justified arguments for the existence of such a positive selection bias. Shaver and Flyer (2000), for instance, find evidence for an adverse selection effect, meaning that very innovative firms have relatively high incentives to avoid collocating in clusters, as the prevailing knowledge spillovers within clusters will especially favour weak innovative firms than the strong ones, which are rather confronted with knowledge drains (negative knowledge spillovers).

Our results also show that the number of formal linkages between organizations has a reversed u-shape relation to the emergence of radical innovations. This outcome is significant throughout all models and supports our hypothesis 3. Thus, we can say that it is favourable for radically innovating firms to collaborate with other firms up to a certain degree. After a turning point, it is probably too much coordination effort to be effective.

In Model 1, the pace of technology evolution has a negative and significant influence at least on the 10% level. Hence, it is more difficult for firms in rapidly developing industries to come up with radical innovations. However, when we include an interaction term between our cluster dummy and the pace of technology evolution in our Model 2, we find evidence, that firms located in clusters can deal with fast developments in their focal industry better and transform them into radically new ideas. This supports our hypothesis 4. At the 5% level we can see, that the interaction term has a positive correlation to the emergence of radical innovations. Hence, under the condition that a firm is located in a cluster, faster technology evolution increases the probability to produce radical innovations. This outcome is also observable if we apply the cluster index instead of the cluster dummy. We also tested, whether it plays a role in this context if the firm is located in the centre or the periphery of the cluster. To do that, we fitted Model 2 with a subsample, including all firms located in clusters, but we did not find a significant difference between firms in the centre and the periphery.[11]

Models 3 and 4 include a cluster size variable to test our hypothesis 5 that the size of a cluster has a reversed u-shape relation to the emergence of radical innovations. Although we find evidence that cluster size is positively related, we do not find proof for the aforementioned assumption.

Model 4 offers additional interesting insights. When we include an interaction term between the cluster dummy and the cluster index, we find a significantly negative influence on radical innovations, which supports our hypothesis 2.[12] The results of the interaction effect suggest that the previously shown positive effect of being located in a cluster on the probability to produce radical innovations is significantly reduced when the value of the cluster index increases.[13] Hence, this suggests that radically innovating firms are more likely to be located in the periphery of a cluster rather than in the centre. We use Figure 2 to illustrate the results of our Model 4. It shows the density of the cluster index (Red – high values to blue – low values). One cluster is represented by the colour tones red to yellow. Firms with a high cluster index are located in the centre of the cluster core and hence would be located in the red part. These firms are less likely to engage in radically innovating processes, because central actors share knowledge

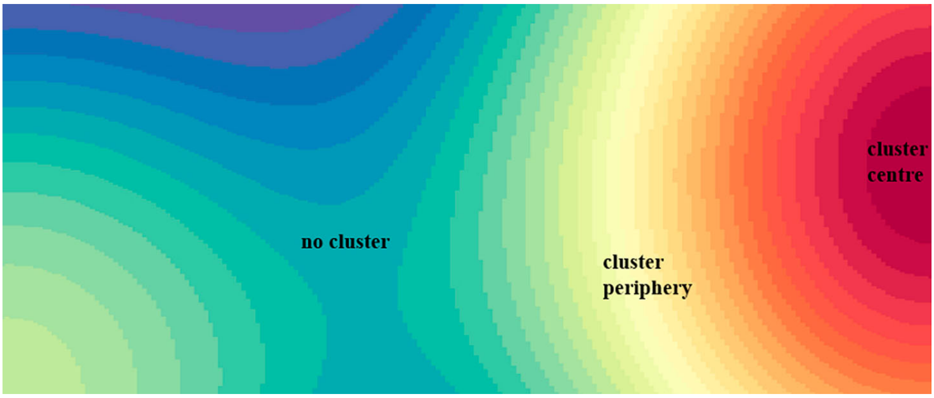


**Figure 2.** The emergence of radical innovations in clusters – centre vs. periphery (own illustration). The figure is created with kde2d from R package 'MASS'.

only up to a certain degree in order to secure their position in the centre. This, in turn, hinders the opportunities to engage in radical innovation processes. As the cluster index decreases (and the colour tones get cooler), we move towards the periphery of the cluster. Firms located in the yellow part, in the periphery, are more likely to come up with radically new knowledge combinations, since they are more open to new knowledge from outside the firm. Firms located in the blue part have a very low cluster index and are not located in a cluster. Hence, they are less likely to generate radical innovations.

We included several control variables in our models, namely a dummy indicating whether the firm is active in research-intensive industries, the number of research institutes, the regional knowledge base, a dummy whether the organization is independent and firm's age. We find evidence that firms from research-intensive industries are more likely to engage in radical innovations. This finding is highly significant and remains stable over all models. Also, we observe that rather older firms engage in radical innovations, indicated by the (small) positive and significant influence of the variable in all models. The number of research institutes and the independence dummy are both positive but have no significant effect in any of the models. By contrast, the regional knowledge base has a (small) positive and significant influence throughout Models 1 and 2 but loses its explanatory power in Models 3 and 4, which is likely to be driven by the explanatory power of the cluster index.

In sum, based on our empirical findings we can accept four out of five hypotheses. First, being located in a cluster is positively associated with the emergence of radical innovations (hypothesis 1). Second, the centrality of a firms' cluster core position shows a negative relation which means that firms located in the periphery rather engage in radical innovations (hypothesis 2). Third, having a high amount of relationships with other actors has a positive influence on the likelihood to create radical innovations up to a certain degree and afterwards it diminishes (hypothesis 3). Fourth, firms located in clusters can better seize fast technological development in industries to generate radical innovations (hypothesis 4), while the pace of technological evolution in general negatively influences the emergence of radical innovations. Finally, in contrast to our hypothesis 5, the size of the cluster has a positive association with radical innovations. We do not observe a reversed u-shape relation and hence cannot confirm this hypothesis. In the context of radical innovations it thus seems that competition, enhanced by a high geographical concentration of similar firms, rather promotes the creation of radical innovations on the firm-level, as firms recognize the need to be particular innovative in order to differentiate from the nearby competitors and create an competitive advantage (Zhou, Yim, & Tse, 2005).

As robustness checks for our Models 1-4, we also used the amount of radical innovations per firm as dependent variable and fitted a negative binomial regression. We were able to confirm the overall results of our Models 1-4.[14] However, we were not able to find results supporting our hypothesis concerning the negative influence of a firm's central position in the cluster core. Despite the fact that the coefficient is still negative, it is not significant. Thus, with regard to our hypothesis 2, we can indeed observe that rather firms in the periphery of a cluster come up with radically new ideas for the first time. Nevertheless, soon as a firm has had a radical innovation and is trying to produce more the firm's location within the cluster becomes not statistically important anymore.

## 5. Concluding remarks and outlook

Literature in the recent decades has acknowledged innovation to be a key driver of economic success (e.g. Rosenberg, 2004). In the light of an increasing pace of innovation, innovations that are more radical in nature receive more attention by both managers and policy makers, since they can help to secure long-term economic growth (e.g. Arthur, 2007). While regional clusters are found to be an important factor of inventive activities in general (e.g. Bell, 2005), it remains unclear whether they are also beneficial in terms of radical innovation processes (Hervás-Oliver et al., 2018a). We lack knowledge on whether firms in clusters are more likely to generate radical innovations and which conditions might support this effect. On the one hand, radical new ideas could profit from cross-fertilization of knowledge in clusters and in particular from the exchange of tacit knowledge. On the other hand, clusters could lead to inertia and uniform thinking while hampering the emergence of radical innovations.

The studies' descriptive results show that only a small share of firms is responsible for the emergence of radical innovations. These firms are rather large and are mostly based in urban regions in Southern and Western Germany, while rural regions lag behind. Our regression analysis, which is fitted on a sample of German patenting firms between 2012 and 2014, shows that clusters indeed provide a preferable environment for radical innovations. These results remain stable with various independent variables from different levels of analysis as well as with categorical and continuous dependent variables. Furthermore, we find evidence that radical innovations rather occur in the periphery of the cluster, where actors tend to be more open to the exchange of external knowledge. This happens in general through linkages with other actors, which we also find to be beneficial for the emergence of radical innovations up to a certain degree. Moreover, firms located in clusters are able to seize the fast technology evolution in industries to come up with radically new ideas, whereas this is not the case outside of clusters. Finally, we cannot find evidence that supports a reversed u-shape relation of the size of clusters to the emergence of radical innovations.

Our findings have relevant policy implications. It shows that cluster policy not only supports innovation in general but can also enhance the emergence of radical innovations. Furthermore, it helps firms to deal with fast developments in their focal industry better and transform them into radically new ideas. Policy makers should continue to support clusters and further develop funding schemes. Also, we find that firms in the cluster's periphery are more prone to come up with radically new ideas. However, as soon as there has been a radical innovation in a cluster, the firm's position is however not important anymore. Hence, policy measures could call the attention to radical innovations for all cluster firms in order to promote their emergence. Moreover, our results have implications for managers. In particular, it is beneficial for firms to engage in collaborations with other actors for the cross-fertilization of knowledge (up to a certain degree). Different knowledge pieces hence can be combined and turned into radical innovations. This happens particularly in peripheral regions of a cluster, where firms are more open to the exchange of knowledge.

Our paper does not come without limitations, which offer opportunities for further research: First, our dependent variable is based on new combinations of IPC classes present on patent documents. This only focuses on one dimension of the process, namely the emergence. It could be worthwhile to use other measures, which focus e.g. on the diffusion of the invention (e.g. highly cited patents). Not all new combinations might diffuse successfully. In addition, we could think of using other data (e.g. products) to analyse radical innovations. Second, our analysis does not pay attention to the specific stage clusters are actually in regarding their life cycle. Hence, future studies could try to integrate the cluster life cycle model to analyse whether radical innovations rather occur in young, emerging clusters than in sustaining or declining clusters. Related to this promising area for future research is the use of panel data. While our study is, due to data constraints[15], only based on pooled cross-sectional data[16], raising potential concerns of endogeneity, future studies may apply panel-data to also determine rather dynamic effects. Finally, it could also be interesting to analyse further the inter- and intra-regional linkages.

## Notes

1. Although the analysis of our study focuses on invention processes, the paper uses the terms 'innovation' and 'invention' interchangeably.
2. Based on the results of the comparative empirical approach applied in Grashof and Fornahl (2017), highlighting that the spatial connection, the thematic connection and interdependencies are regarded within the literature as the core elements of cluster definitions, industrial districts stressing particularly informal relationships, social capital and trust, are only seen as one specific form of a cluster and hence are not taken explicitly into account here.
3. In line with our cluster definition, we do not consider cities as clusters in this study.
4. A full list of the NACE codes can be found at Eurostat e.g.: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Statistical_classification_of_economic_activities_in_the_European_Community_(NACE).
5. In accordance with the literature, 45 min are here perceived to be an adequate limit for close geographical distance (Brenner 2017; Scholl & Brenner 2016).
6. By using this standard threshold, we avoid to choose arbitrarily a threshold, which constitutes a limitation to several studies dealing with the relationship between clusters and firm performance (e.g. Hervás-Oliver et al. 2018b).

7. Even though patents are commonly used in empirical studies, we still want to acknowledge its flaws. For example, not all innovations are patented and some innovations cannot be patented. For a discussion on shortcomings of patent data, see e.g. Griliches (1990). Nevertheless, patents offer extensive and detailed information on the inventory process such as the date, applicant and technology and over a long time. Hence, it very well fits our empirical approach.
8. A Token algorithm with a log-based weight function has been utilized. It belongs to the group of vectorial decomposition algorithms and compares the elements of two text strings by separating them by their blank spaces (for more information, see e.g.: Raffo 2017; Raffo & Lhuillery 2009).
9. For a detailed overview of the number of radical innovations and the pace of technology evolution by industry, please see Appendix 3.
10. A geographical distribution of the firms in our sample and in total Germany can be found in Appendix 2.
11. The results concerning the application of the cluster index and the interaction term as well as the results of the subsample can be provided by the authors upon request.
12. As indicated by Ai and Norton (2003) problems may raise regarding the interpretation of such an interaction term. However, by using log-odds, we argue that the interpretation problems raised by Ai and Norton (2003) are not that relevant in our case, as the logit model is a linear model in the log odds metric (logit-scale) whereas transformed to the probability scale it indeed becomes nonlinear (Kohler & Kreuter 2008; MacKenzie et al. 2018; UCLA 2018).
13. The cluster index-specific marginal effects of being located in a cluster are illustrated in Appendix 4.
14. Results can be provided by the authors upon request.
15. Particularly referring to the calculation of the cluster index.
16. Since causality is hard to determine with cross-sectional data, in line with Hervás-Oliver et al. (2018b) we claim correlation rather than cause and effect.

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## Disclosure statement

No potential conflict of interest was reported by the authors.

## References

Ahuja, G., & Morris Lampert, C. (2001). Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. *Strategic Management Journal*, *22*(6-7), 521–543. doi:10.1002/smj.176

Ai, C., & Norton, E. C. (2003). Interaction terms in logit and probit models. *Economics Letters*, *80*(1), 123–129. doi:10.1016/S0165-1765(03)00032-6

Albert, M. B., Avery, D., Narin, F., & McAllister, P. (1991). Direct validation of citation counts as indicators of industrially important patents. *Research Policy*, *20*(3), 251–259. doi:10.1016/0048-7333(91)90055-U

Amend, E., & Herbst, P. (2008). *Labor market pooling and human capital investment decisions* (IAB Discussion Paper 4/2008).

Arthur, W. B. (2007). The structure of invention. *Research Policy*, *36*(2), 274–287. doi:10.1016/j.respol.2006.11.005

Audretsch, D. B. (1998). Agglomeration and the location of innovative activity. *Oxford Review of Economic Policy*, *14*(2), 18–29. doi:10.1093/oxrep/14.2.18

Audretsch, D. B., & Feldman, M. P. (1996). Innovative clusters and the industry life cycle. *Review of Industrial Organization*, *11*(2), 253–273. doi:10.1007/BF00157670

Baptista, R., & Swann, P. (1998). Do firms in cluster innovate more? *Research Policy*, *27*(5), 525–540. doi:10.1016/S0048-7333(98)00065-1

Basalla, G. (1988). *The evolution of technology*. Cambridge, UK: Cambridge University Press.

Bekkers, R., & Freitas, I. M. B. (2008). Analysing knowledge transfer channels between universities and industry: To what degree do sectors also matter? *Research Policy*, *37*(10), 1837–1853. doi:10.1016/j.respol.2008.07.007

Bell, G. G. (2005). Clusters, networks, and firm innovativeness. *Strategic Management Journal*, *26*(3), 287–295. doi:10.1002/smj.448

Bers, J. A., Dismukes, J. P., Miller, L. K., & Dubrovensky, A. (2009). Accelerated radical innovation: Theory and application. *Technological Forecasting and Social Change*, *76*(1), 165–177. doi:10.1016/j.techfore.2008.08.013

BMBF. (2018). Startschuss für Agentur zur Förderung von Sprunginnovationen. Pressemitteilung: 075/2018, Bundesministerium für Bildung und Forschung.

Boschma, R. (2005). Proximity and innovation: A critical assessment. *Regional Studies*, *39*(1), 61–74. doi:10.1080/0034340052000320887

Boschma, R. (2017). Relatedness as driver of regional diversification: A research agenda. *Regional Studies*, *51*(3), 351–364. doi:10.1080/00343404.2016.1254767

Braunerhjelm, P., Ding, D., & Thulin, P. (2017). *Labour mobility, knowledge flows and innovation* (Working Paper No. 54). Swedish Entrepreneurship Forum.

Brenner, T. (2017). *Identification of clusters – an actor-based approach* (Working Papers on Innovation and Space). Philipps-Universität Marburg.

Broekel, T. (2015). The co-evolution of proximities – a network level. *Regional Studies*, *49*(6), 921–935. doi:10.1080/00343404.2014.1001732

Broekel, T., & Graf, H. (2012). Public research intensity and the structure of German R&D networks: A comparison of 10 technologies. *Economics of Innovation and New Technology*, *21*(4), 345–372. doi:10.1080/10438599.2011.582704

Brown, J. S., & Duguid, P. (2000). Mysteries of the region: Knowledge dynamics in Silicon Valley. In C.-M. Lee, W. F. Miller, M. G. Hancock, & H. S. Rowen (Eds.), *The Silicon Valley Edge* (pp. 16–45). Stanford, USA: Stanford University Press.

Brown, K., Burgees, J., Festing, M., Royer, S., & Steffen, C. (2007). The value adding web – a conceptual framework of competitive advantage realisation in clusters. ESCP-EAP Working Paper No. 27.

Cantner, U., Graf, H., & Rothgang, M. (2018). Geographical clustering and the evaluation of cluster policies: Introduction. *The Journal of Technology Transfer*. doi:10.1007/s10961-018-9666-4

Casper, S. (2007). *Creating Silicon Valley in Europe: Public policy towards new technology industries*. Oxford: Oxford University Press.

Castaldi, C., Frenken, K., & Los, B. (2015). Related variety, unrelated variety and technological breakthroughs: An analysis of US state-level patenting. *Regional Studies*, *49*(5), 767–781. doi:10.1080/00343404.2014.940305

Castaldi, C., & Los, B. (2012). Are new 'Silicon Valleys' emerging? The changing distribution of superstar patents across US States. DRUID Summer Conference 2012.

Cooper, A. C., & Schendel, D. (1976). Strategic responses to technological threats. *Business Horizons*, *19*(1), 61–69. doi:10.1016/0007-6813(76)90024-0

Cortright, J. C. (2001). New growth theory, new growth theory, technology and learning: Technology and learning: A practitioner's guide a practitioner's guide. Reviews of Economic Development Literature and Practice No. 4.

Daft, R. L., & Lengel, R. H. (1986). Organizational information requirements, media richness and structural design. *Management Science*, *32*(5), 554–571. doi:10.1287/mnsc.32.5.554

Dahlin, K. B., & Behrens, D. M. (2005). When is an invention really radical?: Defining and measuring technological radicalness. *Research Policy*, *34*(5), 717–737. doi:10.1016/j.respol.2005.03.009

Desrochers, P. (2001). Local diversity, human creativity, and technological innovation. *Growth and Change*, *32*(3), 369–394. doi:10.1111/0017-4815.00164

Dosi, G. (1982). Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change. *Research Policy*, *11*(3), 147–162. doi:10.1016/0048-7333(82)90016-6

Dyer, J. H., & Singh, H. (1998). The relational view: Cooperative strategy and sources of interorganizational competitive advantage. *The Academy of Management Review*, *23*(4), 660–679. doi:10.5465/amr.1998.1255632

EFI. (2015). Gutachten zu Forschung, Innovation und Technologischer Leistungsfähigkeit Deutschlands. Expertenkommission Forschung und Innovation.

European Cluster Observatory. (2018). Methodology – indicators. Retrieved from http://www.clusterobservatory.eu/index.html#!view=aboutobservatory;url=/about-observatory/methodology/indicators/

European Communities. (2008). The concept of clusters and cluster policies and their role for competitiveness and innovation: main statistical results and lessons learned. Europe INNOVA / PRO INNO Europe paper N° 9.

Festing, M., Royer, S., & Steffen, C. (2012). Unternehmenscluster schaffen Wettbewerbsvorteile – Eine Analyse des Uhrenclusters in Glashütte. *Zeitschrift Führung und Organisation*, *81*(4), 264–272.

Fleming, L. (2001). Recombinant uncertainty in technological search. *Management Science*, *47*(1), 117–132. doi:10.1287/mnsc.47.1.117.10671

Fleming, L. (2007). Breakthroughs and the 'long tail' of innovation. *MIT Sloan Management Review*, *49*(1), 69.

Folta, T. B., Cooper, A. C., & Baik, Y.-S. (2006). Geographic cluster size and firm performance. *Journal of Business Venturing*, *21*(2), 217–242. doi:10.1016/j.jbusvent.2005.04.005

Fornahl, D., Broekel, T., & Boschma, R. (2011). What drives patent performance of German biotech firms? The impact of R&D subsidies, knowledge networks and their location. *Papers in Regional Science*, *90*(2), 395–418. doi:10.1111/j.1435-5957.2011.00361.x

Frenken, K., Cefis, E., & Stam, E. (2013). *Industrial dynamics and clusters: a survey*. Tjalling C. Koopmans Research Institute, Discussion Paper Series nr: 13-11, Utrecht School of Economics.

Giuliani, E. (2007). The selective nature of knowledge networks in clusters: Evidence from the wine industry. *Journal of Economic Geography*, *7*(2), 139–168. doi:10.1093/jeg/lbl014

Glaeser, E. L., Kallal, H. D., Scheinkman, J. A., & Shleifer, A. (1992). Growth in cities. *Journal of Political Economy*, *100*(6), 1126–1152. doi:10.1086/261856

Grashof, N., & Fornahl, D. (2017). 'To be or not to be' located in a cluster? – A descriptive meta-analysis of the firm-specific cluster effect. Manuscript submitted for publication.

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature*, *28*(4), 1661–1707. doi:10.3386/w3301

Henderson, R. M., & Clark, K. B. (1990). Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly*, 9–30. doi:10.2307/2393549

Hervás-Oliver, J.-L., & Albors-Garrigos, J. (2009). The role of the firm's internal and relational capabilities in clusters: When distance and embeddedness are not enough to explain innovation. *Journal of Economic Geography*, *9*(2), 263–283. doi:10.1093/jeg/lbn033

Hervás-Oliver, J.-L., Albors-Garrigos, J., Estelles-Miguel, S., & Boronat-Moll, C. (2018a). Radical innovation in Marshallian industrial districts. *Regional Studies*, *52*(10), 1388–1397. doi:10.1080/00343404.2017.1390311

Hervás-Oliver, J.-L., Sempere-Ripoll, F., Alvarado, R. R., & Estelles-Miguel, S. (2018b). Agglomerations and firm performance: Who benefits and how much? *Regional Studies*, *52*(3), 338–349. doi:10.1080/00343404.2017.1297895

Hottenrott, H., & Lopes-Bento, C. (2016). R&D partnerships and innovation performance: Can there be too much of a good thing? *Journal of Product Innovation Management*, *33*(6), 773–794. doi:10.1111/jpim.12311

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, *108*(3), 577–598. doi:10.2307/2118401

Kesteloot, K., & Veugelers, R. (1995). Stable R&D Cooperation with spillovers. *Journal of Economics & Management Strategy*, *4*(4), 651–672. doi:10.1111/j.1430-9134.1995.00651.x

Knoben, J., Arikan, A. T., Van Oort, F., & Raspe, O. (2015). Agglomeration and firm performance: One firm's medicine is another firm's poison. *Environment and Planning A*, *48*(1), 1–22.

Kohlbacher, M., Weitlaner, D., Hollosi, A., Grünwald, S., & Grahsl, H.-P. (2013). Innovation in clusters: Effects of absorptive capacity and environmental moderators. *Competitiveness Review: An International Business Journal*, *23*(3), 199–217. doi:10.1108/10595421311319807

Kohler, U., & Kreuter, F. (2008). *Datenanalyse mit Stata – Allgemeine Konzepte der Datenanalyse und ihre praktische Anwendung* (3rd ed.). München: Oldenbourg Verlag.

Kosfeld, R., & Werner, A. (2012). Deutsche Arbeitsmarktregionen– Neuabgrenzung nach den Kreisgebietsreformen 2007–2011. *Raumforschung und Raumordnung*, *70*(1), 49–64. doi:10.1007/s13147-011-0137-8

Lavie, D. (2006). The competitive advantage of interconnected firms: An extension of the resource-based view. *The Academy of Management Review*, *31*(3), 638–658. doi:10.5465/amr.2006.21318922

Lechner, C., & Leyronas, C. (2012). The competitive advantage of cluster firms: The priority of regional network position over extra-regional networks – a study of a French high-tech cluster. *Entrepreneurship & Regional Development*, *24*(5–6), 457–473. doi:10.1080/08985626.2011.617785

MacKenzie, D. I., Nichols, J. D., Royle, J. A., Pollock, K. H., Bailey, L. L., & Hines, J. E. (2018). Chapter 3 - Fundamental Principals of Statistical Inference. In D. I. MacKenzie, J. D. Nichols, J. A. Royle, K. H. Pollock, L. L. Bailey, & J. E. Hines (Eds.), *Occupancy Estimation and Modeling* (pp. 71–111). London: Elsevier.

Marshall, A. (1920). *Principles of economics* (8th ed.). London: Macmillan.

Martin, R. (2009). Rethinking regional path dependence: Beyond lock-in to evolution. Papers in Evolutionary Economic Geography (PEEG), No. 910.

Martin, R., & Sunley, P. (2003). Deconstructing clusters: Chaotic concept or policy panacea? *Journal of Economic Geography*, *3*(1), 5–35. doi:10.1093/jeg/3.1.5

Mascitelli, R. (2000). From experience: Harnessing tacit knowledge to achieve breakthrough innovation. *Journal of Product Innovation Management*, *17*(3), 179–193. doi:10.1016/S0737-6782(00)00038-2

McCann, B. T., & Folta, T. B. (2008). Location matters: Where we have been and where we might go in agglomeration research? *Journal of Management*, *34*(3), 532–565. doi:10.1177/0149206308316057

McCann, B. T., & Folta, T. B. (2011). Performance differentials within geographic clusters. *Journal of Business Venturing*, *26*(1), 104–123. doi:10.1016/j.jbusvent.2009.04.004

McGahan, A. M., & Silverman, B. S. (2001). How does innovative activity change as industries mature? *International Journal of Industrial Organization*, *19*(7), 1141–1160. doi:10.1016/S0167-7187(01)00067-4

Menzel, M.-P., & Fornahl, D. (2010). Cluster life cycles – dimensions and rationales of cluster evolution. *Industrial and Corporate Change*, *19*(1), 205–238. doi:10.1093/icc/dtp036

Munari, F., Sobrero, M., & Malipiero, A. (2012). Absorptive capacity and localized spillovers: Focal firms as technological gatekeepers in industrial districts. *Industrial and Corporate Change*, *21*(2), 429–462. doi:10.1093/icc/dtr053

Nagy, D., Schuessler, J., & Dubinsky, A. (2016). Defining and identifying disruptive innovations. *Industrial Marketing Management*, *57*, 119–126. doi:10.1016/j.indmarman.2015.11.017

Nerkar, A. (2003). Old is gold? The value of temporal exploration in the creation of new knowledge. *Management Science*, *49*(2), 211–229. doi:10.1287/mnsc.49.2.211.12747

Otto, A., & Fornahl, D. (2010). Origins of human capital in clusters: Regional, industrial and academic transitions in media clusters in Germany. In D. Fornahl, S. Henn, & M.-P. Menzel (Eds.), *Emerging clusters: Theoretical, empirical and Political Perspectives on the Initial stage of cluster evolution* (pp. 99–139). Cheltenham, UK: Edward Elgar.
Porter, M. E. (1998). Clusters and the new economics of competitiveness. *Harvard Business Review*, *76*(6), 77–90. doi:10.1201/b14647-11
Pouder, R., & St. John, C. H. (1996). Hot spots and blind spots: Geographical clusters of firms and innovation. *The Academy of Management Review*, *21*(4), 1192–1225. doi:10.5465/amr.1996.9704071867
Raffo, J. (2017). MATCHIT: Stata module to match two datasets based on similar text patterns. Boston College Department of Economics. Retrieved from help file in Stata.
Raffo, J., & Lhuillery, S. (2009). How to play the 'names game': patent retrieval comparing different heuristics. *Research Policy*, *38*(10), 1617–1627. doi:10.1016/j.respol.2009.08.001
Research Explorer. (2018). Research Explorer - The German research directory. Retrieved from http://www.research-explorer.de/research_explorer.en.html?
Rigby, D. L., & Brown, M. W. (2015). Who benefits from agglomeration? *Regional Studies*, *49*(1), 28–43. doi:10.1080/00343404.2012.753141
Rizzo, U., Barbieri, N., Ramaciotti, L., & Iannantuono, D. (2018). The division of labour between academia and industry for the generation of radical inventions. *Journal of Technology Transfer*. doi:10.1007/s10961-018-9688-y
Roesler, C., & Broekel, T. (2017). The role of universities in a network of subsidized R&D collaboration: The case of the biotechnology industry in Germany. *Review of Regional Research*, *37*(2), 135–160. doi:10.1007/s10037-017-0118-7
Rosenberg, N. (2004). *Innovation and economic growth*. Paris: OECD.
Rosenkopf, L., & Nerkar, A. (2001). Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal*, *22*(4), 287–306. doi:10.1002/smj.160
Saxenian, A. (1994). *Regional advantage: Culture and competition in Silicon Valley and Route 128*. Cambridge: Harvard University Press.
Scholl, T., & Brenner, T. (2016). Detecting spatial clustering using a firm-level cluster index. *Regional Studies*, *50*(6), 1054–1068. doi:10.1080/00343404.2014.958456
Shaver, J. M., & Flyer, F. (2000). Agglomeration economies, firm heterogeneity, and foreign direct investment in the United States. *Strategic Management Journal*, *21*(12), 1175–1193. doi:10.1002/1097-0266(200012)21:12<1175::AID-SMJ139>3.0.CO;2-Q
Steffen, C. (2012). How firms profit from acting in networked environments: Realising competitive advantages in business clusters. A resource-oriented case study analysis of the German and Swiss Watch Industry. Schriftenreihe: Internationale Personal- und Strategieforschung.
Strumsky, D., & Lobo, J. (2015). Identifying the sources of technological novelty in the process of invention. *Research Policy*, *44*(8), 1445–1461. doi:10.1016/j.respol.2015.05.008
Suarez, F. F., & Lanzolla, G. (2007). The role of environmental dynamics in building a first mover advantage theory. *Academy of Management Review*, *32*(2), 377–392. doi:10.5465/amr.2007.24349587
Suarez, F., & Lanzolla, G. (2005). The half-truth of first-mover advantage. *Harvard Business Review*, *83*(4), 121–127.
Trajtenberg, M. (1990). A penny for your quotes: Patent citations and the value of innovations. *The Rand Journal of Economics*, 172–187. doi:10.2307/2555502
Tushman, M. L., & Anderson, P. (1986). Technological discontinuities and organizational environments. *Administrative Science Quarterly*, 439–465. doi:10.2307/2392832
UCLA. (2018). Deciphering interactions in logistic regression. Retrieved from https://stats.idre.ucla.edu/stata/seminars/deciphering-interactions-in-logistic-regression/
Verhoeven, D., Bakker, J., & Veugelers, R. (2016). Measuring technological novelty with patent-based indicators. *Research Policy*, *45*(3), 707–723. doi:10.1016/j.respol.2015.11.010
Verspagen, B. (2006). Innovation and economic growth. In J. Fagerberg, D. Mowery, & R. Nelson (Eds.), *The oxford handbook of innovation* (pp. 487–513). New York: Oxford University Press.

Weitzman, M. L. (1998). Recombinant growth. *The Quarterly Journal of Economics*, *113*(2), 331–360. doi:10.1162/003355398555595

Zaheer, A., & George, V. P. (2004). Reach out or reach within? Performance implications of alliances and location in biotechnology. *Managerial and Decision Economics*, *25*(6-7), 437–452. doi:10.1002/mde.1200

Zhang, F., Wei, L., Yang, J., & Zhu, L. (2018). Roles of relationships between large shareholders and managers in radical innovation: A stewardship theory perspective. *Journal of Product Innovation Management*, *35*(1), 88–105. doi:10.1111/jpim.12376

Zhou, K. Z., Yim, C. K. B., & Tse, D. K. (2005). The effects of strategic orientations on technology- and market-based breakthrough innovations. *Journal of Marketing*, *69*(2), 42–60. doi:10.1509/jmkg.69.2.42.60756

Zucker, L. G., Darby, M. R., & Torero, M. (2002). Labor mobility from academe to commerce. *Journal of Labor Economics*, *20*(3), 629–660. doi:10.1086/339613

**Appendix 1: Pairwise correlation matrix and descriptive statistics (own illustration)**

| | 1. | 2. | 3. | 4. | 5. | 6. | 7. | 8. | 9. | 10. | Mean | Std. Dev. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Cluster dummy | 1.000 | | | | | | | | | | 0.122 | 0.328 |
| 2. Cluster index | 0.664* | 1.000 | | | | | | | | | 1.353 | 1.308 |
| 3. Cluster size | 0.092* | 0.052* | 1.000 | | | | | | | | 37.03 | 608.131 |
| 4. Pace of technology evolution | 0.152* | 0.093* | 0.028* | 1.000 | | | | | | | 0.955 | 1.938 |
| 5. Number of linkages | 0.001 | 0.010 | 0.006 | 0.003 | 1.000 | | | | | | 0.292 | 3.584 |
| 6. Research-intensive industry dummy | 0.138* | 0.066* | 0.020 | 0.673* | 0.005 | 1.000 | | | | | 0.277 | 0.447 |
| 7. Number of research institutes | -0.581* | -0.038* | 0.018 | -0.058* | 0.001 | -0.070* | 1.000 | | | | 8.375 | 20.102 |
| 8. Regional knowledge base | -0.034* | -0.021* | 0.035 | -0.020 | 0.026* | -0.033* | 0.423* | 1.000 | | | 180.96 | 602.588 |
| 9. Independence dummy | -0.002 | -0.008 | 0.012 | -0.002 | 0.025* | 0.012 | 0.022* | 0.034* | 1.000 | | 0.032 | 0.176 |
| 10. Age | 0.139* | 0.093* | 0.057* | 0.057* | 0.020 | 0.090* | -0.055* | -0.033* | 0.052* | 1.000 | 28.34 | 32.289 |

*Significance level: * $p < 0.05$*

**Appendix 2: Geographical distribution of firms (own illustration).**[1]

| LMR_Nr | LMR_Name | Number of firms in sample | Total number of firms in LMR (2014) |
|---|---|---|---|
| 1 | Kiel | 37 | 9.885 |
| 2 | Luebeck | 18 | 9.037 |
| 3 | Dithmarschen | 4 | 6.506 |
| 4 | Flensburg | 19 | 3.856 |
| 5 | Hamburg | 304 | 8.427 |
| 6 | Braunschweig | 38 | 10.066 |
| 7 | Wolfsburg | 10 | 3.341 |
| 8 | Goettingen | 37 | 10.341 |
| 9 | Goslar | 32 | 5.650 |
| 10 | Hannover | 121 | 50.867 |
| 11 | Hameln | 17 | 6.165 |
| 12 | Celle | 12 | 7.135 |
| 13 | Luechow-Dannenberg | 5 | 2.129 |
| 14 | Stade | 12 | 8.080 |
| 15 | Uelzen | 5 | 3.658 |
| 16 | Emden | 28 | 1.907 |
| 17 | Oldenburg | 34 | 7.751 |
| 18 | Osnabrueck | 52 | 7.793 |
| 19 | Emsland | 59 | 14.360 |
| 20 | Wilhelmshaven | 4 | 2.749 |
| 21 | Vechta | 44 | 7.751 |
| 22 | Bremen | 112 | 10.094 |
| 23 | Bremerhaven | 18 | 7.308 |
| 24 | Duesseldorf | 236 | 40.950 |
| 25 | Essen | 167 | 15.670 |
| 26 | Wuppertal | 95 | 4.916 |
| 27 | Kleve | 26 | 14.312 |
| 28 | Bonn | 97 | 16.243 |
| 29 | Koeln | 161 | 61.299 |
| 30 | Aachen | 103 | 25.548 |
| 31 | Olpe | 83 | 12.565 |
| 32 | Muenster | 154 | 14.567 |
| 33 | Borken | 62 | 18.189 |
| 34 | Bielefeld | 137 | 14.457 |
| 35 | Hoexter | 9 | 6.159 |

[1] Information on total number of firms in labour market regions retrieved from the "Regionaldatenbank Deutschland" (Table 52111-01-01-4), Source: Statistische Ämter des Bundes und der Länder, Deutschland, 2019.

| | | | |
|---|---|---|---|
| 36 | Minden | 114 | 4.908 |
| 37 | Bochum | 87 | 8.058 |
| 38 | Dortmund | 80 | 22.826 |
| 39 | Hagen | 180 | 7.245 |
| 40 | Siegen | 42 | 11.908 |
| 41 | Soest | 153 | 13.615 |
| 42 | Darmstadt | 63 | 8.513 |
| 43 | Frankfurt am Main | 206 | 43.590 |
| 44 | Giessen | 98 | 11.881 |
| 45 | Limburg-Weilburg | 36 | 9.121 |
| 46 | Kassel | 41 | 9.339 |
| 47 | Fulda | 40 | 4.579 |
| 48 | Waldeck-Frankenberg | 25 | 6.970 |
| 49 | Koblenz | 102 | 5.965 |
| 50 | Altenkirchen | 15 | 5.569 |
| 51 | Bad Kreuznach | 20 | 6.954 |
| 52 | Bitburg | 4 | 4.321 |
| 53 | Vulkaneifel | 3 | 2.825 |
| 54 | Trier | 17 | 5.366 |
| 55 | Kaiserslautern | 25 | 4.658 |
| 56 | Landau | 22 | 2.494 |
| 57 | Ludwigshafen | 62 | 1.992 |
| 58 | Mainz | 58 | 15.887 |
| 59 | Stuttgart | 325 | 34.060 |
| 60 | Boeblingen | 102 | 17.644 |
| 61 | Goeppingen | 47 | 12.319 |
| 62 | Heilbronn | 110 | 6.471 |
| 63 | Schwaebisch Hall | 22 | 9.352 |
| 64 | Heidenheim | 67 | 5.349 |
| 65 | Karlsruhe | 151 | 3.839 |
| 66 | Heidelberg | 101 | 13.952 |
| 67 | Pforzheim | 66 | 6.139 |
| 68 | Freiburg | 74 | 12.096 |
| 69 | Ortenaukreis | 71 | 20.304 |
| 70 | Rottweil | 129 | 7.078 |
| 71 | Konstanz | 35 | 14.078 |
| 72 | Loerrach | 24 | 9.746 |
| 73 | Waldshut | 18 | 7.456 |
| 74 | Reutlingen | 88 | 14.664 |
| 75 | Zollernalbkreis | 40 | 9.661 |
| 76 | Ulm | 103 | 6.709 |
| 77 | Ravensburg | 145 | 8.584 |
| 78 | Sigmaringen | 16 | 6.473 |
| 79 | Ingolstadt | 41 | 5.691 |
| 80 | Muenchen | 494 | 99.812 |

| | | | |
|---|---|---|---|
| 81 | Altoetting | 52 | 5.209 |
| 82 | Traunstein | 80 | 4.181 |
| 83 | Weilheim-Schongau | 19 | 6.352 |
| 84 | Deggendorf | 20 | 6.239 |
| 85 | Freyung | 6 | 4.034 |
| 86 | Passau | 16 | 3.297 |
| 87 | Landshut | 48 | 3.715 |
| 88 | Cham | 13 | 6.384 |
| 89 | Amberg | 32 | 2.199 |
| 90 | Regensburg | 55 | 5.563 |
| 91 | Bamberg | 29 | 4.285 |
| 92 | Bayreuth | 44 | 3.754 |
| 93 | Coburg | 52 | 2.244 |
| 94 | Hof | 57 | 2.296 |
| 95 | Kronach | 10 | 3.151 |
| 96 | Erlangen | 56 | 5.130 |
| 97 | Nuernberg | 156 | 6.446 |
| 98 | Ansbach | 25 | 2.036 |
| 99 | Weissenburg-Gunzenhausen | 8 | 4.676 |
| 100 | Aschaffenburg | 66 | 4.748 |
| 101 | Schweinfurt | 27 | 2.776 |
| 102 | Wuerzburg | 81 | 6.168 |
| 103 | Augsburg | 82 | 13.169 |
| 104 | Memmingen | 28 | 2.513 |
| 105 | Donau-Ries | 22 | 6.396 |
| 106 | Kempten | 43 | 2.253 |
| 107 | Saarbruecken | 56 | 15.431 |
| 108 | Pirmasens | 27 | 2.155 |
| 109 | Berlin | 305 | 181.313 |
| 110 | Frankfurt (Oder) | 8 | 2.463 |
| 111 | Elbe-Elster | 9 | 4.534 |
| 112 | Havelland | 7 | 6.458 |
| 113 | Maerkisch-Oderland | 4 | 8.760 |
| 114 | Oberhavel | 19 | 8.883 |
| 115 | Ostprignitz-Ruppin | 4 | 4.375 |
| 116 | Potsdam-Mittelmark | 24 | 2.687 |
| 117 | Prignitz | 6 | 3.385 |
| 118 | Cottbus | 6 | 4.535 |
| 119 | Teltow-Flaeming | 10 | 7.376 |
| 120 | Uckermark | 6 | 4.550 |
| 121 | Schwerin | 31 | 4.479 |
| 122 | Mecklenburgische Seenplatte | 7 | 11.670 |
| 123 | Rostock | 22 | 8.387 |

| | | | |
|---|---|---|---|
| 124 | Nordvorpommern | 4 | 11.657 |
| 125 | Suedvorpommern | 2 | 10.276 |
| 126 | Chemnitz | 96 | 11.449 |
| 127 | Dresden | 116 | 25.220 |
| 128 | Bautzen | 31 | 13.559 |
| 129 | Leipzig | 83 | 25.715 |
| 130 | Dessau-Rosslau | 17 | 3.456 |
| 131 | Magdeburg | 27 | 9.564 |
| 132 | Halle | 41 | 8.212 |
| 133 | Stendal | 2 | 4.574 |
| 134 | Erfurt | 53 | 10.029 |
| 135 | Gera | 16 | 4.334 |
| 136 | Jena | 57 | 4.271 |
| 137 | Nordhausen | 7 | 3.299 |
| 138 | Eisenach | 12 | 1.932 |
| 139 | Unstrut-Hainich | 12 | 4.350 |
| 140 | Suhl | 18 | 1.890 |
| 141 | Saalfeld-Rudolstadt | 18 | 4.901 |

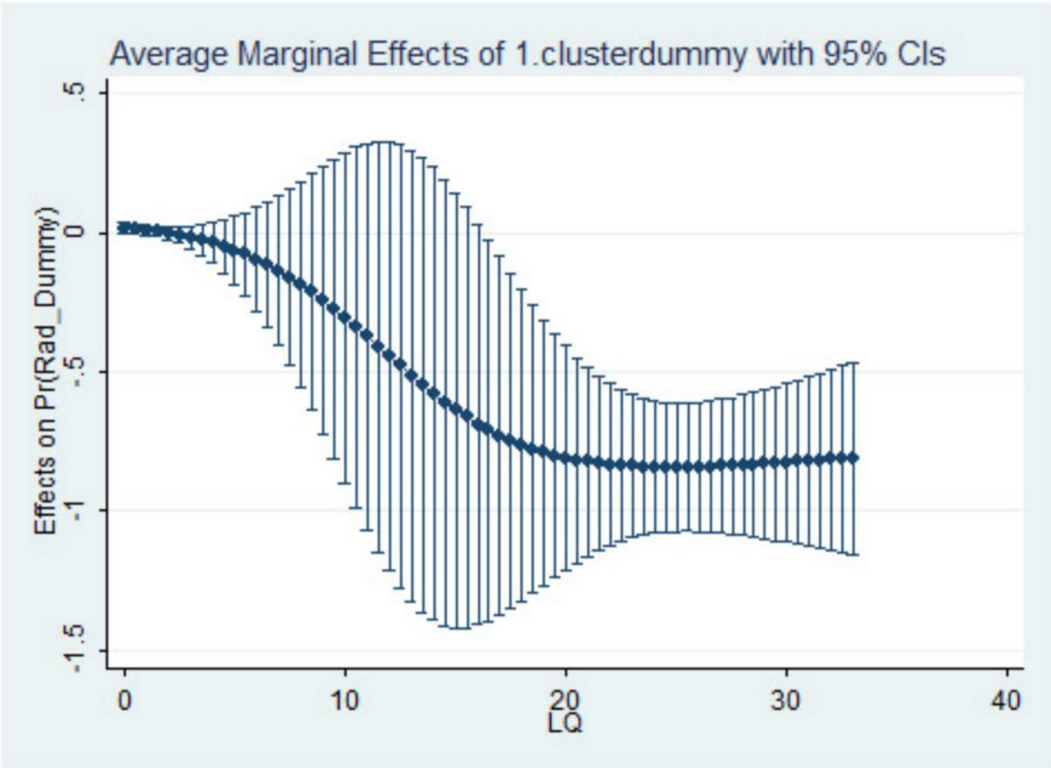
**Appendix 3: Number of radical innovations and pace of technology evolution by industry (own illustration)**

| Nace Rev. 2 (3 digit) | nace2_descr | Number of radical innovations | Pace of technology evolution |
|---|---|---|---|
| 13 | Manufacture of textiles | 0 | 0,28177274 |
| 14 | Manufacture of wearing apparel | 0 | 0,30241946 |
| 15 | Manufacture of leather and related products | 0 | 0,70966104 |
| 16 | Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials | 0 | 0,08583509 |
| 17 | Manufacture of paper and paper products | 0 | 0,10775505 |
| 22 | Manufacture of rubber and plastic products | 0 | 0,57822708 |
| 23 | Manufacture of other non-metallic mineral products | 0 | 0,2970084 |
| 24 | Manufacture of basic metals | 4,166667 | 0,29848192 |
| 31 | Manufacture of furniture | 0 | 0,49651124 |
| 32 | Other manufacturing | 0 | 0,63358925 |
| 62 | Computer programming, consultancy and related activities | 0 | 0,10650202 |
| 105 | Manufacture of dairy products | 0 | 0,04409859 |
| 181 | Printing and service activities related to printing | 1 | 0,18353164 |
| 201 | Manufacture of basic chemicals, fertilisers and nitrogen compounds, plastics and synthetic rubber in primary forms | 3 | 3,4999302 |
| 202 | Manufacture of pesticides and other agrochemical products | 0 | 18,484503 |
| 203 | Manufacture of paints, varnishes and similar coatings, printing ink and mastics | 0 | 1,2748416 |
| 204 | Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations | 0 | 3,1890023 |
| 205 | Manufacture of other chemical products | 26,5 | 1,503437 |
| 206 | Manufacture of man-made fibres | 1 | 0,46032655 |

| | | | |
|---|---|---|---|
| 221 | Manufacture of rubber products | 3 | 0,04525304 |
| 222 | Manufacture of plastic products | 16,5 | 0,048407 |
| 231 | Manufacture of glass and glass products | 0 | 0,69151176 |
| 233 | Manufacture of clay building materials | 0 | 0,52791783 |
| 234 | Manufacture of ceramic sanitary fixtures | 4 | 0,20364125 |
| 235 | Manufacture of cement, lime and plaster | 0 | 4,8413978 |
| 244 | Processing of nuclear fuel | 3 | 0,00054483 |
| 251 | Manufacture of structural metal products | 5 | 0,08891822 |
| 252 | Manufacture of tanks, reservoirs and containers of metal | 1 | 1,4301869 |
| 253 | Manufacture of steam generators, except central heating hot water boilers | 0,5 | 2,7272727 |
| 254 | Manufacture of weapons and ammunition | 0 | 4,4457768 |
| 255 | Forging, pressing, stamping and roll-forming of metal; powder metallurgy | 3 | 0,28183427 |
| 256 | Treatment and coating of metals; machining | 2 | 0,06838364 |
| 257 | Manufacture of cutlery, tools and general hardware | 11 | 1,1935578 |
| 259 | Manufacture of other fabricated metal products | 10,5 | 0,56622332 |
| 261 | Manufacture of electronic components and boards | 10 | 3,1746207 |
| 262 | Manufacture of computers and peripheral equipment | 7 | 13,318338 |
| 263 | Manufacture of communication equipment | 0 | 14,826277 |
| 264 | Manufacture of consumer electronics | 1 | 4,2745613 |
| 265 | Manufacture of instruments and appliances for measuring, testing and navigation; watches and clocks | 10 | 5,5112076 |
| 266 | Manufacture of irradiation, electromedical and electrotherapeutic equipment | 1 | 3,5343565 |
| 267 | Manufacture of optical instruments and photographic equipment | 4 | 3,7697644 |
| 268 | Manufacture of magnetic and optical media | 0 | 0,11976418 |
| 271 | Manufacture of electric motors, generators, transformers | 6 | 1,3219231 |

| | | | |
|---|---|---|---|
| | and electricity distribution and control apparatus | | |
| 272 | Manufacture of batteries and accumulators | 1 | 18,650265 |
| 273 | Manufacture of wiring devices | 0 | 6,4529217 |
| 274 | Manufacture of electric lighting equipment | 1 | 2,6457348 |
| 275 | Manufacture of domestic appliances | 4 | 8,047186 |
| 279 | Manufacture of other electrical equipment | 9,2 | 1,7055257 |
| 281 | Manufacture of general-purpose machinery | 11 | 3,7033847 |
| 282 | Manufacture of other general-purpose machinery n,e,c, | 17,5 | 2,4144443 |
| 283 | Manufacture of agricultural and forestry machinery | 1 | 2,6091809 |
| 284 | Manufacture of metal forming machinery and machine tools | 8,666667 | 2,8218097 |
| 289 | Manufacture of other special-purpose machinery | 37,5 | 2,0929091 |
| 291 | Manufacture of motor vehicles | 11 | 2,7047767 |
| 293 | Manufacture of parts and accessories for motor vehicles | 13,5 | 0,20427778 |
| 325 | Manufacture of medical and dental instruments and supplies | 4 | 3,1896744 |
| 329 | Manufacturing n,e,c, | 1 | 5,2267314 |
| 422 | Construction of utility projects | 0 | 0,23551028 |
| 429 | Construction of water projects | 0 | 0,2576032 |

**Appendix 4: Cluster index-specific marginal effects of being located in a cluster (own illustration)**



### A.3. University-industry collaborations – The key to radical innovations?

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**Share by the author of the dissertation in the publication:** 30%

**Type of participation:**

- Methodology development
- Creation of the dataset
- Analysis of the data
- Interpretation of the results

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ORIGINAL PAPER

# University-industry collaborations—The key to radical innovations?

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**Abstract** Radical innovations are an important factor for long-term economic growth. Universities provide basic research and knowledge that form the basis for future innovations. Previous research has investigated the effects of universities, university-industry partnerships and proximity on factors such as innovations, knowledge spillovers, entrepreneurial activities, as well as regional growth, wealth and competitiveness. However, the role that university-industry collaborations play in radical innovations, mediated by various measures of proximity such as cognitive or geographic distance, has not yet been explored. With this study, we illuminate the conditions under which university-industry collaborations are the key to radical innovations in German firms.

Combining firm, patent and subsidy data, we built a data set consisting of 8404 firms that patented between the years 2012 and 2014. Based on the patent data, we identified the emergence of radical innovations by using new technology com-

The datasets generated during and/or analysed during the current study are available from the authors on reasonable request.

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binations as a proxy for (radical) novelty. As our main independent variables, we computed the cognitive distance of firms, universities and research institutions as well as the geographic distance between these partners. We identified formal relationships through publicly supported R&D collaborations between universities, firms, and research institutions using the German subsidy catalogue.

Our research is vital for understanding the conditions under which university-industry collaborations contribute to the creation of radical innovations. While not only closing a research gap, this paper has practical ramifications for companies, universities as well as policy-makers by evaluating the concrete effects of university-industry collaborations on the probability to generate radical innovations.

**Keywords** Radical innovations · Cognitive distance · Geographic distance · University-industry collaboration

**JEL Codes** 031 · 032 · 034

## Universität-Industrie-Kooperationen – Der Schlüssel zu radikalen Innovationen?

**Zusammenfassung** Radikale Innovationen stellen einen wichtigen Faktor für langfristiges ökonomisches Wachstum dar. Universitäten betreiben Grundlagenforschung und generieren Wissen, dass die Basis für zukünftige Innovationen legt. Bisherige Forschung hat den Einfluss von Universitäten, Kooperationen zwischen Universitäten und Industrie sowie deren Nähe zueinander sowohl auf Innovationsprozesse, Wissensspillover und Gründungsaktivitäten als auch auf regionales Wachstum, Wohlstand und Wettbewerbsfähigkeit untersucht. Allerdings wurde die Rolle von Universität-Industrie-Kooperationen kombiniert mit verschiedenen Nähekonzepten wie geographische und kognitive Nähe bisher nicht untersucht. Mit dieser Studie geben wir Einblicke, unter welchen Gegebenheiten Universitäten-Industrie-Kooperationen der Schlüssel zu radikalen Innovationen sind.

Hierfür kombinieren wir Firmen-, Patent- und Fördermitteldaten zu einem Datensatz, der 8404 Firmen beinhaltet, die zwischen 2012 und 2014 patentiert haben. Basierend auf den Patentdaten haben wir die Entstehung von radikalen Innovationen identifiziert, indem wir neue Technologiekombinationen als Proxy für (radikale) Neuheit genommen haben. Unsere erklärenden Variablen geographische und kognitive Distanz haben wir zwischen Firmen, Universitäten und Forschungsinstituten kalkuliert. Kooperationen zwischen diesen Akteuren haben wir mittels öffentlich geförderten Forschungsprojekten aus dem Deutschen Förderkatalog identifiziert.

Unsere Studie hilft dabei die Bedingungen, unter denen Kooperationen zwischen Universitäten und Firmen zu einer höheren Wahrscheinlichkeit für die Entstehung von radikalen Innovationen führen, besser zu verstehen. Dabei wird nicht nur eine Forschungslücke geschlossen, sondern es können auch Handlungsempfehlungen für Unternehmen, Universitäten und politische Entscheidungsträger aufgezeigt werden.

## 1 Introduction

During the last decades, scientists have demonstrated that innovations are a core factor for economic growth. Most innovation processes happen along well-defined trajectories. By contrast, innovations that are radical in nature happen discontinuously and can bring about paradigm shifts (Dosi 1982). These discontinuities can support sustainable economic growth (Castaldi et al. 2015) and the emergence of new industries (Arthur 2007). Radical innovations are a rare event and come with a higher degree of uncertainty in the search process (Fleming 2001). Nevertheless, radical innovations are acknowledged as a driving force of technological, industrial and societal change (Schoenmakers and Duysters 2010). Particularly in light of the increasing pace of innovation, radical innovations are important in order to obtain a competitive advantage (Castaldi et al. 2015).

Due to higher risks (Fleming 2001), private organizations may choose not to engage in the radical innovation processes. In this regard, basic research conducted at universities could provide valuable knowledge (Fleming and Sorenson 2004). However, universities may lack the capacity to commercialize radical new ideas themselves. University-industry collaborations can overcome these difficulties by facilitating access to firm-/university-external knowledge and complementary resources, ultimately enhancing knowledge diffusion between partners through collaboration (Wirsich et al. 2016).

An example for the new combination of different technological fields is the self-driving car, where automotive technology is combined for the first time with communication systems, sensor-based safety systems and high-resolution mapping (Boschma 2017). This innovation was driven by university-industry collaboration (Uber, University of Arizona). Another example of a radical innovation stemming from university-industry collaboration is a drone package delivery system (RWTH Aachen 2018). These collaborations paved the way for cross-fertilization of complementary knowledge which is an important mechanism for new knowledge combinations.

Although scholars have recognized the importance of public research institutions in supporting innovation in general (e.g. Fritsch and Schwirten 2006), the specific role public research plays in innovation processes that are radical in nature has been scarcely examined. Belderbos et al. (2004) found that university-industry collaborations in particular target more market-oriented or radical innovations. Recently, Wirsich et al. (2016) discovered that linkages between academia and industry drive technological novelty. However, especially the circumstances under which collaborations between academia and industry are successful remain rather unclear. Hence, we want to analyse whether and under which conditions university-industry collaborations are the key to radical innovations in German firms.

Furthermore, our research is vital for understanding the conditions under which university-industry collaborations contribute to the creation of radical innovations. In particular, we investigate the role of geographic distance which has a significant influence on university-industry linkages (Drejer and Østergaard 2017). Moreover, we analyze the role of cognitive distance. Following Nooteboom (2000), it might be important for actors to have a certain degree of cognitive distance in order to combine knowledge in new ways. While not only closing a research gap, this paper has practical ramifications for companies, universities as well as policy-makers by evaluating the concrete effects of university-industry collaborations on the probability to generate radical innovations. Further relevance is proven by the increasing attention that radical innovations attract from German policy makers (Koalitionsvertrag 2018).

The remainder of this paper is organized as follows. Sect. 2 deals with the theoretical background on radical innovations and distances in university-industry collaborations, deducting three hypotheses. Subsequently, Sect. 3 presents the databases as well as the methodology applied. In Sect. 4 we present and discuss our empirical results, concluding with some final remarks in Sect. 5.

## 2 Theory and hypotheses

### 2.1 Radical innovations

Innovation is commonly recognized as a cumulative process in which existing knowledge is combined in new ways to create something new (Basalla 1988; Arthur 2007). In this regard, Weitzman (1998) defined the reconfiguration of existing knowledge in a new fashion to form new artefacts as "recombinant innovation". This concept can be dated back to Schumpeter, who already spoke of the term "Neue Kombinationen" (Schumpeter 1939) in respect to innovation processes.

In contrast to incremental innovations, which are considered to develop mostly alongside well-known trajectories, radical innovations can lead to a paradigm shift and thus radical change (Dosi 1982; Verhoeven et al. 2016). This radical change can lead to the emergence of new markets or industries while causing old ones to disappear (e.g. Henderson and Clark 1990; Tushman and Anderson 1986). This may be caused by the great advancement of the new technology, which drives the old one from the market instead of competing with the previous generation of technology (Arrow 1962). Hence, radical innovations can serve as the basis of future sustainable economic growth (Ahuja and Lampert 2001; Arthur 2007).

In line with the above-mentioned concept, innovations that are radical in nature are the result of recombinant search processes where former unconnected knowledge pieces are combined for the first time (Fleming 2001; Nerkar 2003; Weitzman 1998). These processes which introduce novelty by combining unconnected knowledge domains are difficult to engage in and also riskier regarding commercialisation, since it is uncertain if the activities will have an economic impact in the future (Fleming 2001; Strumsky and Lobo 2015). However, if the innovation activities can be commercialised, they can lead to a strong competitive advantage (Castaldi et al. 2015).

Scholars have proposed several methodologies to capture radicalness empirically, which have both pros and cons (e.g. Schoenmakers and Duysters 2010; Dahlin and Behrens 2005; Strumsky and Lobo 2015). Most recent studies have focused on patent-based indicators to investigate radical inventions. Patents have become quite popular in this regard since they offer extensive information, including prior patents to which they are referring (citations). Albert et al. (1991) and Trajtenberg (1990) found out that forward citations are a good indicator to measure a patent's impact. For instance, Schoenmakers and Duysters (2010) use forward citations to measure an invention's influence on future technological development. Another common approach is to analyse backward citations. Several scholars argue that radical inventions rather cite patents from technology classes not belonging to the one of the focal patents (Rosenkopf and Nerkar 2001).

Besides information on cited prior artefacts, patents offer different possibilities to study radical innovations. Fleming (2007) uses the technological subclasses to which a patent is assigned in order to observe the emergence of new combinations. Strumsky and Lobo (2015) also identify patents with combinatorial novelty in a similar way. Following these authors, Verhoeven et al. (2016) detect technological novelty based on new combinations of IPC classes. In this study, radical innovations are seen as the output of recombination processes bringing together unconnected knowledge domains (Fleming 2001, 2007; Rizzo et al. 2018). Even though these new combinations do not necessarily cause a paradigm shift, they certainly introduce totally novel component combinations and can therefore be characterized as radical (Verhoeven et al. 2016; Rizzo et al. 2018).

### 2.2 Radical innovations and university-industry collaborations

There is consensus amongst scholars that public research has a positive effect on technological development in general (e.g. Jaffe 1989; Salter and Martin 2001). Exchange and coordination between public and private R&D are an important driver of technological development and the diffusion of new knowledge between collaboration partners and hence drive innovation processes (Metcalfe 1995). The knowledge transfer between academia and industry often requires direct interaction because of the tacit nature of the exchanged knowledge (Rosenberg and Nelson 1994). In order to enhance knowledge transfer between science and the private sector, governments have expanded policy measures to offer incentives for collaboration between the two (Henderson et al. 1998; Mowery et al. 2001; Geuna 2001). Most empirical studies analyse the link between public research facilities and industry based on patent data, in particular via patent citations (Rizzo et al. 2018). However, there is not much research done so far investigating the special role university-industry collaborations play in the emergence of radical innovations. Belderbos et al. (2004) found that collaborations between firms and universities are aimed at more market-oriented or radical innovations than other types of collaborations. Wirsich et al. (2016) recently provided evidence that university-industry linkages have a positive effect on technological newness, which they defined as completely new technologies or the novel combination of already existing technological areas. In our study we apply a similar approach and detect radical innovations by totally new combinations.

As knowledge production comes with certain externalities as e.g. it can be consumed freely by others, there is a reduced incentive to generate it privately, which leads to market failure (Nelson 1959; Arrow 1962). This is especially the case for basic research, which is considered a public good. Hence, policy makers have established public R&D support mechanisms to overcome this market failure (Beck et al.

2016). By doing that, the public sector plays an important role in the emergence of radical innovations (Mazzucato 2015).

Combining knowledge in new ways, leading to radical innovations, can correspond to an explorative, distant search (Arts and Veugelers 2014; March 1991). Since this is rather uncertain and risky, private organizations might refuse to focus on such research activities (Friis et al. 2006). By contrast, universities and public research institutions might provide valuable knowledge in this regard. Universities can add a complementary perspective in the research process and reveal opportunities for novel combinations of knowledge capabilities. In particular, universities may provide a different approach (compared e.g. to other firms) of how to search for new solutions by providing inventors with the underlying theories which may represent "areal maps" of the search ground (Fleming and Sorenson 2004). Furthermore, universities might provide high cost equipment such as research laboratories and the skilled personnel to run these facilities (Baba et al. 2009; Higgins et al. 2011), which could be important for radical innovation processes, as for those experimentation in unexplored domains might be required (Ahuja and Lampert 2001). Hence, firms could profit from such facilities and the know-how to run them without having to invest in this themselves. In summary, university-industry collaborations facilitate the access to firm-/university-external knowledge and complementary resources and enhances the knowledge diffusion through collaboration. Hence, combining basic research conducted in universities and applied private research efforts can foster the emergence of technological novelty by revealing novel combinations through multiple, complementary perspectives (Wirsich et al. 2016), thus leading to our first hypothesis:

**H1** The greater the number of university-industry collaborations a firm has, the higher the probability for the emergence of radical innovations.

Another factor influencing the exchange of knowledge and hence the radicalness of innovations is the cognitive distance between collaboration partners. A high cognitive distance stands for novelty and hence a higher chance for new combinations of knowledge, while a mutual understanding might be hindered by the occurring knowledge gap. In the opposite case of cognitively close partners, the overlapping knowledge bases can achieve an efficient communication, however with a reduced chance for new combinations (Nooteboom 2000; Broekel and Boschma 2012; Boschma and Frenken 2010). As Nooteboom (2000) and Boschma and Frenken (2010) argue, an optimal cognitive distance has to be found, which can still be bridged with a certain degree of absorptive capacity and can hence lead to the generation of new ideas (Cohen and Levinthal 1990). With regard to the creation of radical innovations, knowledge bases should differ strongly to offer the possibility of new combinations (Fleming 2001; Nerkar 2003). Hence, the second hypothesis is as follows:

**H2** The greater the number of cognitively distant university-industry linkages a firm has, the higher the probability to generate radical innovations.

Geographic distance also plays a significant role in how universities affect the innovative capacity of firms and regions. University spillovers can affect new firm location (Audretsch et al. 2005). Additionally, Audretsch et al. (2012) demonstrated that having a research-intensive university in a region tends to influence innovative firm behaviour. Moreover, geographic proximity is an important factor in university-industry collaborations (Drejer and Østergaard 2017). While much of the literature on geographical distance and universities focuses on innovation and entrepreneurship, it does not address universities' role in producing radical innovations. Hereby, knowledge is combined in ways that were never the case before (Fleming 2001; Nerkar 2003; Weitzman 1998).

In this regard, several scholars have found that knowledge from outside an innovator's region might be a potential source for radically new ideas (Miguelez and Moreno 2018) and have argued that external knowledge can solve situations of regional lock-in (Boschma 2005). Formal collaborations are a possible way to access this knowledge (Singh 2008; Singh and Fleming 2010). Phene et al. (2006) proposed that external knowledge is a key factor to increase the likelihood of the creation of radical innovations. However, the specific role of geographically distant universities in the emergence of new knowledge combinations has not been explored before. In this regard, we propose that collaborating with a geographically distant university, meaning one with potentially new perspectives and routines (even if from a similar technological field) from that of the partner firm, is important for radical innovations. Consequently, our third hypothesis is that:

**H3** The greater the number of geographically distant university-industry linkages a firm has, the higher the probability that the firm will generate radical innovations.

## 3 Data and methodology

We employed several databases to construct our dataset. The primary database for firm-specific information is the AMADEUS database provided by Bureau van Djik (BvD). This database contains extensive firm-level data such as year of establishment, the firm's independence and employment. We retrieved patents from the European database PATSTAT. With this patent data we measured the emergence of radical innovations, which we approximate by new combinations of formerly unconnected technology domains (new dyads). Specifically, we identify new dyads by looking at IPC combinations between 2012 and 2014 in Germany. We compared combinations to a dataset that contained all existing IPC classes between 1983 and one year before the focal year. A combination was considered new if it had not existed in Germany in the previous years since 1983. We look at novelty in the German knowledge space since we focus on formal collaborations within the German funding scheme. Patents include highly valuable and detailed information about the inventory process such as the date, applicant and technology (for a discussion on patents as data source see e.g. Cohen et al. 2000 or Griliches 1990). We aggregated the data to the four-digit IPC level, which differentiates between 636 different technology classes[1]. This level offers the best trade-off between a sufficiently large number of patents in the classes and a maximal number of technologies.

[1] Hence, this aggregation level includes 403,860 potential linkages.

To combine both datasets, we matched the corresponding names of the companies listed in the AMADEUS database with the applicants in the patent data. For this we applied the Token algorithm with a log-based weight function. The Token algorithm, belonging to the group of vectoral decomposition algorithms, compares the elements of two text strings by splitting them by their blank spaces (Raffo 2017; Raffo and Lhuillery 2009). The result of this matching procedure are 8404 companies, which are part of the AMADEUS database and had patenting activities during the years 2012 to 2014.

To identify formal relationships in the innovation process, we employed data about subsidized R&D collaborations from the German subsidy catalogue ("Förderkatalog"). The database consisted of more than 160,000 running or completed R&D projects subsidized by six different ministries[2] in the time span between 1960 and 2016 (Roesler and Broekel 2017). This database has been chosen in order to avoid potential biases resulting from the repeated use of patent data. It has already been used to capture cooperative relations in knowledge networks. In comparison with patent data, being also a potential source for the measurement of cooperative relations, the German subsidy catalogue provides information at an earlier stage and therefore fits the purpose of this study better (Broekel 2015; Broekel and Graf 2012). Additionally, the data from the German subsidy catalogue is better applicable for the purpose of this study, as universities and research institutes are underrepresented in the patent data. Contrary, the data from the German subsidy catalogue includes private actors as well as research institutes (ibid; Ter Wal and Boschma 2009). To identify the corresponding universities and research institutes within the German subsidy catalogue, we make use of the German research directory ("Research Explorer"). This database contains information on over 25,000 university and non-university research institutes in Germany (Research Explorer 2018). In light of the existing time lag between patent data and received subsidies, the unweighted number of firm linkages to universities, research institutes and other companies was calculated based on all corresponding co-funded R&D projects between 2007 and 2009 (Fornahl et al. 2011).

The determined firm linkages were additionally used to calculate the cognitive distance between the organizations. In a first step, the technological information of the organizations was reorganized using the classification developed by Schmoch (2008) (35 technological fields). Consequently, we constructed a vector for every firm consisting of all the technological fields appearing on field patents in the years 2010–2014. If two firms were listed as collaboration partners, their technological similarity was calculated based on their technological vectors, using the cosine index,

[2] More specifically, these ministries are the Federal Ministry of Education and Research (BMBF), Federal Ministry for Economic Affairs (BMWi), Federal Ministry for Environment, Nature Conservation and Nuclear Safety (BMU), Federal Ministry of Transport, Building and Urban Development (BMVBS), the Federal Ministry of Food, Agriculture (BMEL) and Consumer Protection.

generating one value for each collaboration. Following Ejermo (2003), the cosine index is defined as follows:

$$r_{ij} = \frac{\sum_{k=1}^{n} w_{ik} \ \ w_{jk}}{\sqrt{\sum_{k=1}^{n} w_{ik}^2 \sum_{k=1}^{n} w_{jk}^2}}$$

with $n$ representing the number of technologies and $i, j, k$ being the indicators of the technologies that are considered. The index can take a value between zero and one, where one signifies perfect similarity. For the analysis, a threshold of 20% was calculated, defining the upper 20% of the data (accordingly the relatedness value was 0.605 and higher) as cognitively close and the rest as distant. Then we counted for each company the number of collaborations to cognitively distant collaboration partners, accounting for each type (other companies, research institutes, universities). As robustness checks we tested different thresholds (10 and 30%). However, the direction of the coefficients remained stable.

The last main independent variable of interest is the geographic distance. The basis for the corresponding calculation were again the firm linkages from the subsidy catalogue. To control for potential headquarter effects, the exact location of the executing organizations, in contrast to the recipient organizations, is employed here. The Administrative District Directory ("Gemeindeverzeichnis") from the German Federal Statistics Office provided the longitudes and latitudes of all administrative communities ("Gemeindeebene") in Germany. By using them, we could calculate the most direct geographic path between all actors of all corresponding co-funded R&D projects.[3] To define near and distant relations we used the second quantile of all ranges of all relationships as a threshold, which corresponded to 60 km. This is in a range that can be reached within 45–60 min, which is the definition used by Kosfeld and Werner (2012) to define 141 labour market regions in Germany.[4] We think, that a link between partners within a labour market region can be seen as geographically close. As a robustness check, we also tested different thresholds, corresponding to different quantiles. However, the corresponding results for the first (10 km) and third (110 km) quantile remained stable.

We must elaborate on how we operationalized our two proximity variables, cognitive and geographic distance, in our models. The quantiles were utilized in order to define the number of relationships up to a defined threshold. More specifically, the cognitive distance variable in our model represents the number of universities, research institutes or firms with which a firm has a formal collaboration, that are either near (under the threshold) or far (above the threshold). The same can be said for geographic distance. For example, our geographic distance variable demonstrates the number of formal collaborations with either universities, research institutions, or firms that are within a radius of 60 km or farther than 60 km from the firm of interest. This understanding of our operationalization is necessary for properly interpreting our results in the next section.

[3] Thereby we employed the R package "geosphere".

[4] The social security statute book also refers to this definition when talking about commuter structures.

To control for firm-specific variables, we included the average number of employees from 2008 to 2014. Moreover, based on the independence indicator offered by BvD, we created an independence dummy, which indicates that no shareholder owns more than 25% percent of the corresponding company (AMADEUS). On the regional level, we also controlled for the regional knowledge base, measured by the number of patenting companies in each administrative community (retrieved from PATSTAT), as well as by the number of research institutes (community level) based on data from Research Explorer (Research Explorer 2018). Additionally, we also controlled for possible industry-specific effects. Employing data from the German Federal Statistics Office, we therefore created a dummy variable that controls for research-intensive industries, which might tend to increase the likelihood of the emergence of radical innovations. Last, we calculated the pace of technology evolution between 2011 and 2013 by dividing the average technological improvement (measured with the number of patents in one specific industry) by the size of the corresponding industry. This indicator is used as a proxy for the specific stage of the industry life cycle, as it can be assumed that radical innovations are occurring particularly in emerging industries (Klepper 1997; Menzel and Fornahl 2009).

Since we make use of co-funded R&D projects as our relation-specific variable of interest, our database may suffer from a selection bias (Czarnitzki and Lopes-Bento 2010). In order to avoid such a bias, we reduce our former sample to only those companies that executed patent activities in the years 2012–2014 and at the same time received R&D funding (including single as well as co-funding).[5] Thus, the final sample of our unique database compromises 583 companies.

## 4 Empirical results and discussion

As indicated in Table 1 our unique sample includes firms of different size classes.[6] The size of firms is thereby relatively equally distributed. 169 firms are small enterprises, another 193 are medium sized enterprises and 221 are large firms. However, regarding the creation of radical innovations, the distribution becomes rather unequal. Only a tenth of the considered firms also create radical innovations (61 in total).[7] In this group of radical innovating companies, we can observe that large companies represent the vast majority (73.77%). Medium sized companies created 19.67% of radical innovations, while only 6.56% of all radical innovations between 2012 and 2014 came from small companies.

Furthermore, we also calculated the number of radical innovations per organization based on patent data. If the patent was filed by more than one organization, we assigned the patent partially to all partners. We used this indicator to analyse the

[5] As a further sensitivity analysis, we also reduced our sample to those organizations that executed patent activities in the years 2012–2014 and at the same time received only R&D co-funding. The corresponding results remain stable and can be provided upon request.

[6] The different firm-size categories are defined according to the European Commission Recommendation of 6 May 2003 (http://ec.europa.eu/growth/smes/business-friendly-environment/sme-definition_de).

[7] For an overview the share of all innovations (not just radical innovations), please see Appendix Fig. 3.

**Table 1** Radical innovations and firm size 2012–2014

| | Firm Size | | | Total |
|---|---|---|---|---|
| Radical innovation dummy | Small | Medium | Large | |
| 0 | 165 (31.61%) | 181 (34.67%) | 176 (33.72%) | 522 (100%) |
| 1 | 4 (6.56%) | 12 (19.67%) | 45 (73.77%) | 61 (100%) |
| *Total* | 169 (28.99%) | 193 (33.10%) | 221 (37.91%) | 583 (100%) |

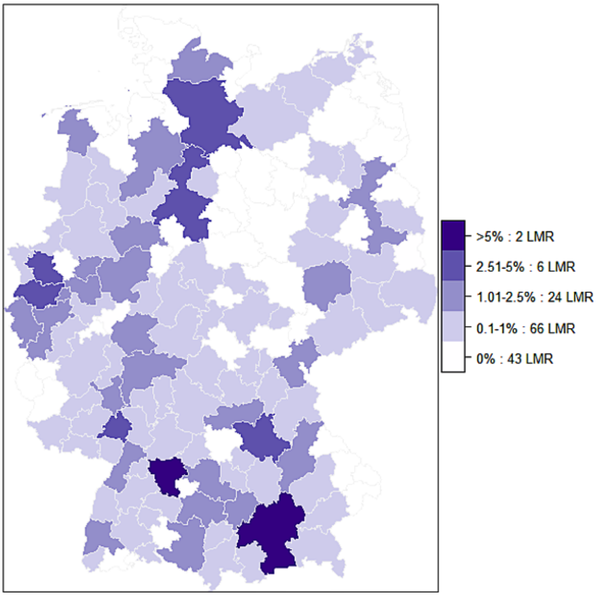


**Fig. 1** Share of radical innovations in German labour market regions (LMR) 2012–2014

geographical distribution of radical innovations between 2012 and 2014 (see Fig. 1). We follow Kosfeld and Werner (2012) to assign the patents to 141 labour market regions based on the firms' addresses (retrieved from AMADEUS). This definition is used in order to minimize the bias of commuter and urban-periphery structures in the results. While the majority of regions (66) at least have a share between 0 and 1%, we cannot observe any radical innovations in nearly one third of all labour market regions (43 of 141). In general, we can see that Southern and Western German regions tend to be stronger in radical innovation processes, whereas most regions without radical innovations belong to Eastern Germany. The regions with the highest share are Stuttgart and Munich, located in Southern Germany, not surprising since both labour market regions are among the economically strongest in the country. Companies such as Bosch, Daimler and Siemens are located here as well as prestigious universities and research institutions such as the Technical University Munich and the Fraunhofer Society, Europe's largest application-oriented research organization. The Western German regions of Essen, Ludwigshafen (South-West) and Dusseldorf are also among the top five regarding the share of radical innovations. The strongest regions in the North include Hamburg and Hannover, while those in the East are Berlin and Leipzig. Hence, we also find evidence for a strong core-periphery gap,

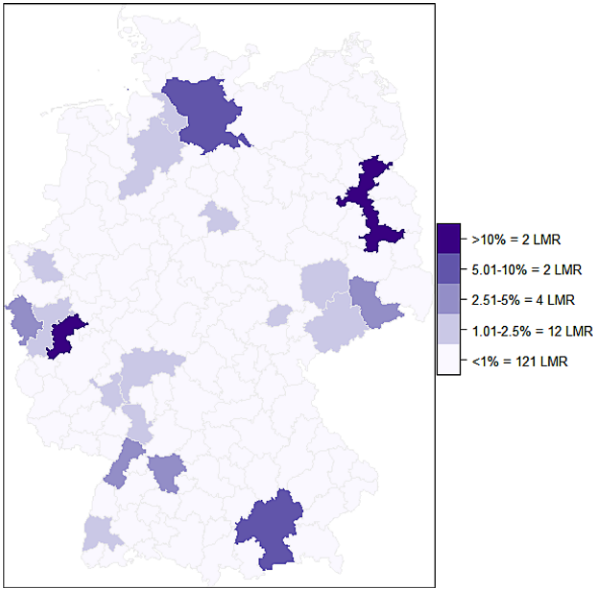


**Fig. 2** Please change to: Share of public funding in German labour market regions (LMR) 2007–2009

since all these regions include a major city. The areas without radical innovations are primarily peripheral regions e.g. in Mecklenburg-Western Pomerania, Saxony and Lower Saxony. Finally, we have to acknowledge that bias would normally be a danger because we assign patents to labour market regions based on the applicants' addresses. As mentioned above, we avoid this problem by utilizing the exact location of the executing organizations from the subsidy data instead of the address of the company headquarters.

Similarly, Fig. 2 shows the geographical distribution of public funding between 2007 and 2009. First, we can observe that funding is more evenly distributed. All regions have received at least a small share of total funding. Thereof, about 85% (121) of the regions have obtained less than 1%. Berlin and Bonn get the highest share of public funding. Munich and Stuttgart, being leaders in radical innovations, are also among the regions with the highest share of public funding. A reason for this could be because actors in these regions are established players capable of relatively high private R&D expenditures (Stifterverband 2016, 2017). The above-mentioned regions Hamburg and Leipzig also receive a significant share of public funding. Equally to Fig. 1 we find evidence that most of the public funding is distributed to core regions rather than to the periphery. In summary, Figs. 1 and 2 offer first hints to the positive correlation between public funding and the emergence of radical innovations. Most regions receiving a significant share of public funding also are responsible for a higher share of radical innovations.[8]

[8] To verify the graphical results, we also did proportion tests, which indicate that the proportion of radical innovations is significantly higher in the group of firms that received funding (single or co-funding). The corresponding results can be provided upon request.

**Table 2** R&D collaborations and radical innovations (Odds ratios, Standard errors are in brackets, Significance level: *$p<0.10$, **$p<0.05$, ***$p<0.01$)

| Radical innovation | Model 1a $n=583$ | Model 1b $n=583$ | Model 1c $n=583$ |
|---|---|---|---|
| **Collaborations with Universities** | 1.079** (0.034) | – | – |
| **Collaborations with Research Institutes** | – | 1.124** (0.054) | – |
| **Collaborations with Companies** | – | – | 1.043** (0.018) |
| **Number of Research Institutes** | 1.013 (0.008) | 1.013 (0.008) | 1.013 (0.008) |
| **Independence dummy** | 0.853 (0.514) | 0.879 (0.528) | 0.875 (0.528) |
| **Regional knowledge base** | 0.996 (0.003) | 0.996 (0.003) | 0.997 (0.003) |
| **Pace of technology evolution** | 1.012 (0.032) | 1.015 (0.033) | 1.015 (0.033) |
| **Research-intensive industry dummy** | 1.516 (0.485) | 1.430 (0.456) | 1.397 (0.447) |
| **Average firm size** | 1.000** (0.000) | 1.000** (0.000) | 1.000** (0.000) |
| *Constant* | *0.075**** | *0.075**** | *0.071**** |
| *Pseudo $R^2$* | *0.0673* | *0.0675* | *0.0684* |

Now, we turn to our regression analysis. In order to test our proposed hypotheses, we apply a logistic regression model. By analyzing the pairwise correlation matrix shown in Appendix Table 5, one can see that the collaboration-specific variables are highly and significantly correlated (between 0.79 and 0.84). In order to avoid this multicollinearity, we analyze the collaboration specific variables separately in three different models. All analyses are performed on the firm level.

In Model 1 (see Table 2) we analyse R&D collaborations between different types of organizations and their influence on the emergence of radical innovations in general. We calculated three different variations, all having very significant results for the main explaining variables. In Model 1a the main independent variable of interest is the number of collaborations with universities which has a positive coefficient and hence increases the likelihood to generate radical innovations. Model 1b tests how collaboration with research institutes influences the likelihood to develop radical innovations. Here the coefficient is as well positive. Finally, Model 1c shows that collaborations with companies increase the probability for the generation of radical innovations as well (positive and very significant coefficient).[9] Our control variables do not have significant results, except for average firm size which has a very significant and positive coefficient in all three models as can be expected. As far as hypothesis H1 is concerned, it can hence be confirmed, that more university-industry

[9] By additionally testing differences in the corresponding means, the presented results can be further strengthened as evidence is found that significant differences between the three independent variables exist. The corresponding results can be provided upon request.

**Table 3** Cognitive distance and radical innovations (Odds ratios, Standard errors are in brackets, Significance level: *$p<0.10$, **$p<0.05$, ***$p<0.01$)

| Radical innovation | Model 2a $n=68$ | Model 2b $n=68$ | Model 2c $n=68$ |
|---|---|---|---|
| **Distant Universities** | 1.515 (0.411) | – | – |
| **Distant Research Institutes** | – | 2.165* (0.986) | – |
| **Distant Companies** | – | – | 1.192 (0.127) |
| **Number of Research Institutes** | 0.989 (0.035) | 0.994 (0.034) | 1.008 (0.041) |
| **Independence dummy** | 1.55e–07 (0.000) | 3.22e–06 (0.000) | 3.63e–07 (0.000) |
| **Regional knowledge base** | 0.974 (0.017) | 0.975 (0.017) | 0.965 (0.024) |
| **Pace of technology evolution** | 1.237 (0.243) | 1.258 (0.263) | 1.219 (0.234) |
| **Research-intensive industry dummy** | 0.498 (0.546) | 0.497 (0.550) | 0.528 (0.573) |
| **Average firm size** | 1.000** (0.000) | 1.000* (0.000) | 1.000** (0.000) |
| *Constant* | *0.344** | *0.320*** | *0.350** |
| *Pseudo* $R^2$ | *0.3034* | *0.3101* | *0.3137* |

collaborations increase the likelihood for the emergence of radical innovations. At the same time, it must be mentioned that collaborations with other companies or research institutes increase the probability for radical innovations as well. Therefore, collaborating in general increases the likelihood for the emergence of radical innovations. As this is the case, it is worth investigating further for the particular role that proximity plays in collaborations.

Beginning with Model 2 (see Table 3) we incorporate the mediating role of proximity by investigating the influence of cognitive distance between collaboration partners on the emergence of new dyads. We calculated again three different versions, including cognitive distance to companies (Model 2c), to research institutes (Model 2b) or to universities (Model 2a) as our main independent variable of interest.[10] Model 2b has a large, positive and significant result, signifying that from a firm's perspective, collaborating with research institutes that are more cognitively distant leads to a large increase in the likelihood to generate radical innovations. At the same time, collaborating with companies or universities that have a different knowledge base has no significant effect on the likelihood to create radical innovations. Therefore, we lack evidence to accept hypothesis H2, as there is no significant effect of collaborating with cognitively distant universities on the likelihood to develop radical innovations.

While there is no evidence for the role of cognitive distance and collaborations between firms and universities, this is not the case for research institutions. They

[10] Cognitively close collaborations are not illustrated because they perfectly predict failure.

**Table 4** Geographical distance and radical innovations (Odds ratios, Standard errors are in brackets, Significance level: *$p<0.10$, **$p<0.05$, ***$p<0.01$)

| Radical innovation | Model 3a $n=583$ | Model 3b $n=583$ | Model 3c $n=583$ | Model 3d $n=583$ | Model 3e $n=583$ | Model 3f $n=583$ |
|---|---|---|---|---|---|---|
| **Distant Universities** | 1.020** (0.009) | – | – | – | – | – |
| **Nearby Universities** | – | 1.037 (0.073) | – | – | – | – |
| **Distant Research Institutes** | – | – | 1.055** (0.024) | – | – | – |
| **Nearby Research Institutes** | – | – | – | 1.083* (0.049) | – | – |
| **Distant Companies** | – | – | – | – | 1.033** (0.015) | – |
| **Nearby Companies** | – | – | – | – | – | 1.038** (0.018) |
| **Number of Research Institutes** | 1.012 (0.008) | 1.010 (0.008) | 1.012 (0.008) | 1.012 (0.008) | 1.013 (0.008) | 1.013 (0.008) |
| **Independ. dummy** | 0.909 (0.540) | 0.866 (0.516) | 0.934 (0.555) | 0.882 (0.523) | 0.909 (0.544) | 0.899 (0.533) |
| **Regional knowledge base** | 0.996 (0.003) | 0.997 (0.003) | 0.996 (0.003) | 0.996 (0.003) | 0.997 (0.003) | 0.996 (0.003) |
| **Pace of technology. Evolution** | 1.010 (0.032) | 1.010 (0.032) | 1.012 (0.032) | 1.010 (0.032) | 1.012 (0.033) | 1.010 (0.033) |
| **Research-intensive industry dummy** | 1.551 (0.500) | 1.466 (0.467) | 1.547 (0.498) | 1.513 (0.484) | 1.566 (0.506) | 1.539 (0.494) |
| **Average firm size** | 1.000*** (0.000) | 1.000*** (0.000) | 1.000*** (0.000) | 1.000*** (0.000) | 1.000** (0.000) | 1.000*** (0.000) |
| *Constant* | *0.079**** | *0.084**** | *0.076**** | *0.082**** | *0.069**** | *0.079**** |
| *Pseudo $R^2$* | *0.0645* | *0.0553* | *0.0669* | *0.0613* | *0.0792* | *0.0683* |

appear to play a very important role in creating radical innovations when firms collaborate with more cognitively distant research institutions. One reason for this could be that research institutions' expertise are located closer to the development and commercialization phase of the innovation process than the basic research that occurs at universities. For radical innovations, it appears this could be a deciding factor. Another factor could also be the nature of our data. Our sample in this model is comparatively small ($n=68$). The reason for this is that it was not possible to calculate a knowledge profile for many collaboration partners.

In the third model (see Table 4), we investigate the impact of geographical distance between collaboration partners and employ six different variations. We differentiate between the number of geographically close and distant universities, research institutions, and companies. The estimation results show that collaborations with geographically distant universities (Model 3a), research institutes (Model 3c) or companies (Model 3e) increase the likelihood (very significant results) to produce radical innovations. Collaborations with nearby research institutes (Model 3d) or nearby companies (Model 3f) have significant and positive coefficients as well.

Consequently, we have evidence to support our hypothesis (H3) that collaborations with geographically distant universities increase the likelihood of producing radical innovations. Having a greater number of distant university relationships demonstrates a positive and very significant effect. Interestingly, collaborating with nearby universities is the only statistically insignificant main variable in our models of the series 3 (Model 3b), although it is indeed positive.

It is worth noting that collaborations in general appear to play a vital role in the emergence of radical innovations. But interestingly, when accounting for geographic proximity, the only collaboration form that does not have a statistically significant effect are nearby universities. There could be several reasons for this. It could be that collaborating with a greater number of close universities does not provide the necessary newness of knowledge that radical innovations require. Additionally, perhaps this lack of significance has to do with the nature of our data. It could be that firms tend to collaborate with geographically close universities anyway. As our data considers only subsidized collaborative relationships, it may be that government action has encouraged a greater number of collaborations with distant universities while close collaborations tend to occur on their own without the role of government. Our data would not be able to identify other relationships, e.g. informal ones.

## 5 Concluding remarks and outlook

Although scholars commonly acknowledge that public R&D enhances technological development in general (e.g. Salter and Martin 2001; David et al. 2000; Sorenson and Fleming 2004), the specific role public research plays for radical innovations has been scarcely examined. In particular the effect of collaborations between academia and industry remain rather unclear.

As radical innovations are an important factor in creating competitive advantage, the present paper makes an attempt to shed light on the role of university-industry collaborations on the emergence of radical innovations. As has been argued, universities may possess valuable knowledge yet lack the resources to commercialize it, while firms face the opposite situation (Fleming and Sorenson 2004). Hence, university-industry collaboration might be the perfect way to combine their strengths (Wirsich et al. 2016). A special focus has been laid on the influence of cognitive and geographic distance of the collaborating parties. The former is decisive for successful knowledge exchange, while the latter is vital as the proximity of new knowledge in the region in which the firm is located drives the radical innovation processes.

This paper argues that radical innovations benefit from university-industry collaborations. Also, we form the hypothesis that especially collaborations with geographically or cognitively distant universities are important for firms in producing radical innovations. To test the hypotheses, we use patent data from the European database PATSTAT to proxy for radical innovations. In particular, new combinations of technology classes presented on patent documents are used to build an indicator for the (radical) introduction of novelty. Furthermore, we use data from the German subsidy catalogue to build our key independent variables.

Our descriptive results show that indeed radical innovations are a rare event and their distribution is rather unequal. Only a tenth of the analyzed firms create radical innovations. These firms are mostly large firms and are not evenly distributed geographically. The regression analysis, based on German patenting firms between 2012 and 2014, shows that in general more university-industry collaborations rise the probability for the emergence of radical innovations; however, this is not significantly more than collaborations with research institutes or other firms. Moreover, although the effect is positive, we cannot find a statistically significant effect from collaborating with cognitively distant universities for the increase of the likelihood to develop radical innovations. However, we find evidence that a greater number of collaborations with geographically distant universities enhances the probability to generate radical innovations. This could be due to the fact that it is easier for collaborative partners from industry and academia to overcome geographic distance than cognitive distance. Although the exchange of tacit knowledge gets more difficult with increasing distance (Boschma 2005), this finding is somewhat plausible since it can be easier to cross-fertilize ideas that are cognitively related over longer distances than to assimilate ideas stemming from completely different knowledge bases even though the partner might be in the vicinity. Considering the tacit dimension of knowledge, it is important that the actors have the absorptive capacity to assimilate the new knowledge (Cohen and Levinthal, 1990), which requires certain cognitive proximity to be able to absorb it (Nooteboom 2000). Hence, cognitive proximity makes it easier for the partners to communicate (Boschma 2005), also over longer distances. For instance, Miguelez and Moreno (2018) find that region-external knowledge supports technological breakthroughs if the knowledge is related to the focal knowledge base. Rallet and Torre (1999) also found evidence that tacit knowledge can be transferred over larger distances through other forms of proximity. Moreover, Ponds et al. (2010) showed that collaborative research networks in science-based industries are less reliant on geographical proximity. Furthermore, this effect could be becoming stronger through the diffusion of ICT technologies, which can facilitate interaction between geographically distant partners (Bathelt and Turi 2011; Cairncross 2001). At the same time the different spatial setting might offer as well different perspective on the same problems and hence lead to new ways in solving them.

Our findings have relevant policy implications. In Germany, the results can be of particular interest since the government is planning an agency to support radical innovations (BMBF 2018). Policy makers should continue to support collaborative R&D in general and university-industry collaborations in particular. Furthermore, they could require that policy measures dictate that collaborations include a variety of players (both industrial and scientific) and comprise partners from geographically distant locations, as collaborations with nearby institutions might take place even without funding. This would not only support efforts to come up with radical innovations but also prevent situations of lock-in (Boschma 2005). Such terms could also complement policy measures from the Europe 2020 Growth strategy.

Furthermore, our findings have practical ramifications for managers. In line with previous research (Wirsich et al. 2016), we show that it is fruitful for firms to engage in collaborations with scientific partners in order to gain access to new knowledge pieces which can be transformed into radical innovations. Additionally, we find first evidence indicating that collaboration with geographically distant universities has a very significant impact on the likelihood to develop innovations close to the technological frontier, hence managers should engage in these collaborations. Moreover, cognitively distant partners from research institutes might lead sooner to radical outputs than partners from cognitively distant universities (the latter ones being too far away from the commercialization phase of the innovation), making research institutes in this context more attractive partners.

Finally, our study does not come without limitations. First, we proxy radical innovations based on new combinations of IPC classes presented on patent documents. On the one hand, future studies could use other measures for radical innovations (e.g. highly cited patents) in order to pay attention to the diffusion of a patent. On the other hand, it could be worthwhile to use other data (e.g. products) to analyze radical innovations. Moreover, patents do not necessarily bring commercial success. Thus, future research could investigate the role of university-industry collaborations on performance indicators of firms.

Furthermore, some of our models may lack statistical significance because of the nature of our data set. For example, we were unable to calculate the knowledge profile for many organizations. Therefore, we could only calculate the cognitive distance for a limited number of collaborations. Perhaps cognitive distance would have had a more statistically significant effect on the probability of the emergence of radical innovations when a larger sample size would have been possible.

In addition, the present study does not account for the quality of universities. Intuitively, it could make a difference whether a scientific partner is at the forefront in the research field of interest or not. A university's number of scientific publications could serve as a proxy for this. Furthermore, it could be worthwhile to extend a broader sample of collaborations and consider more years, thereby generating more observations, in order to further validate our results. Also, geographic distance should be regressed in one model to check whether geographic proximity can overcome high cognitive distance and vice versa. This was not possible in our models because of high correlation. Finally, if it could be useful to operationalize geographic and cognitive proximity in a way that an interaction term could be built in order to observe the interplay of both proximity measures in regard of the emergence of radical innovations.

# Appendix

**Table 5** Pairwise correlation matrix and descriptive statistics (own illustration)

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Mean | Std. Dev |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. No. collaboration with companies | 1.0000 | – | – | – | – | – | – | – | – | 3.885 | 7.778 |
| 2. Number of research institutes | –0.0851* | 1.0000 | – | – | – | – | – | – | – | 9.458 | 19.264 |
| 3. Independence dummy | 0.1335* | 0.0464 | 1.0000 | – | – | – | – | – | – | 0.070 | 0.256 |
| 4. Regional knowledge base | –0.0481 | 0.3668* | 0.0192 | 1.0000 | – | – | – | – | – | 41.180 | 73.954 |
| 5. Pace of technology evolution | –0.0245 | –0.1198* | –0.0319 | –0.0533 | 1.0000 | – | – | – | – | 2.031 | 4.419 |
| 6. Research-intensive industry dummy | 0.0522 | –0.1318* | –0.0532 | –0.0865* | 0.4957* | 1.0000 | – | – | – | 0.437 | 0.496 |
| 7. Average firm size | 0.3375* | 0.1014* | 0.2802* | 0.0247 | –0.0133 | 0.0351 | 1.0000 | – | – | 2076.036 | 13519.14 |
| 8. No. collaboration with research institutes | 0.8411* | –0.0740 | 0.0898* | 0.0167 | –0.0432 | 0.0283 | 0.2443* | 1.0000 | – | 0.973 | 2.327 |
| 9. No. collaboration with universities | 0.7943* | –0.0618 | 0.1023* | 0.0488 | –0.0442 | –0.0310 | 0.2441* | 0.8442* | 1.0000 | 1.269 | 3.541 |

The correlation for the number of collaborations with cognitive distant partners and with geographical distant partners will be provided by request. Due to the similarity of these variables with the actual number of collaborations, it is argued that the shown pairwise correlation matrix gives an adequate impression

Significance level: $*p < 0.05$

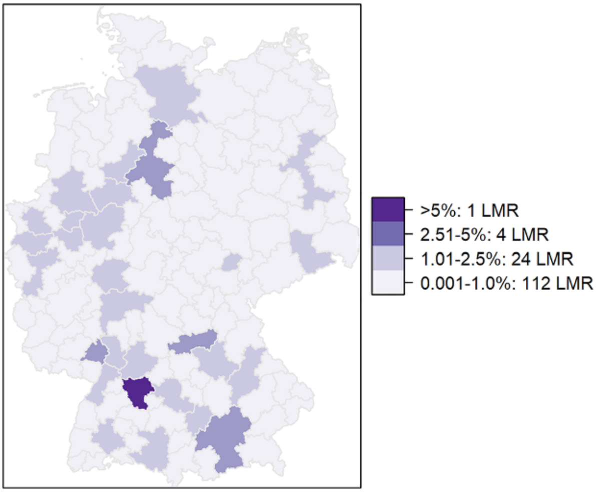


**Fig. 3** Share of innovations in German labour market regions 2012–2014

## References

Ahuja G, Lampert C (2001) Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. Strateg Manage J 22(6–7):521–543. https://doi.org/10.1002/smj.176

Albert MB, Avery D, Narin F, McAllister P (1991) Direct validation of citation counts as indicators of industrially important patents. Res Policy 20(3):251–259. https://doi.org/10.1016/0048-7333(91)90055-U

Arrow KJ (1962) Economic welfare and the allocation of resources for invention. In: Nelson R (ed) The rate and direction of inventive activity. Princeton University Press, Princeton, pp 609–626

Arthur WB (2007) The structure of invention. Res Policy 36(2):274–287. https://doi.org/10.1016/j.respol.2006.11.005

Arts S, Veugelers R (2014) Technology familiarity, recombinant novelty, and breakthrough invention. Ind Corp Change 24(6):1215–1246. https://doi.org/10.1093/icc/dtu029

Audretsch D, Lehmann E, Warning S (2005) University spillovers and new firm location. Res Policy 34:1113–1122. https://doi.org/10.1016/j.respol.2005.05.009

Audretsch D, Hülsbeck M, Lehmann EE (2012) Regional competitiveness, university spillovers and entrepreneurial activity. Small Bus Econ 39(3):587–601. https://doi.org/10.1007/s11187-011-9332-9

Baba Y, Shichijo N, Sedita SR (2009) How do collaborations with universities affect firms' innovative performance? The role of "Pasteur scientists" in the advanced materials field. Res Policy 38(5):756–764. https://doi.org/10.1016/j.respol.2009.01.006

Basalla G (1988) The evolution of technology. Cambridge University Press, Cambridge

Bathelt H, Turi P (2011) Local, global and virtual buzz: The importance of face-to-face contact in economic interaction and possibilities to go beyond. Geoforum 42(5):520–529. https://doi.org/10.1016/j.geoforum.2011.04.007

Beck M, Lopes-Bento C, Schenker-Wicki A (2016) Radical or incremental: Where does R&D policy hit? Res Policy 45(4):869–883. https://doi.org/10.1016/j.respol.2016.01.010

Belderbos R, Carree M, Lokshin B (2004) Cooperative R&D and firm performance. Res Policy 33(10):1477–1492. https://doi.org/10.1016/j.respol.2004.07.003

Bundesministerium für Bildung und Forschung (2018) Startschuss für Agentur zur Förderung von Sprunginnovationen. Pressemitteilung: 075/2018

Boschma R (2005) Proximity and innovation: A critical assessment. Reg Stud 39(1):61–74. https://doi.org/10.1080/0034340052000320887

Boschma R (2017) Relatedness as driver of regional diversification: A research agenda. Reg Stud 51(3):351–364. https://doi.org/10.1080/00343404.2016.1254767

Boschma R, Frenken K (2010) The spatial evolution of innovation networks: A proximity perspective. In: Boschma R, Martin R (eds) The handbook of evolutionary economic geography. Edward Elgar, Cheltenham, pp 120–135

Broekel T (2015) The co-evolution of proximities—A network level study. Reg Stud 49(6):921–935. https://doi.org/10.1080/00343404.2014.1001732

Broekel T, Boschma R (2012) Knowledge networks in the Dutch aviation industry: The proximity paradox. J Econ Geogr 12:409–433. https://doi.org/10.1093/jeg/lbr010

Broekel T, Graf H (2012) Public research intensity and the structure of German R&D networks: A comparison of 10 technologies. Econ Innovat New Technol 21(4):345–372. https://doi.org/10.1080/10438599.2011.582704

Cairncross FC (2001) The death of distance: How the communications revolution is changing our lives. Harvard Business School Press, Boston

Castaldi C, Frenken K, Los B (2015) Related variety, unrelated variety and technological breakthroughs: An analysis of US state-level patenting. Reg Stud 49(5):767–781. https://doi.org/10.1080/00343404.2014.940305

Cohen W, Levinthal D (1990) Absorptive capacity: A new perspective on learning and innovation. Adm Sci Q 35:128–152. https://doi.org/10.2307/2393553

Cohen WM, Nelson RR, Walsh JP (2000) Protecting their intellectual assets: Appropriability conditions and why US manufacturing firms patent (or not). NBER working paper no. 7552. https://doi.org/10.3386/w7552

Czarnitzki D, Lopes-Bento C (2010) Evaluation of public R&D policies: A cross-country comparison. ZEW discussion paper no. 10-073. ZEW, Mannheim

Dahlin KB, Behrens DM (2005) When is an invention really radical? Defining and measuring technological radicalness. Res Policy 34(5):717–737. https://doi.org/10.1016/j.respol.2005.03.009

David PA, Hall BH, Toole A (2000) Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. Res Policy 29(4–5):497–529. https://doi.org/10.1016/S0048-7333(99)00087-6

Dosi G (1982) Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change. Res Policy 11(3):147–162. https://doi.org/10.1016/0048-7333(82)90016-6

Drejer I, Østergaard CR (2017) Exploring determinants of firms' collaboration with specific universities: Employee-driven relations and geographical proximity. Reg Stud 51(8):1192–1205. https://doi.org/10.1080/00343404.2017.1281389

Ejermo O (2003) Patent diversity as a predictor of regional innovativeness in Sweden. CESPRI working paper 140

Fleming L (2001) Recombinant uncertainty in technological search. Manage Sci 47(1):117–132. https://doi.org/10.1287/mnsc.47.1.117.10671

Fleming L (2007) Breakthroughs and the "long tail" of innovation. MIT Sloan Manage Rev 49(1):69–74 (+93)

Fleming L, Sorenson O (2004) Science as a map in technological search. Strateg Manage J 25(8–9):909–928. https://doi.org/10.1002/smj.384

Fornahl D, Broekel T, Boschma R (2011) What drives patent performance of German biotech firms? The impact of R&D subsidies, knowledge networks and their location. Pap Reg Sci 90(2):395–418. https://doi.org/10.1111/j.1435-5957.2011.00361.x

Friis C, Karlsson C, Paulsson T (2006) Relating entrepreneurship to economic growth. In: Johansson B, Karlsson C, Stough R (eds) The emerging digital economy. Advances in spatial science. Springer, Berlin, Heidelberg

Fritsch M, Schwirten C (2006) Enterprise-University Co-operation and the Role of Public Research Institutions in Regional Innovation Systems. Ind Innov 6(1):69–83. https://doi.org/10.1080/13662719900000005

Geuna A (2001) The changing rationale for European university research funding: Are there negative unintended consequences? J Econ Issues 35(3):607–632. https://doi.org/10.1080/00213624.2001.11506393

Griliches Z (1990) Patent statistics as economic indicators: A survey. J Econ Lit 28(4):1661–1707. https://doi.org/10.3386/w3301

Henderson RM, Clark KB (1990) Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. Adm Sci Q 35(1):9–30. https://doi.org/10.2307/2393549

Henderson R, Jaffe AB, Trajtenberg M (1998) Universities as a source of commercial technology: A detailed analysis of university patenting, 1965–1988. Rev Econ Stat 80(1):119–127. https://doi.org/10.1162/003465398557221

Higgins MJ, Stephan PE, Thursby JG (2011) Conveying quality and value in emerging industries: Star scientists and the role of signals in biotechnology. Res Policy 40(4):605–617. https://doi.org/10.1016/j.respol.2011.01.006

Jaffe AB (1989) Real effects of academic research. Am Econ Rev 79(5):957–970

Klepper S (1997) Industry life cycles. Ind Corp Change 6(1):145–182. https://doi.org/10.1093/icc/6.1.145

Koalitionsvertrag (2018) Koalitionsvertrag zwischen CDU, CSU und SPD. Ein neuer Aufbruch für Europa Eine neue Dynamik für Deutschland Ein neuer Zusammenhalt für unser Land, 12.03., Berlin

Kosfeld R, Werner A (2012) Deutsche Arbeitsmarktregionen – Neuabgrenzung nach den Kreisgebietsreformen 2007–2011. Raumforsch Raumordn 70(1):49–64. https://doi.org/10.1007/s13147-011-0137-8

March JG (1991) Exploration and exploitation in organizational learning. Organ Sci 2(1):71–87. https://doi.org/10.1287/orsc.2.1.71

Mazzucato M (2015) The entrepreneurial state: Debunking public vs. private sector myths (Vol. 1)

Menzel M-P, Fornahl D (2009) Cluster life cycles—Dimensions and rationales of cluster evolution. Ind Corp Change 19(1):205–238. https://doi.org/10.1093/icc/dtp036

Metcalfe JS (1995) Technology systems and technology policy in an evolutionary framework. Cambridge J Econ 19(1):25–46. https://doi.org/10.1093/oxfordjournals.cje.a035307

Miguelez E, Moreno R (2018) Relatedness, external linkages and regional innovation in Europe. Reg Stud 52(5):688–701. https://doi.org/10.1080/00343404.2017.1360478

Mowery DC, Nelson RR, Sampat BN, Ziedonis AA (2001) The growth of patenting and licensing by US universities: An assessment of the effects of the Bayh–Dole act of 1980. Res Policy 30(1):99–119. https://doi.org/10.1016/S0048-7333(99)00100-6

Nelson RR (1959) The simple economics of basic scientific-research. J Polit Econ 67(3):297–306

Nerkar A (2003) Old is gold? The value of temporal exploration in the creation of new knowledge. Manage Sci 49(2):211–229. https://doi.org/10.1287/mnsc.49.2.211.12747

Nooteboom B (2000) Learning by interaction: Absorptive capacity, cognitive distance and governance. J Manag Gov 4:69–92. https://doi.org/10.1023/A:1009941416749

Phene A, Fladmoe-Lindquist K, Marsh L (2006) Breakthrough innovations in the U.S. biotechnology industry: The effects of technological space & geographic origin. Strateg Manage J 27:369–388. https://doi.org/10.1002/smj.522

Ponds R, van Oort F, Frenken K (2010) Innovation, spillovers and university—Industry collaboration: An extended knowledge production function approach. J Econ Geogr 10(2):231–255. https://doi.org/10.1093/jeg/lbp036

Raffo J (2017) MATCHIT: Stata module to match two datasets based on similar text patterns

Raffo J, Lhuillery S (2009) How to play the "names game": Patent retrieval comparing different heuristics. Res Policy 38(10):1617–1627. https://doi.org/10.1016/j.respol.2009.08.001

Rallet A, Torre A (1999) Is geographical proximity necessary in the innovation networks in the era of global economy? GeoJournal 49(4):373–380. https://doi.org/10.1023/A:1007140329027

Research Explorer (2018) Research explorer—The German research directory. http://www.research-explorer.de/research_explorer.en.html. Accessed 10 Mar 2018

Rizzo U, Barbieri N, Ramaciotti L, Iannantuono D (2018) The division of labour between academia and industry for the generation of radical inventions. J Technol Transf. https://doi.org/10.1007/s10961-018-9688-y

Roesler C, Broekel T (2017) The role of universities in a network of subsidized R&D collaboration: The case of the biotechnology-industry in Germany. Rev Reg Res 37(2):135–160. https://doi.org/10.1007/s10037-017-0118-7

Rosenberg N, Nelson RR (1994) American universities and technical advance in industry. Res Policy 23(3):323–348. https://doi.org/10.1016/0048-7333(94)90042-6

Rosenkopf L, Nerkar A (2001) Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. Strateg Manage J 22(4):287–306. https://doi.org/10.1002/smj.160

RWTH Aachen (2018) DHL Paketkopter 3.0. http://www.fsd.rwth-aachen.de/cms/fsd/Forschung/Projekte/~pcul/DHL-Paketkopter-3/. Accessed 7 Dec 2018

Salter AJ, Martin BR (2001) The economic benefits of publicly funded basic research: A critical review. Res Policy 30(3):509–532. https://doi.org/10.1016/S0048-7333(00)00091-3

Schmoch U (2008) Concept of a technology classification for country comparisons. Final report to the world intellectual property organization (WIPO). http://www.wipo.int/export/sites/www/ipstats/en/statistics/patents/pdf/wipo_ipc_technology.pdf. Accessed 30 Aug 2018
Schoenmakers W, Duysters G (2010) The technological origins of radical inventions. Res Policy 39(8):1051–1059. https://doi.org/10.1016/j.respol.2010.05.013
Schumpeter JA (1939) Business cycles. McGraw-Hill, New York
Singh J, Fleming L (2010) Lone inventors as sources of breakthroughs: Myth or reality? Manage Sci 56(1):41–56. https://doi.org/10.1287/mnsc.1090.1072
Singh J (2008) Distributed R&D, cross-regional knowledge integration and quality of innovative output. Res Policy 37(1):77–96. https://doi.org/10.1016/j.respol.2007.09.004
Sorenson O, Fleming L (2004) Science and the diffusion of knowledge. Res Policy 33(10):1615–1634. https://doi.org/10.1016/j.respol.2004.09.008
Stifterverband (2016) Wo Unternehmen forschen – Verteilung und Veränderung
Stifterverband (2017) ˌɑːr ən ˈdiː: Zahlenwerk 2017
Strumsky D, Lobo J (2015) Identifying the sources of technological novelty in the process of invention. Res Policy 44(8):1445–1461. https://doi.org/10.1016/j.respol.2015.05.008
Ter Wal ALJ, Boschma R (2009) Applying social network analysis in economic geography: Framing some key analytic issues. Ann Reg Sci 43(3):739–756. https://doi.org/10.1007/s00168-008-0258-3
Trajtenberg M (1990) A penny for your quotes: Patent citations and the value of innovations. Rand J Econ 21(1):172–187. https://doi.org/10.2307/2555502
Tushman ML, Anderson P (1986) Technological discontinuities and organizational environments. Adm Sci Q 31(3):439–465. https://doi.org/10.2307/2392832
Verhoeven D, Bakker J, Veugelers R (2016) Measuring technological novelty with patent-based indicators. Res Policy 45(3):707–723. https://doi.org/10.1016/j.respol.2015.11.010
Weitzman ML (1998) Recombinant growth. Q J Econ 113(2):331–360
Wirsich A, Kock A, Strumann C, Schultz C (2016) Effects of university—industry collaboration on technological newness of firms. J Prod Innov Manage 33(6):708–725. https://doi.org/10.1111/jpim.12342

## B. Author biography

Nils Grashof has been a research associate at the Centre for Regional and Innovation Economics (CRIE) at the University of Bremen since March 2016. In 2015 he successfully completed his Master´s degree in International Management Studies – Spanish at the European University of Flensburg. Previously, he completed his Bachelor´s degree in International Management – Spanish at the European University of Flensburg and spent a semester abroad at the Universidad Técnica Federico Santa María in Chile. At the CRIE he has worked on various projects dealing with the internationalisation of clusters/networks (InterSpiN and InterSpiN+), the transformation-oriented innovation policy in the bioeconomy (BioTOP) and with the evaluation of the funding initiative "Zwanzig20 – Partnerschaft für Innovation". Furthermore, he has been the manager of the Bremen Research & Policy Lab (BreLAB) at the University of Bremen since 2019. The thematic and application-oriented focus of Nils Grashof lies in the areas of regional innovation systems, innovation policy, effects of clusters and value-adding networks. His methodological competencies are in the field of qualitative (e.g. expert interviews) as well as quantitative (e.g. network analysis) research.

## C. Statutory declaration

**Erklärung**

Hiermit erkläre ich, dass ich die vorliegende Arbeit ohne unerlaubte Hilfe angefertigt habe und dass keine anderen als die angegebenen Quellen und Hilfsmittel benutzt wurden. Die den benutzten Werken wörtlich oder inhaltlich entnommenen Stellen habe ich als solche kenntlich gemacht. Ich gestatte hiermit zudem eine Überprüfung der Dissertation mit qualifizierter Software im Rahmen der Untersuchung von Plagiatsvorwürfen.

Bremen, 12.10.2020

Nils Grashof