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Firm-specific cluster effects - A meta-analysis

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Abstract

The tendency of industries to cluster in some areas and possible effects of this regional clustering have fascinated researchers from multiple disciplines alike. Driven by the success of some clusters, as for example Silicon Valley, the concept has also become quite popular among politicians. Despite the already substantial financial support, a positive cluster effect on the success of the corresponding companies has not been consistently asserted yet. In this context, recently it has been accentuated to further examine the role of contextual influences that might explain the ambiguous effect of clusters on firm's success. The aim of this paper is therefore 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. Therefor four different performance variables from four separate publication databases are considered. After the selection and exclusion process, 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 exists 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. For example, it is pointed out that the probability for a positive firm-specific cluster effect is significantly higher in high-tech industries as well as for small and medium-sized companies. Depending on the specific conditions, clusters can therefore be blessing and curse at the same time.

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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 multiple 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 contradictory (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 Tripl (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 Tripl, 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, 2019). 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 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, focussing in particular on potential moderating influences, will therefore be presented.

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 agglomeration 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).¹ 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

¹ 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.

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 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 Viegelaahn, 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).² 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

² For important exceptions, see for example De Groot et al., 2007; Fang, 2015 or Melo et al., 2009.

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 and offers a great transparency as well as reproducibility (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).³

In general, the final dataset for the meta-analysis is based on the procedure presented in detail in Grashof and Fornahl (2019). 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. 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

³ Nevertheless, other performance variables, such as wages, may also be interesting to consider in future meta-analysis.

already shown keyword combinations are therefore additionally used for a search query in the Social Science Research Network (SSRN). 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.⁴ 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 (2019), 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, 2019, p. 4). 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 interdependencies (Grashof and Fornahl, 2019). Consequently, studies focusing only on networks, industrial parks or urbanization are not included in the final sample. Third, relative cluster measures⁵, 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

⁴ 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.

⁵ For a detailed overview about different cluster measures see for example Brenner, 2017.

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.⁶ 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 have been implicitly taken into consideration by investigating for example the firm-specific cluster effect in a particular industry setting.

⁶ The full list of all considered articles is provided per request.

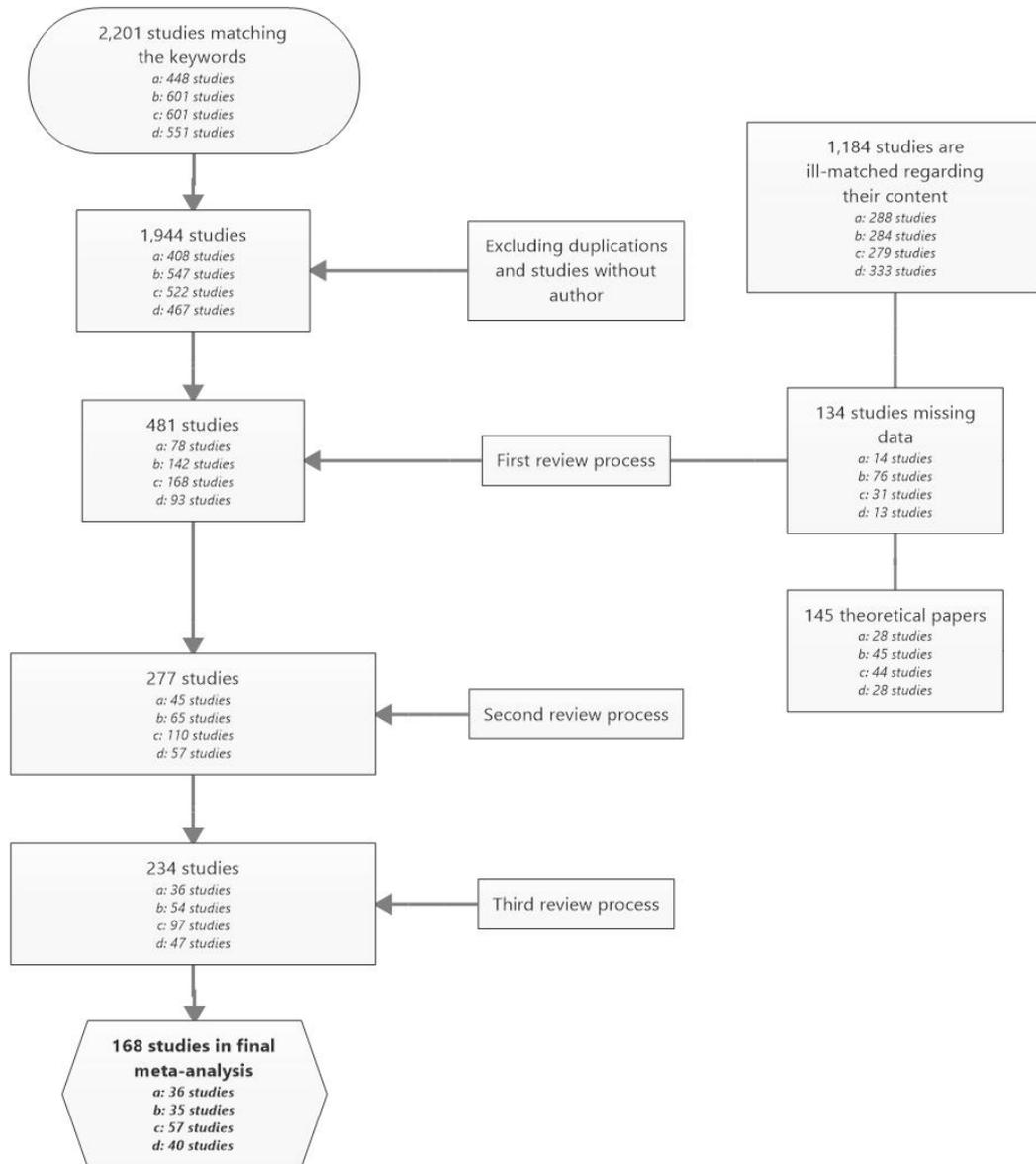


Figure 1: Selection and exclusion process of the considered empirical studies
 (Source: Grashof and Fornahl, 2019)

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.⁷ The shown moderating variables are only those that have also been considered in at least three different empirical

⁷ The full list of moderating variables is, however, available upon request.

studies. In light of the underlying research question, the actual level of analysis is therefore on 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 major 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 variables⁸ across all four performance variables are presented in table 1. 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

⁸ As already indicated, for a simplified presentation of the results, moderating variables that are only analyzed in relatively small number of empirical studies (less than 3 studies) are not illustrated.

performance in absence of potential moderating variables.⁹ In the case of positive estimation results, for example, only 8.4% can be traced back towards a pure firm-specific cluster effect.

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

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

Estimation results	Across all four performance variables		
Moderation effects	+	±	-
Pure	75 (8.4%)	78 (8.2%)	26 (7.5%)
<i>Micro-level</i>	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
<i>Meso-level</i>	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%)
<i>Macro-level</i>	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%)
<i>Interaction effects</i>	207 (23.3%)	293 (30.9%)	97 (27.9%)
<i>Micro-level x Macro-level</i>			
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
<i>Meso-level x Macro-level</i>			
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%)
<i>Macro-level x Macro-level</i>			
Spatial regimes x industry	4 (0.4%)	3 (0.3%)	3 (0.9%)

⁹ This would be the case if the impact of clusters on firm's performance is investigated in a generic way, e.g. across all industries and all firm sizes.

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.¹ 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; Knoblen 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.

¹ 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).

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.

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.² 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

² 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.

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 π 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 ε 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.³ Due to the relatively high number of missing values in some cases, separate regression analysis are conducted. The standard procedure of an 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. The baseline model consists primarily of variables that are not explicitly analysed in the original studies, such as the quality of method⁴ 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.

³ For the results, please see appendix 2.

⁴ The underlying classification is provided upon request.

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

<i>EstimationPositive</i>	<i>Model 1</i> <i>n = 2093</i>	<i>Model 2</i> <i>n = 887</i>	<i>Model 3</i> <i>n = 295</i>	<i>Model 4</i> <i>n = 30</i>	<i>Model 5</i> <i>n = 23</i>	<i>Model 6</i> <i>n = 41</i>
PerformanceEmploymentGrowth	0.466***	-0.240	2.298***	ommitted ¹	19.098	ommitted ¹
PerformanceProductivity	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***
<i>Constant</i>	0.960***	1.091***	0.591	-2.639**	-16.488	4.583**
<i>Pseudo R²</i>	0.0564	0.1484	0.1163	0.1193	0.6221	0.3673
<i>Significance level: * p < 0.10, ** p < 0.05, *** p < 0.01</i>						
¹ Omitted because it predicts success/failure perfectly						
² Omitted because of collinearity with USA						
/ means that there are no observations						

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.⁵ 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. 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 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 1⁶, 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.⁷ 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

⁵ The logistic regression (baseline model) for the negative estimation results is depicted in appendix 3.

⁶ 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.

⁷ The corresponding results are depicted in appendix 3.

negative performance effect than in other countries of investigation.⁸ Thus, a similar dualistic pattern, as in the case of Western Europe and the Anglo-Saxon countries, also applies to Japan and China.⁹ 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 major driver in the national innovation system are large companies. The 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 realising 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 Mühligh, 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

⁸ The corresponding results are depicted in appendix 3.

⁹ The sign change of the China dummy in model 6 can be explained by the smaller number of observations compared with model 1.

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.¹⁰ 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 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.¹¹ Their complex internal structure and the related inflexibility thus tend to prevent large firms from 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 previous case of the interaction effect of industry and distance, to define the exact borders of large firms

¹⁰ 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.

¹¹ 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.

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.¹²

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. Conclusions

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 (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.

¹² 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 analyzed. The corresponding results can, however, be provided upon request.

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. Tödting and Trippel, 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.

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Appendix

A1: 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
PureClusterEffect	Correlation according to Pearson	0.005	0.001	-0.008
	Significance (1-sided)	0.815	0.958	0.696
	N	2201	2201	2201

A2: Bivariate correlation analysis of moderating variables and the estimation results across all four performance variables (own illustration)

Bivariate correlation analysis (across all four performance variables)				
		Estimation Positive	Estimation Insignificant	Estimation Negative
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
PerformanceProductivity	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).

A3: Logistic regression: Negative estimation results of being located in a cluster
 (own illustration, coefficients)

<i>EstimationNegative</i>	<i>Model 1 n = 2093</i>
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**
<i>Constant</i>	-1.026***
<i>Pseudo R²</i>	0.0695
<i>Significance level: * p < 0.10, ** p < 0.05, *** p < 0.01</i>	

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