Fachbereich Wirtschaftswissenschaft

Drivers and mechanisms of the emergence and diffusion of radical innovations

Treiber und Mechanismen der Entstehung und Diffusion von radikalen Innovationen

Kumulative Dissertation

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Abstract (English)

Innovation has become a key factor for economic growth. However, actors cannot rely only on incremental improvements but also need radical innovations now and then in order to stay competitive. These radical novelties may provide a sustainable competitive advantage and thus long-term economic growth. Thus, due to its catalysing role, radical innovations receive attention by policy makers. In spite of ample research on the drivers of innovation processes, the specific mechanisms underlying the emergence and diffusion of radical innovations remain unresolved. This dissertation takes a first step in closing this research gap. Applying an innovation systems approach, the thesis focuses the analysis on the actors and their relations to each other within different boundaries what, put together, forms the central motor for the emergence and diffusion of radical innovations in an innovation system.

The present work highlights that several actors (e.g. patenting organisations, technological frontier firms, universities) are important players regarding radical innovation processes within an innovation system. Patenting firms need certain internal knowledge capabilities for an efficient emergence and diffusion of radical innovations. Moreover, public agencies providing R&D funding play a significant role in supporting radical innovation processes. In terms of relations, this dissertation argues that specific regional context conditions and R&D collaboration enhance interactive learning processes aiming at radical novelty within an innovation system. In particular, cognitive relatedness to regional frontier firms is essential to create radical novelty. With regard to the diffusion of radical innovations, it is important for firms to be related to the overall regional knowledge base. R&D collaboration especially increases the generation of radical innovations when building bridges across boundaries such as organisation types, industrial sectors, regions and regional clusters. Finally, the present work provides relevant implications for future research and derives ramifications for policy makers and managers.

Abstract (Deutsch)

Innovation stellt einen Schlüsselfaktor wirtschaftlichen Wachstums dar. Um wettbewerbsfähig zu bleiben, können sich Akteure dabei nicht nur auf inkrementelle Verbesserungen verlassen, sondern benötigen hin und wieder auch radikale Innovationen. Diese radikalen Neuerungen können einen nachhaltigen Wettbewerbsvorteil und damit langfristiges Wachstum ermöglichen. Deshalb rücken radikale Innovationen in den Fokus politischer Entscheidungsträger. Trotz umfangreicher Forschung über die Triebkräfte von Innovationsprozessen ist die Frage der spezifischen Wirkmechanismen der Entstehung und Diffusion radikaler Innovationen noch nicht hinreichend beantwortet. Die vorliegende Dissertation soll einen ersten Schritt zur Schließung dieser Lücke vollziehen. Unter Anwendung des Innovationssystemansatzes fokussiert die Dissertation die Analyse auf die Akteure und ihre Beziehungen zueinander innerhalb verschiedener Grenzen, was zusammengenommen den zentralen Motor für die Entstehung und Diffusion von radikalen Innovationen in einem Innovationssystem bildet.

Die vorliegende Arbeit macht deutlich, dass mehrere z.B. patentierende Firmen, und Unternehmen an der technologischen Grenze wichtige Akteure für radikale Innovationsprozesse innerhalb eines Innovationssystems sind. Patentierende Firmen benötigen bestimmte interne Wissenskapazitäten für eine effiziente Entstehung und Verbreitung von radikalen Innovationen. Darüber hinaus spielen öffentliche Fördereinrichtungen eine wichtige Rolle bei radikalen Innovationsprozessen. In Bezug auf die Beziehungsdimension argumentiert diese Dissertation, dass spezifische regionale Kontextbedingungen und F&E-Kooperationen interaktive Lernprozesse fördern, die auf radikale Neuerungen innerhalb eines Innovationssystems abzielen. Insbesondere optimale kognitive Nähe zu regionalen Firmen an der technologischen Spitze sind maßgeblich, um radikale Neuheit zu schaffen. Für die Diffusion radikaler Neuheit ist es unerlässlich, dass Unternehmen zu einem gewissen Grad kognitiv in die Wissensbasis der Region eingebettet sind. Insbesondere Cross-Innovationsaktivitäten, bei denen Akteure mit unterschiedlichen Organisationstypen, aus verschiedenen Industrien, Regionen oder regionalen Clustern kooperieren, haben einen positiven Effekt auf die Entstehung radikaler Innovationen. Abschließend zeigt die vorliegende Arbeit mögliche Ansätze für zukünftige Forschungsarbeiten auf und leitet Implikationen für politische Entscheidungsträger und Manager ab.

Contents

Figures

Tables

List of relevant publications

Core papers

Hesse, K. (2020). Unlocking the radical potential of German innovators – How can R&D policy foster radical innovation? *Lund University, CIRCLE-Center for Innovation, Research and Competences in the Learning Economy (No. 2020/5)*. (submitted to *Research Policy*).

Hesse, K. (2020). Related to whom? The impact of relatedness to regional frontier firms on radical innovations. *Bremen Papers on Economics & Innovation (# 2005)*. (submitted to *Small Business Economics*).

Hesse, K., & Fornahl, D. (2020). Essential ingredients for radical innovations? The role of (un-)related variety and external linkages in Germany. *Papers in Regional Science*. DOI: www.doi.org/10.1111/pirs.12527.

Contextual papers

Arant, W., Fornahl, D., Grashof, N., Hesse, K., & Söllner, C. (2019). University-industry collaborations—The key to radical innovations? *Review of Regional Research*, **39**(2), 119-141. DOI: www.doi.org/10.1007/s10037-019-00133-3.

Grashof, N., Hesse, K., & Fornahl, D. (2019). Radical or not? The role of clusters in the emergence of radical innovations. *European Planning Studies*, **27**(10), 1904-1923. DOI: www.doi.org/10.1080/09654313.2019.1631260.

1 Introduction

1.1 Motivation and objective

During the last decades, innovation has been highlighted as an essential factor for economic growth (Rosenberg 2004; Verspagen 2005). Consequently, economic actors need knowledge in order to create innovations and stay competitive (Bathelt and Depner 2003). Thus, knowledge lies at the heart of innovation processes (Edquist 2005). In spite of research from several disciplines stressing that knowledge differs extensively with regard to the degree of novelty or the impact (Trajtenberg 1990; Hargadon 2003; Sood and Tellis 2005), scholars tend to assess the production of knowledge and its uneven distribution across space only in quantitative terms, for instance by patent output of entities (Rodríguez-Pose 1999; Acs et al. 2002; Fritsch 2002; Fritsch and Franke 2004; Rodríguez-Pose and Crescenzi 2008). Policy makers likewise mainly look at indicators such as R&D investment or number of patents with regard to innovation activities (e.g. EFI 2015).

The focus on quantitative indicators regarding innovation activities amongst researchers and policy makers is particularly striking since in the long-term it may become increasingly challenging for knowledge-based economies to rely on incremental improvements for their economic prosperity and therefore these economies also need radical innovations now and then (Asheim and Coenen 2005). Earlier research has acknowledged that these innovations in particular offer great economic potential (Castaldi et al. 2015). Innovations that are radical in nature combine previously unconnected knowledge domains, which is more uncertain and riskier than combining knowledge that has been combined before (Fleming 2001). However, in the case, that such innovations are successful, they can provide the basis for long-term economic growth (Ahuja and Lampert 2001).

Figure 1 visualises an important aspect in this regard. It shows the trend in patent applications for the top five patent offices from 1883 to 2018. Looking at the figure, it becomes apparent that not only the number of patented inventions has increased steadily worldwide over the last century but also that regarding the sheer number of patents, China surpassed the EU[1] and the Republic of Korea in 2005, Japan in 2010 and the U.S. in 2011

[1] EPO refers to the European patent office.

(WIPO 2019). Taking into account the exponential growth rate in China, it is unlikely that the above-mentioned countries will be able to close the already existing gap regarding quantity of patenting activities. In view of the fact that the speed of technological development is constantly increasing, radical innovations, thus, may provide a solution to this situation and could be a key asset in global competition (Mokyr 2008; OECD 2018).

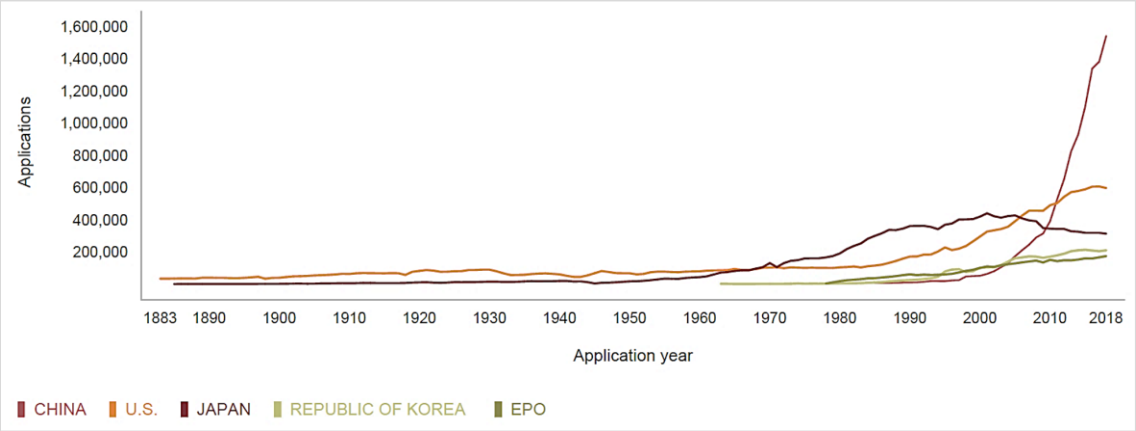

Figure 1. Trend in patent applications for the top five patent offices, 1883-2018 (WIPO 2019, p.14).

Only very recently, the possible catalysing role of radical innovations for the economy has started to get more attention by policy makers. This has led to the establishment of specific innovation agencies such as the JEDI (Joint European Disruptive Initiative) on the European level (JEDI 2018), or the SprinD (Agentur für Sprunginnovationen) in Germany (BMBF 2018). Their purpose is to create an environment that fosters the production of radical innovations. Thereby, organisations on the micro scale and regions or nations on the macro scale can build a competitive advantage that ensures sustainable economic growth (Boschma and Frenken 2006; Castaldi et al. 2015; Kogler 2015).

In spite of ample research on the drivers of innovation processes in general, the driving forces of radical innovations still remain unresolved. Recent research in the realm of economic geography suggests that the production of radical innovations is enhanced by strong capabilities in unrelated knowledge domains (Castaldi et al. 2015; Miguelez and Moreno 2018). However, these studies only look at the impact dimension of such innovations. This dissertation argues that it is important to consider both the emergence and diffusion dimensions that shape these innovations in order to gain a deeper understanding of radical innovations. Hence, it complements an indicator to identify radical innovations in the field of (evolutionary) economic geography.

Assessing the driving forces of different dimensions (emergence and diffusion) of radical innovations thus can improve our knowledge on how firms and, in turn, regions and nations can build a competitive advantage for long-term economic growth. Accordingly, this dissertation aims to answer the following question:

What are drivers and mechanisms of the emergence and diffusion of radical innovations?

As starting point, this dissertation focuses on internal condition factors of economic actors in the radical innovation process. Particularly, it aims to explain how firm internal knowledge capabilities drive radical innovation as empirical studies so far mainly focus on this potential driver with regard to quantitative innovation output (e.g. Garcia-Vega 2006; Leten et al. 2007).

Then, the underlying thesis aims to assess regional context conditions that favour radical innovation processes. In particular, it analyses which effect the cognitive proximity of economic agents to the regional knowledge base has on radical innovation output. Although earlier research proposes that an optimal degree of cognitive proximity to other actors enhances innovation performance (Boschma and Frenken 2010; Fornahl et al. 2011), there exists no empirical evidence on how the cognitive proximity between economic actors and the corresponding regional knowledge base influences the ability of economic agents to generate radical novelty.

Furthermore, the present work seeks to understand whether the knowledge relatedness to specific actors in the regional knowledge base is relevant, rather than the overall cognitive proximity to the region. Even though scholars have emphasised that cognitive proximity to actors at the technological frontier enhances the ability to focus on new and emerging technology domains (Sørensen and Stuart 2000), it remains unclear whether it is essential to enhance the emergence and diffusion of radical innovations. After that, this dissertation aims to shed light on the role of regional industrial structures for radical innovations and thus to complement recent findings by other scholars (Castaldi et al. 2015, Miguelez and Moreno 2018).

Additionally, this thesis investigates specific channels of knowledge exchange, namely R&D collaboration, for the emergence and diffusion of radical innovations. Following Boschma (2005), who emphasises that external linkages can resolve situations of regional lock-in, the present work aims to contribute to an understanding of how external linkages drive radical innovation processes and how they can substitute missing regional

knowledge capabilities.

Moreover, the thesis analyses whether funding of collaborative R&D more generally and R&D collaboration across organisational, industrial and regional boundaries more specifically foster radical innovation. Despite many studies suggesting the positive effect of such cross-innovation activities, the specific role government support can play remains unclear (Belderbos et al. 2004; Castaldi et al. 2015; Miguelez and Moreno 2018). Thus, the dissertation sheds light on the role of innovation policy for the emergence of radical innovations. Recent research suggests that many major technological changes were realised by an active role of the state (Mazzucato 2014). However, research on how direct R&D funding can enhance radical innovation is underdeveloped (e.g. Beck et al. 2016).

Finally, within the broader scope of this work, it is examined how specific economic environments such as regional clusters influence the emergence of radical innovations and also how specific cross-organisational collaboration conditions increase the likelihood of the generation of radical innovations as secondary aspects to the overall research question.

1.2 Outline of the thesis

The remainder of the dissertation is organised as follows: The next section (section 2) develops the analytical framework of the thesis and integrates the individual papers within this context. Subsequently, the specific research questions of each contribution are presented. Section 3 provides the theoretical foundation for this research endeavour by defining radical innovations especially with regard to the emergence and diffusion dimensions. Section 4 then gives an overview of the potential approaches to measure both dimensions. From that, the applied methodology in this dissertation is derived. Section 5 summarises each contribution and the main findings are presented (the full papers are provided in the appendix). Subsequently, the section provides an answer to the overall research question. Finally, section 6 discusses the main contribution and puts it in context with the analytical framework. From that, implications for future research and practical implications are derived.

2 Theoretical framework and research questions

The subsequent section derives an analytical framework in order to answer the overall research question proposed in the first section. Therefore, the research question is embedded in a broader research context:

Nowadays, it is commonly accepted that innovation is a central factor for economic growth (e.g. Verspagen 2005). Firms rely on knowledge to produce innovations and remain competitive. However, their ability to create new knowledge depends not only on their own skills, but also on how they can draw on external resources. As a result, innovation becomes a social process, linking organisations in different locations and taking on a spatial dimension (Bathelt and Depner 2003).

During the last decades, it has been highlighted by numerous scholars that a systemic perspective helps to understand and explain this innovation process (e.g. Fagerberg 2005; Lundvall 2007a). The innovation systems approach developed as an integral part of the work of several innovation economists in the 1980's (e.g. Freeman 1982; Nelson 1984; Lundvall 1985) and led to the publication of two major books on the concept of national innovation systems by Lundvall (1992) and Nelson (1993). Since then, the approach has gained great popularity amongst researchers in disciplines such as economics, sociology, political science and especially economic geography (Lundvall 2007a). It has also become a prominent concept for policy makers to analyse economic performance of spatial entities such as countries or regions (e.g. OECD 2005).

While the concept of Lundvall (1992) and Nelson (1993) delineates the system on a national scale, other scholars have adapted the systemic context on a regional dimension (Cooke 1996; Maskell and Malmberg 1997). Furthermore, several authors have modified the innovation system concept with regard to technologies (Carlsson and Stankiewitz 1991), sectors (Breschi and Malerba 1997) and corporations (Granstrand 2000). These approaches co-exist and complement each other (Lundvall 2007a).

The rising popularity of the systems approach has been a major step towards understanding knowledge as essential production factor. Regarding this, Lundvall (1992, p. 1) proposes that ''[…] the most fundamental resource in the modern economy is knowledge and, accordingly, the most important process is learning''. Knowledge creation and learning, then, happens as an interactive process between agents in a system because essential pieces of knowledge are manifested in economic actors and their

routines and in the relationships between these agents (Lundvall 2007b). Consequently, the entire system can be defined as "[…] the elements and relationships which interact in the production, diffusion and use of new, and economically useful knowledge [...] and are either located within or routed inside the borders of a nation state" (Lundvall 1992, p. 1). Subsequently, Edquist (1997b) has provided a more general definition where he describes systems of innovation as "all important economic, social, political, organizational, institutional and other factors that influence the development, diffusion and use of innovations" (Edquist 1997b, 14).

Edquist's more general approach is based on the assumption that an innovation system should have several characteristics. First, it consists of *actors* and *relations* among them. Second, it has a certain function. Third, a system requires *boundaries* to be able to discriminate between the system and the outside world (Edquist 2005). Consequently, the main components of an innovation system are organisations and institutions. Primarily, these are firms, universities and research institutes but also venture capital organisations and public agencies responsible for, e.g. innovation policy amongst others. These organisations are, individually or in cooperation with one another, involved in the creation, diffusion and application of knowledge, which can be considered as the function of the system (Edquist 2005). The approach thereby assumes that the interaction involves skilful but imperfectly rational agents. These actors are capable of increasing their competence through search and learning processes which is done in interaction with other agents (Lundvall 2007a). The innovation process in such a system thus can be described in simplified terms as follows: Starting with research and development (R&D) in universities, research institutes and firms, knowledge is transferred between the organisations in various ways (e.g. through research collaborations, labour mobility and patents), ultimately being translated into concrete innovations. Although institutions are also sometimes understood as actors in the system, in this dissertation they are defined as a set "of common habits, norms, routines, established practices, rules or laws that regulate the relations and interactions between individuals, groups and organizations" (Edquist and Johnson 1997, 46). Finally, boundaries can be specified on a spatial, technological, sectoral or corporate scale (Edquist 2005).

Within the conceptual framework of innovation systems, scholars have investigated several actors. For instance, Agrawal and Cockburn (2003) test the anchor tenant hypothesis and propose that particularly large, local, R&D-intensive firms enhance

innovation activities within (regional) innovation systems. Muller and Zenker (2001) rather scrutinize the intermediary role of knowledge-intensive business services (KIBS) in knowledge transformation. Ample research is also conducted on the role of universities in innovation systems (e.g. Charles 2006; Gunasekara 2006). Fiore et al. (2011) assess the role of public policies and innovation agencies and argue that they are important to reinforce innovation processes in regions. Moreover, scholars investigate organisational arrangements favouring innovation processes (Nooteboom 2000; Gilsing and Nooteboom 2006; Strambach 2008).

Furthermore, empirical studies have highlighted the essential role of relations to other actors for knowledge production and thus innovation (Powell et al. 1996; Hagedoorn 2002). In order to stay competitive and to solve complex problems, economic agents are required to interact with other actors (Rycroft 2007; Wuchty et al. 2007). This is a difficult task given the fact that some forms of knowledge are harder to communicate than others. In particular, this is the case for tacit knowledge (Polanyi 1966) which is routed in individual routines and experiences. By contrast, explicit knowledge contains information that can be described in formal language such as mathematical expressions, manuals or recipes and thus can be communicated rather easily (Smith 2001). Due to its non-explicit characteristics, tacit knowledge is responsible to a significant degree for the spatial concentration of knowledge. Actors in the same region thus profit from local knowledge spillovers which are facilitated by face-to-face contacts on a regular basis and thus the exchange of tacit knowledge (Gertler 2003). Numerous studies have provided empirical evidence for the phenomenon that knowledge creation is spatially concentrated (Audretsch and Feldman 1996; Breschi 2000; Oerlemans et al. 2001; Fornahl and Brenner 2009).

In this sense, earlier research has indicated that relations on a local scale provide important inputs to the innovation process (Almeida and Kogut 1999) and the exchange of knowledge with other organisations in a region is a crucial factor to combine unconnected knowledge pieces (Fleming 2001). Many scholars have shown that collaboration in R&D enhances innovativeness of regions and firms (e.g. Rigby and Zook 2002; Fitjar and Rodríguez-Pose 2013). Formal collaborations allow firms to gain access to complementary knowledge (Powell et al. 1996) and thereby enhance knowledge diffusion (Wirsich et al. 2016). Furthermore, firms engage in collaboration to improve the quality of their inventions in order to create radical breakthroughs (Singh 2008).

While formal collaborations can be a specific channel to exchange knowledge, information can also spill over unintendedly between economic agents since organisations are also embedded in a broader social context and regional systems of innovation (Boschma 2005). This embeddedness in a regional knowledge base has increasingly been recognized as an important determinant of the innovative performance of economic actors (Uzzi 1996; Cantner and Graf 2004). Both intended and unintended knowledge spillovers increase the probability that economic agents in close geographic proximity to each other engage in knowledge exchange (Uzzi 1997; Bathelt et al. 2004).

Moreover, empirical findings suggest that actors need a certain level of cognitive proximity for an efficient knowledge exchange and thus a successful cross-fertilisation of ideas (e.g. Nooteboom et al. 2007). For instance, Boschma and Frenken (2010) propose that a positive result concerning the successful exchange of knowledge and performance of firms depends on the (optimal) level of cognitive proximity between actors in a region. This way, agents can gain access to complementary knowledge. However, the differences between the knowledge bases must not be too large so that actors can still understand the knowledge. The ability to incorporate new knowledge and to apply it in internal processes greatly depends on the absorptive capacity of economic actors (Cohen and Levinthal 1990). Consequently, cognitive proximity can both enable and constrain interactive learning processes (Balland et al. 2020).

Effective interactive learning aiming at bringing forth radical innovations may be realised by collaboration with different organisation types (institutional/organisational distance) (e.g. Boschma 2005). Research endeavours in this regard provide empirical evidence that particularly collaborations between firms and universities have a positive effect on radical innovations (e.g. Belderbos et al. 2004). It is argued that especially universities can provide a different view on problems firms are facing in innovation processes (Fleming and Sorenson 2004). Moreover, recent research suggests that the cross-fertilisation of ideas for radical novelty is particularly fruitful across industry sectors (e.g. Corradini and De Propris 2017; Montresor and Quatraro 2017). While some authors point to the fact that unrelated knowledge capabilities are needed (Castaldi et al. 2015; Miguelez and Moreno 2018), others find that strong related knowledge competencies help new knowledge to diffuse into unrelated areas (Asheim et al. 2011). Additionally, scholars have stressed the fact that knowledge flows from actors in other regions can overcome situations of regional lock-in and enhance the likelihood to generate radical innovations

(Boschma 2005; Singh 2008; Miguelez and Moreno 2018). Building bridges to other regions can provide access to complementary knowledge which is important for innovation processes (Bathelt et al. 2004).

As Edquist (2005) highlights, it is particularly important to study further the activities in innovation systems, that is the determinants that shape the emergence and diffusion of innovations. This dissertation aims to shed light on these driving forces of innovation processes. The systemic approach thereby functions as conceptual framework. While much research has been done on the mechanisms enhancing innovation output in general, the drivers shaping radical innovation are still relatively unclear. Hence, this dissertation aims to address this research gap. Thereby, it focuses particularly on the emergence and diffusion dimensions in order to gain a deeper understanding on the driving forces that shape radical innovations within an innovation system.

Figure 2 illustrates the analytical framework of this dissertation. The scheme incorporates the *emergence* and *diffusion* dimensions of radical innovations on the horizontal axis and *actors & institutions, relations* and *boundaries* as characteristics of the innovation system concept on the vertical axis. The individual empirical investigations of this thesis are located within this framework.

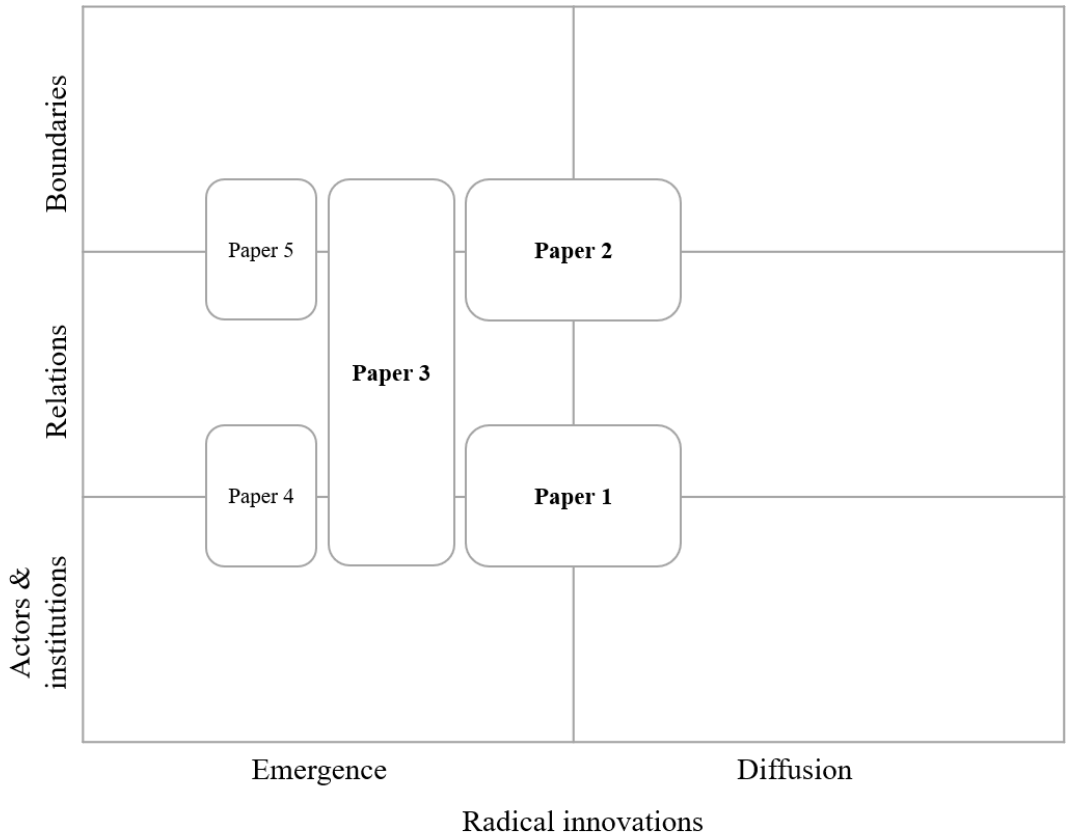

Figure 2. Analytical framework (own illustration).

In total, five papers (three core papers and two contextual papers) are included in the analysis. The individual papers focus on different aspects within the analytical framework. Paper 1 ("Related to whom? The impact of relatedness to regional frontier firms on radical innovations") pays special attention to innovating (patenting) organisations and firms at the technological frontier regarding radical innovation (section 5.1). It examines firm internal knowledge and regional context conditions and thus is embedded in the actors as well as the relations dimensions. These drivers and mechanisms are explored for the emergence and diffusion dimensions of radical innovations. Paper 2 ("Essential ingredients for radical innovations? The role of (un-) related variety and external linkages in Germany") investigates regional context conditions in a broader context as driver of radical innovation with regard to emergence and diffusion (section 5.2). Additionally, the second paper focuses on R&D collaboration as specific channel within the relations dimension and addresses the building of bridges across spatial boundaries. Thus, it contains elements of relations and boundaries. Subsequently, paper 3 ("Unlocking the radical potential of German innovators – How can R&D policy foster radical innovation?") applies a broad perspective on the role of policy-induced R&D collaboration and thereby focuses on the effect of cross-innovation activities (formal collaboration across different boundaries) on the emergence of radical innovations (section 5.3). Particularly, it explores relations between different organisation types (firms and universities/research facilities), linkages across sectoral boundaries, inter-organisational learning across regions and, as a special form of spatial dimension, linkages between regional clusters. Thus, the third paper covers aspects of actors (in particular public agencies that fund R&D projects), relations and boundaries. However, only the emergence dimension of radical innovations is scrutinised due to data constraints. The two papers not belonging to the core of the dissertation emphasise secondary aspects of the overall research question. Paper 4 ("Radical or not? The role of clusters in the emergence of radical innovations") examines the particular context conditions within regional clusters and, thus, pays attention to regionally clustered firms as special actor for the emergence of radical novelty (section 5.4). It is connected in terms of content to paper 1. Paper 5 ("University-industry collaborations—The key to radical innovations?") explores specific collaboration conditions with regard to cross-organisational innovation activities (section 5.5) and is thus connected to paper 3.

The main research question of each paper is derived from the above-mentioned overall research issue. These are subdivided further depending on the focus of the study. The embedding of the individual research questions in the relevant literature is done in the respective subsections. Subsequently, the research questions of each paper are presented:

The first contribution focuses on firm internal knowledge capabilities and regional context conditions. Therefore, it adopts an organisational perspective. Additionally, this analysis considers how particularly innovations that have been detected as novel combinations diffuse subsequently. The analysis is led by the following central research question:

> *RQ1: How do firm internal knowledge capabilities and regional context conditions influence the emergence and diffusion of radical innovations?*

First, this contribution (section 5.1) examines the effect of internal technological diversity on radical innovation. Second, it looks at interactions with other actors and assesses whether relatedness to the overall regional knowledge base or rather being related to specific regional actors improves radical innovation activity. Consequently, the subordinate questions are the following:

> RQ1.1: How does the technological diversity of an organisation influence the emergence and diffusion of radical innovations?
>
> RQ1.2: Does cognitive proximity to the overall regional knowledge base enhance the emergence and diffusion of radical innovations?
>
> RQ1.3: Does cognitive proximity to regional frontier firms enhance the emergence and diffusion of radical innovations?
>
> RQ1.4: Do the effects of internal technological diversity and relatedness to the regional knowledge base and to regional frontier firms differ when focusing on the emergence dimension or the diffusion dimension of radical innovation?

The second publication (section 5.2) then scrutinises further regional context conditions and complements them with external linkages as drivers of radical innovation. This is done by applying a regional perspective. Furthermore, two complementary indicators are used to scrutinize further possible differences with regard to the emergence and the diffusion dimensions.

The leading research question is posed as follows:

RQ2: How do regional context conditions and external linkages influence the generation of radical innovations?

This paper aims to shed further light on the role of related and unrelated variety in the regional knowledge base for the generation of radical innovations and examines how external linkages drive radical innovation processes. Additionally, it analyses whether external linkages can substitute missing sources of complementary knowledge in the region. The subordinate questions are as follows:

RQ2.1: How does related and unrelated variety in the region drive radical innovation processes?

RQ2.2: How do external linkages drive radical innovation processes?

RQ2.3: Do external linkages substitute for missing unrelated competences in the region?

RQ2.4: Do the effects of (un-)related variety and external linkages differ when taking indicators focusing on the emergence and the diffusion of radical innovation?

The third publication (section 5.3) takes a broad perspective and focuses on the role of formal collaborations as specific channel to gain access to complementary knowledge. Thereby, it explores particularly policy-induced R&D activities in the emergence of radical innovations. The leading research question is posed as follows:

RQ3: How can R&D policy foster the emergence of radical innovations?

The aim of the investigation is to understand whether direct funding of R&D collaboration can enhance the emergence of radical innovations and whether, in particular, the support of activities inducing cross-fertilisation increases radical innovation. Three subordinate research questions are employed to analyse this:

RQ3.1: Does direct funding of R&D projects support the emergence of radical innovations?

RQ3.2: Do collaborative R&D grants support the emergence of radical innovations?

RQ3.3: Do policy-induced cross-innovation activities enhance the emergence of radical innovations?

Besides the central research questions presented above, the present work examines two secondary aspects of the central research questions. The first of the two contextual papers (section 5.4) focuses on a special form of regional industrial structure, namely regional clusters, and inspects its role in the emergence of radical innovations. Thus, it is mainly connected to the central research question how regional context conditions drive radical innovation processes (RQ1). The secondary research question is proposed this way:

RQ4: Which regional context conditions are provided by regional clusters?

For that, it investigates whether the location in a regional cluster enhances the likelihood to produce radical innovations. In addition to that, the contribution further analyses which location within the cluster is most fruitful for the generation of radical innovations and pays attention to the role of linkages to other actors:

RQ4.1: Does being located in a regional cluster foster the emergence of radical innovations?

RQ4.2: If so, do they tend to arise in the periphery or at the core of the cluster?

RQ4.3: Do clustered firms also profit from collaboration?

The second additional study (section 5.5) examines closer the role of formal collaborations in radical innovation processes. Hence, it is connected to the core aspect of R&D collaboration as specific channel for interactive learning. Therefore, it contributes to the research question on how R&D policy can foster the emergence of radical innovations (RQ3). This is done by posing the following research question:

RQ5: Do specific collaboration conditions enhance the emergence of radical innovations?

Thereby, it focuses on collaborations between different types of organisations. In addition, it sheds light on the effects of geographic and cognitive distance between these actors for the emergence of radical innovations.

RQ5.1: Do specific partner combinations enhance the emergence of radical innovations?

RQ5.2: What role does the cognitive distance between the cooperation partners play?

RQ5.3: What role does the geographic distance between the cooperation partners play?

In order to answer the research questions, however, the theoretical foundation of radical innovations needs to be addressed further in order to justify the derivation of the two dimensions (emergence and diffusion) proposed in the analytical framework (see section 3). Furthermore, adequate methodologies to measure these dimensions need to be elaborated (see section 4).

3 Radical innovations – what are we dealing with?

The concept of radical innovations is the subject of several bodies of literature such as management, economics or economic geography (Henderson 1993; McDermott and O'Connor 2003; Frenken and Boschma 2007). The management literature thereby in general adopts a firm perspective, (evolutionary) economics and (evolutionary) economic geography rather focus on the technological characteristics. While studying the literature on radical innovation it becomes apparent that there is no coherent definition of the term, although some scholars have defined and distinguished it before (Dahlin and Behrens 2005; Arts et al. 2013; Arts and Veugelers 2015). This has led to different understandings and interpretations amongst researchers. Thus, the following section discusses and afterwards summarises the relevant definitions and characteristics in order to form the theoretical foundation for the analysis and to derive the two dimensions regarding radical innovations within the analytical framework. Table 1 at the end of section 2.4 gives a brief guide how to define radical innovations.

3.1 Invention, innovation and breakthrough

The term 'invention' can be located at the beginning of the innovation process. Ahuja and Lampert (2001) describe the invention process as "[…] *development of a new idea or an act of creation* […]" (p. 523). In the management literature the process is also specified as product development (Ahuja and Lampert 2001) or the detection of new methods and materials, which is closely related to the emergence of new knowledge and technology (Hill and Rothaermel 2003). The result of the invention process can be described as "[…] *a unique or novel device, method, composition, or process. Distinct from technology, an invention integrates distinct technological functionalities.*" (Strumsky and Lobo 2015, p. 1446). However, inventions do not come out of the blue but build on existing expertise. In particular, technological inventions build on prior scientific achievements (Lundvall 2016). Two main concepts have evolved in the literature that describe how inventions come about. The first describes inventions as recombination of existing knowledge pieces (Weitzman 1998)[2]. In this line of reasoning, inventions that are radical in nature combine previously unconnected knowledge domains (Fleming 2001). The second concept depicts them as the aggregation of existent knowledge and completely new technological

[2] The concept of recombinant innovation by Weitzman (1998) uses the term 'innovation' although it focuses on the invention process.

knowledge pieces (Della Malva and Riccaboni 2015). Yet, not every combination of knowledge must lead to a radical innovation.

At this stage, however, the invention is non-commercial or not yet commercialised, as many scholars state explicitly or implicitly (Ahuja and Lampert 2001; Garcia and Calantone 2002; Dahlin and Behrens 2005; Arts 2012). The inventions first have to prove their practical use for the economy (Lundvall 2016). If they do so, the new knowledge created in inventive processes leads to innovation (Forés and Camisón 2016). Thus, inventions that are commercialised can be termed 'innovations' (Ahuja and Lampert 2001; Hill and Rothaermel 2003; Schoenmakers and Duysters 2010; Lundvall 2016). However, not all inventions reach the market stage (Dahlin and Behrens 2005; Lundvall 2016).

In evolutionary thinking, firms are constantly competing based on routines, which are built over time (Nelson and Winter 1982). Thereby, they are in continuous search for novelty and competitive advantage (Boschma and Frenken 2006; Kogler 2015). Bringing forth innovations helps them to achieve this advantage and shows their ability to find new solutions to continuously evolving challenges within existing structures (Büschgens et al. 2013). The development of a new product, process or material component which will be adopted by other economic actors and integrated into daily routines are at the heart of such innovations (Dewar and Dutton 1986). Consequently, an invention can be seen as the nucleus of innovation, but not all inventions become innovations.

Finally, the term 'breakthrough' depends on the degree of impact a successful invention, and thus an innovation, has. Most inventions represent small improvements or refinements of existing knowledge (Dewar and Dutton 1986; Kasmire et al. 2012; Arts and Veugelers 2013; Arts et al. 2013; Arts and Veugelers 2015). However, some inventions stand out of the mass and alter the usage of technologies and/or have an enormous impact on the current economic system and thus represent 'breakthroughs' (Arts and Veugelers 2015). The literature combines the term with either 'invention', when focusing on the technological dimension or with 'innovation', when dealing with the impact on the market (Ahuja and Lampert 2001; Kerr 2010; Phene et al. 2006; Arts and Veugelers 2015; Colombo et al. 2015). It is evident in the literature that the terms 'radical' and 'breakthrough' often are used synonymously although there can be a difference (Schoenmakers et al. 2008; Arts and Veugelers 2013; Arts et al. 2013; Della Malva and Riccaboni 2015).

Even though most radical innovations have a breakthrough-like effect, also marginal technological improvements can have an enormous effect on the market (Dahlin and Behrens 2005; Lundvall 2016). In sum, breakthroughs characterise the diffusion dimension of radical innovations.

3.2 Radical versus incremental innovation

After discussing the different characteristics of the terms 'invention', 'innovation' and 'breakthrough', this paragraph focuses on the different types of innovations. The cumulative process in which existing knowledge is combined in unique ways to create something new can lead to different outcomes (Basalla 1988; Arthur 2007). As stated above, most technological inventions represent small improvements or refinements of existing technologies or products (Dewar and Dutton 1986; Kasmire et al. 2012; Arts and Veugelers 2013; Arts et al. 2013; Arts and Veugelers 2015). Innovation processes of this type are termed 'incremental' in the literature. Usually, the novelty degree and impact are rather marginal, although in the long run these innovations can have significant effects on the economy (Dewar and Dutton 1986; Henderson and Clark 1990; Schoenmakers and Duysters 2010; Lundvall 2016). By contrast, innovations termed 'radical' embody major enhancements. They introduce novelty by combining new knowledge and knowledge combinations from more distant existing technologies (Schoenmakers and Duysters 2010; Castaldi et al. 2015) or they combine technological fields for the first time in history (Arts and Veugelers 2013; Arts and Veugelers 2015). The high degree of novelty can change the way of thinking in the existing system and thereby may introduce major changes (Dewar and Dutton 1986; Büschgens et al. 2013). While some authors consider these results as opposites (Arts et al. 2013; Colombo et al. 2015), others make it clear that they see them as two possible outcomes of the same continuum (Dewar and Dutton 1986; Germain 1996; Broekel 2016).

From an evolutionary perspective, incremental innovations develop mostly alongside well-known trajectories and particularly refine existing technologies. By contrast, radical innovations may cause a paradigm shift away from those established trajectories and thus may lead to radical change (Dosi 1982; Arthur 2007; Verhoeven et al. 2016). However, at first, radical innovations might have to struggle more with poor performance than the established technology (Hermann et al. 2007; Forés and Camisón 2016). Moreover, radical innovations can form the basis for subsequent (incremental) innovations and thus act as the starting point of new technological trajectories and paradigms.

Hence, these innovations can serve as the basis of future technologies (Ayres 1988; Ahuja and Lampert 2001; Arts and Veugelers 2013; Büschgens et al. 2013; Colombo et al. 2015; Lundvall 2016; Verhoeven et al. 2016).

Compared to incremental innovation, engaging in radical innovation is more costly and risky and furthermore the outcome is more uncertain as invention processes that are radical in nature much more often lead to failure (Ayres 1988; Germain 1996; Fleming 2007). Moreover, the successful engagement in radical innovation often requires longer time periods and more intangible assets as well as the application of tacit knowledge (Forés and Camisón 2016). Thus, organisations face significant challenges with regard to the development and integration of radical innovation activities (Büschgens et al. 2013).

Despite the acknowledged characteristics of radical innovations and especially with regard to the degree of novelty, various empirical studies differ in their exact definition of radical innovations depending on the way they measure them (Schoenmakers and Duysters 2010; Verhoeven et al. 2016). This in turn is influenced by the general approach in the research field. While studies in the realm of (evolutionary) economics and (evolutionary) economic geography mostly focus on technologies (e.g. Castaldi et al. 2015), many papers in the management literature place the firm at the heart of their research (e.g. Ahuja and Lampert 2001). With regard to the technology perspective, scholars investigate, for instance, the uneven distribution of technological inventions that have an enormous economic impact (Miguelez and Moreno 2018). Applying the firm-perspective, radical innovations represent artefacts that are new to the firm or alter the way of doing business for firms and the market (O'Connor 1998; O'Connor and Ayers 2005). The impact of these innovations leads to new market opportunities for firms by destroying or transforming the existing supply and demand (Hill and Rothaermel 2003). Hence, with regard to whole industries and markets, radical innovations have a transformative character (Lundvall 2016).

3.3 Radical versus disruptive innovation

The discontinuous character of (radical) innovations can cause disruption in established industries and markets (Tushman and Anderson 1986; Henderson and Clark 1990). Consequently, they are termed 'disruptive innovations' (e.g. Colombo et al 2015). The invention introduces new solutions that are better in satisfying the consumer needs than the existing products or services whereby these become obsolete (Colombo et al. 2015; Hao and Feng 2016; Hervás-Oliver et al. 2018).

From an evolutionary perspective disruptiveness and radicalness fit together well, as radical innovations are a "[…] *disruption of an existing technological trajectory* […]" (Hao and Feng 2016, p. 769). However, incremental improvements can also cause the disruption of an economic system (Govindarajan and Kopalle 2006). At the same time radical innovations do not always have a disruptive character (O'Connor and Ayers 2005). Hence, although many radical innovations disruptive in nature, it is important to distinguish between both (Bers et al. 2009; Arts et al. 2013).

3.4 Summarising the different characteristics of radical innovations

To sum up, it can be said that most inventions are incremental refinements and only few are radical. An invention represents the nucleus of an innovation, however not all inventions are commercialized as an innovation. Inventions recombine existing knowledge in new ways or combine existing and new knowledge. Incremental inventions represent small improvements/adjustments of an existing technology. By contrast, radical inventions introduce major changes. These major changes are introduced by combining knowledge pieces for the first time or combining new knowledge and more distant existent knowledge. Radicalness is thus introduced by a high degree of novelty. The combination of such knowledge is a discontinuity and can break the technological trajectory. These characteristics depict the emergence dimension of radical innovations.

Discontinuity and disruptiveness can be but are not necessarily characteristics of radical innovations. A technologically incremental innovation can also have significant influence on the economy. However, generally, radical innovations have a larger impact than incremental ones. Radicalness implies a strong technological and economic impact, since these innovations open new trajectories and can be the base for subsequent innovations. Radical innovations also often lead to breakthroughs because they can have an enormous impact on technological development or the market. However, on the one hand not all radical innovations lead to a breakthrough and on the other hand also incremental innovations can lead to a breakthrough. These attributes can be ascribed to the diffusion dimension of radical innovations.

Furthermore, this dissertation employs the term 'radical innovation' because the term best fits the studied characteristics of the introduction of (radical) novelty and the impact on future technological developments. However, technological achievements are the focus here and successful commercialisation is not addressed.

Figure 3 illustrates the characteristics of radical innovations and ascribes them to the respective dimensions studied in this thesis. In the emergence dimension, radical novelty is created during innovation processes. Not all ideas (represented by the grey dots) lead to an innovation and not all introduce radical novelty (hence, the dotted arrow). Subsequently, radical innovations are generated by radical novelty. In the diffusion dimension, innovations that diffuse successfully (again a dotted arrow since not all innovations diffuse well), can be considered as radical breakthroughs. Diffusion is understood here in terms of knowledge not with regard to market penetration. These breakthroughs can cause an existing system (e.g. market) to change drastically.

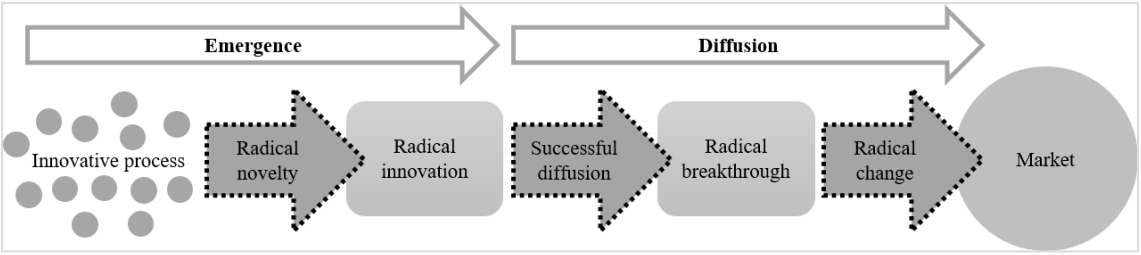

Figure 3. Characteristics of the emergence and diffusion of radical innovations (own illustration).

Table 1. Brief summary of the definition of radical innovations.

How to define radical innovations?
Radical innovation combines knowledge pieces for the first time or new knowledge and more distant existent knowledge. The combination of such knowledge is a discontinuity and can break the technological trajectory. Discontinuity and disruptiveness can be but are not necessarily characteristics of radical innovations. Radicalness implies a strong technological and economic impact, since these innovations open new trajectories and can be the base for subsequent innovations. The high degree of novelty in radical innovations often leads to high economic value. Definitions should pay attention to the two dimensions, namely emergence and diffusion.

4 Radical innovations – how can we measure them?

As presented above, radical innovation can be depicted with regard to different characteristics for the emergence and the diffusion of such innovations. Hence, this work proposes that it is important not to focus on one dimension only, but that both the emergence as well as the diffusion dimension of radical innovations require further investigation, a research gap that this dissertation addresses. Therefore, the following paragraph presents relevant approaches to measure radical innovation with regard to these two dimensions. In general, there exist multiple indicators of innovation, each of which grasps slightly different features of the innovation process (e.g. Archibugi and Pianta 1996). Unfortunately, none of them can comprise the entire spectrum of innovative activity. This thesis relies on patent-based measures, since they can best depict both the emergence and diffusion dimensions of radical innovation. Furthermore, it allows to study the combination of (technological) knowledge. In addition to that, patenting has the advantage that it is consistently applied in many areas of academic research and reflects innovations of a certain degree of significance (few would patent a trivial innovation). Patents are discussed further in the subsequent paragraph, followed by an overview of patent-based measures (see section 4.1). Other approaches include survey-based measures, the use of (scientific) publication data or the utilisation of data from websites via web scrapping (see section 4.2). Section 4.3 summarises the different approaches and Table 2 gives a brief guide of how to measure radical innovations. Subsequently, the methodology which is applied in this dissertation is explained (see section 4.4).

4.1 Patent-based measures

Most approaches use patent-based indicators to investigate radical innovations (Ahuja and Lampert 2001; Fleming 2007; Castaldi et al. 2015). Patents contain comprehensive data on the innovation process. However, it has to be acknowledged that not all patents become innovations. It might also be the case that inventions that perform better than the equivalent in the existing system never become an economically viable market option (Campbell and Nieves 1979). Furthermore, not all ideas are suitable for a patent application and not all patentable ideas are actually filed as a patent (Basberg 1987). Nonetheless, they hold ample and detailed information on the content, time and location of the inventory process. Furthermore, this info is available over very long time periods (Petralia et al. 2016).

Additionally, the quality (the degree of novelty or the impact) varies largely across patents (Griliches 1998). Hence, patents are widely used in empirical research to study the quantitative and qualitative dimension of knowledge creation (Feldman 1994; Acs et al. 2002; Dahlin and Behrens 2005; Castaldi et al. 2015).

4.1.1 Measuring the emergence dimension

In order to detect the emergence of radical innovations, scholars have used particularly references to prior art (backward citations) (e.g. Dahlin and Behrens 2005) and technology classes present on patent documents (e.g. Fleming 2007). Backward citations show upon which previous knowledge the invention builds upon and are added by the applicant as well as the patent examiner. This can provide guidance about the novelty content of the invention (Ellis et al. 1978). It also signifies to which technologies the invention is related (Jaffe et al. 1993). The fact that references tend to be geographically localised further indicates that explicit knowledge flows can be studied with patent citations, especially when focusing on the inventor-added references (Jaffe et al. 1993; Thompson 2006).

The specific backward citation structure of a radical patent is however controversial: Several scholars argue that novel and unique patents have a low overlap in the citation structure with past and present patents (Campbell and Nieves 1979; Lanjouw and Schankerman 1999; Banerjee and Cole 2001; Dahlin and Behrens 2005). Ahuja and Lampert (2001) point to the fact that radical innovations do not build on any prior art and thus do not cite at all. By contrast, Schoenmakers and Duysters (2010) find evidence that many backward citations indicate impactful innovations, although this could be due to endogeneity issues between their backward and forward citation indicators (Trajtenberg et al. 1997). Besides the sheer number of backward citations, several scholars also analyse the age structure of the citations, which can provide information about whether the technology is in an emerging (low average age) or declining (high average age) stage (Campbell and Nieves 1979; Ahuja and Lampert 2001). Subsequently, declining technologies tend to yield inventions with less impact (Sørensen and Stuart 2000; Schoenmakers and Duysters 2010).

Kelley et al. (2013) find that breakthroughs consist of more citations and these reference recent inventions. Furthermore, they provide evidence that building on the work of others increases the likelihood of generating highly cited patents.

Particularly, absorbing knowledge from other technological areas can enhance the degree of novelty as Schoenmakers and Duysters (2010) find by looking at the number of different technology classes a patent cites. Such inventions are termed 'basic' by Trajtenberg et al. (1997), because this knowledge can be applied across a large number of different technology domains. Rosenkopf and Nerkar (2001) combine both dimensions and find that relying on work from others (less self-citations) in the same technological area increases the impact in this technological realm, while building on knowledge from other, more distant domains enhances the impact in these areas. Moreover, Verhoeven et al. (2016) look at pairwise combinations of technology classes and with regard to backward citations they investigate the novelty degree of the technological sources. Thereby, they take a closer look at the role of scientific actors for the novelty degree and investigate the first-time appearance of scientific classifications, since Trajtenberg et al. (1997) find that universities often produce high-impact patents.

Another approach widely used by scholars is to focus on the technology classes present on patents rather than on citations. The analysis of technology classes can provide useful insights about the degree of novelty as well as on the future value of the invention. For instance, Fleming (2001) shows that the combination of recently and frequently used technology classes enhances the likelihood to receive citations, which points to the role of emerging technologies. Following the notion of recombinant innovation, Fleming (2007) proposes that radical innovations are combination of technological subclasses for the first time ever. He argues that in this way, different knowledge bases are being connected to each other and can create great value.[3] Verhoeven et al. (2016) take up the idea introduced by Fleming (2007) and define one of their radical innovation indicators as having at least one entirely novel combination of technological subclasses on a patent. Arts and Veugelers (2015) also build on the idea by the above-mentioned authors and find evidence for a positive effect of the share of novel combinations on the likelihood that a patent leads to a breakthrough.

Strumsky and Lobo (2015) go one step further, distinguishing between four indicators to detect radical inventions. Thus, they depict patents with exclusively first-time used technology classes (originations), inventions with combinations between at least one new technology class and existing classes (new combinations), patents with novel

[3] Subsequently, Arts (2012) provides evidence that high-impact patents (many forward citations in the same technology field) contain a higher share of such novel combinations.

combinations of existing technologies (combinations, similar to Fleming 2007), and inventions that combine commonly used technology classes (refinements). They propose that particularly 'originations' and 'new combinations' increase the likelihood to produce high-impact patents. Mewes (2019) also uses technology classes to identify atypical combinations, which can be interpreted as the combination of previously disconnected components, by applying z-scores. A z-score indicates whether any pair of knowledge pieces on documents such as patents or scientific contributions emerged for the first time or whether it is linked regularly (Uzzi et al. 2013).

Additional approaches relying on the technology classes embodied on patents include, for instance, the effort taken by Della Malva and Riccaboni (2015), who build a relatedness measure based on co-occurrences of technology classes to investigate the impact of inventions. They suggest that high-impact patents tend to combine rather unrelated technology classes and that actors become more familiar with this combination subsequently. Moreover, Kelley et al. (2013) indicate that the more different three-digit technology classes[4] appear on a patent, the higher the probability that the invention is in the highest percentile of the distribution (top 1% forward citations). Thus, technological breadth has a positive effect on the value of an innovation.

4.1.2 Measuring the diffusion dimension

Most empirical analyses studying the diffusion dimension of radical innovations focus on the citations that an invention receives from subsequent works (forward citations) and thus hint to a patent's impact (Trajtenberg et al. 1997).[5] Many scholars have used and validated this approach in order to measure technological impact (Carpenter et al. 1981; Narin et al. 1984; Trajtenberg 1990; Albert et al. 1991; Griliches 1998; Fleming 2001; Jaffe and Trajtenberg 2002). Dahlin and Behrens (2005) also find evidence that impactful patents have high similarity with the citation structure of future patents. However, it has to be acknowledged that the inventor's reputation can influence the citation structure causing some noise in the measure of the economic value of an invention (Stuart and Podolny 1996). Furthermore, one has to bear in mind that citations are not only made by external actors but as well by the inventor or the applicant of the respective patent himself.

[4] Patents are classified regarding their technological domains they are used for. Patent offices, such as the EPO (Europe) or the USPTO (USA), provide universal classifications for a better comparison, namely the Cooperative Patent Classification (CPC) or the International Patent Classification (IPC). For instance, a complete IPC code consists of a combination of the symbols for section, class, subclass and main group or subgroup, for example A01B 33/00. Kelley et al (2013) use the United States Patent Classification (USPC), but three digits also refer to technology subclasses.

[5] Diffusion here means with regard to knowledge, not market penetration.

On the one hand, self-citations can indicate a specific way of problem-solving in a firm and may not be suitable for others (Campbell and Nieves 1979). On the other hand, scholars argue that self-citations may be more valuable than citations by external patents (Hall et al. 2005).

Empirical studies differ in their methodological approach for measuring forward citations to study high-impact patents or 'breakthroughs'. While Carpenter et al. (1981) and Ahuja and Lampert (2001) measure the exact citation count, for instance Schoenmakers and Duysters (2010) define a threshold of 20 citations for detecting radical inventions. Many other studies use thresholds of 1, 2 or 5 % of the highest forward citation counts within the same technology class and year (Kelley et al. 2013). Another approach commonly used studies the distribution of citations and considers patents as 'breakthroughs' if their citation count is two, three or x standard deviations above the technology class mean (Arts 2012; Arts et al. 2013; Verhoeven et al. 2016). Furthermore, some scholars distinguish between the citations received in the focal technology class and the whole amount of received citations so they can detect the impact in a certain technology area and for the whole economy (Trajtenberg et al. 1990). If an invention receives citations from patents within a wide range of technology classes, this indicates the generality of the invention (Trajtenberg et al. 1997). To ensure a better comparability of the citation counts, most approaches use the number of references received in the subsequent five years after a patent has been granted. Additionally, research has indicated that most patents lose their value for subsequent technological developments after five years (Nooteboom et al. 2007).

With regard to the impact of inventions, scholars have also used patent-based indicators such as the number of countries (or patent offices) where the same patent is registered which indicates that the applicant expects high returns by the patent (number of claims made in a patent and the patent family respectively) (Lanjouw and Schankerman 1999; Ejermo 2009). Patent lifetime has also been considered by scholars since a long time period of active legal protection could also indicate economic value (Basberg 1987).

Analysing the diffusion patterns more in depth, Phene et al. (2006) study the technological and geographical distribution of citations and thereby build on Rosenkopf and Nerkar (2001). However, the use backward citations in order to study the diffusion. On the one hand, the technology dimension describes whether backward citations stem from the same or different technological fields (cognitive proximity versus distance).

On the other hand, the geographical dimension is captured by dividing backward citations between national and international origin (geographical proximity versus distance). In the case of the US-Biotech-industry, they provide evidence that, due to the role of absorptive capacity (Nooteboom et al. 2007), only the openness towards one dimension at a time yields potential for impactful inventions (either technology or geography). While proximity in both dimensions would be insufficient for radical novelty, receiving knowledge from other technological areas in other countries might just be too difficult to absorb.

Furthermore, the emerging use of network analysis can hold huge potential for the analysis of radical innovations. The network approach can be used to investigate the development of technological trajectories and to shed light on mechanisms forcing technological paths to break and to open new trajectories (Momeni and Rost 2016). Finally, in light of increasing digitisation in general and the ability to work with enormous datasets or the use of machine learning techniques in particular, the research on invention processes holds new opportunities. In this regard, Gerken and Moehrle (2012) have introduced a new approach based on semantic patent analysis. This allows them to detect novelty in patents and thus identify inventions of high novelty content. In another contribution they measure textual similarity between patents (Moehrle and Gerken 2012). This can for instance be applied for the mapping of patents. Kelly et al. (2018) also use textual analysis to study patent data. They identify breakthrough innovations as the most significant patents based on low textual similarity to previous work but high relatedness to subsequent inventions.

4.2 Non-patent-based measures

Particularly empirical studies in management literature use survey-based measures to analyse radical innovations (e.g. Keupp and Gassmann 2013; Hervás-Oliver et al. 2018). The surveys are usually based on questionnaires and are mostly conducted online, via telephone or sent in printed form to firm executives. Most survey-based studies investigate radical innovations on the firm-level. Thereby, Likert scales are commonly used to evaluate the quality dimension of a firm's innovation processes (Keupp and Gassmann 2013; Souto 2015; Cheng et al. 2016; Sheng and Chien 2016;). Additionally, radical innovation is often measured as the share of sales from new-to-the-firm products (Keupp and Gassmann 2013) or the share of new-to-the-market products (Delgado-Verde et al. 2016).

Furthermore, scholars also use ratings (Forés and Camisón 2016; Azar and Ciabuschi 2017) or binary outcome variables (Guisado-González et al. 2016). Conducting surveys across the same firm population in several waves allows scholars to analyse dynamics in the radical innovation processes of firms (Keupp and Gassmann 2013). The main advantages of survey-based measures are that they can cover both innovating and non-innovating firms. Therefore, hampering factors of innovation can also be studied. Moreover, they allow to also investigate industries that do not file patents for their creative activities, such as the service industry. However, survey-based measures rather embody radical innovations as products or processes and do not contain information on the technological nature of innovations. In order to gain information in this regard, patents are more suitable since they focus on the production of new knowledge which fits better the analytical approach of this thesis (Archibugi and Pianta 1996).

The general approach to study the nucleus of innovation processes is by relying on scientific publication data (e.g. Agarwal and Searls 2009; Uzzi et al. 2013). Agarwal and Searls (2009) use publications to identify driving forces in the innovation process of new medical drugs. Uzzi et al. (2013) detect unregularly combined scientific knowledge and thus radical novelty based on publication data. Boschma et al. (2014) investigate relatedness of scientific knowledge (measured by co-occurrence of topics in publications) to explain dynamics in the evolution of the biotech sector. Information retrieved from that data is closest to the actual invention. However, innovation processes are the focus of this dissertation and hence, patent data is favoured over scientific publication data.

The increasing digitisation has enabled the utilisation of data from websites via web scraping and data mining techniques. For that, information on products and services is gathered from firm websites (e.g. Kinne and Axenbeck 2018; Kinne and Lenz 2019). For instance, Youtie et al. (2012) conduct a pilot study of small and medium-sized enterprises (SMEs) to investigate nanotechnology firm transitions from discovery to commercialisation and how firm characteristics influence this transition. Kinne and Lenz (2019) combine traditional survey-based measures to train an artificial neural network classification model and apply this information to the web text of survey firms using web mining, thus predicting innovative firms. Apart from the fact that data collection is much more economically than for traditional methods, the use of website data has similar advantages and disadvantages as survey-based measures, which is why the approach is not used in the present work (Kinne and Axenbeck 2018).

4.3 Summarising the different approaches to measure radical innovations

Most approaches use patent-based indicators to investigate radical innovations. Other approaches include survey-based measures, the use of (scientific) publication data or the utilisation of data from websites via web scrapping. However, patent-based measures best fit the analysis of the present work.

In order to measure the emergence of radical innovations, backward citations as well as technology classes on patent documents can be used. Backward citations indicate on which previous knowledge the invention builds upon. In a nutshell, they are used to study the novelty content of inventions focusing on the overlap with existent knowledge, often to predict the influence an invention will have in the future.

Indicators based on technology classes, detect the novelty content by looking at combinations of technology classes on patent documents. Earlier research suggests that radical innovations combine former unconnected technology pieces. Thus, technological subclasses are used to indicate radical novelty of an invention and to study the subsequent impact.

The diffusion dimension of radical innovations is commonly investigated using forward citations as indicator. These citations depict the relevance an invention has on subsequent works. Thus, forward citations are used to study the impact an invention has on the technological development and hence on the economy. Recent approaches include network and textual analysis techniques.

Table 2. Brief summary of the measurement of radical innovations.

How to measure radical innovations?
The measurement of radical innovations should include both the emergence and the diffusion dimension to gain a deeper understanding of the processes that are at the heart of creating radical novelty and the reasons why some innovations create great economic value. Backward citations and technology classes on patent documents can be used to study the emergence of radical innovations. With regard to the diffusion dimension, forward citations are a widely used indicator. Survey-based measures, scientific publications and gathering information from websites via web scraping offer an alternative to patent-based indicators.

4.4 Applied methodology in this thesis

This dissertation argues, that it is important to distinguish between the emergence and the diffusion of radical innovations and to study both in order to detect potential differences in the underlying mechanisms. Hence, the present work uses measures for the two dimensions and applies them in the individual papers that comprise the thesis.

Following the notion of recombinant innovation (Weitzman 1998) and adapting earlier research (Fleming 2007; Verhoeven et al. 2016), the emergence of radical innovations is detected by searching for combinations of technological subclasses that have not been combined before (new dyads). This measure complements the common approaches in (evolutionary) economic geography. The indicator is preferred over backward citations because the measure fits very well to the notion of recombinant innovation. Furthermore, it is closer to the nucleus of the knowledge creation process since here technological knowledge is actually combined, whereas backward citations just point to prior art.

In particular, the German knowledge base is searched to detect new dyads. They are identified by looking at combinations of technology subclasses on patent documents. Technologies are classified according to the International Patent Classification (IPC), which classifies patents regarding the technological domains for which they are used.[6] These are aggregated to the four-digit level, which offers the best trade-off between a sufficiently large number of patents in the classes and a maximum number of technologies (Broekel and Mewes 2017). Subsequently, technology combinations in each year are compared to a large dataset with all realised combinations in the 30 years before. Combinations that emerge for the first time are considered as new dyads. Thus, a new combination is radical in the sense that it is completely new to Germany with reference to the last 30 years.[7] By the fact that the present work focuses on Germany, the measure could include novel combinations which have been adopted from other countries. However, they are still radically new to Germany. Furthermore, radicalness is characterised through the entirely new combination of two knowledge pieces, even though these new combinations do not necessarily cause a paradigm shift.

Figure 4 illustrates the emergence of a new dyad. The knowledge base is represented by a network consisting of relations (edges) between technology subclasses (nodes) which

[6] For details see:
http://www.wipo.int/classifications/ipc/en/ITsupport/Version20100101/transformations/stats.html.
[7] It is assumed that a combination that has not appeared in the 30 years before, has actually never occurred.

can be termed as 'technology space'. The black arrow in the technology space at time t represents a new dyad between two technology subclasses that have not been connected in the technology space at time t-1.

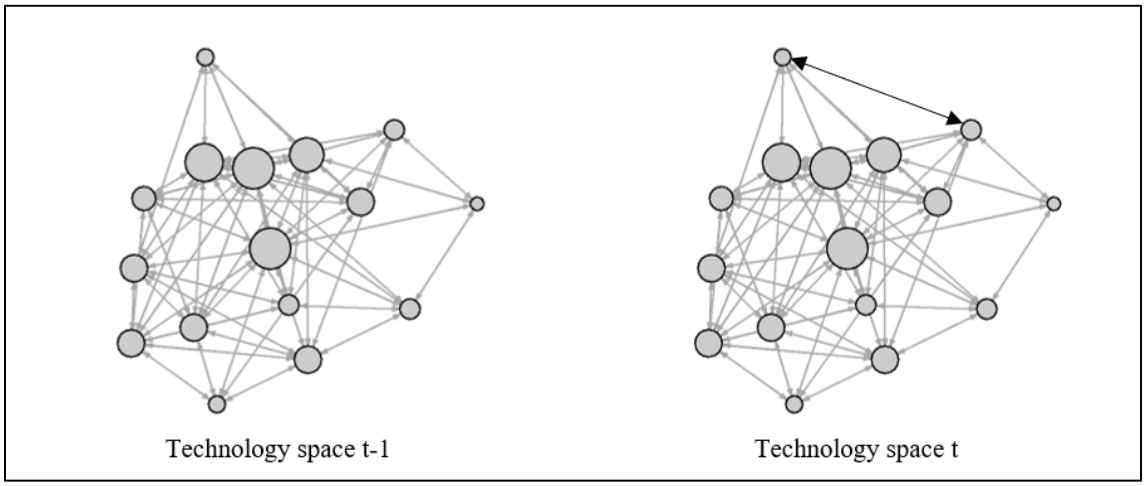

Figure 4. New dyad in a technology space (own illustration).

In the paper that has regions as observations (see section 5.2), new dyads are counted for each of the 141 labour market regions in Germany, defined by Kosfeld and Werner (2012). This definition is used so that commuter and urban-periphery structures are unlikely to bias the results. The other investigations (see sections 5.1 and 5.3-5.5) have patenting firms as the unit of observation (pooled for the years 2010-12 and 2012-14 respectively). Hence, new dyads are counted for each organisation in the dataset.

With regard to the diffusion dimension, the present work makes use of forward citations to analyse radical innovations (e.g. Dahlin and Behrens 2005). As new dyads build on an ex-ante perspective where radicalness stems from the introduced novelty, the contribution on the regional level (see section 5.2) also uses an indicator which considers the impact the innovation has on future technological developments. In order to account for high-impact innovations, following other studies, the number of forward citations is used as an indicator (Dahlin and Behrens 2005). Self-citations are included as these may be more valuable than citations by external patents (Hall et al. 2005). The cut-off point for subsequent references is set to five years after the patent has been filed (Squicciarini et al. 2013) to obtain a fair comparison between patents with different technological backgrounds and ages. Furthermore, following Srivastava and Gnyawali (2011), the indicator is scaled for year and technology by dividing the counts by the mean value of citations based on all patents granted in the same year and the same technology field.

Radical innovations are then defined as the top 1 % of all cited patents based on this scaled measure. Finally, these are counted per year for each labour market region. Finally, one contribution on the firm-level (see section 5.1) captures the diffusion of new dyads in particular. Therefore, the number of citations is counted for patents that contain at least one new dyad. The indicator includes citations in the subsequent five years after the patent filing. Self-citations are included because of the above-mentioned reason (Hall et al. 2005). Subsequently, the mean number of citations received to the focal patents is calculated to achieve a count variable on the organisation level (patenting organisations in Germany between 2010 and 2012).

5 Analysing the emergence and diffusion of radical innovations

Although many scholars have studied influencing factors of innovation processes in general, the driving forces of radical innovations still remain relatively unclear. Understanding the drivers and mechanisms behind the generation of radical innovations is, however, of great importance for both scholars and practitioners (JEDI 2018; Miguelez and Moreno 2018). Hence, this dissertation aims to determine the central influential factors behind radical innovation processes. Thereby, it has the goal to scrutinize how these driving forces influence the different dimensions of radical innovation, namely emergence and diffusion. Methods to detect the emergence and diffusion of radical innovation were presented in section 4, following the current scientific discourse. These findings are used and extended in the context of this dissertation. In particular, it will be examined how different driving forces and processes can explain radical innovation by means of emergence and diffusion. In order to answer this question, studies are carried out which each refer to possible driving forces and processes with regard to radical innovation. In total, five papers (three core papers and two contextual papers) are included in the analysis as demonstrated in section 2. The central research questions (RQ1-RQ3) as well as the secondary aspects to these questions (RQ4 and RQ5) are answered on the basis of the individual publications. Therefore, the individual contributions, their empirical settings and main results will be presented in the following section briefly. The full papers can be found in Appendix B (core papers) and Appendix C (contextual papers).

5.1 How do firm internal knowledge capabilities and regional context conditions influence the emergence and diffusion of radical innovations?[8]

This section deals with the role of firm internal knowledge capabilities and regional context conditions in the emergence and diffusion of radical innovations. Subsequently, the theoretical background is presented and afterwards the empirical approach and the main findings are proposed. Finally, the research question is answered.

[8] The paper presented in this section is a single authored paper published in 2020 as "*Related to whom? The impact of relatedness to regional frontier firms on radical innovations*" in *Bremen Papers on Economics & Innovation* (# 2005).

5.1.1 Theoretical background

From an evolutionary perspective, competition between organisations is based on routines that are built over time (Nelson and Winter 1982). Thereby, firms are always searching for novelty to develop new routines to stay competitive (Boschma and Frenken 2006; Kogler 2015). Relatedness between economic actors has proven to be an important catalyst of such search processes on the regional level. Several studies have shown that related competences drive technological change, economic competitiveness and diversification processes (Frenken et al. 2007; Boschma and Iammarino 2009; Neffke et al. 2011). Investigations on the role of unrelated competences in these processes have provided mixed results so far (Bishop and Gripaios 2010; Boschma et al. 2012) but have highlighted that they enhance the generation of technological breakthroughs (Castaldi et al. 2015; Miguelez and Moreno 2018). However, these papers are silent about the organisational level characteristics and the relation of the specific agents introducing radical novelty to the region in which they are active. The present work aims to address these unsolved issues.

In order to successfully engage in the search for novel combinations of knowledge, firms have to cultivate particular skills which add up to their knowledge base (Boschma and Frenken 2006). This can be achieved through internal R&D, which increases an organisations' diversity and absorptive capacity (Cohen and Levinthal 1990), and by collaborative R&D with other actors (Balland et al. 2015). More diverse organisational knowledge bases that include multiple technologies have better problem-solving competences and are able to conduct extensive search activities (Nelson and Winter 1982; Dosi 1988). Several studies have found empirical evidence for the positive impact of technological diversity on innovativeness and survival of firms (Breschi et al. 2003; Nesta and Saviotti 2005; Garcia-Vega 2006). However, technological diversification comes at a cost, such as greater coordination and communication expenses (Granstrand 1998). Thus, previous studies have found support for this non-linear relationship between an organisation's technological diversity and its performance (Palich et al. 2000; Leten et al. 2007).

Furthermore, actors in the same region profit from local knowledge flows which are facilitated by face-to-face contacts on a regular basis and the exchange of tacit knowledge (Gertler 2003). Earlier research has indicated that regional knowledge networks provide important inputs to the innovative process (Almeida and Kogut 1997), and the interaction

with other organisations in a region is found to be a crucial factor to combine unconnected knowledge pieces (Fleming 2001). However, Boschma and Frenken (2010) propose a 'proximity paradox' which states that the successful exchange of knowledge and performance depends on the (optimal) level of cognitive proximity between partners in a network. Although there are studies showing that an optimal degree of cognitive proximity to other actors enhances innovation performance (e.g. Fornahl et al. 2011), there is no investigation on the relationship between organisations' knowledge base and the regional knowledge network as a whole and how this influences the ability of economic agents to create radical novelty.

Moreover, it has been argued in the literature that relatedness to other innovating organisations can facilitate the knowledge exchange between firms (Almeida and Kogut 1997). Additionally, scholars argue that cognitive proximity to actors at the technological frontier enhances the ability to focus on new and emerging technology domains (Sørensen and Stuart 2000). However, the cognitive proximity to actors at the technological frontier should not be too close so that there is enough potential to exchange new knowledge (Nooteboom et al. 2007). Nonetheless, research is silent about the role of relatedness to industry leaders in the region in order to engage successfully in radical innovation processes. This contribution aims to close these research gaps. Delineating from the other two core papers (see sections 5.2 and 5.3), it also strives to detect possible differences in the mechanisms that enhance the emergence of radical innovations and their subsequent diffusion.

5.1.2 Empirical approach and main findings

The empirical analysis is conducted using several data sources. In particular, organisation-level information from the ORBIS database and information on innovation activity from the PATSTAT database are combined to construct a unique data set of actively patenting organisations in Germany between 2010 and 2012. The final sample consists of 10,779 innovating organisations. Negative binomial regression models are used to test the hypotheses. The study indicates that the mechanisms at the heart of the emergence and diffusion of radical novelty differ. Evidence is found that an optimal degree of internal technological variety enhances radical innovation output. Furthermore, the results suggest that not overall relatedness to the regional knowledge base is important but rather being related to actors at the technological frontier enhances an organisations' ability to produce novel combinations.

Despite the positive effect of relatedness to radical innovators for the emergence of radical novelty, it is rather cognitive proximity to the regional knowledge base that facilitates the diffusion of such ideas, at least up to a certain degree, after which the effect vanishes. Moreover, the internal knowledge capabilities of organisations have to reach a certain threshold of diversity so they can make use of them for diffusion efforts.

RQ1: How do firm internal knowledge capabilities and regional context conditions influence the emergence and diffusion of radical innovations?
An optimal level of technological diversity of firms that enhances the emergence of radical innovations. Second, it shows that relatedness to the overall regional knowledge base is not important but rather the optimal cognitive distance to firms at the technological frontier is essential for the emergence of radical innovations. However, for this radical novelty to diffuse, rather diverse actors and cognitive relatedness to the regional knowledge base is important.

5.2 How do regional context conditions and external linkages influence the generation of radical innovations?[9]

This section scrutinises the role of regional context conditions and external linkages in radical innovation processes. After providing the theoretical background, the empirical approach and the main findings are presented. Finally, the research question is answered.

5.2.1 Theoretical background

Knowledge variety, created over time and embedded in organisations, is an important factor for economic growth (Saviotti 1996). The interaction between economic actors is considered an essential factor for the generation of new knowledge (Fleming 2001). However, knowledge spillovers from one actor to another require certain absorptive capacities (Cohen and Levinthal 1990). These spillovers are more effective when organisations are cognitively related to each other (Nooteboom et al. 2007). Related knowledge capabilities are represented by a certain degree of overlap and if they develop through similar skills and abilities (Nooteboom 2000).

[9] The paper presented in this section is co-authored with Dirk Fornahl. The PhD candidate is the first author of the article. It is published in 2020 as "*Essential ingredients for radical innovations? The role of (un-) related variety and external linkages in Germany*" in *Papers in Regional Science.*

The concept of knowledge relatedness is thus important in order to understand the collective learning and development of regional capabilities as a path-dependent process. Regions are unlikely to acquire new knowledge independent of existing competences. This has been verified by scholars for different dimensions (e.g. products, industries, technologies) and spatial units (e.g. countries, regions, cities, labour market areas) (Frenken et al. 2007, Hidalgo et al. 2007; Boschma and Iammarino 2009). Regardless of many studies that emphasise the positive effect of localised knowledge variety on economic growth (e.g. Boschma et al. 2012) or innovation in general (e.g. Tavassoli and Carbonara 2014), its role for the emergence and diffusion of radical novelty remains vague. First attempts to shed light on this issue yield mixed results. While Castaldi et al. (2015) find evidence that only unrelated variety positively influences technological breakthroughs, Miguelez and Moreno (2018) discover that not only unrelated knowledge competencies but also related one's favour breakthrough innovations. These results suggest that further analysis is required to understand the impact of knowledge variety on radical innovations in a more comprehensive way.

Besides, regional capabilities may become redundant at some point. This can lead to situations of lock-in (Boschma 2005). Such situations may be resolved by building bridges to other regions through which regions can acquire new knowledge capabilities (Bathelt et al. 2004). Formal collaborations may be a specific channel to access this knowledge especially in light of highly specialized and spatially concentrated knowledge (Singh 2008). Collaborations between economic actors have already been found to increase innovativeness of regions and firms (Fitjar and Rodríguez-Pose 2013).

The present work takes these issues as the starting point and analyses how (un-) related variety and external linkages drive radical innovation processes. In this way, this paper inspects further the aspects of cross-industry and cross-regional spillovers. Thereby, the analysis is additionally strengthened by measuring radical innovations from two complementary perspectives, looking at the emergence as well as at the diffusion dimension.

5.2.2 Empirical approach and main findings

The empirical approach in this study relies on patents from the PATSTAT database. Patents are assigned to German labour market regions based on the inventor's residences. Then, the contribution investigates the link between (un-)related variety and external linkages with radical innovation output for 141 German labour market regions between

2001 and 2010. Performing negative binomial panel regression models, it is found that related and unrelated variety both have a positive effect on the emergence of radical innovations. This underscores the assumption that related and unrelated capabilities are not opposites but rather both increase the opportunities for new knowledge combinations (Frenken et al. 2007; Sun and Liu 2016). Surprisingly, the role of related variety is more pronounced, especially with regard to the diffusion dimension. The fact that related competences are more important than unrelated capabilities could be explained by risk-aversion of German managers and venture capitalists (Wüstenhagen and Teppo 2006; Hauschildt and Salomo 2007). Moreover, cross-regional linkages are found to enhance the emergence of radical innovations, at least up to a certain degree and can substitute missing local unrelated capabilities. This finding is also in line with the assumption that simultaneous large cognitive and geographic distances are too much of a hindrance to allow for the use of knowledge (Nooteboom 2000; Boschma 2005).

RQ2: How do regional context conditions and external linkages influence the generation of radical innovations?
The second paper shows that related and unrelated variety in the region both have a positive effect on radical innovation processes. Other than expected, the role of related variety is more pronounced. External linkages also have a positive effect up to a certain extent, after which it diminishes. Additionally, they can serve as a substitute for absent unrelated capabilities in a region. The pronounced effect of related variety is even stronger for the indicator that measures radical innovation from the diffusion dimension.

5.3 How can R&D policy foster radical innovation?[10]

This section explores the role of R&D policy for the emergence of radical innovations. First, the theoretical background is provided, afterwards the empirical approach and the main findings are shown. Finally, the research question is answered.

[10] The paper presented in this section is a single authored paper published in 2020 as "*Unlocking the radical potential of German innovators – How can R&D policy foster radical innovation?*" in *Papers in Innovation Studies* (No. 2020/5).

5.3.1 Theoretical background

Many scholars have shown that collaboration in R&D enhances innovativeness of regions and firms (e.g. Rigby and Zook 2002; Fitjar and Rodríguez-Pose 2013). Formal collaborations allow firms to gain access to complementary knowledge (Powell et al. 1996) and thereby enhance knowledge diffusion (Wirsich et al. 2016). Furthermore, firms engage in collaboration to improve the quality of their inventions in order to create radical breakthroughs (Singh 2008).

Numerous studies provide empirical evidence that collaborations between partners with different organisational, industrial or regional backgrounds particularly foster the emergence of radical innovations. For instance, several scholars propose that university-industry linkages enhance the production of radical novelty (Belderbos et al. 2004; Wirsich et al. 2016). It is argued that especially universities can provide a different view on problems firms are facing in innovation processes (Fleming and Sorenson 2004). Furthermore, recent research suggests that the cross-fertilisation of ideas for radical novelty is particularly fruitful across industries (e.g. Corradini and De Propris 2017; Montresor and Quatraro 2017). While some authors argue that these mechanisms need unrelated industries (Castaldi et al. 2015; Miguelez and Moreno 2018), others find that strong related capabilities help new knowledge to reach unrelated areas (Asheim et al. 2011). Additionally, in order to overcome situations of regional lock-in and to increase the likelihood to generate radical innovation, knowledge flows from actors in other regions are fruitful (Boschma 2005; Singh 2008; Miguelez and Moreno 2018).

Moreover, linkages between actors from different regional clusters may supply the essential new knowledge for the emergence of radical innovations. Regional clusters have been found to increase the innovativeness and productivity of firms (Porter 1998; Martin and Sunley 2003). Furthermore, recent studies have stressed the role played by global pipelines in fostering the performance of clusters (Bathelt et al. 2004; Owen-Smith and Powell 2004). Moreover, combining deep knowledge in one strong industry sector with deep knowledge of another strong industry sector could be fruitful (Fleming 2001, Janssen and Frenken 2019).

Although such activities have been shown to be successful, due to market imperfections, firms do not engage in R&D processes aiming at generating radical innovation to a socially desirable degree (Arrow and Lind 1970). Hence, governments have established support measures to compensate the under-investment in R&D of private organisations,

also with regard to radical innovation. While the U.S. have relied upon its Defense Advanced Research Projects Agency (DARPA) since a long time, the JEDI on the European level (JEDI 2018), or the SprinD in Germany (BMBF 2018) have just been established recently.

For one thing, empirical studies show that public R&D support positively affects indicator such as patenting performance and novelty sales (Czarnitzki and Hussinger 2004; Czarnitzki and Licht 2006; Czarnitzki and Lopes-Bento 2014). Then again, there is not much empirical evidence as to whether research grants can support radical innovation output. A pioneering approach is conducted by Beck et al. (2016), who show that policy-induced R&D expenditures (only) have an effect on radical innovation. The present paper takes this research gap as the starting point and scrutinises further the effect of subsidised R&D collaborations. Moreover, although the support of the above-mentioned cross-innovation activities is often proposed as policy recommendation, it is unclear whether the funding of such research projects has an effect on radical innovation. Therefore, it seems important to shed light on the question of whether public R&D support in general and policy-induced cross-innovation activities in particular can support such innovation processes.

5.3.2 Empirical approach and main findings

The empirical approach applies organisation-level information from the ORBIS[11] database and information on innovation activity form the PATSTAT database to create a data set of actively patenting organisations in Germany between 2012 and 2014. Furthermore, data from the German subsidy catalogue[12] is employed to assess the effect of public R&D funding on the ability to create radical innovations. The final sample consists of 8,404 innovating organisations, out of which 524 received a subsidy between 2008 and 2010. Distinguishing between treated (subsidized) and untreated firms, the results of the negative binomial regression models confirm prior studies: cross-innovation activities are an important explanation for successful radical innovations in German firms. Regarding innovation policy, the paper shows that public R&D support in general and collaborative research project grants in particular can enhance the emergence of novel combinations. Also, it finds empirical evidence that policy-induced cross-innovation activities indeed can support radical innovation output.

[11] ORBIS provides comparable data from private companies.
[12] The funding catalogue is a publicly available database with more than 110,000 completed and ongoing projects funded by the federal government.

This can be done through linking different organisation types and funding collaboration between actors from different industries or regions. Furthermore, it provides first empirical evidence that the cross-innovation activities between regional clusters has a positive effect on radical innovation.

RQ3: How can R&D policy foster radical innovation?
Direct funding of R&D projects has a positive effect on the emergence of radical innovations by means of novel combinations. Moreover, not only funding in general, but collaborative research grants in particular support the emergence of radical innovation. Furthermore, as suggested by numerous contributions, policy-induced cross-innovation activities enhance radical innovation output. This is the case for cross-organisational, cross-industrial, cross-regional and cross-cluster activities.

5.4 Which regional context conditions are provided by regional clusters?[13]

This section deals with a special regional context condition, namely regional clusters. Subsequently, the theoretical background is presented and afterwards the empirical approach and the main findings are proposed. Finally, the research question is answered.

5.4.1 Theoretical background

Regional clusters are a popular structure through which innovation policy instruments can be employed (Festing et al. 2012; EFI 2015; Cantner et al. 2019). This is empirically grounded in evidence that shows that being located in a cluster enhances the innovativeness of firms (Baptista and Swann 1998; Bell 2005). Regardless, there are also studies with contradicting evidence (e.g. Pouder and St. John 1996). Thus, it can be stated that there is no consensus amongst scholars whether clusters are a beneficial environment for innovations in general (Martin and Sunley 2003) and the generation of radical innovations in particular (Hervás-Oliver et al. 2018). The literature provides us with two possible outcomes. On the one hand, radical innovations may be triggered by the relatively fast and eased diffusion of knowledge within clusters (e.g. via labour mobility), particularly of the tacit dimension, which is important in order to produce radical novelty

[13] The paper presented in this section is co-authored with Nils Grashof and Dirk Fornahl. It is published in 2019 as "*Radical or not? The role of clusters in the emergence of radical innovations*" in *European Planning Studies*, 27(10), 1904-1923.

(Mascitelli 2000; Otto and Fornahl 2010; Braunerhjelm et al. 2017). On the other hand, firms located within clusters may be exposed to the danger of uniform thinking and the lack of new challenging external ideas and thus might not be able to generate radical novelty (Pouder and St. John 1996; Martin and Sunley 2003; Boschma 2005).

In order to contribute to a clarification, the present study analyses whether being located in a cluster increases the likelihood to create radical innovations. It is reasonable to assume that these potential benefits are not equally distributed (Martin 2009; Frenken et al. 2015). It is argued that the established and leading firms in clusters, for example, organise 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 promotes an inertia (Munari et al. 2012; Hervás-Oliver et al. 2018).

5.4.2 Empirical approach and main findings

The basic database for the empirical analysis providing detailed firm-specific information is the AMADEUS[14] database. Relevant clusters in Germany are identified based on a method by Brenner (2017) which uses employment data of the Institute for Employment Research (IAB). Patent data retrieved from PATSTAT is used to identify innovation activity. The logistic regression analysis, which is fitted on a sample of 8,404 German patenting firms between 2012 and 2014, shows that clusters indeed provide a preferable environment for radical innovations. Furthermore, evidence is found 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 are also found to be beneficial for the emergence of radical innovations up to a certain degree.

RQ4: Which regional context conditions are provided by regional clusters?
As a special regional context condition, being located in a regional cluster enhances the likelihood to produce radical innovations. This is more likely, however, if innovators are located in the periphery, where actors are more open to the exchange of knowledge, than at the core of the cluster. Furthermore, linkages with other actors are beneficial up to a certain degree for clustered firms seeking to innovate radically.

[14] Amadeus is a comprehensive database of companies from all over Europe.

5.5 Do specific collaboration conditions enhance the emergence of radical innovations?[15]

This section explores further specific collaboration conditions, particularly university-industry linkages in radical innovation processes. After providing the theoretical background, the empirical approach and the main findings are presented. Finally, the research question is answered.

5.5.1 Theoretical background

As knowledge production comes with certain externalities, 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 2014). Combining knowledge in new ways, leading to radical innovations, can correspond to an explorative, distant search (March 1991; Arts and Veugelers 2015). Since this is rather uncertain and risky, private organisations might refuse to focus on such research activities (Friis et al. 2006).

However, universities and public research institutions might provide valuable knowledge in this regard. It is argued amongst scholars that public research contributes substantially to the technological development in regions and countries (e.g. Jaffe 1989; Salter and Martin 2001). Coordination between public and private R&D efforts drives progress in technological evolution and exchange between the two enhances knowledge diffusion and hence innovative outcome (Metcalfe 1995). Due to its tacit nature, the knowledge transfer between academia and industry often requires direct interaction to be effective (Rosenberg and Nelson 1994). To encourage the exchange of knowledge between science and the private sector, policy makers provide incentives for formal collaborations between the two (Henderson et al. 1998; Geuna 2001; Mowery et al. 2001). Linkages between industrial actors and public research facilities are often studied by looking at citations on patent documents (Rizzo et al. 2020). Thus, if a firm refers to a scientific contribution on a patent, this is treated as knowledge flow between the two.

[15] The paper presented in this section is co-authored with William Arant, Nils Grashof, Dirk Fornahl and Cathrin Söllner. The PhD candidate is the corresponding author. It is published in 2019 as "*University-industry collaborations—The key to radical innovations?*" in *Review of Regional Research*, 39(2), 119-141.

However, there is not much research so far investigating the special role university-industry collaborations play in the emergence of radical innovations. First research endeavours in this regard provide evidence that collaborations between firms and universities have a positive effect on radical innovations (Belderbos et al. 2004; Wirsich et al. 2016). This work adds to this line of research by investigating the role of university-industry linkages for the emergence of radical innovations. Thereby, it not only looks at collaborations per se, but also takes the cognitive and geographic proximity into account.

The cognitive relation between public and private collaboration partners may influence the exchange of knowledge and hence the radicalness of innovations. While certain cognitive distance can increase the chance for new combinations of knowledge, too much distance could hinder mutual understanding (Nooteboom et al. 2007; Boschma and Frenken 2010). Geographic relation also plays a significant role in how universities affect the innovative capacity of firms and regions. Geographic proximity has proposed to be 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. In this regard, several scholars have found that knowledge from outside an innovator's region might be a potential source for radically new ideas (Phene et al. 2006; Miguelez and Moreno 2018).

5.5.2 Empirical approach and main findings

The empirical approach again fuses together information from the databases AMADEUS, PATSTAT and the German subsidy catalogue, resulting in a dataset of 8,404 patenting firms in Germany between 2012 and 2014. Fitting logistic regression models, the contribution shows that in general university-industry collaborations enhance the probability to produce radical innovations; however, this is also found for collaborations with research institutes or other firms. Furthermore, the effect of collaborating with cognitively distant universities is not significant. Conceivably, high distance on the cognitive and the organisational level could represent a gap in too many dimensions which does not allow for knowledge to spill over effectively. However, evidence is provided that 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.

RQ5: Do specific collaboration conditions enhance the emergence of radical innovations?
Firms collaborating with universities are more likely to produce radical innovations, however this effect is also significant for other research facilities and firms. While cognitive distance between university-industry collaboration partners has no effect, geographic distance is positively associated with radical innovation.

5.6 Answering the overall research question

Having addressed the separate contributions of this dissertation, the overall research question is answered in the following section within the analytical framework proposed in section 2:

Regarding *actors* in an innovation system, this thesis argues that patenting firms with an optimal firm internal technological diversity are key players for the *emergence* of radical innovations. Firms at the technological frontier of their industry sector are also important agents in this regard. Additionally, firms in the periphery of regional clusters play an important role for the emergence of radical innovations in an innovation system context. In contrast, the *diffusion* of radical novelty is especially driven by technologically diverse patenting firms. Furthermore, *public agencies* directly support radical knowledge creation via the funding of inter-organisational learning. This is particularly fruitful if innovation agencies support cross-innovation activities.

In terms of *relations*, the *emergence* of radical innovations is enhanced by several regional context conditions. First, an optimal cognitive proximity between patenting firms and regional frontier firms leads to the creation of radical novelty. Second, related and unrelated variety in the regional industrial structure favour inter-organisational learning processes aiming at the creation of radical innovations. Regional clusters provide a special regional context conditions which is favourable for the emergence of radical innovation. This context condition is particularly striking in the periphery where firms are more prone to inter-organisational learning. Formal R&D collaborations also drive the emergence of radical innovations. Aiming at the emergence of radical novelty, learning processes between actors are most effective between agents with different organisational backgrounds (firms and universities / research institutes).

Particularly, linkages between firms and universities over longer distances hold significant potential for the emergence of radical innovations. Building bridges across industrial sectors, regions and regional clusters also strengthens radical innovation capabilities of actors. These relations can be supported effectively by public funding. Extra-regional linkages can, furthermore, compensate for missing unrelated knowledge capabilities within a region.

The *diffusion* of radical innovations is increased by other regional context conditions. Radical novelty diffuses most effectively when firms have an optimal cognitive proximity to the overall regional knowledge base. However, related and unrelated variety in the regional industrial structure also favours the diffusion of radical innovations. R&D collaboration between actors across regions as specific channel of interactive-learning can also enhance the dissemination of radical innovations and, moreover, make up for missing unrelated knowledge competencies in a region.

Finally, with regard to *boundaries* within an innovation system, the *emergence* of radical innovations can be enhanced by collaboration activities leading to cross-fertilisation of economic agents such as cross-organisational, cross-industrial, cross-regional and cross-cluster efforts. The efficient diffusion of radical innovations can be secured by building bridges across regional and sectoral boundaries.

6 Conclusions

The aim of this dissertation has been to identify central driving forces of the emergence and diffusion of radical innovations. The analysis is embedded within the analytical framework derived in section 2. Within this framework, drivers and mechanisms are at the core of the research questions that have been investigated in section 5. From this, an answer for the overall research question has been extracted (section 5.6). In the subsequent section, the main contribution of the dissertation will be discussed (section 6.1), before implications for future research and practical implications for policy makers and managers are derived in the sections 6.2 and 6.3.

6.1 Main contribution

During the last decades, innovation has been recognised as central ingredient of economic growth (Rosenberg 2004; Verspagen 2005). For that, economic actors need knowledge to create innovations and stay competitive (Bathelt and Depner 2003). In order to stay competitive, actors in knowledge-based economies cannot rely only on incremental improvements but also need radical innovations now and then (Asheim and Coenen 2005). Just recently, the great economic potential of these innovations has been acknowledged by scholars and policy makers (Castaldi et al. 2015; JEDI 2018).

Consequently, identifying drivers and mechanisms behind the production of radical innovation is important to understand how actors can stay competitive in the long-term. Furthermore, it is essential to investigate how these driving forces influence the different dimensions of radical innovation, namely emergence and diffusion. This dissertation has aimed to address this research gap. The first contribution of the present work is that it has complemented an indicator to identify radical innovations in the field of (evolutionary) economic geography and that it has investigated not only one dimension but two dimensions (emergence and diffusion) of radical innovations.

The innovation systems approach is used as analytical framework within this thesis (e.g. Lundvall 1992; Nelson 1993; Edquist 1997). It focuses the analysis on the *actors* and their *relations* to each other within different *boundaries* what, put together, forms the central motor for the *emergence* and *diffusion* of radical innovations in an innovation system.

The present work, thereby, contributes to a common understanding of how the specific routines of *actors* drive the emergence and diffusion of radical innovations. The specific *firm internal knowledge capabilities* enhancing radical innovation processes in *patenting organisations* can be explained by the fact that, on the one hand, a diverse technology base yields the potential to combine former unconnected knowledge from different technology fields and thereby increases the potential for cross-fertilisation (Fleming 2001). On the other hand, it may keep organisations from strengthening capabilities in specific technological fields (Leten et al. 2007) and may hamper the aim of balancing exploitation and exploration (March 1991). Especially with regard to processes introducing radical novelty, this thesis argues that it is likely that technological diversity may become too costly at some point since they demand large investments in R&D and also are accompanied with higher risks and uncertainty (Fleming 2001; Strumsky and Lobo 2015). Additionally, the present work showcases the role of *technological frontier firms* as important actors of radical innovation. Interactive learning with such firms can enhance the ability to focus on new and emerging technology domains (Sørensen and Stuart 2000). Furthermore, it is highlighted that especially *firms in the periphery of regional clusters*, which are more open to the exchange of knowledge, have the ability to realise radical innovations.

With regard to *public agencies funding R&D* within an innovation system, this dissertation provides evidence that policy-induced R&D can boost the emergence of radical innovations. This is important in order to cure the market failure that the level of radical innovation production is below the social optimum (Arrow and Lind 1970). The present thesis argues that innovation policy can overcome this by subsidising R&D in general and collaborative R&D in particular, thereby enhancing the emergence of radical innovations. Moreover, this work finds that radical novelty is especially supported through providing research grants for cross-organisational, cross-industrial, cross-regional, cross-cluster activities, which are discussed further subsequently. Thus, it extends knowledge in the realm of innovation policy research.

Regarding the *relations* dimension of the analytical framework, this thesis contributes to the fact that *regional context conditions* as well as interactive learning via *R&D collaborations* enhances the emergence and diffusion of radical innovations. Focusing on specific *regional context conditions*, this dissertation contributes to the relatedness concept (Boschma and Frenken 2010).

While earlier studies focus only on the overall relatedness structure in the region (Boschma and Iammarino 2009; Castaldi et al. 2015), the work at hand argues that not relatedness per se, but an optimal cognitive proximity to regional frontier firms drives the *emergence* of radical innovations. While firms need a cognitive overlap to be able to absorb different knowledge from other actors, they also require a certain degree of cognitive distance for the exchange of new knowledge (Cohen and Levinthal 1990; Nooteboom et al. 2007; Boschma and Frenken 2010).

For the subsequent *diffusion* of radical novelty, however, other *regional context conditions* apply. The present dissertation argues that an optimal cognitive proximity to the regional knowledge base is important, at least up to a certain degree. This can be explained by the fact that knowledge diffuses faster among related capabilities (Cohen and Levinthal 1990; Fleming 2001; Frenken et al. 2007). Strong related competences, in turn, ensure that the new knowledge also reaches unrelated knowledge domains (Asheim et al. 2011). Related capabilities thereby strengthen the process of cross-fertilisation and help to integrate unrelated knowledge (Boschma 2017). Thus, this thesis showcases that the diffusion of radical innovations rather profits from knowledge relatedness to the overall knowledge base and thereby underlines the different mechanisms behind the emergence and diffusion dimensions.

However, other *regional context conditions* enhance both the *emergence* and *diffusion* dimensions of radical innovations. The present work shows that for knowledge to spill over between actors, the presence of related and unrelated capabilities in a region is fruitful since it is likely that new activities build on both related and unrelated capabilities (Boschma 2017). Additionally, the presence of both increases the number of possible new combinations (Sun and Liu 2016). Thus, this thesis argues that related and unrelated variety should not be seen as opposites but rather complement each other. Within the broader context of this dissertation, it is exposed that regional clusters not only provide preferable *regional context conditions* for the general innovativeness of firms (Porter 1998; Martin and Sunley 2003) but also for the emergence of radical innovations. Thus, the present thesis also contributes to cluster research with regard to radical innovations.

Furthermore, *R&D collaboration* as specific channel of inter-organisational learning constitutes an important building block of radical knowledge creation and diffusion in an innovation system. The present research shows that collaborations in general and between actors across different boundaries in particular drive radical knowledge creation.

In light of highly specialised and spatially concentrated knowledge, firms engage in collaborations in order to improve the quality of their inventions with the motive of creating radical innovations (Singh 2008).

First of all, collaborations between actors with different organisational backgrounds hold potential for the *emergence* of radical innovations. These actors can profit, for instance, from different approaches to find solutions for complex problems (Fleming and Sorenson 2004). While university-industry linkages are certainly important, this finding is not limited to this specific type of cooperation within the context of this thesis. Regarding collaborations between firms and universities the present work has underlined as secondary aspect that geographic distance has a positive effect, whereas increasing distance on the cognitive dimension has no significant effect. Hence, this thesis broadens the knowledge on specific collaboration conditions aiming at bringing forth radical novelty.

Knowledge spillovers between different industries are another important mechanism behind the *emergence* and *diffusion* of radical innovations. Recent research has also suggested that inter-sectoral linkages provide complementarity (Broekel and Brachert 2015) and several scholars have provided evidence that partnerships with actors from different industries can enhance the cross-fertilisation of ideas (e.g. Corradini and De Propris 2017; Montresor and Quatraro 2017).

Moreover, inter-regional linkages between actors can trigger new ideas and enhance the *emergence* and *diffusion* dimensions of radical innovations. As earlier research suggested, global pipelines can help to access complementary knowledge for new knowledge creation (Bathelt et al. 2004). Thereby, it can overcome situations of regional lock-in and increase the likelihood to generate radical innovations (Boschma 2005; Singh 2008; Miguelez and Moreno 2018). However, this thesis emphasises that at some point the efforts of coordinating an increasing amount of collaborations become greater than the benefits resulting from joint research. This is in line with earlier research (e.g. Broekel 2012). Additionally, the present work highlights that external-to-the-region linkages can compensate for missing unrelated capabilities in a region. Although both have a positive effect on the emergence of radical innovations, combining cognitively and geographically distant knowledge pieces might be too difficult to absorb for economic actors, as suggested by several scholars (Boschma 2005; Nooteboom et al. 2007). Hence, the present dissertation expands the mutual understanding of how relationships of actors

across regions drive the emergence and diffusion of radical innovations.

Furthermore, the work at hand emphasises that combining deep knowledge stemming from two industrial strongholds holds great potential for the *emergence* of radical innovations. This can be explained by the exchange of specialised knowledge through global pipelines, for which the positive effect regarding the prosperity of strongholds has been stressed earlier (Bathelt et al. 2004; Owen-Smith and Powell 2004). The cross-fertilisation between two industrial strongholds can be particularly effective if the collaboration partners engage in different industries or the regional clusters are located in different regions (Boschma 2005; Nooteboom et al. 2007). To sum up, Table 3 gives an overview of the main stylised facts within the analytical framework elaborated in section 2.

Table 3. Main stylised facts within the analytical framework.

	Emergence	Diffusion
Boundaries	• building bridges across boundaries enhances the emergence of radical innovations, particularly through: ○ cross-organisational, ○ cross-regional, ○ cross-sectoral, ○ cross-cluster linkages	• building bridges across boundaries enhances the diffusion of radical innovations, particularly through cross-regional linkages
Relations	• regional context conditions that favour the emergence of radical innovations are: ○ optimal cognitive proximity between innovating firm and regional frontier firms ○ presence of related and unrelated variety in the regional industrial structure ○ location in a regional cluster, particularly in periphery • R&D collaboration enhances the emergence of radical innovations, in particular: ○ with universities & research institutes ○ across industrial sectors ○ across regions ○ across regional clusters • these R&D collaborations can be supported by policy measures • external-to-the region linkages can supplement missing regional unrelated variety for the emergence of radical innovations	• regional context conditions that favour the diffusion of radical innovations are: ○ optimal cognitive proximity between innovating firm and regional knowledge base ○ presence of related and unrelated variety in the regional industrial structure • an optimal amount of R&D collaboration with actors from other regions increases the diffusion of radical innovations • external-to-the region linkages can supplement missing regional unrelated variety for the diffusion of radical innovations
Actors & institutions	• key players of the emergence of radical innovations are: ○ patenting firms with optimal technological diversity ○ technological frontier firms ○ firms in the cluster periphery • public agencies funding R&D support the emergence of radical innovations	• technologically diverse patenting firms enhance the diffusion of radical innovations

Radical innovations

6.2 Implications for future research

This dissertation has aimed to address drivers and mechanisms for the emergence and diffusion of radical innovations. For that, it has applied an innovation systems approach. The results of the present work show that there are multiple actors and relations amongst them across different boundaries that drive the emergence and diffusion of radical innovations. These driving forces can differ with regard to the processes that are integral for the emergence and the diffusion of radical innovations. Therefore, it is important to draw a more fine-grained picture of the processes that are at the heart of such innovations. This holds several implications for future research which are presented in individual paragraphs:

Further development of a set of indicators for the analysis of radical innovations

The horizontal dimension of the analytical framework can be studied further. So far, empirical studies in (evolutionary) economic geography have focused on the impact dimension, when investigating radical innovations (Castaldi et al. 2015; Miguelez and Moreno 2018). However, the results of this dissertation suggest that it is important to incorporate the emergence dimension as well, since the mechanisms driving radical innovation may differ between the two. This thesis has used the first-time combination of technology subclasses as the indicator for the emergence of radical innovations. While this certainly introduces radical novelty, a patent with several novel combinations might yield even more radicality (Arts 2012).

Alternatively, the emergence dimension could be sub-divided even further, following Strumsky and Lobo (2015), who distinguish between four indicators (see section 4.1). This could provide more insights into the driving forces behind the emergence dimension of radical innovation. Besides sub-dividing possible indicators, the application of measures from other fields could be fruitful. For instance, social network analysis, which has received increasing attention in the realm of economic geography, could be used to study path-breaking processes and the emergence of new technological trajectories (Momeni and Rost 2016). Furthermore, the use of machine learning techniques holds new opportunities. For example, radical innovations could be detected through textual analysis of patent documents (Kelly et al. 2018).

Regarding the diffusion dimension, this dissertation has used forward citations, thereby including self-citations because these have been suggested to be more valuable than citations by external patents (Hall et al. 2005). However, it could be interesting to investigate whether external citations differ in their structure. Further research could take another step in this direction and distinguish between regional, national and international citations to shed light on the question of how radically new knowledge diffuses on different regional scales, building on the work of Phene et al. (2006) (see section 4.1). This could also answer the question of whether new knowledge based on related competences really diffuses faster in Germany because of risk-aversion (Wüstenhagen and Teppo 2006; Hauschildt and Salomo 2007). Finally, this work has used patent data to study radical innovations. Particularly, it has focused on technological knowledge combinations to detect the emergence of radical novelty. Alternatively, future research could use semantic patent analysis instead (Gerken and Moehrle 2012). Even though patent data provides rich information on the innovation process, it has several well-discussed drawbacks (see e.g. Griliches 1990). Hence, future studies could tackle the analysis using other data (e.g. product data or trademarks) retrieved from surveys or websites via web scraping.

The role of the state in the emergence and diffusion of radical innovations

Furthermore, future studies could scrutinize further the role of policy measures within innovation systems with regard to radical innovations. This dissertation has shown that public funding enhances the emergence of radical innovation. Access to private R&D investment data could determine the input additionality of the public subsidy (Beck et al. 2016). By having access to panel data, future research could analyse firms before and after the treatment (Sadraoui and Zina 2009). This would allow a more dynamic perspective, as already discussed in the previous paragraph. Especially with regard to European countries, not only national funding plays an important role, but European funding schemes are also important. Hence, future research could assess the role of public R&D funding on an international scope given the fact that new knowledge for radically new ideas in particular might be found beyond national borders (Bathelt et al. 2004; Aguiar and Gagnepain 2017). This could be done by looking at EU funding schemes (Scherngell and Barber 2009).

Moderating influence of other proximity factors on the emergence and diffusion of radical innovations

The relations dimension within the analytical framework can be addressed by future research in order to analyse regional context conditions further. Relatedness between economic actors has proven to be an important catalyst of innovation processes on the regional level. Several studies have shown that related competences drive technological change, economic competitiveness and diversification processes (Frenken et al. 2007; Boschma and Iammarino 2009; Neffke et al. 2011). However, until now these studies have just looked at the overall relatedness in a region but have been silent about the favourable conditions for the organisations that actually introduce radical novelty. Hence, more studies should use an organisational-level approach to analyse how economic actors actually profit from processes within the region in which they are embedded. With regard to the realm of (evolutionary) economic geography, the findings of the present dissertation suggest that not relatedness per se but being related to firms at the technological frontier is essential for the emergence of radical innovations. Hence, the results add to the relatedness concept (Boschma and Frenken 2010).

Further research could add more insights by incorporating other proximity dimensions, particularly more informal ones (Boschma 2005). For instance, it has been emphasised recently that regional openness can explain a significant amount of geographical variation concerning impactful innovations (Castaldi and Los 2017). This suggests that related scientific fields such as geographical psychology could complement research in (evolutionary) economic geography. Methodologies such as personality-based approaches may be better at capturing intangible indicators such as social norms, values and cultures (Obschonka 2017; Obschonka and Audretsch 2019). Furthermore, the cognitive proximity to specific actors outside a firm's region could be fertile ground for new insights. Miguelez and Moreno (2018) so far only suggested that overall relatedness of the external-to-the-region knowledge is important for radical innovation.

Dynamic approach to the driving forces of the emergence and diffusion of radical innovations

Moreover, the empirical approach in this dissertation has been static. However, interactive learning within innovation systems is a dynamic process (Balland et al. 2020). Thus, the present work has left space for future research to investigate the driving forces of radical innovations from a dynamic perspective. Adding a dynamic perspective could

be interesting since unrelated domains become related as soon as they are combined for the first time (Castaldi et al. 2015). Hence, for instance, the change in the relatedness structure of the region or between firms could be analysed. With regard to the dynamic perspective, it could be worthwhile to incorporate the industry life-cycle approach (Klepper 1997), as there might be differences depending on the stage of the industry. Earlier research has already shown that radical innovation rather builds on technologies in an emerging stage (Campbell and Nieves 1979; Ahuja and Lampert 2001). Regarding the role of clusters for the emergence of radical innovations it would be interesting to integrate the cluster-life-cycle approach (Menzel and Fornahl 2010).

The role of radical innovation in catching-up processes of lagging regions

The innovation approach can also be applied to system building in lagging regions (Lundvall 2007a). Thus, future research could deal with the question of how lagging or peripheral regions can catch-up to their prospering counterexamples. For instance, empirical studies could scrutinize the role of collaborations between peripheral and central regions for the production of radical innovations. Recent research has found that collaborations with leading regions help peripheral regions to adopt new technologies faster (Barzotto et al. 2019) and that the integration of external knowledge can lead to new industrial path-creation (Isaksen and Trippl 2017). Additionally, it has been suggested that extra-regional collaborations with advanced regions hold more benefits (enhancing knowledge capabilities and capacities) for lagging regions than for the former ones (De Noni et al. 2018). Also, it has been found that innovative firms are able to compensate for a poor regional knowledge environment with extra-regional collaborations (Grillitsch and Nilsson 2015).

Nonetheless, it remains unclear whether organisations in peripheral regions benefit from the exchange of knowledge (catching-up), or rather the actors in central regions (exploitation) or even both (win-win). A cluster perspective could be added to this investigation. In this regard, it has been proposed that small clusters with a poor knowledge base can improve their performance through external linkages (Morrison et al. 2013). Moreover, this question could be tackled on a national (inter-regional collaborations) or an international (inter-national collaborations) scope. Furthermore, future research could investigate whether the funding of cross-innovation activities as suggested in this dissertation could also be used for the acceleration of catching-up processes of lagging regions.

Table 4 gives an overview of the potential future research endeavours presented in this section, with regard to focus and possible approaches within the analytical framework of the present work.

Table 4. Potential future research endeavours within the analytical framework.

Focus	Approach
Horizontal dimension (indicators for radical innovations)	• sub-dividing the emergence of radical innovations (Strumsky and Lobo 2015) • social network analysis (Momeni and Rost 2016) • text-based analysis (Kelly et al. 2018; Moehrle and Gerken 2012) • different data usage (e.g. products, trademarks)
Actors & institutions	• input additionality (Beck et al., 2016) • dynamic approach (Sadraoui and Zina 2009) • international scope (Scherngell and Barber 2009)
Relations	• interplay with other proximity dimensions (Boschma 2005), especially informal dimension (Castaldi and Los 2017) • relatedness to specific actors outside the region (Miguelez and Moreno 2018)
Dynamic perspective	• industry life-cycle (Klepper 1997) • cluster-life-cycle (Menzel and Fornahl 2010)
Catching-up processes	• inter-regional collaboration (Barzotto et al. 2019) • trans-national collaboration (De Noni et al. 2018) • supra-regional collaborations of clusters (Morrison et al. 2013) • policy-induced collaboration (Isaksen and Trippl 2017)

6.3 Policy and managerial implications

While the previous section has presented potential future research endeavours, the following will derive practical ramifications from the findings of this dissertation. The findings provide insights for innovation policy more generally and are of particular interest for policy makers aiming to support radical innovation. They show that public R&D support in general and collaborative research project grants in particular can enhance the emergence of radical innovation. Also, it shows that policy-induced cross-innovation activities can support radical innovation output. Therefore, they provide implications that can help to design measures for innovation agencies such as the German SprinD or the European JEDI. Table 5 provides an overview of the derived policy and managerial implications.

First of all, such agencies should monitor radical innovation processes with regard to the emergence and the diffusion, since the mechanisms driving radical innovation may differ between the two. Then, they could set up public research grants that include criteria to induce cross-innovation activities through different channels (organisational, industrial and regional).

This can be done through linking different organisation types and funding collaboration between actors from different industries or regions. Particularly, research grants could include criteria that make it mandatory to have research consortia with partners from different organisational backgrounds. Additionally, cross-regional research activities could be pursued particularly in regions without unrelated competences. Another criterion could be that collaboration partners should engage in different industries. Thereby, policy makers could take into account the relatedness structure of economic actors in order to increase the likelihood of generating radical innovations. Hence, based on technology profiles, they could monitor the relatedness of partners applying for collaborative research grants and make some degree of cognitive distance a requirement for partner selection in collaborative R&D projects. However, these criteria should not be applied all at the same time, since this would be too much for an effective flow of knowledge.

Moreover, innovation agencies could increase funding of supra-regional collaborations via cluster funding. In particular, policies such as the funding measure 'Internationalisation of Leading-Edge Clusters, Forward-Looking Projects and Comparable Networks' (InterClust), attempting to connect innovative places, could be expanded (Dohse et al. 2018). This could help to build bridges between industrial strongholds.

In particular the above-mentioned relatedness criterion could be used to refine the relatedness concept within the smart specialisation framework. Within this framework, policy makers target regional development from the European level (EU Commission 2012; Foray 2014; McCann and Ortega-Argilés 2014). Regions have been urged to identify diversification opportunities based on their specific strengths. The insights of this thesis can help to refine these strategies with regard to radical innovation. For that, regions could encourage collaborations that include the above-mentioned criteria to enhance cross-fertilisation of ideas. Missing regional capabilities could be compensated by promoting cross-regional cooperation to gain access to new knowledge.

Furthermore, the findings of the present work have some interesting implications for managers. Firms aiming to explore radical novelty should diversify their capabilities at least to a certain degree in order to enhance their ability to successfully engage in such processes. Then, firms could incorporate regional knowledge compositions as a factor in their location decisions. After developing technology profiles, they could identify the relatedness of their knowledge portfolio to frontier firms in the region and to the region

as a whole. With regard to the emergence of radical innovations, knowledge exchange with related actors at the technological frontier in the region should be pursued. Regarding the diffusion of radical novelty, cognitive similarity to the overall regional knowledge portfolio should be stressed. Moreover, R&D project development could pursue the selection of partners with different organisational backgrounds. Firms located in a cluster could aim to build bridges to firms in other industrial strongholds. Finally, firms could engage in cross-innovation activities on their own account or apply for research grants that support the engagement in such activities.

Table 5. Policy and managerial implications.

Dimensions	Policy implications	Managerial implications
Indicators	focus on emergence and diffusion	-
R&D consortia	mandatory research consortia with firms and universities and/or research institutes	develop R&D projects with universities and research institutes
Knowledge relatedness	criterion that collaboration partners need to have a certain cognitive distance if they come from the same region	collaboration with related actors at the technological frontier in the region to produce with radical novelty
Region	criterion that collaboration partners have to be from different regions	incorporate regional knowledge compositions in location decisions
Cluster	funding of supra-regional collaborations via cluster funding	develop R&D projects with partners from other innovative places

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Appendix A: Declaration on the author's contribution

The following table gives an overview of the contributions of the author of this dissertation in the individual publications. No. 1-3 comprises the core publications, No. 4-5 refers to the other publications that are not part of the core of this dissertation.

No.	Publication	Share	Contribution
1	Related to whom? The impact of relatedness to regional frontier firms on radical innovations	100%	• Single authorship
2	Essential ingredients for radical innovations? The role of (un-)related variety and external linkages in Germany	90%	• Conceptualisation • Theory development • Methodology • Data collection and cleansing • Empirical analysis • Writing (Original draft, Review & Editing) • Visualisation • Interpretation of results • Correspondence author
3	Unlocking the radical potential of German innovators – How can R&D policy foster radical innovation?	100%	• Single authorship
4	Radical or not? The role of clusters in the emergence of radical innovations	45%	• Joint conceptualisation • Theory development with focus on radical innovations • Methodology with focus on radical innovations • Joint data collection and cleansing • Joint empirical analysis • Joint writing (Original draft, Review & Editing) • Joint visualisation • Joint interpretation of results
5	University-industry linkages – the key to radical innovations?	35%	• Joint conceptualisation • Theory development with focus on radical innovations • Methodology with focus on radical innovations and cognitive proximity • Joint data collection and cleansing • Joint empirical analysis • Joint writing (Original draft, Review & Editing) • Joint visualisation • Joint interpretation of results • Correspondence author

Appendix B: Core Papers

Paper 1

Hesse, K. (2020). Related to whom? The impact of relatedness to regional frontier firms on radical innovations. *Bremen Papers on Economics & Innovation (# 2005).* (submitted to *Small Business Economics*).

Paper 2

Hesse, K., & Fornahl, D. (2020). Essential ingredients for radical innovations? The role of (un-)related variety and external linkages in Germany. *Papers in Regional Science*. DOI: www.doi.org/10.1111/pirs.12527.

Paper 3

Hesse, K. (2020). Unlocking the radical potential of German innovators – How can R&D policy foster radical innovation? *Lund University, CIRCLE-Center for Innovation, Research and Competences in the Learning Economy (No. 2020/5).* (submitted to *Research Policy*).

Related to whom? The impact of relatedness to regional frontier firms on radical innovations

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Abstract

This paper aims to explain the emergence and diffusion of novel combinations in Germany. On the one hand, it scrutinizes on the effect of internal technological diversity. On the other hand, it looks at interactions with other actors and assesses whether relatedness to the overall regional knowledge base or rather being related to specific regional actors improves radical inventive activity in German organisations. It is demonstrated that the emergence of radical novelty is positively influenced by an optimal degree of internal diversity as well as relatedness to actors at the technological frontier. However, for this radical novelty to diffuse, rather diverse actors and relatedness to the regional knowledge base is important. The results call for a more fine-grained picture in the relatedness debate and deliver interesting insights for inventive organisations in terms of partner choice and policy-makers for future initiatives.

Keywords: relatedness, cognitive proximity, technological diversity, emergence, diffusion, radical innovations

JEL codes: O31, O33, R11

1 Introduction

Recently, relatedness has become a popular concept amongst scholars and policy makers. A number of studies have highlighted the importance of the relatedness of technologies for technological change, economic competitiveness and diversification processes (Frenken et al. 2007; Boschma and Iammarino 2009; Castaldi et al. 2015). This has led to an increasing amount of studies aiming at incorporating the notion of relatedness in regional innovation policy concepts (Asheim et al. 2011; Boschma 2014; Balland et al. 2019). Simultaneously, the concept has been applied by policy makers to target regional development in European regions (EU Commission 2012; Foray 2014; McCann and Ortega-Argilés 2014). Moreover, there is increasing interest by policy makers to seize the potential of radical innovations which offer great economic potential (Ahuja and Lampert 2001; Castaldi et al. 2015).

However, the above-mentioned investigations focus on the overall relatedness structure in a region so far to explain why regions differ in their innovative capabilities. Thus, we lack information on the characteristics of the organisations that actually introduce novelty. Is it by itself rather specialized or diversified? And even more, how is its knowledge structure compared to the regional knowledge base? Does its cognitive proximity to certain key players in the region play a significant role?

This paper aims to shed light on these issues, thereby focusing on radical innovation processes. In doing so, it has four main objectives. The first objective is to assess how the technological diversity of an organisation improves the ability to generate radical innovations. Although there have been many studies on the impact of technological diversity on innovation output in general (e.g. Garcia-Vega 2006; Leten et al. 2007), empirical evidence on how technological diversity shapes radical innovation output is scarce (Fleming 2002).

The second goal is to estimate which role the similarity between the technology portfolio of the specific organisation and the technological knowledge base of the region, where it is located plays. For instance, Boschma and Frenken (2010) propose that a positive result concerning the successful exchange of knowledge and performance depends on the (optimal) level of cognitive proximity between partners in a network. However, although there are studies showing that an optimal degree of cognitive proximity to other actors enhances innovation performance (e.g., Fornahl et al. 2011), to the knowledge of the

author there exists no investigation on the relation between the organisations' knowledge base and the regional knowledge portfolio as a whole and how this influences the ability of economic agents to come up with radical novelty.

The third aim is to scrutinize whether the overall cognitive proximity is relevant, or rather the knowledge similarity to specific actors in the regional knowledge base. Earlier research has found that cognitive proximity to actors at the technological frontier enhances the ability to focus on new and emerging technology domains (Sørensen and Stuart 2000). Moreover, relatedness to other innovating institutions can facilitate the knowledge exchange (Almeida and Kogut 1997). Nonetheless, research is silent so far about the role of relatedness to industry leaders in the region in order to engage successfully in radical innovation processes.

Finally, this study investigates radical innovations from two perspectives, namely emergence and diffusion. The aim is to detect possible differences in the mechanisms that enhance the emergence of novel combinations and their diffusion. Most studies until now only focus on the diffusion perspective, when explaining differences of economic agents in the ability to produce radical innovations (e.g., Castaldi et al. 2015).

The paper is structured as follows: Section 2, provides the theoretical foundation, starting with the relatedness concept and then describing a number of potential drivers of radical innovations of organisations. Section 3 provides, the description of the employed databases and the construction of the variables. The applied methodology is presented in Section 4, followed by a discussion of the main findings. The final section concludes.

2 Theoretical background

In evolutionary thinking, organisations are constantly competing based on routines, which are built over time (Nelson and Winter 1982). Thereby, they are in continuous search for novelty and competitive advantage (Boschma and Frenken 2006; Kogler 2015). (Technological) knowledge relatedness between economic actors has proven to be an important catalyst of such search processes on the regional level. Several studies have shown that related competences drive technological change, economic competitiveness and diversification processes (Frenken et al. 2007; Boschma and Iammarino 2009; Neffke et al. 2011). Content and Frenken (2016) provide a comprehensive review of these studies. Investigations on the role of unrelated competences in these processes have provided mixed results so far (Bishop and Gripaios 2010; Boschma et al. 2012), but have

highlighted that they enhance the generation of technological breakthroughs (Castaldi et al. 2015; Miguelez and Moreno 2018). However, these papers are silent about the organisational level characteristics of the specific agents introducing radical novelty to the region they are active in. Furthermore, they do not pay attention to the role of cognitive proximity to the regional knowledge base and to distinctive actors within the region.

Inventions introducing radical novelty combine previously unconnected knowledge domains, which is accompanied by high uncertainty and risk (Fleming 2001). The search processes that pursue these kinds of inventions particularly are extensive and of explorative nature (March 1991). However, if these inventions turn out to be successful, they can cause a paradigm shift and thus radical change (Dosi 1982; Verhoeven et al. 2016). This can cause the disruption of old markets and the formation of new ones (Tushman and Anderson 1986). Thus, radical innovations hold great economic potential (Ahuja and Lampert 2001; Castaldi et al. 2015). Consequently, radical innovations are acknowledged to be a driver of technological, industrial and societal change (Schoenmakers and Duysters 2010). Recent empirical studies have used patent-based indicators to investigate radical innovations mostly focusing on forward and backward citations (e.g. Ahuja and Lampert 2001; Schoenmakers and Duysters 2010). Following the concept of recombinant novelty (Weitzman 1998) several scholars have also used novel combinations of technology domains on patents to detect radical innovations (Fleming 2007; Verhoeven et al 2016). This study applies two dimensions to shed light on the drivers behind the emergence and the diffusion of radical innovations.

To successfully search for such novel combinations, an organisation has to develop certain skills which cumulate to the organisation's knowledge base (Boschma and Frenken 2006). This can be achieved through internal R&D, which increases an organisations' diversity and absorptive capacity (Cohen and Levinthal 1990), and by collaborative R&D with other actors (Balland et al. 2015). More diverse organisational knowledge bases that include multiple technologies have better problem-solving competences and are able to conduct extensive search activities (Nelson and Winter 1982; Dosi 1988). A broad technological base also helps to search for complementarities and novel combinations (Quintana-García and Benavides-Velasco 2008). Organisations that build up knowledge in several areas create the potential for cross-fertilisation, which may lead to new inventions and functionalities or to increased product and process

performance (Granstrand 1998; Leten at al. 2007). Closely associated with this a diverse technology base yields the potential to combine former unconnected knowledge from different technology fields (Fleming 2001; Nerkar 2003). Several studies have found empirical evidence for the positive impact of technological diversity on innovativeness and survival of firms (Breschi et al. 2003; Nesta and Saviotti 2005; Garcia-Vega 2006).

However, technological diversification comes at a cost. First, it may keep organisations from strengthening capabilities in specific technological fields which can ensure economies of scale in these areas (Leten et al. 2007). Second, a diversified technological portfolio entails greater coordination and communication expenses (Granstrand 1998). These efforts may increase in particular when organisations try to combine new, emerging technologies with mature technologies which represent their core area of expertise (Leten et al. 2007). High levels of technological diversity may hamper the organisation's aim to balance exploitation and exploration (March 1991). Moreover, especially with regard to processes introducing radical novelty it seems likely that technological diversity may become too costly at some point since they demand large investments in R&D and also are accompanied with higher risks and uncertainty (Fleming 2001; Strumsky and Lobo 2015). Furthermore, Van den Bergh (2008) also proposes an optimal degree of diversity to avoid an organisational lock-in. Accordingly, previous studies have found support for this non-linear relationship between an organisation's technological diversity and its performance (Leten et al. 2007; Palich et al. 2000). Hence, this suggests that there is an optimal level of an organisation's technological diversity in order to increase the ability to come up with radical novelty as well as their subsequent diffusion.

Accordingly, this leads to the following hypotheses:

> Hypothesis 1a: Technological diversity of an organisation has an inverted u-shape relation to the emergence of radical innovations.
>
> Hypothesis 1b: Technological diversity of an organisation has an inverted u-shape relation to the diffusion of radical innovations.

Especially in knowledge-based economies, an organisation needs access to the most recent scientific and technical knowledge to innovate successfully (Fornahl et al. 2011). For that, they also look beyond their boundaries to gain external knowledge (Rigby and Zook 2002). Access to external knowledge is essential to complement their own knowledge for innovation activities (Powell et al. 1996). Besides direct links to

collaboration partners, organisations are also embedded in a broader social context and regional systems of innovation (Boschma 2005). This embeddedness in a regional knowledge network has increasingly been recognized as an important determinant of their innovative performance (Uzzi 1996; Cantner and Graf 2004). Actors in the same region profit from local knowledge flows which are facilitated by face-to-face contacts on a regular basis and the exchange of tacit knowledge (Gertler 2003). Earlier research has indicated that regional knowledge networks provide important inputs to the innovative process (Almeida and Kogut 1997) and the interaction with other organisations in a region is found to be a crucial factor to combine unconnected knowledge pieces (Fleming 2001). However, to be able to absorb different knowledge from other actors, organisations need to be related to each other in terms of their knowledge to a certain extent (Cohen and Levinthal 1990). Building on the concept of technological distance from Nooteboom (2000) two actors are considered to be related when their expertise derived from a common, underlying knowledge base and their development requires similar competencies and skills (Boschma and Iammarino 2009). Actors (individuals, organisations) with technologically related knowledge bases learn from each other more efficient than those whose knowledge bases do not overlap. At the same time, some degree of cognitive distance is important so that actors can profit from new knowledge spilling over from other actors (Nooteboom et al. 2007).

Following this principle, it is expected that the inventive organisation needs an optimal degree of cognitive similarity to the region where it is located in order to benefit from the knowledge accumulated in the region's knowledge base. First, the innovative organisation needs some cognitive distance to access complementary knowledge for novel combinations while at the same time it needs to be related to the regional knowledge base so it can absorb this external knowledge (Boschma and Frenken 2010). Second, a certain degree of cognitive proximity can help with the effective diffusion of new inventions as related competences induce spillovers and ensure that other actors are able to absorb knowledge stemming from unrelated areas (Asheim et al 2011). Following this reasoning, an optimal degree of cognitive proximity to the regional knowledge base should enhance both the output of novel combinations and its diffusion.

Thus, the following hypotheses are proposed:

Hypothesis 2a: Cognitive proximity between an organisation and the region has an inverted u-shape relation to the emergence of radical innovations.

Hypothesis 2b: Cognitive proximity between an organisation and the region has an inverted u-shape relation to the diffusion of radical innovations.

However, maybe it is rather not the relatedness to the overall regional knowledge portfolio but the cognitive relation to specific actors in the region that is important in order to enhance the radical inventive activity of organisations. In particular, organisations may need to be related to other radically innovating organisations. Actors engaging in radical inventive processes tend to be at the technological frontier of their area of expertise, as being at the technological frontier enhances the ability to focus on new and emerging technology domains (Sørensen and Stuart 2000). Hence, organisations might also gain access to complementary knowledge for the introduction of radical novelty and potentially can reduce uncertainty in the search process. Moreover, cognitive proximity to other innovating institutions can create a geographic space where knowledge can be exchanged more rapidly and efficiently (Almeida and Kogut 1997). On the other hand, the cognitive proximity to these actors at the technological frontier should not be too close so there is enough potential to exchange new knowledge (Nooteboom et al. 2007).

Assuming that organisation A is at the technological frontier in electrical engineering and also is active in mechanical engineering while organisation B is engaging in electrical engineering and chemistry. The common activity would ensure that both organisations can communicate efficiently. In their search for external knowledge organisation B gathers information about other actors, especially the ones at the technological frontier and may be able to access knowledge from mechanical engineering through the efficient communication channels to make use of it in chemistry, where it has not been applied yet. Thereby, it combines complementary, unconnected knowledge pieces. In turn, organisation A could assimilate this new knowledge and enter new activities thus accelerating the diffusion of organisation B's new invention. Indeed, radical innovations often produce positive externalities through spillovers, from which other organisations benefit by introducing follow-on innovations (Colombo et al. 2015). Furthermore, as engaging in radical innovation processes involves high uncertainty (Fleming 2001) it may

be fruitful for competing organisations to use similar capabilities for the commercialisation of radical new inventions (Ritala and Sainio 2014). Accordingly, an optimal level of cognitive proximity to organisations at the technological frontier may enhance novel combinations and its diffusion. Consequently, the following hypotheses are tested:

> Hypothesis 3a: Cognitive proximity between an organisation and regional frontier firms takes an inverted u-shape relation to the emergence of radical innovations.
>
> Hypothesis 3b: Cognitive proximity between an organisation and regional frontier firms takes an inverted u-shape relation to the diffusion of radical innovations.

3 Empirical Background

3.1 Construction of the sample

The empirical analysis is conducted using several data sources. In particular, organisation-level information from the ORBIS database and information on inventive activity from the PATSTAT database (Version 2019) are combined to construct a unique data set of actively patenting organisations in Germany between 2010 and 2012. ORBIS database by Bureau von Djik (BvD) provides extensive information on organisations such as year of establishment and employment data. PATSTAT offers extensive and detailed information on inventory processes such as date, applicant and technology. In addition, this information is provided over a long time. However, the shortcomings of patent data are acknowledged. For instance, not all inventors seek to file a patent (for different reasons) and some inventions are not patentable at all (see e.g., Griliches (1990) for a discussion on imperfections of patent data). The final sample consists of 10,779 innovating organisations. Table 4 in the appendix reports the regional distribution.

3.2 Construction of variables

This study includes two dependent variables to detect possible differences in the emergence and diffusion of radical novelty. First, the emergence of radical innovations is approximated by entirely new combinations of technology domains (Grashof et al. 2019; Verhoeven et al. 2016). This is based on Fleming's (2001) argument that radical innovations stem from former uncombined knowledge domains. For this, all four-digit

International Patent Classification (IPC) codes[16] present on patent filings in the years 2010-2012 are identified and compared with a sample of all registered IPC combinations in Germany between 1981 and one year before the focal year. Thus, a new combination is radical in the sense that it is completely new to Germany (since 1981). Radicalness is characterised through the entirely new combination of two knowledge pieces, even though these new combinations do not necessarily cause a paradigm shift (Arant et al. 2019). Then, the variable is summed for each organisation in the dataset resulting in the first dependent variable (new_dyad).

Second, the diffusion of these new combinations is studied by counting the forward citations the patent including the new dyad received in the subsequent five years after it has been filed.[17] Several scholars have argued that forward citations are a good indicator to measure the diffusion of new inventions (Albert et al. 1991; Dahlin and Behrens 2005; Trajtenberg 1990). Self-citations are included as these may be more valuable than citations by external patents (Hall et al. 2005). Subsequently, the mean number of citations received to the focal patents is calculated to get a count variable on the organisation level (cit_new_dyad_mean). The regional distribution of the share of the dependent variables is shown in Table 5 in the appendix.

To assess the mechanisms shaping an organisation's ability to generate radical innovations, several explanatory variables are constructed:

First, to measure technological diversity of the organisation's technology portfolio the Herfindahl index of diversification is used (Berry 1975). This measure is derived from the Herfindahl-Hirschman Index (HHI), which is often used to estimate industry concentration but has become commonly accepted to measure technological diversification as well (e.g., Garcia-Vega 2006; Leten et al. 2007; Quintana-Garcia and Benavides-Velasco 2008).[18]

[16] This aggregation level is used to have a sufficiently large number of patents in the classes and a maximal number of technologies.
[17] For sensitivity purposes, a three-year window was also used, which produced similar results. However, the author thinks that a longer time window is more appropriate especially since the diffusion of radical novelty is expected to take more time. Unfortunately, an even longer period cannot be used due to time lag of the patent filing, the disclosure of filing information by the patent office, and data processing by the database provider.
[18] For a discussion on different diversity indicators, see e.g., Guevara et al. (2016).

The Herfindahl index of diversification is constructed as the inverse of the HHI and can be expressed as follows:

$$Tech\_diversity = 1 - HHI = 1 - \sum_i p_i^2$$

where p_i denotes the proportion of activities in an organisation in technical field i. The index equals zero when an organisation is active only in a single technology, and it is close to one when the organisation spreads its activities over a broad technological knowledge base. This measure has the advantage that it is independent from changes in the distribution of activities of other organisations and solely focuses on the distribution of a specific organisation (Rao et al. 2004). Moreover, less significant activities in the technology portfolio receive less weight in the calculation (Quintana-Garcia and Benavides-Velasco 2008).

To build the diversity indicator, information on inventive activity (applicant-based) of all organisations in the dataset between 1995 and 2009 are retrieved from PATSTAT to construct organisation-specific technology vectors. IPC codes appearing on the patents are shortened to the four-digit level and transformed into 35 technology fields (Schmoch 2008).[19] Hence, the vector indicates in which technological fields each organisation is active. Finally, these organisation-specific technology portfolios are used to calculate the diversity indicator (tech_diversity).

Second, the study's aim is to analyse the influence of the cognitive similarity between the technological knowledge base of an organisation and its corresponding region. Hence, in a first step the organisation's addresses are used to assign them to 141 German labour market regions as defined by Kosfeld and Werner (2012).[20] This definition is used so that commuter and urban-periphery structures are unlikely to bias the results. Then, similar to the organisation's technology portfolios, the patenting activity (inventor-based) in up to 35 technology fields of each German labour market region between 1995 and 2009 is used to calculate region-specific technology vectors (again retrieved from PATSTAT). Thus, the vectors show the regional technological knowledge portfolios. After that, to be able to compare the organisation-specific technology portfolio to the region-specific technology competences, the individual organisation's activities are removed from the

[19] For a full list see: https://www.wipo.int/export/sites/www/ipstats/en/statistics/patents/pdf/wipo_ipc_technology.pdf.
[20] A list with all labour market regions is provided in Table 5 in the appendix.

regional technology knowledge base. Otherwise, the knowledge base of the organisation would be partly compared to itself, which would give a distorted picture. Finally, the cognitive proximity between each organisation and its corresponding region is calculated using the cosine index. Following Ejermo (2003), the cosine index can be 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 technology fields and i, j, k being the indicators of the technology fields that are considered. The index can take a value between 0 and 1, where 1 signifies perfect similarity between the organisation's and the region's technology portfolio (sim_org_reg).

Third, a measure for the cognitive proximity to local actors at the technological frontier is needed. Here, the approach by Breschi et al. (2003) is followed to measure the relatedness of the technology profiles of two actors based on the above described technology vectors. Next, the similarity of the 35 technology fields is constructed. This measure is based on the number of the technology fields' co-occurrences between 1982 and 2013. Similar to Ejermo (2003) and Breschi et al. (2003), indirect associations are also accounted for to get a cosine index for the co-occurrence of technology fields (see above). Based on this similarity index a matrix M is constructed, linking the portfolio of organisation A to the one of organisation B, which provides the similarity values of each technology field pair. Afterwards, the actors at the technological frontier in each labour market region have to be identified. We define these as the organisations with the highest share of new dyads between 2010 and 2012, in particular the TOP 1 % of radically innovating organisations.[21] Then, the similarity values between each organisation in the dataset and the radical leaders, which are located in the same labour market region are calculated. Thereby, it is made sure that if an organisation in the sample is a radical leader, the distance to itself is not included in the measurement. Finally, the mean value is taken as similarity index as potentially there are several frontier firms in the region (sim_mean_rad). The index ranges from 0 to 1 as well, with 1 representing perfect similarity.

[21] For sensitivity purposes the same measure was calculated with the TOP 3 and TOP 10 % radical inventors, which did not change the results.

Moreover, several variables are included to control for organisation-specific effects which are retrieved from the ORBIS database. In particular, age, size and patent stock are considered. The former represents the age (years since foundation) in 2012 (age). The age of organisations founded in 2012 is set to a value of one. The size of the organisations is measured by the average number of employees between 2008 and 2012 (size). The patent stock is calculated as the average number of patents in the years 2007-2009 to control for possible outlier years (patent_stock).

Furthermore, to control for industry-specific effects a research-intensive industry dummy is added, which takes the value of 1 if the organisation is active in a research-intensive industry and 0 otherwise based on corresponding NACE codes (Gehrke et al. 2013).[22] Additional regional effects are controlled for by taking the number of employees with an academic career in year 2009 in each labour market region into account (academics), which is based on IAB employment data. The descriptive statistics and correlations of the above-mentioned variables are reported in Tables 1 and 2.

4 Explaining the emergence and diffusion of radical novelty

4.1 Method

The data in this paper is cross-sectional and pooled with organisations as object of investigation. Both dependent variables represent count variables, which suffer from over-dispersion. The sample variance of "new_dyad" and "cit_new_dyad_mean" are 46, respectively 10 times the sample mean. Also, the likelihood ratio test speaks in favour of the negative binomial model. Hence, negative binomial regression models are fitted to test the proposed hypotheses.

As can be seen in Table 2, the explanatory variables correlate only slightly with each other. Except for the dummy variable all the control variables are log-transformed in the estimations because of skewness.

[22] NACE codes refer to the statistical classification of economic activities in the European Community. A full list 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).

Table 1. Descriptive statistics.

	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
new_dyad	10,779	0.26	3.47	0	0	0	281
cit_new_dyad_mean	10,779	0.18	1.34	0	0	0	36
tech_diversity	6,698	0.35	0.26	0.00	0.00	0.55	0.95
sim_org_reg	6,600	0.21	0.17	0.003	0.10	0.28	0.98
sim_mean_rad	10,111	0.35	0.07	0.01	0.31	0.39	1.00
age	10,248	30.37	34.92	1.00	9.00	37.00	556.00
size	8,580	809.57	10,610.10	1.00	16.00	220.00	437,905.60
patent_stock	5,599	31.79	323.40	0.33	0.67	9.00	12,230.33
academics	10,779	53,444.21	60,052.46	728	11,858	61,164	210,937

Table 2. Correlation table.

	new_dyad	cit_new_dyad_mean	tech_diversity	sim_org_reg	sim_mean_rad	age	size	patent_stock
new_dyad	1							
cit_new_dyad_mean	0.41***	1						
tech_diversity	0	0	1					
sim_org_reg	0.06***	0.08***	-0.03**	1				
sim_mean_rad	-0.04***	-0.05***	0	-0.18***	1			
age	0.03**	0.05***	-0.05***	0.03*	0.05***	1		
size	0.10***	0.07***	0	0.02	-0.02	0.03**	1	
patent_stock	0.32***	0.19***	-0.02	0.16***	-0.06***	0.06***	0.19***	1
academics	0.12***	0.03**	0	-0.07***	-0.17***	-0.09***	0.03**	0.11***

A significance level of 0.1 is indicated by "*", a level of 0.05 corresponds to "**" and "***" indicates a significance level of 0.01.

Table 6: Negative binomial regression results.

	Dependent variable:							
	new_dyad	cit_new_dyad_mean	new_dyad	cit_new_dyad_mean	new_dyad	cit_new_dyad_mean	new_dyad	cit_new_dyad_mean
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
tech_diversity			2.661***	-1.700	2.073**	-1.837*	2.708***	-1.743
			(0.917)	(1.035)	(0.922)	(1.088)	(0.963)	(1.193)
tech_diversity^2			-3.741***	3.100**	-3.370***	3.260**	-3.813***	3.418**
			(1.258)	(1.418)	(1.299)	(1.492)	(1.352)	(1.633)
sim_org_reg					-1.609	3.416**	-0.767	4.224**
					(1.354)	(1.575)	(1.427)	(1.757)
sim_org_reg^2					2.422	-2.816	1.795	-3.339
					(1.841)	(2.110)	(1.917)	(2.340)
sim_mean_rad							17.685**	2.376
							(7.040)	(7.053)
sim_mean_rad^2							-23.688**	-4.569
							(9.241)	(9.067)
log(age)	-0.253***	-0.289***	-0.382***	-0.266***	-0.315***	-0.308***	-0.401***	-0.355***
	(0.087)	(0.099)	(0.087)	(0.099)	(0.086)	(0.105)	(0.088)	(0.115)
log(size)	0.104**	0.276***	0.545***	0.287***	0.383***	0.308***	0.394***	0.317***
	(0.051)	(0.055)	(0.048)	(0.056)	(0.049)	(0.059)	(0.050)	(0.065)
log(patent_stock)	0.590***	0.680***	0.123**	0.670***	0.297***	0.672***	0.241***	0.667***
	(0.050)	(0.056)	(0.051)	(0.057)	(0.053)	(0.063)	(0.054)	(0.069)
Research-intensive industry dummy	-0.078	0.105	0.031	0.131	0.083	0.149	0.320**	0.232
	(0.157)	(0.177)	(0.159)	(0.178)	(0.156)	(0.187)	(0.160)	(0.204)
log(academics)	0.156**	-0.034	0.256***	-0.049	0.163**	-0.046	0.373***	-0.004
	(0.066)	(0.074)	(0.066)	(0.075)	(0.067)	(0.080)	(0.073)	(0.092)
Constant	-3.553***	-3.300***	-5.801***	-3.291***	-4.592***	-3.845***	-10.288***	-4.717***
	(0.773)	(0.855)	(0.772)	(0.870)	(0.812)	(0.974)	(1.629)	(1.797)
Observations	4,765	4,765	4,753	4,753	4,669	4,669	4,457	4,457
Log Likelihood	-2,052.228	-1,547.618	-2,053.238	-1,544.477	-1,886.971	-1,441.329	-1,644.913	-1,277.042
theta	0.047*** (0.003)	0.048*** (0.004)	0.047*** (0.004)	0.048*** (0.004)	0.054*** (0.004)	0.045*** (0.004)	0.059*** (0.005)	0.039*** (0.004)
Akaike Inf. Crit.	4,116.456	3,107.235	4,122.476	3,104.953	3,793.942	2,902.657	3,313.826	2,578.084
Note:	*p<0.1; **p<0.05; ***p<0.01							

4.2 Results

Table 3 shows the results of the negative binomial regressions with new_dyad as dependent variable in Models 1a-4a and cit_new_dyad_mean in Models 1b-4b respectively. In Model 1a,b, the basic firm-specific features of the estimations together with the basic regional and industry variables are reported. Organisation size is positively significant throughout all the models which is suggested by earlier findings (Becker and Dietz 2004), while the age of organisations has a negative influence which is also in line with previous research (Shefer and Frenkel 1998). Similar to other empirical investigations, young innovative organisations are found to be key catalysts of the emergence and diffusion of radical innovations (e.g., Schneider and Veugelers 2010). Patent stock is also positively significant in all models, which seems obvious as the engagement in R&D activity in general and patenting activity in particular should enhance the possibility to create radical novelty. The research-intensive industry dummy is only significant in Model 3a, which may be explained by the effect of the similarity to actors at the technological frontier. Organisations at the technological frontier are likely to be active in research-intensive industries. The number of academics, which proxies the regional absorptive capacity, only seem to matter for the emergence of radical novelty, which is consistent throughout all models. Regional absorptive capacity may help organisations to detect potentials for combinations amongst unrelated areas and with the successful exchange of complementary knowledge needed for novel combinations.

Models 2a and b introduce technological variety in the organisation as explanatory variable. With regard to the emergence of novel combinations the variable takes an inverted u-shape relation. This is consistent in all the models and supports hypothesis 1a. Thus, an optimal level of technological variety inside the firm enhances the ability of organisations to produce novel combinations. While at first a broader technological diversity increases the potential to detect complementarities and novel combinations (Quintana-García and Benavides-Velasco 2008), at some point diversity becomes too costly in terms of coordination expenses risk (Granstrand 1998; Fleming 2001). Surprisingly, with regard to the diffusion of novel combinations the effect of technological diversity is different. Models 2b-4b rather point to an u-shaped relation, which would indicate that either specialisation or diversification of organisational competences enhances the possibility of diffusion. However, this effect is only significant in Model 3b. In the other models only the coefficient for the second-degree polynom of

the variable is significant, which points to a threshold effect so that technological diversity only enhances an organisation's ability to diffuse novel combinations when they are sufficiently diverse. Hence, no support for hypothesis 1b is found. Figure 1 illustrates the marginal effects of internal technological variety. While it shows the above-mentioned inverted u-shape relation with the number of novel combinations (see left graph), it indicates the u-shaped relation with regard to the subsequent citations, which is not significant for low values of technological variety (see right graph). The findings rather suggest that in order to diffuse radical novelty, organisation's only profit from their own technological diversity if they are sufficiently diverse. This way, they have the potential to cross-fertilise radical new ideas amongst other areas of expertise of their own as well as with other actors that absorb the new knowledge.

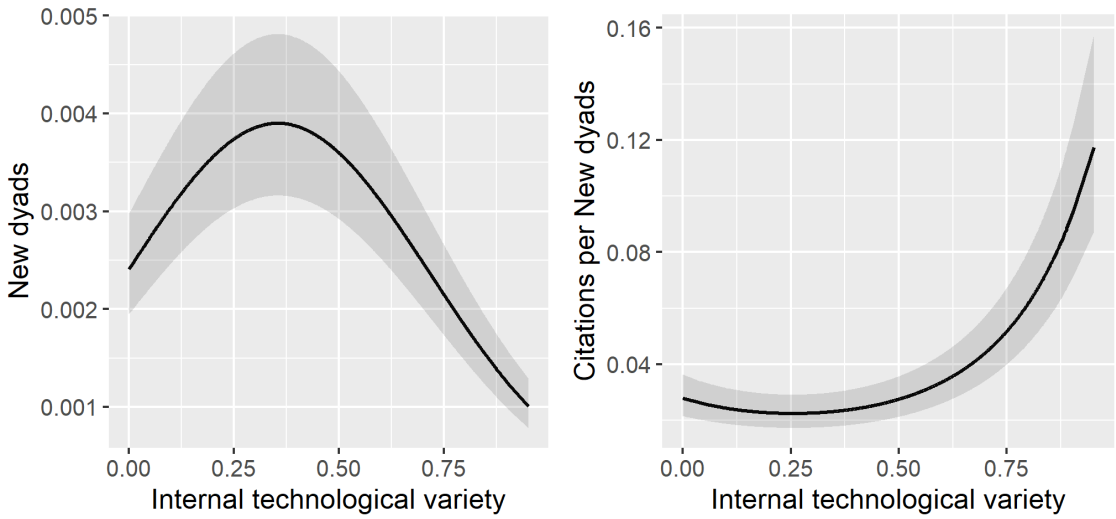

Figure 1. Predicted values of new dyads (left) and citations per new dyad (right).[23]

Models 3a, b and 4a, b test the influence of cognitive proximity to the regional knowledge base more generally and to regional actors at the technological frontier in particular on the emergence and diffusion of radical novelty. In terms of the ability of organisations to come up with novel combinations the results show no significant effect of cognitive proximity to the regional knowledge base. Hence, hypothesis 2a is rejected. However, the estimations provide evidence for our hypothesis 3a that an optimal level of cognitive proximity to actors at the technological frontier is needed to find novel combinations. The left graph in Figure 2 illustrates the inverted u-shape relation between cognitive proximity to frontier firms and the emergence of radical innovations. Thus, organisations do not

[23] inner and outer probabilities for the uncertainty intervals (HDI) are set to 0.25.

have to be related to the overall regional knowledge base but rather need an optimal level to specific actors also engaging in radical innovation processes to enhance their ability to generate radical novelty. This facilitates their access to complementary knowledge for radical novelty and simultaneously helps them to absorb this knowledge.

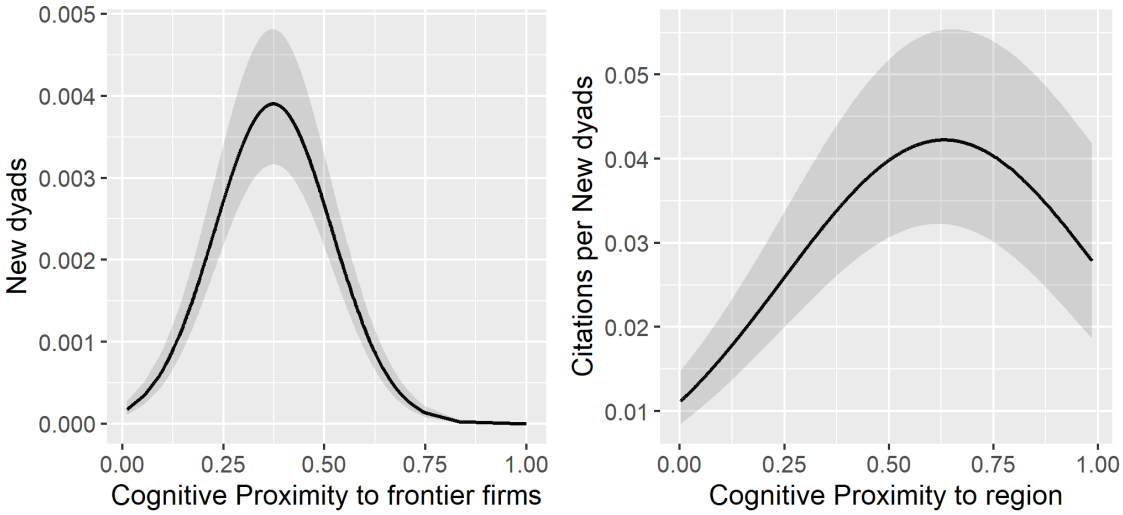

Figure 2. Predicted values of new dyads (left) and citations per new dyad (right).[24]

In terms of the diffusion of radial novelty a different picture is drawn. Here, the cognitive proximity to the regional knowledge base as a whole is more important. Even though the coefficients point to an inverted u-shaped relation, only the positive effect of cognitive proximity is significant. The marginal effects underline this finding (see right graph in Figure 2). This points to a saturation effect so that increasing cognitive proximity has a positive effect until a certain saturation point, where increasing cognitive proximity becomes negative but has no effect. Hence, hypothesis 2b has to be rejected. Furthermore, although the coefficients concerning cognitive proximity to actors at the technological frontier point to an inverted u-shape relation, the effect is not significant. Therefore, hypothesis 3b is also rejected.

Other than expected, cognitive similarity to the region's knowledge base is positively associated with the diffusion of radical novelty. However, it has no effect if similarity becomes too high. This points to the fact that radical novelty can diffuse best if organisations are well embedded into regional clusters of technologically similar firms. In this context, spillovers from (radical) new inventions result in other organisations introducing follow-on innovations which in turn increases the diffusion of the initial

[24] inner and outer probabilities for the uncertainty intervals (HDI) are set to 0.25.

invention (Colombo et al. 2015). Moreover, the positive effect of cognitive similarity to the regional knowledge base may stem from the relatively short time period of five years for the patent to receive citations. While novel combinations may diffuse in cognitively similar technology fields quite fast, it may take more time for them to be applied in more unrelated areas.

In sum, the overall results show that the mechanisms at the heart of the emergence and diffusion of radical novelty differ. On the one hand, the emergence of radical novelty is positively influenced by an optimal degree of internal technological variety and a certain degree of relatedness to actors at the technological frontier. On the other hand, organisations seeking to diffuse this radical novelty have to reach a certain threshold of diversity so that they can profit from their diverse capabilities. Moreover, cognitive proximity to the regional knowledge base enhances the diffusion of radical novelty until a certain degree where the effect loses significance.

5 Conclusion

The starting point of this research endeavour was the fact that studies on the impact of relatedness of (technological) knowledge for (radical) inventive performance just look at the overall relatedness in a region but are silent about the favourable conditions for the organisations that actually introduce radical novelty. Following this reasoning, this paper's aim was to scrutinize on the role of internal technological variety and cognitive proximity to the regional knowledge base in organisation's radical innovation processes in German labour market regions. Thereby, the study intended to investigate whether the overall regional knowledge base plays are role or rather the relatedness to specific actors at the technological frontier is essential. Furthermore, the purpose was to detect possible differences in the mechanisms enhancing the emergence and diffusion of radical novelty on the organisational level.

The study provides three main results. First, it shows that the mechanisms at the heart of the emergence and diffusion of radical novelty differ, pointing to the fact that both dimensions have to be considered. Second, evidence is found that the emergence of radical novelty is positively affected by an optimal degree of internal technological variety, which is in line with previous research (Leten et al. 2007). Furthermore, the results point out that not overall relatedness to the regional knowledge base is important but rather being related to actors at the technological frontier enhances an organisations'

ability to come up with novel combinations. This sheds new light on the proximity paradox literature (Boschma and Frenken 2010). Third, while relatedness to radical innovators may be essential for the emergence of radical novelty, it is rather the cognitive proximity to the regional knowledge base that is key for the diffusion of such ideas, at least up to a certain degree after which the effect vanishes. Moreover, the internal knowledge capabilities of organisations have to reach a certain threshold of diversity so they can make use of them for diffusion efforts. The results show that it is important to draw a more fine-grained picture of the processes that are at the heart of radical innovations. In particular, an organisational level perspective helps to analyse how economic actors actually profit from relatedness to the region where they are embedded, thereby adding to the relatedness literature.

The results call for further research. For instance, the approach in this study is static. Adding a dynamic perspective could be interesting since unrelated domains become related as soon as they are combined for the first time (Castaldi et al. 2015). With regard to the dynamic perspective, it could be worthwhile to incorporate the industry life-cycle approach, as there might be differences depending on the stage of the industry. Besides that, future research could increase the time lag of the citations to see whether radical novelty takes more time to be adapted in unrelated areas. However, there is a time lag until the data gets updated in PATSTAT and thus in the most recent years the data is quite fragmented which is why here the 5-year citation lag was selected.

The findings provide some insights for innovating organisations and policy-makers. Organisations should diversify their capabilities at least to a certain degree in order to enhance their ability to successfully introduce radical innovations. Furthermore, our results suggest that organisations and policy-makers should bear in mind the overall regional knowledge composition as well as the one of specific actors in the region in order to increase the likelihood to generate radical innovations. With regard to the emergence of these innovations, knowledge exchange with related actors at the technological frontier in the region should be pursued. Regarding the diffusion of radical novelty cognitive relatedness to the overall regional knowledge portfolio is important. Policy-makers should consider these findings when designing new policy initiatives. Especially in terms of supporting research on cross-innovations and taking into account requirements for partner selection in collaborative R&D projects.

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Appendix

Table 4. Regional distribution of sample and share of dependent variables.

LMR Number	LMR Name	Number of organisations	Share of new_dyads	Share of cit_new_dyad_mean
1	Kiel	44	1,35%	1,29%
2	Luebeck	33	0,21%	0,46%
3	Dithmarschen	8	0,00%	0,00%
4	Flensburg	33	0,00%	0,00%
5	Hamburg	358	3,93%	3,48%
6	Braunschweig	49	0,14%	0,15%
7	Wolfsburg	9	0,74%	0,00%
8	Goettingen	51	0,67%	0,62%
9	Goslar	34	0,07%	0,35%
10	Hannover	180	1,63%	1,59%
11	Hameln	26	0,00%	0,00%
12	Celle	12	0,07%	0,20%
13	Luechow-Dannenberg	2	0,00%	0,00%
14	Stade	17	0,00%	0,00%
15	Uelzen	6	0,00%	0,00%
16	Emden	20	9,95%	0,31%
17	Oldenburg	49	0,00%	0,00%
18	Osnabrueck	90	0,32%	0,20%
19	Emsland	63	0,18%	0,00%
20	Wilhelmshaven	9	0,00%	0,00%
21	Vechta	54	0,11%	0,41%
22	Bremen	144	1,20%	0,65%
23	Bremerhaven	18	0,04%	0,00%
24	Duesseldorf	338	3,86%	0,86%
25	Essen	195	1,56%	0,51%
26	Wuppertal	131	0,89%	0,61%
27	Kleve	22	0,00%	0,00%
28	Bonn	103	0,81%	0,00%
29	Koeln	225	2,94%	1,32%
30	Aachen	113	0,85%	0,15%
31	Olpe	116	0,28%	0,05%
32	Muenster	209	1,38%	0,87%
33	Borken	70	0,07%	0,00%
34	Bielefeld	168	1,20%	2,25%
35	Hoexter	19	0,11%	0,20%
36	Minden	202	1,03%	4,82%
37	Bochum	113	0,32%	0,51%
38	Dortmund	104	0,92%	2,96%
39	Hagen	241	0,39%	0,96%
40	Siegen	72	0,81%	0,46%

41	Soest	188	0,64%	2,73%
42	Darmstadt	74	0,96%	1,16%
43	Frankfurt am Main	277	4,22%	6,06%
44	Giessen	134	1,10%	0,89%
45	Limburg-Weilburg	42	0,04%	0,20%
46	Kassel	60	0,89%	0,95%
47	Fulda	48	0,57%	0,51%
48	Waldeck-Frankenberg	23	0,04%	0,00%
49	Koblenz	123	0,85%	0,64%
50	Altenkirchen	27	0,07%	0,00%
51	Bad Kreuznach	27	0,04%	0,00%
52	Bitburg	4	0,00%	0,00%
53	Vulkaneifel	8	0,00%	0,00%
54	Trier	30	0,04%	0,20%
55	Kaiserslautern	30	0,04%	0,05%
56	Landau	25	0,11%	0,71%
57	Ludwigshafen	85	0,50%	1,13%
58	Mainz	80	0,57%	1,17%
59	Stuttgart	416	6,52%	5,11%
60	Boeblingen	142	0,67%	0,65%
61	Goeppingen	63	0,11%	0,76%
62	Heilbronn	139	0,18%	0,35%
63	Schwaebisch Hall	32	0,07%	0,00%
64	Heidenheim	105	1,20%	1,98%
65	Karlsruhe	160	1,59%	1,75%
66	Heidelberg	127	0,85%	1,16%
67	Pforzheim	92	0,07%	0,10%
68	Freiburg	91	0,39%	0,25%
69	Ortenaukreis	85	0,11%	0,25%
70	Rottweil	186	0,53%	1,75%
71	Konstanz	43	0,35%	0,30%
72	Loerrach	32	0,28%	0,81%
73	Waldshut	25	0,04%	0,10%
74	Reutlingen	112	0,43%	1,24%
75	Zollernalbkreis	49	0,53%	0,41%
76	Ulm	131	0,14%	0,25%
77	Ravensburg	177	3,12%	1,66%
78	Sigmaringen	18	0,00%	0,00%
79	Ingolstadt	45	0,28%	0,10%
80	Muenchen	591	15,59%	10,96%
81	Altoetting	52	0,28%	0,38%
82	Traunstein	110	0,18%	0,30%
83	Weilheim-Schongau	36	0,32%	0,81%

84	Deggendorf	25	0,00%	0,00%
85	Freyung	12	0,00%	0,00%
86	Passau	26	0,00%	0,00%
87	Landshut	59	0,28%	0,10%
88	Cham	15	0,00%	0,00%
89	Amberg	41	0,85%	0,41%
90	Regensburg	68	1,91%	3,00%
91	Bamberg	38	0,04%	0,20%
92	Bayreuth	50	0,18%	0,15%
93	Coburg	60	0,18%	0,00%
94	Hof	70	0,35%	0,15%
95	Kronach	19	0,04%	0,30%
96	Erlangen	79	1,45%	3,27%
97	Nuernberg	184	0,99%	2,18%
98	Ansbach	29	0,18%	0,41%
99	Weissenburg-Gunzenhausen	8	0,00%	0,00%
100	Aschaffenburg	69	0,21%	1,62%
101	Schweinfurt	35	0,11%	0,00%
102	Wuerzburg	91	0,92%	0,35%
103	Augsburg	95	0,32%	2,13%
104	Memmingen	43	0,07%	0,05%
105	Donau-Ries	22	0,50%	0,91%
106	Kempten	59	0,04%	0,20%
107	Saarbruecken	67	0,39%	0,63%
108	Pirmasens	29	0,39%	0,25%
109	Berlin	348	2,52%	2,76%
110	Frankfurt (Oder)	11	0,00%	0,00%
111	Elbe-Elster	15	0,32%	0,29%
112	Havelland	12	0,32%	0,22%
113	Maerkisch-Oderland	6	0,00%	0,00%
114	Oberhavel	16	0,07%	0,05%
115	Ostprignitz-Ruppin	6	0,00%	0,00%
116	Potsdam-Mittelmark	33	0,07%	0,46%
117	Prignitz	2	0,00%	0,00%
118	Cottbus	8	0,00%	0,00%
119	Teltow-Flaeming	17	0,25%	0,10%
120	Uckermark	6	0,00%	0,00%
121	Schwerin	34	0,25%	1,01%
122	Mecklenburgische Seenplatte	10	0,04%	0,05%
123	Rostock	35	0,28%	0,51%
124	Nordvorpommern	4	0,00%	0,00%
125	Suedvorpommern	3	0,00%	0,00%

126	Chemnitz	191	2,80%	1,82%
127	Dresden	136	0,50%	1,16%
128	Bautzen	54	0,00%	0,00%
129	Leipzig	72	0,00%	0,00%
130	Dessau-Rosslau	31	0,00%	0,00%
131	Magdeburg	50	0,00%	0,00%
132	Halle	50	0,35%	0,15%
133	Stendal	1	0,00%	0,00%
134	Erfurt	73	0,07%	0,15%
135	Gera	24	0,07%	0,05%
136	Jena	54	0,07%	0,25%
137	Nordhausen	10	0,00%	0,00%
138	Eisenach	13	0,00%	0,00%
139	Unstrut-Hainich	15	0,00%	0,00%
140	Suhl	30	0,00%	0,00%
141	Saalfeld-Rudolstadt	22	0,14%	0,56%

Essential ingredients for radical innovations? The role of (un-)related variety and external linkages in Germany[25]

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Abstract

The role of radical innovations for the economy has received increasing attention by German policy makers. This paper investigates how (un-)related variety and external linkages influence these innovations in German labour market regions. Evidence is found that related and unrelated knowledge capabilities both support the emergence of radical innovations, although strong related capabilities are especially important. External linkages have an inverted u-shape relation to radically new ideas and can act as substitute for missing unrelated competences in a region. The results shed new light on the emergence of radical innovations and thus have interesting scientific and practical implications.

Keywords: Radical innovations, related variety, unrelated variety, external linkages, labour market regions

JEL codes: O31, O33, R11

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1 Introduction

During the last decades, innovations have been highlighted as key factor for economic growth (Rosenberg, 2004; Verspagen, 2005). Recently, it has been acknowledged that in particular radical innovations offer great economic potential (Castaldi et al., 2015). Innovations that are radical in nature combine previously unconnected knowledge domains, which is more uncertain and riskier than combining knowledge that has been combined before (Fleming, 2001). In the event, that such innovations are successful, they can form completely new markets and industries and provide the basis for long-term economic growth (Ahuja and Lampert, 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). The possible catalysing role of radical innovations for the economy has also received increasing attention by policy makers. For instance, the German government just recently established a public agency for the promotion of radical innovations (BMBF, 2018).

Recently, the importance of the relatedness of technologies for technological change, economic competitiveness and diversification processes has been highlighted in a series of studies (Breschi et al., 2003; Boschma & Iammarino, 2009; Frenken et al., 2007, Hidalgo et al., 2007). In spite of many papers on the drivers of innovation processes in general and especially the role of existing localized knowledge variety, the driving forces of radical innovations remain relatively unclear. Lately, scholars have started research endeavours in this regard. While Castaldi et al. (2015) find evidence that only unrelated variety positively influences technological breakthroughs, Miguelez & Moreno (2018) discover that not only unrelated knowledge competencies but also related one's favour breakthrough innovations. These results show that further analysis is required in order to understand the impact of knowledge variety on radical innovations in a more comprehensive way.

Moreover, radical innovations may not solely draw from local knowledge sources since it can become redundant at some point and cause situations of lock-in (Boschma, 2005). Hence, actors might find complementary knowledge for radical innovation processes through linkages with actors from outside the region (Bathelt et al., 2004). Formal collaborations may be a specific channel to access this knowledge (Singh, 2008), which have been acknowledged to enhance innovativeness of regions and firms (Fitjar &

Rodríguez-Pose, 2013). Although, De Noni et al. (2017) have analysed the effects of technological variety and (non-)local linkages on regional inventive performance, it remains unclear how they influence radical innovation processes.

This paper aims to shed further light on the determinants enhancing the emergence of radical innovations. In particular, it analyses how (un-)related variety and external linkages drive radical innovation processes. The paper contributes to this issue in several ways: First, we analyse radical innovations from two complementary perspectives, looking at the emergence as well as at the diffusion. Thereby, we include a new indicator to detect radical innovations in the research on regional diversification. Furthermore, we expand the analysis by inspecting the role of linkages with external actors through collaborations and how this influences radical innovation output in the region. Despite contributing to close a research gap, this study also has important implications for policy makers and managers.

The remainder of the paper is structured as follows: The next section gives an overview of the theoretical background and leads to the hypotheses. The third section describes the data and methods. The main empirical results are presented and discussed in the fourth section and the fifth section concludes and gives an outlook of possible future research endeavours.

2 Theoretical background and hypotheses

During the past decades, innovation processes have been acknowledged as important factor for economic growth (Rosenberg, 2004; Verspagen, 2005). Thereby, innovations are commonly understood as a cumulative process where existing knowledge is combined in unique ways to create something new (Arthur, 2007; Basalla, 1988). Weitzman (1998, p.333) defined the reconfiguration of existing knowledge in a unique fashion to form new artefacts as "recombinant innovation". This process can lead to both incremental and radical innovations.[26] While the former are considered to develop mostly alongside well-known trajectories and particularly refine existing technologies, the latter introduce a novel artefact or technological approach, which can lead to a paradigm shift and thus radical change (Arthur, 2007; Dosi, 1982; Verhoeven et al., 2016). This radical change

[26] Radical innovations have also been framed i.e. 'technological breakthroughs' (Castaldi et al., 2015), 'disruptive innovations' (Tushman & Anderson, 1986), 'atypical innovations' (Uzzi et al., 2013). In this paper we call them 'radical' if they introduce totally novel knowledge combinations (Grashof et al., 2019; Rizzo et al., 2018; Verhoeven et al., 2016) or if they are 'radical' in terms of their impact (Castaldi et al., 2015). Methods to measure radical innovations are discussed in the data and methods section.

may open up new markets or even industries while causing old ones to disrupt (Henderson & Clark, 1990, Tushman & Anderson, 1986). Hence, radical inventions „serve as the basis of ‚future‘ technologies, products and services" (Ahuja & Lampert, 2001, p. 522). The search processes at the heart of these inventions find novelty through the recombination of former unconnected knowledge (Fleming, 2001; Hargadon, 2003; Nerkar, 2003). New combinations then are the result of such search processes, when actors discover a new purpose for their existing knowledge or they fuse together some external expertise with their own mind-set (Desrochers, 2001). These processes introducing novelty are difficult to engage in and also riskier in regard of commercialisation since it is uncertain if the activities will have an economic impact in the future (Fleming, 2001; Schoenmakers & Duysters, 2010; Strumsky & Lobo, 2015). As radical innovations can be radical in terms of their degree of novelty as well as with regard to their impact, it is important to analyse them in both dimensions (Dahlin & Behrens, 2005).[27]

Radically new ideas emerge through existing knowledge pieces, which are unevenly distributed over regions. However, radical innovations can help regions to obtain a competitive advantage. Hence, scholars and policy makers seek to understand how regions can strengthen their ability to produce these innovations. To study the impact of localized knowledge on radical innovations we make use of the concept of knowledge variety. The knowledge created over time and embedded in organizations leads to variety of knowledge in an economy, which can be seen as a crucial factor of economic growth (Saviotti, 1996). Although knowledge is based in individual firms, the interaction with other firms in the region is important for the creation of new knowledge (Fleming, 2001). However, to be able to absorb new knowledge spilling over from other firms, actors need to be related to each other in terms of their knowledge to a certain extent (Cohen & Levinthal, 1990). Following the concept of Nooteboom (2000), two knowledge bases are viewed as related to one another if they have a certain degree of overlap and develop through similar skills and abilities.

Knowledge variety can be divided into related and unrelated variety. Related variety describes the situation where actors in a region engage in industries with similar

[27] Same as Castaldi et al. (2015) we use the terms ‘innovation’ and ‘invention’ interchangeably since the theory of recombinant innovation uses the term ‘innovation’. However, technological achievements are the focus of our study and we do not address successful commercialization.

knowledge bases. Several empirical studies have shown for different dimensions (e.g. products, industries, technologies) and spatial units (e.g. countries, regions, cities, labour market areas) that variety in related industries builds the basis for knowledge diffusion and hence economic growth (e.g. Frenken et al., 2007). Content & Frenken (2016) have provided a comprehensive review of these studies. On the other hand, unrelated variety describes the situation when a region hosts firms from unrelated industries. Empirical findings concerning unrelated variety have been discussed more controversial amongst scholars (Bishop & Gripaios, 2010; Boschma et al., 2012). Not until recently, scholars have started to examine direct connections between variety measures and inventive processes. These studies find for different spatial dimensions that related variety especially supports general innovation output (Castaldi et al., 2015; Miguelez & Moreno, 2018; Tavassoli & Carbonara, 2014). Regarding innovation's impact, Castaldi et al. (2015) find only a significant effect of unrelated variety. By contrast, Miguelez & Moreno (2018) encounter that both variety measures have a positive effect. Consequently, the effects of related and unrelated variety on radical innovations are far from conclusive.

Following Miguelez & Moreno (2018), we think that it is favourable to have both related and unrelated knowledge capabilities in a region in order to come up with radical innovations. Frenken et al. (2007) also have stated in their seminal paper that related and unrelated variety should not be considered as opposites but rather complement each other. Moreover, Boschma (2017) has argued, that it seems more likely that new activities build on both related and unrelated capabilities. First, the presence of related and unrelated variety increases the number for possible new combinations (Sun & Liu, 2016). Second, competences amongst related areas can help to understand so far unconnected knowledge pieces (Asheim et al., 2011). Related variety thereby strengthens the process of cross-fertilization and helps to integrate unrelated knowledge (Boschma, 2017). Hence, we suggest the following hypothesis:

> Hypothesis 1: Related and unrelated variety in a region both have a positive effect on radical innovations.

We think that related variety might be important since knowledge needed for the creation of new knowledge flows easier between related actors (Cohen & Levinthal, 1990; Fleming, 2001; Frenken et al., 2007). Related competences induce spillovers and ensure to be able to absorb knowledge stemming from unrelated areas (Asheim et al., 2011). However, we think that unrelated variety has a stronger effect since knowledge

combinations from unrelated areas can introduce more radical novelty (Saviotti & Frenken, 2008). Also, it may trigger radically new ideas by an increasing number of possible new combinations between related and unrelated industries (Sun & Liu, 2016). Although it is more uncertain and riskier to experiment with unusual components, if successful, new combinations of unrelated knowledge pieces might pave the way for technological breakthroughs (Fleming, 2001; Castaldi et al., 2015). The corresponding hypothesis is posed as follows:

> Hypothesis 2: The effect of unrelated variety in bringing forth radical innovations is more pronounced than the effect of related variety.

While knowledge variety in a region is "in the air", formal collaboration can be a specific channel to gain access to complementary knowledge. In the light of highly specialized and spatially concentrated knowledge (Singh, 2008), collaboration is recognized as important competence to strengthen the innovativeness of firms and regions (Fitjar & Rodríguez-Pose, 2013). Inventive actors not only engage in collaboration because of productivity and efficiency reasons, but also in order to improve the quality of their inventions with the motive to create radical breakthroughs (Singh, 2008).

Several authors have stressed the fact that complementary knowledge needed for radically new ideas might be found outside one's own region (Miguelez & Moreno, 2018) and have argued that external knowledge can solve situations of regional lock-in (Boschma, 2005). This external knowledge can flow into a region through inter-regional collaborations and thereby support the emergence of radical innovations. This can happen most effectively, if the knowledge is different but still cognitively related to the local knowledge (Boschma & Iammarino, 2009; Miguelez & Moreno, 2018). However, we expect that inter-regional collaborations have an optimal level. At first, a higher amount of collaborations yields increasing opportunities for novel combinations of complementary resources. But at a certain point the cost of finding new partners with complementary knowledge and the organisational effort of maintaining relationships become too large to be beneficial (Broekel 2012; Hottenrott & Lopes-Bento 2016). Hence, we test the following hypothesis:

> Hypothesis 3: External-to-the-region linkages have an inverted u-shape relation to radical innovations.

Finally, while strong related variety ensures that unrelated competences can be absorbed (Asheim et al., 2011), these unrelated knowledge pieces needed for radical novelty can either be found through unrelated variety in a region or inter-regional knowledge links (Miguelez & Moreno, 2018). Actors in regions aiming for radical innovations could source complementary knowledge from local unrelated actors or from actors outside their region. However, combining both cognitively distant and geographically distant knowledge pieces might be too difficult to absorb for economic actors (Boschma, 2005; Nooteboom, 2000). First research endeavours in this regard have found that geographically distant knowledge is most effective if it is different but still cognitively related (Boschma & Iammarino, 2009; Miguelez & Moreno, 2018). Hence, we propose that unrelated variety and external linkages have a substitutive effect on radical innovations. Therefore, the following hypothesis should hold:

Hypothesis 4: Unrelated variety and external-to-the-region linkages substitute each other in bringing forth radical innovations.

3 Data and methods

Most recent studies have focused on patent-based indicators to investigate radical innovations. We can identify three major approaches. First, backward citations are used because several scholars argue that novel and unique patents have a low overlap in the citation structure with past and present patents (Dahlin & Behrens, 2005). By contrast, Ahuja & Lampert (2001) point to the fact that radical innovations do not build on any prior art and therefore lack backward citations. Second, Albert et al. (1991) and Trajtenberg (1990) find that forward citations are a good indicator to measure a patents impact. Dahlin & Behrens (2005) also find evidence that a patent with high impact has high similarity with the citation structure of future patents. Third, another approach is to study technology classes listed on patents. Based on Fleming's (2001) argument that radical innovations stem from former uncombined knowledge domains, radical innovations can be detected by technology classes which are combined for the first time. Radicalness is hence measured by their degree of novelty (Fleming, 2007; Strumsky & Lobo, 2015; Verhoeven et al., 2016). Mewes (2019) also uses technology classes two identify atypical combinations, which can be interpreted as previously disconnected components, by applying z-scores (Uzzi et al., 2013). Forward citations are used in recent studies on the role of knowledge variety on radical innovations (Castaldi et al., 2015, Miguelez & Moreno, 2018), thereby focusing on the impact an innovation has in the

future. In our study, we want to expand this perspective and add an indicator for the emergence of radical novelty, using new combinations of technology classes as proxy.

For this, radical innovation output is proxied by patent data retrieved from the EPO PATSTAT (2016b) database. [28] The focus of the analysis are patents filed between 2001 and 2010 with at least one German inventor. Based on inventor's residences, patents are assigned to 141 German labour market regions as defined by Kosfeld & Werner (2012).[29] This definition is used so that commuter and urban-periphery structures are unlikely to bias the results.

Technologies are classified according to the International Patent Classification (IPC), which classifies patents regarding their technological domains they are used for.[30] The authors aggregate the data to the four-digit level, which differentiates between 635 different technology classes. This level offers the best trade-off between sufficiently large number of patents in the classes and a maximum number of technologies (Broekel & Mewes 2017).

Following the notion of recombinant innovation (Fleming, 2001; Weitzman, 1998) radical innovations are defined as the emergence of new dyads in the German knowledge base (Grashof et al., 2019). They are identified by looking at IPC combinations in each year and each region between 2001 and 2010. Combinations are compared to a dataset, which contains all existing dyads between 1981 and one year before the focal year. A combination is therefore considered new, if it has not been existent in Germany in the previous years since 1981. Thus, the identified dyads are new to Germany.[31] The approach is comparable to the method used by Verhoeven et al. (2016).[32] The dependent variable is constructed as a count variable indicating the number of new dyads that have emerged in each region and each year.

[28] Despite well-discussed drawbacks, patents are available over long time periods and offer extensive and detailed information on the inventory process such as the date, applicant and technology. See e.g. Griliches (1990) for a discussion on patents in this regard.
[29] Since Germany changed its postcode system (4-digits to 5-digits) in 1993, a concordance table between the old and new postcodes has been constructed.
[30] For details see: http://www.wipo.int/classifications/ipc/en/ITsupport/Version20100101/transformations/stats.html.
[31] By the fact that we focus on Germany, our measure could include novel combinations which have been adopted from other countries. However, they are still radically new to Germany.
[32] See Mewes (2019) for another interesting approach to detect radical novelty by building z-scores which indicate how rare technology combinations are.

Since new dyads build on an ex-ante perspective where radicalness stems from the introduced novelty, another indicator for radical innovations is constructed which considers the impact the innovation has on future technological developments. In order to account for high-impact innovations, following other studies, the number of forward citations is used as indicator (Ahuja & Lampert, 2001).[33] Self-citations are included as these may be more valuable than citations by external patents (Hall et al. 2005). We assume that radical inventions quickly affect development processes and are rapidly adopted by economic actors. Hence, citations in a relatively short period of five years after the patent has been filed are considered, following Squicciarini et al. (2013). This approach also takes into account the time lag of the data provided by PATSTAT.[34] This is done in order to provide a fair comparison between patents of different technological areas and age. Also, following Srivastava and Gnyawali (2011), the indicator is scaled for year and technology by dividing the counts by the mean value of citations based on all patents granted in the same year and the same technology field. Radical innovations are then defined as the top 1 % of all cited patents based on this scaled measure (Miguelez & Moreno, 2018).[35] These patents are also assigned to the labour market regions. Finally, the variable is constructed as a count variable indicating the number of highly cited patents per region and year. Thus, it is possible to analyse radical innovations from two complementary perspectives.

Both dependent variables suffer from over-dispersion. The sample variance of new dyads and high impact innovations are 13, respectively 9 times the sample mean. Also, the likelihood ratio test speaks in favour of the negative binomial model.[36] As we have longitudinal data from 2001-2010, we apply the balanced panel application of the negative binomial model. As the Hausman test speaks in favour of the fixed-effects estimator we use it in our models (see next section for more details).[37]

[33] Also see Squicciarini et al. (2013) for a discussion on different indicators.
[34] There is a time lag until the data gets updated in PATSTAT. In the most recent years the data is quite fragmented which is why we stuck to the 5-year citation lag. However, to check the robustness of the results we also used a 7-year lag structure, which did not change our overall results. E.g., Mukherjee et al. (2017) take 8 years.
[35] We calculated the same indicator with the top 3 and top 5 % thresholds as robustness checks. The results remained stable.
[36] The mean value for new dyads is 3.88 and the variance is 50.46 and for high impact innovations it is 2.08 and 19.14 respectively.
[37] Moran's I and LM tests for spatial dependencies are both insignificant.

In line with previous studies, related and unrelated variety are used as proxy to investigate the role of regional knowledge variety (Mewes & Broekel, 2017; Miguelez & Moreno, 2018). Both variety indicators are measured with entropy measures (Frenken et al. 2007). The indexes are constructed based on the technological classifications provided in patent documents. Related variety (RV) is then defined as the difference of variety between the three-digit class level and the four-digit subclass level and is measured as follows:

$$RV_i = -\sum_{m \in M}^{M} p_{mi} \log_2(p_{mi}) - \sum_{k \in K}^{K} p_{ki} \log_2(p_{ki})$$

where p_{mi} represents the share of technology m on the four-digit level and p_{ki} the share of technology k on the three-digit level in region i. The difference between the variety on both aggregation levels is considered as related variety.

Unrelated variety (UV) is defined as variety on the most aggregated level (one-digit), which is measured as follows:

$$UV_i = -\sum_{g \in G}^{G} p_{gi} \log_2(p_{gi})$$

where p_{gi} represents the share of technology g in region i.[38]

Many studies on the geography of knowledge spillovers have used patent citations to investigate knowledge flows (Miguelez & Moreno, 2018; Sorenson et al., 2006). However, this methodology has been criticised to have the flaw that not the inventors but rather the patent examiners include citations in patent documents (Breschi & Lissoni, 2004). Hence, we proxy knowledge spillovers from external linkages by formal collaborations between co-inventors as agents of knowledge exchange (Gao et al., 2011).[39] Non-local linkages indicate the unweighted number of inter-regional collaborations (co-inventors from outside the focal region) in year t-1 and region i.

Additionally, several control variables have been considered. Most of the data is retrieved from EUROSTAT on NUTS-3 level and aggregated for each labour market region. First, we control for existing R&D efforts in the region, measured by the number of patent applications. Then, we calculated the GDP per capita. Moreover, we control for

[38] For detailed information on the entropy measures see Frenken (2007) or Castaldi et al. (2015). Balland (2017) is followed to operationalize the variety measures.
[39] We acknowledge, though, that there are many other possible ways for the exchange of knowledge (see e.g. Gao et al., 2011).

urbanisation effects by taking into account the population density. Furthermore, to control for the region's absorptive capacity we include the number of employees with an academic career which is based on IAB employment data. Finally, based on firm-level data from ORBIS, we calculate the number of firms in research-intensive industries following the definition of Gerhke et al. (2013) to take into account industry effects.[40] We also include year dummies. All explanatory and control variables are time-lagged by one year.

4 Empirical results and discussion

In order to test if it is worthwhile to analyse both dependent variables the Spearman correlation between the two is tested. Results show that, as expected, they are significantly and positively correlated (0.59). Hence, the results of this study confirm empirical findings by other scholars such as Dahlin & Behrens (2005) or Verhoeven et al. (2016) who also mention a positive relation between new knowledge combinations and the impact an invention has. Nevertheless, the positive relationship is far from perfect which is why both variables are used in the analysis.

Radical innovations are considered a rare event (Fleming, 2001), which is confirmed by our results (see Table 1). Between 2001 and 2010 5,471 new dyads have been observed that were new to Germany. That is an average sum of 547 new dyads per year. 136 out of 141 regions (96 %) have at least one new dyad in the focal period. The maximum number of 83 new dyads p.a. is identified in the Munich region. We can detect 476 (new dyads) and 729 (high impact) observations where no radical innovation is introduced in a region. Table 2 gives a short description of our variables and contains the descriptive statistics.

Table 1. Radical innovations in German labour market regions 2001-2010.

Indicator	Sum
New dyads	5,471
Zero new dyads	476
High-impact innovations	2,938
Zero high-impact innovations	729

[40] Research-intensive industries include the high-tech sectors "leading-edge technology" and "high-quality technology" based on 4-digit NACE codes.

Table 2. Variables and descriptive statistics (N=1,410).

Variable	Description	Min	Max	Mean	SD
New dyads	Number of new combinations of two IPC classes (4-digit-level) in year t in region r	0	83	3.88	7.1
High-impact innovations	Number of top 1 % of cited patents in a 5-year window from the filing date (scaled for year and technology) in year t in region r	0	46	2.084	4.375
Related variety	Variety between the 4-digit IPC-level and the 3-digit IPC-level in year t-1 in region r	0	2.11	1.129	0.477
Unrelated variety	Entropy at the 1-digit IPC-level year t-1 in region r	0	2.911	2.392	0.391
External linkages	Number of inter-regional inventor collaborations in year t-1 in region r	0	9,771	1,126	1654.152
Patents p.c.	Number of patent applications per 10,000 inhabitants in year t-1 in region r	0	10.92	2.357	1.898
GDP p.c.	GDP per capita in year t-1 in region r	13,102	59,762	25,161	6,669.44
Population density	Population density in year t-1 in region r	39.2	11,502	1,486.8	1,986.79
Academics p.c.	Number of employees with an academic career per 1,000 inhabitants in year t-1 in region r	6.976	78.808	24.587	12.026
High-Tech firms p.c.	Number of firms in research-intensive industries per 10,000 inhabitants in year t-1 in region r	0.014	13.27	3.275	1.791

As Figure 1 shows, the output of radical innovations varies strongly across labour market regions. The mean number of new dyads is the highest in Munich (I). Other strong regions include Stuttgart (II), Frankfurt am Main (III), Hamburg (IV) and Dusseldorf (V). Then, looking at the distribution of high-impact inventions, German labour market regions have a mean of about two highly cited patents. Over the complete focal period from 2001-2010 a total number of 2,938 high-impact patents can be observed in Germany. 89 % of regions (125) have at least one high-impact innovation. The maximum number of highly cited patents is 46, which is identified in Frankfurt am Main (I), which has also the highest average number followed by Munich (II), Dusseldorf (III), Stuttgart (IV) and Darmstadt (V) as seen in Figure 2. This shows that there is an overlap of top regions, but still there are some slight differences regarding order and Hamburg as well as Darmstadt only appear in one of the top five statistics. In sum, we can see Southern and Western German

regions being stronger.

Most of the weak regions in terms of radical innovation processes belong to Eastern Germany. Also, labour market regions with the highest number of radical innovations are among the economically strongest in the country. Companies such as Bosch, Daimler and Siemens are located e.g., in Stuttgart and Munich 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. Additionally, we find evidence for a strong core-periphery gap as the strong regions all locate a major city.

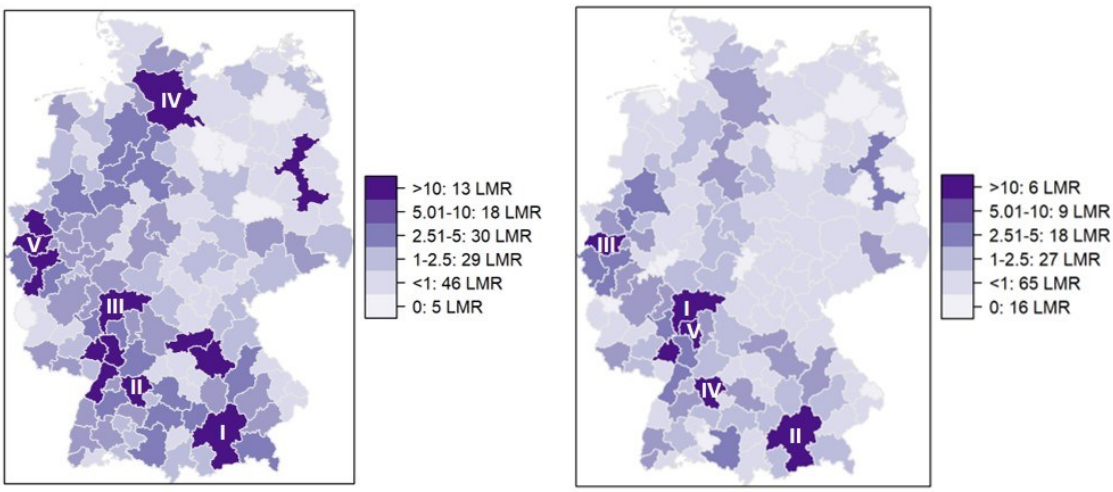

Figure 1. Average number of radical innovations in German labour market regions 2001-2010 (left: new dyads, right: high-impact innovations).

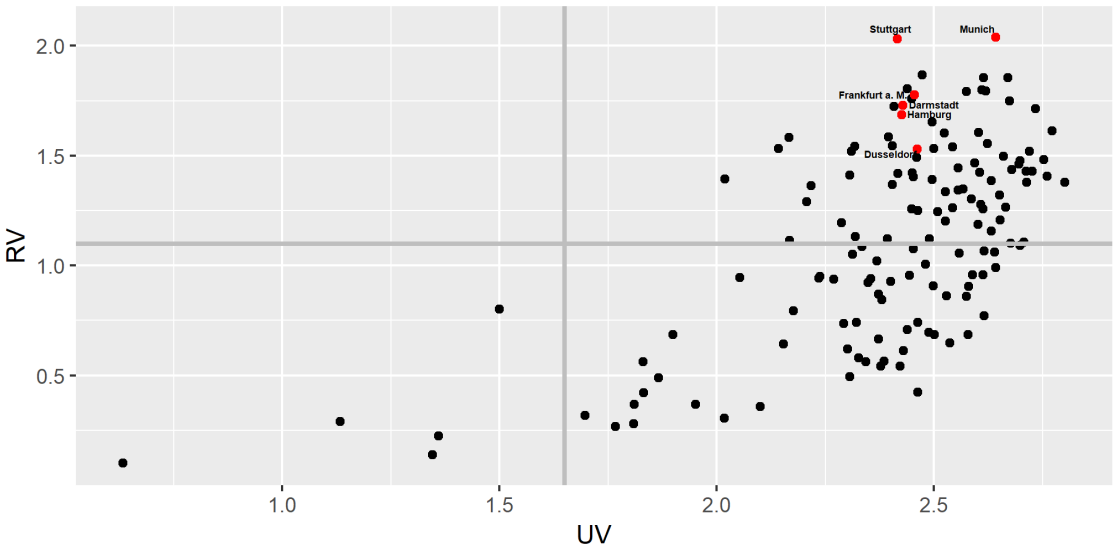

Figure 2. Related (RV) and unrelated variety (UV), bullets show labour market region averages between 2001-10.

Figure 2 contains aggregated observations of the 141 labour market regions for all years in a four-field diagram. The horizontal axis shows the average value of unrelated variety over the focal period, while the vertical axis indicates the average value of related variety in the regions over the same time frame. The scatterplot reveals that both measures are positively correlated. Also, we can see that the above-mentioned top regions are all located in the top right quadrant which contains high values for both related and unrelated variety. This draws first hints towards the fact that both variety measures might positively influence the emergence of radical innovations.

Table 3 presents the pairwise (Pearson) correlations between the variables that enter the regression equations. Overall, results show that the variables are significantly and (positively) correlated. The main explanatory variables RV and UV are moderately correlated (0.47), which also confirms the above-mentioned findings. The correlations for population density clearly show that a lot of variation is explained by inventors being located in urban areas. Also, external linkages explain a lot of the variation in the ability to produce radical innovations.

Table 3. (Pearson) Correlation analysis (N=1,410).

	New dyads	High-impact innovations	Related variety	Unrelated variety	External linkages	Patents p.c.	GDP p.c.	Population density	Academics p.c.
High-impact innovations	0.717**								
Related variety	0.481**	0.441**							
Unrelated variety	0.146**	0.096**	0.471**						
External linkages	0.631**	0.66**	0.598**	0.188**					
Patents p.c.	0.443**	0.407**	0.673**	0.294**	0.572**				
GDP p.c.	0.479**	0.427**	0.599**	0.303**	0.63**	0.673**			
Population density	0.554**	0.601**	0.489**	0.201**	0.755**	0.626**	0.49**		
Academics p.c.	0.451**	0.431**	0.476**	0.145**	0.583**	0.414**	0.463**	0.453**	
High-tech firms p.c.	0.177**	0.13**	0.405**	0.291**	0.264**	0.581**	0.489**	0.082**	-0.009

Note: ** Significant at 5% level.

Table 4. Negative binomial panel regression with fixed-effects results: Related/ unrelated variety and external linkages. Coefficient estimates are standardized.

N = 1,410	Model 1a (dep. Var.: new dyads)	Model 1b (dep. Var.: high-impact innovations)	Model 2a (dep. Var.: new dyads)	Model 2b (dep. Var.: high-impact innovations)	Model 3a (dep. Var.: new dyads)	Model 3b (dep. Var.: high-impact innovations)	Model 4a (dep. Var.: new dyads)	Model 4b (dep. Var.: high-impact innovations)
Related variety			0.397***	0.508***	0.334***	0.498***	0.348***	0.594***
			(0.067)	(0.092)	(0.065)	(0.089)	(0.066)	(0.093)
Unrelated variety			0.226***	0.182**	0.237***	0.175**	0.218***	0.167**
			(0.056)	(0.075)	(0.054)	(0.072)	(0.057)	(0.074)
External linkages					0.434***	0.465***	0.454***	0.483***
					(0.097)	(0.127)	(0.098)	(0.127)
External linkages^2					-0.083***	-0.055**	-0.079***	-0.053**
					(0.019)	(0.022)	(0.018)	(0.021)
Patents p.c.	0.299***	0.298***	0.224***	0.244***	0.147***	0.14**	0.12**	0.113
	(0.055)	(0.076)	(0.050)	(0.069)	(0.051)	(0.071)	(0.053)	(0.073)
GDP p.c.	0.177***	0.215**	0.177***	0.124	0.175***	0.081	0.166***	0.074
	(0.074)	(0.103)	(0.058)	(0.088)	(0.055)	(0.083)	(0.055)	(0.083)
Population density	0.495***	0.552***	0.364***	0.421***	0.249***	0.247***	0.232***	0.227***
	(0.062)	(0.083)	(0.045)	(0.068)	(0.052)	(0.075)	(0.053)	(0.075)
Academics p.c.	0.116*	0.252***	0.063	0.138*	0.035	0.071	0.055	0.086
	(0.064)	(0.087)	(0.05)	(0.073)	(0.048)	(0.072)	(0.049)	(0.072)
High-tech firms p.c.	0.158**	0.158	0.036	0.01	0.023	-0.009	0.04	0.004
	(0.07)	(0.097)	(0.056)	(0.083)	(0.051)	(0.077)	(0.052)	(0.077)
Unrelated variety*External linkages							-0.144***	-0.11*
							(0.051)	(0.06)
y2002	-0.203***	-0.119	-0.164***	-0.073	-0.181***	-0.093	-0.19***	-0.097
	(0.067)	(0.08)	(0.068)	(0.08)	(0.069)	(0.081)	(0.068)	(0.081)
y2003	-0.4***	-0.218***	-0.372***	-0.188***	-0.411***	-0.242***	-0.402***	-0.227***
	(0.072)	(0.082)	(0.072)	(0.083)	(0.073)	(0.084)	(0.073)	(0.085)
y2004	-0.538***	-0.432***	-0.529***	-0.408***	-0.541***	-0.447***	-0.51***	-0.41***
	(0.075)	(0.088)	(0.076)	(0.09)	(0.076)	(0.091)	(0.077)	(0.094)
y2005	-1.113***	-0.761***	-1.082***	-0.712***	-1.092***	-0.758***	-1.06***	-0.727***
	(0.088)	(0.097)	(0.089)	(0.099)	(0.089)	(0.101)	(0.09)	(0.103)
y2006	-1.199***	-0.92***	-1.154***	-0.872***	-1.164***	-0.888***	-1.131***	-0.852***
	(0.089)	(0.1)	(0.09)	(0.102)	(0.089)	(0.102)	(0.09)	(0.104)
y2007	-1.178***	-1.491***	-1.097***	-1.383***	-1.11***	-1.404***	-1.076***	-1.363***
	(0.091)	(0.124)	(0.091)	(0.125)	(0.09)	(0.124)	(0.091)	(0.126)
y2008	-1.407***	-1.627***	-1.307***	-1.497***	-1.306***	-1.489***	-1.259***	-1.438***
	(0.103)	(0.138)	(0.1)	(0.136)	(0.099)	(0.134)	(0.1)	(0.137)
y2009	-1.401***	-1.576***	-1.268***	-1.394***	-1.293***	-1.404***	-1.249***	-1.359***
	(0.111)	(0.148)	(0.106)	(0.144)	(0.104)	(0.141)	(0.105)	(0.143)
y2010	-1.291***	-2.269***	-1.151***	-2.085***	-1.169***	-2.111***	-1.123***	-2.064***
	(0.107)	(0.174)	(0.103)	(0.172)	(0.101)	(0.171)	(0.103)	(0.173)
Constant	1.435***	0.614***	1.405***	0.508***	1.513***	0.605***	1.499***	0.594***
	(0.07)	(0.1)	(0.066)	(0.093)	(0.068)	(0.093)	(0.068)	(0.093)
Number of regions	141	141	141	141	141	141	141	141
LR chi2	1350.2	1244.7	1403.4	1285.0	1423.8	1298.7	1431.9	1302.1
Log-likelihood	-2674.9	-1893.4	-2648.3	-1873.3	-2638.1	-1866.4	-2634.1	-1864.7
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Significance codes: '***' 0.01 '**' 0.05 '*' 0.1. Robust standard errors in parentheses.

Table 5. Negative binomial panel regression with fixed-effects results: Unrelated density and external linkages. Coefficient estimates are standardized.

N = 1,410	Model 5a (dep. Var.: new dyads)	Model 5b (dep. Var.: high-impact innovations)	Model 6a (dep. Var.: new dyads)	Model 6b (dep. Var.: high-impact innovations)	Model 7a (dep. Var.: new dyads)	Model 7b (dep. Var.: high-impact innovations)
Unrelated density	0.798***	0.742***	0.749***	0.71***	0.717***	0.654***
	(0.056)	(0.094)	(0.059)	(0.072)	(0.062)	(0.094)
Unrelated density^2	-0.142***	-0.258***	-0.134***	-0.251***	-0.089**	-0.175***
	(0.025)	(0.04)	(0.024)	(0.039)	(0.036)	(0.054)
External linkages			0.286***	0.403***	0.34***	0.514***
			(0.085)	(0.126)	(0.091)	(0.133)
External linkages^2			-0.044***	-0.043**	-0.039**	-0.041**
			(0.017)	(0.021)	(0.017)	(0.021)
Patents p.c.	0.168***	0.247***	0.114***	0.159**	0.108**	0.146**
	(0.041)	(0.068)	(0.043)	(0.069)	(0.043)	(0.07)
GDP p.c.	0.12**	0.097	0.113**	0.062	0.12***	0.076
	(0.047)	(0.086)	(0.046)	(0.081)	(0.046)	(0.082)
Population density	0.223***	0.348***	0.142***	0.2***	0.139***	0.198***
	(0.035)	(0.068)	(0.041)	(0.073)	(0.042)	(0.074)
Academics p.c.	0.084**	0.215***	0.053	0.016**	0.06	0.171**
	(0.041)	(0.072)	(0.04)	(0.069)	(0.041)	(0.069)
High-tech firms p.c.	-0.011	-0.015	-0.016	-0.023	-0.012	-0.019
	(0.045)	(0.081)	(0.043)	(0.075)	(0.043)	(0.076)
Unrelated density*External linkages					-0.065	-0.124**
					(0.04)	(0.055)
y2002	-0.165**	-0.096	-0.18***	-0.114	-0.172**	-0.105
	(0.07)	(0.08)	(0.067)	(0.08)	(0.068)	(0.08)
y2003	-0.332***	-0.183**	-0.367***	-0.235***	-0.355***	-0.217***
	(0.071)	(0.082)	(0.072)	(0.084)	(0.072)	(0.084)
y2004	-0.457***	-0.407***	-0.475***	-0.45***	-0.469***	-0.45***
	(0.075)	(0.088)	(0.075)	(0.089)	(0.075)	(0.089)
y2005	-0.987***	-0.664***	-1.008***	-0.721***	-1.012***	-0.74***
	(0.086)	(0.096)	(0.087)	(0.099)	(0.087)	(0.099)
y2006	-1.019***	-0.823***	-1.037***	-0.849***	-1.038***	-0.854***
	(0.089)	(0.1)	(0.088)	(0.1)	(0.088)	(0.1)
y2007	-1.0***	-1.378***	-1.02***	-1.412***	--1.014***	-1.401***
	(0.088)	(0.121)	(0.087)	(0.121)	(0.087)	(0.121)
y2008	-1.19***	-1.485***	-1.199***	-1.493***	-1.192***	-1.479***
	(0.096)	(0.132)	(0.095)	(0.13)	(0.095)	(0.13)
y2009	-1.151***	-1.4***	-1.175***	-1.422***	-1.172***	-1.418***
	(0.1)	(0.14)	(0.099)	(0.137)	(0.099)	(0.137)
y2010	-1.066***	-2.104***	-1.086***	-2.141***	-1.084***	-2.141***
	(0.096)	(0.167)	(0.095)	(0.166)	(0.095)	(0.166)
Constant	1.468***	0.746***	1.528***	0.831***	1.518***	0.83***
	(0.063)	(0.094)	(0.064)	(0.093)	(0.064)	(0.094)
Number of regions	141	141	141	141	141	141
LR chi2	1476.2	1306.5	1487.2	1318.2	1489.8	1321.6
Log-likelihood	-2611.9	-1862.6	-2606.4	-1856.7	-2605.1	-1855.0
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000

Significance codes: '***' 0.01 '**' 0.05 '*' 0.1. Robust standard errors in parentheses.

Our study now turns to the regression analysis. In order to analyse the impact of knowledge variety and external linkages on radical innovations we make use of two complementary indicators (new dyads, high-impact innovations). First, we compare the goodness of fit for the panel models with the common OLS model. Here, we report only the results concerning the baseline model (Model 1a, b in Table 4), however all the models show the same significance. The F-test (F=6.541 and p=0.000 in Model 1a, F=7.074 and p=0.000 in Model 1b) confirms that both fixed effect and random effect panel models fit better than OLS. Second, the Hausman test indicates that fixed-effects are consistent and hence to be used (chisq = 184.25, df = 14, p-value = 0.000 in Model 1a, chisq = 129.54, df = 14, p-value = 0.000 in Model 1b). Table 4 reports the results of our Models 1-4.[41] The baseline Models 1a, b only include the controls. Models 2 through 4 include explanatory variables to test our hypotheses. All models show that related and unrelated variety both significantly drive the emergence of radical innovations, which is in line with Miguelez & Moreno (2018). This evidence supports hypothesis 1 that radical innovations benefit from knowledge capabilities in both related and unrelated technological areas, since this offers possibilities for new combinations across industries (Sun & Liu, 2016). Hence, radical innovations do not only emerge from unrelated competences but are also supported by strong abilities among related areas.

However, we do not evidence for our second hypothesis. In fact, related variety has a stronger effect than unrelated variety throughout all models. The strong effect of related variety points to the fact that it is easier to combine knowledge pieces for the first time, if they are unconnected but origin from related industries with at least some overlap in the knowledge structure. The effect of related variety is even higher in the models with high impact innovations as dependent variable. The results are definitely surprising since previous studies investigating the role of knowledge variety in radical innovation processes found evidence that especially unrelated variety supports radical innovations (Castaldi et al., 2015). There could be several explanations for the pronounced effect of related variety: First, as Pinheiro et al. (2018) show, although from a dynamic perspective, unrelated competencies are triggered especially in countries at an intermediary stage of economic development where economies experience a structural transformation towards more complex products. Hence, for highly industrialized countries like Germany it is

[41] There are no problems with multicollinearity in the models. All VIF values are below 5 except for external linkages, as it is included as second-degree polynomial.

favourable to engage in products that are more complex in order to gain a competitive advantage. These, however, are among the most related. Furthermore, the strong effect of related variety could stem from the fact that patents originating from rather related knowledge competences diffuse faster because of risk-aversion in Germany. As Hauschildt & Salomo (2007) show, innovations are often accompanied by social resistance and scepticism. Belitz et al. (2006) find that this behaviour and attitude indeed hampers innovativeness in Germany. Thus, managers might opt to invest in R&D in areas closer to their knowledge portfolio to reduce risk, while in the US, for instance, managers might rather take the risk and seek the opportunity of combining totally unrelated knowledge pieces. This might also be the case for venture capitalists, where Wüstenhagen & Teppo (2006) have shown that their investment is a path dependent process. As a result, venture capital might rather flow into related industries.

Model 3 introduces our measure for external linkages. We find evidence, that external linkages have an inverted u-shape relation to radical innovations. Hence, we can accept our third hypothesis. It is favourable to engage in inter-regional collaborations to a certain extend in order to come up with radically new ideas. Complementary knowledge from outside the region can help to overcome situations of lock-in and trigger radically new ideas (Boschma, 2005; Miguelez & Moreno, 2018). However, after a certain point the effect declines due to costs and organisational efforts (Broekel, 2012; Hottenrott & Lopes-Bento 2016).

Finally, in model 4 we find evidence for our fourth hypothesis. The negative interaction term between unrelated variety and external linkages points to the substitutive effect of both knowledge sources. Local unrelated competences and linkages to non-local actors can both drive the emergence of radical innovations. However, combining both cognitively distant and geographically distant knowledge pieces might be too difficult to absorb for economic actors (Boschma, 2005; Nooteboom, 2000). This is in line with the findings of Boschma & Iammarino (2009) and Miguelez & Moreno (2018) who found that geographically distant knowledge is most effective if it is different but still cognitively related.

With regard to our control variables we find that population density is a strong predictor of the emergence of radical innovations. Hence, regions with larger cities rather come up with radically new ideas. This may be driven i.e. by higher diversity in general in cities as well as by universities, which are often located in dense areas. R&D efforts in terms

of patenting are also positively significant throughout all models, except for model 4b, which could be due to the introduction of the interaction term. However, our results show that regions engaging in R&D are more likely to bring forth radical innovations. GDP per capita is also positive and significant in all but models 2b, 3b and 4b, which could stem from the pronounced effect of some of the exploratory variables such as related variety and external linkages, which correlate with the variable. Our control for absorptive capacity is positive and significant in our baseline models but loses its explanatory power when we introduce our key independent variables (except for model 2b). The number of high-tech firms in a region are only significant in our first model. One has to be careful about interpretation with regard to the non-significant coefficients. Yet, the data at hand does not allow a better indicator, leaving this as an interesting starting point for further research. Nevertheless, the variables control for absorptive capacities and industry structure in the region and our main results remain stable.

In sum, both related and unrelated variety drive the emergence of radical innovations in regions. Other than expected, strong abilities among related areas have an even stronger effect than the potential stemming from unrelated capabilities. Another possible ingredient for new knowledge combinations resulting in radical innovations can be added by collaborating with actors from other regions. However, this effect is only positive up to a certain point and afterwards it diminishes. Finally, with regard to the emergence of radical innovations, new knowledge stemming from unrelated sectors and external linkages have a substitutive effect.

In order to test the robustness of the results, all models are run with unrelatedness density instead of the variety measures as alternative exploratory variable, which is the inverse measure of relatedness.[42] Breschi et al. (2003) is followed to measure technological unrelatedness between technologies (IPC classes) based on their co-classification pattern. We normalize the co-occurrence using an association probability measure (van Eck & Waltman, 2009). Then a density measure is constructed following Hidalgo et al. (2007) to analyse the influence of unrelatedness at the regional level. As we would expect that having both related and unrelated competences enhance a region's ability to produce radical innovations, we also include the squared term of the variable. As presented in Table 5, the results indeed show an inverted u-shape relationship between unrelated

[42] We use unrelatedness, since we think that it better fits the notion of variety in a region as it represents competencies in areas unrelated to the regional knowledge portfolio.

density and radical innovations. This indicates that there is an optimal amount of unrelated competences in a region in order to come up with radical novelty. Hence, regions cannot only rely on unrelated knowledge domains but also need related capabilities in order to be able to assimilate new knowledge and turn it into radical innovations (Asheim et al., 2011). The results concerning external linkages remain stable. However, the substitutive effect between unrelated density and external linkages is only significant with regard to high impact innovations. In terms of new dyads, the coefficient misses to be significant by a conceivable margin, which could be due to the inverted u-shape effect of unrelated density as opposed to unrelated variety. Thus, the results support the main findings of the study.[43]

5 Concluding remarks and outlook

Recently, some scholars have started to investigate the impact of technological variety on technological breakthroughs in particular (Castaldi et al., 2015; Miguelez & Moreno, 2018). However, there is still much work to do regarding which role related and unrelated knowledge capabilities play in radical innovation processes. Furthermore, it remains unclear how external linkages affect the emergence of radical innovations.

Performing negative binomial panel regression models, we find that related and unrelated variety both have a positive effect on the emergence of radical innovations in German labour market regions. This underpins further the assumption that related and unrelated capabilities offer more opportunities for new knowledge combinations (Sun & Liu, 2016). However, the potential of related variety is even higher than the one of unrelated variety. The pronounced effect of related variety could stem from the fact that especially similar knowledge, which is easier to assimilate by actors, is exploited faster in Germany, where managers and venture capitalists tend to be more risk-averse (Hauschildt & Salomo, 2007; Wüstenhagen & Teppo, 2006).

Moreover, we find external linkages to have a positive effect up to a certain extend and hence positively influence the emergence of radical innovations through facilitating the access to complementary knowledge (De Noni et al., 2017). Besides, our results show that external linkages represent a substitute for local unrelated capabilities. Although both have a positive effect on the emergence of radical innovations, combining cognitively and geographically distant knowledge pieces might be too difficult to absorb for economic

[43] The authors can provide the results upon request.

actors (Boschma, 2005; Nooteboom, 2000).

Understanding better the emergence of radical innovations and the drivers behind it is of major interest for German policy makers. Especially in the light of founding a public institution to support radical innovations. This institution could set up measures to further support cross-innovations stemming from different technological backgrounds. For instance, it could fund joint R&D projects with partners from different cognitive and geographical backgrounds. In addition, crowd-investment could be promoted as an alternative to foster unrelated knowledge domains.

Furthermore, the results can help optimize smart specialization strategies. First of all, regions could strengthen their competencies in related industries to enhance the ability to assimilate new knowledge. At the same time, regions could promote activities in unrelated sectors to increase possibilities for new knowledge combinations which result in radical innovations. Alternatively, regions could strengthen linkages to other regions in order to gain access to new knowledge. Additionally, the results can help managers setting up strategies for radical innovation processes. For instance, they could look for partners in R&D projects with both related and unrelated knowledge capabilities or outside their own region.

This paper has some limitations which can represent starting points for further investigations. The pronounced effect of related variety might be explained to a certain extend by risk-aversion of German managers and venture capitalists. While analysing this is beyond the scope of our study it could be interesting to differentiate between national and international citations to see, whether this assumption is actually true. Furthermore, given the limitations of patent data, future studies could tackle the analysis using other data (e.g. product data or trademarks). Related and unrelated variety could also be measured by using employment data for instance. Linkages could be quantified by other formal collaborations such as joint R&D projects through data from the German subsidy catalogue ("Förderkatalog") or by other forms of relationships (formal and informal). Finally, an interesting research endeavour would be to analyse which technologies are actually combined when novel combinations are realised. Hence, one could gain more knowledge on which local capabilities these radically new ideas actually build on.

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Unlocking the radical potential of German innovators – How can R&D policy foster radical innovation?

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Abstract

Recently, the outstanding potential of radical innovations has been acknowledged to foster the economic development of countries and regions. However, due to market imperfection, economic actors do not engage in radical innovation to a socially desirable degree. Hence, governments have established measures to compensate the under-investment in private R&D. For instance, in Germany and on the European level innovation agencies have been established to support innovations that move the technological frontier. In the light of this development, this study aims to answer the question whether direct funding of R&D projects in general and collaborative R&D grants in particular can support the emergence of radical innovations. Furthermore, this study scrutinises on the effect of policy-induced cross-innovation activities on radical innovation processes. Although many scholars advise policy makers to support activities inducing cross-fertilisation in order to enhance radical innovation, we lack evidence whether the funding of such research projects actually has an effect. The results can be of interest for scholars as well as policy makers aiming to support this type of innovation.

Keywords: Innovation policy, R&D subsidies, R&D collaboration, cross-innovation activities, radical innovation

JEL codes: C30, H20, O31, O38

1 Introduction

Innovation has become a central factor to explain the economic development of countries and regions (Rosenberg 2004; Verspagen 2005). Besides, it has been acknowledged that the potential of R&D is not seized by economic actors to a socially desirable degree due to market imperfection. Nelson (1959) and Arrow (1962) have been the first to describe this concept and have argued that negative externalities such as i.e. high uncertainty and costs related to R&D projects, difficult access to private financing, risks due to unresolved technological standards or lower private than social returns, lead to this market imperfection (Martin and Scott 2000). Hence, policy makers have established support measures to compensate the under-investment in R&D of private organisations.

Recently, especially the great economic potential of radical innovations has been acknowledged (Castaldi et al. 2015). As engaging in research focusing on radical novelty is even more uncertain and risky (Fleming 2001), organisations may decide to refrain from pursuing such endeavours. Hence, the engagement in radical innovation is particularly below the social optimum (Arrow and Lind 1970). Therefore, government support seems even more important in this regard. While the U.S. have had an innovation agency (DARPA - Defense Advanced Research Projects Agency) to support disruptive innovation for a long time, the need for such an institution has been recognized recently by German policy makers. This has led to the founding of the SprinD (Agentur für Sprunginnovationen) to support innovations that move the technological frontier (BMBF 2018). Shortly before, the EU launched the JEDI (Joint European Disruptive Initiative) as a supranational initiative (JEDI 2018).

Thus, this study aims to answer the question whether direct funding for R&D projects can support the emergence of radical innovations. First research has found a positive impact of public R&D support on radical innovation (Beck et al. 2016), but evidence is far from conclusive. This study delineates from the above-mentioned work by focusing on German organisations in the light of the establishment of a specific agency to support frontier-breaking innovations and by focusing on the technology dimension instead of the product dimension. In particular, it looks at completely novel technology combinations as proxy for radical innovation output (e.g. Verhoeven et al. 2016). Furthermore, it scrutinizes on specific selection criteria for the inclusion into treatment, namely cross-innovation activities. Although, the positive effect of university-industry linkages (e.g. Belderbos et al. 2004), cross-industrial (e.g. Castaldi et al. 2015) and cross-regional (e.g. Miguelez and

Moreno 2018) as well as cross-cluster collaboration (e.g. Owen-Smith and Powell 2004) on (radical) innovation has been acknowledged in the literature, there is no empirical evidence so far whether policy-induced cross-innovation activities can enhance radical innovation output. Hence, this paper contributes mainly in three ways. First, it sheds light on the question whether public R&D support can support the emergence of novel combinations. Second, it scrutinizes on the effect of collaborative R&D support for the emergence of radical innovation. The third contribution relates to the focus on cross-innovation activities. Although many scholars advise policy makers to support these activities, we do not know whether the funding of such research projects has an effect on radical innovation. The results can be of particular interest for scholars focusing on innovation policy and for policy makers aiming to support this type of innovation and can help to design measures for innovation agencies such as the above-mentioned SprinD or JEDI.

The paper is structured as follows: Section 2 deals with the research question in light of the recent literature, starting with the effect of R&D support and then dealing with the impact of R&D collaboration in general and the effect of cross-innovation activities in particular on the emergence of radical innovation. The description of the employed databases and the construction of the variables is presented in Section 3. Section 4 describes the applied methodology, followed by a discussion of the main findings. The final section concludes.

2 Theoretical background

Unlike incremental innovation, which is considered to particularly refine existing practices, products and services, radical innovation introduces new solutions that are different from existing ones (Ritala and Hurmelinna-Laukkanen 2013; Schilling 2013). While it can have a significant impact on the performance of firms, it also can have major effects on the whole economy by creating new markets and causing old ones to become obsolete (Tushman and Anderson 1986). Furthermore, radical innovations can provide the basis of future sustainable economic growth (Ahuja and Lampert 2001). Following the principle of recombinant innovation (Weitzman 1998), radical novelty is introduced through the recombination of former unconnected knowledge (Fleming 2001; Hargadon 2003). These processes often, however, are associated with higher costs and risks (Fleming 2001; Strumsky and Lobo 2015).

Not only with regard to radical innovation but more generally scholars have argued that R&D projects are accompanied by negative externalities which lead to the fact that private organisations invest less in such projects than socially desirable (Nelson 1959; Arrow 1962; Martin and Scott 2000). Hence, governments have established measures to cure this market failure. However, radical innovation seems to rely even more on such public support. Due to the higher risks of these research endeavours organisations may decide against engaging in projects of radical nature (Friis et al. 2006). Additionally, the high uncertainty makes it more difficult to find investors and external financiers as these generally are more reluctant towards supporting such projects (Czarnitzki et al. 2011). Assuming that firms tend to be risk-averse and financially constrained, this could result in a sub-optimal allocation of radical innovation (Arrow and Lind 1970). Furthermore, risk-aversion may be especially high in Germany, as Belitz et al. (2006) have stressed, which might make it even more important to subsidise such research efforts.

Several studies have found empirical evidence that subsidies have a positive impact on different innovation indicators such as patenting performance (e.g., Czarnitzki and Hussinger 2004; Czarnitzki and Licht 2006) or novelty sales (e.g., Czarnitzki and Lopes-Bento 2014). However, research is rather silent about the effects of R&D support on radical innovations. Therefore, it is important to scrutinize more on radical innovation processes in the context of policy measures to better target such innovations that can provide a long-lasting competitive advantage.

The work by Beck et al. (2016) is one of very few studies that look at the impact of public R&D support on innovation and thereby distinguish between incremental and radical innovation outcome, measured by the sales percentage of substantially improved products and newly introduced products respectively. On a sample of Swiss firms, they find that policy-induced R&D expenditures only have an effect on radical innovation. Thereby, it takes a survey-based approach to measure innovations of radical nature. However, the role of public R&D support on radical innovations measured as novel combinations of (technological) knowledge pieces (Fleming 2007; Verhoeven et al. 2016) has not yet been investigated to the best of the author's knowledge. Hence, this study proposes the following hypothesis:

> Hypothesis 1: Policy-induced R&D enhances the emergence of radical innovations.

With regard to innovation in general terms, earlier research underlines the positive effect of subsidized collaborative R&D. For instance, Czarnitzki et al. (2007) find that policy-induced collaboration has a positive influence on R&D per sales and patent performance of German and Finnish firms likewise. Fornahl et al. (2011) provide empirical evidence that research collaboration, financially supported by the German government, fosters the innovativeness of German Biotech-firms. Furthermore, Hottenrott and Lopes-Bento (2014) provide empirical evidence on a sample of Belgian firms that the treatment effect of public research grants is higher for collaborative projects. This relationship is even stronger in the case of international collaboration. With regard to policy-induced collaboration, Szücs (2018) finds a positive effect of the number of project partners in general and university participants in particular on innovation outcome.

Recently, Beck et al. (2016) have scrutinized on the effect of various partner types (horizontal, vertical or collaboration with science) within a subsidy scheme but do not find an enhanced policy effect by a specific collaboration strategy on either incremental or radical innovation. Then again, research focusing on the effect of collaborative subsidies on radical innovation is far from conclusive.

Generally, there is consensus in the literature that R&D collaboration enhances innovativeness of regions and firms (e.g. Rigby and Zook 2002; Fitjar and Rodríguez-Pose 2013). Economic actors can gain access to complementary knowledge through formal collaborations with other actors (Powell et al. 1996) and thereby enhance

knowledge diffusion (Wirsich et al. 2016). Furthermore, organisations seek to improve the quality of their inventions by engaging in collaboration with the aim to create radical breakthroughs (Singh 2008). Consequently, the following hypothesis is posed:

> Hypothesis 2: Policy-induced collaborative R&D enhances the emergence of radical innovations.

Indeed, many studies provide empirical evidence that cross-innovation activities are important for radical innovation. With regard to cross-organisational activities, several scholars find support for the positive effect of university-industry linkages on radical novelty (Belderbos et al. 2004; Wirsich et al. 2016; Arant et al. 2019). Such partnerships can enhance cross-fertilisation since the actors may have a complementary perspective in the research process which might open up opportunities for novel combinations of knowledge capabilities. In particular, universities may stimulate the search for new solutions by providing underlying theories which may act as "areal maps" of the search ground (Fleming and Sorenson 2004). Hence, combining research conducted in universities and other research institutions and private research efforts can foster the emergence of novel combinations, leading to the following hypothesis:

> H3: Policy-induced cross-organisational R&D collaboration enhances the emergence of radical innovations.

Concerning cross-industry activities, earlier research suggests that inter-sectoral linkages provide complementarity (Broekel and Brachert 2015). Several scholars have found evidence that partnerships with actors from different industries can enhance cross-fertilisation of ideas (e.g. Corradini and De Propris 2017; Montresor and Quatraro 2017). Although this might be especially the case for unrelated industries (Castaldi et al. 2015; Miguelez and Moreno 2018), it might also be evident amongst related ones (Hesse and Fornahl 2020). For instance, Boschma (2017) has argued, that it seems more likely that new activities build on both related and unrelated capabilities. Related to this reasoning, engaging in collaborations across industries increases the number of possible new combinations (Sun and Liu 2016). Thus, cross-industry collaborations can enhance the ability of actors to find radically new solutions:

> H4: Policy-induced cross-industrial R&D collaboration enhances the emergence of radical innovations.

Furthermore, recent empirical work has documented the positive relationship between

extra-regional knowledge sources and radical innovation output (Singh 2008; Miguelez and Moreno 2018; Hesse and Fornahl 2020) and have stressed that external-to-the-region knowledge can solve situations of regional lock-in (Boschma 2005). Miguelez and Moreno (2018) point to the fact, that this knowledge can be absorbed most effectively if it is related to the own knowledge base. Thus, collaborations with actors from other regions can provide the complementary knowledge that is not extant in regional knowledge base and hence support the emergence of novel combinations. Consequently, the hypothesis is formulated as follows:

> H5: Policy-induced cross-regional R&D collaboration enhances the emergence of radical innovations.

Finally, as a special form of the above-mentioned collaborations, cross-innovation activities between actors from different regional clusters may also foster the emergence of radical innovations. Empirical evidence shows that regional clusters enhance firm's innovativeness and productivity (Martin and Sunley 2003; Porter 1998). Also, they can provide a preferable environment for radical innovations (Grashof et al. 2019). However, it may be important to have linkages to actors in other clusters to gain access to complementary knowledge for these innovations as recent studies have stressed the role played by global pipelines in fostering the performance of clusters (Bathelt et al. 2004; Owen-Smith and Powell 2004). Besides, it may be important as well that the cross-cluster activity combines knowledge from different industries and thereby enhances cross-specialisation linkages. This way, particularly promising opportunities could arise when deep knowledge in one strong industry sector is combined with deep knowledge of another strong industry sector (Fleming 2001, Janssen and Frenken 2019). Therefore, the final hypothesis is tested:

> H6: Policy-induced cross-cluster R&D collaboration enhances the emergence of radical innovations.

As Beck et al. (2016) already have pointed out, it is important to acknowledge that collaboration may also be accompanied by certain risks. Amongst others, there is the possibility of free riding by of one of the partners. Furthermore, absorptive capacity of organisations is important in order to benefit from knowledge spillovers and assimilate new knowledge stemming from collaboration partners (Cohen and Levinthal 1990). Otherwise the coordination efforts may exceed the benefits of collaborating. While the

risks of collaborating are present in every case, they might be more pronounced in subsidized collaboration as organisations may engage in collaborative R&D projects in order to increase the probability of being selected for treatment rather than because the partners provide complementary knowledge that is important for radical innovation processes.

3 Empirical Background

3.1 Construction of the sample

Several data sources are applied for the empirical analysis. First, organisation-level information from the ORBIS database (Bureau van Djik) and information on inventive activity from the PATSTAT database (Version 2019) are combined to construct a unique data set of actively patenting organisations in Germany between 2012 and 2014. The ORBIS database provides extensive information on organisations such as year of establishment, whether the organisation is independent or employment data. PATSTAT offers extensive and detailed information on inventory processes such as date, applicant and technology. However, patent data does not come without flaws. For instance, some inventions are not patentable, in some sectors it is not common to patent and also some inventors do not strive to file a patent (for different reasons). For a discussion on imperfections of patent data, see e.g., Griliches (1990). Nonetheless, patents are commonly used amongst scholars to investigate innovation processes. To combine both datasets, the organisation's names where matched using a Token algorithm with a log-based weight function (Raffo 2017; Raffo and Lhuillery 2009).

In order to assess the effect of public R&D funding on an organisation's ability to generate radical innovations, data on funded projects launched between 2008 and 2010 from the German subsidy catalogue ("Förderkatalog") is employed as the third main data source. The database consists of more than 160,000 present or finished R&D projects subsidized by six different ministries in the time span between 1960 and 2016 (Roesler and Broekel 2017).

Furthermore, to identify universities and research institutes within the German subsidy catalogue, the German research directory ("Research Explorer") is used. It contains information on over 25,000 university and non-university research institutes in Germany. Moreover, IAB employment data and information from the German Federal Statistical Office are used to complement the dataset.

The final sample then is a pooled cross-section and consists of 8,404 innovating organisations, out of which 524 received a subsidy.

3.2 Construction of variables

Radical innovations are approximated by entirely new combinations of technology domains (Grashof et al. 2019; Verhoeven et al. 2016) as they tend to combine former unconnected knowledge pieces (Fleming 2001). In order to detect these novel combinations, all four-digit International Patent Classification (IPC) codes[44] present on patent filings in the years 2012-2014 are compared with all IPC combinations that appeared in Germany between 1983 and one year before the focal year. Therefore, new combinations are completely new to Germany (since 1983). Even though it is not yet sure whether they will have an impact on the economy in the future, radicalness is characterised through the entirely new combination of two knowledge pieces (Arant 2019). Then, the new combinations are summed for each organisation in the dataset which represents the dependent variable (new_dyad).

The information on public R&D funding is used to construct several explanatory variables. To acknowledge that a patent filing usually is the result of a R&D project and gets filed rather at the end, a time lag of 4 years is applied in the study, following Fornahl et al. 2011.[45] Hence, information on funded R&D projects between 2008 and 2010 is used. First, the binary variable R&D_funding takes the value of one if the organisation received a subsidy or zero otherwise. As an alternative to assess the effect of public research grants, the variable R&D_funded_projects represents the number of funded projects per organisation. Table 1 shows the subsidy distribution over the sample.

Table 1. Subsidy distribution over sample.

	NUMBER OF ORGANISATIONS	% OF NON-SUBSIDIZED ORGANISATIONS	% OF SUBSIDIZED ORGANISATIONS
TOTAL	8,404	93.76	6.24
NON-RADICAL	8,039	96.07	89.51
RADICAL	365	3.93	10.49

[44] This aggregation level is used to have a sufficiently large number of patents in the classes and a maximal number of technologies.
[45] For sensitivity purposes a 3 and a 5-year lag was also tested.

Then, as the role of collaborative R&D projects is of particular interest, co_funding indicates the number of publicly funded collaborative R&D projects an organisation has been active in. Furthermore, to assess the effect of funding cross-innovation activities, three indicators where constructed which are based on these dimensions: organisational, industrial and regional.

First, one possibility to engage in cross-innovation activities is by collaborating with partners from a different organisational background. For instance, university-industry linkages are considered to be important for the generation of radical innovations (Wirisch et al. 2016; Arant et al. 2019). Thus, cross-orga_funding counts the number of funded projects with partners having a different organisational background (industry vs. university/research institute) for each organisation in the dataset. Second, another possible source to get complementary knowledge for radical novelty is through spillovers from different industries (Castaldi et al. 2015; Miguelez and Moreno 2018; Hesse and Fornahl 2020). Hence, cross-industry_funding counts the number of funded projects with partners active in different industries. For this, two-digit NACE Rev. 2 code[46] industries are used. Third, turning to the regional dimension, scholars have provided empirical evidence that complementary knowledge for radical new ideas can be found in other regions (Singh 2008; Miguelez and Moreno 2018; Hesse and Fornahl 2020). Hence, each organisation is assigned to 141 German labour market regions as defined by Kosfeld and Werner (2012). This definition is used so that commuter and urban-periphery structures are unlikely to bias the results. In particular, the address of the executing entity in the German subsidy catalogue is used to allocate the organisations in the dataset. Then, the number of funded projects with partners from different labour market regions is calculated (cross-region_funding).

Finally, as a special form of the above-mentioned indicators, a cluster dimension is introduced as research suggests that cross-specialisation linkages can enhance novel combinations (Fleming 2001; Janssen and Frenken 2019). Thus, the number of funded projects with partners from different regional clusters, is estimated (cross-cluster_funding). For this, the method by Brenner (2017) is borrowed to identify German clusters on the community level ('Gemeindeebene') based on IAB employment data from

[46] NACE codes refer to the statistical classification of economic activities in the European Community. A full list 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).

2012 in three-digit NACE Rev. 2 industries. This actor-based approach is border-free, leaving it independent of any regional boundaries. Also, it uses a distance decay function based on travel times to prevent a possible overvaluation of very large companies. Additionally, the indicator takes employment in absolute and relative terms into account. Thus, it considers three main characteristics of cluster definitions, namely geographical proximity, regional concentration and specialisation (Grashof 2020). Subsequently, the indicator counting the number of collaborative research projects across different clusters is split up further into organisations engaging in different industries (cross-cluster_funding (cross-industry)) and organisations coming from different regions (cross-cluster_funding (cross-region)).

Moreover, a set of variables is included to control for characteristics that might influence the selection into public funding and/or foster radically innovative outcome. Having received a subsidy in the past might signal existing competences of the applicant and thus might lead to a higher probability of receiving a grant again (Beck et al. 2016). Past_funding is included to control for that and takes a value of one if the organisation already received a subsidy in the previous period or zero otherwise. Patenting activity may also reflect an organisation's ability to successfully engage in R&D (Griliches et al. 1986). Therefore, a variable is included that measures patent applications per 100 employees to avoid multicollinearity with organisation size (patentsp100emp). It is calculated as the average number of patent filings in the years 2010-2012. Furthermore, age and (the log of) size are considered as central organisational characteristics. The former represents the age (years since foundation) in 2014 (age). The size of the organisations is measured by the average number of employees between 2008 and 2014 (size). Both variables are expected to take a non-linear relationship which is why the squared term is included as well (age^2, $log(size)^2$). Moreover, a variable was included, which indicates that no shareholder owns more than 25% of the corresponding organisation (independent). The indicator takes a value of one if this is the case and zero otherwise.

Furthermore, to control for industry-specific effects a categorical variable is added, which takes the values of either not being engaged in an industry (no_industry), being active in an industry (industry_rest) or engaging in knowledge-intensive industries (industry_ki) based on corresponding NACE codes (Gehrke et al. 2013). The industry distribution over the sample is presented in Table 2.

Table 2. Industry distribution over (un-)subsidized organisations.

	NUMBER OF ORGANISATIONS	% OF NON-SUBSIDIZED ORGANISATIONS	% OF SUBSIDIZED ORGANISATIONS
NO_INDUSTRY	4,293	51.65	42.56
INDUSTRY_REST	2,124	25.79	17.56
INDUSTRY_KI	1,987	22.56	39.89
TOTAL	8,404	100	100

Additionally, a dummy variable is created to control whether the organisation is located in an Eastern or Western German labour market region (East_West). The variable takes the value of 1 if the organisation is located in Eastern Germany zero otherwise. On the one hand one could argue that a funding agency might want to foster the transformation process of regions in Eastern Germany after the reunification (Czarnitzki and Lopes-Bento 2014) while on the other hand it may seem attractive to fund highly innovative organisations of which many are located in Western German regions such as Bavaria or Baden-Wuerttemberg (Cantner and Kösters 2012). Moreover, as absorptive capacity plays an important role in the integration of new knowledge (Cohen and Levinthal 1990) the regional workforce is controlled for by taking the number of employees with tertiary education in each labour market region into account. The variable is measured per capita to avoid multicollinearity with population density (academics_p.c.). Consequently, population density in the labour market region is also controlled for as important regional urbanisation characteristic (pop_density). Finally, the number of research institutes in the region (community level) are taken into account as this might influence the general tendency towards R&D engagement of organisations in a region (research_facilities).

Table 3. Descriptive statistics of categorical variables on (un-)subsidized organisations.

		NUMBER OF ORGANISATIONS		% OF NON-SUBSIDIZED ORGANISATIONS		% OF SUBSIDIZED ORGANISATIONS	
	N	**0**	**1**	**0**	**1**	**0**	**1**
INDEPENDENT	8,404	8,135	269	96.80	3.20	92.18	7.82
PAST_FUNDING	8,404	8,076	328	97.18	2.82	79.77	20.23
EAST_WEST	8,240	820	7,420	9.29	88.63	16.79	83.21

Table 4. Descriptive statistics of continuous variables on (un-)subsidized organisations.

	UNSUBSIDIZED ORGANISATIONS, N=7,880			SUBSIDIZED ORGANISATIONS, N=524			RESULTS OF T-TESTS ON MEAN DIFFERENCES
Variables	N	Mean	St. Dev.	N	Mean	St. Dev.	
age	7,784	26.27	31.83	523	32.87	38.47	***
age²	7,784	1703	7618.23	523	2558	8461.60	**
log(size)	1,448	760.88	5,998.40	199	4,107.18	22,054.16	**
log(size)²	1,448	5.245	20.36	199	5.996	24.92	
patentsp100emp	925	4.08	46.24	141	2.31	3.84	
academics_p.c.	7,716	36.46	15.91	524	40.46	16.69	***
pop_density	7,716	2,953.02	2,711.21	524	2,918.96	2,493.84	
research_facilities	7,880	8.33	20.18	524	9.01	18.95	
new_dyad	7,880	0.05	0.28	524	0.21	0.94	***

A significance level of 0.1 is indicated by "*", a level of 0.05 corresponds to "**" and "***" indicates a significance level of 0.01.

3.3 Descriptive statistics

Tables 3 and 4 present descriptive statistics on the above-mentioned variables. As visible in Table 3, differences in the categorical variables between subsidized and non-subsidized organisations are apparent. In particular, subsidized organisations are more likely to be independent, they tend to have received a subsidy in the past and the share of organisations located in Eastern German labour market regions is higher. Moreover, Table 4 shows that there are significant differences in the means of a number of the continuous variables between subsidized and non-subsidized organisations. On average, subsidized organisations are older, larger and located in labour market regions with a higher amount of academics per capita. However, they do not differ significantly with regard to patents per 100 employees, population density and the number of research facilities in their vicinity. Furthermore, the results of the t-tests indicate that the emergence of new dyads (dependent variable), on average, is higher amongst subsidized organisations. The number of new dyads of subsidized organisations is almost 20% of a standard deviation higher than that of non-subsidized organisations.[47] The difference-in-means is statistically significant at a 95% confidence interval. Whether this is due to the subsidy or because of other characteristics is yet to be investigated.

[47] Note that the outcome variable has been standardized (mean = 0, sd = 1).

4 Analysing the effect of public R&D support on the emergence of radical novelty

4.1 Method

In general, organisations receiving R&D grants may be different from organisations which do not get subsidized. Hence, to identify the effect of public R&D funding on an organisation's ability to come up with radical novelty it is important to identify attributes for the inclusion into treatment. Thus, a propensity score matching is applied to get more credible estimates of the role of R&D funding. Before applying the matching estimation, a logistic regression is run to predict the propensity of receiving public R&D funding. The equation includes important characteristics for the selection into the funding scheme. As can be seen in Table 5, except for age and patents per 100 employees all covariates are important drivers of being selected for treatment. Being larger, being active in knowledge-intensive industries, having received a subsidy in the past, being independent and being located in an Eastern German labour market region drives the likelihood to receive public funding.

Next, a matching procedure is applied to find pairs of observations that have very similar propensity scores, but that differ in their treatment status. This leaves us with 141 organisations in the treatment group and in the control group respectively. Table 6 reports the results of the econometric matching estimation. It can be seen that the difference-in-means is statistically slightly significant only for patents per 100 employees (on the 10% level). Hence, the matching was successful and a close neighbour was found for each of the treated organisations.

Table 5. Logit estimation on the probability of receiving a subsidy.

	Dependent variable:
	R&D_funding
age	-0.008
	(0.006)
age²	0.00003
	(0.00003)
log(size)	0.946**
	(0.393)
log(size²)	-0.043
	(0.028)
patentsp100emp	0.001
	(0.003)
industry_rest	-0.195
	(0.273)
industry_ki	0.543**
	(0.241)
past_subsidy	1.307***
	(0.269)
independent	0.712**
	(0.329)
EastWest	0.692**
	(0.308)
Constant	-5.371***
	(1.318)
Observations	1,065
Log Likelihood	-369.782
Akaike Inf. Crit.	761.563
Note:	*p<0.1; **p<0.05; ***p<0.01
	Robust standard errors in parentheses

Table 6. Results of econometric matching estimation.[48]

	SELECTED CONTROL GROUP, N=141		SUBSIDIZED ORGANISATIONS, N=141		RESULTS OF T-TESTS ON MEAN DIFFERENCES
Variables	Mean	St. Dev.	Mean	St. Dev.	
age	47.83	44.883	47.248	44.06	
age²	4287.915	9935.58	4160.227	8438.335	
log(size)	6.207	1.484	6.272	1.676	
log(size²)	40.716	20.356	42.123	24.92	
patentsp100emp	1.60	2.67	2.31	3.84	*
academics_p.c.	36.59	14.23	36.58	15.74	
pop_density	3,038.96	2,599.22	2,828.69	2,663.42	
research_facilities	10.83	22.66	7.34	17.05	

A significance level of 0.1 is indicated by "*", a level of 0.05 corresponds to "**" and "***" indicates a significance level of 0.01.

[48] Values for the categorical variables are not reported here but can be provided by the author upon request.

Subsequently, the effect of R&D funding on radical innovations is analysed. The continuous dependent variable suffers from over-dispersion. Hence, negative binomial models are applied to test the proposed hypotheses which is emphasised by the likelihood-ratio test.

4.2 Results

Before turning to the analysis, some additional descriptive information is provided on the variables that have not been used so far. Table 7 shows statistics on the variables concerning the number of public R&D grants in general and the number of granted collaborative R&D projects in particular. As can be seen, the organisations in the sample are supported with two grants on average. Furthermore, cross-industrial and cross-regional are the most common form of supported cross-innovation activities.

Table 7. Additional descriptive statistics, N= 524.

Variables	Observations	Mean	St. Dev.	Min.	Max.
R&D_funded_projects	524	2.06	3.73	1	64
co_funding	524	1.81	2.99	0	44
cross-orga_funding	524	0.05	0.24	0	2
cross-industry_funding	524	0.76	1.44	0	19
cross-region_funding	524	0.80	1.41	0	18
cross-cluster_funding	524	0.13	0.85	0	16
cross-cluster_funding (cross-industry)	524	0.10	0.77	0	16
cross-cluster_funding (cross-region)	524	0.12	0.83	0	16

Table 8 reports the results of the negative-binomial regression models on radical innovation outcome. Model 1 represents the baseline model and Models 2-6 subsequently introduce the variables of interest. With regard to the control variables, as expected, age and size both have a non-linear relationship. Age takes an u-shaped relation with the emergence of novel combinations, which means that not only young organisations are more likely to come up with radical novelty but also rather old organisations. Young innovative organisations have already found to be key actors for the emergence of radical innovations (e.g., Schneider and Veugelers 2010). A reason for the positive effect concerning older organisations could be that they possess deep knowledge in a certain field and are able to combine it with complementary knowledge, for instance, through collaborations with other actors (Leten et al. 2007). Then, (the log of) organisation size has an inverted u-shaped relation to the emergence of radical novelty, although the negative effect of size is not significant in the first two models. Both relations have

already been suggested by previous research (e.g. Beck et al. 2016). Furthermore, an organisation's general innovativeness has a positive effect throughout all models (except for Model 2a) same as the number of research institutions in the local ecosystem of the organisation. This has been found by earlier studies (e.g. Grashof et al. 2019). (The log of) Population density has a negative effect only in Model 6. This may be explained through the fact that policy-induced inter-regional collaborations are aimed at enhancing the catching-up process of peripheral regions (Isaksen and Trippl 2017).

Model 2a and 2b show that, in line with earlier research (Beck et al. 2016), public R&D support indeed enhances the emergence of radical innovations (measured with a binary and a continuous variable respectively). Hence, we find support for hypothesis 1. Model 3 provides evidence that the funding of collaborative R&D projects indeed has a positive effect on radical innovations, supporting hypothesis 2. This finding complements earlier research which has already found that policy-induced collaborations have a positive influence on R&D per sales and patent performance in general (Czarnitzki et al. 2007; Hottenrott and Lopes-Bento 2014).

Models 4-6 analyse the effect of funded cross-innovation activities. The results show that funding the cross-fertilisation of knowledge through linking actors with different organisation types, different industrial specialisation or located in different regions can enhance an organisation's ability to come up with radically new knowledge. Although earlier research has already found evidence for the positive effect of university-industry linkages (e.g. Belderbos et al. 2004), cross-industrial (e.g. Castaldi et al. 2015) and cross-regional (e.g. Miguelez and Moreno 2018) collaboration, the results provide first evidence that policy makers can support the emergence of radical innovations by funding cross-innovation activities. Thus, hypotheses 3,4 and 5 can be accepted.

Subsequently, Table 9 shows the effect of cross-cluster activities on radical innovations. First of all, Model 7 shows that funding collaborations across regional clusters has a positive effect on radical innovation output of organisations, supporting hypothesis 6. This suggests that it is fruitful to link two industrial strongholds to combine deep knowledge from both sources for radical novelty as proposed by Janssen and Frenken (2019). Models 8 and 9 further point to the fact that these strongholds should have different industrial specialisations or should be located in different regions to provide complementary knowledge for radical search processes. This can also help to overcome possible cognitive or regional lock-in (Boschma 2005). This unveils that cross-

specialisation policy can work in order to foster radical innovation. Cross-fertilisation can be induced most effectively when the treated organisations have a different industrial or regional background. The influence of the control variables is mostly consistent with the discussed results in Models 1-6.

In sum, the results of this study show that R&D policy can foster radical innovation. In particular, funding of collaborative R&D projects renders fruitful for radical innovation processes. Furthermore, the findings provide evidence that cross-innovation activities where collaboration partners have different organisational backgrounds, are active in different industries or are located in different regions, enhance the emergence of radical innovations. Moreover, funding of collaborations between innovative actors from two regional clusters positively affects radical innovation output.

In order to assess the robustness of the results, the models in Table 8 and 9 have been calculated for general innovation output. This way it can be detected whether the observed effects refer to radical innovation processes particularly or to innovation processes in general. The results are reported in the Appendix (Tables 10 and 11). While R&D support in general and collaborative R&D in particular also have a positive effect as earlier research suggests (e.g. Rigby and Zook 2002), the funding of cross-innovation activities does not enhance general inventive performance of organisations (only cross-organisational projects are positively significant). This is also the case regarding cross-specialisation policy.

The results point to the fact that overall innovativeness is mostly characterised by incremental improvements (Arts and Veugelers 2015). Organisations do not need so much new knowledge to successfully engage in such invention processes with relatively low novelty content (Nooteboom 2000). Therefore, collaborations between more distant (cognitively or geographically) partners do not have a significant effect. However, in the case of radical innovation processes a certain difference between the collaborators are essential in order to gain access to new knowledge (Nooteboom et al. 2007). As this study shows, this can be enhanced through cross-innovation efforts.

Table 8. Negative binomial regression results.

	Dependent variable:						
	new_dyad						
	(1)	(2a)	(2b)	(3)	(4)	(5)	(6)
age	-0.027**	-0.025**	-0.032***	-0.032***	-0.029***	-0.033***	-0.037***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
age²	0.0001*	0.0001*	0.0001**	0.0001**	0.0001*	0.0001**	0.0001**
	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)	(0.00004)
log(size)	2.163**	2.256**	3.329***	3.203***	2.884***	3.516***	3.463***
	(0.984)	(0.945)	(0.995)	(0.995)	(0.989)	(1.048)	(1.038)
log(size²)	-0.064	-0.075	-0.145**	-0.136**	-0.113*	-0.159**	-0.152**
	(0.059)	(0.056)	(0.060)	(0.060)	(0.059)	(0.064)	(0.063)
patents_p100emp	0.118*	0.103	0.119*	0.116*	0.122*	0.105*	0.120*
	(0.068)	(0.065)	(0.063)	(0.064)	(0.065)	(0.064)	(0.067)
industry_rest	-0.402	-0.303	-0.227	-0.243	-0.315	-0.399	-0.268
	(0.754)	(0.728)	(0.686)	(0.693)	(0.716)	(0.715)	(0.721)
industry_ki	0.514	0.577	0.344	0.348	0.461	0.296	0.395
	(0.506)	(0.496)	(0.464)	(0.471)	(0.479)	(0.478)	(0.492)
independent	-0.168	-0.267	-0.480	-0.461	-0.299	-0.369	-0.073
	(0.637)	(0.636)	(0.640)	(0.645)	(0.629)	(0.659)	(0.655)
academics_p.c	-0.026	-0.024	-0.023	-0.022	-0.023	-0.026	-0.020
	(0.021)	(0.020)	(0.019)	(0.020)	(0.020)	(0.021)	(0.021)
log(pop_density)	-0.219	-0.160	-0.349	-0.349	-0.295	-0.327	-0.397*
	(0.251)	(0.237)	(0.232)	(0.236)	(0.242)	(0.237)	(0.240)
research_facilities	0.020*	0.018*	0.026***	0.026***	0.023**	0.027***	0.028***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
R&D_funding		0.849*					
		(0.453)					
R&D_funded_projects			0.107**				
			(0.042)				
co_funding				0.108**			
				(0.048)			
cross-orga_funding					0.992*	-0.803	-0.978
					(0.568)	(1.025)	(1.061)
cross-industry_funding						0.297**	-0.864
						(0.132)	(0.651)
cross-region_funding							1.241*
							(0.656)
Constant	-10.937***	-12.114***	-14.084***	-13.670***	-13.044***	-14.640***	-14.359***
	(4.244)	(4.144)	(4.173)	(4.183)	(4.255)	(4.312)	(4.251)
Observations	282	282	282	282	282	282	282
Log Likelihood	-104.481	-102.953	-101.350	-101.843	-103.247	-101.570	-100.184
theta	0.382***	0.491**	0.630*	0.577**	0.483**	0.544**	0.566**
	(0.148)	(0.211)	(0.325)	(0.283)	(0.217)	(0.248)	(0.245)
Akaike Inf. Crit.	232.962	231.907	228.700	229.685	232.494	231.140	230.368

Note: *p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses

Table 9. Negative binomial regression results, cross-cluster variables.

	Dependent variable:		
	new_dyad		
	(7)	(8)	(9)
age	-0.031***	-0.031***	-0.031***
	(0.011)	(0.011)	(0.011)
age²	0.0001**	0.0001**	0.0001**
	(0.00004)	(0.00004)	(0.00004)
log(size)	3.185***	3.193***	3.185***
	(0.992)	(0.992)	(0.992)
log(size²)	-0.134**	-0.134**	-0.134**
	(0.059)	(0.059)	(0.059)
patents_p100emp	0.121*	0.121*	0.121*
	(0.065)	(0.065)	(0.065)
industry_rest	-0.306	-0.304	-0.307
	(0.698)	(0.698)	(0.698)
industry_ki	0.338	0.339	0.337
	(0.483)	(0.482)	(0.483)
independent	-0.358	-0.359	-0.356
	(0.626)	(0.625)	(0.626)
academics_p.c	-0.024	-0.024	-0.024
	(0.020)	(0.020)	(0.020)
log(pop_density)	-0.337	-0.339	-0.337
	(0.238)	(0.238)	(0.238)
research_facilities	0.027***	0.027***	0.027***
	(0.010)	(0.010)	(0.010)
cross-cluster_funding	0.216**		
	(0.106)		
cross-cluster_funding (cross-industry)		0.218**	
		(0.106)	
cross-cluster_funding (cross-region)			0.216**
			(0.106)
Constant	-13.621***	-13.640***	-13.620***
	(4.184)	(4.182)	(4.184)
Observations	282	282	282
Log Likelihood	-102.058	-102.014	-102.051
theta	0.553** (0.267)	0.556** (0.269)	0.553** (0.267)
Akaike Inf. Crit.	230.116	230.028	230.101
Note:			*p<0.1; **p<0.05; ***p<0.01
			Robust standard errors in parentheses

5 Conclusion

The starting point of this study was the fact that although many scholars advise policy makers to support cross-innovation activities in order to enhance radical innovation, we do not know whether the funding of such research projects has an effect on radical innovation. These innovations can provide the basis of future sustainable economic growth (Ahuja and Lampert 2001). Especially, in the light of the founding of innovation agencies to support such innovations that move the technological frontier in Germany and the EU, it seems important to shed light on the question whether public R&D support in general and policy-induced cross-innovation activities in particular can support such innovation processes.

This paper provides three main results. First, it shows that policy support can enhance the emergence of radical innovations by taking a technology-based approach. This complements earlier findings on the role of public R&D for radical innovation output (Beck et al. 2016). Second, it finds that collaborative research project grants in particular can enhance the emergence of novel combinations (Singh 2008). Third, it shows that policy-induced cross-innovation activities can support radical innovation output. This can be done through linking different organisation types and funding collaboration between actors from different industries or regions as suggested by earlier research (e.g., Belderbos et al. 2004; Castaldi et al. 2015; Miguelez and Moreno 2018). Furthermore, it provides first empirical evidence that the cross-specialisation policy, proposed by Janssen and Frenken (2019) has a positive effect on radical innovation.

The analysis could be further strengthened by having access to private R&D investment data and thus being able to determine the input additionally of the public subsidy. Also, access to panel data would allow to investigate organisations over time. This way one could analyse the effect of public R&D grants by looking at the organisations before and after treatment. Furthermore, it could be fruitful to assess the role of public R&D funding on an international scope as new knowledge for radically new ideas in particular might be found beyond national borders. This could be done by looking at EU funding schemes. Finally, future research could investigate whether the policy criteria could be used for catching-up processes of lagging regions.

The findings provide insights of particular interest for policy makers aiming to support radical innovation and can help to design measures for innovation agencies such as the

German SprinD or the JEDI on the European level. Public research grants should include criteria to induce cross-innovation activities through different channels (organisational, industrial and regional). Furthermore, policies such as the InterClust contest, trying to connect innovative places, could be expanded (Dohse et al. 2018). Finally, the results are also interesting for managers of organisations planning to engage in radical innovation processes. For instance, they could engage in cross-innovation activities either through private efforts or by applying for research grants that seek to support these activities.

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Appendix

Table 10. Robustness check: Negative binomial regression results, general innovation output.

				Dependent variable:			
				patent_count			
	(1)	(2a)	(2b)	(3)	(4)	(5)	(6)
age	-0.002	-0.002	-0.003	-0.003	-0.002	-0.002	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
age²	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
log(size)	0.898***	0.931***	1.085***	1.031***	0.955***	1.047***	0.853***
	(0.235)	(0.234)	(0.242)	(0.241)	(0.235)	(0.246)	(0.248)
log(size²)	-0.006	-0.009	-0.022	-0.017	-0.011	-0.018	-0.004
	(0.016)	(0.016)	(0.017)	(0.017)	(0.016)	(0.017)	(0.017)
patents_p100emp	0.176***	0.172***	0.177***	0.176***	0.177***	0.178***	0.175***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
industry_rest	0.218	0.232	0.261	0.253	0.261	0.259	0.283
	(0.177)	(0.176)	(0.175)	(0.175)	(0.176)	(0.176)	(0.176)
industry_ki	0.346**	0.375***	0.357**	0.353**	0.370***	0.365**	0.420***
	(0.143)	(0.143)	(0.142)	(0.142)	(0.143)	(0.143)	(0.143)
independent	0.464***	0.489***	0.442**	0.442**	0.468***	0.457**	0.470***
	(0.179)	(0.178)	(0.178)	(0.178)	(0.178)	(0.178)	(0.180)
academics_p.c	0.008*	0.007	0.009*	0.009*	0.009*	0.010**	0.010**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
log(pop_density)	-0.090	-0.075	-0.110	-0.109	-0.107	-0.115*	-0.128*
	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)
research_facilities	0.0004	0.0002	0.001	0.001	0.0003	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
R&D_funding		0.226*					
		(0.117)					
R&D_funded_projects			0.053**				
			(0.021)				
co_funding				0.048**			
				(0.023)			
cross-orga_funding					0.472*	0.295	0.264
					(0.258)	(0.304)	(0.305)
cross-industry_funding						0.057	0.088
						(0.048)	(0.216)
cross-region_funding							-0.040
							(0.227)
Constant	-3.300***	-3.566***	-3.773***	-3.608***	-3.423***	-3.643***	-2.926***
	(0.965)	(0.966)	(0.973)	(0.971)	(0.961)	(0.978)	(0.987)
Observations	282	282	282	282	282	282	282
Log Likelihood	-910.230	-908.480	-907.089	-907.948	-908.005	-907.485	-908.538
theta	1.297***	1.315***	1.331***	1.321***	1.319***	1.326***	1.315***
	(0.116)	(0.118)	(0.120)	(0.119)	(0.119)	(0.120)	(0.118)
Akaike Inf. Crit.	1,844.461	1,842.959	1,840.178	1,841.897	1,842.009	1,842.969	1,847.077

Note: *p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses

Table 11. Robustness check: Negative binomial regression results, cross-cluster variables on general innovation output.

	Dependent variable:		
	patent_count		
	(7)	(8)	(9)
age	-0.003	-0.002	-0.002
	(0.003)	(0.003)	(0.003)
age²	-0.00001	-0.00001	-0.00001
	(0.00002)	(0.00002)	(0.00002)
log(size)	1.001***	1.000***	1.003***
	(0.242)	(0.243)	(0.242)
log(size²)	-0.015	-0.014	-0.015
	(0.017)	(0.017)	(0.017)
patents_p100emp	0.175***	0.175***	0.175***
	(0.018)	(0.018)	(0.018)
industry_rest	0.223	0.222	0.224
	(0.176)	(0.176)	(0.176)
industry_ki	0.330**	0.331**	0.329**
	(0.144)	(0.144)	(0.144)
independent	0.439**	0.439**	0.438**
	(0.179)	(0.179)	(0.179)
academics_p.c	0.009*	0.009*	0.009*
	(0.005)	(0.005)	(0.005)
log(pop_density)	-0.103	-0.103	-0.104
	(0.068)	(0.068)	(0.068)
research_facilities	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)
cross-cluster_funding	0.078		
	(0.058)		
cross-cluster_funding (cross-industry)		0.075	
		(0.058)	
cross-cluster_funding (cross-region)			0.081
			(0.058)
Constant	-3.509***	-3.507***	-3.510***
	(0.975)	(0.975)	(0.974)
Observations	282	282	282
Log Likelihood	-909.103	-909.162	-909.162
theta	1.310*** (0.118)	1.309*** (0.118)	1.311*** (0.118)
Akaike Inf. Crit.	1,844.205	1,844.324	1,844.054
Note:			*p<0.1; **p<0.05; ***p<0.01
			Robust standard errors in parentheses

Appendix C: Contextual Papers

Paper 4

Grashof, N., Hesse, K., & Fornahl, D. (2019). Radical or not?. The role of clusters in the emergence of radical innovations. *European Planning Studies*, **27**(10), 1904-1923. DOI: www.doi.org/10.1080/09654313.2019.1631260.

Paper 5

Arant, W., Fornahl, D., Grashof, N., Hesse, K., & Söllner, C. (2019). University-industry collaborations—The key to radical innovations?. *Review of Regional Research*, **39**(2), 119-141. DOI: www.doi.org/10.1007/s10037-019-00133-3.

Radical or not? The role of clusters in the emergence of radical innovations[49]

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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.

Keywords: radical innovations, regional clusters, centre, periphery, recombinant novelty, firm-level

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1 Introduction

Innovations are commonly accepted to be a key factor for economic growth (e.g. Rosenberg 2004, Verspagen 2005). Recently, especially the outstanding opportunities arising from rather radical innovations have been highlighted (Castaldi et al. 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 and Clark 1990, Verhoeven et al. 2016). From a firm's perspective, they are desirable to enhance their competitiveness (Zhang et al. 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).

An already prevalent instrument of innovation policy are regional clusters (Brown et al. 2007, Cantner et al. 2018, EFI 2015, Festing et al. 2012), which have been shown to foster the innovativeness of firms (Baptista and Swann 1998, Bell 2005). Nevertheless, there also exist contradictory evidence about the effect of clusters on firm´s innovativeness (e.g. Pouder and St. John 1996). It therefore still remains unclear whether clusters are a beneficial environment for innovations in general (Martin and Sunley 2003) and the generation of radical innovations in particular (Hervás-Oliver et al. 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 et al. 2017, Mascitelli 2000, Otto and 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 and Sunley 2003, Pouder and 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 (Corthright 2001, Rosenberg 2004, Verspagen 2005). 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 (Basalla 1988, Arthur 2007).

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 mind-set (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 and 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 and Clark 1990, Tushman and Anderson 1986). Radical innovations can introduce a new set of performance features or have a higher functional quality and improve performance significantly (Bers et al. 2009). Also, they may reduce cost compared to existing products and may alter the characteristics of the market, such as consumer expectations (Nagy et al. 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 and Lampert 2001, Arthur 2007).

Scientific literature has used several methodologies to analyse radical innovations empirically mainly based on indicators using forward (e.g. Trajtenberg 1990, Albert et al. 1991) and backward (e.g. Rosenkopf and 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 and 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 et al. 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 (Verhoeven et al. 2016, Rizzo et al. 2018). In line with, e.g. Dahlin & Behrens (2005), we argue that radical innovations have two dimensions (emergence and impact) which are worth inspecting.[50]

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 and 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

[50] Although the analysis of our study focuses on invention processes, the paper uses the terms 'innovation' and 'invention' interchangeably.

knowledge base, technologies and/or product-market." (Grashof and Fornahl 2017, p. 4).[51] It has been emphasized that clusters can be a preferable environment for fostering firm´s innovativeness (Baptista and 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 et al. 2013, Knoben et al. 2015, Rigby and Brown 2015).

In his pioneering contribution, Marshall (1920) considers the firm-specific advantages of being located in close proximity to similar firms.[52] 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 and 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 and 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 and Herbst 2008, Otto and 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 et al. 2008, Braunerhjelm et al. 2017, Zucker et al. 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 et al.

[51] 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.

[52] In line with our cluster definition, we do not consider cities as clusters in this study.

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 and 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 et al. (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 and Los 2012, Castaldi et al. 2015).

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 and 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 et al. 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 realisation of a competitive advantage, but additionally it is essential to consider relational resources, such as inter-firm relationships and routines (Dyer and Singh 1998, Lavie 2006, Steffen 2012). This relational dimension has also been investigated in the context of clusters (Giuliani 2007, Hervás-Oliver and 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 and Albors-Garrigos 2009, Zaheer and 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 and Lopes-Bento 2016, Kesteloot and 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 et al. 2013). Building on the theoretical insights proposed by Suarez and Lanzolla (2005 and 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 and Schendel 1976, Suarez and 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 and Lanzolla 2005, Suarez and 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 et al. 2006, McCann and 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 and 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 and 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 and 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[53] 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).[54] 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 and 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).[55]

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

[53] 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).

[54] In accordance with the literature, 45 minutes are here perceived to be an adequate limit for close geographical distance (Brenner 2017, Scholl and Brenner 2016).

[55] 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).

in the sense that it is completely new to Germany (since 1983).[56] 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 and Feldman 1996, McGahan and 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 and 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 and 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 et al. 2011).

Regarding a firm´s cluster position, various measures have been used (Broekel and Graf 2012, Lechner and 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

[56] 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.

that companies are located in the periphery, whereas high values emphasize that they are in the centre of the corresponding cluster (Brenner 2017, Scholl and 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 and 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.[57] 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 et al. 2018b, McCann and Folta 2011) we applied logistic regression to test our hypotheses. The logistic regression model has the following form:

$$\text{Logit}(\pi_i) = \beta 0 + \beta 1 \text{ Cluster dummy} + \beta 2 \text{ Central position} + \beta 3 \text{ Relationships} + \beta 4 \text{ Technology evolution} + \beta 5 \text{ Cluster size} + \beta 6 \text{ Controls}_i + \varepsilon_i ,$$

[57] 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 and Lhuillery 2009).

where π is the natural log of the odds for company *i* to introduce a radical innovation (between 2012 and 2014) and ε represents the corresponding error term.

4 Empirical results and Discussion

As can be seen in Table 1, our sample consists of 8,404 organisations 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 organisations engage in incremental innovating processes. Moreover, 1,028 organisations 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	8,039 (95.66%)	7,376 (87.77%)
1	365 (4.34%)	1,028 (12.23%)
Total	8,404 (100%)	8,404 (100%)

Furthermore, we calculated the number of radical innovations per organisation 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).[58] 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 & Werner (2012). We used this definition so that commuter and urban-periphery structures are 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

[58] For a detailed overview of the number of radical innovations and the pace of technology evolution by industry, please see appendix 3.

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 organisation. 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.[59]

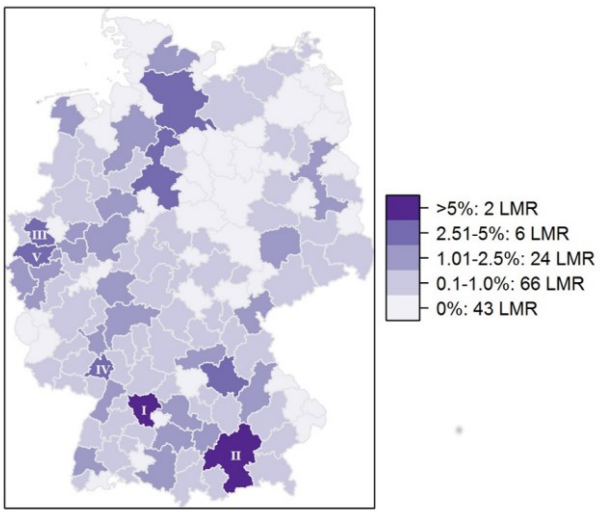

Figure 1. Share of radical innovations in German labour market regions 2012-2014 (own illustration).

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 8,404 organisations. 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.

[59] A geographical distribution of the firms in our sample and in total Germany can be found in the appendix 2.

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 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 organisations 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.[60]

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 prove 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.[61] 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.[62] 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 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

[60] 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.

[61] 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 and Kreuter 2008, MacKenzie et al. 2018, UCLA 2018).

[62] The cluster index-specific marginal effects of being located in a cluster are illustrated in the appendix 4.

cluster. Hence, they are less likely to generate radical innovations.

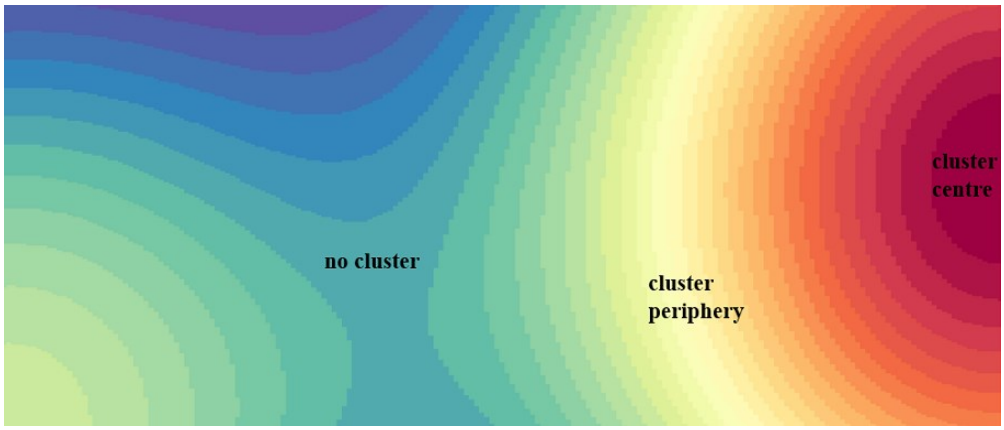

Figure 2. The emergence of radical innovations in clusters - centre vs. periphery (own illustration).

Table 2. Logistic regression results.

Radical innovation dummy n = 8,404	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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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 organisation 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 et al. 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.[63] However, we were not able to find results

[63] Results can be provided by the authors upon request.

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, itis 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 are 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[64], only based on pooled cross sectional data[65], 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.

[64] Particularly referring to the calculation of the cluster index.
[65] 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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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).[66]

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
36	Minden	114	4.908
37	Bochum	87	8.058
38	Dortmund	80	22.826
39	Hagen	180	7.245

[66] 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.

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

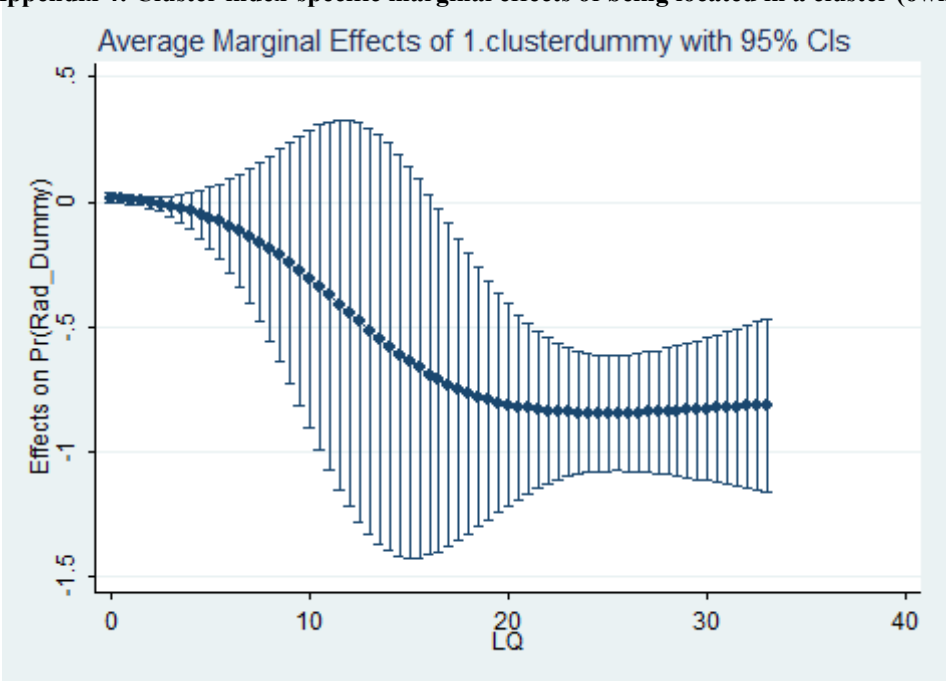
129	Leipzig	83	25.715
130	Dessau-Rosslau	17	3.456
131	Magdeburg	27	9.564
132	Halle	41	8.212
133	Stendal	2	4.574
134	Erfurt	53	10.029
135	Gera	16	4.334
136	Jena	57	4.271
137	Nordhausen	7	3.299
138	Eisenach	12	1.932
139	Unstrut-Hainich	12	4.350
140	Suhl	18	1.890
141	Saalfeld-Rudolstadt	18	4.901

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 and electricity distribution and control apparatus	6	1,3219231
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)



University-Industry collaborations – The key to radical innovations?[67]

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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 8,404 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 combinations 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

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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

I 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. Section 2 deals with the theoretical background on radical innovations and distances in university-industry collaborations, deducting three hypotheses. Subsequently, section 3 presents the databases as well as the methodology applied. In section 4 we present and discuss our empirical results, concluding with some final remarks in section 5.

2 Theory and hypotheses

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).

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:

> Hypothesis 1: 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:

> Hypothesis 2: 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 & 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[68]. This level offers the best trade-off between a sufficiently large number of patents in the classes and a maximal number of technologies.

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 8,404 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[69] 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

[68] Hence, this aggregation level includes 403,860 potential linkages

[69] 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.

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, 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.[70] To define near and distant relations we used the second quantile of all ranges of all relationships as a threshold, which corresponded to 60 kilometers. This is in a range that can be reached within 45-60 minutes, which is the definition used by Kosfeld and Werner (2012) to define 141 labour market regions in Germany.[71] 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.

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

[70] Thereby we employed the R package "geosphere".
[71] The social security statute book also refers to this definition when talking about commuter structures.

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).[72] 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.[73] 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).[74] 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.

[72] 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.
[73] 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).
[74] For an overview the share of all innovations (not just radical innovations), please see Appendix 2.

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%)

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 geographical distribution of radical innovations between 2012 and 2014 (see Figure 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, 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.

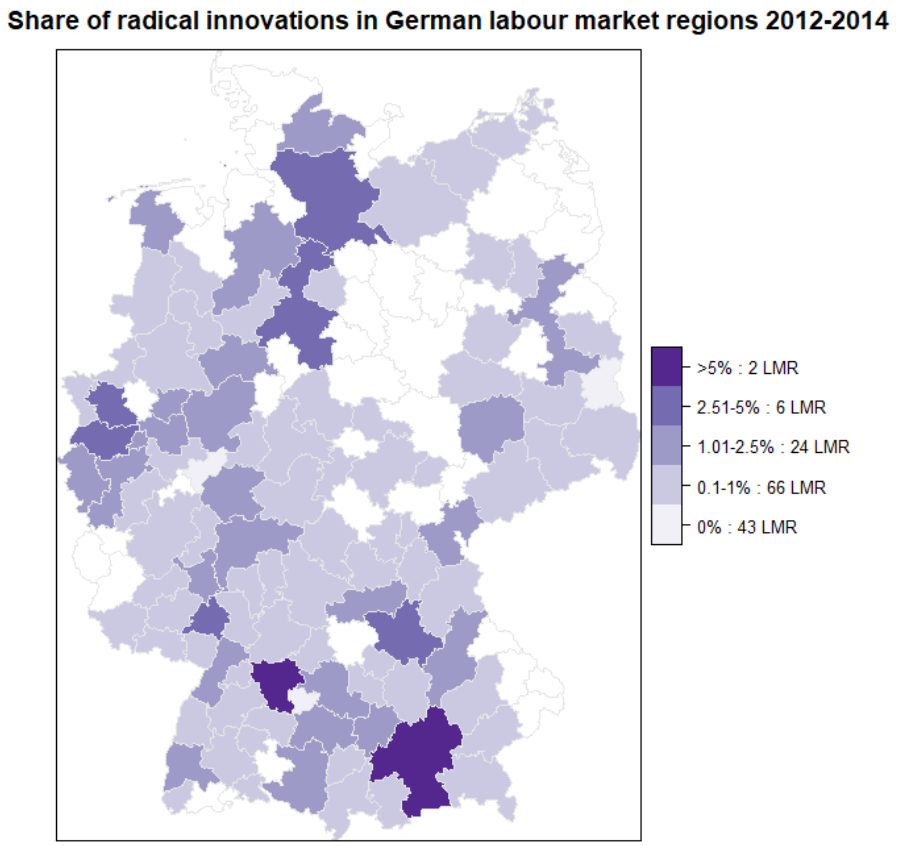

Figure 1. Radical innovations 2012-2014 (own illustration).

Similarly, Figure 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 Figure 1 we find evidence that most of the public funding is distributed to core regions rather than to the periphery. In summary, Figures 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.[75]

[75] 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.

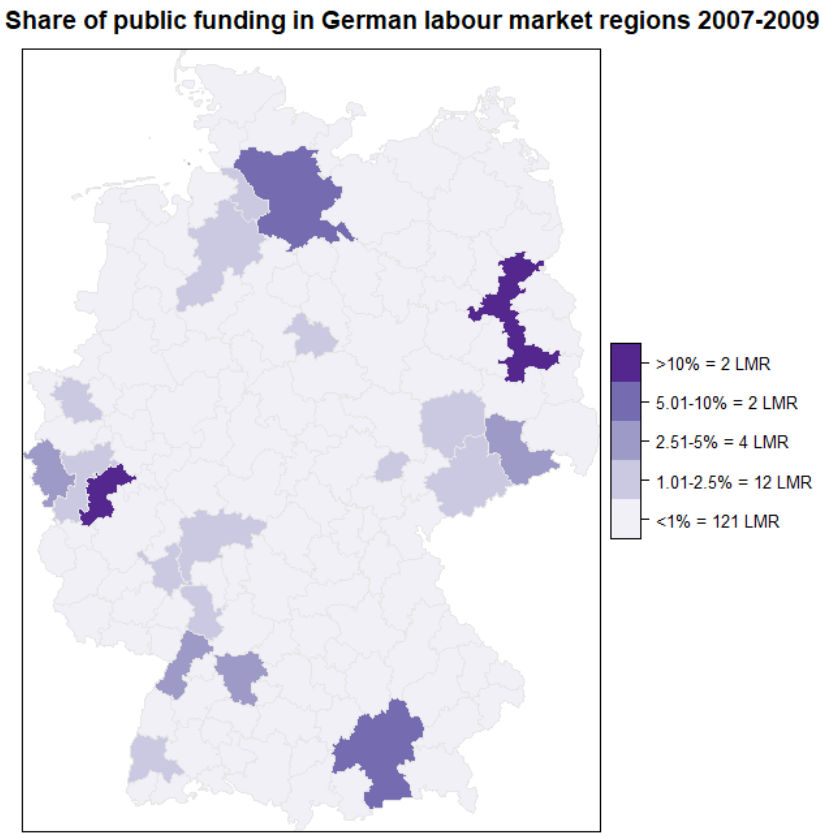

Figure 2. Public funding 2007-2009 (own illustration).

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 1, 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).[76] 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 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.

Table 2. R&D collaborations and radical innovations (Odds rations, 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*

[76] 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.

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.[77] 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 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.

[77] Cognitively close collaborations are not illustrated because they perfectly predict failure.

Table 3. Cognitive distance and radical innovations (Odds (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*

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.

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*

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.

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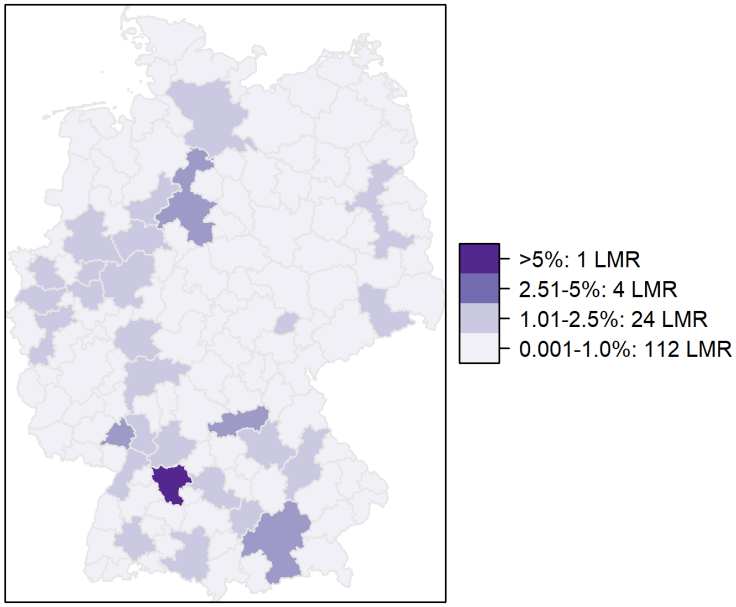
Appendix 1. Pairwise correlation matrix and descriptive statistics (own illustration) [78]

	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

[78] 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.

Appendix 2: Share of innovations in German labour market regions 2012-2014



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Curriculum vitae

Kolja Hesse war seit Ende 2016 wissenschaftlicher Mitarbeiter am Centre for Regional and Innovation Economics im Fachbereich Wirtschaftswissenschaft der Universität Bremen. Die von Herrn Hesse betreuten Projekte haben stets regionalwirtschaftliche Fragestellungen mit starkem Fokus auf mögliche Wissens- und Innovationspotenziale behandelt, um regionale Stärken zu identifizieren und zu fördern. Seit Oktober 2017 ist er Doktorand an der Universität Bremen. Im Rahmen seiner Promotion hat Herr Hesse Treiber und Wirkmechanismen bei der Entstehung radikaler Innovationen und ihrer geographischen Verteilung untersucht. Dabei verwendet er äußerst große Datenmengen (insb. Patent- und Fördermitteldaten) für seine Analysen. Er besitzt einen Masterabschluss (M.Sc.) in Management & Engineering der Leuphana Universität Lüneburg. Zuvor hat er erfolgreich ein Bachelorstudium der Volkswirtschaftslehre (B.A.) in Bremen mit einem Auslandssemester in Neuseeland und einem Praktikum in Spanien absolviert.

Eidesstattliche Erklärung

Hiermit erkläre ich, dass ich die vorliegende Dissertation zum Thema **„Drivers and mechanisms of the emergence and diffusion of radical innovations“** ohne unerlaubte Hilfe angefertigt habe, keine anderen, als die angegeben Quellen und Hilfsmittel benutzt habe, die den benutzen Werken wörtlich oder inhaltlich entnommenen Stellen als solche kenntlich gemacht habe und eine Überprüfung der Dissertation mit qualifizierter Software im Rahmen der Untersuchung von Plagiatsvorwürfen gestatte.

Bremen, 23.04.2020

Jan Kolja Hesse