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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 Classifications

O31 ; O33 ; R11

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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 the 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[1] 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

[1] This aggregation level is used to have a sufficiently large number of patents in the classes and a maximal number of technologies.

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.[2] 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).[3] 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

[2] 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.

[3] For a discussion on different diversity indicators, see e.g., Guevara et al. (2016).

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).[4] 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).[5] 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 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

[4] For a full list see: https://www.wipo.int/export/sites/www/ipstats/en/statistics/patents/pdf/wipo_ipc_technology.pdf.

[5] A list with all labour market regions is provided in Table 5 in the appendix.

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.[6] 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.

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).[7] 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.

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

[7] 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).

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.

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	academics
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***	1

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[8] 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

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

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.

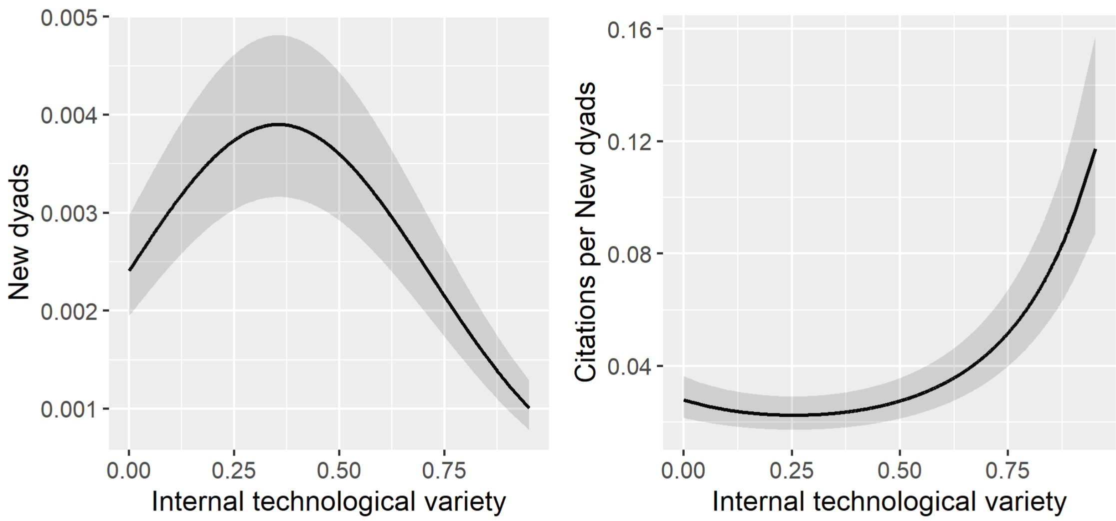

Figure 1. Predicted values of new dyads (left) and citations per new dyad (right).

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 **Fehler! Verweisquelle konnte nicht gefunden werden.**[9] illustrates the inverted u-shape relation between cognitive proximity to frontier firms and the emergence of radical innovations. Thus, organisations do not 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.

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

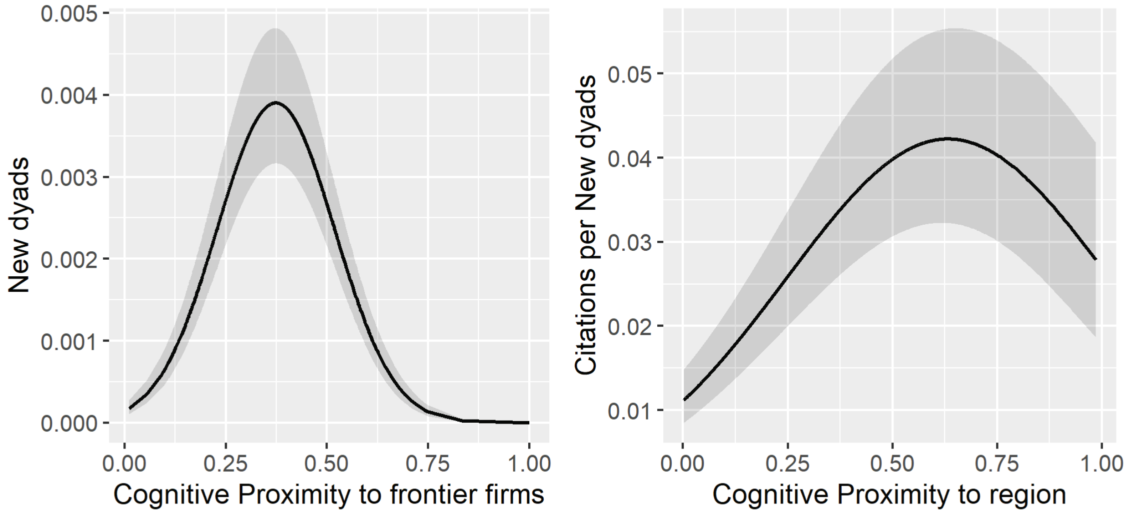

Figure 2. Predicted values of new dyads (left) and citations per new dyad (right).

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 **Fehler! Verweisquelle konnte nicht gefunden werden.**). 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 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.

Table 3: 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(aca-demics)	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***	-10.29**	-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	-2,052.23	-1,547.62	-2,053.24	-1,544.48	-1,886.97	-1,441.33	-1,644.91	-1,277.04
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.	4,116.46	3,107.24	4,122.48	3,104.95	3,793.94	2,902.66	3,313.83	2,578.08
Note:								*p<0.1; **p<0.05; ***p<0.01

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 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 similarity 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%
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