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

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Essential ingredients for radical innovations?

The role of (un-)related variety and external linkages in Germany

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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.

JEL classifications: O31, O33, R11

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

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.

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.[1] 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 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; 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).[2]

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

[1] 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.

[2] 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.

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 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.

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. [3] 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).[4] 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.[5] 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

[3] 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.
[4] 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.
[5] For details see:
http://www.wipo.int/classifications/ipc/en/ITsupport/Version20100101/transformations/stats.html.

new, if it has not been existent in Germany in the previous years since 1981. Thus, the identified dyads are new to Germany.[6] The approach is comparable to the method used by Verhoeven et al. (2016).[7] The dependent variable is constructed as a count variable indicating the number of new dyads that have emerged in each region and each year.

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).[8] 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.[9] 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).[10] These patents are also assigned to the labour market regions. Finally, the variable is

[6] 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.
[7] See Mewes (2019) for another interesting approach to detect radical novelty by building z-scores which indicate how rare technology combinations are.
[8] Also see Squicciarini et al. (2013) for a discussion on different indicators.
[9] 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.
[10] We calculated the same indicator with the top 3 and top 5 % thresholds as robustness checks. The results remained stable.

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.[11] 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).[12]

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:

[11] 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.
[12] Moran's I and LM tests for spatial dependencies are both insignificant.

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

where p_{gi} represents the share of technology g in region i.[13]

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).[14] 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 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.[15] We also include year dummies. All explanatory and control variables are time-lagged by one year.

[13] For detailed information on the entropy measures see Frenken (2007) or Castaldi et al. (2015). Balland (2017) is followed to operationalize the variety measures.
[14] We acknowledge, though, that there are many other possible ways for the exchange of knowledge (see e.g. Gao et al., 2011).
[15] Research-intensive industries include the high-tech sectors "leading-edge technology" and "high-quality technology" based on 4-digit NACE codes.

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 near here]

[Table 2 near here]

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 near here]

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.

[Figure 2 near here]

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 near here]

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.[16] 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

[16] 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.

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 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.

[Table 4 near here]

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.[17] 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. The results indeed show an inverted u-shape relationship between unrelated 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).

[17] 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.

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.[18]

[Table 5 near here]

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

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

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 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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Tables

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

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

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*** (0.067)	0.508*** (0.092)	0.334*** (0.065)	0.498*** (0.089)	0.348*** (0.066)	0.594*** (0.093)
Unrelated variety			0.226*** (0.056)	0.182** (0.075)	0.237*** (0.054)	0.175** (0.072)	0.218*** (0.057)	0.167** (0.074)
External linkages					0.434*** (0.097)	0.465*** (0.127)	0.454*** (0.098)	0.483*** (0.127)
External linkages^2					-0.083*** (0.019)	-0.055** (0.022)	-0.079*** (0.018)	-0.053** (0.021)
Patents p.c.	0.299*** (0.055)	0.298*** (0.076)	0.224*** (0.050)	0.244*** (0.069)	0.147*** (0.051)	0.14** (0.071)	0.12** (0.053)	0.113 (0.073)
GDP p.c.	0.177*** (0.074)	0.215** (0.103)	0.177*** (0.058)	0.124 (0.088)	0.175*** (0.055)	0.081 (0.083)	0.166*** (0.055)	0.074 (0.083)
Population density	0.495*** (0.062)	0.552*** (0.083)	0.364*** (0.045)	0.421*** (0.068)	0.249*** (0.052)	0.247*** (0.075)	0.232*** (0.053)	0.227*** (0.075)
Academics p.c.	0.116* (0.064)	0.252*** (0.087)	0.063 (0.05)	0.138* (0.073)	0.035 (0.048)	0.071 (0.072)	0.055 (0.049)	0.086 (0.072)
High-tech firms p.c.	0.158** (0.07)	0.158 (0.097)	0.036 (0.056)	0.01 (0.083)	0.023 (0.051)	-0.009 (0.077)	0.04 (0.052)	0.004 (0.077)
Unrelated variety*External linkages							-0.144*** (0.051)	-0.11* (0.06)
y2002	-0.203*** (0.067)	-0.119 (0.08)	-0.164*** (0.068)	-0.073 (0.08)	-0.181*** (0.069)	-0.093 (0.081)	-0.19*** (0.068)	-0.097 (0.081)
y2003	-0.4*** (0.072)	-0.218*** (0.082)	-0.372*** (0.072)	-0.188*** (0.083)	-0.411*** (0.073)	-0.242*** (0.084)	-0.402*** (0.073)	-0.227*** (0.085)
y2004	-0.538*** (0.075)	-0.432*** (0.088)	-0.529*** (0.076)	-0.408*** (0.09)	-0.541*** (0.076)	-0.447*** (0.091)	-0.51*** (0.077)	-0.41*** (0.094)
y2005	-1.113*** (0.088)	-0.761*** (0.097)	-1.082*** (0.089)	-0.712*** (0.099)	-1.092*** (0.089)	-0.758*** (0.101)	-1.06*** (0.09)	-0.727*** (0.103)
y2006	-1.199*** (0.089)	-0.92*** (0.1)	-1.154*** (0.09)	-0.872*** (0.102)	-1.164*** (0.089)	-0.888*** (0.102)	-1.131*** (0.09)	-0.852*** (0.104)
y2007	-1.178*** (0.091)	-1.491*** (0.124)	-1.097*** (0.091)	-1.383*** (0.125)	-1.11*** (0.09)	-1.404*** (0.124)	-1.076*** (0.091)	-1.363*** (0.126)
y2008	-1.407*** (0.103)	-1.627*** (0.138)	-1.307*** (0.1)	-1.497*** (0.136)	-1.306*** (0.099)	-1.489*** (0.134)	-1.259*** (0.1)	-1.438*** (0.137)
y2009	-1.401*** (0.111)	-1.576*** (0.148)	-1.268*** (0.106)	-1.394*** (0.144)	-1.293*** (0.104)	-1.404*** (0.141)	-1.249*** (0.105)	-1.359*** (0.143)
y2010	-1.291*** (0.107)	-2.269*** (0.174)	-1.151*** (0.103)	-2.085*** (0.172)	-1.169*** (0.101)	-2.111*** (0.171)	-1.123*** (0.103)	-2.064*** (0.173)
Constant	1.435*** (0.07)	0.614*** (0.1)	1.405*** (0.066)	0.508*** (0.093)	1.513*** (0.068)	0.605*** (0.093)	1.499*** (0.068)	0.594*** (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**	**Model 6a**	**Model 6b**	**Model 7a**	**Model 7b**

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

Figures

Figure 1: Average number of radical innovations in German labour market regions 2001-2010

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

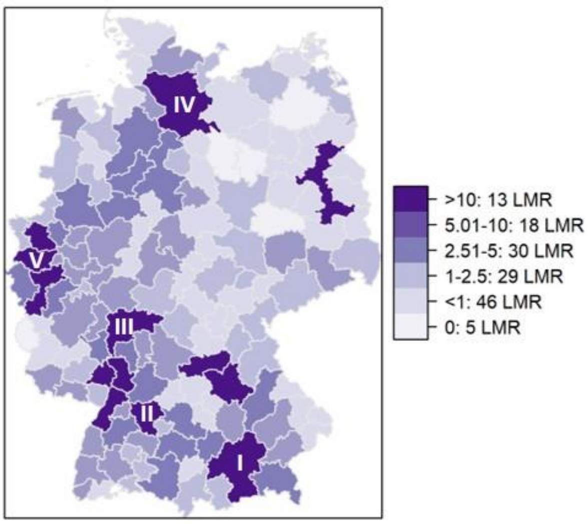

Figure 1: Average number of radical innovations in German labour market regions 2001-2010 (left: new dyads, right: high-impact innovations).

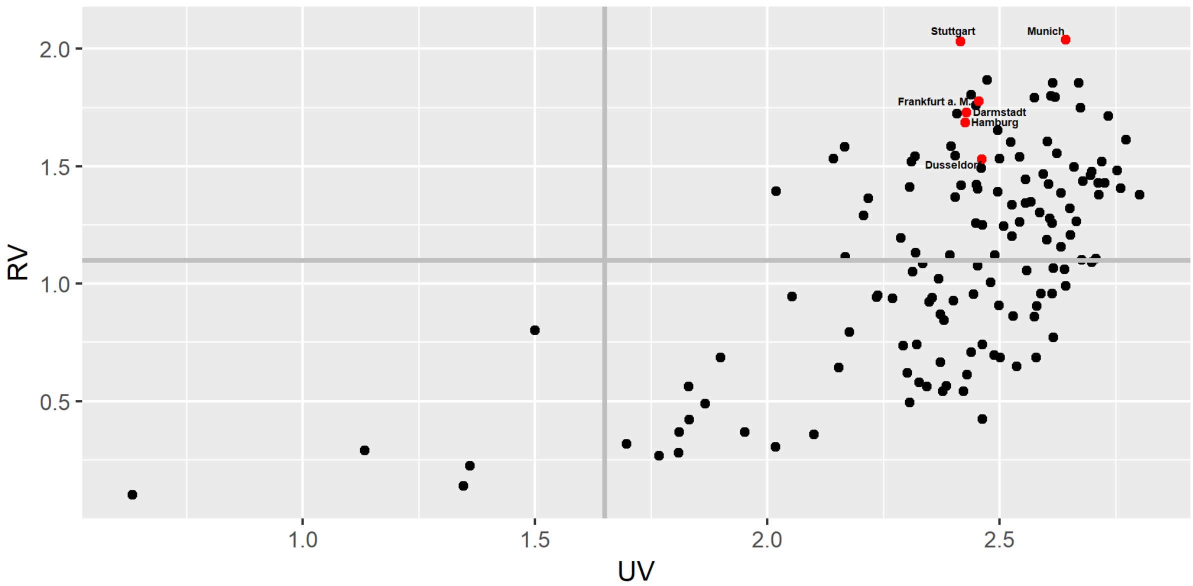

Figure 2: Related (RV) and unrelated variety (UV), bullets show labour market region averages between 2001-10.