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Diffusion of radical innovation for the case of biotechnology SMEs: does proximity matter?

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Abstract

Radical innovations by definition have a great influence on the future of the existing economic systems. It means that not only radical innovators, but also other stakeholders can experience their impact. The factors, influencing the direction and strength of this impact are far from being understood. Early appropriation of radical innovator's knowledge may be especially important for small and medium-sized firms (SMEs), serving as the source of competitive advantage. Here different proximity dimensions (geographical, cognitive, institutional, organizational and social), measuring respective distances to a radical innovator, may play a crucial role. Thus, this paper opts at revealing the importance of proximity measures for the case of German biotechnology SMEs. A longitudinal dataset covering the period from 1996 to 2016 for the innovative performance of SMEs, that are citing radical innovators, is used as the base of the analysis. Results only partially confirm the findings of previous research by indicating the negative effect of higher distance and organizational proximity. However, the effect of both cognitive and social dimension could not be confirmed. Reasons for that potentially lie both in unique character of radical innovation and peculiarities of the biotechnology field in Germany.

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1. Introduction

Biotechnology in Germany is a highly innovative field, where many small and medium enterprises (SMEs) operate. They compete with biotech and pharma “giants” and find a niche to operate (Hannan and Freeman 1977; Feldman and Francis 2003). Therefore, their innovations may break field routines (Dahlin and Behrens 2005), open new trajectories and influence future inventions, thus, becoming the radical changers.

Research on sources and ways of radical innovation measurement can be found in literature (Dahlin and Behrens 2005; Verhoeven, et al. 2016) along with the investigation of effects, that radical innovation has on firm´s creation (Shane 2001) and importance of specific factors for its emergence and diffusion (e.g. clusters in Grashof et al. 2019; cognitive proximity to regional knowledge in Hesse 2020). However, its influence on the other actors inside and across the fields is far from being understood. Previous research (Shkolnykova and Kudic 2020) shows a positive effect of cooperation with radical innovators. Nevertheless, knowledge exchange not always happens over contractual relations. The informal communication or even just observation of successful innovators, without them intendedly transferring the knowledge, may lead to improvement of innovative performance. The factors, influencing success of these externalities are still remaining a ‘black box’.

Possible explanations may lie in different proximity measures, i.e. closeness to radical innovators according to particular criteria. Previous research identified a big number of such measures. The classification of Boschma (2005), who distinguished between five dimensions of proximity: geographical, cognitive, institutional, organizational and social, has received acceptance in evolutionary economics and economic geography.

In this paper these proximity dimensions are used to follow their influence on the innovative performance of the inventors, citing radical innovators. Citations here are used as well-accepted measure this knowledge exchange (Jaffe et al. 1993; further used for example in Maurseth and Verspagen 2002; Breschi et al. 2005). The focus of the paper is made on the SMEs innovations in the field of biotechnology for several reasons. First, the field is highly concentrated, which means that firms can profit from being located in the centers of excellence, using so-called “local buzz”. Second, the complexity of the knowledge in the field may restrain actors from fully profiting from the know-how of the others, especially if the actors are cognitively distant from each other (Boschma and Martin 2010). However, as radical innovation presents the combination of previously unconnected fields, it may stand out from the technological profile of the radical innovator. Thus, it may happen, that technologically distant firms may profit from it as well. Lastly, although SMEs are well-presented across German biotechnology, big corporations still play important role both with respect to financial and innovative performance. Thus, biotech SMEs may communicate more with pharmaceutical corporations internationally, than with biotechnological peers (Kahl 2015), meaning that organizational and social proximity also in this case are unpredictable.

In order to identify the direction and strength of these effects, a longitudinal unbalanced panel dataset for the period from 1996 to 2016 is created. This dataset reflects innovative performance of citing SMEs as well as different proximity measures and firm and regional characteristics. The negative binomial regression analysis is performed in order to prove the importance of particular proximity dimension. In order to show that the results are not random, the same analysis is also performed for the control sample of the firms with the same characteristics as the ones, citing radical innovators.

These findings contribute to contemporary discussion of influence of radical innovation on other firms within and across regions and fields. Firstly, dependence of innovative performance on different proximity measures gives policymakers an idea of potential of SMEs in particular regions and fields. Secondly, it provides the hint for entrepreneurs how they can profit from outside knowledge. Lastly, it enriches the scientific literature on radical innovation of SMEs.

Thus, this paper proceeds as follows. Next section presents existing state of the art on the topics of knowledge externalities as well as proximity and presents research hypotheses. Apart from that, it discusses the importance of the radical innovation case. Third section provides the overview of specificity of biotechnology field in Germany with a particular focus on SMEs and presents used data. The fourth section overviews research design and methodology, with showing, how applied variables were created, as well as presents econometric approach. In the fifth section results of the analysis are presented and discussed, whereas sixth section deals with limitations and possible avenues for further research.

2. State of the art

2.1. Knowledge generation and diffusion

The question of knowledge emergence, diffusion and appropriation appeared to be in the core of many economic disciplines, including growth theory, neo-Schumpeterian and evolutionary economics. Knowledge stock, according to growth theory, is the only source of possible growth, whereas the new growth theory extends this notion to the feature of knowledge to spill over across time and space (Döring and Schnellenbach 2006). Resource-based view on the firm sees extension of knowledge as one of the main motives for a firm to engage itself in a cooperation (Cantner and Meder 2007). Thus, a knowledge stock is anything but stable. According to Neo-Schumpeterian theory, knowledge has cumulative and complex character (Hanusch and Pyka 2006). This statement outlines, that the stock of the knowledge grows with time both within and across the boundaries of the firm, thus, knowledge diffusion is also of high relevance.

However, the character and speed of this process depends on the type of knowledge. It is normally distinguished between explicit and tacit knowledge (Polaniy 1966). Whereas the former type of the knowledge can be transmitted with the help of "formal language", for the case of tacit knowledge formal language expression is just not possible (Fallah and Ibrahim 2004). Thus, for exchanging the latter type of knowledge closer communication of the holders of this knowledge and its meticulous analysis. Whenever the holders of the knowledge want to secure themselves from negative effects explicit knowledge to be copied by others, the way of knowledge protection, e.g. with the help of patents, is used (Döring and Schnellenbach 2006).

Both face-to-face communication for the case of tacit knowledge and usage of formal language sources for the case of explicit one allows knowledge to be transmitted to other actors. This transmission may have either intended or unintended character. In the first case it can be thought of cooperation projects, where knowledge is willingly and intentionally exchanged. In such situation knowledge transfer usually occurs (Fallah and Ibrahim 2004). In other cases of unintended knowledge exchange it is normally considered as knowledge spillovers. They may happen as the result of employees changing working place, informal communications between firms, exchange on conferences and workshops etc. (Howells 2002). For spillovers to occur it is important, that the value of the knowledge is recognized through the other firm (Ibrahim et al. 2008).

The strength of knowledge diffusion, being intended or unintended, however, is not the same for all firms. A large strand of literature has tried to identify the factors, which may influence the scale and direction of it. Some of these factors, which will be further used in analysis are outlined in the next subchapter.

2.2. Importance of different proximity measures

As already mentioned, knowledge may spread across time and space. Thus, researchers have been interested in factors, which may influence the success of knowledge diffusion for a long time. One of the important issue raised in this regard is the notion of absorptive capacity, introduced by Cohen and Levinthal (1990). Absorptive capacity relates to the capability of a firm to identify and implement knowledge and gain a competitive advantage from it. However, there are also other factors, which may positively or negatively influence the success of knowledge spillovers (Broekel and Boschma 2012). Most of them are based on different dimensions of proximity between the actor, from whom spillover stems and the one, who receives it.[1] One of the well-accepted and widely used, as well as comprehensively developed classifications was introduced by Boschma (2005), who distinguished between geographical, cognitive, institutional, organizational and social proximity. This classification is further used for the analysis in this paper.

Geographical proximity is probably the most well researched proximity type, especially for the case of economic geography. It reflects the idea, that knowledge better spills over across small distances (Polaniy 1966; Polaniy 1967; Kesidou 2004), which is especially the case for the tacit knowledge, that cannot be transmitted with the help of words, but includes rather “learning by doing” component. Although some authors argue, that nowadays several meetings at the conferences and skype calls for year may compensate long distance at least for the case of scientist (Breschi et al. 2005), the composite character of innovation as well as additional level of complexity, caused by organizational structures still call for benefits, that firms may get from being located close to innovative actors. Reason for that is that closely located firms can better track innovation trajectories by observing neighbours (Hohberger 2014).

Many research papers have shown the negative effect of increasing distance on the knowledge diffusion (e.g. Broekel and Boschma 2012; Bednarz and Broekel 2019). However, it was also acknowledged that geographical closeness is not the only factor influencing the success and intensity of knowledge diffusion. Furthermore, Boschma (2005) has seen it as neither sufficient nor necessary condition for it.

Cognitive or technological proximity was established as one of other factors, influencing success of knowledge diffusion. The idea behind it is that the recipient of knowledge can better understand the external knowledge, when it is related to its own knowledge base (Boschma 2005; Cantner et al. 2010). This notion reflects the cumulative character of knowledge (Boschma 2005). However, Nooteboom et al. (2007) claimed that the optimal cognitive distance function has an inverted U-shaped form, which means that too much proximity may have negative effect on knowledge diffusion and absorptive capacity of receiving firm. Reason for that is that in case of too close knowledge base the probability of new knowledge creation will be lower (Broekel and Boschma 2012).

Apart from that, institutional proximity was mentioned as a factor, influencing knowledge spillovers. This proximity type reflects the situation and regime on the macro-level (Boschma 2005). As Sternberg (2007) mentions, that this factor may be of a higher importance for old and well-established firms, whereas knowledge-based entrepreneurial ventures, having higher flexibility, are less dependent on institutional closeness. Furthermore, in the scope of this paper only biotechnology SMEs are taken

[1] Which could be not only a person or a firm, but also a region or a country.

into account. They experience similar institutional influence, therefore, this factor is not taken into account in the analytical part.

Nevertheless, there exists the other important proximity measure, relevant for biotechnology case: organizational proximity. It can be broadly defined as the level of interdependences between organizations (Boschma 2005). Balland (2012) identified two views on this proximity measure. According to the first, it is defined based on the interactions between two firms. Furthermore, Broekel and Boschma (2012) have seen organizational proximity as the interactions between different types of firms and organizations (public and private). The second view sees organizational proximity as the closeness between firms from the same corporate group. Following Balland (2012), this paper takes the latter view of organizational proximity in order to distinguish it from the last type of proximity – social one.

Lastly, social proximity is seen as the one of the most important factors of knowledge diffusion, especially for innovative SMEs (Sternberg 2007), as such firms often cannot rely completely on formal relationships or capital investments. Social proximity depends on the presence and strength of social ties between actors. As its establishment may be a long-lasting process (Balland et al. 2015), the strength of social proximity may vary over time.

2.3. Research hypotheses for the case of radical innovation

Next, it would be interesting to see how above-stated factors may influence the knowledge diffusion for the case of radical innovators' knowledge. The peculiarity of this type of innovation is that it opens new technological trajectories in the field, thus, having impact on its future (Dahlin and Behrens 2005; Verhoeven, et al. 2016).

Radical innovation, thus, may disrupt the knowledge, which influences both the radical innovator himself and the industry in general. Clusters appear to be one of the factors of radical innovation occurrence (Grashof et al. 2019), which raises the question of the importance of geographical closeness. Thus, other firms, located close to radical innovation may profit from it first, especially for the case of tacit knowledge diffusion. However, this effect may be diminished by the active interaction of SMEs with international corporations and the fact, that repeated communication with the same actors in the region may diminish the opportunity to get new knowledge and use it for the creation of the new knowledge (Zuluaga 2013). However, tacitness of knowledge, generated by radical innovation, especially for the case of knowledge intensive industries, speaks for the importance of short distances on the knowledge diffusion, or:

H1: Higher geographical distance has a negative influence on the radical innovators' knowledge diffusion

Furthermore, radical innovation is often seen as the combination of existing knowledge in an unusual way (Fleming 2001; Fleming 2007) and the knowledge base of such innovation is different from what radical innovator usually does (Verhoeven et al. 2016), too much complementarity between radical innovator and other firms may negatively influence innovative performance of the latter. Hesse (2020) has investigated the influence of cognitive proximity between radical innovator and regional knowledge database on the emergence and number of citations of radical patents. In general, u-shaped effect of cognitive similarity was supported here in the most of the cases, whereas the presence of certain "saturation point" for the case of forward citations measurement was observed (Hesse 2020). Furthermore, it can be assumed, that completely distant firms may not be able to understand the information, obtained from radical innovator. Thus, it can be stated that:

H2: Cognitive proximity has a U-shaped influence on the radical innovators' knowledge diffusion

Organizational proximity generally may have a negative effect on speed of knowledge diffusion via hierarchy and bureaucracy or a positive effect, because of the support, existing between different corporative units. However, for the case of knowledge-based SMEs rather flat hierarchies are present, so, this issue should not have that high importance, whenever the firm is not connected to big corporation (Sternberg 2007). Apart from that, according to Sternberg, SMEs should not profit from being located in the same organizational structure – the knowledge flows are relatively fast either way because of the small size of the firm. Thus, it can be expected that:

H3: Organizational proximity has a negative influence on the radical innovators' knowledge diffusion

For the case of social proximity, a different picture can be expected. Here the size of the firm and lack of resources may motivate SMEs to (informally) contact peers (Sternberg 2007). The presence of such connections may be long-lasting and stay even if one of the firm's collapses (Broekel and Boschma 2012). This may lead to sharing of the tacit, sometimes even secret knowledge (Balland 2012), which is especially important for the case of radical innovation, as it is may not be fast accepted by other firms in the field because of the complexity. Thus, it can be supposed that:

H4: Social proximity has a positive influence on the radical innovators' knowledge diffusion

3. Data and research field

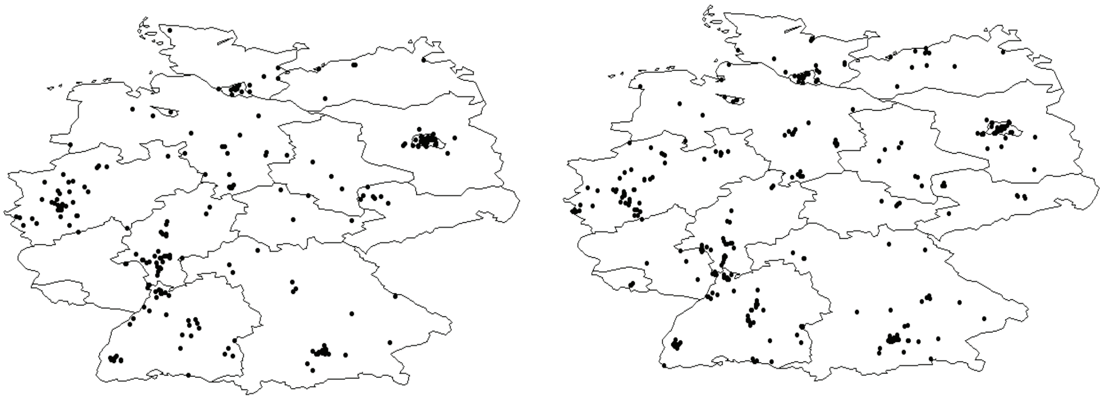
3.1. Spatial and organizational peculiarity of biotechnology in Germany

Biotechnology in Germany has an intensive history, which started in 1990s with several incentives from policy-makers, that promoted the development of the industry in general around the country as well as in particular regions. Thus, BioRegio competition led to four regions receiving financial support for the period from 1997 until 2005. Other initiatives, (1999-2003) and BioChancePlus (2004-2007) were exclusively oriented at funding start-ups.

As the result, the number of SMEs in German biotechnology is relatively high. According to the data from BIOCOM AG[2], in 2005 88% of dedicated biotechnology firms (DBFs) had less than 50 employees. In 2015 this number fell only to about 85%[3]. Thus, SMEs play important role on the innovative landscape of German biotechnology. However, they have to compete with a number of large corporations from biotechnology, chemical or pharmaceutical industry. In the mid and end 2000s, as the result, many SMEs had to exit the market, some due to financial situations and others because of being acquired by large corporations. This situation leads not only to the motivation for SMEs, that stay in the market, to innovate radically in order to stand out. It may also foster the communication between the most innovative SMEs and the ones, still trying to find their niche. As not every contact, however important, may lead to successfully funded project, spillovers due to social proximity may be important here.

As the result of BioRegio competition, as well as of frequent industry-university cooperation (Zucker 1998), the biotechnology industry is rather concentrated (Belenzon and Schankerman 2013). Fornahl et al. (2011) identified seven clusters of the highest biotechnology patent activity: Berlin, Göttingen, Hamburg, Munich, Rhine-Main, the Rhineland and Rhine-Neckar. Most of them also correspond to the areas with highest number of dedicated biotechnology firms present. Apart from that, Jena region, also funded by BioRegio competition[4] can be distinguished because of the SMEs' activities.

[2] A firm, that specializes on gathering statistics on enterprises working in the field of life sciences and particularly biotechnology.
[3] This number includes both independent SMEs and subsidiaries.
[4] BioRegio Initiative winning regions: Rheinland ("BioRiver"), Heidelberg (Rhein-Neckar-Dreieck), Munich and Jena



DBFs location, 1996 *DBFs location, 2016*

Figure 1: Location of dedicated biotechnology firms in Germany

Figure 1 presents location of DBFs in Germany in two periods of time: 1996, which is approximate initialization of biotechnology in Germany, and 2016, as the most recent available year. As can be seen, main centers of excellence in Western and Southern Germany, as well as in Hamburg and Berlin, remained stable over time. Apart from that, East of Germany has become more active with regards to biotechnology firms: apart from small firm cluster in Jena, more firms appeared in Saxony-Anhalt, Brandenburg and Mecklenburg-Vorpommern. In Mecklenburg-Vorpommern a small cluster of firms was built around Rostock, probably caused by the presence of university and Leibniz Society institutions.

As can be seen, spin-offs are quite common in the industry. Scientists, who have a commercial idea, may a firm, that continues operating on the area of the campus or close to it. Such constellation is especially favorable for SMEs, who are profiting from synergetic effects of external knowledge (Simmie 2002).

The biotechnology field in Germany is rather complex, with wide classification of subfields (e.g. McCormick and Kautto 2013; Richardson 2012) and high interdependencies with pharmaceutical and chemical industries. Apart from that, it can be stated, that biotechnology in Germany appeared to be based on recombination of already existing knowledge bases of these industries (Nesta and Dibiaggio 2003). Thus, the level of cognitive proximity along biotechnology SMEs may vary greatly and influence their innovative performance.

3.2. Data

In order to assess the effect of different proximity measures on the knowledge diffusion of radical innovation, the population of firms, subject to this diffusion needed to be identified. For that, citations of the radical innovators' patents were used. Patent citations are proved to be the indicator of knowledge diffusion (Jaffe et al., 1993) and further used to follow them (e.g. Bednarz and Broekel 2019; Breschi and Lissoni 2003). Although usage of the patent data has its limitations as not everything can be patentable, for the case of biotechnology (e.g. Pajunen and Järvinen 2018).

As the focal sample of radical innovators the data from a previous research article (Shkolnykova and Kudic 2020) was used as a base. Radical patents there were identified based on new combinations of technology classes, new to the field, associated with high number of forward citations. On the next step, among all radical innovators SMEs were identified, based on number of employees and turnover[5].

As here the focus was shifted from radical innovators to the actors citing them, extended sample of 29 firm[6] entries was taken into account, including the ones, not engaged in subsidized projects. For these firms the patents, citing their patent applications and publications were identified, starting one year before radical patent's earliest application year. The reason for that is to be sure, that the ones, citing radical innovators, were basing on the knowledge, coming from it and on subsequent inventors[7].

As the result 9082 patents from 3470 patent families were identified[8]. The average time between focal patent and citation lies at around 5.6 years. Citing patents come from 399 companies as applicants[9]. Out of these applicants SMEs had to be identified. For that an enterprise should include less 250 employees and less than 50 m Euro turnover[10]. Thus, additionally to the data on BIOCOM AG and Orbis firm database was used for this purpose. As the result of filtering, only 78 firms were left, including spin-offs and subsidiaries. The list of the firms is presented in Appendix A.

[5] According to EU recommendation 2003/361 less than 250 employees and 50 m Euro turnover.
[6] One of them appears in dataset under two different names
[7] Coming from the idea, that radical innovations change the future of the field as well as the innovative portfolio of radical innovators.
[8] With the help of PATSTAT 2017b.
[9] Private applications were excluded.
[10] Classification according to EU recommendation 2003/361.

4. Methodology

4.1. Research design

In order to check the stated hypotheses, following steps needed to be conducted on the sample of 78 citing SMEs:

1. Innovative performance of the firm, which presents dependent variable, needed to be identified. It is done with the help of number of patents, which a firm applied for each year, starting from the year of radical innovator's patent citation and ending with 2016.
2. Each of four proximity dimensions, discussed in the paper, needed to be presented in the form of the variable, based on existing literature. The values of these variables were calculated pro firm pro year and used in order to support or reject hypotheses.
3. Control variables, reflecting firm and regional dimensions were calculated for each firm for each year.
4. An unbalanced panel was created and the estimation of the negative binomial regression was performed.

Then, in order to prove, that proximity measures really reflect the diffusion of knowledge from radical innovators, innovative performance of the control group of firms, that haven't cited radical innovators' patents needed to be evaluated. Thus, for every firm in the citing sample a non-citing twin was created with the help of propensity score matching, basing on the similarity of the following criteria, which are expected to influence innovative performance of each firm (e.g. Acs et al. 2002; Beugelsdijk 2009):

Table 1. Control variables

Level	Description	Data source
Firm level	Whether the firm is stock-exchange quoted;	Orbis
	Number of employees in the firm (last available year)	Orbis
	Number of firms in corporate group	Orbis
Regional level	R and D expenditure by NUTS 2 region, Euro/inhabitant	Eurostat
	Persons with tertiary education (ISCED) and / or with a scientific and technical career by NUTS2 region, thd	Eurostat
	Whether the region, where the firm is located, was a BioRegio winner	BMBF, Orbis

Apart from that, only those firms were taken, which were assigned to the same NACE categories as the sample of citing firms. Furthermore, for citing firms, which belong to the same corporate group as the radical innovator, twins belonging to the same corporate group were identified. After twins' identification, the values of proximity dimensions were identified and the model was evaluated with respect to hypotheses. As the firms, which do not cite radical innovation are expected not to receive its knowledge, it is supposed, that none of the coefficients for proximity variables is significant, thus, for the case of non-citing firms no effect of closeness to radical innovator on the innovative performance is expected[11]. The list of the twin firms is presented in Appendix A, whereas the results of the analysis are presented in Appendix B.

4.2. Variables of interest

After identification of the sample of citing SMEs as well as number of patents, which each of them applied for each year, variables, reflecting each of the hypotheses needed to be introduced.

First, geographical proximity was measured as the the distance in km between radical innovator and citing firm (based on e.g. Maurseth and Verspagen 2002; Broekel and Boschma 2o12). The logarithm of distance was used in the estimations in order to account for possible outliers (Broekel and Boschma 2012). Whenever citing or cited firms moved according to the used database, the distance was recalculated[12].

Second, cognitive proximity was identified based on technological classes according to International Patent Classification (IPC)[13] assigned to the patents of radical innovator and citing firm. These classes may serve as the representation of technological fields, in which the firm is located (Jaffe et al. 1993). Following the approach, which Broekel and Boschma (2012) used for the case of NACE classifications, cognitive proximity was calculated with the help of following formula:

$$COG = \frac{\sum_{i=1}^{n} l_i m_i}{\sqrt{l_i^2}\sqrt{m_i^2}} \quad (1)$$

Where *i* - index for technology class, and *l* and *m* indicate number of patents of a radical innovator and citing firm respectively in the class *i*. The indicator is calculated for each firm and for each year. As the knowledge according to the theory of evolutionary economics has a cumulative character (e.g. Hanusch and Pyka 2006), the knowledge base, reflected in number of patents in particular class was accumulated over time. As the result, the cognitive proximity of two firms could increase or decrease over time. The

[11] The only hypotheses, that could not be tested for the case of twin firms is H4, because of impossibility to calculate respective indicator for twins.

[12] The situation, where the firm moved to another region was extremely rare across both radical innovators' and citing actors' sample. The most moves included change of the city inside of the region or change of the address inside the city.

[13] Accessed via https://www.wipo.int/classifications/ipc/en/, last retrieved in January 2020.

indicator could vary between 0 and 1[14] with 0 meaning that radical innovator and citing firm are completely technologically dissimilar and 1 meaning complete technological similarity. Apart from that squared term was calculated for this indicator in order to check, whether there exists predicted inversed U-shaped relationship between cognitive proximity and innovative performance.

Third, the organizational proximity needed to be estimated. As already stated, this paper follows the definition, stated by Balland (2012). In this sense firms are seen as organizationally close if they belong to the one corporate group and organizationally distant if they do not. Thus, the variable can take the value of either 0 or 1 and change in the case of firm joining or leaving the corporate group.

Last, the social proximity measure was defined. For that the definition of Marrocu et al. (2013) was used, who have defined this measure based on the patent co-inventorship between cited and citing firms. The idea behind it lies in the emergence of network links following the exchange of tacit or explicit knowledge. To extend the indicator, the patents where the same inventors-physical persons appear were also taken into account, coming from the thought, that this could mean employees' changing working places or just co-working on a specific project of the other firm.

Thus, the measure for each firm in each year was equal to the share of the common patents between radical innovator and citing firm. Also here cumulative number of patents was taken. Social proximity thus ranges from 0 to 1 with 0 meaning that the firms are completely socially distant and 1 meaning that firms are completely socially close. As trust needs time to be built and result in a common patent, the lags of zero, one, and two years were checked[15]. Baseline model presents the results without lags, other model specifications are available in Appendix C.

Table 2 presents the overview of proximity measures with the data sources for their extraction as well as possible values.

Table 2. Proximity measures

Variable	Description	Data source	Values
GEO	Logarithm of distance in km	Orbis, BIOCOM AG	Real numbers
COG	Similarity of knowledge based, based on patent technology classes	PATSTAT	0 to 1
ORG	Firms belonging to the same corporate group	Orbis	0 or 1
SOC	Share of co-invented/co-applied patents	PATSTAT	0 to 1

[14] Because there can be no negative number of patents in a specific class.
[15] Because of data availability (the latest available PATSTAT version – PATSTAT 2019a)

Additionally, the special case, when one firm cites two or more radical innovators needs to be discussed. If this situation occurs, minimum value for distance and maximum value for technological, social and organizational proximity was taken. In the present dataset this situation, where a firm cites two radical innovator happens four times with no situation, where more than two radical innovators are cited.

4.3. Control variables

Apart from proximity measures, several control variables, which could influence innovative performance, were introduced. These variables could be divided between two categories: firm-level and regional-level ones, as both situation in the region (through regional innovation system) and individual firm characteristics may lead to increase/decrease in the number of its patents.

Regarding firm-level variables, the standard measures were taken (e.g. Acs et al. 2002; Díez-Vial and Ferández-Olmos 2014). These include:

- Number of employees, which a firm has pro year;
- Age of the firm in years from founding;
- Presence of common patents with universities or research institutions;
- Location in technological park in a particular year;
- Whether a firm was a subsidiary in a particular year.

The latter variable needs more explanation. Díez-Vial and Ferández-Olmos (2014) have found out, that firms, located in such park may profit from it, especially through the cooperative agreements with universities and research centers. Apart from that, such firm may share benefits of close location to peers via getting access to the wider knowledge base.

Apart from that, regional variables may be important, as the environment may play an important role in fostering performance. Following regional variables were thus included in the model (taken e.g. from Beugelsdijk 2009):

- R&D expenditure of a NUTS region, where the firm is located;
- Persons with tertiary education in the region, where the firm is located;
- Region being the winner of BioRegio competition;
- Presence of at least one of 100 biggest pharmaceutical or biotechnological firms in the region, where the firm is located. These firms were identified according to revenue and number of employees according to Orbis firm database.

The overview of the variables is presented in table 3.

Table 3. Control variables

Level	Variable	Description	Data Source	Value
Firm-level variables	**EMPL**	Logarithm of the no. of employees per firm per year	BIOCOM AG, Orbis	Real numbers
	AGE	Logarithm of the age of the firm, years[16]	BIOCOM AG, Orbis	Real numbers
	TECHPARK	Logarithm of distance from technology park in km	Germany Trade and Invest (GTAI)	0 or 1
	UNI	Common patent with university/ research institution	PATSTAT	0 or 1
	SUBS	Firm being a subsidiary in a particular year	Orbis	0 or 1
Regional level variables	**BIGCOMP**	Presence of 100 biggest biotech/ pharma company in the NUTS2 region	Orbis	0 or 1
	FEREG	Logarithm of R&D expenditure by NUTS 2 region, Euro/inhabitant	Eurostat	Real numbers
	HUMRES	Logarithm of persons with tertiary education (ISCED) and / or with a scientific and technical career by NUTS2 region, thd.	Eurostat	Real numbers
	BIOREGIO	Funded region according to BioRegio or BioProfile	BMBF	0 or 1

4.4. Econometric specification

As hypotheses stated in this paper relate to the innovative performance of the firm, estimated in the number of patents per year, a count model appeared to be suitable for hypotheses testing. Based on the analysis of the existing literature, negative binomial regression model was chosen. This model corresponds to other literature sources, dealing with topic of knowledge diffusion (e.g. Bednarz and Broekel 2019; Gilbert et al. 2008).

Apart from being appropriate for the analysis of spatial data, negative binomial regression also can reflect the unbalanced panel structure of the dataset. Moreover, negative binomial regression allows accounting for overdispersion in the data. Thus, the model, used in this paper, can be generalized as follows (e.g. Cincera, 1997):

[16] In this case 0.1 was added to age in order to get rid of possible problem of calculating of the ln of age for firm in founding year

$$\widehat{\lambda_{it}} = \exp(\textstyle\sum_k \beta_k X_{it} + \varepsilon_i) \tag{2}$$

where X stands for independent and control variables.

According to the results of Hausman test as well as likelihood ratio, fixed-effects model was preferred to the random-effects one.

5. Results

5.1. Descriptive statistics

In order to perform the analysis, an unbalanced panel, reflecting dependent and independent variables for each citing SME, needs to be created. For each firm the observation period started with the year of citation and ending with 2016, if the citing firm or radical innovator had not been dissolved earlier[17]. The year of dissolution was identified according to Orbis database[18]. As the result of such analysis for 78 firms a panel with 678 observations was created.

Table 4 presents descriptive statistics with regards to patent variable as well as measures, reflecting all proximity dimensions. Thus, it can be seen, that the number of patents, which a firm filed each year varies greatly. Most of the firms have zero to one application each year, however, there are several firms in the sample, which have relative high patents' application statistics. Additional checks of these firms did not show any peculiarity of their characteristics, which would suggest deleting these firms from the sample. It should be done even less, taking into account the possibility, that the legacy of radical innovator could boost the innovative performance of a particular firm.

Table 4. Descriptive statistics, dependent variable and proximity measures

Variable	Obs	Mean	Std. Dev.	Min	Mdn	Max
PAT	678	1.73	3.57	0	0	39
GEO	678	5.03	1.47	-2.73	5.53	6.37
COG	678	0.45	0.22	0.00	0.46	0.90
ORG	678	0.07	0.26	0.00	0.00	1.00
SOC	678	0.12	0.30	0.00	0.00	1.00

[17] As after the successful exit (e.g. through acquisition) firm stays in the market, such exit did not influence end observation year. However, in the case of acquisition the value of subsidiary variable for that firm changed.
[18] Last retreived in January 2020.

Proximity dimensions also show different tendencies. Whereas social and organizational proximity is on average rather low, cognitive proximity shows generally high to medium level. Large variation can also be seen in distance dimension. These variables need additional exploration, which is presented further.

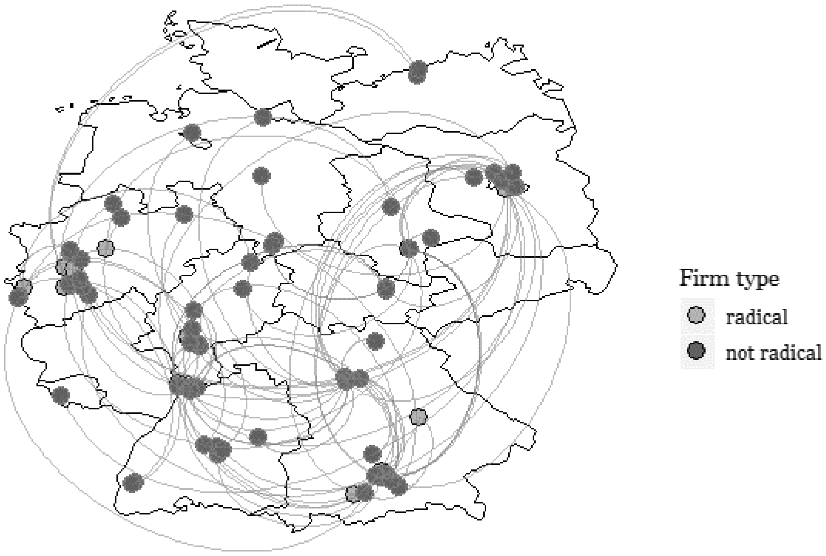


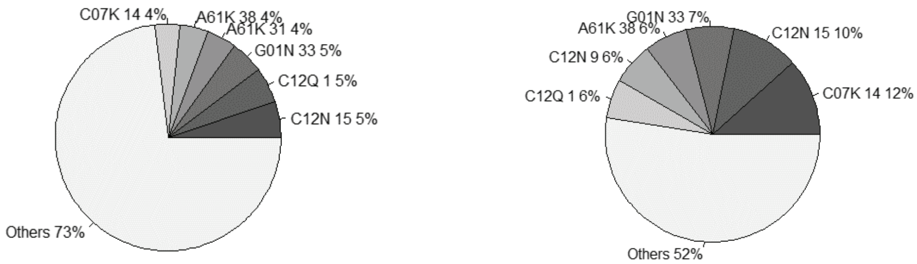
Figure 2: Location of citing and radical firms

As can be seen on figure 2[19], not all firms stick to their region when citing. There can be seen some small citation distances in West (North Rhine-Westphalia, Hessen) and South Germany (Bavaria – Munich, Nuremberg; Heidelberg region). It can also be seen that whereas radical innovators are mostly located close to traditional biotechnology clusters, especially the regions, funded by BioRegio, this is not the case for citing actors, which are spread across Germany.

Apart from that, technological proximity also shows on average medium technological similarity between cited and citing firms. Moreover, the most popular classes along citing and cited patents do not differ much. The most popular technological class of citing papers, C07K 14 ("Peptides having more than 20 amino acids; Gastrins; Somatostatins; Melanotropins; Derivatives thereof") can also be seen in radical patents. The same can be said about the most popular classes across radical innovators: C12N 15 ("Mutation or genetic engineering…") and C12Q 1 ("Measuring or testing processes involving enzymes, nucleic acids or microorganisms"). The only class, which is present in citing sample but not in the radical sample is C12N 9 ("Enzymes, e.g. ligases (6.); Proenzymes; Compositions thereof"); the only one that is present in radical and not in citing sample is A61K 31 ("Medicinal preparations containing organic active ingredients"),

[19] Here only those radical innovators, that are cited by SMEs are presented.

which are also connected among themselves. It means, that these are the less popular classes among radical and non-radical innovators that are different, or that specialization of both cited and citing firms differs.



Technological classes, radical firms *Technological classes, citing firms*

Figure 3: Location of citing and radical firms

Additionally, only six firms appear to be in one corporate group with cited radical innovator and 15 firms have positive social proximity, meaning common patent with the radical innovator. Being connected to radical innovator on the corporative level, however, does not necessarily indicates social connection: only three out of six firms from the same organizational structure show positive social proximity.

*Table 5. Descriptive statistics, control variables**

Variable	Obs	Mean	Std. Dev.	Min	Mdn	Max
EMPL	678	2.81	1.33	0.00	3.26	5.26
AGE	678	2.17	1.25	-2.30	2.31	5.38
TECHPARK	678	1.77	2.10	-3.17	2.57	4.84
UNI	678	0.30	0.46	0.00	0.00	1.00
SUBS	678	0.16	0.37	0.00	0.00	1.00
BIGCOMP	678	0.82	0.38	0.00	1.00	1.00
FEREG	678	6.90	0.66	5.19	7.01	8.35
HUMRES	678	6.66	0.51	5.37	6.89	7.37
BIOREGIO	678	0.38	0.49	0.00	0.00	1.00

Table 5 shows descriptive statistics for control variables. As can be seen, the number of employees as well as age of the firm varies greatly. Largest firm in the sample has the size of 192 employees, whereas the smallest has only one employee. Age of the firm also differs between founding in the year of citation and family firm, which was found in 19th century. Further, the distance to technology park among the firms also has a high variation, from less than one kilometer to more than 500 km.

Apart from that, more than 80% of the firms can be found in the same region with biggest pharma and biotech corporations. This could happen for several reasons: first, because such firms are well spread across the country and second, because citing firms are trying to find themselves close to big actors, either with the hope for acquisition or for doing services for such corporations (e.g. Kahl 2015).

Furthermore, about one third of the firms have connections to universities and are located in BioRegio funded regions. This additionally shows, that citing firms stick less to the standard biotechnology clusters than radical firms do. Apart from that, the relatively low number of university patent cooperation may show the higher industrial orientation of citing firms. Comparing to it, only each sixth firm is a subsidiary, which is not usual for the case of biotechnology. It may signal additionally that these are rather independent SMEs tend to rely on the knowledge of their innovative peers, whereas the ones, engaged in corporate relations, communicate more with mother companies.

Next, correlations between variables are calculated in order to see, whether all of the variables are necessary to be included into the model without possible multicollinearity problem to occur. Results of correlation analysis are presented in the table 6[20]. As can be seen from the table, the coefficients vary from low to moderate, which means, that no variable should be excluded from the model.

[20] Polychoric correlations were alternatively calculated for binary variables, however, they do not differ significantly from Pearson correlations. Apart from that, variance VIFs were calculated and did not show the multicollinearity potential for any of the variables.

Table 6. Correlation coefficients

	GEO	COG	ORG	SOC	EMPL	AGE	TECHPARK	UNI	SUBS	BIGCOMP	FEREG	HUMRES	BIOREGIO
GEO	1.000												
COG	0.027	1.000											
ORG	-0.392 ***	-0.007	1.000										
SOC	-0.262 ***	-0.032	-0.246 ***	1.000									
EMPL	0.090 **	0.015	-0.171 ***	-0.031	1.000								
AGE	0.133 ***	-0.100 **	-0.161 ***	-0.121 ***	0.212 ***	1.000							
TECHPARK	0.148 ***	-0.090 **	-0.204 ***	0.187 ***	-0.090 **	0.112 ***	1.000						
UNI	0.167 ***	-0.009	-0.185 ***	-0.195 ***	0.213 ***	0.080 **	-0.052 *	1.000					
SUBS	-0.045	-0.185 ***	0.195 ***	0.052	0.174 ***	0.035	-0.052	0.075 *	1.000				
BIGCOMP	-0.052	-0.150 ***	0.103 ***	0.160 ***	0.007	0.004	-0.022	-0.287 ***	0.062	1.000			
FEREG	-0.096 **	0.219 ***	-0.113 ***	-0.221 ***	-0.002	0.269 ***	0.097 **	0.055	0.026	-0.017	1.000		
HUMRES	0.003	0.053	-0.019	-0.078 **	-0.267 ***	0.153 ***	-0.115 ***	0.097 **	-0.040	0.055	0.511 ***	1.000	
BIOREGIO	0.076	-0.138 ***	-0.091 **	0.027	-0.019	0.022	0.008	0.135 ***	-0.014	0.039	0.070 *	0.163 ***	1.000

***- significance at 0.01 level, ** - significance at 0.05 level, * - significance at 0.1 level

5.2. Results of model estimation

Table 7 presents the results of negative binomial regression analysis across six model specifications. Specifications 1-5 relate to testing hypotheses and present the estimation of the influence of different proximity dimensions on the innovative performance of the citing firms, whereas model 6 includes control variables and model 7 demonstrates the results for both proximity dimensions and control variables.

Model 1 shows the slightly significant negative effect of the distance (GEO) on innovative performance of the firms, citing radical innovators. It means generally, that firms, related closer to innovative peers, are highly innovative themselves, which supports hypothesis 1. Interestingly, from the models 6 and 7 it can be learned that the closeness to technological park (TECHPARK) does not necessarily have an impact on firm's innovations. The reason for that may lie in sectoral differences between citing firms.

Moreover, no influence on cognitive proximity (COG) could be identified: neither positive, nor negative or U-shaped. This contradicts to the hypothesis 2 as well as results of the previous research. It means, that both technologically close and distant SMEs can profit from citing radical innovators. Reasons for that may lie in the nature of radical innovation. As already mentioned, radical innovation often differs significantly from the technological portfolio of radical innovators (Verhoeven et al. 2016), which means, that firms can profit from using its knowledge irrespective of technological closeness to radical innovator. The same may be true when later patents of radical innovator are cited. Peculiarity and complexity of biotechnology field may only strengthen this effect.

Model 4 supports the hypothesis 3 regarding the negative influence of being related to radical innovator organizationally (ORG). This is additionally supported by generally lower innovative performance of subsidiaries (SUBS), shown in the models 6 and 7. Explanation for these strong negative effect may lie not only in the bureaucracy but also in the task division within corporation. With the time some smaller subsidiaries may switch their activities to performing supportive tasks for mother firm, which may limit the potential of filing new patents. Even if it is not the case, independent SMEs may often faster obtain information directly from their radical peers than along long corporative communication channels. Apart from that, presence of corporative ties may restrict the directions, in which innovative activities of the firm can go. However, the small proportion of the firms with positive organizational proximity to radical innovator may limit this result and causes precaution in its interpretation.

Contrary to the expectation, no effect of social proximity (SOC) on SMEs' innovative performance was seen, thus, hypothesis 4 could not be supported. The addition of lags (see Appendix C) did not change the situation. The cause of that may be the chosen measure of social proximity itself. Not all trust relations between SMEs end in a common patent or project. It happens even less in the case of unintended knowledge transfer. Further refinement and specification of this measure may help in reaching more reliable results.

Appendix B shows the results of negative binomial regression for the case of control sample. As expected, no significant coefficients could be seen there, apart from slightly significant negative coefficient for organizational proximity[1], which additionally shows, that results for the case of citing firms did not occur by accident.

[1] This coefficient was, apart from that, achieved with the help of zero-inflated negative binomial model, as many firms had all zero patent applications and no proper coefficient with negative binomial regression model could be achieved for this case.

Table 7. Results of regression analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GEO	-0.197* (0.110)	-	-	-	-	-	-0.240** (0.119)
COG	-	-0.019 (0.507)	-0.784 (1.811)	-	-	-	-0.544 (0.540)
COG^2	-	-	0.892 (2.026)	-	-	-	-
ORG	-	-	-	-2.007*** (0.512)	-	-	-2.396*** (0.677)
SOC	-	-	-	-	-0.828 (0.959)	-	0.744 (1.109)
EMPL	-	-	-	-	-	0.171 (0.127)	0.413*** (0.157)
AGE	-	-	-	-	-	0.028 (0.073)	0.012 (0.738)
TECHPARK	-	-	-	-	-	-0.162* (0.083)	-0.200** (0.086)
UNI	-	-	-	-	-	0.149 (0.322)	0.044 (0.328)
SUBS	-	-	-	-	-	-0.604** (0.274)	-0.629** (0.285)
BIGCOMP	-	-	-	-	-	0.172 (0.222)	0.198 (0.230)
FEREG	-	-	-	-	-	0.418 (0.318)	0.465 (0.318)
HUMRES	-	-	-	-	-	0.109 (0.389)	-0.114 (0.401)
BIOREGIO	-	-	-	-	-	-0.264 (0.283)	-0.179 (0.301)
CONSTANT	4.101*** (0.806)	-3.106* (0.691)	3.151*** (0.582)	3.075*** (0.564)	3.109*** (0.568)	-0.139 (2.660)	2.168 (2.907)
Year efects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	-676.700	-699.553	-699.456	-692.694	-699.550	-691.348	-682.398
Observations	676	676	676	676	676	676	676

Standard errors in parentheses,

***- significance at 0.01 level, ** - significance at 0.05 level, * - significance at 0.1 level

6. Discussion and conclusion

This paper provides new insights about the importance of different proximity dimensions for the knowledge diffusion for the case of the special kind of innovation, radical innovation. The results, obtained across negative binomial regression model specifications show the positive influence of geographical closeness to radical innovator and negative influence of organizational closeness on the innovative performance of SMEs, that base on the knowledge of radical innovator. However, the influence of cognitive and social proximity could not be supported by the analysis.

The study has several important implications. First, it complements the literature on radical innovation via showing, which influence it has on the future knowledge flow within and across the field. It also shows, which actors may profit at most from this knowledge. The paper also produces implications for policy makers by showing the importance of promoting independent SMEs, both radical innovators as well as the ones, learning from them Furthermore, this promotion should not be limited to a specific field, as radical innovation seems to have an impact on the radical performance of the firms both inside and outside biotechnology. Apart from that, the study shows, that knowledge distribution is still regionally bounded, which calls for the importance of regional funding programs. These programs, however, should not limit to creation of technology parks, but also create the space of the knowledge exchange (e.g. in terms of workshops or conferences).

Several limitations can be seen in scope of above stated research, that further can be developed to support the results or question them. First, the chosen sample of independent dedicated biotechnology firms was filtered out not restrictively. The analysis could be limited only to the firms, citing radical innovations, without taken all subsequent patents of radical innovator into account. However, this may limit the possible population considerably, which either calls for extending the definition of radical innovation, or inclusion of all firms (not only SMEs) and individual-applicants in the population.

Apart from that, social proximity variable needs to be elaborated. As already mentioned, the co-patenting activities do not include all possible trust relations between firms, even less can they show the tacit knowledge transfer. Apart from that, the possible lags between trust-building and common patent may be extended to three to five years (e.g. Bednarz and Broekel 2019), which was not possible in this paper due to PATSTAT data limitations.

Furthermore, the limitations of used databases could be mentioned. Because of gaps in Orbis and PATSTAT, the data could include false positive and false negative entries. For the case of Orbis not all up-to-date employees number and turnover as well as firm address could be identified. This could bias the recognition of SMEs. For the case of PATSTAT the typos and translation ambiguities (especially for the case of umlauts) could lead to the situation, where not all patents, belonging to a specific firm, could be determined.

The performed analysis also provides several avenues for further research. First, the identified importance of geographical proximity shows, that for the special case of the radical innovation it cannot be replaced by other proximity types, as in Boschma (2005). The reason for that may lie in the chosen proxy (citations) or chosen units of analysis (SMEs). Therefore, future analysis may concentrate on adding other firms to the analysis, for example, estimate the influence of the radical innovation of big corporations. The different way of measuring whether spillover occurs, such as questionnaire directed at potential knowledge recipients, could be used in the future research.

Moreover, the analysis could be extended to different proximity dimensions' specifications as well as for different industries. Even more challenging may be the analysis of radical innovation diffusion for the case of pharmaceutical or chemical industry. Furthermore, different sources of innovation measurement, apart from the usage of patent data, could be used in further research. They may include Community Innovation Survey (CIS) as well as the direct usage of products and trademarks.

References

Acs, Z.J., Anselin, L., Varga, A. (2002) Patents and innovation counts as measures of regional production of new knowledge, Research Policy, 31(7), 1069-1085. https://doi.org/10.1016/S0048-7333(01)00184-6

Balland, P.-A. (2012) Proximity and the Evolution of Collaboration Networks: Evidence from Research and Development Projects within the Global Navigation Satellite (GNSS) Industry, Regional Studies, 46(6), 741-756. https://doi.org/10.1080/00343404.2010.529121

Balland, P.-A., Boschma, R., Frenken, K. (2015) Proximity and Innovation: From Statics to Dynamics, Regional Studies, 49(6), 907-920. https://doi.org/10.1080/00343404.2014.883598

Bednarz, M., Broekel, T. (2019) The relationship of policy induced R&D networks and inter-regional knowledge diffusion, Journal of Evolutionary Economics, 29, 1459-1481. https://doi.org/10.1007/s00191-019-00621-2

Belenzon, S., Schankerman, M. (2013) Spreading the Word: Geography, Policy and Knowledge Spillovers, Review of Economics and Statistics, 95(3), 884-903. https://doi.org/10.1162/REST_a_00334

Beugelsdijk, S. (2009) A Multilevel Approach to Social Capital, International Studies of Management & Organisation, 39(2), 65-89. https://doi.org/10.2753/IMO0020-8825390203

Boschma, R. (2005) Proximity and Innovation: A critical assessment. Regional Studies, 39(1), 61-74. https://doi.org/10.1080/0034340052000320887

Boschma, R., Martin, R. (2010) The Aims and Scope of Evolutionary Economic Geography. Papers in Evolutionary Economic Geography, 1. http://econ.geo.uu.nl/peeg/peeg1001.pdf. Accessed 07 February 2020.

Breschi, S., Lissoni, F. (2003) Mobility and Social Networks: Localised Knowledge Spillovers Revisted. Cespri, WP n. 142. https://www.nber.org/criw/papers/breschi.pdf. Accessed 08 February 2020.

Breschi, S., Lissoni, F., & Montobbio, F. (2005) The geography of knowledge spillovers: conceptual issues and measurement problems. in Breschi S., Malerba F. (ed.) (2005): Clusters, networks and innovation, 343-378.

Broeckel, T., Boschma, R. (2012) Knowledge networks in the Dutch aviation industry: the proximity paradox. Journal of economic geography 12, 409-433. https://doi.org/10.1093/jeg/lbr010

Cantner, U., Meder, A. (2007) Technological proximity and the choice of cooperation partner, J Econ Interac Coord 2, 45-65. https://doi.org/10.1007/s11403-007-0018-y

Cantner, U., Meder, A., Ter Wal, A.L.J. (2010) Innovator networks and regional knowledge base. Technovation, 30(9-10), 496-507. https://doi.org/10.1016/j.technovation.2010.04.002

Cincera, M. (1998) Patents, R&D, and technological spillovers at the firm level: some evidence from econometric count models for panel data. Journal of Applied Economics, 12(3), 265-280. https://doi.org/10.1002/(SICI)1099-1255(199705)12:3<265::AID-JAE439>3.0.CO;2-J

Cohen, W.M., Levinthal, D.A. (1990) Absorptive Capacity: A New Perspective on Learning and Innovation, Administrative Science Quarterly, 35(1), 128-152. https://doi.org/10.2307/2393553

Dahlin, K.B., Behrens, D.M. (2005) When is an invention really radical?: Defining and measuring technological radicalness, Research Policy, 34(5), 717-737. https://doi.org/10.1016/j.respol.2005.03.009

Díez-Vial, I., Fernández-Olmos, M. (2014) Knowledge spillovers in science and technology parks: how can firms benefit most? The Journal of Technology Transfer 40, 70-84. http://doi.org/10.1007/s10961-013-9329-4

Döring, T, Schnellenbach, J. (2006) What do we know about geographical knowledge spillovers and regional growth?: A survey of the literature, Regional Studies, 40:03, 375-395. https://doi.org/10.1080/00343400600632739

Fallah, M. H., & Ibrahim, S. (2004) Knowledge spillover and innovation in technological clusters. In Proceedings, IAMOT 2004 Conference, Washington, DC (pp. 1-16). https://www.semanticscholar.org/paper/KNOWLEDGE-SPILLOVER-AND-INNOVATION-IN-TECHNOLOGICAL-Fallah-Howe/7624da7d86932d1c3537ffa73557d0f86dbf6f2c. Accessed 28 February 2020.

Feldman, M.P., Francis, J.L. (2003) Fortune Favours the Prepared Region: The Case of Entrepreneurship and the Capitol Region Biotechnology Cluster, European Planning Studies, 11(7), 765-788. https://doi.org/10.1080/0965431032000121337

Fleming, L. (2001) Recombinant uncertainty in technological search. Management science, 47(1), 117-132. https://doi.org/10.1287/mnsc.47.1.117.10671

Fleming, L. (2007) Breakthroughs and the" long tail" of innovation. MIT Sloan Management Review, 49(1), 69. http://sloanreview.mit.edu/wp-content/uploads/saleable-pdfs/49114.pdf. Accessed 07 January 2020

Fornahl, D., Broekel, T. Boschma, R. (2001) What drives patent performance of German biotech firms? The impact of R&D subsidies, Knowledge networks and their location, Papers in Regional Science, 90(2), 395-419. https://doi.org/10.1111/j.1435-5957.2011.00361.x

Gilbert, B.A., McDougall, P.P., Audretsch, D.B. (2008) Clusters, knowledge spillovers and new venture performance: An empirical examination. Journal of Business Venturing 23(4), 405-422. http://doi.org/10.1016/j.jbusvent.2007.04.003

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

Hannan, M.T., Freeman, J. (1977) The population ecology of organizations, American journal of sociology, 82(5), 929-964. https://doi.org/10.1086/226424

Hanusch, H., Pyka, A. (2006) Principles of Neo-Schumpeterian Economics, Cambridge Journal of Economics, 31(2), 275-289. https://doi.org/10.1093/cje/bel018

Hesse, K. (2020) Related to whom? The impact of organizational and regional capabilities on radical breakthroughs. https://elib.suub.uni-bremen.de/edocs/00108600-1.pdf. Accessed 20 March 2020.

Hohberger, J. (2014) Searching for Emerging Knowledge: The Influence of Collaborative and Geographically Proximate Search, European Management Review, 11(2), 139-157. https://doi.org/10.1111/emre.12031

Howells, J.R.L. (2002) Tacit Knowledge, Innovation and Economic Geography, Urban Studies, 39(5-6), 871-884. https://doi.org/10.1080/00420980220128354

Ibrahim, S. E., Fallah, M. H., & Reilly, R. R. (2009) Localized sources of knowledge and the effect of knowledge spillovers: an empirical study of inventors in the telecommunications industry. Journal of Economic Geography, 9(3), 405-431. https://doi.org/10.1093/jeg/lbn049

Jaffe, A.B., Trajtenberg, M., Henderson, R. (1993) Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations, The Quarterly Journal of Economics, 108(3), 577-598. https://doi.org/10.2307/2118401

Kahl, J. (2015) The Determinants of Firm Growth in High-Technology Industries. An Empirical Analysis of Spatial, Relational and Institutional Factors in the German Biotechnology Industry. Schriftenreihe innovative betriebswirtschaftliche Forschung und Praxis, Band 443, Hamburg.

Kesidou, E. (2004) Knowledge Spillovers in High-tech Clusters in Developing Countries. Globelics Academy. http://www.globelicsacademy.org/pdf/EffieKesidou_paper.pdf. Accessed 07 February 2020.

Marrocu, E., Paci, R., Usai, S. (2013) Proximity, networking and knowledge production in Europe: What lessons for innovation policy? Technological Forecasting & Social Change 80, 1484-1498. http://dx.doi.org/10.1016/j.techfore.2013.03.004

Maurseth, P.B., Verspagen, B. (2002) Knowledge Spillovers in Europe: A Patent Citations Analysis, The Scandinavian Journal of Economics, 104(4), 531-545. https://doi.org/10.1111/1467-9442.00300

McCormick, K., Kautto, N. (2013) The Bioeconomy in Europe: An Overview, Sustainability, 5(6), 2589-2608. https://doi.org/10.3390/su5062589

Nesta, L., Dibiaggio, L. (2003) Technology Strategy and Knowledge Dynamics: The Case of Biotech, Industry and Innovation, 10(3), 331-349. https://doi.org/10.1080/1366271032000141670

Nooteboom, B., Van Haverbeke, W., Duysters, G., Gilsing, V., van der Oord, A. (2007) Optimal cognitive distance and absorptive capacity, Research Policy, 36(7), 1016-1034. https://doi.org/10.1016/j.respol.2007.04.003

Pajunen, K., Järvinen, J. (2018) To survive or succeed? An analysis of biotechnology firms, Small Business Economics, 51, 757-771. https://doi.org/10.1007/s11187-017-9963-6

Polanyi, M. (1966) The Logic of Tacit Inference, Philosophy, 41(155), 1-18. https://doi.org/10.1017/S0031819100066110

Polanyi, M. (1967) Sense-Giving and Sense-Reading, Philosophy, 42(162), 301-325. https://doi.org/10.1017/S0031819100001509

Richardson, B. (2012) From a fossil-fuel to a biobased economy: the politics of industrial biotechnology. Environment and Planning C: Government and Policy, 30(2), 282 – 296. https://doi.org/10.1068/c10209

Shane, S. (2001) Technological Opportunities and New Firm Creation, Management Science, 47(2), 205-336. https://doi.org/10.1287/mnsc.47.2.205.9837

Simmie, J. (2002) Knowledge Spillovers and Reasons for the Concentration of Innovative SMEs. Urban Studies, 39(5-6), 885-902. https://doi.org/10.1080/00420980220128363

Shkolnykova, M. & Kudic, M. (2020) Who benefits from radical innovations of SMEs? –Empirical evidence from the German Biotechnology. Bremen Papers on Economics & Innovation. No. 2003. https://elib.suub.uni-bremen.de/edocs/00108572-1.pdf. Accessed 27 February 2020

Sternberg, R. (2007) Entrepreneurship, Proximity and regional innovation systems. Royal Dutch Geographical Society KNAG, 98(5), 652-666. https://doi.org/10.1111/j.1467-9663.2007.00431.x

Verhoeven, D., Bakker, J., & Veugelers, R. (2016) Measuring technological novelty with patent-based indicators. Research Policy, 45(3), 707-723. http://dx.doi.org/10.1016/j.respol.2015.11.010

Zucker L.G., Darby M.R., Armstrong J. (1998) Geographically localized knowledge: spillovers or markets? Economic Inquiry 36, 65-86. https://doi.org/10.1111/j.1465-7295.1998.tb01696.x

Zuluaga, J.C. (2013) Knowledge sourcing, local and international spillovers and the novelty of technological innovation in developing countries. A panel data. http://www.redesist.ie.ufrj.br/lalics/papers/121_Knowledge_sourcing_local_and_international_spillovers_and_the_novelty_of_technological_innovation_in_developing_countries.pdf. Accessed 07 February 2020.

Appendix A. Control sample

Citing firm	Control firm	Citing firm	Control firm
ACGT PROGENOMICS AG	HPI AG	**HTE GMBH THE HIGH THROUGHPUT EXPERIMENTATION COMPANY**	SCRAPETEC GMBH
ACTC-ANTI CRIME TECHNOLOGY CORPORATION GMBH	THEATERTECHNISCHE SYSTEME GMBH	**HYGLOS INVEST GMBH**	BAUCH ENGINEERING GMBH and CO. KG
ADRENOMED AG	GRIMSEL VERWALTUNGS GMBH and CO. KG	**IBA GMBH**	NOVOPLAST VERPACKUNGEN GMBH and CO. KG
ADVALYTIX AG	KUGLER-ALARM GESELLSCHAFT FUER ALARM- UND SICHERHEITSANLAGEN MBH	**IBIDI GMBH**	HUDORA GMBH
AGENNIX AG	ERGOLABS GMBH	**IDENTIF GMBH**	ALPHA CAPITAL MANAGEMENT GMBH
AGROBIOGEN GMBH	ER and GE GMBH	**IFAC INSTITUT FUER ANGEWANDTE COLLOID-TECHNOLOGIE GMBH and CO. KG**	AF S HOLDING GMBH C/O WTS MANAGEMENT SERVICES
AJ INNUSCREEN GMBH	CARL ZEISS OPTOTECHNIK GMBH	**IFG - INSTITUTE FOR SCIENTIFIC INSTRUMENTS GMBH**	KOJU - MASCHINENTECHNIK E.K.
ALNYLAM EUROPE AG	MUE INNOVATIONSFOERDERUNG GMBH	**IMMATICS BIOTECHNOLOGIES GMBH**	NEUROVISION PHARMA GMBH
AMBION GMBH	PLAN OPTIK AG	**JESALIS PHARMA GMBH**	RUCH NOVAPLAST GMBH and CO. KG
APOTHEKER WALTER BOUHON GESELLSCHAFT MIT BESCHRAENKTER HAFTUNG	ECOBILITY GMBH	**JUNO THERAPEUTICS GMBH**	AKASOL AG

APURANO PHARMACEUTICALS GMBH	BSS BOHNENBERG GMBH	**KTB TUMORFORSCHUNGSGESELLSCHAFT MBH**	GASKATEL GESELLSCHAFT FUER GASSYSTEME DURCH KATALYSE UND ELEKTROCHEMIE MBH
ARTHROGEN GMBH	INGENIEURGESELLSCHAFT ROEHRIG GMBH	**LAVISION BIOTEC GMBH**	EBERHARDHOEFE GMBH and CO. KG
BAVARIAN NORDIC GMBH	INNOROUTE GMBH	**LIPOCALYX GMBH**	BIOAGENCY AKTIENGESELLSCHAFT
BERGOLIN GMBH and CO. KG	OT MEDIZINTECHNIK GMBH	**MAGNAMEDICS GMBH**	SCINTOMICS GMBH
BIOGENERIX GMBH	HUMANOPTICS AG	**MEDIGENE AG**	FORMYCON AG
BPE E.K.	HEATEC THERMOTECHNIK GMBH	**MJR PHARMJET GMBH**	IBB INGENIEURBUERO BAUWESEN GMBH CHEMNITZ
BUCK-CHEMIE GMBH	4SC AG	**NEUROPROOF GMBH**	KUNSTSTOFFVERARBEITUNG REICH GMBH
CELARES GMBH	SEIBERT GMBH	**NOVALIQ GMBH**	AROTA GMBH
CELLGENIX GMBH	SILVER-PLASTICS GMBH and CO. KOMMANDITGESELLSCHAFT	**OTC GMBH**	EUROPLAST-NYCAST GMBH
CFC EUROPE GMBH	CURASAN AG	**PELIKAN TECHNOLOGIES GMBH and CO. KG**	CERO GMBH
CYBIO AG	SOEHNLE INDUSTRIAL SOLUTIONS GMBH	**PILOT PFLANZENOELTECHNOLOGIE MAGDEBURG E.V. (PPM E.V.)**	PAPST INVEST GMBH and CO. KG
CYTOCENTRICS BIOSCIENCE GMBH	AUTOMESS AUTOMATION UND MESSTECHNIK GESELLSCHAFT MIT BESCHRAENKTER HAFTUNG	**PLS - DESIGN GESELLSCHAFT MIT BESCHRAENKTER HAFTUNG**	HOLOGRAM. INDUSTRIES RESEARCH GMBH
DEKLATEC GMBH	EFS SCHERMBECK GMBH	**PROGEN BIOTECHNIK GMBH**	NIMAK VERMOEGENSVERWALTUNGS GMBH and CO. KG
DELPHIN WATER SYSTEMS GMBH and CO. KG	BIOTESYS GMBH	**RandD-BIOPHARMACEUTICALS GMBH**	TVM MEDICAL VENTURES GMBH and CO. KG

DIRECTIF GMBH	BIOMED BETEILIGUNGSGESELLSCHAFT MBH	**RESPONSIF GMBH**	MA LIGHTING TECHNOLOGY GMBH
DR. RIMPLER GMBH	KRAMPE GMBH and CO. KG	**SCHEBO BIOTECH AKTIENGESELLSCHAFT**	ITOS GESELLSCHAFT FUER TECHNISCHE OPTIK MIT BESCHRAENKTER HAFTUNG
EPIGENOMICS AG	BAUMOT GROUP AG	**SCIENTIFIC BIOTECH GMBH**	KIMA PROCESS CONTROL GMBH
ERWEKA GESELLSCHAFT MIT BESCHRAENKTER HAFTUNG	SIEMENS HEAT TRANSFER TECHNOLOGY B.V, NIEDERLASSUNG DEUTSCHLAND	**SECURETEC DETEKTIONS-SYSTEME AG**	SENSOR-DATA INSTRUMENTS E.K.
ETHRIS GMBH	PROTEROS BIOSTRUCTURES GMBH	**SPINTEC ENGINEERING GMBH**	POSTNOVA ANALYTICS GMBH
FRITZMEIER UMWELTTECHNIK GMBH and CO. KG	ORGANISATION FOR MARKETING BETRIEBSGESELLSCHAFT FUER MARKETING MBH	**SUPRAMOL-PARENTERAL COLLOIDS GMBH**	SCHUNK GERHARD CARBON TECHNOLOGY GMBH
FRIZ BIOCHEM GMBH	BIP GMBH INGENIEURGESELLSCHAFT FUER DAS BAUWESEN	**TESA SCRIBOS GMBH**	OPTIMALTEX TEXTIL-HYGIENE UND GEBAEUDEREINIGUNG UG (HAFTUNGSBESCHRAENKT) and CO. KG
GEN-IAL GEN-INSTITUT FUER ANGEWANDTE LABORANALYSEN GMBH	NOELLE HANDELS- UND BETEILIGUNGS-KG	**TETEC TISSUE ENGINEERING TECHNOLOGIES AG**	PTA SOLUTIONS GMBH
GERONTOCARE GMBH and CO. KG	WEBER TECHNIK GMBH	**TOPOTARGET GERMANY AG**	SOLARBAYER GMBH
GERSTEL SYSTEMTECHNIK GMBH and CO. KG	WT and S GMBH	**U3 PHARMA GMBH**	DENTACO GMBH and CO. KG
GREENOVATION BIOTECH GMBH	RUEBSAMEN + HERR ELEKTROBAU GMBH	**VERIGEN AG**	FAMLO VERWALTUNGS GMBH
GUSTAV PIRAZZI and COMP. GMBH and CO. KG	FELLER ENGINEERING GESELLSCHAFT MIT BESCHRAENKTER HAFTUNG	**VEYX PHARMA GMBH**	COFRESCO FRISCHHALTEPRODUKTE GMBH and CO. KG
HAIN LIFESCIENCE GMBH	PHOENIX SOLAR AG	**VIVORYON THERAPEUTICS AG**	BIOFRONTERA AG

HEIDELBERG PHARMA AG	CREDITPASS GMBH	**ZELL-KONTAKT GMBH**	K + K MESSTECHNIK GMBH
HOSOKAWA MICRON POWDERS GMBH	ACCURAMICS GMBH	**ZENTERIS GMBH**	PHARMA TEST APPARATEBAU AG

Appendix B. Control sample check#

	(1)	(2)	(3)	(4)	(5)
GEO	0.0125 (0.110)	-	-	-	-
COG	-	5.893 (2.435)	22.190 (31.732)	-	-
COG^2	-	-	-14.151 (27.366)	-	-
ORG	-	-	-	-1.631* (0.827)	-
SOC	-	-	-	-	-
CONSTANT	2.443 (4.962)	-2.434 (1.775)	2.416 (1.764)	0.827*** (0.238)	-
Year efects	No	No	No	No	-
Log likelihood	-171.819	-170.946	-170.816	-122.914	-
Observations	330	330	330	72	-

Standard errors in parentheses, calculation of model 5 not possible, because of all social proximities equal to zero, 31 firms deleted from analysis because of all zero outcomes,

***- significance at 0.01 level, ** - significance at 0.05 level, * - significance at 0.1 level

The values of model 4 relate to the results of zero-inflated negative binomial (zinb) regression model because of the structure of the data. For other variables the usage of zinb did not change the significance and the direction of the coefficient-

Appendix C. Social proximity lags

	1-year lag	2-years lag
SOC	-0.490 (0.825)	-0.810 (0.857)
CONSTANT	3.117*** (0.568)	-3.133* (0.568)
Year efects	Yes	Yes
Log likelihood	-699.397	-699.207
Observations	676	676

Standard errors in parentheses,

***- significance at 0.01 level, ** - significance at 0.05 level, * - significance at 0.1 level

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