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Who benefits from radical innovations of SMEs? – Empirical evidence from the German Biotechnology

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Abstract

Radical innovations are of key importance from an economic point of view since they bear the potential to trigger the emergence of new technological trends and fuel economic prosperity while simultaneously causing far-reaching structural change processes. In this paper we focus on the transfer channels of radical innovations launched by small and medium-sized firms (SMEs). Based on a unique longitudinal dataset covering the observation period 1996 - 2016, we identify and trace back radical innovations of SMEs in the German Biotech in order to analyze the extent to which SMEs themselves or eventually also other organizations in their direct cooperation surrounding benefit from radical innovations in terms of subsequent innovation performance. Results from panel data count models indicate that direct cooperation partners of “radical innovators” generally seem to show higher innovative performance than partners of the control group, i.e. not radical innovating “statistical twin” firms. A more differentiated picture emerges if one considers the geographical and technological proximity of the cooperation partners.

Keywords
radical innovation, biotech, ego-networks, SME, patent applications, innovative performance

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1. Introduction

The ability of firms to create novelty in terms of innovation is considered to be a necessary prerequisite for gaining a sustainable competitive advantage and keeping pace with competitors. Firms typically follow unique innovation strategies to cope with high levels of ambiguity and complexity, particularly prevalent in knowledge intensive technological fields such as biotechnology.

In this paper we turn our attention to innovation activities of small and medium-sized enterprises (SME[1]) in the field of biotechnology, mostly occupied with application of biotechnology techniques for the production of goods or services and actively involved in research and development (R&D). These firms are frequently referred to as dedicated biotech firms (DBFs) (OECD, 2005). DBFs have highly specialized business models, which is typically reflected in a very unique resource and knowledge endowment and their R&D activities are not seldom subjected to high risks. Accordingly, entry and exit dynamics as well as the chance of discovering entirely new methods and applications in terms of products and services is certainly overrepresented among DBFs. Radical innovations are typically discussed only under the light of radical inventor's performance (e.g. Katila, 2000). However, they bear also the potential to affect other actors and even change the technological fields in a fundamental way (Dahlin, Behrens, 2005). It is, however, anything but clear to what extent radical innovation remain limited to the radical innovator itself or influences its closer surrounding by triggering follow-up innovations. Accordingly, we are curious to understand who benefits from radical innovations of dedicated biotech firms. More precisely, we apply a network perspective and analyze the extent to which firm-specific network structures of small and medium-sized dedicated biotech firms – based on formal, publicly-funded R&D partnerships – foster the transfer of radically new ideas in a knowledge intensive technological field such as biotechnology.

We compile and employ a longitudinal unbalanced panel dataset encompassing the full set of DBFs in Germany between 1996 and 2016. At the very heart of our analytical approach we specify firm-specific ego-network[2] for each radical innovator and check if (and to what extent) spillovers moves through it by testing if ego-network partners show significantly higher patenting activities (in terms of patenting counts) compared to partners of statistically equivalent benchmarks of radical innovators ("statistical twins") by using a negative-binomial regression model. We employ a propensity score matching procedure two identify a set of "statistical twins" for each radical innovator and set up two benchmark datasets in order to evaluate the patenting

[1] Here we use the definition of SME, proposed by European Commission: the enterprise is considered an SME, if it has less than 250 employees and "annual turnover not exceeding EUR 50 million, and/or an annual balance sheet total not exceeding EUR 43 million" (Recommendation 2003/361/EC)
[2] Ego-networks encompass the ego itself and all its directly linked partners. Indirect connections between the alters are included while second tire ties are not included (Hite and Hesterly, 2001).

performance of the firms in our sample. The combination of these analytical approaches allows us to gain a much deeper understanding of how radical innovations may spill over in knowledge intensive technological fields.

The paper is structured as follows: in Section 2 we first summarize the main contributions of previous SMEs research in general and describe existing literature on radical innovation and knowledge spillovers. In the end of the chapter hypotheses are outlined. Section 3 includes overview of data sources used. Next, we provide an overview of the development of the biotechnology industry in Germany. In Section 4 we outline our research methodology. In Section 5, we provide basic descriptive statistics and results from our statistical analyses. Finally, in Section 6 we provide a brief discussion of main findings and outline of some fruitful avenues for further research.

2. Theory background – externalities, networks and innovations

Economists usually draw upon the concept of 'externalities' to approach a question like the one we raise above. The externality concept goes back the late 19th century (Marshall, 1890) and is still one of the fundamental concepts in welfare economics and dominates the debate in economic policy on market failures and interventions. The basic idea behind the concept is straightforward. In its most basic sense, an externality exists (i.) in consumption, when the shape and position of an individual's indifference curve is affected by the consumption of another individual, (ii.) in production, when the production function of one firm depends on use of inputs and outputs of another firm (Graaf, 1957; Buchanan and Stubblebine, 1962). Over the years two rather contradictory concepts emerged. On the one hand, so-called Marshall-Arrow-Romer (MAR) externalities – originally developed by Marshall (1890), Arrow (1962), and Romer (1986) and later formalized and tested by Glaeser et al., (1992) – are based on the notion that knowledge is industry-specific and spillovers appear mainly among similar and closely co-located firm in the same industry. On the other hand, so-called 'Jacobs externalities' go back to the idea that spillovers take place between complementary rather than similar industries (Jacobs, 1969). Common to both approaches, however, is that the transfer channels and mechanisms often remain unspecified.

Scholars from evolutionary economics contributed to this debate by introducing the systemic innovation perspective (Lundvall, 1992) and emphasizing the role of formal and informal networks (Freeman, 1991) for intra-industry and inter-industry knowledge transfer processes. In general, networks consist of a well-defined set actors and direct or indirect connections among them (Wassermann and Faust, 1994). The specification of actors and ties determines the type of network we look at. Innovation networks are embedded in a broader socio-economic environment and considered to be an integral part of an industry's innovation system[3] (Kudic, 2015). Inter-organizational innovation networks incorporate all type of actors actively involved in R&D processes. Formal as well as informal connections among them allow for unilateral, bilateral, or multilateral exchange of ideas, information knowledge, and expertise. This, in turn, enables the actors involved to recombine and generate new knowledge enclosed in novel goods or services to meet market demands and customer needs (cf. Kudic, 2015, p. 47).

To analyze whether the radical innovations of SME's spill over to its direct partners, we focus on egocentric, inter-firm innovation networks composed of formal links within the technological field of biotechnology. Ego-networks are composed of one focal actor (ego), his direct connected partners (alters) connections among the alters (Ahuja, 2000; Hite and Hesterly, 2001). In other fields, 'ego networks' are also referred to as 'alliance network compositions' (Baum et al., 2000), 'alliance constellations' (Das and Teng, 2002; Gomes-Casseres, 2003), 'alliance portfolios' (George et al., 2001; Hoffmann, 2005; Hoffmann, 2007; Lavie, Miller, 2008), or 'portfolios of interfirm agreements' (Wuyts et al., 2004).

However, it is important to note that the existence of direct and indirect ties among network actors does not necessarily mean that knowledge identification, transfer and learning across firm boundaries takes place without any obstacles or frictions. Cohen and Levinthal (1990) were among the first to acknowledged this issue by introducing the 'absorptive capacity' concept which draws attention to an actor's ability to identify, assimilate and use externally available knowledge to commercial ends[4]. In a similar vein, Simonin (1999) provided us with deep insights on the simultaneous effects of knowledge ambiguity and its antecedents – i.e. tacitness, asset specificity, prior experience, complexity, partner protectiveness, cultural distance, and organizational distance – for the success of technological knowledge transfer through inter-firm alliances.

The preceding considerations clearly indicate that the 'network approach' bear the potential to complement and specify the wide-spread but rather abstract notion of 'knowledge externality' since it explicitly acknowledges the often ambiguous nature knowledge transfer and learning processes through the channels and conduits of complex adaptive systems. A closer look at the empirical literature indicates that we are certainly not the first to focus on the relatedness between knowledge exchange, ego-networks and innovation performance. Previous research mainly focused on the extent to which ego-network affect the innovative performance of the focal actor itself. For instance, Ahuja (2000) focus on the relatedness between three aspects of firm's ego-network characteristics – direct ties, indirect ties as well as structural holes – and

[3] Based on the initial 'national innovation system' approaches (Lundvall, 1992, Nelson, 1992, Freeman, 1992), various specifications were developed, including 'regional innovation systems' (Braczyk et al., 1998), 'sectoral innovation system' (Malerba, 2002), 'technological innovation systems' (Carlsson et al., 2002).

[4] This important insight has been adapted and extended in several ways. For conceptual extensions, see for example: Van Den Bosch et al. (1999); Zahra and George (2002); Lane, et al. (2001).

subsequent firm level innovation outcomes and raises awareness for the negative innovation effects of structural holes at the network level. Baum et al. (2000) demonstrates that the early innovative performance of Canadian biotech startups' – measured by patent grant counts and R&D spending growth – is strongly affected by the alliance network composition of these firms at founding. Wuyts et al. (2004) explore the impact of different types of alliance portfolio characteristics on firms' incremental and radical innovations as well as on firm profitability. To the best of our knowledge, there is no prior research on the extent to which radical innovations of a focal actor affect (or 'spill-over') to its directly – and eventually indirectly – connected alters.

However, which effect does this special type of innovation bring to companies, cooperating close with radical innovators, is still unknown. The research of radical innovations in this sense is still limited to focal firms, performing it: investigation of the effects, that radical innovation may have on firm´s creation (Shane, 2001) or cooperation patterns that help firms to reach radical innovation (Tether, 2002). Thus, it is plausible to assume that in case of radical innovations, which present exclusive and unique knowledge of one particular actor, spillovers may exist. As direct cooperation partners of radical innovators do not bear the risks, connected to its development and introduction, we expect positive influence on such activity on partners. Thus, our first hypothesis can be stated as follows:

H1: Radical innovation has a positive impact on innovative performance of direct project partners of radical innovators.

However, there are several factors affecting this relationship. One of them is the geographical distance. Closely related firms can better observe development trajectories of their neighbors (Hohberger, 2014), which is especially important for the case of tacit knowledge transmission. This can explain the success facilitation of innovation performance, provided by technological parks (Díez-Vial and Fernández-Olmos, 2015) and geographic clusters (Gilbert et al., 2008). On the other hand, it can be stated that several meetings pro year along with the usage of modern technologies may make distance between partners unimportant for transmitting even tacit knowledge (Breschi and Lissoni, 2003). However, we argue that the effect of local (intraregional) knowledge spillover may be higher for the case of SMEs, who mostly rely on the local contacts (Beugelsdijk, 2009), especially on the connections with universities and successful peers. Apart from that, some non-local firms may just do not possess necessary capabilities in order to understand local knowledge (Boschma, 2005). Thus, we can state that:

H2: Partners, located in the same region with radical innovator, experience a higher influence of radical innovation on their innovative performance.

Another strand of literature shows, that not only geography matters. In order to learn, the cognitive abilities of firms should be close enough, but not identical (Boschma, 2005). Biotechnology firms are often reported to engage in collaborations in order to develop new products and services (Hohberger, 2014). However, according to the literature, they rather prefer looking for collaboration that complements their capabilities (e.g. clinical testing, marketing, management, distribution) (Hohberger, 2014). This can also be seen in practice: among the subsidized projects biotechnology firms often have soft- and hardware developers or service providers as partners. Apart from that, it is often reported that biotechnology SMEs rather communicate with pharmaceutical corporations than peers (Kahl, 2015). Thus, we can suppose that:

H3: Non-biotechnology partners of radical innovation experience a higher influence of a radical innovation on their innovative performance.

3. Technological field and data consolidation

3.1. Technological field and research focus

In our paper we are dealing with the case of German biotechnology. The industry presents a case of high-tech sector with the high spatial concentration of the firms. Apart from that, inventive outcomes in biotechnology are normally documented in form of patents (e.g. Aggarwal and Hsu, 2014), which enables calculation of innovative performance indicators.

As already stated in chapter two, the concept of radical innovation and its spillovers is especially important for the case of SMEs. Due to a lack of abundant resources small entrepreneurial firm typically fail more often than their larger competitors which is referred to in the literature as liability of smallness (Aldrich and Auster, 1986).

German biotechnology was from its origin driven by several policy initiatives (e.g. BioRegio Competition or BioProfile), which explicitly promoted emergence of start-ups. This numerous firms, however, appeared to be in the hard financial position after the drop of funding in the middle 2000s (Häussler, 2007). On the other hand, independent start-ups have to bear with all the costs and risks of failure at any stage of product development, production and sales alone. It is especially complicated by the long time period between development and sales of specific biotechnology products (Zidorn and Wagner, 2012). Thus, in order to mitigate lack of capabilities, these firms need access to external knowledge of other firms, research institutions and universities. Therefore, different forms of alliances are extremely popular in biotechnology. They are analyzed by a number of studies (e.g. Gay and Dousset, 2005; Zidorn and Wagner, 2012; Shin et al., 2016), mostly reporting positive influence of being in alliance on different dimensions of firm's performance.

In addition, described SMEs have to find niche to operate and specify their activities towards special solutions (Zidorn and Wagner, 2012). This may bring new products and processes, not known to the field in this combination before. The latter, according to Schumpeterian notion, can be related to as radical innovation. Thus, we can expect that radical innovations will be the driving power of SMEs activities in biotechnology and will be seen relatively often.

3.2. Data sources

To construct panel dataset several data sources were used complementary, as neither of them could provide full data regarding firm characteristics as well as patenting and funding data. The use of raw data sources is outlined below.

To start with, the population of dedicated biotechnology firms needed to be generated for the purpose of radical patents´ identification as well as definition of firm characteristics, such as size or age. For that purpose, the dataset provided by BIOCOM AG, which is a firm, consolidating statistics on life sciences, was used. Datasets for the years 1996-2016 were available for our usage.

Apart from providing industry books, which consist of the general statistical indicators of the field, BIOCOM AG also structures overall firms' population into different categories (e.g. research, pharma, IND1, IND2). IND1 category corresponds to dedicated biotechnology firms, which have biotechnology as main field of activity. Exactly these firms have served as an initial sample to reach our research goals, by constituting narrow dataset, used for radical patents identification. Broader dataset, including other firm categories, was used for control purposes.

However, as we are interested in following radical innovations coming from SMEs, the information about firm status and ownership structure was an important component needed for the dataset. Thus, in order to follow the firm history chronologically, including such events as possible mergers, acquisitions or insolvency procedures, other data sources are needed. Apart from that, several entries regarding the size of particular firms were not available in BIOCOM AG data. Therefore, several additional sources were used complementary to fill this gaps.

First, Amadeus database from Bureau van Dijk[5] was used to additionally checked whether firm can be considered SME in particular year with the help of ownership

[5] Accessed in January 2019.

structure of a firm. This information was additionally checked in Wiso-Net database[6], including firm data from register portal. Amadeus database also includes data on employees´ number for each firm over the last ten years, which helped to close some white spaces.

To get more information about the history of each firm as well as to learn, which of them were founded as university spin-offs, we have additionally manually screened firm websites. This information was further used as a control variable and acted as one of the predictors of innovative activity.

As the dependent variable presents the number of patent applications, a decent measure reflecting this innovative output had to be chosen. We have used PATSTAT Database (Autumn edition 2016) in order to filter patents coming from dedicated biotechnology SMEs, which were applied for between 1996 and 2016 for the first time. As this version of the database provides the full patent coverage only until 2014, the later version of PATSTAT (Spring edition 2019) was used to add patents for the last two years. PATSTAT Database, created by European Patent Office (EPO), includes patents applied by firms worldwide. Apart from being reliable source of patent data, PATSTAT combines data on application itself with data on applicants and inventors, related to patent, as well as technological classes (IPC and CPC) assigned to it and number of citations that patent received, in a convenient way.

In order to construct cooperation networks of radical partners, Funding database (Förderkatalog) of Federal Ministry of Education and Research was used. Alternative way of cooperation measurement, number of co-applied or co-invented patents, was additionally checked. However, common subsidized projects have appeared to be a better measure of cooperative activity for several reasons: 1) Because of historical circumstances, underlined in 2, funding projects was one of the driving forces of biotechnology, being thus a common practice in the field; 2) Projects include date of cooperation begin, which is for the case of patent application not so clear, as cooperative patents may appear several years or several months after start of the cooperation; 3) Funding projects present external source of data, whereas patents were included in model as a dependent variable. Thus, we exclude selectivity in this case by including in the model only those firms, which have patents; 4) Cooperation may not always be expressed in terms of patent, especially when it comes to project partners, working in different sectors of biotechnology. Overarching projects may be better source of knowledge for that case. Funding database could also be used in order to identify whether cooperation with universities have taken place for a particular firm.

[6] Accessed in December 2018.

3.3. Sample specification

We first identify all actively operating small and medium sized dedicated biotech firms (DBF) in Germany between 1996 and 2016. This time period of 20 years involves all stages of industry cycle: emergence of the field, founding of many entrepreneurial ventures and industry rapid development in the end of 90s and beginning of 2000s, followed by falling of patent activities and numerous exits, starting in the middle of 2000s, as well as appearance of new fields, originating from biotechnology, and technological change in the end of 2000s and beginning of 2010s. After combining yearly firm datasets and identifying firms, that appear in the dataset several times under different names, 1583 dedicated biotechnology firms, that were actively operating in this time period, were left[7].

Majority of identified firms can be related to as SMEs. BIOCOM AG reports, that around 85-90% of all dedicated biotechnology enterprises have less than 250 employees (e.g. Mietzsch, 2006; Mietzsch, 2016). After accounting for those firms, who were already founded as subsidiaries, about 1200 of firms were left (see figure 1)[8].

Figure 1. Structure of biotechnology field in Germany

Out of these firms around a half could be found in PATSTAT, which meant that they were seen as an applicant or inventor on at least one patent during the period. Patents for sample were filtered basing on the level of patent families in order to ensure that no double count is present. Thus, patents included should have their earliest filing year between 1996 and 2016. As the result, 4521 family ids or 4937 unique applications were defined. These patents further served for the radical entities´ identification.

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[7] Help in creation of firm dataset for project purposes was provided by Leonard Prochaska, University of Greifswald.

[8] These firms were independent at founding, which does not mean that they were not acquired at some point of time. This factor was then taken into account after patent identification.

However, in order to perform this issue, control (baseline) group of patents need to be created. For it, the sample of 2200 dedicated biotechnology firms (both SMEs and large ones), pharmaceutical firms and research institutions[9] was combined from BIOCOM AG data. After checking for patents, 17280 unique applications could be identified[10].

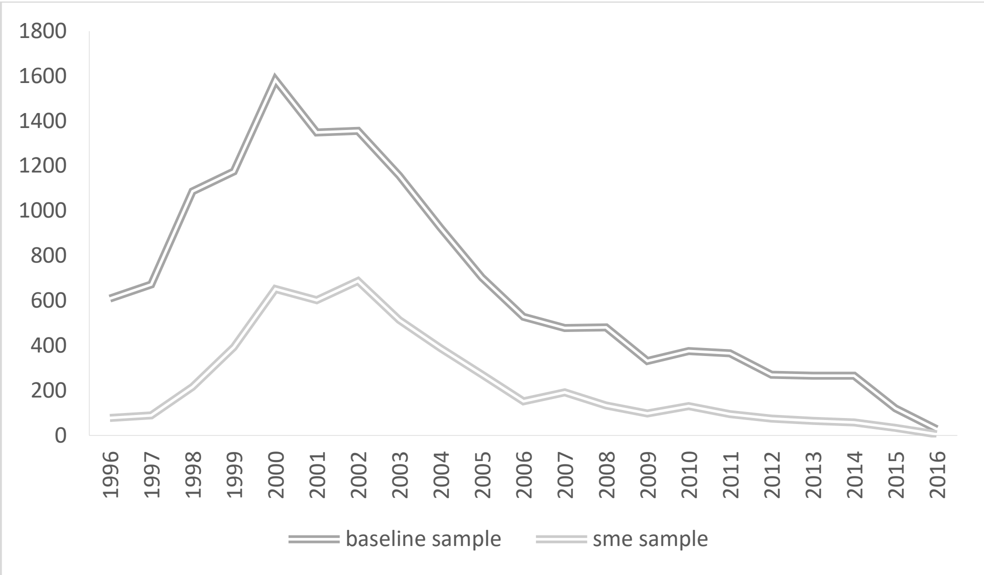


Figure 2. Patents from SME vs. baseline sample

Figure 2 shows that trend of SMEs patents corresponds to general patent statistics in the field. Most of the patents for both samples are related to the period 2000-2003, which is a couple of years after most of the firms were founded. The rapid decline in patents can be explained by tendencies in the field, stated above (e.g. according to Kahl (2015) re-profiling of many of SMEs) and also negative attention, which genetic research has received.

4. Methodology

4.1. Research design

In order to test hypotheses, we combine four analytical approaches (cf. figure 3). The first step is to identify radical patents based on technology class information. As can be seen, steps two and three can be implemented in any order. Finally, the outcomes of the initial analytical steps are included in our estimation model which allows us to

[9] For Research institutions years 2005-2006; 2009; 2011; 2013-2016 are missing, however, the population appears to be stable.

[10] Here no filter on application year was needed.

distinguish between radical innovators and non-radical "twins" and elaborate on innovation outcomes of their direct partners measured by patent counts.

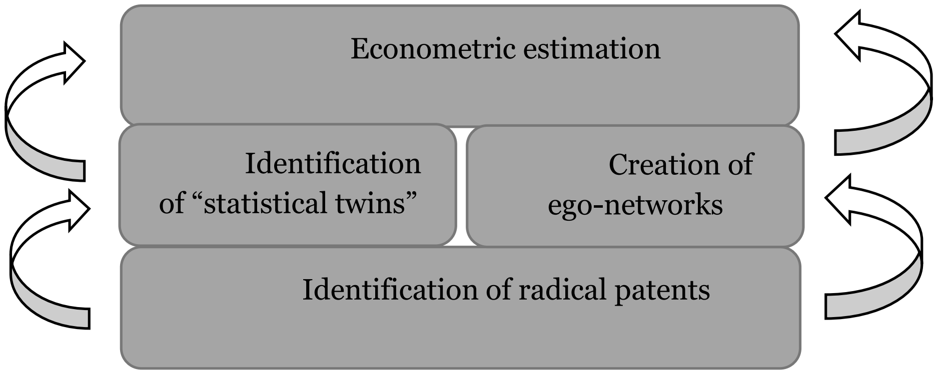


Figure 3. Research design

1. Identification of patents, presenting radical innovation as well as SMEs, that applied for these patents. At this step the definition of radical patent was elaborated, based on existing literature. Besides, several filters were applied, in order to ensure that only SMEs are included in the radical innovators´ sample.
2. Creation of ego-networks of radical innovators. Here only those radical innovators, having funded projects, were taken into account. Their ego-networks, including all project partners, were constructed.
3. Identification of "statistical twins" of radical innovators and their ego-networks. Partners of these firms served as the control group for further econometric analysis.
4. Econometric estimation approach. At the final step hypotheses were tested with the help of different specifications of negative binomial regression model. Apart from that several robustness checks including the usage of the lagged patent variable, were introduced.

4.2. Identification of radical patents and radical innovators

As indicated in above, our analysis starts from the identification of radical innovations. There exists strand of literature, dealing with identification such kind of innovations. However, there still exists no unified definition of what characteristics should a patent possess in order to be considered radical. Thus, we apply procedure, composed and refined, based on the literature. Firstly, we take method, originally applied by Fleming (2001; 2007) in the studies about collaborative creativity and further replicated by several other studies for patent data (e.g. Verhoeven et al., 2016; Dahlin and Behrens, 2005; Arts et al., 2012, Grashof et al., 2019; Arant et al., 2019). It is based on Schumpeterian definition of innovation as a recombinatorial process of existing knowledge (Weitzmann, 1998) and is characterized as the novel dyad of IPC classes, which did not appear in industry before. Verhoeven et al. (2016) relate to this term as "Novelty in Recombination".

However important the recombination of classes may be for a patent to be radical, the usage of composite indicators is empirically proven to be more reliable in this case. Thus, we also relate to the other important characteristic of radical innovation – impact that it has on the future of the field. This can be measured using forward citations indicator (e.g. Dahlin and Behrens, 2005). Going further, we suggested, that in some cases application of important knowledge, created by a radical patent, may take some time, therefore, second-order forward citations should also be looked at.

Apart from that, backward citations can be looked at in order to identify the novelty of the patent. Verhoeven et al. (2016) relate to these patent characteristics as to “Novelty in Technological Origins” and “Novelty in Scientific Origins”. Analogously to “Novelty in Recombination”, this indicator is based on the new dyad of IPC classes, however, focal patents´ technology classes here are connected to classes of their backward citations. Latter indicator is computed as connection between IPC-code and Non-Patent Reference (scientific field) that has not occurred before.

The difference between first and third indicator lies in the different understanding of “new combination”: whereas in the first case patent itself presents a new combination of previously unrelated technological categories, in the second case patent uses existing knowledge in a novel way. We mostly refer to the first case, therefore, last indicator is not investigated thoroughly.

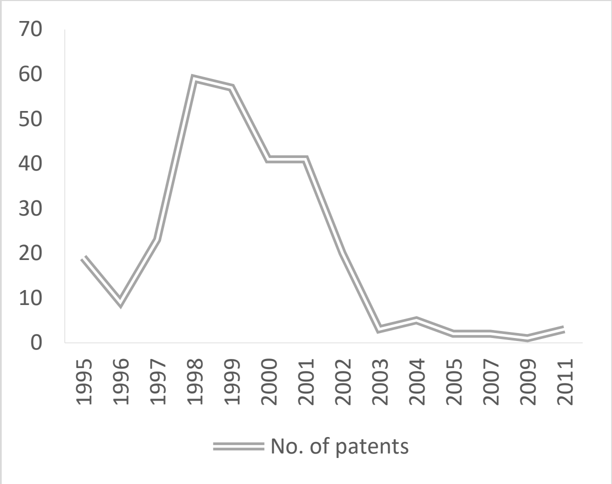
Applying methodology described above, we needed to identify all possible dyads of IPC subclasses[11], belonging to the patents of both SMEs´ and baseline sample. Thus, in total there occurred to be 31727 of such combinations for SMEs and 111272 for baseline sample[12]. Next, SMEs dyads were juxtaposed to baseline dyads. The patent was suspected to be radical if it: 1) was not found within control sample OR 2) appeared in control sample later than or in the same year as in SME sample OR 3) appeared in control sample 1 year earlier than in SME sample. The latter condition was introduced because of 18 months between patent application and publication as well as because we are not genuinely interested in radical patents themselves, but rather in firms, that possess disruptive potential.

As the result of this comparison, 396 of potentially radical dyads could be identified, belonging to 286 patents. Looking at the timeline of these innovations one can see, that most of them relate to 1998 or 1999, which is in line with general peak in biotechnology patents. Most favorite patent classes were related to red biotechnology (Preparation ...

[11] We are performing comparison on the level of four digits, e.g. A01H.

[12] Number of patents x number of IPC codes combinations.

for medical purposes; …therapeutic activity of chemical compounds/medical preparations) or generally to enzymes and peptides research[13].



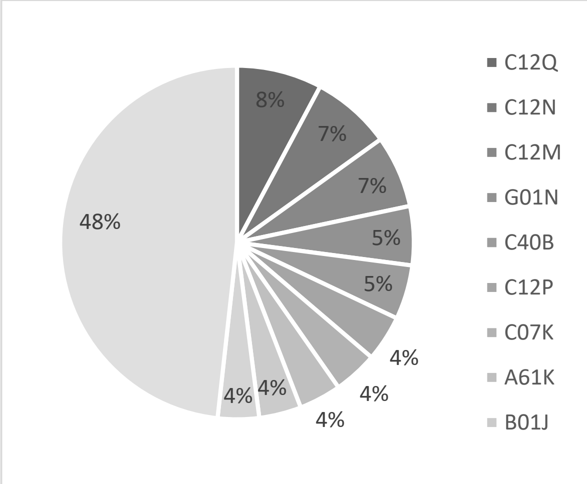


Figure 4. Radical combinations of IPC classes per year

Then, we checked forward citations of patents, identified before. In order to guarantee, that patent received citations (at least initial ones), we only included patents, first applied before or in 2012). All 286 patent applications satisfied this condition, however, only 108 of them appear to have forward citations. Cutting value here was set at 3 citations, which corresponds to about upper 30%. Number of citations of forward citations mostly corresponds to forward citations statistics. Here two cases can be especially noted: „Kopplung von Proteinen an ein modifiziertes Polysaccharid" (English: *"Coupling proteins to a modified polysaccharide"*) – four 1st order citations and 83 2nd order citations; „Verfahren zur Gewinnung von Proteinen aus Pflanzen in reiner Form" (English: *"Process for extracting proteins from plants in their pure form"*) – eight 1st order citations, 153 2nd order citations.

As the result, 77 patents were left, which belong to 43 firms. These firms were additionally checked in order to secure that only SMEs are left in the sample. The reason for it are often acquisitions in area of biotechnology: thus, even if the firm was initially founded as an entrepreneurial SME, one has to check whether it still had this characteristic at the time, when patent was applied for. As the result, 29 firms were left, which constituted our end sample.

[13] IPC codes of radical candidates and names of specific subclasses from figure 4 can be found in Appendix A.

4.3. Creation of ego-networks of radical innovators

On the first step we could identify radical innovators. However, we are not interested in the radical performance of these authors, but rather in that of their project partners. Thus, the best methodological way to visualize these partners is via building ego-networks around radical firms. As we are not interested in the innovative performance of exactly these actors, but their project partners, ego-networks of radical innovators needed to be constructed Here focal actor, in our case radical innovator, is seen as “ego”. Ego is connected to its alters, in our case project partners of radical innovators, via ties. Network also includes ties between partners, but does not look at their ties beyond that (e.g. Borgatti et al., 2018).

Thus, at the next step we screened funding database of German Federal Ministry of Education and Research (Förderkatalog) in search of project partners. It appeared that only 13 firms had projects, involving more than one actor. By connecting obtained firms, ego-networks were built (see figure 5[14]). As can be seen, the network shows two big components of relatively big project networks. Connectivity there is mostly granted through universities or big corporations. Both of these categories, however, are not of our primary interest, as it is hard to disentangle influence of radical innovation from other factors influencing their innovative performance. For other small firms in biotechnology, however, knowledge, created by radical innovation, may be crucial.

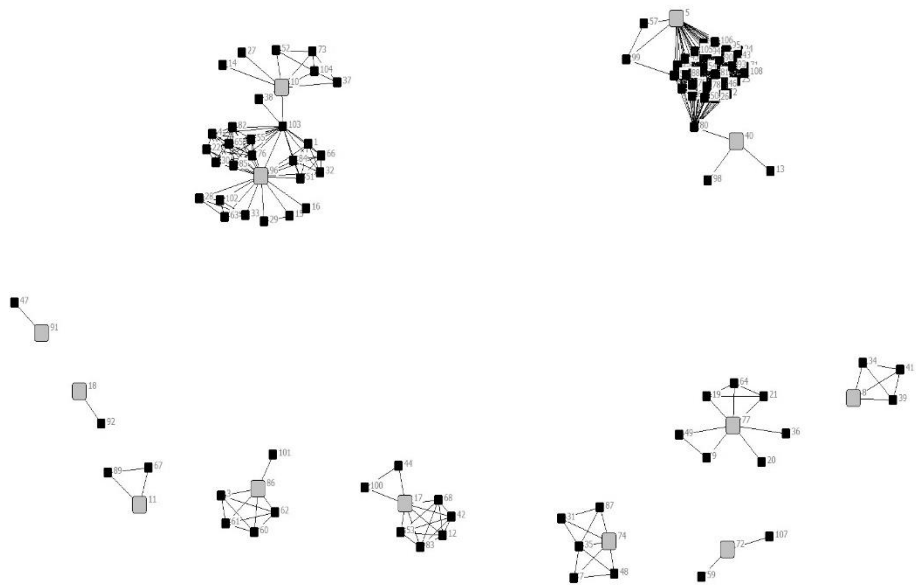


Figure 5. Ego-networks of radical SMEs

[14] List of the nodes can be found in Appendix B. Universities are presented at the level of working groups. If network is built on the level of university, much higher connectivity is seen. Universities thus are serving as bridges between SMEs. However, in the scope of this paper we are not primarily interested in university-SME cooperation, therefore no detailed analysis of this issue is provided.

Thus, from the scope of project partners, only small, medium and large firms, being however single location, were taken into account. After filtering other actors out, 35 actors were left. Starting from the year of collaboration, number of applied patent families pro firm was checked for each firm, using PATSTAT (Autumn 2017 edition)[15]. Number of patents is further used as the dependent variable for count model.

4.4. Identification of "twin" firms

Thus, we already identified radical innovators, as well as their partners, which are further used for econometric estimation. However, to calculate the effect of radical innovation, control sample of firms, who are partners of non-radical dedicated biotechnology SMEs, needs to be established. This is done with the help of propensity score matching – technique that matches each individual from the sample of radical innovators to one or more statistical twins, based on particular characteristics, which both firms possess. In the case of these characteristics, also known as baseline covariates, they must have two following properties: 1) be independent from each other; 2) have an influence on outcome and differ between conditions at baseline (Tanner-Smith and Lipsey, 2014).

It is important to note, that this method is usually used for sociology studies or to test the effect of a particular treatment. In these cases, baseline covariates reflect the state of subjects to be divided into the groups before the treatment. For the case of statistical twins of radical innovators´ it may become complicated for two reasons: First, different firms applied for radical innovations in different time periods and its preparation could have taken a firm several years. Second the knowledge, which was produced by radical innovation most probably appears before the patent is applied for and stays with the firm over time, thus, firm stays "radical" by its nature even after that, so, it is hard for these case to take before/after snapshot. Therefore, we identify the firms, which, having the same characteristics, appear to be not radical. Thus, we tried to stick to characteristics which are relatively stable over time or applied characteristics at current period of time, which are:

- Number of employees that firm has;
- Size of the network, measured by the number of unique project partners;
- Whether the firm was founded as spin-off (1) or not (0);
- Whether the firm has universities in the network (1) or not (0);
- Whether firm is situated in technology center (1) or not (0)

[15] With adding PATSTAT 2019 Spring edition for 2016 patents.

Latter variable can be explained by the fact, that technological centers can promote communication among firms, create creative performance and propose technical equipment, which are all necessary factors for radical innovation creation.

For each of the radical firms five “twins” were identified from SME sample (excluding radical firms and their partners), from which the most suitable one was manually chosen, basing on characteristics provided above. Apart from that, to ensure that the result, obtained using radical and selected sample, has not occurred by chance, one more “twin” is chosen manually as the second best candidate and one “twin” is chosen using random numbers generator. Two additional samples are used to perform robustness checks[16].

4.5. Econometric approach

Our hypotheses target innovative performance of the partners of both radical innovators as well as partners of their statistical “twin” firms. In that case patents serve as a well-accepted proxy for measuring innovative performance, especially for such industries as biotechnology or pharmaceuticals, where patent applications are important and wide-spread form of invention protection and appropriation (e.g. Aggarwal and Hsu, 2014, Hohberger, 2014). Thus, dependent variable, further used in the model, is the number of patents, applied by a firm each year after cooperation with radical innovator started. As radical patents usually come close after the founding of the firm and it is usually the result of long invention process, no projects had to be excluded from the sample.

When using patent counts as dependent variable, one has to think whether lags are reasonable to take into account. It can be explained that patent preparation length is from one individual case to another may be different. On the other hand, taking into account the field dynamics and the fact, that cooperation could have started earlier than a funded project, therefore the patents starting from t year of cooperation are the correct measure. Patent lags of one and two years are presented within paper as robustness checks.

In order to account for three hypotheses, three independent variables, related to each of them, were built. Thus, to check whether the partnership with radical innovators is beneficial, we introduce variable RADICAL, which takes value one whenever the firm was the partner of radical innovator and zero if the firm is the partner of its twin. The variable is constant for a particular firm across years. If same firm appears in both radical and non-radical ego-networks, it was deleted from the panel.

[16] List of twins and all matches can be found in Appendix C.

In order to test second hypothesis, the variable REGION was included. It was equal to one for interregional and zero for intraregional partners on the NUTS2 level[17]. For the third hypothesis testing another binary variable BIOTECH, taking the value of one for dedicated biotechnology firms and zero otherwise. This variable was based on the presence of the firm in BIOCOM yearbooks. Both variables according to stated hypotheses relate only to the partners of radical innovators.

Apart from these independent variables several controls were introduced in the model. First, variables of age (AGE) and size (EMPL) of the firm were presented. Variable AGE presents number of years between firm´s founding and year of observation, whereas EMPL corresponds to the number of employees, reported by the firm in the observation year. Both variables vary for a firm across panel. Variable SUBS estimates whether the firm was a subsidiary or an independent entity in a year of observation, whereas SPINOFF reflects whether the firm was founded as a university or industry spin-off. Variable UNI identifies whereas a firm had a cooperation with the university in form of joint project. This variable takes value of 1 since the start of the cooperation with the university and zero if no cooperation tool place.

Table 1 presents short description of all variables with sources of data, used for their collection.

Table 1. Control variables

Variable	Description	Data source
PATENT	Number of patent applications of a firm per year	PATSTAT 2017b
RADICAL	Firm being partner of radical innovator (1) or non-radical twin	Identification procedure, explained in 4.2, Förderkatalog
REGION	Partner located in the same NUTS2 region with focal firm (1) or in different region (0)	BICOM AG, Amadeus, WISO-Net
BIOTECH	Dedicated biotechnology firm (1) or not (0)	BICOM AG, Amadeus
AGE	Years between founding of the firm and year of observation	BIOCOM AG, Amadeus
EMPL	Number of employees in a particular year	BICOM AG, Amadeus, WISO-Net
UNI	Firm having university as a partner in funded project in the year of observation or before (1) or not (0)	Förderkatalog
SUBS	Firm being subsidiary in the observation year (1) or not (0)	Amadeus
SPINOFF	Firm being spin-off at founding (1) or not (0). Variable is constant for one firm across all observation periods	Amadeus, Firms´ websites

Dependent variable (number of patents per year) has a count character and is represented by the equation below. Patents per firm do not normally have a normal

[17] The introduction of the variable on NUTS3 level was checked and did not significantly changed results.

distribution, being right skewed. Therefore, count model for this case should be preferred to linear model specification (e.g. Cincera, 1997). Thus, we limit ourselves to this list of models. Furthermore, our data shows overdispersion, confirmed by likelihood-ratio test of alpha. In this case negative binomial regression is usually used instead of the Poisson specification (e.g. Petruzzelli et al., 2015), and was also applied in this paper. Thus, our model generally takes following form (Petruzzelli et al., 2015, Beaujean, Morgan, 2016, Cincera, 1997):

$$\widehat{\lambda_{it}} = \exp\left(\sum_k \beta_k X_{it} + \varepsilon_i\right)$$

where X refers to independent and control variables.

Our data shows panel structure, as we are dealing with patent applications per firm per year. This allows accounting for different firm-specific characteristics, firm heterogeneity as well as helps to avoid the problem of multicollinearity (Kennedy, 2003). Additionally, likelihood-ratio test vs. pooled model favors the usage of panel structure. Thus, it will be used in the paper predominantly[18].

5. Results

5.1. Basic descriptive statistics

On the next step, having the research question in mind, we construct an unbalanced panel dataset, including partners of radical innovators and partners of its radical “twins”[19]. For each firm observations start with the year of the cooperative project start and finish 2016 or the year when the firm was dissolved, the latter was taken from Amadeus or Handelsregister entries, accessed via WISO-net database. In total, 532 entries from 56 (35 partners of radical firm and 21 partners of non-radical ones) firms were included.

[18] However, by looking at patent data from the firms, several cases are possible here. First, there may be firms, who are constantly (or periodically) apply for patents. For such firms count is positive. Second, there may be firms, that are not engaged in patenting at all. The reason for that may lie in different operations scope or different way of property rights protection. For these firms count is equal to zero. Third, there may exist firms in the sample, that are generally involved in patenting activities, however, during the observation period no patent application was filed. In that case, although despite being positive over the total period of firm´s functioning, count for the period of interest is equal to zero. As presented situation may favor usage of zero-inflated models, such specification is presented for all panel samples in Appendix D.

[19] Here the results of analysis with the first manually chosen “twins” sample are presented.

When talking about REGION and BIOTECH variables, out of 35 firms 21 can be related to as dedicated biotech ones and 20 appear to share the region with their radical firms)[20].

Patenting activities of partners of both radical and non-radical firms are presented in table 2. As can be seen, many of the firms, especially those of non-radical "twins" do not possess any patent. Apart from that, half of the patenting firms more than half have 1-10 patents. Additionally, from firms having applications, radical partners show much higher diversity of patenting. The most patents (107) are applied for by Vectura GmbH, small firm, which is however a subsidiary of international corporation Vectura Group. This trend is observed also for other subsidiaries.

Table 2. Patenting activities, partners of radical and non-radical firms

Variable	Obs	Mean	Std. Dev.	Min	Mdn	Max
Patents, non-radical partners	21	1.90	2.93	0	0	10
Patents, radical partners	35	8.57	22.48	0	3	107

In the case of control variables, the entries were taken for according years for the case of negative binomial regression for panel data and were taken as averages for the case of zero-inflated negative binomial regression. Main descriptive statistics for these variables across both radical and non-radical firms´ partners are provided in the table below.

Table 3. Descriptive statistics

Non-radical partner						
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Mdn**	**Max**
AGE	244	13.93	7.98	0	11	166
EMPL	244	13.06	11.37	1	9	55
UNI	244	0.96	0.20	0	1	1
SUBS	244	0.18	0.39	0	0	1
SPINOFF	244	0.30	0.46	0	0	1
Radical partner						
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Mdn**	**Max**
AGE	288	10.56	8.23	0	8	39
EMPL	288	38.51	60.12	2	20	329
UNI	288	0.90	0.31	0	1	1
SUBS	288	0.34	0.48	0	0	1
SPINOFF	288	0.27	0.44	0	0	1

[20] Additionally, two of the firms have moved in different region, which changed the value of REGION variable for corresponding year.

By looking at these measures, several conclusions can be made. First, partners of radical innovators are on average much younger than that of non-radical ones. Even not accounting for outliers, one can state 3-year difference based on the median value. It points at radical innovators´ seeking partnership with younger and probably more ambitious firms. Apart from that, partners of radical innovators are generally bigger and more independent (not subsidiaries) than that of non-radical partners. However, non-radical partners are more often founded as spin-offs and have joint projects with universities and research institutions. Variables show low to medium level of pairwise correlations (see table 4).

Table 4. Correlation coefficients

	RADICAL	AGE	EMPL	UNI	SUBS	SPINOFF
RADICAL	1.000					
AGE	-0.203	1.000				
EMPL	0.272	0.387	1.000			
UNI	-0.119	0.125	-0.182	1.000		
SUBS	0.184	-0.107	0.245	0.012	1.000	
SPINOFF	-0.035	-0.176	-0.067	-0.217	-0.078	1.000

5.2. Results of panel regression analysis

Results of analysis[21] are provided in table 6. First, results of the baseline negative binomial regression for an unbalanced panel are analyzed. As can be seen, the coefficients remain stable for almost all variables, however, the significance of coefficients generally decreases when lags are used. The main variable of interest, RADICAL, shows positive significant coefficient, meaning that for our sample partners of radical innovators show higher innovative performance than that of partners of their twins. This result goes in line with our hypothesis, showing presence of positive externalities. Apart from that, across all models variables AGE and EMPL show significant negative and positive results correspondingly. Therefore, younger and bigger partner have higher innovative performance. This may show the presence of certain inertia, which does not allow firm continue patenting. Apart from that, constant patenting requires substantial financial resources, which micro firms may not possess. In this respect, however, it is important to mention that the variable SUBS shows slightly significant negative coefficient, meaning that stand-alone SMEs generally tend to patent more than subsidiaries. This may be in line with the idea of Kahl (2015), that SMEs in

[21] With first self-matched sample. Other samples as well as different model specifications are presented in Appendix D as robustness checks.

biotechnology often preform services for big corporations (in this case - parent companies), which does not call for own patenting.

Next, we move to testing hypotheses two and three. For that only partners of radical innovators were taken into account, composing 288 observations. As the result of negative binomial regression, including only NUTS2 regional coincidence variable, one can see negative significant coefficient of REGION variable. This means, that interregional partners profit from cooperation with radical partner more, than intraregional ones. This contradicts our hypothesis, however, goes in line with some literature, in particular note of Breschi and Lissoni (2003), that nowadays even tacit knowledge can be translated over distance. Apart from that, competition with other SMEs from the region may be tough enough.

Latter may also serve as an explanation of the result of the model, dealing with cognitive similarity between radical innovator and its partner. The variable BIOTECH has a negative significant, showing that biotech firms experience lower influence of cooperation with radical innovator on their innovative performance. This result goes in line with our hypothesis. Thus, radical innovators rather prefer sharing their experience with firms, which complement their capabilities rather than with ones, which may substitute them.

By looking at the model with both geographical and cognitive dimension, one can see stability of the direction of coefficients, however, distance dimension loses its significance. Apart from that, significant results for AGE and EMPL variables are confirmed across all models. For the last model UNI variable also shows slightly positive coefficient, meaning that firms, cooperating with universities, have higher number of patent applications than non-cooperating ones.

In sum, we find support for hypotheses one and three and could not confirm hypothesis two. Generally, partners of radical innovators are more innovative than partners of their non-radical twins. Radical innovators tend to exchange knowledge with partners across regions and industries.

Table 5. Results of regression analysis

	Baseline model			Intra vs. interregional partners			Biotech vs. non-biotech partners			Intra vs. interregional and biotech vs. non-biotech partners		
	0 year patent lag	1 year patent lag	2 years patent lag	0 year patent lag	1 year patent lag	2 years patent lag	0 year patent lag	1 year patent lag	2 years patent lag	0 year patent lag	1 year patent lag	2 years patent lag
RADICAL	1.045** (0.430)	0.855** (0.395)	0.593 (0.384)	-	-	-	-	-	-	-	-	-
AGE	-0.089*** (0.024)	-0.068*** (0.021)	-0.049** (0.020)	-0.129*** (0.034)	-0.097*** (0.030)	-0.079*** (0.282)	-0.162*** (0.0364)	-0.098*** (0.033)	-0.075** (0.030)	-0.164*** (0.036)	-0.107*** (0.032)	-0.085*** (0.029)
EMPL	0.012** (0.005)	0.016*** (0.005)	0.018*** (0.005)	0.010** (0.005)	0.139*** (0.005)	0.014*** (0.005)	0.010* (0.005)	0.012** (0.006)	0.013** (0.005)	0.009* (0.005)	0.013** (0.006)	0.014*** (0.005)
UNI	0.651 (0.571)	0.860 (0.548)	1.610** (0.683)	0.806 (0.571)	0.962* (0.556)	1.800** (0.712)	0.994* (0.553)	0.916 (0.560)	1.729** (0.705)	1.015* (0.550)	1.002* (0.557)	1.816** (0.711)
SUBS	-0.703* (0.362)	-0.401 (0.325)	-0.174 (0.315)	-0.399 (0.394)	-0.106 (0.350)	0.172 (0.340)	-0.273 (0.361)	-0.017 (0.344)	0.264 (0.343)	-0.215 (0.364)	-0.010 (0.352)	0.232 (0.349)
SPINOFF	-0.305 (0.429)	-0.222 (0.405)	0.173 (0.391)	0.336 (0.631)	0.294 (0.557)	0.349 (0.514)	0.437 (0.710)	0.239 (0.596)	0.175 (0.514)	0.662 (0.722)	0.387 (0.604)	0.350 (0.530)
REGION	-	-	-	-1.680** (0.672)	-1.247** (0.577)	-1.045** (0.515)	-	-	-	-0.924 (0.665)	-0.888 (0.635)	-0.855 (0.577)
BIOTECH	-	-	-	-	-	-	-2.519*** (0.901)	-1.389* (0.755)	-0.941 (0.618)	-1.975** (0.997)	-0.814 (0.833)	-0.430 (0.684)
CONSTANT	-0.672 (0.760)	-1.272* (0.691)	-2.228*** (0.792)	1.544* (0.891)	0.407 (0.790)	-1.086 (0.882)	2.410** (1.012)	0.731 (0.948)	-0.984 (0.977)	2.610** (1.016)	0.826 (0.911)	-0.854 (0.953)
Log likelihood	-394.931	-422.021	-436.373	-294.085	-312.022	-319.750	-296.483	-313.579	-320.882	-291.991	-311.496	-319.545
Observations	532	532	532	288	288	288	288	288	288	288	288	288

Standard errors in parentheses, ***- significance at 0.01 level, ** - significance at 0.05 level, * - significance at 0.1 level

Year effects are absent in all of present specifications, because of their insignificance.

6. Discussion and conclusion

This paper has an aim to show whether the unique knowledge, created by radical innovations spreads out across firm boundaries and may influences cooperation partners of radically innovating SMEs in biotech. We have obtained highly robust result over all model specification, which shows that SMEs profit from being involved in cooperation with a radical innovator. As already stated, there may be several reasons for it. Firstly, communication existing between firms, engaged in scientific cooperation, is usually more intense than between firms, that do not cooperate. For sure, in case of joint work, knowledge and experience is shared, cooperation partners are not seen as competitors. Apart from that, a partner SME has a better possibility to observe routines of radical innovators and learn, how innovations are done there. Besides, our results show that for non-biotech firms as well as for firms across regions positive influence of partnership with radical innovator is higher than for the counterparts. It shows, that because of the high overlap of the capabilities, which exists among firms from the same industry and same region, less opportunities for learning can be found. From the other hand, firms from different regions and complementary industries can profit from engaging in the cooperation via extending their knowledge space.

Our study complements the existing body of literature in several ways. Based on a unique longitudinal dataset and a conceived research design we combine different analytical instruments to answer a still unexplored research question, i.e. the extent to which partners of radical innovations may benefit for their radical innovation activities. Our findings have far-reaching implications for policy makers. The promotion of young and highly innovative companies can have positive consequences for other firms and organizations within an economy. More precisely, regional funding programs designed to stimulate and support radical innovation within SMEs may have a positive effect on economic actors in other regions. Often neglected network between radically innovating SMEs and their direct partners allow for bridging long geographical distances and thus serve as important transmission channels for knowledge spillovers. Even more important, radical innovations also spill over to companies from other fields of technology. Hence, our findings suggest that technology-centered funding programs may exert a much broader impact than previously assumed. At the same time, our study allows for deriving some interesting recommendations for managers and decision-makers in companies. The establishment and maintenance of partnerships to companies with radically new ideas can pay off in terms of innovation outcomes. When choosing a partner, geographical closeness is often overestimated, especially in the age of digital technologies, making it easier than ever to bridge the even far distances.

However, there may be some limitations of our study. First, we have focused on ego-networks of the radical innovators, not taking into account second and third tier partners of their partners. Extending the research to full networks may complement our understanding of knowledge spillovers via much more complex overall industry or technology network. Apart from that, the propensity score matching technique used is a very sensitive instrument. Usage of one or two different parameters could have brought somehow different results for the twins. Whenever more data is available, the procedure can be run one more time and more robustness checks, using different samples of twins, may be performed. One dimension that needs to be examined more thoroughly is geographic distance between radical innovators and its partners. For the purpose of this study we used a very simplistic and coarse geographical measure. Here we see great opportunities for future research contributions.

The successful entrepreneurs of tomorrow are often those who think out of the box and deviate from established paths. Our study highlights the outstanding importance of ingenious, creative, risk affine individuals and their radically innovative companies for the technological prosperity of an economy, an aspect that Joseph Alois Schumpeter emphasized over 100 years ago. Cooperation with these players provides an important vehicle for other technologically and geographically distant economic actors participating in their success.

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Appendix A. IPC codes of candidates for radical patents

IPC code	Name of the subclass
C12Q	Measuring or testing processes involving enzymes, nucleic acids or microorganisms (immunoassay G01N 33/53); compositions or test papers therefor; processes of preparing such compositions; condition-responsive control in microbiological or enzymological processes
C12N	Microorganisms or enzymes; compositions thereof (biocides, pest repellants or attractants, or plant growth regulators containing microorganisms, viruses, microbial fungi, enzymes, fermentates, or substances produced by, or extracted from, microorganisms or animal material A01N 63/00; medicinal preparations A61K; fertilisers C05F); propagating, preserving, or maintaining microorganisms; mutation or genetic engineering; culture media (microbiological testing media C12Q 1/00)
C12M	Apparatus for enzymology or microbiology (installations for fermenting manure A01C 3/02; preservation of living parts of humans or animals A01N 1/02; brewing apparatus C12C; fermentation apparatus for wine C12G; apparatus for preparing vinegar C12J 1/10)
G01N	Investigating or analysing materials by determining their chemical or physical properties (measuring or testing processes other than immunoassay, involving enzymes or microorganisms C12M, C12Q)
C40B	Combinatorial chemistry; libraries, e.g. chemical libraries, in silico libraries
C12P	Fermentation or enzyme-using processes to synthesise a desired chemical compound or composition or to separate optical isomers from a racemic mixture
C07K	peptides (peptides containing β-lactam rings C07D; cyclic dipeptides not having in their molecule any other peptide link than those which form their ring, e.g. piperazine-2,5-diones, C07D; ergot alkaloids of the cyclic peptide type C07D 519/02; single cell proteins, enzymes C12N; genetic engineering processes for obtaining peptides C12N 15/00)
A61K	Preparations for medical, dental, or toilet purposes (devices or methods specially adapted for bringing pharmaceutical products into particular physical or administering forms A61J 3/00; chemical aspects of, or use of materials for deodorisation of air, for disinfection or sterilisation, or for bandages, dressings, absorbent pads or surgical articles A61L; soap compositions C11D)
B01J	Chemical or physical processes, e.g. catalysis or colloid chemistry; their relevant apparatus
C07H	Sugars; derivatives thereof; nucleosides; nucleotides; nucleic acids (derivatives of aldonic or saccharic acids C07C, C07D; aldonic acids, saccharic acids C07C 59/105, C07C 59/285; cyanohydrins C07C 255/16; glycals C07D; compounds of unknown constitution C07G; polysaccharides, derivatives thereof C08B; DNA or RNA concerning genetic engineering, vectors, e.g. plasmids, or their isolation, preparation or purification C12N 15/00; sugar industry C13)

Appendix B. List of nodes of ego-networks, radical firms

Node	Node number	Ego?
3T TextilTechnologieTransfer GmbH	1	
4SC Discovery GmbH - F&E Abt.	2	
ACGT ProGenomics AG - Geschäftsbereich 3 - Therapeutika	3	
Amedrix GmbH	4	
AMSilk GmbH	5	yes
AptaIT GmbH	6	
Aventis Research & Technologies GmbH & Co. KG - Operative Forschung	7	
Axiogenesis AG	8	yes
Bayer Technology Services GmbH - BTS-PT-Process Design- Process Analysis	9	
BIOPHARM Gesellschaft zur biotechnologischen Entwicklung von Pharmaka mbH	10	yes
Biotechnologie-Gesellschaft Mittelhessen mbH	11	yes
Braunform GmbH	12	
Cellzome AG	13	
Charité - Universitätsmedizin Berlin - Campus Virchow-Klinikum - Institut für Medizinische Genetik	14	
Charité - Universitätsmedizin Berlin - Labor für Tissue Engineering	15	
Charité - Universitätsmedizin Berlin - Medizinische Klinik mit Schwerpunkt Rheumatologie und Klinische Immunologie	16	
chimera biotec GmbH	17	yes
chimera biotec GmbH - Biomedizinzentrum Dortmund	18	yes
Christian-Albrechts-Universität zu Kiel - Agrar- und Ernährungswissenschaftliche Fakultät - Institut für Phytopathologie	19	
Christian-Albrechts-Universität zu Kiel - Agrar- und Ernährungswissenschaftliche Fakultät - Institut für Phytopathologie - Abt. Molekulare Phytopathologie	20	
Christian-Albrechts-Universität zu Kiel - Universitätsklinikum Schleswig-Holstein - Campus Kiel - Hautklinik	21	
co.don Aktiengesellschaft	22	
Coley Pharmaceutical GmbH	23	
conoGenetix biosciences GmbH	24	
Corimmun GmbH	25	
Crelux GmbH - F&E Abteilung	26	
Deutsches Krebsforschungszentrum (DKFZ) - Abt. Translationale Immunologie (D015)	27	
DOT GmbH - Bereich Forschung und Entwicklung	28	
Dr. Lerche KG	29	
Endolab Mechanical Engineering GmbH	30	
Eppendorf Instrumente GmbH	31	

FEG Textiltechnik Forschungs- und Entwicklungsgesellschaft m.b.H.	32	
FEG Textiltechnik Forschungs- und Entwicklungsgesellschaft m.b.H. - Abt. Entwicklung	33	
Fraunhofer-Institut für Angewandte Informationstechnik (FIT)	34	
Fraunhofer-Institut für Siliziumtechnologie (ISIT)	35	
Freie Universität Berlin - Fachbereich Biologie, Chemie, Pharmazie - Institut für Biologie - Angewandte Genetik	36	
Freie Universität Berlin - Fachbereich Biologie, Chemie, Pharmazie - Institut für Chemie und Biochemie	37	
Friedrich-Schiller-Universität Jena - Physikalisch-Astronomische Fakultät - Institut für Materialwissenschaft und Werkstofftechnologie	38	
GeSIM Gesellschaft für Silizium-Mikrosysteme mbH	39	
Graffinity Pharmaceuticals GmbH	40	yes
GS Gebhardt & Schäfer Industrie-Elektronik GmbH	41	
Hahn-Schickard-Gesellschaft für angewandte Forschung e.V. - Institut für Mikro- und Informationstechnik (IMIT)	42	
Helmholtz Zentrum München Deutsches Forschungszentrum für Gesundheit und Umwelt (GmbH) - Institut für Lungenbiologie	43	
Helmholtz-Zentrum für Infektionsforschung GmbH - Abt. Molekulare Biotechnologie	44	
humediQ GmbH	45	
ibidi GmbH	46	
In Vitro Biotec GmbH	47	
Infineon Technologies AG	48	
Inosim GmbH	49	
Intana Bioscience GmbH	50	
Jenpolymer Materials LTD & Co. KG	51	
Julius-Maximilians-Universität Würzburg - Physiologisch-Chemisches Institut	52	
Kliniken der Stadt Köln gGmbH - Klinik für Anästhesiologie und operative Intensivmedizin	53	
Klinikum der Universität München - Campus Großhadern - Medizinische Klinik und Poliklinik I	54	
Klinikum rechts der Isar der Technischen Universität München - Klinik für Orthopädie und Unfallchirurgie	55	
KTB Tumorforschungsgesellschaft mbH	56	
Lindauer DORNIER Gesellschaft mit beschränkter Haftung - Abt. GS	57	
Ludwig-Maximilians-Universität München - Fakultät für Chemie und Pharmazie - Department Pharmazie - Pharmazeutische Technologie und Biopharmazie	58	
Ludwig-Maximilians-Universität München - Fakultät für Physik	59	
Martin-Luther-Universität Halle-Wittenberg - Fachbereich Ingenieurwissenschaften - Institut für Biogineering	60	
Martin-Luther-Universität Halle-Wittenberg - Naturwissenschaftliche Fakultät I - Institut für Biochemie und Biotechnologie	61	

Martin-Luther-Universität Halle-Wittenberg - Naturwissenschaftliche Fakultät I - Institutes für Biologie - Genetik	62	
Mathys Orthopädie GmbH	63	
Medizinische Hochschule Hannover - Klinik und Poliklinik für Dermatologie und Venerologie	64	
Medizinische Hochschule Hannover - Orthopädische Klinik (im Annastift)	65	
Medizinische Hochschule Hannover - Zentrum Innere Medizin - Klinik für Nieren- und Hochdruckerkrankungen	66	
Milupa GmbH - Numico Research - Group Germany	67	
Molzym GmbH & Co. KG	68	
MorphoSys AG	69	
MPB Cologne GmbH	70	yes
NanoTemper Technologies GmbH	71	
nanotype GmbH	72	yes
NMI Naturwissenschaftliches und Medizinisches Institut an der Universität Tübingen	73	
november Aktiengesellschaft Gesellschaft für Molekulare Medizin - MD1/Medizinische Diagnostik	74	yes
ONCOLEAD GmbH & Co. KG	75	
Orthopädische Universitätsklinik Heidelberg	76	
Planton GmbH	77	yes
Priaxon AG	78	
Proteome Sciences R&D GmbH & Co. KG	79	
Proteros Biostructures GmbH	80	
QUALIMED Innovative Medizinprodukte Gesellschaft mit beschränkter Haftung	81	
Rheinisch-Westfälische Technische Hochschule Aachen - Fakultät 4 - Maschinenwesen - Lehrstuhl und Institut für Allgemeine Mechanik	82	
Robert Bosch GmbH - Zentralbereich Forschung und Vorausentwicklung - Mikrosystemtechnik	83	
Ruprecht-Karls-Universität Heidelberg - Medizinische Fakultät und Universitätsklinikum Mannheim - Neurochirurgische Klinik	84	
Ruprecht-Karls-Universität Heidelberg - Medizinische Fakultät und Universitätsklinikum Mannheim - Orthopädisch-Unfallchirurgisches Zentrum	85	
Scil Proteins GmbH	86	yes
Siemens Aktiengesellschaft - Zentralabt. Technik (ZT EN 1)	87	
SIRION BIOTECH GmbH	88	
Südzucker Aktiengesellschaft Mannheim/Ochsenfurt - Zentralabt. Forschung, Entwicklung und Services (ZAFES)	89	
SuppreMol GmbH	90	
SWITCH Biotech AG	91	yes
Technische Universität Dortmund - Fakultät Chemie - Lehrstuhl für Biologisch-Chemische Mikrostrukturtechnik	92	
Technische Universität München - Fakultät für Medizin - Institut für Medizinische Mikrobiologie, Immunologie und Hygiene	93	

Technische Universität München - Fakultät für Medizin - Institut für Pharmakologie und Toxikologie	94	
Technische Universität München - Wissenschaftszentrum Weihenstephan - Forschungsdepartment Biowissenschaftliche Grundlagen - Lehrstuhl für Biologische Chemie	95	
TransTissue Technologies GmbH	96	yes
Trianta Immunotherapies GmbH	97	
Universität Bayreuth - Fakultät für Angewandte Naturwissenschaften - Lehrstuhl Bioprozesstechnik	98	
Universität Bayreuth - Fakultät für Angewandte Naturwissenschaften - Lehrstuhl für Biomaterialien	99	
Universität Bremen - Fachbereich 02 Biologie/Chemie - Institut für Biochemie - Centrum für Biomolekulare Interaktionen in Bremen (CBIB)	100	
Universität Regensburg - Universitätsklinikum - Klinik und Poliklinik für Innere Medizin I	101	
Universitätsklinikum Jena - AG Experimentelle Rheumatologie	102	
Universitätsklinikum Jena - Medizinische Fakultät - AG Experimentelle Rheumatologie - Lehrstuhl für Orthopädie	103	
Universitätsklinikum Würzburg - Neurologische Klinik und Poliklinik	104	
Vectura GmbH	105	
Wilex AG	106	
Xerion Pharmaceuticals AG	107	
XL-protein GmbH	108	

Appendix C. List of nodes of ego-networks, radical firms

Radical firm	Manual match 1	Manual match 2	Random match 1	Random match 2
MPB Cologne GmbH	Kelman Gesellschaft für Geninformation mbH	LipoNova AG	Kelman Gesellschaft für Geninformation mbH	Otogene AG
Switch Biotech AG	Xenomed GmbH	TherapySelect GmbH & Co. KG	TherapySelect GmbH & Co. KG	Xenomed GmbH
Biotechnologie-Gesellschaft Mittelhessen mbH	GAMU - Gesellschaft für angewandte Mykologie und Umweltstudien mbH	m-phasys GmbH	GAMU - Gesellschaft für angewandte Mykologie und Umweltstudien mbH	EnerGene
Scil Proteins GmbH	DECODON GmbH	Cevec Pharmaceuticals GmbH	Exosome Diagnostics GmbH	Ganomycin GmbH
AMSilk GmbH	Across Barriers GmbH	Exosome Diagnostics GmbH	XanTec bioanalytics GmbH	DECODON GmbH
nanotype GmbH	Lionex GmbH	Arthro kinetics AG	BCP AG evolutionary concepts	Cavis GmbH
Chimera Biotec GmbH	ProteoSys AG	NascaCell Technologies AG	N-Zyme BioTec GmbH	NascaCell Technologies AG
november AG	BIOSERV AG	Institut für Pflanzenkultur	Biotype Diagnostic GmbH	BIOSERV AG
metanomics GmbH	Tinplant	TraitGenetics GmbH	Genotype GmbH	Biognosis GmbH
BIOPHARM GmbH	Autoimmun Diagnostika GmbH	Mediagnost GmbH	Senova	Lophius Biosciences GmbH
Axiogenesis AG	GENterprise GmbH	Bioglobe GmbH	JPT Peptide Technologies GmbH	GENterprise GmbH
Planton GmbH	Bioglobe GmbH	GENterprise GmbH	GENterprise GmbH	PSF biotech AG
TransTissue Technologies GmbH	SILANTES GmbH	Capsulution Pharma AG	SILANTES GmbH	Protagen AG

Random matches were identified with Random Number Service random.org. For that reason, some randomly chosen "twin" firms coincide with manually chosen ones.

Appendix D. Robustness checks

Manual check 2

	Negative binomial regression			Zero-inflated negative binomial model		
	0 year patent lag	1 year patent lag	2 years patent lag	0 year patent lag	1 year patent lag	2 years patent lag
RADICAL	0.364 (0.359)	0.180 (0.346)	0.094 (0.342)	0.897** (0.352)	0.911*** (0.341)	1.036*** (0.347)
AGE	-0.074*** (0.023)	-0.050*** (0.018)	-0.041*** (0.015)	0.179 (0.032)	0.014 (0.032)	0.008 (0.030)
EMPL	0.008** (0.004)	0.010** (0.004)	0.008** (0.004)	-0.001 (0.005)	-0.001 (0.004)	0.001 (0.004)
UNI	0.793 (0.489)	0.775* (0.447)	1.120** (0.448)	-0.533 (0.922)	-0.656 (0.886)	-0.814 (0.880)
SUBS	-0.403 (0.293)	-0.152 (0.269)	0.077 (0.262)	0.942*** (0.355)	0.949*** (0.343)	0.845** (0.351)
SPINOFF	0.128 (0.365)	0.138 (0.355)	0.256 (0.351)	0.318 (0.377)	0.292 (0.366)	0.283 (0.370)
CONSTANT	-0.399 (0.622)	-0.599 (0.554)	-1.138** (0.540)	1.192 (0.923)	1.460* (0.882)	1.687* (0.876)
Log likelihood	-488.553	-519.235	-532.756	-147.093	-152.140	-154.232
Observations	628	628	628	74	74	74

Standard errors in parentheses, ***- significance at 0.01 level, ** - significance at 0.05 level, * - significance at 0.1 level

Zero-inflated negative binomial model was evaluated only with the variable of prior interest because of convergence issues

Random match 1

	Negative binomial regression			Zero-inflated negative binomial model		
	0 year patent lag	1 year patent lag	2 years patent lag	0 year patent lag	1 year patent lag	2 years patent lag
RADICAL	0.229 (0.349)	0.133 (0.351)	0.304 (0.325)	1.402*** (0.350)	1.350*** (0.351)	-0.077 (0.531)
AGE	-0.051*** (0.019)	-0.025** (0.017)	-0.030* (0.017)	-	-	-
EMPL	0.006 (0.004)	0.008* (0.004)	0.008* (0.004)	-	-	-
UNI	0.342 (0.524)	0.497 (0.502)	1.436** (0.663)	-	-	-
SUBS	-0.300 (0.283)	-0.089 (0.264)	0.095 (0.258)	-	-	-
SPINOFF	0.201 (0.401)	-0.246 (0.406)	0.409 (0.386)	-	-	-
CONSTANT	-0.154 (0.638)	-0.467 (0.608)	-1.892** (0.753)	1.079 (0.238)	1.224 (0.237)	0.316 (0.345)
Log likelihood	-508.986	-538.593	-542.819	-166.623	-172.891	-88.631
Observations	649	649	649	53	53	53

Standard errors in parentheses, ***- significance at 0.01 level, ** - significance at 0.05 level, * - significance at 0.1 level

Zero-inflated negative binomial model was evaluated only with the variable of prior interest because of convergence issues

Random match 2

	Negative binomial regression			Zero-inflated negative binomial model		
	0 year patent lag	0 year patent lag	0 year patent lag	0 year patent lag	1 year patent lag	2 years patent lag
RADICAL	0.303 (0.376)	0.178 (0.356)	0.134 (0.335)	0.050 (0.414)	0.136 (0.402)	0.192 (0.403)
AGE	-0.089*** (0.022)	-0.052*** (0.020)	-0.038* (0.020)	0.070* (0.039)	0.073* (0.038)	0.068* (0.037)
EMPL	0.011*** (0.004)	0.011** (0.005)	0.010** (0.005)	-0.003 (0.005)	-0.003 (0.005)	-0.002 (0.004)
UNI	0.646 (0.484)	0.537 (0.454)	0.832* (0.473)	-0.641 (1.331)	-0.892 (1.289)	-1.088 (1.252)
SUBS	-0.316 (0.309)	0.012 (0.279)	0.238 (0.274)	0.809* (0.418)	0.854** (0.406)	0.853** (0.411)
SPINOFF	-0.191 (0.398)	-0.136 (0.383)	-0.007 (0.364)	0.542 (0.443)	0.437 (0.433)	0.388 (0.421)
CONSTANT	-0.113 (0.602)	-0.441 (0.545)	-1.136** (0.543)	1.357 (1.322)	1.584 (1.282)	1.791 (1.252)
Log likelihood	-505.249	-530.046	-542.310	-141.796	-141.816	-145.921
Observations	563	563	563	64	64	64

Standard errors in parentheses, ***- significance at 0.01 level, ** - significance at 0.05 level, * - significance at 0.1 level

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