Unlocking the radical potential of German innovators

How can R&D policy foster radical innovation?

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JEL codes: C30; H20; O31; O38

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Abstract

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1 Introduction

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

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

Thus, this study aims to answer the question whether direct funding for R&D projects can support the emergence of radical innovations. First research has found a positive impact of public R&D support on radical innovation (Beck et al. 2016), but evidence is far from conclusive. This study delineates from the above-mentioned work by focusing on German organisations in the light of the establishment of a specific agency to support frontier-breaking innovations and by focusing on the technology dimension instead of the product dimension. In particular, it looks at completely novel technology combinations as proxy for radical innovation output (e.g. Verhoeven et al. 2016). Furthermore, it scrutinizes on specific selection criteria for the inclusion into treatment, namely cross-innovation activities. Although, the positive effect of university-industry linkages (e.g. Belderbos et al. 2004), cross-industrial (e.g. Castaldi et al. 2015) and cross-regional (e.g. Miguelez and Moreno 2018) as well as cross-cluster collaboration (e.g. Owen-Smith and Powell 2004) on (radical) innovation has been acknowledged in the literature, there is no empirical evidence so far whether policy-induced cross-innovation activities can enhance radical innovation output. Hence, this paper contributes mainly in three ways. First, it sheds light on the question whether public R&D support can support the emergence of novel combinations. Second, it scrutinizes on the effect of collaborative R&D support for the emergence of radical innovation. The third contribution relates to the focus on cross-innovation activities. Although many scholars advise policy makers to support these activities, we do not know whether the funding of such research projects has an effect on radical innovation. The results can be of particular interest for scholars focusing on innovation policy and for policy makers aiming to support this type of innovation and can help to design measures for innovation agencies such as the above-mentioned SprinD or JEDI.

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

2 Theoretical background

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

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

Several studies have found empirical evidence that subsidies have a positive impact on different innovation indicators such as patenting performance (e.g., Czarnitzki and Hussinger

2004; Czarnitzki and Licht 2006) or novelty sales (e.g., Czarnitzki and Lopes-Bento 2014). However, research is rather silent about the effects of R&D support on radical innovations. Therefore, it is important to scrutinize more on radical innovation processes in the context of policy measures to better target such innovations that can provide a long-lasting competitive advantage.

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

H1: Policy-induced R&D enhances the emergence of radical innovations.

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

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

Generally, there is consensus in the literature that R&D collaboration enhances innovativeness of regions and firms (e.g. Rigby and Zook 2002; Fitjar and Rodríguez-Pose 2013). Economic actors can gain access to complementary knowledge through formal collaborations with other actors (Powell et al. 1996) and thereby enhance knowledge diffusion (Wirsich et al. 2016). Furthermore, organisations seek to improve the quality of their inventions by engaging in collaboration with the aim to create radical breakthroughs (Singh 2008). Consequently, the following hypothesis is posed:

H2: Policy-induced collaborative R&D enhances the emergence of radical innovations.

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

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

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

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

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

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

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

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

As Beck et al. (2016) already have pointed out, it is important to acknowledge that collaboration may also be accompanied by certain risks. Amongst others, there is the possibility of free riding by of one of the partners. Furthermore, absorptive capacity of organisations is important in order to benefit from knowledge spillovers and assimilate new knowledge stemming from collaboration partners (Cohen and Levinthal 1990). Otherwise the coordination efforts may exceed the benefits of collaborating. While the risks of collaborating are present in every case, they might be more pronounced in subsidized collaboration as organisations may engage in collaborative R&D projects in order to increase the probability of being selected for treatment rather than because the partners provide complementary knowledge that is important for radical innovation processes.

3 Empirical Background

3.1 Construction of the sample

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

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

Furthermore, to identify universities and research institutes within the German subsidy catalogue, the German research directory ("Research Explorer") is used. It contains information on over 25,000 university and non-university research institutes in Germany. Moreover, IAB employment data and information from the German Federal Statistical Office are used to complement the dataset. The final sample then is a pooled cross-section and consists of 8,404 innovating organisations, out of which 524 received a subsidy.

3.2 Construction of variables

Radical innovations are approximated by entirely new combinations of technology domains (Grashof et al. 2019; Verhoeven et al. 2016) as they tend to combine former unconnected knowledge pieces (Fleming 2001). In order to detect these novel combinations, all four-digit International Patent Classification (IPC) codes[1] present on patent filings in the years 2012-2014 are compared with all IPC combinations that appeared in Germany between 1983 and one year before the focal year. Therefore, new combinations are completely new to Germany (since 1983). Even though it is not yet sure whether they will have an impact on the economy in the future, radicalness is characterised through the entirely new combination of two knowledge pieces (Arant 2019). Then, the new combinations are summed for each organisation in the dataset which represents the dependent variable (new_dyad).

The information on public R&D funding is used to construct several explanatory variables. To acknowledge that a patent filing usually is the result of a R&D project and gets filed rather at the end, a time lag of 4 years is applied in the study, following Fornahl et al. 2011.[2] Hence, information on funded R&D projects between 2008 and 2010 is used. First, the binary variable R&D_funding takes the value of one if the organisation received a subsidy or zero otherwise. As an alternative to assess the effect of public research grants, the variable R&D_funded_projects represents the number of funded projects per organisation. Table 1 shows the subsidy distribution over the sample.

[Table 1 about here]

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

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

First, one possibility to engage in cross-innovation activities is by collaborating with partners from a different organisational background. For instance, university-industry linkages are considered to be important for the generation of radical innovations (Wirisch et al. 2016; Arant et al. 2019). Thus, cross-orga_funding counts the number of funded projects with partners having a different organisational background (industry vs. university/research institute) for each organisation in the dataset. Second, another possible source to get complementary knowledge for radical novelty is through spillovers from different industries (Castaldi et al. 2015; Miguelez and Moreno 2018; Hesse and Fornahl 2020). Hence, cross-industry_funding counts the number of funded projects with partners active in different industries. For this, two-digit NACE Rev. 2 code[3] industries are used. Third, turning to the regional dimension, scholars have provided empirical evidence that complementary knowledge for radical new ideas can be found in other regions (Singh 2008; Miguelez and Moreno 2018; Hesse and Fornahl 2020). Hence, each organisation is assigned to 141 German labour market regions as defined by Kosfeld and Werner (2012). This definition is used so that commuter and urban-periphery structures are unlikely to bias the results. In particular, the address of the executing entity in the German subsidy catalogue is used to allocate the organisations in the dataset. Then, the number of funded projects with partners from different labour market regions is calculated (cross-region_funding).

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

[3] NACE codes refer to the statistical classification of economic activities in the European Community. A full list can be found at Eurostat, e.g.: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Statistical_classification_of_economic_activities_in_the_European_Community_(NACE).

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

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

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

[Table 2 about here]

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

[Table 3 and 4 about here]

3.3 Descriptive statistics

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

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

4.1 Method

In general, organisations receiving R&D grants may be different from organisations which do not get subsidized. Hence, to identify the effect of public R&D funding on an organisation's ability to come up with radical novelty it is important to identify attributes for the inclusion into treatment. Thus, a propensity score matching is applied to get more credible estimates of the role of R&D funding. Before applying the matching estimation, a logistic regression is run to predict the propensity of receiving public R&D funding. The equation includes important

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

characteristics for the selection into the funding scheme. As can be seen in Table 5, except for age and patents per 100 employees all covariates are important drivers of being selected for treatment. Being larger, being active in knowledge-intensive industries, having received a subsidy in the past, being independent and being located in an Eastern German labour market region drives the likelihood to receive public funding.

[Table 5 about here]

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

[Table 6 about here]

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

4.2 Results

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

[Table 7 about here]

Table 8 reports the results of the negative-binomial regression models on radical innovation outcome. Model 1 represents the baseline model and Models 2-6 subsequently introduce the variables of interest. With regard to the control variables, as expected, age and size both have a non-linear relationship. Age takes an u-shaped relation with the emergence of novel combinations, which means that not only young organisations are more likely to come up with radical novelty but also rather old organisations. Young innovative organisations have already found to be key actors for the emergence of radical innovations (e.g., Schneider and Veugelers 2010). A reason for the positive effect concerning older organisations could be that they possess deep knowledge in a certain field and are able to combine it with complementary knowledge, for instance, through collaborations with other actors (Leten et al. 2007). Then, (the log of) organisation size has an inverted u-shaped relation to the emergence of radical novelty, although the negative effect of size is not significant in the first two models. Both relations have already been suggested by previous research (e.g. Beck et al. 2016). Furthermore, an organisation's general innovativeness has a positive effect throughout all models (except for Model 2a) same as the number of research institutions in the local ecosystem of the organisation. This has been found by earlier studies (e.g. Grashof et al. 2019). (The log of) Population density has a negative effect only in Model 6. This may be explained through the fact that policy-induced inter-regional collaborations are aimed at enhancing the catching-up process of peripheral regions (Isaksen and Trippl 2017).

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

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

[Table 8 about here]

Subsequently, Table 9 shows the effect of cross-cluster activities on radical innovations. First of all, Model 7 shows that funding collaborations across regional clusters has a positive effect on radical innovation output of organisations, supporting hypothesis 6. This suggests that it is fruitful to link two industrial strongholds to combine deep knowledge from both sources for radical novelty as proposed by Janssen and Frenken (2019). Models 8 and 9 further point to the fact that these strongholds should have different industrial specialisations or should be located in different regions to provide complementary knowledge for radical search processes. This can also help to overcome possible cognitive or regional lock-in (Boschma 2005). This unveils that cross-specialisation policy can work in order to foster radical innovation. Cross-fertilisation can be induced most effectively when the treated organisations have a different industrial or regional background. The influence of the control variables is mostly consistent with the discussed results in Models 1-6.

[Table 9 about here]

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

Moreover, funding of collaborations between innovative actors from two regional clusters positively affects radical innovation output.

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

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

5 Conclusion

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

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

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

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

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Tables

Table 1. Subsidy distribution over sample.

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

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

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

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

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

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

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

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

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

	Dependent variable:
	R&D_funding
age	-0.008
	(0.006)

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

Table 6. Results of econometric matching estimation.[5]

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

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

Table 7. Additional descriptive statistics, N= 524.

Variables	Observations	Mean	St. Dev.	Min.	Max.
R&D_funded_projects	524	2.06	3.73	1	64

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

co_funding	524	1.81	2.99	0	44
cross-orga_funding	524	0.05	0.24	0	2
cross-industry_funding	524	0.76	1.44	0	19
cross-region_funding	524	0.80	1.41	0	18
cross-cluster_funding	524	0.13	0.85	0	16
cross-cluster_funding (cross-industry)	524	0.10	0.77	0	16
cross-cluster_funding (cross-region)	524	0.12	0.83	0	16

Table 8. Negative binomial regression results.

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

Observations	282	282	282	282	282	282	282
Log Likelihood	-104.481	-102.953	-101.350	-101.843	-103.247	-101.570	-100.184
theta	0.382*** (0.148)	0.491** (0.211)	0.630* (0.325)	0.577** (0.283)	0.483** (0.217)	0.544** (0.248)	0.566** (0.245)
Akaike Inf. Crit.	232.962	231.907	228.700	229.685	232.494	231.140	230.368
Note:							*p<0.1; **p<0.05; ***p<0.01
							Robust standard errors in parentheses

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

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

Appendix

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

	Dependent variable:						
	patent_count						
	(1)	(2a)	(2b)	(3)	(4)	(5)	(6)
age	-0.002	-0.002	-0.003	-0.003	-0.002	-0.002	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
age²	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001	-0.00001
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
log(size)	0.898***	0.931***	1.085***	1.031***	0.955***	1.047***	0.853***
	(0.235)	(0.234)	(0.242)	(0.241)	(0.235)	(0.246)	(0.248)
log(size²)	-0.006	-0.009	-0.022	-0.017	-0.011	-0.018	-0.004
	(0.016)	(0.016)	(0.017)	(0.017)	(0.016)	(0.017)	(0.017)
patents_p100emp	0.176***	0.172***	0.177***	0.176***	0.177***	0.178***	0.175***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
industry_rest	0.218	0.232	0.261	0.253	0.261	0.259	0.283
	(0.177)	(0.176)	(0.175)	(0.175)	(0.176)	(0.176)	(0.176)
industry_ki	0.346**	0.375***	0.357**	0.353**	0.370***	0.365**	0.420***
	(0.143)	(0.143)	(0.142)	(0.142)	(0.143)	(0.143)	(0.143)
independent	0.464***	0.489***	0.442**	0.442**	0.468***	0.457**	0.470***
	(0.179)	(0.178)	(0.178)	(0.178)	(0.178)	(0.178)	(0.180)
academics_p.c	0.008*	0.007	0.009*	0.009*	0.009*	0.010**	0.010**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
log(pop_density)	-0.090	-0.075	-0.110	-0.109	-0.107	-0.115*	-0.128*
	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)
research_facilities	0.0004	0.0002	0.001	0.001	0.0003	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
R&D_funding		0.226*					
		(0.117)					
R&D_funded_projects			0.053**				
			(0.021)				
co_funding				0.048**			
				(0.023)			
cross-orga_funding					0.472*	0.295	0.264
					(0.258)	(0.304)	(0.305)
cross-industry_funding						0.057	0.088
						(0.048)	(0.216)
cross-region_funding							-0.040
							(0.227)
Constant	-3.300***	-3.566***	-3.773***	-3.608***	-3.423***	-3.643***	-2.926***
	(0.965)	(0.966)	(0.973)	(0.971)	(0.961)	(0.978)	(0.987)
Observations	282	282	282	282	282	282	282
Log Likelihood	-910.230	-908.480	-907.089	-907.948	-908.005	-907.485	-908.538
theta	1.297*** (0.116)	1.315*** (0.118)	1.331*** (0.120)	1.321*** (0.119)	1.319*** (0.119)	1.326*** (0.120)	1.315*** (0.118)
Akaike Inf. Crit.	1,844.461	1,842.959	1,840.178	1,841.897	1,842.009	1,842.969	1,847.077
Note:							*p<0.1; **p<0.05; ***p<0.01
							Robust standard errors in parentheses

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

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