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Joint R&D subsidies, related variety, and regional innovation.

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Abstract:

Subsidies for R&D are an important tool of public R&D policy, which motivates extensive scientific analyses and evaluations. The paper adds to this literature by arguing that the effects of R&D subsidies go beyond the extension of organizations' monetary resources invested into R&D. It is argued that collaboration induced by subsidized joint R&D projects yield significant effects that are missed in traditional analyses.

An empirical study on the level of German labor market regions substantiates this claim showing that collaborative R&D subsidies impact regions' innovation growth when providing access to related variety and embedding regions into central positions in cross-regional knowledge networks.

Keywords: collaborative R&D projects, related variety, regional innovation

JEL Classifications: L14, O31, R12

1 Introduction

The systemic view on innovation emphasizes that innovation is a result of the division and interaction of innovate labor and their embeddedness into knowledge networks (Lundvall 1992). The relevance of such interactions and networks is evident and increasing (Hagedoorn 2002). These insights have been taken up by policy seeking to facilitate innovation activities. While in the past policy focused on stimulating firm-internal R&D processes, today, R&D policies more and more support knowledge sharing and the creation of knowledge networks (Muldur et al. 2006). Amongst the most common tools to achieve these goals are subsidies for joint R&D projects. In such joint R&D projects consortia of organizations share the subsidization grant and realize the project in a collaborative manner. For example in Germany, about 30% of today's R&D subsidies are given to (collaborative) joint R&D projects (Broekel and Graf 2012).

This shift has severe implications for the scientific analysis of R&D subsidies, which have so far not received sufficient attention (but see Czarnitzky and Fier 2003, Fornahl et al. 2011, Broekel 2013). First, this concerns the fact that effects of subsidies are no longer restricted to individual organizations and hence may be missed in firm-level studies. Second, by subsidizing collaborative R&D, innovation policy does not only impact the embeddedness of firms into territorial innovation systems, it may also alter the mode of operation of such systems. The aim of the paper is to contribute to this discussion by picking up the insights from research on territorial innovation systems and translate them to the context of public subsidies for R&D projects. This particularly concerns the importance of access to knowledge from within and outside regional borders (Maskell and Malmberg 2002, Audretsch and Feldmann 2004, Bathelt et al. 2004); the type of knowledge resources shared in research collaboration (Nooteboom 2000, Branstetter and Sakakibara 2002, Breschi et al. 2003); and the embeddedness of regional organizations into inter-organizational knowledge networks (Powell et al. 1999, Fornahl et al. 2011).

The arguments are tested by means of an empirical study on the determinants of regions' innovation growth with a particular focus on subsidies for joint R&D. The study utilizes a dataset for 150 German labor markets regions and twenty-one manufacturing industries covering the periods 1999-2003 and 2004-2008. To address endogeneity and spatial as well as relational dependencies, a Heckit two-stage procedure in combination with spatial regression techniques is employed. The results confirm the importance of collaboration initiated or facilitated by subsidies for joint R&D projects for regions' ability to increase innovation output. The effectiveness of policy measures however crucially depends on whether subsidized projects bring together organizations with similar but not too similar (i.e. related) knowledge bases. Moreover, being central in inter-regional networks of subsidized R&D collaboration stimulates regions' innovation growth.

The paper is structured as follows. The subsequent section presents theoretical insights and empirical evidence on the role of (collaborative) R&D subsidies at the firm and region level. The description of the empirical data is content of section three. Section four explicates the empirical approach and the models used to analyze determinants regions' innovation growth. The presentation and discussion of the results are subject of the forth section. Section six summarizes and concludes the paper.

2 Innovation policy, collaborative R&D subsidies and innovative outcomes

Innovation is undoubtedly the driver of persistent (regional) competitive advantage and development. However, social returns to innovation and R&D investments exceed private returns, which may lead to an underinvestment in R&D from a societal perspective (Arrow 1962). The positive externalities associated with the generation of innovation give the prime justification for public support to private R&D activities. While policy employs a wide range of tools in this context, R&D subsidies to private R&D projects are among the most important and most frequently used (Aschhoff 2008). Empirical literature on R&D subsidies so far concentrates on the allocation and the effects of R&D subsidies at the firm level. Common findings concerning the allocation of R&D subsidies are a higher likelihood of subsidization being positively related to the number of business units, collaboration with universities, previous experiences and high R&D intensity (Busom 2000, Blanes and Busom 2004). Regarding the effects of R&D subsidies, the literature shows that they positively impact firms' patenting, innovation efficiency, employment growth, and R&D efforts (Czarnitzki and Fier 2003, Czarnitzki and Hussinger 2004, Czarnitzki et al. 2007, Koski 2008, Zúñiga-Vicente et al. 2014).

However, the way R&D subsidization programs are designed has been subject to significant changes. R&D subsidies were traditionally awarded to projects conducted by an individual organization. This organization was in charge and solely responsible for completing the project. Since the middle of the nineteen eighties this way of allocating R&D subsidies was extended by the subsidization of joint R&D projects. In this case, R&D subsidies are granted to research consortia that realize R&D projects in a collaborative fashion. Moreover, they have to grant each other access to knowledge, R&D resources, and intellectual property related to the project (for a more extensive discussion see Broekel and Graf, 2012).

The shift in the design of R&D subsidization policies reflects the increasing emphasis on territorial and sectoral innovation systems in the scientific literature (Lundvall 1992, Breschi and Malerba 1997, Cooke et al. 1997). The systems view on innovation highlights that firms do not innovate in isolation but extensively rely on collaboration and interactions with firm-external actors. Accordingly, Broekel (2013) argues that by subsidizing joint R&D projects, policy does not only influence organizations' internal R&D process but also collaboration and interaction activities. For instance, by providing monetary incentives to collaborate, organizations are more likely to engage into collaborative activities in general and thereby increase their interdependence with external actors. This is however not uniform over all types of organizations, technologies, and industries. R&D subsidies are used by policy to support areas, which it perceives to be of special importance. In Germany, this particularly applies to new technologies and so-called key technologies (Fier 2002). Some R&D subsidization initiatives are also selective in terms of supported collaboration partner combinations. For instance, some programs explicitly seek to strengthen regional collaboration (Koschatzky and Zenker 1999) and some even support only regional collaboration within the boundaries of a particular technological field (Dohse, 2000). Another configuration of collaboration that is more likely to be supported than others is when public science organizations partner with firms. Such interactions are perceived to be essential for society-wide knowledge diffusion and exploitation of basic research (Beise and Stahl 1999). Broekel and Graf (2012), moreover show that by participating in subsidized joint R&D projects, organizations are embedded into inter-organizational knowledge networks. These networks emerge either without policy intervention or by organizations participating in multiple subsidized R&D projects and organizations transferring experiences and knowledge between projects. In these cases, organizations' knowledge may diffuse along the direct and indirect relations in the network. The more prominent (central) an organization's position in such (subsidized or unsubsidized) knowledge network, the more likely it will be exposed to and gain access to innovation-relevant knowledge in the network (Powell et al. 1999, Fornahl et al. 2011).

In summary, subsidies for joint R&D projects may have two distinct impacts that go beyond the boundaries of a single organization. First, the effects at the organizational level emerging from the subsidies for joint R&D are likely to translate to the more aggregate level of innovation systems, as organizations interact with their local surroundings (Camagni 1991, Oerlemans and Meeus 2005). That is, through manifold intended and unintended interactions, effects of R&D subsidies granted to one organization are likely to be transmitted to other organizations part of the same territorial innovation system.[1] Second, Broekel (2013) argues that subsidies for joint R&D additionally influence the embeddedness of organizations into such systems and thereby impact its entire working and set-up, since subsidized R&D collaboration are one way of how organizations interact with the innovation systems. In addition, the availability of subsidized R&D collaboration alters the attraction of other modes of interaction (e.g. unsubsidized collaboration).

The extent and significance of the two effects thereby depends on a number of factors. Amongst these is the magnitude of changes at the organizational level. That is, the impact of subsidies at the organizational level has to be significant in relation to an organization's activities. The organization also needs to be strongly embedded into the system. Therein, the importance of organizations for the functioning of territorial innovation systems varies considerably (Ter Wal and Boschma 2007). It seems plausible that in particular gatekeeper organizations, which keep regional networks integrated and maintain connections to inter-regional networks, are crucial in this context (Morrison 2008). If these significantly change their behavior according to R&D subsidization, this change is most probable to feedback into the entire system. For instance, R&D subsidization may allow these organizations to tap into new knowledge bases that were too expensive to connect to prior subsidization.

The paper seeks to add to this literature by studying what regions gain from their organizations' participation in subsidized R&D in general and in subsidized joint R&D in particular. With respect to the latter, in the foreground are especially implications of collaboration partner choice in terms of (1) their geographic location, (2) their knowledge resources, and (3) their importance in inter-regional knowledge networks.

Concerning the first, we can expect a strengthening of the territorial innovation system when R&D subsidies bring together regional organizations and initiate regional collective learning processes (Isaksen 2001). The benefits of these may include cheaper and more frequent face-to-face communication, as well as easier establishment of trust (Storper and Venables 2004, Williamson 1999). However, there might be instances when regional interactions are already fully developed and further support is unnecessary or even harmful. This particularly concerns regional lock-in situations in which regional organizations are unable to leave a particular development trajectory, which delivers suboptimal economic

[1] Similar can be argued for sectoral innovation systems, these are however beyond the scope of the present paper.

results (Grabher 1993). Such situations are likely to be characterized by dense regional networks with few outside relations. The stimulation of inter-regional collaboration is more beneficial in this case (Broekel 2012).

Second, the fit of knowledge resources among partners in subsidized R&D collaboration matters. It is empirically shown that R&D collaboration offers maximal value creation potentials when providing access to related (knowledge) resources (Gulati, 1998, Das and Teng 2000). Partners with related knowledge are characterized by sufficient potentials to develop novel solutions and at the same time are still able to engage in efficient communication (Nooteboom 2000). Hence, as for unsubsidized collaboration, subsidized R&D collaboration will be particularly beneficial when partners with related knowledge come together (Breschi et al. 2003). Fornahl et al. (2011) provide some evidence for this argument at the firm-level, which we seek to extent to the regional level.

Moreover, knowledge networks play a crucial role for the diffusion and dissemination of knowledge in space (Castells 1996, Boschma and Ter Wal 2007). In order to benefit from knowledge diffusing in these networks, organizations need to hold central positions. Organizations can obtain central positions when linking to other organizations in central positions. Hence, it can be expected that subsidized R&D collaboration is particularly beneficial for regions when it is used to establish links to other central organizations and regions.

These claims are tested by an empirical study relating the dynamics in regions' innovation output to their organizations' participation in subsidized R&D, which is presented in the following.

3 Data

3.1 Data on R&D employees, patents, and regional characteristics

In order to assess the contribution of R&D subsidies to regions' growth in innovation output dynamics, we relate regional knowledge inputs to the changes in innovative output generated by organizations located within a region. We thereby take into account that industries vary considerably in their innovation intensities (Arundel and Kabla 1998), which implies that the industrial structure of regions heavily impacts regions' innovative success. To deal with this, we follow Broekel (2012) and estimate all variables in an industry-specific fashion. To do so, we differentiate between 21 manufacturing related industrial sectors, which are defined on the basis of Schmoch et al. (2003). These sectors are defined such that patent data (organized according to the International Patent Classification) can be matched to industrial employment data, which is organized by the industrial classifications NACE[2]. While Schmoch et al. (2003) put forward 44 sectors, some of these are defined on the basis of three-digit NACE codes. Our data at hand only provides information at the two-digit NACE level. For this reason, we aggregate the 44 sectors into 22 sectors that can be assigned to two-digit NACE industries. One of these sectors (Publishing & Printing) does not account for positive patent numbers in any of the labor market regions and is therefore dropped (see Table A1 in the Appendix). We refer to these sectors as industries in the following.

[2] Nomenclature Générale des Activités Économiques dans les Communautés Européennes (NACE).

As regional units we chose the 150 German labor market regions as defined by Eckey et al. (2006). The choice of labor market regions as spatial unit of analysis is based on Eckey et al. (1990). They point out that regions defined on behavioral settings generally perform better than administrative units, because the former do reflect economic relations in terms of, for example, commuting flows and reachability. Their demarcation was confirmed to be suitable in various other studies (see, e.g., Kosfeld et al. 2006, Broekel 2012). By means of spatial regression techniques we will nevertheless take further spatial dependencies into account.

As usual in this type of literature, innovation output is approximated by patent counts, which are taken from the German Patent and Trademark Office (DPMA) within the period from 1999 to 2008. The inventor principle is applied to regionalize the patent data, i.e. each patent is assigned to the labor market region where its inventor is located. In the event a patent being developed by multiple inventors located in different regions, it is equally assigned to each region.

Accordingly, our empirical observations are industry-regions. The growth of innovations (patents) (gI) in region r and industry i is calculated as the log difference between the levels of $I_{r,i}$ in two time periods t and $t\text{-}1$.

$$gI_{r,i} = log\ (I_{r,i,t}) - log\ (I_{r,i,t-1}) \qquad (1)$$

At the regional level, patent numbers are known to fluctuate strongly between years (Buerger et al., 2012). Moreover, we are particularly interested in the long-term effects of subsidies. Looking at the data for two 5-years periods (1999 to 2003 and 2004 to 2008) addresses both issues. That is, we average the patent numbers for each of the two 5-years periods and calculate the growth rate as log difference between the base period ($t\text{-}1$: 1999-2003) and the subsequent period (t: 2004-2008). The resulting growth rate $gI_{r,I}$ is then related to a range of regional characteristics and subsidization-based variables presented later.

However, few regions with positive patent numbers exist for some of the industries, which prevent the estimation of meaningful patent growth rates. We also have little reason to expect significant variations between industries in the impact of R&D subsidies on innovation activities. For these reasons, we increase the robustness of the estimation by pooling all industry-specific observations. To account for any potential biases related to the pooling, we introduce six industry dummies, which will capture potential differences between the five industries defined in Broekel (2007) and a miscellaneous industry (see Table A1 in the Appendix).

Besides the industry dummies, the first explanatory variable considered is the number of patents (PATENTS_i) generated in the base period 1999-2003 by regional organizations of industry i. This variable captures that regions with low levels of patenting in the base period might find it easier to increase their patenting than regions that are already patenting at higher levels.

In addition to the number of patents, we control for effects related to the size of R&D activities located in a region by taking into account the number of R&D employees in industry i ($\text{R\&D EMP}_i$). We obtain data on R&D employees from the employment statistics of the Federal Employment Agency of Germany. The employees are classified according to the NACE-classification. By using the concordance of Schmoch et al. (2003), this data is matched to the 21 industries.

Private R&D can benefit from being co-located to public R&D as provided by universities, research institutes, and a like. Universities and technical colleges generate qualified human capital and may act as knowledge spillover sources. The likelihood of these spillovers seems to decrease with increasing geographic distance, hence yielding the largest advantages to firms located close by (Beise and Stahl 1999). In order to capture the wide variety of such organizations, we approximate their presence and quality by means of their R&D output (Moed et al., 2004). More precisely, we consider all publications registered in the Web of Science. The variable PUBLICATIONS is the sum of publications weighted by the number of authors located in a particular region in the period 1999-2003.

It is also widely accepted that firms' innovation output is impacted by agglomeration externalities (Beaudry and Schiffauerova 2009). These include urbanization advantages such as a higher utilization of public infrastructure, a richer labor market, and smaller distances to suppliers and customers. In a common fashion urbanization externalities are approximated by population density (POP_DEN). The data is obtained from the German Federal Office for Building and Regional Planning. Another form of externalities arises from regional specialization into certain industries. To approximate such type of agglomeration externalities, we calculate the Herfindahl index on the basis of two-digit NACE manufacturing industries' R&D employment data (HERFINDAHL*)*. This index is considered in squares as well.

Lastly, a dummy variable *EAST* indicates the location of a region in East Germany. East German regions (still) tend to be characterized by lower innovation performance (Broekel et al. 2013). Moreover, regions in East Germany might benefit from a number of public programs being especially designed to decrease the innovation performance gap between the two parts of Germany.

3.2 Information on R&D subsidies and empirical variables

3.2.1 Subsidization, joint projects, and collaboration

Comprehensive information on projects subsidized by the federal government is published in the so-called subsidies database ("*Förderkatalog*").[3] The subsidies database lists detailed information on projects supported by federal ministries between 1960 and 2012. We estimate all figures on the basis of the base period (years 1999 to 2003) in which 16,114 projects split into 27,428 individual funds were granted to 8,489 German organizations.[4] For the definition of variables we utilize information concerning projects' starting and ending data, the magnitude of the granted fund, NACE industry class for each subsidized organization, and the collaborative nature of the project. Moreover, all funds are classified according to an internal hierarchical classification scheme developed by the German Federal Ministry of Education and Research (BMBF) called "*Leistungsplansystematik*". The 16 main areas are disaggregated into a varying numbers of sub-classes.

The available industrial classification (NACE) of project participants allows for differentiating between two-digit NACE industries. Subsidized projects can be either individual or joint projects. Joint projects are granted to consortia of organizations ("*Verbundprojekte*") realizing a particular research projects. Individual projects are conducted by a single organization. Participants in joint projects agree to a number of regulations that guarantee significant knowledge exchange between the partners. Broekel and Graf (2012)

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[3] http://foerderportal.bund.de/foekat/jsp/StartAction.do.

[4] We follow Broekel and Graf (2012) in defining an organization as a unique combination of the name of the receiving organization and the location of the actual executing unit.

argue therefore that two organizations can be assumed to collaborate and potentially exchange knowledge when participating in the same joint project at the same time.

The first variable created on the basis of the subsidization data is SUBS.INDI$_i$. It sums the number of individual projects granted to regional organizations of industry *i*. A similar variable is defined on the basis of joint projects representing the number of subsidized joint R&D projects (SUBS.COLL$_i$). We have to use project counts instead of sums of Euros to approximate the extent of inflow of public support to R&D because of the diversity in project sizes, scopes, and financial framework. Moreover, all projects are co-financed by the receiving organization. The relative magnitude of the co-financing is however unknown and may potentially bias the results. The studies by Fornahl et al. (2011) and Broekel (2013) support this decision, as they find effects on innovation activities being related to project counts rather than to the sum of project grants.

On the basis of information on subsidized joint R&D projects, we create an inter-organizational R&D collaboration network. For this, we extract all subsidized joint R&D projects in which at least one organization of the focal industry *i* is participating. Hence, the industry-specific networks are not restricted to organizations of the focal industry. To the contrary, in most instances they include considerable numbers of organizations belonging to other industries. Such corresponds to a broad definition of an industry network, as it includes its organizations' knowledge sources (universities, research institutes, firms in other industries). Alternatively, one might define a network exclusively on relations between organizations belonging to one industry. However, such a network does not allow for identifying the role collaborative R&D subsidies play for accessing and exploiting external knowledge since it represents only a small fraction of organizations' knowledge sources. The network's nodes are subsidized organizations and link weights are the count of two organizations' joint appearance in (potentially multiple) subsidized joint R&D projects. The first variable calculated on the basis of this network is the total number of regional collaborations (i.e., links), which organizations in a particular region and industry realized in the period 1999-2003. It is denoted as REG.COLL$_i$. In an identical manner we define INTER.COLL as the total number of inter-regional collaboration.

3.2.2 Similarity and related variety

We pointed out above that the potential benefits of collaboration depend strongly on the similarity and relatedness of the collaborating organizations' R&D resources. To approximate the degree of relatedness between two organizations we rely on their industrial classification and establish an index of inter-industrial technological similarity. The measure S_{ij}, which indicates the degree of similarity between industry *i* and *j*, is estimated on the basis of information on individual R&D subsidization grants, i.e. only subsidized projects executed by a single organization are considered. The basic idea behind the measure is that most R&D subsidization programs have a clear technological focus, which is represented in the subsidies data' technological classification scheme ("*Leistungsplansystematik*"). It can then be argued that two industries' R&D resources are similar the more frequently their organizations are subsidized through the same R&D subsidization scheme. That is, the more frequently they obtain (individual) grants classified into the same technological class. Since the frequency of co-occurrences of industries within the same technological class will increase with the number of grants acquired by their organizations, we resemble the measure of Teece et al. (1994) and Bryce and Winter (2009). That is, we count the number of co-occurrences of grants attributed to two industries' organizations within each of the more than 1,100 6-digit technological classes in the R&D subsidies data. This number is denoted as J_{ij} and represents the number of individual projects granted to organizations of industry i and organizations of industry j classified into the same 6-digit technological class. J_{ij} will naturally increase with the number of subsidized projects the organizations of the two focal industries acquire. It is therefore adjusted with the number of co-occurrence that can be expected if all industries are randomly assigned to 6-digit technological classes. K is the number of technological classes and n_i represents the total number of individual projects organizations of industry i are active in. n_j is the corresponding number for industry j. The expected number of projects within the same technological class in which industry i and j are active (x_{ij}) can then be seen as hypergeometric random variable (Bryce and Winter 2009, p. 1575f.):

$$P\left[X_{ij} = x\right] = \frac{\binom{n_i}{x}\binom{K-n_i}{n_j-x}}{\binom{K}{n_j}} \qquad (2)$$

Its mean can be estimated as

$$\mu_{ij} = E\left(X_{ij}\right) = \frac{n_i n_j}{K} \qquad (3)$$

and its variance by

$$\sigma_{ij}^2 = \mu_{ij}\left(1 - \frac{n_i}{K}\right)\left(\frac{K-n_j}{K-1}\right) \qquad (4)$$

The difference between J_{ij} and the expected value μ_{ij} is estimated and standardized according to:

$$\tau_{ij} = \frac{J_{ji-}\mu_{ij}}{\sigma_{ij}} \qquad (5)$$

τ_{ij} is based on “raw” counts co-occurences within the same technological class. The resulting index is standardized and divided by the maximum similarity score in the sample. Negative values imply strong dissimilarity and hence their interpretation is the same as in the case of zero values. They are set to zero implying that the final similarity index ranges between 0 and 1 with values close to one indicating maximal resource similarity. For the calculation of similarity in the context of this paper, we estimate the annual similarity index for each year between 1999-2003 and average the annual values over all years of the base period.

Equipped with this measure, we weight each inter-organizational link by the bilateral resource similarity of the collaborating organizations’ industries. On this basis two variables are built: The average similarity of industry i’s regional collaboration (SIM.REG_i), and the average similarity of its inter-regional collaboration (SIM.INTER_i). Here, inter-regional collaboration are defined as the number of collaboration that regional organizations maintain with organizations located outside their region. Following a standard approach in the literature both values additionally enter the regression equation in squared values to model relatedness (Nooteboom 2000; Frenken et al. 2007). Since related resources are characterized by some technological similarity (some but not too much), a positive impact of related variety is confirmed when the linear term will obtain a positive coefficient and the squared term a negative coefficient.

3.2.3 Embeddedness into cross-regional collaboration networks

To model effects related to organizations' embeddedness into subsidized knowledge networks, we construct industry-specific cross-regional (subsidized) collaboration networks. This is, we are aggregating the previously constructed inter-organizational networks to the regional level by combining all link information of organizations located in the same region.

Variable name	Description (all variables are at the level of 149 regions)	Data source
gI_i	Growth of patents in industry i	Patstat
$PATENTS_i$	Number of patents in industry i	Patstat
PUBLICATIONS	Number of publications	Web of science
R&D $EMPL_i$	Number of R&D employees in industry i	German labor market statistics
POP.DEN	Population Density	INKAR (2012)
HERFINDAHL	Herfindahl index of R&D employees based on 2 and 3 digit NACE	German labor market statistics
EAST	Dummy for regions in East Germany	INKAR (2012)
$SUBS.COLL_i$	Total number of subsidized joint R&D projects of industry i	Extended funding database BMBF
$SUBS.INDI_i$	Total number of subsidized individual R&D projects of industry *i*	Extended funding database BMBF
$BETWEENNESS_i$	Betweenness centrality measure based on none-technology specific, inter-regional (LMR), network in industry i	Extended funding database BMBF
$REG.COLL_i$	Number of regional collaboration of industry *i*	Extended funding database BMBF
INTER.COLL	Number of inter-regional collaboration of industry *i*	Extended funding database BMBF
$SIM.REG_i$	Average similarity of regional collaboration of industry i	Extended funding database BMBF
$SIM.INTER_i$	Average similarity of inter-regional collaboration in which regional organizations of industry i are participating	Extended funding database BMBF
INDUSTRY.dummies	Dummy variables for six industries	Definition according to Broekel (2007)

Table 1: Overview of empirical variables

As a result, the networks' nodes are regions with links between two regions indicating the co-presence of their organizations in at least one joint project in which an organization of industry *i* is participating. The actual number of joint appearances defines the weight attributed to the link. The prominence of a region in the network and hence the potential of its organizations to benefit from network based knowledge diffusion depends on the global centrality of the region in this network. A common measure of global centrality is betweenness centrality, which represents the frequency of a node (region) being part of the shortest paths between any two nodes (regions) in an industry specific network. Given that the network includes link weights, we employ the weighted betweenness centrality measure put forward by Opsahl et al. (2010) to construct the variable BETWEENNESS_i.[5]

All empirical variables are summarized in Table 1. The descriptives and correlations can be found in Table A2 and A3 in the Appendix.

4 Empirical approach

4.1 Growth of innovative output

We identify the contribution of R&D subsidies to regions' industry-specific innovation growth with the following equation:

$$gI_{r,i} = a + b\boldsymbol{K}_{r,i} + c\boldsymbol{S}_{r,i} + u_{r,i} \qquad (6)$$

where $gI_{r,i}$ represents the growth of innovative (patent) output in industry i and region r, $\boldsymbol{K}_{r,i}$ is a matrix of region and industry-specific characteristics that are probable to facilitate innovation growth, $S_{r,i}$ is a matrix of variables based on R&D subsidies, and $u_{r,i}$ is the error term.

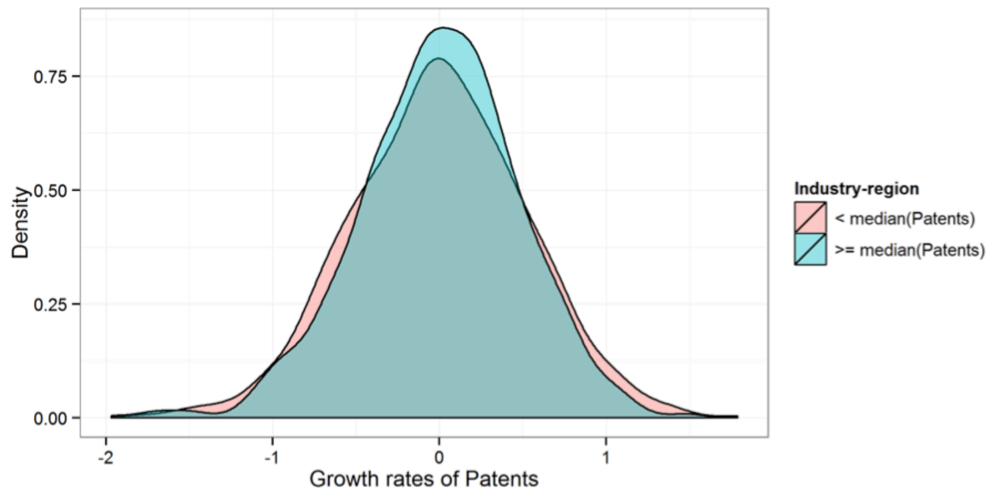

Figure 1: Density distribution of unconditional growth rates of patents

Figure 1 shows the density distributions of $gI_{r,i}$ for those industry-regions having either more or less patents than the median.[6] The distributional mass for the industry-regions with less than median patents is more wide spread than that of industry-regions with more than median patents. Simply stated, regions with more patents fluctuate less in their industry-specific patent growth rates than regions with fewer patents. It is regarded as a universal feature in the growth of complex organisations that the variance of the growth rates scales inversely with the levels, usually by a factor that follows a power-law (Stanley et al. 1996, Amaral et al. 2001). We follow Bottazzi et al. (2014) in modelling this variance-scaling relationship directly by introducing a heteroskedasticity term into the stochastic growth process. The identified scaling parameter □ is -0.172, which is very close to the parameters

[5] We also estimated a region's degree centrality, which however turned out to be highly correlated to SUBS.COLL and was therefore dropped.
[6] Both distributions are de-meaned to facilitate the comparison of variances.

reported in the literature on regional employment growth (Duschl and Brenner 2013) or firm growth (Stanley et al. 1996). This parameter is used to rescale the growth rate ($gI_{r,i}$) and thus to clean it from heteroskedasticity.

4.2 Endogeneity

We also treat potential endogeneity issues related to the allocation of public R&D funds (Czarnitzki et al. 2007, Aschhoff 2008) by means of econometric model specification, as put forward in Hall et al. (2009). Lacking sufficient instrumental variables[7], we employ a two-stage Heckit approach. As the focus of this study is primarily on subsidies for joint projects, we account only for potential endogeneity related to these variables, leaving subsidies for individual projects untreated. Besides the smaller relevance in the paper, it is also the case that noticeably less industry-regions receive individual subsidies, which results in too few observations for a Heckit approach in their case. There are only 344 industry-regions with positive individual subsidized project counts. In contrast, for joint R&D projects this number is as high as 736.

In case of subsidies for joint R&D, we first estimate a probit equation for joint project subsidization in dependence on regional characteristics explaining their allocation, namely, the number of patents in industry *i* (PATENTS), R&D employment in industry *i*, (R&D EMPL) population density (POP.DEN), industry dummies, and a dummy for East Germany (EAST). In order to meet the exclusion restriction, we include the number of individual and joint projects in the outcome equation that have been granted to (industry-specific) regional organizations in the years before the base period (between 1990 and 1998). The idea is that the latter variables are clearly exogenous, strongly predictive for future subsidization, and in contrast to the previously mentioned variables, do not enter the final model predicting regional innovation growth.

The obtained estimates from the two-stage Heckit model subsequently enter the final regression relating innovation growth to regional characteristics and subsidies, as an instrument for the subsidization of joint R&D. This final regression additionally includes publications (PUBLICATIONS) and the Herfindahl index (HERFINDAHL), which are likely to impact the effect of R&D subsidies but not their allocation. Moreover, the final regression is constrained to observations with at least one subsidized joint or individual R&D project.

4.3 Spatial and relational spillover

It is widely accepted that regions located next to other regions with significant R&D activities benefit from knowledge spillover (Breschi and Lissoni 2001). The magnitude of these spatial knowledge spillovers decreases with increasing distances between regions (Bode 2004). This may lead to spatially correlated regression errors. We address this is issue in two common ways (Anselin 1988, LeSage 2009). Firstly, we include a spatially lagged variable in the final model accounting for the innovative output of neighboring regions. For the type of regions studied in the paper, (row standardized) direct neighborhood relations seem to be most meaningful for creating the according spatial weights matrix. The variable PATENTS.*spatial* represents the sum of a region's neighboring regions' patent output weighted with these spatial weights. However, despite considering this spatially lagged variable, severe spatial autocorrelation in the error term still remains in a standard OLS model. We therefore apply a

[7] We tried a vast range of potential instrumental variables. However, all were suffered from the weak instruments problem.

spatial simultaneous autoregressive error model (hereafter, spatial error model). Here, spatial dependence is explicitly modeled in the error term:

$$u_{r,i} = \lambda W u_{r,i} + e_{r,i} \quad (7)$$

whereby lambda is the coefficient of the spatially lagged autoregressive errors Wu and W contains the spatial weights representing the structure of the spatial dependence. e are the independent disturbances. Maximum likelihood is employed, as it provides the most efficient estimator for equation (Eq. 7) when the error term is normal distributed.[8]

However, knowledge may not only spillover through space, as it is also shared and transferred within inter-organizational R&D collaboration networks. Accordingly, we also need to control for dependencies potentially arising from regions' network embeddedness and so-called relational spillovers (Maggioni et al. 2007). To do so, we apply the same methodology as in the case of spatial spillovers. That is, we establish a relational weights matrix on the basis of the focal industry's subsidized R&D collaboration network with two regions being relational "neighbors" when being directly linked in the subsidized R&D collaboration network. We then construct a relational lag variable similar to the spatial one. It is denoted as PATENTS.*relational* and represents the sum of a region's relational neighbors' patent output weighted with the (row-standardized) relational weight matrix. In addition, we use the relational weights matrix to test for relational dependencies in the OLS regressions' error terms. Similarly to the spatial dependencies, our results suggest the presence of relational dependencies, which imply that we need to estimate the final model accounting for relational dependencies in the error term. While the spatially and relationally lagged variable can be simultaneously included in one model, we have to specify in the context of dependencies in the error term two final models: one with spatial and one with relational dependencies modeled in the errors. [9]

While we successfully remove spatial dependencies from the error term of the first model (Table 3: insignificant Moran's I), we are not able to obtain a model with relationally uncorrelated errors (significant Moran's I statistic in Table 3). However, the Moran's correlation coefficient is very low, which indicates significant but uncritical relational dependencies.[10]

5 Results

5.1 Regional characteristics and innovative growth

Table 2 shows the results of the first-stage Heckit estimation with the probability of subsidization as dependent variable, which is used to generate the instrumentation for the second-stage regression variable SUBS.COLL. All variables considered in the estimation gain significance and their positive coefficients meet our expectations. Hence, urban regions

[8] The Kolmogorov-Smirnov (KS) test in our model diagnostics (see bottom of Table 3) reveals that our assumption is met. Moreover, the spatial error model specification successfully captures the residual spatial autocorrelation, as Moran's I test statistic becomes insignificant. By comparing the models to OLS, both the likelihood ratio (LR) test as well as the Wald test confirms that the captured share of spatial dependence in ▱ is significant. The spatial version of the Breusch-Pagan (BP) test also fails in identifying the presence of heteroskedasticity.

[9] Of course, the optimal strategy would be to simultaneously model both dependencies in the error term. Such is however not implemented in standard statistical software.

[10] The other model diagnostics are similar to the spatial weight matrix specification (see Footnote 8).

(POP.DEN) that are doing well in terms of innovations (PATENTS) and public (PUBLICATIONS) as well as private R&D activities (R&D EMPL) are more likely to participate in subsidization schemes for R&D projects. Moreover, regions in East Germany (EAST) are more frequently subsidized than West German regions underlining a certain political motivation to use R&D subsidies to support this part of Germany even twenty-five years after the reunification. HERFINDAHL gains a negative significant coefficient indicating that diversified regions are more likely to be subsidized. Past subsidization (SUBS.COLL.9098 and SUBS.INDI.9098) is also not surprisingly a strong predictor for future subsidization.

	Probit Selection	**Outcome**
Intercept	-4.630 *** 0.000	-77.887 *** 0.000
PATENTS	0.304 *** 0.000	6.869 *** 0.000
PUBLICATIONS		0.510 *** 0.000
R&D EMPL	0.253 *** 0.000	4.462 *** 0.000
POP.DEN	0.290 *** 0.000	
HERFINDAHL		-9.028 ** 0.0050
EAST	0.685 *** 0.000	13.131 *** 0.000
SUBS.COLL.9098		0.873 *** 0.000
SUBS.INDI.9098		0.052 ** 0.007
INDUSTRY.dummies	not reported	not reported
N observations	1671	736
Adj. R-squared		0.8582
Inverse Mills Ratio (p-value)	1.217 (0.332)	
*p-values given below coefficients. Significance symbols: ‘ < 0.1, * < 0.05, ** < 0.01, *** < 0.001*		

Table 2 First-stage Heckit model

The results for the final models (using spatial or relational dependencies) are presented in **Table 3**. The first observation is that controlling for spatial or relational dependencies does not impact the coefficients' significances at all. All significant coefficients remain by and large identical. Hence, we will not differentiate between the two models in the interpretation and just refer to the results of the model using spatial dependencies.

A number of basic regional characteristics gain significance in all models. Most notably, this concerns PATENTS and R&D EMPL with the first obtaining a negative and the second a positive coefficient. The negative coefficient of PATENTS suggests that regions are, on average, able to sustain a high level of patenting only if the local conditions support this level. Given the same local conditions in two regions the region with the lower patent activity will, on average, show the higher growth in patenting, leading to convergence. The positive coefficient of R&D employment suggests that regions with large R&D capacities are more probable to expand in patent output, which is very plausible as well.

The positive coefficient for PUBLICATIONS confirms the impact of the quality of the public R&D infrastructure and its potential for knowledge spillover (Audretsch and Feldman 1996, Jaffe 1989). We also confirm benefits related to regions' specialization (HERFINDAHL). The coefficients of HERFINDAHL and HERFINDAHL^2 are positive and negative, respectively indicating an inverted u-shape relationship with innovation growth. Low levels of specialization as well as very high levels reduce innovation growth, while average levels seem to be most beneficial. The finding relates to the presence of Marshall-Arrow-Romer externalities (Glaeser et al. 1992) and supports previous findings in the literature of diversification and specialization being jointly conducive for innovation (van der Panne and van Beers 2008). In addition, we find a number of industry dummies to be highly significant underlining the heterogeneity of industries with respect to the determinants of regional patent growth.

5.2 R&D subsidies and innovative growth

The results obtained from the first model are used to define variable SUBS.COLL, which is used in the final model and represents an instrumentation of the expected subsidized joint R&D projects. However the instrumentation on the basis of the Heckit model does not impact our results by and large (see **Table 3**). Most likely, this is due to the numbers of subsidized individual and joint R&D projects remaining insignificant in the final models even when not being instrumented. The observation suggests two things. First, the relation between subsidization and patent growth at the regional level does not seem to be characterized by strong endogeneity. Second, and this is even more important, the subsidization of R&D projects does not directly improve regions' capacities to increase their patent output. While, the finding for SUBS.INDI confirms the firm-level results of Fornahl et al. (2011), it contrasts the results of Broekel (2013) who identifies a negative impact of these types of subsidies on annual changes in regions' innovation efficiency. The discrepancy suggests that negative effects related to the subsidization of individual R&D projects are of short-term nature and do not persist in the long run. Potentially, Broekel (2013) picks up a resource enlargement effect. That is, R&D subsidies expand regional R&D resources, which (if not simultaneously compensated by additional output) will lower regions' innovation efficiency.

The insignificance of subsidized joint R&D projects (SUBS.COLL) contradicts our expectations of a positive impact, which has also been reported by Broekel (2013). However, the variable gains a positive significant coefficient when the industry dummies are omitted. It might therefore be the case that Broekel (2013) either picks up a short-term effect or that his use of a larger industrial aggregation is responsible for this finding. The latter would imply that industries with higher subsidization of joint R&D projects are, on average, those industries that show higher growth in patent activities.

Nevertheless, the insignificance of the variables SUBS.INDI and SUBS.COLL indicates the absence of direct effects on regions' long-term innovation growth that emerges from the subsidization of R&D projects. The question is therefore why do firm-level studies frequently observe significant relations between R&D subsidization and firms' innovation output (see e.g. Czarnitzki et al 2007)? There are two potential explanations. First, the positive effects are restricted to the firm level and may simply be too small to be identified at the regional level. Or, second, the existing firm-level studies pick up indirect effects related to the subsidization of joint R&D projects. These will be discussed in the following.

The first observation on indirect effects is that subsidizing joint projects with strong regional participation (REG.COLL) might add a bonus to regions' innovation growth. However, we are careful in interpreting this, as the variable is only significant at the 0.1 level. As discussed in the theory section, the potential reason for the relatively low significance is that REG.COLL captures all types of subsidized regional collaboration irrespective of the type of partners involved. Moreover, the significance of regional collaboration only becomes visible when considering the degree of similarity of partner resources, whereby SIM.REG and SIM.REG^2 remain insignificant. Accordingly, subsidizing joint R&D projects play a subordinate role when including intra-regional collaboration, i.e. when multiple organizations from the same region participate in the same joint project. This finding adds to the cue of empirical studies confirming positive effects of regional collaboration (e.g., Arndt and Sternberg 2000). However, our results, as the results of Broekel (2013), might only apply to subsidized R&D collaboration.

Similarly to subsidies for regional R&D collaborations, our results show that supporting inter-regional R&D collaboration generally does not facilitate regions' innovation growth. The coefficient of INTER.COLL remains insignificant in all models. However, when controlling for resource similarity a positive significant coefficient is obtained for inter-regional collaboration (SIM.INTER). The significance of the positive coefficient is conditional on the inclusion of SIM.INTER^2, which obtains a negative but insignificant coefficient.[11] While insignificant, it still signals that collaborations with very high similarity values are not beneficial. This meets the idea of related variety. Some resource similarity is necessary to allow for efficient communication and ensure complementary resources (Frenken et al. 2007). However, the higher the degree of partner resource similarity in subsidized R&D collaboration, the more likely are combinations of redundant knowledge resources (Nooteboom 2000). Put differently, similar knowledge resources imply that firms share similar cognition, perceptions, interpretations, and evaluations. The innovative potential for novel resource (re-)combination is therefore reduced in collaborative projects involving similar knowledge resources. While plausible, it still remains unclear why we observe this for inter-regional and not for regional collaboration. Potentially, this is because R&D projects are relatively more costly when partners are located in different regions. As a result, such collaboration particularly hurt organizations when they do not add value, which translates into a negative coefficient of SIM.INTER^2. The missing shared regional context of inter-regional collaboration makes free-riding, moral hazard, and untrustworthy behavior more likely and attractive (Storper and Venables 2004, Asheim and Isaksen 2002). In other words, as inter-regional collaboration are more prone to yield negative effects in general, partner selection in terms of related resources is even more crucial than in the case of regional collaboration. In this sense, our findings extend the analysis of Broekel (2013), who tests for collaboration between science organizations and firms. In our definition of similarity, we also include similarity potentially existing between firms in distinct industries and with science organizations. The conclusions are nevertheless similar: The effectiveness of R&D subsidies crucially depends on whether joint projects bring the right partners together. In this case, these are organizations from different regions with related knowledge resources.

[11] By means of testing a linear hypothesis, it can be shown that SIM and SIM^2 are also jointly significant in the Spatial Error Model using either the spatial or relational error matrix.

	Regression with spatial weights		Regression with relational weights	
	Controls	**Full**	**Controls**	**Full**
Intercept	0.169	0.179	0.191	0.198
	0.453	0.4237	0.3414	0.3253
PATENTS	-0.215 ***	-0.221 ***	-0.214 ***	-0.203 ***
	0.0000	0.0000	0.0000	0.0000
PUBLICATIONS	0.038 ***	0.034 ***	0.035 ***	0.032 ***
	0.0000	0.0000	0.0000	0.0002
R&D EMPL	0.007 ***	0.007 ***	0.007 ***	0.006 ***
	0.0002	0.0005	0.0005	0.0008
POP.DEN	-0.125 ***	-.121 ***	-0.129 ***	-0.126 **
	0.0005	0.0007	0.0000	0.0000
HERFINDAHL	1.949 *	1.950 *	2.375 **	2.341 **
	0.0241	0.0230	0.0054	0.0058
HERFINDAHL^2	-4.886 **	-4.762 **	-5.752 **	-5.538 **
	0.0080	0.0094	0.0017	0.0024
EAST	-0.011	-0.019	-0.005	-0.013
	0.8641	0.7800	0.9281	0.8060
SUBS.COLL (instrumented)	0.006	-0.005	0.001	-9.13e-4
	0.8333	0.8773	0.9638	0.7546
SUBS.INDI	-0.005	-0.006	-0.005	-0.006
	0.4136	0.3137	0.3486	0.2827
PATENTS.*spatial*	5.00e-5	4.23e-5	6.08e-5	5.52e-5
	0.4033	0.4339	0.2919	0.3371
PATENTS.*relational*	1.47e-6	6.76e-7	1.60e-5	9.13e-7
	0.5198	0. 7661	0.4944	0. 7546
REG.COLL	0.005	0.006 ‘	0.005	0.006 ‘
	0. 1494	0. 0972	0. 11451	0. 098
INTER.COLL	-4.60e-5	-1.26e-4	-2.69e-5	-6.57e-5
	0. 7037	0. 3362	0. 8806	0. 6124
BETWEENESS		3.81e-4 *		3.28e-4 *
		0.0431		0.0471
SIM.REG		-0.004		-0.002
		0.7446		0.8308
SIM.INTER		0.082 *		0.085 *
		0.0286		0.0240
SIM.REG^2		9.40e-5		4.11e-4
		0.7071		0.8652
SIM.INTER^2		-0.008		-0.084
		0.2208		0.2059
INDUSTRY.dummies	not reported	not reported	not reported	not reported
AIC	825.25	824.21	823.45	822.92
KS-Test (p-value)	0.2652	0.3341	0.2407	0.4756
BP-Test (p-value)	0.2715	0.3912	0.3115	0.3621
Moran’s I (p-value)	0.6515	0.6385	0.000 ***	0.000 ***

Lambda	0.2917	0.2832	0.1787	0.1688
LR-test (p-value)	0.0272 *	0.0351 *	0.0097 **	0.0166 *
Wald test (p-value)	0.0171 *	0.0205 *	0.0048 **	0.0082 **
VIF	1.750	1.8563	1.750	1.8563
*p-values given below coefficients. Significance symbols: ‘ < 0.1, * < 0.05, ** < 0.01, *** < 0.001*				

Table 3 Second-stage SEM Model (spatial weights)

BETWEENNESS also obtains a positive significant coefficient in all models. The variable approximates regions’ global centrality in the (industry-specific) German (subsidized) R&D collaboration network and reflects the idea of easy access to knowledge diffusing in the network. This finding is remarkable, as it points to the relevance of structural features at the level of the entire industrial knowledge network. Betweenness centrality only partly depends on direct links of a region to other regions. The measure is strongly shaped by the centrality of these adjacent regions in the overall network and on the absence of links (collaboration) between regions to which the focal region is only indirectly linked to. In this sense, our finding suggests that the effects of subsidizing joint R&D projects go beyond the establishment of direct relations between organizations and regions. Subsidizing joint R&D projects implies that a network of subsidized collaborations is established. Some regions become very central in this network, while other regions are rather peripheral in this network. Our results give evidence for the existence of a *network effect*: Innovation grows, on average, more in the central (betweenness centrality) regions in this network than in other regions. Hence, the network structure generated by subsidizing joint R&D projects seems to have a more significant level on the innovation output than the subsidies themselves. This surely deserves more attention in future research.

5.3 Implications

The study shows that collaboration established by organizations participating in subsidized joint R&D impact regions’ innovation growth. However, the interpretation of the findings is constrained by the unclear relation between subsidized and unsubsidized R&D collaboration. To be more precise, the *substitution* and *additionality* hypotheses concerning the relation between public R&D subsidies and private R&D efforts may in a refined way also apply to subsidized R&D collaboration.

Substitution hypothesis: It can be argued that subsidized R&D collaboration simply replace collaboration that would have been realized without subsidies anyway. In this case, subsidies for R&D collaboration are subject to a bandwagon effect. If this applies, we can interpret patterns of subsidized R&D collaboration as “*representatives*” of unsubsidized collaboration. In this case, our results suggest that inter-regional collaboration with access to related variety stimulate regional innovation growth. Whether such collaboration are subsidized or not does not matter. The substitution hypothesis is however a very strong one, as the subsidized collaboration need to be absolutely identical to those realized without subsidization. Hence, we rather believe that the additionality hypothesis is at least partly true.

Additionality hypothesis: The additionality hypothesis suggests that subsidies for collaborative R&D stimulate R&D collaboration that otherwise would not have been realized. According to this line of argument, it can be expected that subsidized R&D collaboration are structurally different from and thereby unrepresentative for unsubsidized R&D collaboration. It implies that our results do not hold for collaboration activities in general, as they are restricted to subsidized collaboration. Accordingly, organizations in regions with strong innovation growth are able to utilize subsidies for joint R&D projects to get access to related resources outside their region. Crucially, these organizations cannot or at least do not sufficiently accomplish such access with unsubsidized collaboration. The subsidization of joint R&D projects seems to be an effective tool for innovation stimulation in this case. However, our results also call for more research on this issue.

The findings for betweenness centrality are also difficult to be considered in policy design. This is because regions' betweenness centrality defies central planning: Betweenness centrality cannot be directly considered in or directly influenced by R&D subsidization policies, as a particular region's betweenness centrality emerges as a feature of the total network. Accordingly, the finding calls for a system (network) perspective on the subsidization of joint R&D projects, which has yet to be developed.

6 Summary and conclusion

So far, studies on the effects of public (collaborative) R&D subsidies predominantly focus on the inflow of monetary resources into firms linked to the successful acquisition of subsidies. The literature is particularly concerned about whether subsidies partly crowd out private sector R&D investments or not (cf. Zúñiga-Vicente et al. 2014). However, the insight that R&D subsidies are increasingly granted to joint R&D projects demands for a more differentiated analysis on this type of policy tool (Czarnitzky and Fier 2003, Fornahl et al. 2011, Broekel 2013).

The paper at hand contributes to this discussion and puts forward the existence of at least two effects being related to the subsidization of joint R&D projects that are rarely discussed in the existing literature. The first effect concerns the access of organizations to additional resources by participating in subsidized joint R&D (*collaboration effect*). This effect (which to some extent overlaps with the cooperation additionality argument by Wanzenböck et al. (2013)) is conditional on the type of resources subsidized collaboration add to joint projects, whereby particularly related inter-regional resource combinations are argued to be most valuable. The second effect emerges as a consequence of subsidized collaboration: Organizations become embedded into (subsidized) inter-organizational R&D collaboration networks (*network effect*) and thereby gain access to knowledge diffusing therein. We argue that traditional evaluation approaches at the firm-level are likely to miss these two effects and, in addition to explicitly consider firm-level effects, such evaluation approaches should be complemented by studies on more aggregated (innovation system) levels.

These arguments are backed by means of an empirical study investigating the relevance of these effects in the development of German regions' innovation growth between 1999-2003 and 2004-2008. The results show that regions can improve innovation output when collaborative R&D subsidies provide access to related resources, as these allows for combining distant but not too distant knowledge (Frenken et al. 2007).

The paper moreover shows that centrality in subsidized cross-regional R&D collaboration networks gives access to valuable knowledge spillover. Hence, the paper shows that there are strong indirect effects related to the subsidization of joint R&D projects that are rarely considered in the existing literature.

The empirical study has a number of shortcomings that need to be discussed. They particularly concern unobserved R&D collaboration and networks. In this sense, our results remain somewhat difficult to interpret, as unobserved R&D collaboration are a crucial omitted variable and hence a potential source of biases. Future studies might have the possibility to draw on even more comprehensive databases and overcome this shortcoming. Another data-related problem concerns the limitation of the data source to R&D subsidies by the federal government in Germany. Unfortunately, no information is currently available on R&D subsidies by the federal states, which are however also important sources of R&D subsidization.

Despite these restrictions, the present study has a number of important implications. First of all, it shows that subsidies for collaborative R&D do impact regional R&D activities. However, their impact strongly depends on whether collaboration created by R&D subsidies are additional to unsubsidized R&D collaboration or whether they represent collaborations that would have been realized anyhow without subsidies. If it is the case, and this is still to be shown by future research, that they are additional to unsubsidized ones, the granting of subsidies to collaborative R&D should be extended, as currently just about one third of all R&D projects subsidized by the federal government of Germany are joint projects (Broekel and Graf 2012). Second, the effectiveness of R&D subsidies for joint R&D strongly depends on the right combination of organizations teaming up. Hence, partner choice is brought into the context of R&D subsidization and consequently should become a central element of R&D policy. The study shows that this goes beyond simply mixing public research organizations and private firms. Third, we show that firm-level studies evaluating R&D subsidies can and should be complemented by empirical studies at other levels. Given the strong relevance of territorial innovation policies in subsidization schemes, this particularly concerns the regional level.

7 Literature

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APPENDIX

Industry	Dummy (Broekel 2007)	Industry (Schmoch et al. 2007)	NACE	Description
1	1	1	15	Food beverages
2	1	2	16	Tobacco products
3	1	3	17	Textiles
4	1	4	18	Wearing apparel
5	1	5	19	Leather articles
6	1	6	20	Wood products
7	1	7	21	Paper
		8	22	Publishing, printing
8	2	9	23	Petroleum products, nuclear fuel
9	2	10	24.1	Basic chemical
9	2	11	24.2	Pesticides agro-chemical products
9	2	12	24.3	Paints, varnishes
9	2	13	24.4	Pharmaceuticals
9	2	14	24.5	Soaps, detergents, toilet preparations
9	2	15	24.6	Other chemicals
9	2	16	24.7	Man-made fibers
10	2	17	25	Rubber and plastics products
11	3	18	26	Non-metallic mineral products
12	3	19	27	Basic metals
13	3	20	28	Fabricated metal products
14	3	21	29.1	Energy machinery
14	3	22	29.2	Non-specific purpose machinery
14	3	23	29.3	Agricultural and forestry machinery
14	3	24	29.4	Machine-tools
14	3	25	29.5	Special purpose machinery
14	3	26	29.6	Weapons and ammunition
14	3	27	29.7	Domestic appliances
15	4	28	30	Office machinery and computers
16	4	29	31.1	Electric motors, generators, transformers
16	4	30	31.2,31.3	Electric distribution, control, wire, cable
16	4	31	31.4	Accumulators, battery
16	4	32	31.5	Lightening equipment
16	4	33	31.6	Other electrical equipment
17	5	34	32.1	Electronic components
17	5	35	32.2	Signal transmission, telecommunications
17	5	36	32.3	Television and radio receivers, audiovisual electronics
18	5	37	33.1	Medical equipment
18	5	38	33.2	Measuring instruments
18	5	39	33.3	Industrial process control equipment
18	5	40	33.4	Optical instruments
18	5	41	33.5	Watches, clocks
19	6	42	34	Motor vehicles
20	6	43	35	Other transport equipment
21	1	44	36	Furniture, consumer goods

Table A1: Overview industries

	min	max	mean	median	sd
PATENTS growth rates	-2.55	1.534	-0.420	-0.413	0.529
PATENTS (99-03)	5.020	14363.212	232.532	57.534	661.724
PATENTS (04-08)	5.008	10183.554	163.910	41.280	454.862
R&D EMPL	7.500	128259.384	2471.219	881.162	6156.417
PUBLICATIONS	0.000	7.878	3.656	3.621	2.512
POP.DEN	3.903	7.432	5.432	5.327	0.645
HERFINDAHL	0.060	0.517	0.119	0.094	0.071
HERFINDAHL^2	0.004	0.267	0.019	0.009	0.033
EAST.dummy	0.000	1.000	0.136	0.000	0.343
SUBS.INDI	0.000	38.000	0.656	0.000	2.584
SUBS.COLL	0.000	93.000	2.810	0.000	7.793
SUBS.INDI (90-98)	0.000	128.000	2.838	0.000	8.857
SUBS.COLL (90-98)	0.000	95.000	2.397	0.000	7.396
PATENTS.spatial	9.573	1214.134	270.835	230.640	179.705
PATENTS.relational	0.000	7256.743	446.727	0.000	701.915
REG.COLL	0.000	70.000	2.131	0.000	5.545
INTER.COLL	0.000	2976.000	31.856	0.000	133.667
BETWEENESS	0.000	612.715	53.956	25.362	73.039
SIM.REG	0.000	48.000	1.305	0.000	2.855
SIM.INTER	0.000	8.686	0.327	0.000	0.757
SIM.REG^2	0.000	2304.000	9.847	0.000	87.177
SIM.INTER^2	0.000	75.4514	0.679	0.000	3.318

Table A2: Descriptives

	gI	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) PATENTS (99-03)	-0.232																	
2) PATENTS (04-08)	-0.152	0.984																
3) R&D EMPL	-0.143	0.775	0.795															
4) PUBLICATIONS	-0.103	0.256	0.256	0.222														
5) POP.DEN	-0.190	0.248	0.237	0.259	0.585													
6) HERFINDAHL	0.032	-0.061	-0.055	-0.090	-0.192	-0.199												
7) EAST	0.089	-0.070	-0.068	-0.081	0.081	-0.177	-0.174											
8) SUBS.INDI	-0.126	0.539	0.522	0.344	0.233	0.156	-0.056	0.014										
9) SUBS.COLL	-0.100	0.619	0.630	0.530	0.264	0.209	-0.083	0.058	0.675									
19) SUBS.INDI (90-98)	-0.125	0.663	0.675	0.595	0.220	0.182	-0.091	0.087	0.654	0.737								
11) SUBS.COLL (90-98)	-0.106	0.627	0.636	0.567	0.252	0.216	-0.079	0.033	0.699	0.930	0.756							
12) PATENTS.spatial	-0.021	0.025	0.027	-0.025	0.072	0.159	0.121	-0.301	-0.018	-0.027	-0.058	-0.025						
13) PATENTS.relational	-0.111	0.245	0.252	0.233	0.197	0.212	-0.017	-0.010	0.224	0.357	0.279	0.317	0.040					
14) REG.COLL	-0.068	0.472	0.485	0.463	0.331	0.233	-0.114	0.170	0.532	0.728	0.614	0.687	-0.081	0.319				
15) INTER.COLL	-0.073	0.509	0.523	0.532	0.211	0.201	-0.070	0.005	0.423	0.726	0.604	0.685	-0.014	0.220	0.688			
16) BETWEENESS	-0.065	0.205	0.211	0.202	0.350	0.320	-0.090	0.002	0.219	0.298	0.234	0.263	0.023	0.370	0.254	0.169		
17) SIM.REG	-0.067	0.209	0.215	0.185	0.094	0.134	-0.040	-0.018	0.306	0.417	0.317	0.364	0.016	0.401	0.133	0.210	0.339	
18) SIM.INTER	-0.058	0.380	0.393	0.318	0.219	0.210	-0.071	0.024	0.411	0.628	0.465	0.562	0.011	0.464	0.443	0.550	0.287	0.544

Table A3: Correlations