Do Cooperative R&D Subsidies Stimulate Regional Innovation Efficiency? Evidence from Germany

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The subsidization of R&D and R&D cooperation has gained in importance in recent years. While existing research focuses primarily on effects at the firm level, the present paper relates these measures to regional innovation efficiency. Building on a rich panel data set, covering 270 German labor market regions and four industries, it is shown that subsidies for R&D cooperation are a suitable policy measure for stimulating the innovation efficiency of regions. The empirical findings suggest that regions with low innovation capacities benefit the most from cooperation among regional firms and subsidized links to non-regional public research institutes. The subsidization of cooperation with non-regional universities is more important for regions with large innovation capacities. Support for non-cooperative projects is related to negative effects.

Key words: innovation policy, regional innovation efficiency, R&D subsidies, cooperation networks

JEL classification: O18, O38, R12

1. Introduction

Regionalized innovation policies have become very popular in recent years (see Storper, 1995). A frequent feature of such programs is the stimulation of cooperation and interaction among regional organizations, which is argued to foster local collective learning processes (Isaksen, 2001). A good example for such an approach is the *BioRegio* program by the German Federal Government, supporting regional cooperation in biotechnology (Eickelpasch and Fritsch, 2005).

Cooperative elements have also become more and more prominent in non-regionalized policy programs aiming at the advancement of particular technological fields. For instance, the granting of R&D subsidies is frequently made conditional to a cooperative research design, implying that consortia of organizations realize joint projects. Consequently, R&D subsidies do not only provide monetary incentives for innovation, they also encourage knowledge sharing between organizations and embed these into subsidized knowledge networks (Broekel and Graf, 2012).

Strong empirical evidence exists that R&D subsidies stimulate firms' innovation activities (see Czarnitzki et al., 2007). Similarly, the embeddedness of firms into knowledge networks has been shown to be essential for their innovative success (Boschma and Ter Wal, 2007). In addition, many studies investigating regionalized policy programs highlight that support for regional cooperation is particularly beneficial for innovation (Eickelpasch and Fritsch, 2005).

However, limited research analyzing whether R&D subsidies are an effective policy measure for regional development exist. In addition, little is known about the contribution of subsidized cooperation to regional innovation performance. The present paper aims to shed light on these issues by taking a regional perspective and investigating the impact of R&D subsidies and subsidized inter-organizational cooperation on regional innovation efficiency.

The study builds on a panel dataset for 270 German labor market regions and four industries, covering the period 1999-2003. Nonparametric efficiency and spatial panel regression methods are employed in the empirical assessment. The findings indicate that regions with below average innovation capacities benefit from subsidized cooperation among regional firms. Cooperation with non-regional public research organizations is also supportive. In the case of regions with above average innovation capacities, the stimulation of cooperation facilitates innovation only when non-regional universities are involved. Subsidies for non-cooperative projects are correlated with negative effects on the innovation efficiency of regions with small innovation capacities. The paper is organized as follows: In Section 2, theoretical considerations of the effects of R&D subsidies on innovation activities are made. The empirical approach is the subject of Section 3. Section 4 provides the description of the data. The results are presented and discussed in Section 5. Section 6 is the conclusion.

2. Cooperative R&D subsidies and innovation

2.1 The evaluation of R&D subsidies

The subsidization of firms' research and development (R&D) activities is one of the most common public policy tools to support firms' innovation activities. The support is motivated by the perception of investments in R&D being below a social optimum. Amongst others, insufficient R&D investment can be a result of the uncertainty and high risks involved in research, which is particularly relevant for long-running innovation projects (Cantwell, 1999). The significance of R&D subsidies as a policy measure has stimulated a rich literature that focuses on empirical evaluation. For instance, Busom (2000) investigates whether the participation in R&D subsidy programs impacts firms' R&D efforts. Her findings suggest that, in most cases, public support leads to an increase in private R&D spending. Girma et al. (2008) provide empirical evidence that subsidies induce additional employment. Positive effects of R&D subsidies on firms' patenting activities have been identified by Czarnitzki and Hussinger (2004).

In addition to R&D subsidies, it is also well known that firms benefit from cooperation, particularly from participating in joint research activities. Benefits include the access to external knowledge (Teece, 1986) and the sharing of risks and costs (Hagedoorn, 2002). Substantial empirical evidence supports these arguments (see Powell et al., 1996). Using CIS data from Finland and Germany, Czarnitzki et al. (2007) simultaneously investigated the effects of cooperation and R&D subsidies. They also confirmed the positive effects of R&D subsidies on firms' patent activities, which can be increased by simultaneous cooperation.[1]

The benefits attributed to cooperation have also been noted by policy, which steadily increases the weight of cooperative elements in R&D support programs. Joint projects are increasingly supported, while the relative importance of subsidies for projects realized by individual firms are consistently decreasing. For example, in Germany, about thirty percent of today's subsidized R&D projects are joint projects (Broekel and Graf, 2012). Such cooperative R&D projects have also seen significant empirical evaluation. Branstetter and Sakakibara (1998) show that the support of research consortia by the Japanese government positively influences the achieved outcomes. The EU framework programme (FP) and the EU EUREKA programs, both of which subsidize research cooperation, have been the particular focus of research. Marín and Siotis (2008) highlight substantial differences between the types of firms participating in either program. According to their results, the EU FP program tends to attract larger firms from R&D intensive sectors. This is not the case for the EUREKA program. It is also shown that the likelihood of applying for support from the FP programs depends on a firm's presence in foreign markets, its absorptive capacity and existing experience concerning the program (Barajas and Huergo, 2010).

Despite some differences, both programs are found to be effective. Concerning the EUREKA program, Fischer and Molero (2011) show that it yields particular benefits for small firms, resulting in additional employment growth. Benfratello and Sembenelli (2002) also report a positive relation between a firms' participation in the EUREKA program and their labor productivity. Similar results are available for the EU FP program. For instance, Barajas et al. (2011) confirm a positive impact of cooperation, subsidized through this program, on firms' technological capacities and thereby indirectly on their productivity. Aguiar and Gagnepain (2012) identify an increase in a firms' labor productivity when firms receive FP grants and Dekker and Kleinknecht (2008) reported that small firms enlarge their R&D efforts substantially when participating in the FP program.

2.2 The regional perspective on R&D subsidies

While the above brief literature review is far from being complete, it shows two things: firstly, there is overwhelming evidence that R&D subsidies and subsidized R&D cooperation have a positive impact on firms' innovation activities. Secondly, all studies focus on the firm-level. However, this is not to say that other levels are neglected in the evaluation. In their study, Czarnitzki and Hottenrott (2009) evaluate the impact of regional characteristics such as the availability of skilled labor and the regions' cooperation intensities on the firms' innovation performance. In addition, they consider the regional "*share of total government and EU R&D subsidies granted in the pre-sample period*" (Table 1, p. 94), in order to explore effects related to a firm being co-located to other firms that acquired R&D subsidies. However, their empirical estimations do not support the existence of such effects.

Fornahl et al. (2011) extend this idea by simultaneously analyzing firm-level and regional-level effects of R&D subsidies on firms' patenting behavior in the German biotechnology industry. In addition, they simultaneously include variables approximating firms' and regions' embeddedness in subsidized R&D cooperation networks. As in previous studies, they confirm the positive effects of subsidized R&D cooperation. In addition, they find that firms benefit from being located in a region in which cooperative R&D subsidies strengthen inter-regional cooperation. From their study, it can be concluded that whether other organizations located in the same region are participating in R&D subsidies programs in general and in cooperative R&D subsidies programs in particular, is important to firms.

The present paper takes up this idea and aims at evaluating the impact of R&D subsidies on innovation performance from a regional perspective. It thereby follows a well-established research strand in the field of economic geography, investigating factors explaining variations in regions' innovative success (see Jaffe, 1989). While it is clear that firms and not regions are the actual units generating innovation, it is also established that firms do not innovate in isolation (Edquist, 1997). By manifold intended and unintended interactions, firms are embedded into their regional surroundings (see Oerlemans and Meeus, 2005). It is therefore argued that a region's innovation performance "*does not depend only on how individual actors (firms, universities, organizations, research institutes, governmental institutions, etc.) perform, but rather on how they interact as parts of a system*" (Andersson and Karlsson, 2006, p. 61). This territorial, systemic approach to innovation is prominently taken up in the innovative milieux and regional innovation system approaches, which particularly highlight the relevance of interaction, collective learning processes and cooperation between regional organizations (see Aydalot and Keeble, 1985; Cooke et al., 1997). Other forms of interaction that are common among regional players are buyer and supplier relations, labor mobility and diverse forms of unintended knowledge spillovers such as observation. In the context of this paper, this means that R&D subsidies granted to one firm may also impact on the innovation activities of other regional organizations. These indirect effects remain unnoticed when employing a firm-level approach.

2.3 Research questions

The study's first aim is to verify the positive impact of R&D subsidies on innovation performance, as found in firm-level studies, at the regional level. In light of the above, it can be expected that the effects of R&D subsidies should be more pronounced at the regional level because indirect effects are not taken into account in firm-level studies. Thus, the first research question can straightforwardly, formulated as follows:

> **Research question 1**: Do R&D subsidies impact regional innovation performance in the same way that they influence individual firm's innovation activities?

The relevance of firms' embeddedness into regional innovation processes is also highlighted by the numerous R&D subsidy programs that are explicitly designed to stimulate regional interaction. In Germany, programs such as the *BioRegio*, *InnoRegio* and *InnoNet* fall in this category. In such programs, public support is granted to self-organized cooperation in R&D among organizations located within the same region (Eickelpasch and Fritsch, 2005). As firms also need to be embedded in knowledge relations that span regional boundaries (Bathelt et al., 2004), the policy also supports inter-regional and international cooperation. In particular, the above-mentioned EUREKA and FP programs by the EU are prominent examples. By substituting particular kinds of cooperation (e.g. regional and / or inter-regional), such programs inherently interfere with the embeddedness of organizations into knowledge networks and thereby may impact on the configuration of regional and sectorial systems of innovation. Accordingly, it can by hypothesized that cooperative R&D subsidies are more influential on a regions' innovation performance than are non-cooperative subsidies. This is taken up in the second research question.

> **Research question 2**: Do differences in the relevance exist between R&D

subsidies granted to individual organizations (individual R&D subsidies) and those that are granted to consortia of organizations (cooperative R&D subsidies) for a regions' innovation performance?

As pointed out previously, participation in a subsidized joint project can be interpreted as a 'knowledge link' between two organizations, implying that all observed joint projects constitute a knowledge network (Broekel and Graf, 2012). Although Fornahl et al. (2011) confirm these networks' relevance for firms' innovation activities; few studies explicitly consider them when evaluating subsidy effects on innovation activities. Even less is known about their effect on regional innovation performance. Studies that take a regional perspective and analyze subsidized cooperation networks primarily focus on these networks' structure and their development (see Scherngell and Barber, 2011). The lack of research motivates the third research question.

Research question 3: Are the effects of cooperative R&D subsidies related to the amount of funding (monetary effect) or to the embedding of firms into subsidized knowledge networks (network effect)?

It is frequently argued that regions with superior innovation performance are characterized by strong regional as well as inter-regional knowledge networks (Camagni, 1991; Bathelt et al., 2004). However, many policy programs are spatially biased in terms of the type of cooperation being supported. For instance, the EU FP program primarily supports international cooperation, while programs such as the *BioRegio* contest have a clear focus on regional cooperation. So far, little quantitative empirical research exists regarding whether supporting cooperation with a clear geographical focus is really conducive to regional innovative success. The fourth research question addresses this issue.

Research question 4: Is support for regional or the subsidization of inter-regional cooperation more conducive to regional innovation?

Universities and research organizations are seen as having extremely valuable knowledge assets, making them attractive cooperation partners (Jaffe, 1989). In addition, universities and research institutes have a non-profit incentive structure that makes them less likely to cheat on their cooperation partners. It reduces the danger of free-riding, which is known to be a serious problem when firms collaborate (Kesteloot and Veugelers, 1995). The last research question therefore focuses on the participation of universities and research organizations in subsidized joint projects.

> **Research question 5**: Is the support for cooperation with universities and / or research institutes more beneficial to regional innovation performance than the facilitation of cooperation among firms?

The research questions are addressed by means of a two-stage empirical approach, presented in the following section.

3. Two-stage empirical approach

3.1 First-stage: nonparametric efficiency analysis

Following Griliches (1979), the innovation performance of regions is commonly evaluated in a knowledge production function framework. In this framework, variables representing knowledge inputs are set into a functional relationship with knowledge outputs generated by regional organizations. On this basis, their innovation performance can be perceived as the efficiency with which knowledge inputs are transformed into innovative outputs. For the empirical estimation, this implies that:

> "*... we would have to measure the number of innovation generators, mainly the R&D employees, and relate this to the innovation output*" (Brenner and Broekel, 2011, p. 24-25).

Accordingly, in the empirical estimation, the number of innovation generators located in a region represents the input (e.g. the number of R&D employees), their innovations represent the innovative output, and the ratio between the two corresponds to a region's innovation efficiency.

Such a conceptualization of regional innovation performance as regional innovation efficiency is applied in a number of recent studies (Fritsch and Slavtchev, 2011; Chen and Guan, 2010). While some studies apply parametric approaches such as the stochastic frontier analysis, I use a nonparametric approach, yielding a number of advantages. Crucially, nonparametric approaches do not require the specification of a parametric model, which significantly reduces the danger of model misspecification.[2] In the present paper, the regional innovation efficiency is estimated using a convex *order-m* analysis that represents a non-deterministic version of the well-known Data Envelopment Analysis. In contrast to the latter, it is much less sensitive to outliers and noise in the data. For more details, please see Daraio and Simar (2007a).

In the estimation, one first benchmarks a region's level of output (Y) against the expected maximal value of output achieved by regions with equal or lower input levels (X).[3] In practice, this means computing the non-convex *order-m* efficiency measure $\hat{\lambda}_m(x_0, y_0)$, which can be done with a Monte Carlo algorithm as proposed by Cazals et al. (2002).

$$\hat{\lambda}_m(x_0, y_0) = E[\tilde{\lambda}_m(x_0, y_0) \mid X \le x_0] = \frac{1}{B}\sum_{b=1}^{B}\tilde{\lambda}_m^b(x_0, y_0). \quad (1)$$

$\tilde{\lambda}_m(x_0, y_0)$ is calculated by

$$\tilde{\lambda}_m(x_0, y_0) = \max_{i=1,\dots,m}\{\min_{j,\dots,q}(\frac{Y_i^j}{y_0^j})\} \quad (2)$$

with Y_i^j (y_0^j) being the j^{th} component of Y^i (of y_0 respectively).

As a substitutive relationship exists between the output and input indicators, it is reasonable to use a convex measure of efficiency. According to Daraio and Simar (2007b), a convex *order-m* efficiency measure ($\tilde{\lambda}^c{}_m(x_0, y_0)$) is obtained by projecting all empirical observations on the above estimated non-convex *order-m* frontier and solving the following program:

$$\lambda_m^C(x,y) = \inf\left\{\begin{array}{l} \lambda \mid \lambda y \le \sum_{i=1}^{n}\gamma_i \hat{Y}_{m,i}^{\delta} \,;\, x_i \sum_{j=1}^{n}\gamma_i x_i \\ for\ (\gamma_{1,} \dots, \gamma_n)\ s.t. \sum_{i=1}^{n}\gamma_i \,;\, \gamma_i \ge 0, i = 1,\dots,n \end{array}\right\} \quad (3)$$

where Y^{δ} is region i's previously estimated non-convex *order-m* level of efficient output. The result of this efficiency analysis is a measure of relative efficiency for each region under the assumption of global convexity. It is denoted by EFF in the remainder of the paper and indicates by how much a region's output has to increase for it to become best practice given its input level.

3.2 Second-stage: panel regression and endogeneity

In a similar set-up to that of Fritsch and Slavtchev (2011), the previously estimated efficiency scores serve as a dependent variable in a panel regression, testing its relation with subsidies variables under consideration of a number of control variables. However, the relationship between subsidies and regional innovation efficiency is not mono-directional, implying that this straightforward approach might be troubled by endogeneity. The likelihood with which organizations in various regions attract subsidies is not independent of their innovation performance. For instance, subsidies might be deliberately granted to support firms in regions with low innovation performance, or they can be focused on sustaining the innovation performance of 'excellence' regions by favoring applications from these regions' organizations. This potential endogeneity problem is addressed in multiple ways. Firstly, regional innovation performance is conceptualized as innovation efficiency. While policy can easily observe total innovation output as approximated by patent numbers, it is more difficult to assess innovation efficiency. The political distribution of subsidies is therefore less likely to depend on regional innovation efficiency than on the total regional innovation output.

Secondly, potential endogeneity is reduced by using time lags between subsidies and innovation efficiency.

Thirdly, past innovative success is among the criteria used for distributing R&D subsidies. For this reason, instead of using the level of innovation efficiency it is focused on the annual change / growth of innovation efficiency.

Fourthly, endogeneity can still be an issue insofar as policy might look at a region's long-term growth patterns in terms of innovation efficiency when deciding on granting subsidies. In this case, the receiving of R&D subsidies will be related to growth trends in innovation efficiency. This potential source of endogeneity is dealt with by employing a fixed effects regression with the growth of regional innovation efficiency as a dependent variable and the levels of received R&D subsidies as independent variables. Accordingly, the empirical analysis tests to what extent deviations from the mean growth of regional innovation efficiency relate to deviations from the mean level of received subsidies in previous years. This research design not only minimizes potential endogeneity, it also controls for potential spurious correlation caused by the intensity of unsubsidized cooperation in a region, which might be correlated to the intensity of subsidized cooperation but it is not covered by the data. However, it seems reasonable to assume that firms' embeddedness into unsubsidized knowledge networks is changing relatively slowly over time and, what is more important, it is unlikely to change simultaneously with subsidized cooperation. Using regional fixed effects will eliminate the unobserved variable bias under this assumption.

A region's estimated innovation efficiency changes over time due to various reasons. For instance, a regions' efficiency can change without any variation in their input × output relation, because of shifts in the best-practice frontier's location. In the remainder of the paper, the focus will be on what is known in the productivity literature as change in 'pure technical' efficiency. In the present context, this is the most relevant type of efficiency change, because it abstracts from non-region specific processes, such as technological progress in innovation creation, economy wide shocks and economies of scale. Change in pure technical efficiency captures a region's movement relative to the best-practice frontier, representing the degree to which it decreases or increases its innovation efficiency relative to best-practice regions. In other words, it captures whether a region is catching-up or falling behind. According to Wheelock and Wilson (2003), the change in technical *order-m* efficiency is defined by:

$$\Delta\lambda_m^c \frac{\lambda_m^c(x_0^{t+1}, y_0^{t+1} | T_m^{t+1})}{\lambda_m^c(x_0^t, y_0^t | T_m^t)} \qquad (4)$$

where T^t and T^{t+1} indicate the 'technological' conditions in period t and t + 1, respectively.[4] In practice, $T_m{}^t$ implies that the efficiency of region (x_0, y_0) is estimated on the basis of all other regions' input × output relations in period t. The inverse of this rate of change is used in the estimations to ensure that large values indicate improvement, while low values indicate decreased innovation efficiency.

4. Data

4.1 Innovations, patents, and R&D

As is common in this type of research, the numbers of regional patent applications approximate the output of innovation activities.[5] When using patent data, it is important that an inventor's residence and his work place are located within the same region. This is the case in the 270 German labor market regions as defined by the German Institute for Labor and Employment (Greif and Schmiedl, 2002). They are frequently used in this type of research (Broekel, 2012) and are therefore chosen as the unit of analysis.

The regionalized data on patent applications are published in Greif and Schmiedl (2002) and Greif et al. (2006), which include applications to the German as well as to the European Patent Office, with a correction for double counts. The patents are assigned to labor market regions according to the inventor principle. Applications by public research institutes such as universities and research organizations and those of private inventors are not included, because the regional knowledge inputs cover only industrial R&D activities. In accordance with the regional innovation efficiency approach, the latter are approximated by the number of R&D employees in a region, representing the innovation generators. This data are obtained from the German labor market statistics, which covers all employees subject to social insurance contributions. When relating patent information to R&D activities, inter-industrial differences have to be taken into account, concerning the innovation productivity of R&D employees and patent propensity (Arundel and Kabla, 1998). The innovation efficiency is therefore estimated separately for four industries, namely chemicals (CHEM), manufacturing of transport equipment (TRANS), manufacturing of electrical and electronic devices (ELEC) and a mixed branch covering manufacturing of precision instruments, measurement devices, optics and medical apparatus (INSTR). For all these industries, patenting represents an important property rights protection mechanism, ensuring that the innovation output measure captures most, or at least a significant share, of their innovations (Arundel and Kabla, 1998).

Estimating industry specific innovation efficiency measures requires matching the patent information to industries' R&D data, which is done on the basis of the concordance between the according classifications by Broekel (2007). It adapts the IPC-NACE concordance by Schmoch et al. (2003) to the data used here. The resulting definition of industries, in terms of considered technological fields of patenting as specified in Greif and Schmiedl (2002) and NACE codes, is presented in Table A.1 in the Appendix.

Utilizing the possibility of considering multiple outputs as well as inputs in the efficiency analysis, each technological field assigned to an industry becomes an output variable and each NACE industry's R&D employment represents an input. As is usual practice, a time lag of two years is assumed between R&D efforts and the patent applications, implying that patent data for the years 2001 to 2005 is matched to R&D employment from 1999 and 2003.

4.2 Regional control variables

The literature suggests a wide range of regional characteristics that influence firms' innovation activities and which need to be considered as control variables (see Feldman and Florida, 1994; Fritsch and Slavtchev, 2011). Foremost, these include urbanization economies that are approximated by population density (POP) and the gross-domestic product (GDP) of a region. The share of employees with high qualifications (HIGH) is considered to capture the availability of highly qualified human capital. The according data are obtained from the German Federal Institute for Research on Building. The location coefficient for each industry's employment accounts for a region's degree of specialization with respect to the analyzed industry (SPEC). In addition, the absolute regional employment (EMPL) and firm number (FIRMS) of the industry is taken into account to control for clustering effects. Potential effects resulting from a region's industrial diversification are accounted for by estimating the inverted-Hirschman-Herfindahl index, on the basis of each industry's own employment and the employment of the other 2-digit NACE code manufacturing industries in a region (DIVERS). The data used to construct these variables are taken from the German labor market statistics.

I also consider non-cooperation related inter-regional spillovers, by accounting for the geographic mobility of university graduates in engineering (ENG) and the natural sciences & mathematics (NAT) (see Faggian and McCann, 2006). Following the procedure proposed by Broekel and Brenner (2007), the numbers of graduates are distributed across the regions, so that a region's probability to obtain another regions' graduates depends positively on its population and hyperbolic negatively on the geographic distance between regions. In addition, a certain share of the graduates is allowed to stay in their university's region. Data on graduates of each German university and technical colleague are obtained from the German Statistical Office. To control for size effects, the distributed graduate counts enter the analysis as ratios of a regions' total employment.

The presence of public research institutes are approximated by the employment of the "*big four*" research organizations in Germany, namely the Helmholtz Association, the Max Planck Society, the Fraunhofer Society and the Leibniz Association. Four variables are constructed (HELM, MPG, FHG, LEIB), each representing the personnel working in these organizations' technological or natural science institutes in the respective years.

4.3 Cooperative and non-cooperative R&D subsidies

As in most other advanced countries, the German federal government is actively supporting public and private research and development activities with subsidies. While the Federal Ministry of Education and Research (BMBF) is the prime source of subsidies, the Federal Ministry of Economics and Technology (BMWi) and the Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU) contribute as well. The federal ministries publish comprehensive information on the supported projects in the so-called "*Förderkatalog*" (subsidies catalog). This lists detailed information on more than 110,000 individual grants supported between 1960 and 2010.

The data also include information on the cooperative nature of projects, in other words it indicates if the projects are joint projects realized by a consortium of organizations. Participants in joint projects agree to a number of regulations that guarantee significant knowledge exchange between the partners (see Broekel and Graf, 2012). Accordingly, two organizations are deemed to cooperate if they participate in the same joint project.

The data also contain information on the 2-digit NACE code of subsidized organizations, allowing the construction of industry-specific measures. It is also possible to differentiate between universities, research organizations, firms and miscellaneous organizations. The information on community locations in the database was employed to regionalize the data. Some descriptives of the obtained subsidies data for the four industries are presented in Table 1.

- Table 1 about here -

In light of the previously formulated research questions, the following regional variables are created for each industry and year.[6] To answer **research question 1**, the variable TOTAL FUNDS is estimated representing the annual amount of subsidies acquired by regional firms. All funds are estimated by taking into account the exact grant period, in days per year.

This figure is split into the sum of non-cooperative (INDIVIDUAL_FUNDS) and the sum of cooperative subsidies (COOP_FUNDS). Comparing their relevance allows for inferences regarding **research question 2**. It might be the case that the effects of subsidies are unrelated to the funds (monetary effect), but rather to the number of subsidized projects in which firms are engaged. This is taken into account by using two variables, representing the number of individual projects (INDIVIDUAL_PROJ) and the number of cooperative projects (COOP_PROJ) in which regional firms participate.

Potential network effects of subsidized R&D cooperation (**research question 3**) are approximated by the number of organizations with which regional firms are connected by participation in subsidized joint projects (COOP_PARTNERS). To answer **research question 4**, the number of links firms in a region have to other organizations located in the same region (REGIONAL) is counted.

The number of links to universities (UNIVERSITY) and research organizations (RESEARCH) are estimated in a similar manner, which allows for addressing **research question 5**. A list of all variables is shown in Table A.2 in the Appendix. The descriptives of all the variables used in the estimation as well as their correlation structure are further presented in Table A.3 and Table A.4 in the Appendix, respectively.

5. Empirical Results

5.1 Regional innovation efficiency

The estimated innovation efficiency scores are briefly presented before their relation with the subsidies variables is analyzed.

- Figure 1 about here -

In the efficiency analysis, all regions with zero R&D employment for at least one year are excluded, because efficiency values for zero-input observations are meaningless. This reduces the total sample from 5 400 (4 industries × 270 regions × 5 years) to 4 950 (990 industry-regions in 5 years). The mean of the estimated efficiency is fairly high with 9.4, which is caused by the number of extremely large values (EFF>100).[7] The median is 3.01 gives a more meaningful impression of the efficiency scores' magnitude. An industry comparison on this basis reveals significant differences, with ELEC having the lowest median efficiency (1.98), which shows that it is most efficient, as large values indicate inefficiency. It is followed by CHEM (2.34) and INSTR (3.72), while TRANS shows the highest median inefficiency (6.7). Figure 2 shows the overall distribution of efficiency values.

- Figure 2 about here -

The map in Figure 1 shows the spatial distribution of innovation efficiency in 2003. It particularly highlights that inefficient regions seem to be geographically clustered. A Moran's I test on industry efficiency scores confirms this for all four industries, as shown in Table 2.

- Table 2 about here -

With few exceptions, regions with the strongest change in innovation efficiency are small in terms of patent output. This is not surprising as, for these regions, efficiency change is often extreme and fluctuates strongly. In general, the estimated change in technical efficiency (gEFF) shows similar patterns as the efficiency levels. The distribution is less skewed, though: the mean is 1.432 and the median 1.012 for the pooled data. The highest median efficiency change is observed for ELEC, followed by TRANS and INSTR. CHEM shows the lowest level of change, but still improves over time, as can be seen in Table 3.

- Table 3 about here –

With the exception of INSTR, all industries' rates of change show significant positive spatial correlation in at least one year (see Table 3), which needs to be considered in the second-stage regression.

5.2 The set-up of the two-stage approach

There are few theoretical reasons why the effects of R&D subsidies on regional innovation efficiency should vary between industries. For this reason, all industry-specific data is pooled in the second-stage regression, increasing the number of available observations. It implies that the sample covers 990 industry-specific regions for which growth rates can be constructed for 4 years, resulting in 3,960 observations. The majority of these industry-specific regions are characterized by zero R&D subsidies.[8] Figures 3 and 4 give an impression of the spatial distribution of the subsidy variables' values.

- Figure 3 about here -

- Figure 4 about here -

In the first model, the change in efficiency is related to the control variables before the subsidies variables are subsequently included. Given the high correlation between HIGH and GDP, as well as between ENG and NAT (see Table A.4 in the Appendix), GDP and NAT are excluded because of their relatively smaller relevance.

In a standard fixed effects panel, regression spatial autocorrelation of the dependent variable translates into spatially correlated error terms.[9] A BSJK test reveals that this is the case and should be taken into account (Baltagi et al., 2007).[10] Accordingly, a spatial panel fixed effects model is used for the second-stage regression as proposed by Elhorst (2009).[11]

The regressions are run on two subsamples. One includes all regions with less the mean R&D employment (752 industry-specific regions), which are denoted as regions with small innovation capacities. The second covers all regions with more than the mean R&D employment (238 industry-specific regions). These are labeled as regions with "*large innovation capacities*" in the following. Splitting the sample is motivated by the fact that significant differences are likely to exist in the types of policy programs accessible to firms in the two types of regions. For instance, firms located in regions with large innovation capacities are more likely to participate in initiatives supporting cluster and "excellence regions". In contrast, firms located in regions with small innovation capacities might have the possibility of profiting from convergence policies.

Given the unclear structure of potential time-lags between the granting of subsidies and their impact on regions' innovation efficiency, lags from one to four years are simultaneously considered.

5.3 Subsidies and regional innovation efficiency

The results of the regression analyses are presented in Table 4 (all regions), in Table 5 (regions with large innovation capacities) and in Table 6 (regions with low innovation capacities).

- Table 4 about here –

- Table 5 about here -

- Table 6 about here -

With the exception of the year dummies and HELM, all control variables remain insignificant in the baseline **model 1**. The explanation is the use of the trend corrected growth rate of innovation efficiency as a dependent variable, which eliminates effects that impact long-term efficiency growth. When using a model without trend correction (**model 0**), more control variables gain significance. Employment (EMPL) positively influences innovation efficiency growth, as does diversification (DIVERS). The presence of institutes of the Max-Planck Society also characterized regions that are advanced in innovation efficiency (MPG). The negative coefficient obtained for the number of firms (FIRMS) seems to indicate the presence of negative agglomeration effects. Accordingly, regional characteristics matter in the long-run, but remain insignificant in the trend-corrected estimates, which will be used to minimize potential endogeneity problems.

The results (models 1 to 15) give a clear answer to **research question 1**. The amount of subsidies granted to regional firms (SUBS) is not gaining significance in any of the models. In this respect, the study fails to replicate the firm-level findings that suggest a positive relationship between subsidies and innovation performance (see Czarnitzki and Hussinger, 2004; Formal et al., 2011). In addition, splitting up the funds into those attributed to cooperative (COOP_FUNDS) and those supporting individual projects (INDIVIDUAL_FUNDS) result in exclusively insignificant coefficients. Hence, the study does not provide evidence for varying effects of these two types of funding, implying that **research question 2** can be negated.

The most likely reason for these findings is that the project costs are systematically underestimated. When R&D subsidies are granted, organizations have to supplement the funding with their own resources, which are often larger than the grant amounts. The extent of private supplementation differs between industries, programs and types of receiving organizations, but clearly lacks a systematic regional structure. Accordingly, to identify the monetary effect of R&D subsidies on a regional level requires information about private contributions to the subsidized projects, which is not included in the data at hand.

An alternative is focusing on the number of subsidized projects in which regional firms are participating. This number can be expected to be less biased. In accordance with the above, it is split into the number of individual projects (INDIVIDUAL_PROJ) and the number of cooperative projects (COOP_PROJ). For the latter, no significant coefficients are obtained. In contrast, the number of subsidized individual projects (INDIVIDUAL_PROJ) gains a significant negative coefficient in all models for all regions (models: 1 to 5) and all models for small regions (models: 11 to 15). From this, it can be inferred that in regions with small innovation capacities and which also dominate the complete sample of firms, innovation efficiency growth is reduced when regional firms are awarded subsidies for individual projects two years before. What is the reason for this negative effect? As the variable becomes significant in a two-year lag specification, a resource enlargement effect could be the cause: the subsidies expand the resources invested into R&D by increasing the number of R&D employees. This reduces innovation efficiency, because it takes some time before these additional resources translate into patentable outcomes. However, a number of reasons speak against this argument. Firstly, if this is a factor, such a relationship should be visible in the one year lag variable, which remains insignificant though. Secondly, the same effect applies to the participation in the number of cooperative projects (COOP_PROJ), which is insignificant as well.

As the resources expansion effect is unlikely to explain the negative coefficient of INDIVIDUAL_PROJ, I suspect that subsidized individual projects have a lower efficiency in terms of the ratio between number of created patents and invested resources than do cooperative projects, or those that are not subsidized. Applying for subsidies seems to be particularly rational when a research project is not cost-efficient by itself. Accordingly, subsidies are more likely to be granted to projects, which would otherwise be cost-inefficient. Furthermore, the existence of cooperation advantages explains the comparatively higher efficiency of subsidized cooperative projects. Consequently, this lower productivity can explain the negative coefficient, but not the specificity of the effect on regions with low innovation capacity. It might be the case that subsidies for individual projects substitute for cooperative projects in these regions, but not in regions with large innovation capacities. The reason for this could be that large firms are more likely to be located in the latter and have the capabilities to simultaneously participate in multiple support programs. By contrast, smaller firms that dominate regions with small innovation capacities might have to choose between participating in cooperative or non-cooperative support programs.

There is some empirical support for this argument. For regions with large innovation capacities, the growth of the number of individual projects and that of cooperative projects is positively correlated with 0.15***. By contrast, in the case of regions with small innovation capacities, the same correlation is (weakly) negative with −0.024*. While being in line with the above, this should not be seen as much more than a first indication of for the effect of such substitutions. More research is certainly needed on this issue in the future.

Concerning **Research question 3**, it can be concluded that little support is found for effects related to the monetary side of the grant subsidies. Rather, the number of supported projects matter in a negative way. By contrast, evidence is provided for the existence of positive network effects, which will be discussed in the following.

The subsidization of cooperation in general, as captured by COOP_PROJ, is not helping regional organizations to improve innovation efficiency. For regions with small innovation capacities, it is the increasing subsidization of cooperation among regional organizations that stimulates innovation efficiency, as captured by REGION in models 15 (2nd lag). This implies that the benefits of having co-located cooperation partners are particularly relevant in regions where few organizations are active in the same technological fields. Regions with small innovation capacities are more frequently characterized by an excess of inter-regional cooperation (Broekel et al., 2010), which can induce negative effects on their innovation performance (Broekel, 2012). In light of the empirical results, it therefore seems to be the case that the subsidization of regional cooperation can reduce such negative effects. Accordingly, **research question 4** can be approved for regions with small research capacities.

Another interesting difference between regions with small and large innovation capacities concerns the type of organizations that are most beneficial when cooperating. In the case of regions with small innovation capacities, the coefficient for cooperating with research institutes (RESEARCH) turns out to be positively significant in model 15 (1st lag and 3rd lag). By contrast, innovation processes in regions with large innovation capacities are rather facilitated when subsidized cooperation includes universities: UNIVERSITY is significant in model 10 (3rd lag). In the model for all regions, the results mirror this ambiguity with the coefficient of RESEARCH and UNIVERSITY being insignificant in model 5.[12]

This difference is somewhat surprising. Both research institutes and universities offer state-of-the-art knowledge that firms can access through cooperating; hence firms should benefit from cooperating with either. A potential explanation for this difference might be as follows: Beise and Stahl (1999) showed that universities are less frequently cited than research institutes as sources for knowledge concerning process innovations. With respect to product innovation, these authors do not detect any differences. Process innovations are more relevant for manufacturing firms. These firms tend to be located outside large agglomerations, frequently in regions with low innovation capacities. Accordingly, these firms benefit more from cooperating with research institutes. For basic research-oriented firms, which tend to be located in large agglomerations, universities would be the preferred cooperation partners. However, it has to be pointed out that both variables UNIVERSITY and RESEARCH are aggregates of particularly heterogeneous organizations. UNIVERSITY includes application-oriented technical colleagues as well as extremely diversified universities. RESEARCH combines institutes of the application-oriented Fraunhofer Society as well as the basic research oriented Max-Planck-Institutes. Some of these differences are accounted for by controlling for the industrial dimension.[13] Nevertheless, I suspect that averaging this technological heterogeneity significantly drives the above results. Thus, **Research question 5** can be clearly answered. In contrast with subsidized cooperation among firms, support for cooperation between firms and universities or public research institutes stimulates regional innovation efficiency.

6 Discussion and conclusion

The study showed that R&D subsidies can be suitable policy measures for stimulating regional innovation efficiency under certain conditions. The empirical assessment failed to detect effects of R&D subsidies that are related to the pure monetary arrangement of the support programs. What is relevant is the number of supported projects. By differentiating between the numbers of supported individual projects (non-cooperative R&D subsidies) and those of joint projects (cooperative R&D subsidies), it was shown that supporting the former yields negative effects on regional innovation efficiency, especially in the case of regions with small innovation capacities. These negative effects are possibly related to non-cooperative R&D projects substituting for cooperative R&D projects. This should be subject to further research in the future.

Furthermore, the empirical findings indicate that support for joint projects (cooperative R&D subsidies) has particular impact on regional innovation processes. For regions with small innovation capacities, these joint projects should focus on including regional firms and non-regional public research institutes. In contrast, firms in regions with large innovation capacities benefit from being engaged in subsidized cooperation with non-local universities. In this respect, the study clearly showed that subsidies for R&D cooperation are a good tool for supporting the knowledge transfer from the public research sphere into the private sector.

The study complements existing empirical investigations at the firm-level by verifying some findings at the regional level. However, it also highlighted that there is more to R&D subsidies than just the monetary benefits, which are in most instances the focus of empirical evaluations. The assessment revealed the presence of a wide range of effects that are related to different characteristics of support programs, including the important differentiation between cooperative and non-cooperative R&D subsidies. In this respect, the present study calls for more attention to be paid to this subject in future research.

The empirical analysis has a number of shortcomings that need to be pointed out. Most importantly, I employed panel regression with a panel covering only a limited time period: trend-corrected growth rate has also been used as a dependent variable to avoid endogeneity issues. Hence, the present study does not allow for inferring the long-term impact of R&D subsidization programs on regional development, which might be crucial. The emergence and evolution of regional innovation structures are long-term processes that may encompass different phases. Varying types of support programs might be crucial at particular phases flanking these developments. For instance, in light of the importance of informal networks in the early stages of technology evolution (Niosi and Banik, 2005), a greater importance might be assigned to policies focusing on regional network building in these stages. In later development stages, the prevention of lock-ins might be the crucial issue (Grabher, 1993).

It is also yet to be shown in more depth how policies can actively stimulate networking and what effects emerge from these activities. A shortcoming of this study lies in the debatable assumption that observed subsidized R&D cooperation is more or less independent of organizations' unsubsidized cooperation activities. Accordingly, the question remains as to whether the observed subsidized cooperation is created by policies, or if they represent unsubsidized relations that have already been in existence for some time.

Notes

1. Note that Czarnitzki et al. (2007) do not differentiate between subsidized and non-subsidized cooperation.

2. Other advantages include the possibility of simultaneously considering multiple output variables and that no distributions have to be specified for the error term, as well as for the efficiency estimate.

3. This represents the so-called output-orientation. One may also ask for the necessary reduction in inputs (input-orientation). I argue that the output-orientation is more appropriate, because the aim is to identify factors that are related to regions showing "maximal" innovation output.

4. Technological conditions refer to the general way innovations are created in a particular year.

5. See Griliches (1990) for a discussion on the use of patents as indicators of innovation.

6. Note that all estimations only consider subsidies from the German federal government, ignoring all support from other administrative levels such as the EU and districts.

7. Values of this magnitude are induced by zero output but positive input. An output value of 0.01 is assigned to these regions to ensure a proper estimation.

8. The highest number of industry-regions with zero subsidies is 763, in 2000.

9. Moran's I statistic for the regression's residuals is: 0.04***.

10. The test statistic is: LM=585.67***.

11. The models were also estimated using a standard fixed effects panel regression with heteroskedasticity-robust standard errors as suggested by Stock and Watson (2008). The results do not conflict with the ones presented in the paper. They can be obtained upon request from the author.

12. I also tested the impact of differentiating between cooperation with regional and non-regional universities, as well as cooperation with regional and non-regional research institutes, respectively. These results indicate that it is cooperation with non-regional organizations - universities as well as research institutes - that matters in this regard. The estimation results can be obtained from the author upon request.

13. I also checked for inter-industrial differences. The industry-specific results for all regions (models 1 to 5) do not indicate differences between the industries. Splitting the sample and running industry-specific regressions for different types of regions is unfortunately not possible due to the lack of observations.

References

Aguiar L. and Gagnepain P. (2012) European cooperative R&D and firm performance, Economics Working Papers of Universidad Carlos III, Departamento de Economía **12-07**.

Andersson M. and Karlsson C. (2006) Regional innovation systems in small and medium-sized regions, The Emerging Digital Economy **A**, 55–81.

Arundel A. and Kabla I. (1998) What percentage of innovations are patented? Empirical estimates for European firms, Research Policy **27**(2), 127–141.

Aydalot P. and Keeble D. (Eds.) (1985) High Technology Industry and Innovative Environments, Routledge, London.

Baltagi B. H., Song S. H., Jung B. and Koh W. (2007) Testing panel data regression models with spatial and serial error correlation, Journal of Econometrics **140**, 5–51.

Barajas A., Hergo E. and Moreno L. (2011) Measuring the economic impact of research joint ventures supported by the EU framework program, Journal of Technology Transfer **DOI 10.1007/s10961-011-9222-y**.

Barajas A. and Huergo E. (2010) International R&D cooperation within the EU framework program: empirical evidence for Spanish firms, Economics of Innovation and New Technology **19**(1), 87–111.

Bathelt H., Malmberg A. and Maskell P. (2004) Clusters and knowledge: Local buzz, global pipelines and the process of knowledge creation, Progress in Human Geography **28**(1), 31–56.

Beise M. and Stahl H. (1999) Public research and industrial innovations in Germany, Research Policy **28**(4), 397–422.

Benfratello L. and Sembenelli A. (2002) Research joint ventures and firm level performance, Research Policy **31**, 493–507.

Boschma R. A. and ter Wal A. L. J. (2007) Knowledge networks and innovative performance in an industrial district: The case of a footwear district in the south of Italy, Industry and Innovation **14**(2), 177–199.

Branstetter L. and Sakakibara M. (1998) Japanese research consortia: a microeconometric analysis of industrial policy, The Journal of Industrial Economics **46**(2), 207–233.

Brenner T. and Broekel T. (2011) Methodological issues in measuring innovation performance of spatial units, Industry and Innovation **18**(1), 7–37.

Broekel T. (2007) A concordance between industries and technologies - matching the technological fields of the Patentatlas to the German industry classification, Jenaer Economic Research Papers **2007-013**.

Broekel T. (2012) Collaboration intensity and regional innovation efficiency in Germany - a conditional efficiency approach, Industry and Innovation **19**(3), 155–179.

Broekel T. and Brenner T. (2007) Measuring regional innovativeness - a methodological discussion and an application to one German industry, DIME Working Paper **2007-13**.

Broekel T., Buerger M. and Brenner T. (2010) An investigation of the relation between cooperation and the innovative success of German regions, Papers in Evolutionary Economic Geography **10.11**.

Broekel T. and Graf H. (2012) Public research intensity and the structure of German R&D networks: A comparison of 10 technologies, Economics of Innovation and New Technology **21**(4), 345–372.

Busom I. (2000) An empirical evaluation of the effects of R&D subsidies, Economics of Innovation and New Technology **9**(2), 111–148.

Camagni R. (1991) Local “Milieu”, uncertainty and innovation networks: Towards a new dynamic theory of economic space, in Camagni R. (Ed.) Innovation Networks: Spatial Perspectives, Belhaven Stress. London, UK and New York, USA.

Cantwell J. (1999) Innovation as the principal source of growth in the global economy, in Archibugi D. and Howells J. (Eds.) Innovation Policy in a Global Economy, pp. 225–241, Cambridge: University Press.

Cazals C., Florens J.-P. and Simar L. (2002) Nonparametric frontier estimation: A robust approach, Journal of Econometrics **106**(1), 1–25.

Chen K. and Guan J. (2010) Measuring the efficiency of China’s regional innovation systems: Application of Network Data Envelopment Analysis (DEA), Regional Studies **DOI: 10.1080/00343404.2010.497479**.

Cooke P., Uranga M. G. and Etxebarria G. (1997) Regional innovation systems: Institutional and organisational dimensions, Research Policy **26**(4-5), 475–491.

Czarnitzki D., Ebersberger B. and Fier A. (2007) The relationship between R&D collaboration, subsidies, and R&D performance, Journal of Applied Econometrics **22**(7), 1347–1366.

Czarnitzki D. and Hottenrott H. (2009) Are Local Milieus the Key to Innovation Performance, Journal of Regional Science **49**(1), 81–112.

Czarnitzki D. and Hussinger K. (2004) The link between R&D subsidies and R&D spending and technological performance, ZEW Discussion Paper **56**.

Daraio C. and Simar L. (2007a) Advanced Robust and Nonparametric Methods in Efficiency Analysis - Methodology and Applications, Kluwer Academic Publishers, Boston / Dordrecht / London.

Daraio C. and Simar L. (2007b) Conditional Nonparametric Frontier Models for Convex and Non Convex Technologies: a Unifying Approach, Journal of Productivity Analysis **28**(1), 13–32.

Dekker R. and Kleinknecht A. H. (2008) The EU framework programs: Are they worth doing?, MPRA Paper **No. 8503**.

DESTATIS (2002) Klassifikation der Wirtschaftszweige, Ausgabe 2003 (WZ2003), Statistisches Bundesamt, Wiesbaden.

Edquist C. (1997) Systems of innovation approaches - their emergence and characteristics, in Systems of Innovation: Technologies, Institutions and Organizations, chap. 1, Pinter Publishers. London, UK / Washington, D.C. USA.

Eickelpasch A. and Fritsch M. (2005) Contests for cooperation - a new approach in German innovation policy, Research Policy **34**, 1269–1282.

Elhorst J. P. (2009) Spatial panel models, in Fischer M. M. and Getis A. (Eds.) Handbook of Applied Spatial Analysis, Springer, Berlin.

Faggian A. and McCann P. (2006) Human capital flows and regional knowledge assets: A simultaneous equation approach, Oxford Economic Papers **52**, 475–500.

Feldman M. P. and Florida R. (1994) The geographic sources of innovation: Technological infrastructure and product innovation in the United States, Annals of the Association of American Geographers **84**(2), 210–229.

Fischer B. B. and Molero J. (2011) Towards a taxonomy of firms engaged in international R&D cooperation programs: the case of Spain in Eureka, Working Papers del Instituto Complutense de Estudios Internacionales **01-11**.

Fornahl D., Broekel T. and Boschma R. A. (2011) What drives patent performance of German biotech firms? The impact of R&D subsidies, knowledge networks and their location, Papers in Regional Science **90**(2), 395–418.

Fritsch M. and Slavtchev V. (2011) Determinants of the efficiency of regional innovation systems, Regional Studies **45**(7), 905–918.

Girma S., Görg H., Strobl E. and Walsh F. (2008) Creating jobs through public subsidies: An empirical analysis, Labour Economics **15**, 1179–1199.

Grabher G. (1993) The weakness of strong ties: The lock-in of regional development in the Ruhr area, in Grabher G. (Ed.) The Embedded Firm - On the Socioeconomics of Industrial Networks, pp. 255–277, Routledge, London, New York, Reprinted in 1994.

Greif S. and Schmiedl D. (2002) Patentatlas 2002 Dynamik und Strukturen der Erfindungst ätigkeit, Deutsches Patent- und Markenamt, München.

Greif S., Schmiedl D. and Niedermeyer G. (2006) Patentatlas 2006. Regionaldaten der Erfindungstätigkeit, Deutsches Patent- und Markenamt, München.

Griliches Z. (1979) Issues in assessing the contribution of R&D to productivity growth, Bell Journal of Economics **10**, 92–116.

Hagedoorn J. (2002) Inter-firm R&D partnerships: An overview of major trends and patters since 1960, Research Policy **31**, 477–492.

Isaksen A. (2001) Building regional innovation systems: Is endogenous industrial development possible in the global economy?, Canadian Journal of Regional Science **24**(1), 101–120.

Jaffe A. (1989) Real effects of academic research, American Economic Review **79**(5), 957–970.

Kapoor M., Kelejian H. and Prucha I. R. (2007) Panel data model with spatially correlated error components, Journal of Econometrics **140**, 97–130.

Kesteloot K. and Veugelers R. (1995) Stable R&D cooperation with spillover, Journal of Economics and Management **4**, 651–672.

Marín P. L. and Siotis G. (2008) Public policies towards research joint venture: institutional design and participants' characteristics, Research Policy **37**, 1057–1065.

Niosi J. and Banik M. (2005) The evolution and performance of biotechnology regional systems of innovation, Cambridge Journal of Economics **25**(3), 343–357.

Oerlemans L. A. G. and Meeus M. T. H. (2005) Do organizational and spatial proximity impact on firm performance?, Regional Studies **39**(1), 89–104.

Powell W. W., Walter W., Koput K. W. and Smith-Doerr L. (1996) Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology, Administrative Science Quarterly **41**(1).

Scherngell T. and Barber M. J. (2011) Distinct spatial characteristics of industrial and public research collaborations: Evidence from the fifth EU Framework Programme, Annals of Regional Science **46**, 247–266.

Schmoch U., Laville F., Patel P. and Frietsch R. (2003) Linking technology areas to industrial sectors, Final Report to the European Commission, DG Research, Karlsruhe, Paris, Brighton .

Stock J. H. and Watson M. W. (2008) Heteroskedasticity-robust standard errors for fixed effects panel data regression, Econometrica **76**(1), 155–174.

Storper M. (1995) Competitiveness policy options: The technology-regions connection, Growth and Change **26**, 285–308.

Teece D. J. (1986) Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy, Research Policy **15**(6), 285–305.

Wheelock D. C. and Wilson P. W. (2003) Robust nonparametric estimation of efficiency and technical change in U.S. commercial banking, The Federal Reserve Bank of St. Louis Working Paper Series **37A**, 1–34.

Appendix

Industries	Technological fields*	NACE**
Chemistry (CHEM)	TF5, TF12, TF13, TF14, TF15, TF24, TF25	DG24, DI26,DJ27, DJ28, DK29, DN36
Transport equipment (TRANS)	TF10, TF22	DM34, DM35
Electrics & electronics (ELEC)	TF27, TF28, TF29, TF30, TF31	DL30, DL31, DL32
Medical optical instruments (INSTR)	TF4, TF16, TF26	DL33, DF23

* As defined in Greif and Schmiedl (2002) ** According to the NACE DESTATIS (2002)

Table A.1: Definition of industries

Variable	Description
gEFF	Annual change in industry-specific regional innovation efficiency
EFF	Regional innovation efficiency *
R&D	Number of R&D employees *
PATENTS	Number of patent applications by firms (inventor principle) *
POP_DEN	Population density
HIGH	Share of employees with high qualifications
GDP	Gross-domestic product per employee
EMPL	Industry-specific number of employees
SPEC	Location coefficient of an industry's employment
FHG	Personnel working at institutes of the Fraunhofer Society**
MPG	Personnel working at institutes of the Max Planck Society**
HELM	Personnel working at institutes of the Helmholtz Association Society**
LEIB	Personnel working at institutes of the Leibniz Association**
FIRMS	Number of firms in the industry
DIVERS	Inverted Hirschman-Herfindahl index on the basis of a respective industry's employment and the employment of the other 2-digit NACE code manufacturing industries
ENG	Regionally distributed graduates from universities and technical colleagues in natural sciences & math (NAT)
NAT	Regionally distributed graduates from universities and technical colleagues in engineering (ENG)
TOTAL_FUNDS	Subsidies acquired by regional firms
INDIVIDUAL_FUNDS	Subsidies acquired by regional firms through non-cooperative projects
COOP_FUNDS	Subsidies acquired by regional firms through cooperative projects
COOP_PROJ	Firms' number of subsidized cooperative projects
INDIVIDUAL_PROJ	Firms' number of subsidized non-cooperative projects
COOP_PARTNER	Firms' number of partner in subsidized cooperative) projects
REGIONAL	Firms' number of links to other organizations located in the region
UNIVERSITY	Firms' number of links to universities *
RESEARCH	Firms' number of links to research organizations *

* Variables are estimated as industry-specific regional aggregates
** Only technological or natural science institutes

Table A.2: Variables employed in the empirical estimation

	n	mean	sd	median	min	max	range
gEFF	3960	0.040	0.736	0.000	-3.313	5.164	8.477
EFF	4950	9.395	30.529	3.011	0.091	419.506	419.416
R&D	4950	442.787	1426.892	88.500	1.000	31243.000	31242.000
PATENTS	4950	22.811	84.815	5.340	0.000	1811.934	1811.934
POP_DEN	4950	878.304	1298.506	268.000	40.000	8495.000	8455.000
EMP_HIGH	4950	11.646	10.591	7.800	2.400	85.400	83.000
GDP	4950	38.831	32.363	25.500	12.200	279.400	267.200
EMPL	4950	106178.039	142024.541	64000.000	15600.000	1139100.000	1123500.000
SPEC	4950	1.037	1.480	0.609	0.002	18.451	18.449
FHG	4950	30.449	118.917	0.000	0.000	1051.000	1051.000
MPG	4950	49.969	255.949	0.000	0.000	3667.000	3667.000
HELM	4950	87.633	468.556	0.000	0.000	4151.000	4151.000
LEIB	4950	37.222	159.569	0.000	0.000	1478.000	1478.000
FIRMS	4950	49.758	71.758	30.000	1.000	896.000	895.000
DIVERS	4950	0.892	0.924	0.582	0.015	6.206	6.192
ENG	4950	143.699	157.950	104.214	8.362	1511.964	1503.602
NAT	4950	116.842	136.369	75.141	4.356	1166.454	1162.098
TOTAL_FUNDS	4950	250720.907	1644507.271	0.000	0.000	47467626.353	47467626.353
INDIVIDUAL_FUNDS	4950	153000.117	1025482.477	0.000	0.000	23786549.961	23786549.961
COOP_FUNDS	4950	97720.790	792845.278	0.000	0.000	27745080.931	27745080.931
COOP_PROJ	4950	1.156	5.171	0.000	0.000	121.000	121.000
INDIVIDUAL_PROJ	4950	0.658	2.446	0.000	0.000	36.000	36.000
COOP_PARTNER	4950	7.533	35.964	0.000	0.000	688.000	688.000
REGIONAL	4950	0.458	3.734	0.000	0.000	93.000	93.000
UNIVERSITY	4950	1.336	6.591	0.000	0.000	116.000	116.000
RESEARCH	4950	1.179	6.078	0.000	0.000	138.000	138.000

Descriptives for the pooled data 2000-2003

Table A.3: Descriptives

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
gEFF	(1)	1***											
EFF	(2)	-0.17***	1***										
POP_DEN	(3)	-0.04	-0.12***	1***									
EMP_HIGH	(4)	0	-0.08**	0.73***	1***								
GDP	(5)	-0.02	-0.14***	0.79***	0.84***	1***							
EMP	(6)	-0.03	-0.12***	0.75***	0.71***	0.72***	1***						
SPEC	(7)	-0.04	-0.06*	0.02	-0.01	0.07**	0	1***					
FHG	(8)	-0.02	-0.07**	0.4***	0.51***	0.44***	0.54***	0.02	1***				
MPG	(9)	-0.03	-0.05*	0.4***	0.56***	0.54***	0.6***	0.01	0.55***	1***			
HELM	(10)	0	-0.05*	0.21***	0.24***	0.22***	0.38***	-0.02	0.3***	0.33***	1***		
LEIB	(11)	-0.02	-0.03	0.26***	0.29***	0.16***	0.55***	-0.05*	0.33***	0.23***	0.25***	1***	
FIRMS	(12)	-0.06**	-0.13***	0.61***	0.62***	0.62***	0.76***	0.08***	0.46***	0.5***	0.29***	0.33***	1***
DIVERS	(13)	0.06*	0.1***	0.19***	0.36***	0.08***	0.24***	-0.08***	0.1***	0.15***	0.1***	0.44***	0.14***
R&D	(14)	-0.04	-0.06**	0.41***	0.43***	0.48***	0.53***	0.4***	0.44***	0.39***	0.14***	0.12***	0.36***
PATENTS	(15)	-0.03	-0.08**	0.42***	0.5***	0.54***	0.57***	0.19***	0.51***	0.57***	0.22***	0.14***	0.45***
ENG	(16)	-0.04	-0.14***	0.54***	0.68***	0.74***	0.72***	0.04	0.58***	0.56***	0.31***	0.19***	0.65***
NAT	(17)	-0.04	-0.14***	0.55***	0.71***	0.74***	0.71***	0.02	0.59***	0.64***	0.32***	0.23***	0.63***
TOTAL_FUNDS	(18)	0	-0.04	0.2***	0.28***	0.26***	0.33***	-0.01	0.3***	0.33***	0.14***	0.3***	0.23***
INDIVIDUAL_FUNDS	(19)	0	-0.04	0.22***	0.29***	0.31***	0.38***	-0.01	0.27***	0.38***	0.18***	0.23***	0.26***
COOP_FUNDS	(20)	0	-0.03	0.13***	0.2***	0.16***	0.2***	-0.01	0.25***	0.22***	0.08**	0.3***	0.14***
COOP_PROJ	(21)	-0.02	-0.06**	0.29***	0.35***	0.33***	0.41***	-0.02	0.38***	0.38***	0.14***	0.22***	0.3***
INDIVIDUAL_PROJ	(22)	0.02	0.02	0.28***	0.32***	0.35***	0.43***	0.01	0.27***	0.36***	0.18***	0.29***	0.21***
REGIONAL	(23)	0	-0.04	0.23***	0.28***	0.25***	0.4***	-0.01	0.39***	0.3***	0.11***	0.23***	0.29***
UNIVERSITY	(24)	-0.02	-0.06*	0.25***	0.31***	0.29***	0.38***	-0.01	0.37***	0.32***	0.12***	0.2***	0.28***
RESEARCH	(25)	-0.01	-0.05*	0.26***	0.33***	0.31***	0.39***	-0.01	0.36***	0.41***	0.14***	0.18***	0.28***
COOP_PARTNER	(26)	-0.02	-0.06*	0.27***	0.34***	0.32***	0.4***	-0.02	0.38***	0.36***	0.13***	0.19***	0.29***
		(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
R&D	(14)	1***											
PATENTS	(15)	0.82***	1***										
ENG_GRAD	(16)	0.55***	0.62***	1***									
NAT_GRAD	(17)	0.49***	0.57***	0.87***	1***								
TOTAL_FUNDS	(18)	0.08**	0.14***	0.32***	0.29***	1***							
INDIVIDUAL_FUNDS	(19)	0.13***	0.2***	0.4***	0.36***	0.86***	1***						
COOP_FUNDS	(20)	0.02	0.05	0.18***	0.16***	0.89***	0.54***	1***					
COOP_PROJ	(21)	0.08**	0.14***	0.38***	0.36***	0.68***	0.64***	0.56***	1***				
INDIVIDUAL_PROJ	(22)	0.19***	0.22***	0.4***	0.38***	0.66***	0.76***	0.42***	0.62***	1***			
REGIONAL	(23)	0.08***	0.13***	0.39***	0.34***	0.52***	0.47***	0.45***	0.8***	0.47***	1***		
UNIVERSITY	(24)	0.08**	0.14***	0.37***	0.35***	0.62***	0.6***	0.5***	0.96***	0.6***	0.84***	1***	
RESEARCH	(25)	0.07**	0.12***	0.37***	0.36***	0.63***	0.64***	0.49***	0.96***	0.6***	0.82***	0.93***	1***
COOP_PARTNER	(26)	0.08***	0.14***	0.39***	0.37***	0.65***	0.61***	0.53***	0.97***	0.59***	0.86***	0.97***	0.97***

Note that the correlation table refers to the inter-regional variance (variance across regions), which is however excluded in the panel regression.

Table A.4: Correlation table

Tables to be integrated into text

	CHEM	TRANS	ELEC	INSTR
Firms	1,381	229	390	138
Projects	2,003	565	475	206
Grants	3,232	678	515	239
Percent of subsidies projects that are cooperative	4%	10%	4%	11%
Percent of subsidized links among organizations located in the same region	6 %	4%	5%	6%
Number of regions with at least one individual project	118	117	62	43
Number of regions with at least one cooperative project	181	35	87	66

All figures based on the period 1995/01/01-2003/31/12.

Table 1: Descriptives of subsidies data

	2000	2001	2002	2003
CHEM EFF	0.22***	0.19***	0.23***	0.17***
TRANS EFF	0.15***	0.24***	0.23***	0.26***
ELEC EFF	0.14***	0.13***	0.14***	0.16***
INSTR EFF	0.41***	0.37***	0.32***	0.33***
CHEM gEFF	0.05*	0.02	0.02	0.07**
TRANS gEFF	0.11**	0.10**	0.04	0.02
ELEC gEFF	0.01	0.01	0.07**	0.01
INSTR gEFF	-0.05	-0.01	0.01	0.02
pooled gEFF	0.03**	0.03**	0.03**	0.03**

Spatial weights are estimated using a k-nearest neighbors method with k=5.

Table 2: Test for spatial autocorrelation

Year / Industry	CHEM	TRANS	ELEC	INSTR
2000	1.03	1.10	1.11	1.00
2001	0.88	0.96	0.98	1.07
2002	1.01	1.01	1.01	1.01
2003	1.02	1.01	1.05	0.98
2001-2003	1.01	1.09	1.27	1.04

Table 3: Mean rates of change in regional innovation efficiency

				Spatial panel regression (a)		
Dependent	EFF			gEFF		
Model	0	1	2	3	4	5
POP_DEN	0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
EMP_HIGH	0.014 (0.015)	0.016 (0.029)	0.016 (0.029)	0.015 (0.029)	0.017 (0.029)	0.018 (0.03)
EMPL	0.000** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
FIRMS	-0.007*** (0.003)	0.004 (0.004)	0.004 (0.004)	0.005 (0.004)	0.005 (0.004)	0.004 (0.004)
SPEC	0.114 (0.073)	-0.103 (0.135)	-0.102 (0.135)	-0.108 (0.135)	-0.11 (0.135)	-0.104 (0.136)
DIVERS	0.214* (0.109)	0.091 (0.134)	0.097 (0.135)	0.098 (0.135)	0.094 (0.135)	0.081 (0.136)
FHG	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.001)
HELM	0.001 (0.000)	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)
MPG	0.000* (0.000)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
LEIB	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
ENG	0.000 (0.001)	0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	0.000 (0.001)
2000						
2001	-0.078*** (0.03)	-0.149*** (0.034)	-0.149*** (0.034)	-0.15*** (0.034)	-0.152*** (0.034)	-0.154*** (0.034)
2002	-0.129*** (0.034)	-0.066* (0.038)	-0.066* (0.038)	-0.069* (0.038)	-0.07* (0.038)	-0.071* (0.038)
2003	-0.173*** (0.036)	-0.075* (0.04)	-0.075* (0.04)	-0.078* (0.041)	-0.08** (0.041)	-0.082** (0.041)
lag(TOTAL_FUNDS, 1)	-	-	0.000 (0.000)	-	-	-
lag(TOTAL_FUNDS, 2)	-	-	0.000 (0.000)	-	-	-
lag(TOTAL_FUNDS, 3)	-	-	0.000 (0.000)	-	-	-
lag(TOTAL_FUNDS, 4)	-	-	0.000 (0.000)	-	-	-
lag(INDIVIDUAL_FUNDS, 1)	-	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(INDIVIDUAL_FUNDS, 2)	-	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(INDIVIDUAL_FUNDS, 3)	-	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(INDIVIDUAL_FUNDS, 4)	-	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(COOP_FUNDS, 1)	-	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(COOP_FUNDS, 2)	-	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(COOP_FUNDS, 3)	-	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(COOP_FUNDS, 4)	-	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(INDIVIDUAL_PROJ, 1)	-	-	-	0.027 (0.031)	0.03 (0.031)	0.031 (0.033)
lag(INDIVIDUAL_PROJ, 2)	-	-	-	-0.07** (0.033)	-0.073** (0.033)	-0.077** (0.034)
lag(INDIVIDUAL_PROJ, 3)	-	-	-	0.035 (0.032)	0.033 (0.032)	0.022 (0.033)
lag(INDIVIDUAL_PROJ, 4)	-	-	-	-0.005 (0.028)	0.001 (0.027)	0.012 (0.029)
lag(COOP_PROJ, 1)	-	-	-	0.002 (0.015)	-	-
lag(COOP_PROJ, 2)	-	-	-	0.007 (0.019)	-	-
lag(COOP_PROJ, 3)	-	-	-	-0.007 (0.021)	-	-
lag(COOP_PROJ, 4)	-	-	-	0.000 (0.017)	-	-
lag(COOP_PARTNER, 1)	-	-	-	-	-0.001 (0.002)	-0.003 (0.005)
lag(COOP_PARTNER, 2)	-	-	-	-	0.003 (0.003)	0.004 (0.006)
lag(COOP_PARTNER, 3)	-	-	-	-	-0.001 (0.003)	-0.008 (0.005)
lag(COOP_PARTNER, 4)	-	-	-	-	-0.002 (0.001)	-0.002 (0.004)
lag(REGIONAL, 1)	-	-	-	-	-	-0.016 (0.019)
lag(REGIONAL, 2)	-	-	-	-	-	0.003 (0.021)
lag(REGIONAL, 3)	-	-	-	-	-	-0.02 (0.024)
lag(REGIONAL, 4)	-	-	-	-	-	-0.003 (0.023)
lag(UNIVERSITY, 1)	-	-	-	-	-	-0.021 (0.017)
lag(UNIVERSITY, 2)	-	-	-	-	-	0.003 (0.018)
lag(UNIVERSITY, 3)	-	-	-	-	-	0.022 (0.019)
lag(UNIVERSITY, 4)	-	-	-	-	-	0.001 (0.018)
lag(RESEARCH, 1)	-	-	-	-	-	0.037 (0.023)
lag(RESEARCH, 2)	-	-	-	-	-	-0.001 (0.024)
lag(RESEARCH, 3)	-	-	-	-	-	0.028 (0.024)
lag(RESEARCH, 4)	-	-	-	-	-	0.001 (0.024)
rho	0.277	0.302	0.291	0.263	0.264	0.277
adj. R^2	0.073	0.093	0.093	0.095	0.095	0.097
n	990	990	990	990	990	990
T	5	4	4	4	4	4
N	4950	3960	3960	3960	3960	3960

Balanced panel, standard errors in parentheses. (a) Estimation according to Stock and Watson (2008). (b) Estimation according to Kapoor et al. (2007).

Table 4: Factors impacting regional innovation efficiency, all regions

	Spatial panel regression (a)				
Dependent	gEFF				
Model	6a	7a	8a	9a	10a
POP_DEN	-0.001 (0.001)	-0.001 (0.001)	0 (0.001)	-0.001 (0.001)	-0.001 (0.001)
EMP_HIGH	-0.013 (0.023)	-0.014 (0.023)	-0.013 (0.024)	-0.016 (0.024)	-0.014 (0.024)
EMPL	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
FIRMS	0.002 (0.003)	0.002 (0.003)	0.001 (0.004)	0.001 (0.004)	0 .000(0.004)
SPEC	-0.053 (0.106)	-0.051 (0.106)	-0.048 (0.107)	-0.052 (0.107)	-0.036 (0.108)
DIVERS	0.047 (0.219)	0.062 (0.23)	0.046 (0.234)	0.052 (0.234)	-0.014 (0.24)
FHG	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
HELM	0 .000(0.001)	0 .000(0.001)	0 .000(0.001)	0 .000(0.001)	0 .000(0.001)
MPG	0 .000(0.001)	0 .000(0.001)	0 .000(0.001)	0 .000(0.001)	0 .000(0.001)
LEIB	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
ENG	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
2001	0.073* (0.043)	0.074* (0.043)	0.073* (0.043)	0.074* (0.043)	0.077* (0.044)
2002	0.054 (0.048)	0.054 (0.048)	0.051 (0.049)	0.059 (0.049)	0.066 (0.049)
2003	0.079 (0.051)	0.081 (0.051)	0.086* (0.052)	0.088* (0.052)	0.102* (0.053)
lag(TOTAL_FUNDS, 1)	-	0.000 (0.000)	-	-	-
lag(TOTAL_FUNDS, 2)	-	0.000 (0.000)	-	-	-
lag(TOTAL_FUNDS, 3)	-	0.000 (0.000)	-	-	-
lag(TOTAL_FUNDS, 4)	-	0.000 (0.000)	-	-	-
lag(INDIVIDUAL_FUNDS, 1)	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(INDIVIDUAL_FUNDS, 2)	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(INDIVIDUAL_FUNDS, 3)	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(INDIVIDUAL_FUNDS, 4)	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(COOP_FUNDS, 1)	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(COOP_FUNDS, 2)	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(COOP_FUNDS, 3)	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(COOP_FUNDS, 4)	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(INDIVIDUAL_PROJ, 1)	-	-	0.015 (0.025)	0.019 (0.026)	0.015 (0.029)
lag(INDIVIDUAL_PROJ, 2)	-	-	-0.031 (0.027)	-0.036 (0.027)	-0.036 (0.028)
lag(INDIVIDUAL_PROJ, 3)	-	-	0.019 (0.026)	0.021 (0.026)	0.017 (0.027)
lag(INDIVIDUAL_PROJ, 4)	-	-	-0.008 (0.022)	0.001 (0.021)	0.009 (0.022)
lag(COOP_PROJ, 1)	-	-	-0.003 (0.011)	-	-
lag(COOP_PROJ, 2)	-	-	-0.016 (0.016)	-	-
lag(COOP_PROJ, 3)	-	-	0.008 (0.017)	-	-
lag(COOP_PROJ, 4)	-	-	0.006 (0.012)	-	-
lag(COOP_PARTNER, 1)	-	-	-	-0.003 (0.002)	-0.003 (0.004)
lag(COOP_PARTNER, 2)	-	-	-	0.001 (0.002)	-0.001 (0.005)
lag(COOP_PARTNER, 3)	-	-	-	0.002 (0.002)	-0.004 (0.005)
lag(COOP_PARTNER, 4)	-	-	-	-0.001 (0.001)	-0.001 (0.004)
lag(REGIONAL, 1)	-	-	-	-	-0.008 (0.015)
lag(REGIONAL, 2)	-	-	-	-	0.003 (0.016)
lag(REGIONAL, 3)	-	-	-	-	-0.003 (0.017)
lag(REGIONAL, 4)	-	-	-	-	0.015 (0.017)
lag(UNIVERSITY, 1)	-	-	-	-	0.002 (0.014)
lag(UNIVERSITY, 2)	-	-	-	-	-0.02 (0.015)
lag(UNIVERSITY, 3)	-	-	-	-	0.032** (0.016)
lag(UNIVERSITY, 4)	-	-	-	-	-0.005 (0.015)
lag(RESEARCH, 1)	-	-	-	-	0.000 (0.02)
lag(RESEARCH, 2)	-	-	-	-	0.02 (0.021)
lag(RESEARCH, 3)	-	-	-	-	-0.001 (0.021)
lag(RESEARCH, 4)	-	-	-	-	0.002 (0.02)
rho	0.244	0.243	0.257	0.265	0.267
adj. R^2	0.085	0.086	0.09	0.091	0.099
n	238	238	238	238	238
T	4	4	4	4	4
N	952	952	952	952	952

Balanced panel, standard errors in parentheses. (a) Estimation according to Kapoor et al. (2007).

Table 5: Factors impacting regional innovation efficiency, large regions

	Spatial panel regression (a)				
Dependent	gEFF				
Model	11	12	13	14	15
POP_DEN	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)
EMP_HIGH	0.055 (0.052)	0.054 (0.053)	0.058 (0.053)	0.061 (0.053)	0.051 (0.053)
EMPL	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
FIRMS	0.007 (0.007)	0.007 (0.007)	0.008 (0.007)	0.008 (0.007)	0.008 (0.007)
SPEC	-0.16 (0.229)	-0.159 (0.229)	-0.167 (0.23)	-0.17 (0.23)	-0.174 (0.23)
DIVERS	0.092 (0.161)	0.093 (0.161)	0.093 (0.162)	0.097 (0.162)	0.085 (0.162)
FHG	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
HELM	-0.00004	-0.00004	-0.007 (0.005)	-0.007 (0.005)	-0.007 (0.005)
MPG	0.001 (0.001)	0.001 (0.001)	0 (0.001)	0 (0.001)	0 (0.001)
LEIB	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)	0 (0.002)
ENG	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)
2001	-0.227*** (0.045)	-0.227*** (0.045)	-0.229*** (0.045)	-0.232*** (0.045)	-0.231*** (0.045)
2002	-0.111** (0.05)	-0.111** (0.051)	-0.121** (0.051)	-0.122** (0.051)	-0.118** (0.051)
2003	-0.131** (0.055)	-0.131** (0.055)	-0.147*** (0.055)	-0.145*** (0.055)	-0.144*** (0.055)
lag(TOTAL_FUNDS, 1)	-	0.000 (0.000)	-	-	-
lag(TOTAL_FUNDS, 2)	-	0.000 (0.000)	-	-	-
lag(TOTAL_FUNDS, 3)	-	0.000 (0.000)	-	-	-
lag(TOTAL_FUNDS, 4)	-	0.000 (0.000)	-	-	-
lag(INDIVIDUAL_FUNDS, 1)	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(INDIVIDUAL_FUNDS, 2)	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(INDIVIDUAL_FUNDS, 3)	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(INDIVIDUAL_FUNDS, 4)	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(COOP_FUNDS, 1)	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(COOP_FUNDS, 2)	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(COOP_FUNDS, 3)	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(COOP_FUNDS, 4)	-	-	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
lag(INDIVIDUAL_PROJ, 1)	-	-	0.038 (0.054)	0.034 (0.053)	0.04 (0.055)
lag(INDIVIDUAL_PROJ, 2)	-	-	-0.123** (0.059)	-0.122** (0.059)	-0.123** (0.061)
lag(INDIVIDUAL_PROJ, 3)	-	-	0.04 (0.059)	0.037 (0.059)	0.036 (0.061)
lag(INDIVIDUAL_PROJ, 4)	-	-	-0.015 (0.052)	-0.021 (0.052)	-0.015 (0.056)
lag(COOP_PROJ, 1)	-	-	0.017 (0.032)	-	-
lag(COOP_PROJ, 2)	-	-	0.035 (0.034)	-	-
lag(COOP_PROJ, 3)	-	-	0.004 (0.038)	-	-
lag(COOP_PROJ, 4)	-	-	-0.01 (0.043)	-	-
lag(COOP_PARTNER, 1)	-	-	-	0 (0.005)	-0.004 (0.011)
lag(COOP_PARTNER, 2)	-	-	-	0.006 (0.006)	0.003 (0.011)
lag(COOP_PARTNER, 3)	-	-	-	-0.002 (0.006)	-0.011 (0.011)
lag(COOP_PARTNER, 4)	-	-	-	-0.003 (0.003)	-0.008 (0.008)
lag(REGIONAL, 1)	-	-	-	-	-0.037 (0.052)
lag(REGIONAL, 2)	-	-	-	-	0.168** (0.077)
lag(REGIONAL, 3)	-	-	-	-	-0.107 (0.09)
lag(REGIONAL, 4)	-	-	-	-	0.045 (0.089)
lag(UNIVERSITY, 1)	-	-	-	-	-0.032 (0.034)
lag(UNIVERSITY, 2)	-	-	-	-	0.021 (0.033)
lag(UNIVERSITY, 3)	-	-	-	-	0.016 (0.039)
lag(UNIVERSITY, 4)	-	-	-	-	0.029 (0.04)
lag(RESEARCH, 1)	-	-	-	-	0.08* (0.043)
lag(RESEARCH, 2)	-	-	-	-	-0.02 (0.043)
lag(RESEARCH, 3)	-	-	-	-	0.074* (0.043)
lag(RESEARCH, 4)	-	-	-	-	-0.004 (0.044)
rho	0.318	0.324	0.337	0.335	0.320
adj. R^2	0.098	0.098	0.102	0.102	0.107
n	752	752	752	752	752
T	4	4	4	4	4
N	3008	3008	3008	3008	3008

Balanced panel, standard errors in parentheses. (a) Estimation according to Kapoor et al. (2007).

Table 6: Factors impacting regional innovation efficiency, small regions

Appendix: Figures

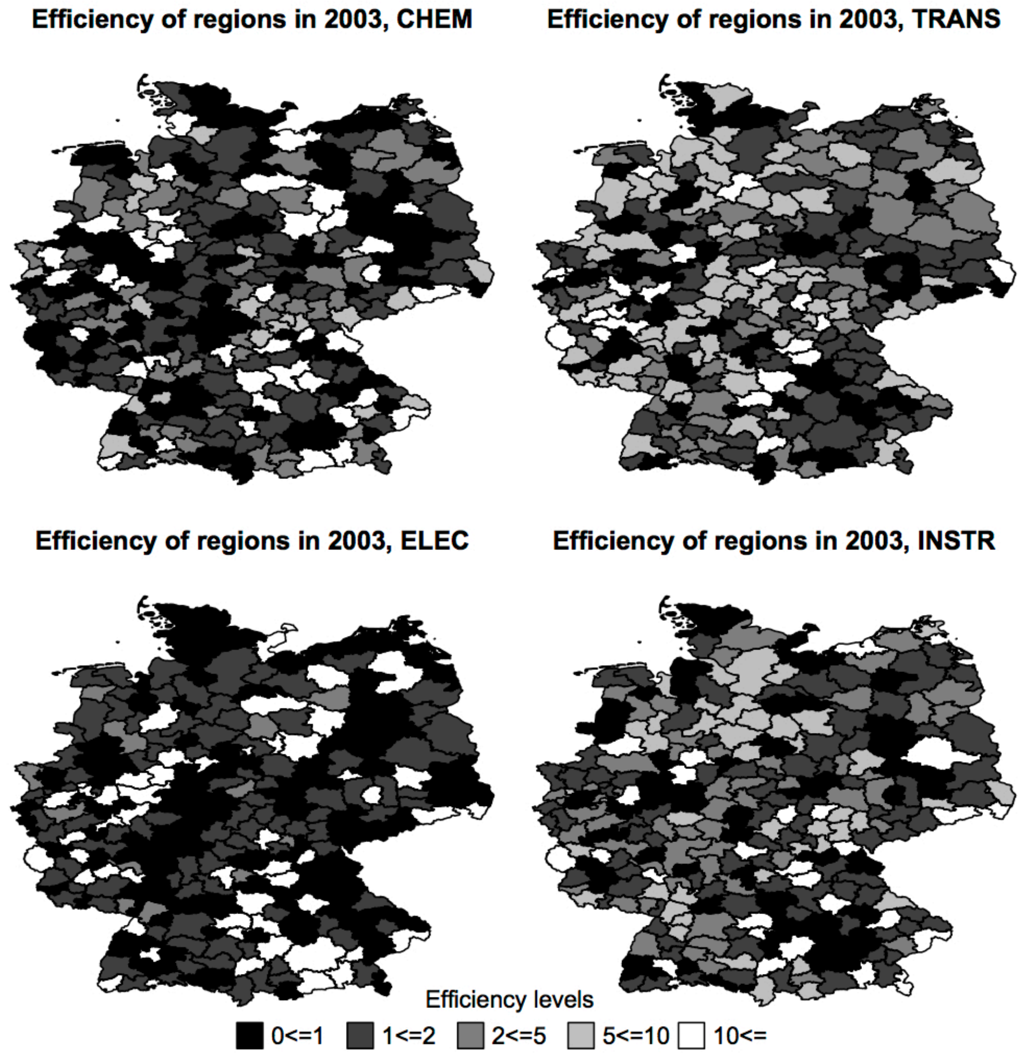

Figure 1: Efficiencies of German LMR

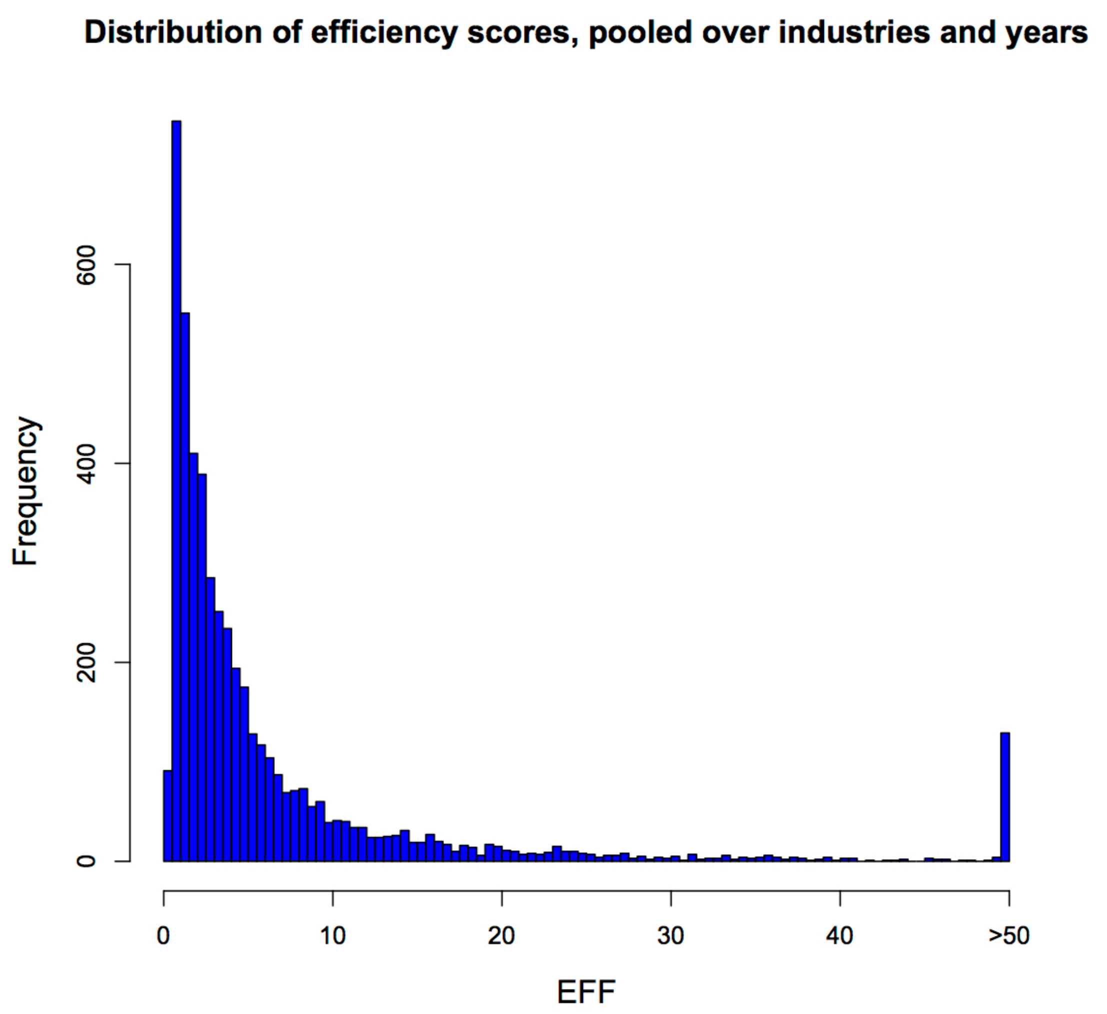

Figure 2: Distribution of innovation efficiency, pooled over years and industries

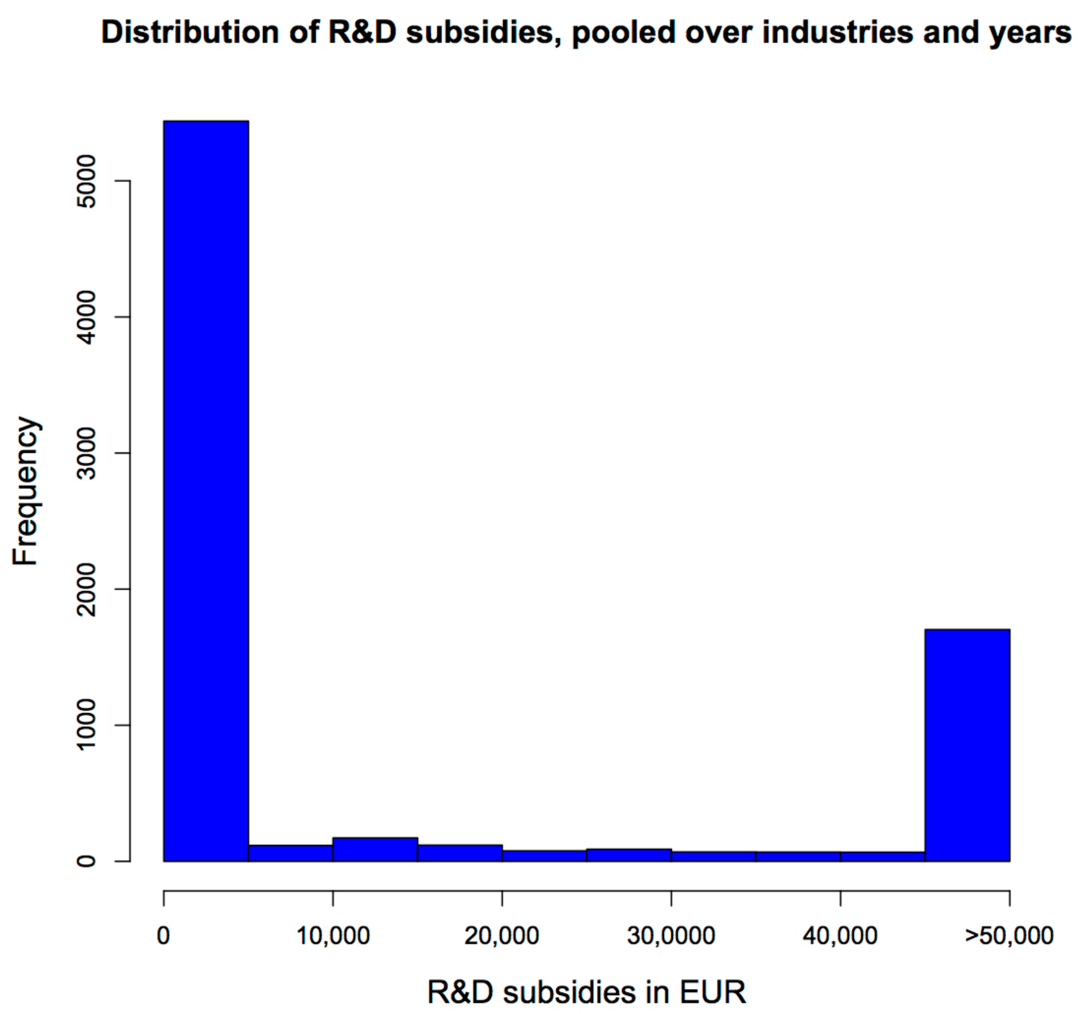

Figure 3: Distribution of R&D subsidies, pooled over years and industries

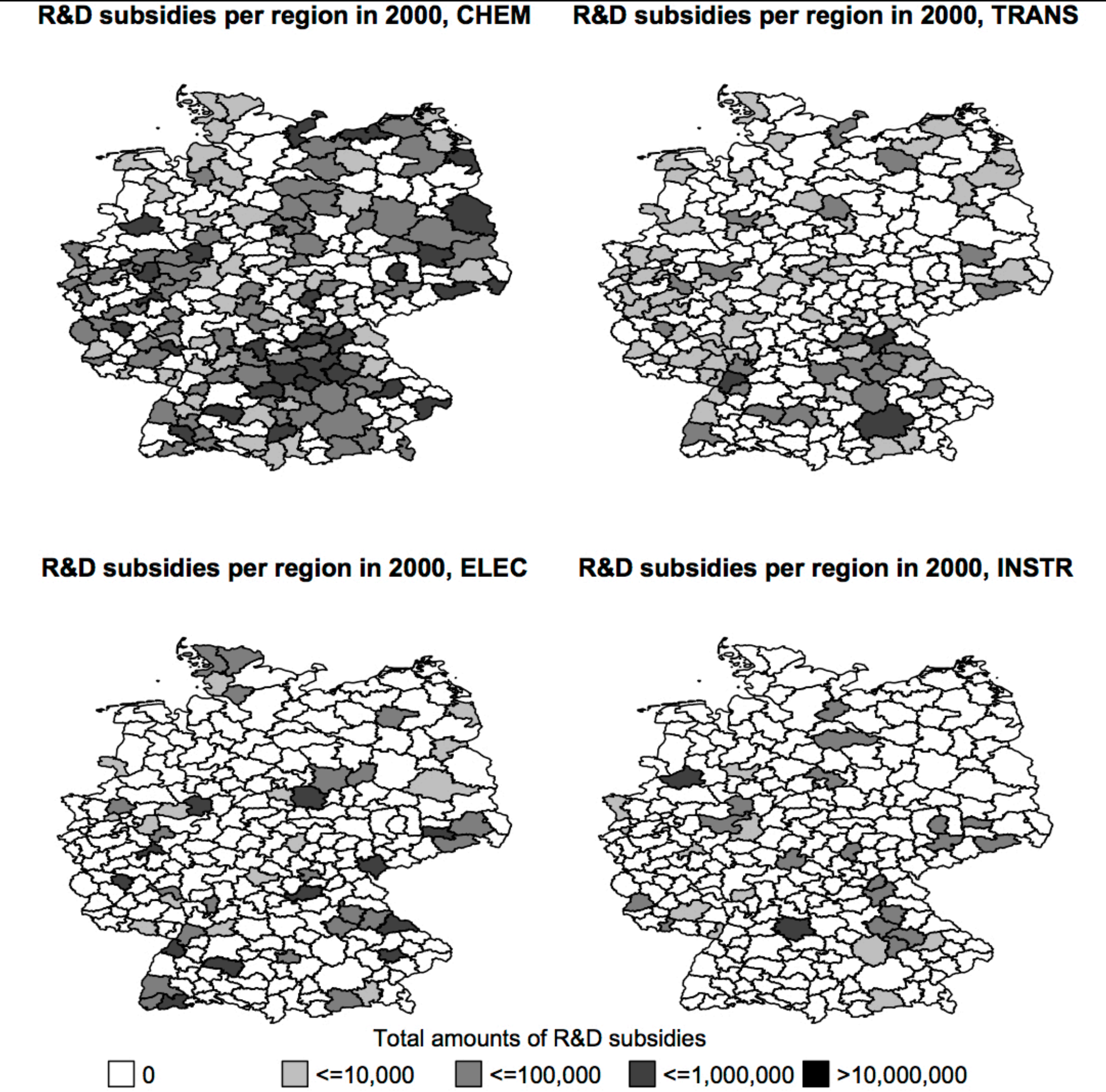

Figure 4: R&D subsidies in German labor market regions