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Do cooperative R&D subsidies stimulate regional innovation efficiency? Evidence from Germany

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Abstract

The paper investigates the impact of R&D subsidies on regional innovation efficiency. Building on a rich panel data set covering 270 German labor market regions and four industries, it is shown that in particular subsidies for R&D cooperation are a suitable policy measure for stimulating the innovation efficiency of regions. The empirical findings moreover suggest that regions with low innovation capacities benefit from subsidized inter-regional cooperation involving partners with diverse industrial and sectoral backgrounds. Establishing inter-regional cooperation that give access to related knowledge and skills is more important for regions with large innovation capacities.

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

JEL classification: O18, O38, R12

1 Introduction

Regions play a crucial role in innovation processes and consequently it is argued that they should be in the focus of innovation policy (see, e.g., Storper, 1995; Cooke et al., 1997). Policy is responding to this argument with an increasing number of regionalized programs supporting technological development and innovation. A frequent feature of such programs is the stimulation of cooperation and interaction, 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 cooperation between organizations active in biotechnology (Eickelpasch and Fritsch, 2005).

In recent years cooperative elements have also become more and more prominent in non-regionalized policy programs that primarily aim at the advancement of particular technological fields or support for individual firms. For instance, the granting of R&D subsidies is frequently made conditional on a cooperative research design. This implies that consortia of organizations realize joint projects. Consequently, R&D subsidies do not only provide monetary incentives for innovating, they also influence organizations' cooperation behavior. By encouraging knowledge sharing between members of joint projects, cooperative R&D subsidies moreover embed organizations and regions into (subsidized) knowledge networks.

Strong empirical evidence exists that R&D subsidies stimulate firms' innovation activities (see, e.g., Czarnitzki et al., 2007). Similar applies to the embeddedness of firms into knowledge networks, which is shown to be essential for their innovative success (Powell et al., 1996; Boschma and ter Wal, 2007). In addition, many studies on regionalized policy programs also highlight that support for intra-regional cooperation is particularly beneficial for innovation (Eickelpasch and Fritsch, 2005). However, limited research exists analyzing whether R&D subsidies are an effective policy measure for regional development. In addition, little is known about the contribution of knowledge networks established by subsidized cooperative research to regions' 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 knowledge networks on regional innovation efficiency.

The empirical assessment builds on a panel dataset for 270 German labor market regions and four industries covering the period 1999-2004. Moreover, nonparametric efficiency, social network, and spatial panel regression methods are employed.

The study shows that regions with below average innovation capacities benefit primarily from subsidizing inter-regional cooperation that gives access to a wide variety of knowledge and skills. In case of regions with above average innovation capacities, the stimulation of inter-regional cooperation is only supportive when partners in related technological fields are involved. In contrast, subsidizing intra-regional cooperation yields negative effects.

The paper is organized as follows. In Section 2 theoretical considerations are made on the effects of R&D subsidies on innovation activities. The empirical approach is subject to Section 3. Section 4 provides the description of the data. The results are presented and discussed in Section 5. Section 6 concludes.

2 Cooperative R&D subsidies and innovation

Innovations are crucial for long-term growth and wealth, however they are unequally distributed in geographic space with some regions achieving higher levels of innovation than others (Feldman, 1994). While the largest portion of this heterogeneity can be attributed to the spatially skewed distribution of R&D capacities (investments into R&D) some regions are also more efficient in exploiting their R&D capacities (Fritsch, 2000).

There are numerous reasons for this variance. Concepts like the *innovative milieu* and *regional innovation system* particularly stress that some regions benefit from collective learning processes among regional organizations (see, e.g., Aydalot and Keeble, 1985; Cooke, 1992). These regional learning processes involve intensive knowledge sharing and collaboration, which stimulate innovation. Moreover, it is not only intra-regional collaboration that matters: Firms need to be embedded into different types of knowledge networks that may or may not be geographically structured. Bathelt et al. (2004) argue that it is the simultaneous participation in "local buzz" and "global pipelines of knowledge" that determines innovative success. In addition, it is crucial with whom firms collaborate as only access to "related variety" fosters innovation because some overlap in knowledge is necessary for effective communication, while there needs to be enough variety for the creation of novelty (Frenken et al., 2007).

Policy responds to these scientific insights in multiple ways. For example, regionalized policy programs are frequently designed to stimulate intra-regional cooperation. In Germany, programs like the *BioRegio*, *InnoRegio*, or *InnoNet* belong to this category. In such programs, public support is granted to self-organized cooperation in R&D among organizations located within a particular region (Eickelpasch and Fritsch, 2005). While this type of support still has some drawbacks "it goes into the right direction by taking the regions seriously and giving prominence to the well-functioning interplay of the various elements of regional innovation systems" (Dohse, 2000, p. 1111).

Policy also puts more weight on cooperative elements in R&D support programs. This applies particularly to the subsidizing of R&D activities: Joint projects are supported to a growing extent, while the relative importance of subsidies for projects realized by individual firms continuously decreases. For example in Germany, about thirty percent of today's subsidized R&D projects are joint projects

(Broekel and Graf, 2010). These joint projects involve significant knowledge sharing between the partners (Broekel and Graf, 2010).

A rich literature evaluates the effects of R&D subsidy programs. Focusing primarily at the firm level, studies investigate their impact on firms' R&D efforts (Busom, 2000), employment growth (Brouwer et al., 1993), as well as on collaboration and patenting activities (see, e.g., Czarnitzki and Hussinger, 2004). For the German biotech industry Fornahl et al. (2010) moreover show that in particular collaborative R&D subsidies matter for firms' patent activities. These authors also provide evidence that some but not too much cognitive distance between organizations involved in subsidized R&D collaborations increase their innovative success.

In contrast to the rich literature focusing on firm-level effects, less is known about the relation between R&D subsidies and regional development. In particular, little research exists evaluating if this policy measure represents a suitable tool for stimulating regional innovation performance. While it is well-accepted that cooperation are crucial for innovation (Powell et al., 1996; Boschma and ter Wal, 2007), research primarily focused on "unsubsidized" interactions, i.e. cooperations without policy being directly involved. Accordingly, the question remains if the embeddedness of regional organizations into *subsidized* cooperation networks also influences their innovation activities. Differences to unsubsidized cooperation can be expected to exist, since policy defines the general conditions of cooperating in the subsidies programs and selects a limited number of proposals that are granted making subsidized cooperation likely to be very different from unsubsidized cooperation. The present paper aims at shedding light on these issues by adopting a regional perspective and evaluating the effectiveness of the policy tool 'R&D subsidies' for stimulating regional innovation performance with a particular focus on the relevance of subsidized joint projects (cooperative subsidies). In the following, four hypotheses are put forward, which provide the basis of the empirical evaluation.

Given the rather positive role for innovation attributed to cooperation, it can be expected that cooperative subsidies are particularly effective for stimulating innovation. Accordingly, the more regional organizations engage in subsidized cooperation the more likely they profit from knowledge sharing, which gives them higher chances of innovative success. However, cooperation is not always beneficial. The establishment and maintenance of cooperation agreements require efforts and many cooperation fail (Bleek and D.Ernst, 1993). Free-riding is also a known problem (Kesteloot and Veugelers, 1995), so are "learning races between the partners [...], diverging opinions on intended benefits [...] and a lack of flexibility and adaptability" (Faems et al., 2005, p. 240) that can reduce potential positive effects. Nevertheless, the first hypothesis emphasizes the potential benefits of cooperation.

Hypothesis 1 : Cooperative subsidies induce greater positive effects than non-cooperative subsidies on regional innovation performance.

It is frequently argued that cooperation is especially profitable when partners are located in geographic proximity, i.e. when they are located within the same region (Audretsch, 1998). Cooperative subsidies may therefore be particularly rewarding if they promote the emergence of regional collective learning processes (Isaksen, 2001).

Hypothesis 2 : Subsidizing cooperation among regional organizations yields greater benefits than support for cooperation between organizations located in different regions.

As pointed out before, being engaged in a subsidized joint project involves substantial knowledge sharing among cooperating partners. Therefore, participation in a joint project can be interpreted as 'knowledge link' between two organizations implying that all observed links constitute a knowledge network (Broekel and Graf, 2010). Accordingly, regions that are highly central in this network are likely to profit the most from knowledge spillovers because they have higher chances of gaining access to novel knowledge generated elsewhere (Freeman, 1979). However, Fornahl et al. (2010) show that firms being located in a region with many links experience negative effects for innovation. A region can be central in a network without necessarily having a great number of links, though. This is the case if it holds a 'brokerage' position in the sense that it can 'control' knowledge flows through the network (Freeman, 1979). For instance, for knowledge to diffuse through the network it has to pass certain bottlenecks, which can be regions that connect very distinct parts of the network and that link areas of the network that are otherwise unconnected.

Hypothesis 3 : Having many links to other regions is not improving innovation performance. Rather regions that hold brokerage positions gain the most from participating in subsidized cooperation networks.

Cooperation is only beneficial if partners can communicate with each other and if their knowledge can be combined in novel ways. Boschma and Frenken (2009) argue that it depends on the (optimal) level of cognitive proximity whether cooperation will yield positive effects on innovation performance. Accordingly, to be positive cooperative subsidies need to give access to 'related variety'.

Hypothesis 4 : To improve regional innovation performance, subsidized R&D cooperation need to link regional actors to 'related' competences and knowledge.

To empirically test the four hypotheses a two-stage procedure is chosen. This approach is frequently applied in studies investigating the impact of environmental factors on firm productivity. It has also been used in settings similar to the present one (see Fritsch and Slavtchev, 2008). In a first stage, regions' 'innovation efficiency' is estimated to obtain a regional innovation performance index. In the subsequent second stage, factors (e.g. R&D subsidies) are tested for their relationship with this index using a panel regression framework.

3 Two-stage empirical approach

3.1 First-stage: nonparametric efficiency analysis

The innovation performance of regions is commonly evaluated in a knowledge production function framework (see, e.g., Griliches, 1979). 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 of as the efficiency with which knowledge inputs are transformed into innovative outputs (Brenner and Broekel, 2011).
For the empirical estimation of this regional innovation efficiency, the robust version of the traditional Data Envelopment Analysis (called *convex order-m* in the following) is employed as introduced by Daraio and Simar (2007b). It is a kind of non-parametric frontier technique, which has been advocated in this context by Bonaccorsi and Daraio (2006). Compared to parametric approaches nonparametric techniques yield a number of advantages. Most crucially, they do not require the specification of a parametric model, which significantly reduces the danger of model misspecification. From a practical perspective, they also allow the simultaneous consideration of multiple input and output indicators (see for a discussion Coelli and Perleman, 1999).
The convex order-m analysis is a non-deterministic approach and little sensitive to outliers and noise in the data (see for more details Daraio and Simar, 2007a). The measure builds upon its non-convex counterpart, namely the order-m analysis developed by Cazals et al. (2002). The basic idea of the later is to examine for each region whether there exists a region that achieves higher levels of output (Y) among m randomly drawn regions with equal or less inputs (X). The distance between the highest level of output observed among the m regions and that of the respective region defines its level of efficiency. Repeating this procedure a great number of times and averaging the estimated distances mitigates the influence of

outliers. Accordingly, a region's level of output is benchmarked against the expected maximal value of output achieved by regions with equal or less levels of input (output-orientation).[1]

In practice, the non-convex order-m measure can be computed the following (for a detailed description see Daraio and Simar (2007b)): $Y^1, ..., Y^m$ are m randomly drawn observations[2] (regions) with $X \leq x_0$. The non-convex order-m efficiency measure $\tilde{\lambda}_m(x_0, y_0)$ is defined by:

$$\tilde{\lambda}_m(x_0, y_0) = \underset{i=1,\ldots,m}{max} \left\{ \underset{j,\ldots,q}{min}\left(\frac{Y_i^j}{y_0^j}\right) \right\} \tag{1}$$

with $Y_i^j(y_0^j)$ being the j^{th} component of Y^i (of y_0 respectively). In order to obtain the final $\tilde{\lambda}_m(x_0, y_0)$, Cazals et al. (2002) suggest a simple Monte-Carlo algorithm in which $\tilde{\lambda}_m(x_0, y_0)$ is estimated B times, where B is large (200). The order-m efficiency measure of region (x_0, y_0) is then defined as

$$\hat{\lambda}_m(x_0, y_0) = E[\tilde{\lambda}_m(x_0, y_0)|X \leq x_0] = \frac{1}{B}\sum_{b=1}^{B} \tilde{\lambda}_m^b(x_0, y_0) \quad . \tag{2}$$

However, in the context of this paper, a convex concept of efficiency is more appropriate because substitutive relationships clearly exist among the output and input indicators. According to Daraio and Simar (2007b) a convex order-m efficiency measure $(\tilde{\lambda}_m^c(x_0, y_0))$ is obtained by projecting all empirical observations on the above estimated non-convex order-m frontier and solving the following program:

$$\tilde{\lambda}_m^c(x_0, y_0) = inf \left\{ \begin{array}{l} \lambda | \lambda y \leq \sum_{i=1}^{n} \gamma_i \hat{Y}_{m,i}^{\delta} \;\; ; x_i \sum_{j=1}^{n} \gamma_i x_i \\ \text{for } (\gamma_1, \ldots, \gamma_n) \text{ s.t. } \sum_{i=1}^{n} \gamma_i \;\; \gamma_i \geq 0, \; i = 1, \ldots, n \end{array} \right\} \tag{3}$$

with $\hat{Y}_{m,i}^{\delta}$ being 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 and the consideration of statistical noise in the data. 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.

[1] One may also ask for the necessary reduction in inputs (input-orientation). It is argued that the output-orientation is more appropriate because the aim is to identify obstacles that hinder regions in achieving "maximal" innovation output.

[2] m can be seen as a trimming parameter, which defines the estimations sensitivity to statistical noise in the data. The best results are achieved with $m = 85$, which implies that about ten percent of the observations show efficiency values less than one.

3.2 Second-stage: panel regression and endogeneity

In the second stage, the first-stage efficiency scores serve as dependent variable in a panel regression testing the its relation with subsidies and control variables. However, the relationship between subsidies and regional innovation efficiency is not mono-directional, though, implying that this straightforward approach might be troubled by endogeneity. The likelihood with which a region, i.e. its organizations, attracts subsidies is not independent of its innovation performance[3]. 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. Hence, it cannot be ruled out that the level of received subsidies is independent of a region's innovation performance, which is however a necessary requirement for the regression analysis. This endogeneity problem is addressed in multiple ways.

Firstly, regions' innovation performance is conceptualized as innovation efficiency. While policy can easily observe total innovation output (e.g. 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 regions' innovation efficiency than on the total regional innovation output. In practice however, innovation efficiency is often correlated to the total innovation output implying that endogeneity cannot completely be ruled out.

Secondly, potential endogeneity is reduced by using a time lag between subsidies and the estimated regional innovation efficiency.

Thirdly, instead of analyzing the relation between subsidies and innovation efficiency *levels*, the relative *change* in innovation efficiency is related to previous *change* in subsidies, i.e. the estimation is based on 'growth' rates. Nevertheless, endogeneity can still be an issue insofar as innovation efficient regions show different growth patterns than less efficient regions. In this case, these two types of regions can become subject to different granting regimes when the subsidization policy pursuits a convergence or divergence strategy, which would (re-)introduce endogeneity.

Fourthly, the latter issue is dealt with by employing a fixed effects regression. The demeaning of the rates of change eliminates potential trends in the changing of subsidies and innovation efficiency variables. Accordingly, the analysis tests to what extent deviations from the average rate of change in regional subsidies correlate to the variance in regions' trend-corrected change in innovation efficiency a number of years later.

Lastly, a regions' level of innovation efficiency is considered as additional indepen-

[3] Blanes and Busom (2004) evaluate firm-level factors that determine a firm's decision to apply for subsidies.

dent variable, which captures any remaining correlation between the dependent variable and the level of regional innovation efficiency.

This research design does not only minimize potential endogeneity, it also controls for potential spurious correlation existing between innovation efficiency and subsidized R&D cooperation. The data at hand covers only subsidized cooperation leaving all unsubsidized cooperation unobserved. However, the latter can also be important: If subsidized cooperation merely represents unsubsidized (and here unobserved) cooperation spurious correlation biases the interpretation. It seems reasonable to assume that firms' embeddedness into (unsubsidized) knowledge networks is changing relatively slower over time and, what is more important, it is unlikely to change simultaneously with subsidized cooperation. Under this assumption, in particular points three and four from above minimize this problem.

The rate of change of all variables that are based on subsidies data are straightforwardly estimated by:[4]

$$\triangle subs_{t+1} = log(subs_{t+1}) - log(subs_t) \tag{4}$$

The later introduced control variables are taken in levels because they rather impact long-term developments and change only little in the considered time period.

A region's innovation efficiency changes over time because of various reasons. For instance, regions can catch-up by decreasing their distance to the best-practice frontier. However, they can also become more or less efficient without any change in their input $\times$ output relation because of shifts in the frontier's location. An increase in the level of input can additionally yield higher efficiency if scale effects are present.

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, it is the most relevant type of efficiency change because it abstracts from non-region specific processes, e.g. technological progress in innovation creation, economy wide shocks, economies of scale, etc. 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 if a region is catching-up or falling behind.

According to Wheelock and Wilson (2003) the change in technical order-m efficiency is defined by

$$\triangle \lambda_m^c = \frac{\lambda_m^c(x_0^{t+1}, y_0^{t+1} | T_m^{t+1})}{\lambda_m^c(x_0^t, y_0 t | T_m^t)} \tag{5}$$

[4] The logs of zero values are estimated by adding a constant equal to the half of the minimum positive value of the variable under consideration.

with T_m^t and T_m^{t+1} indicating the 'technological' conditions in period t and $t + 1$, respectively.[5] 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 $\times$ output relations in period t. The inverse of this rate of change is used in the estimations to ensure that large values indicate improvement and low values decrement of innovation efficiency.

4 Data

4.1 Innovations, patents, and R&D

The units of analysis are the 270 German labor market regions that have been used in related studies (see, e.g., Buerger et al., 2010). These regions are defined by the German Institute for Labor and Employment (Institut für Arbeit und Beschäftigung, IAB) and reflect the spatial dimension of labor mobility in Germany (Haas, 2000). Moreover, they correspond to spatial constraints in firms' search for cooperation partners (Broekel and Binder, 2007). Hence, a significant portion of knowledge spillovers is captured by this level of spatial disaggregation. When using patent data it is also important that an inventor's residence and work place tend to be located within the same labor market region (Greif and Schmiedl, 2002).

For the estimation of regional innovation efficiency, the number of regional patent applications approximate the output of innovation activities.[6] The number of R&D employees represent the regional knowledge input (Fritsch and Slavtchev, 2008). The regionalized data on patent applications for the years 1999-2003 are published by the German Patent Office in Greif and Schmiedl (2002) and Greif et al. (2006). The patents are assigned to labor market regions according to the inventor principle. They are classified according to 31 technological fields (TF). The applications by public research institutes (e.g. universities and research organizations) and those of private inventors are not included because the R&D employment data covers only industrial R&D.

R&D employment numbers are obtained from the German labor market statistics, which covers all employees subject to social insurance contribution. They are organized according to the international NACE classification. In a common manner a time lag of two years is assumed between R&D efforts and the patent applications (Fritsch and Slavtchev, 2006) implying that patent data for the years 2001 to 2005

[5] Technological conditions refer to the general way innovations are created in a particular year.

[6] Patent applications actually represent inventions rather then innovations and therefore speaking of 'invention efficiency' might be more appropriate in this context. However, 'innovation efficiency' is used to stay consistent with the literature (see, e.g., Fritsch and Slavtchev, 2008).

is matched to R&D employment from 1999 and 2003.
When relating patent information to R&D activities significant inter-industrial differences have to be taken into account concerning the innovation productivity of R&D employees and patent propensity (Arundel and Kabla, 1998). For this reason is the innovation efficiency separately estimated for a number of industries. This 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 combinations of technological fields (TF) and NACE codes are presented in Table 1 in the Appendix. Accordingly, the manufacturing sector is disaggregated into five industries of which four are used here: 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 the considered industries patenting represents an important property rights protection mechanism (Arundel and Kabla, 1998) ensuring that the innovation output measure captures most, or at least a significant share, of their innovations. Utilizing the possibility to consider 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.

4.2 Regional control variables

A number of control variables are considered in the second stage regression. Most of these are commonly considered in similar studies, which is why they are only briefly presented. Urbanization economies are frequently shown to enhance firms' innovation performance (Greunz, 2004). They are approximated by population density (POP) and the gross-domestic product (GDP) of a region. The availability of highly qualified human capital also plays a significant role for firms. For this reason, the share of employees with high qualifications (HIGH) enters the analysis. The three variables are taken from the German statistical office.
Industrial agglomeration can stimulate knowledge spillovers, which in turn foster innovation (Feldman and Audretsch, 1999). The location coefficient of the considered industry's employment accounts for a region's degree of specialization with respect to the analyzed industry (SPEC). In addition, the absolute regional employment of the industry is taken into account (EMPL). To control for clustering effects the variable FIRMS is specified as the number of regional firms in the respective industry (Brenner, 2004).
Geographic proximity to firms of other industries can furthermore stimulate innovation activities through exchange of complementary knowledge and labor mobility

(Combes, 2000). Therefore the inverted-Hirschman-Herfindahl index is estimated on the basis of each industry's own employment and the employment of other manufacturing industries in a region. The resulting variable (DIV) captures potential effects emerging from diversification advantages.

Universities and technological colleagues are amongst the most important elements of a region's technological infrastructure. The regional number of graduates of engineering and natural sciences & math approximate their influence. The graduates' mobility patterns are considered explicitly because a certain share moves to other regions after obtaining their degree (Mohr, 2002). Faggian and McCann (2006) show that considering graduates' mobility patterns approximates the majority of spatial spillovers between public research institutes and firms. Following Broekel and Brenner (2007) the numbers of graduates are therefore distributed across regions such that a region's probability to obtain another regions' graduates depends positively on its population and hyperbolically negative on the geographic distance between the regions. Two variables are created on this basis: the spatially distributed numbers of engineering graduates (ENG) and the spatially distributed numbers of natural science & math graduates (NAT).

Public research institutes also constitute important cooperation partners and knowledge spillover generators. They 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 year.

As was previously pointed out, the control variables enter the second-stage regression not in rates of change but in levels. Most of these variables' distributions are strongly skewed wherefore they are logarithmized. The descriptives are presented in Table 5 in the Appendix.

4.3 Cooperative and non-cooperative R&D subsidies

Like in most other advanced countries the German federal government is actively supporting public and private research and development activities with subsidies. For example, in 2008 about 9,126,670,000 Euro were spend on this measure (BMBF, 2008a). While the Federal Ministry of Education and Research (BMBF) is the primary 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). It lists detailed information on more than 110,000 individual grants supported between 1960 and 2009. Amongst this information are a grant's starting and ending date, a title including a short description, the granting sum, the name and location of the receiving organization, as well as a technological classification key.

The title of the project contains information on the cooperative nature of projects. More precise, cooperative (joint) projects are labeled as "Verbundprojekt" or "Verbundvorhaben". Organizations that participate in such projects agree to a number of regulations that guarantee significant knowledge exchange between the partners (see more details Broekel and Graf, 2010). For instance, within the scope of the project partners grant each other a positive and free-of-charge covenant of their know-how and intellectual property rights. Moreover, partners can make unrestricted use of the project's results and they also formally subscribe to cooperation being the core working principle of the project (BMBF, 2008b). Accordingly, two organizations are defined to cooperate if they participate in the same joint project. Joint projects are manually identified on the basis of their title whereby the highest level of project disaggregation is chosen, i.e. in joint projects with multiple work packages two organizations are defined to cooperate only if they participate in the same work package.

A major issue in the evaluation of subsidies' effects is the correct specification of the time lag between received grants and potential patent applications emerging from the supported projects. According to Fornahl et al. (2010), a reasonable time lag between R&D subsidies and patents should encompass three to four years. On this basis, all subsidized projects are extracted form the database that ended after 01.01.1995 but started before 31.12.2001. This applies to more than 33.000 individual grants related to 23,000 projects received by more than 8,500 organizations.[7] In order to match the subsidies to the four industries, NACE codes are manually assigned to each receiving organization using the databases LexisNexis (LexisNexis, n.d.) and CreditReform (CreditReform, n.d.). From these databases one to three 2-digit NACE codes are extracted indicating firms' most important (industrial) activity fields. In absence of this information, the classification is done on the basis of organizations' webpages. Non-profit organizations (universities, research institutes, associations, etc.) are uniquely classified because they cannot be easily matched with the NACE industrial classification. The information on locations (community) in the database was employed to regionalize the data. Some descriptives of the obtained data are presented in Table 2.

- Table 2 about here -

Regional cooperation networks are constructed on the basis of regionally aggregated inter-organizational links. On this basis, the following regional variables

[7] Organizations are defined as unique combinations of a receiving organization's name ("Zuwendungsempfänger") and community code (Broekel and Graf, 2010).

are created separately for each industry and year. To test **hypothesis 1**, the variable SUBS is estimated representing the yearly amount of subsidies acquired by regional firms. Since a project's starting and ending date are known a grant's average amount of subsidies per day is estimated and re-aggregated into an annual figure taking into account the exact granting period (in days) per year. This figure is split into the sum of non-cooperative subsidies (SUBS) and the sum of cooperative subsidies (CSUBS).

In order to assess **hypothesis 2** the variable INTRA is defined capturing the intensity of intra-regional cooperation. It measures the number of links among organizations located in the same region. The focus of cooperation activities on either intra or inter-regional connections is approximated with the share of intra-regional links on total links (S_INTRA). High values of S_INTRA suggest a strong inward (intra-regional) orientation of cooperation activities while low values are obtained when organizations primarily concentrate on inter-regional linkages.

For the evaluation of **hypothesis 3** a region's centrality in the cooperation network is estimated in multiple ways. First, the variable DEG represents the number of other regions a region is linked to. It is equivalent to a region's degree centrality in the subsidized R&D cooperation network. An additional variant of this variable includes information on the intensity of these contacts. W_DEG is estimated as the total number of connections by regional organizations and represents a region's degree centrality in the valued (weighted) cooperation network. Betweenness centrality is additionally considered. It measures if a region holds a 'brokerage' position in the network. The variable BETWEEN captures the extent to which shortest paths linking other regions 'run' through this region (Wasserman and Faust, 1994). Again, a variant is calculated on the basis of the valued network (W_BETWEEN).

It is beyond the scope of the paper to adopt complex measures of technological relatedness used at the firm level to the regional level (see, e.g., Neffke et al., 2008). A more simple approach is chosen instead. To test **hypothesis 4** two types of cooperation networks are constructed. The first network considers only links between *firms* of the respective industry, i.e. it represents subsidized *intra-industrial* cooperation. Figure 2 in the Appendix exemplarily shows this network for INSTR in 1999. The second network additionally includes firms' links to all *other types of organizations*, e.g. other industries' firms, universities, research institutes, and associations. Accordingly, the second network includes organizations with a greater variety of technological and institutional backgrounds. With the exception of betweenness centrality, the previously presented variables are estimated for both networks. In case of the second network, betweenness centrality cannot be estimated because this measure requires a full network, which cannot be created because the sample of regions with firms in the considered industry does not coin-

cide with sample of regions their contacts are located. To mark the differentiation between the two networks, all variables based on the first (intra-industrial) network are indicated by the prefix 'IND_'.[8]
As pointed out in Section 3, all subsidies variables are transformed into rates of change using Equation 4 and denoted with a 'g' in front of the variable name. The descriptives of the resulting variables are presented in Table 5 in the Appendix. The correlation structure is shown in Table 6. This table also includes their correlation to a dummy indicating the location of a region in East Germany (EAST). The correlations with this dummy confirm that regions in East Germany show somewhat different cooperation behavior as well as lower innovation efficiency (Fritsch and Graf, 2010).

5 Empirical Results

5.1 Regional innovation efficiency

The obtained innovation efficiency scores are briefly presented before the relationship between subsidies and regional innovation efficiency are analyzed.

- Figure 1 about here -

In the efficiency analysis all regions are excluded with zero R&D employment in at least one year because the efficiency values for zero-input observations are meaningless. This reduces the total sample from $5,400$ (4 industries $\times$ 270 regions $\times$ 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 a number of extremely large values ($EFF > 100$).[9] The median is 3.01 and 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), i.e. 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).
It is also interesting to compare the shares of regions found efficient (efficiency values below or equal to 1). For ELEC it is 25%, for CHEM 21%, for INSTR 12%, and for TRANS just 7%. Accordingly, there are relatively fewer 'star' regions in TRANS than in the other industries. In general, the most efficient regions correspond to the 'usual suspects'. For example, in ELEC, Munich, Stuttgart, and Erlangen show efficiency scores below one. However, regions like Reutlingen and Ludwigshafen are also among the top-performers.

[8] Accordingly, the variables BETWEEN and W_BETWEEN remain undefined.
[9] 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.

The map in Figure 1 shows the spatial distribution of innovation efficiency for INSTR in 2003. It highlights two things. First, it visualizes the lower efficiency of East German regions, which is inline with the findings by Fritsch and Slavtchev (2008). Second, inefficient regions seem to be geographically clustered. A Moran's I test on the industries' efficiency scores confirms this for all four industries, see Table 3.

- Table 3 about here -

With few exceptions, regions with the strongest improvement in innovation efficiency are small in terms of patent output and not surprising, 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 level of efficiency. The distribution is less skewed, though: the mean is 1.432 and median 1.012. 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 (see Table 4).

- Table 4 about here -

In three of the four industries the burst of the '.com' bubble can be observed in 2001, which reduced innovation output as well as innovation efficiency. East German regions tend to show slightly higher improvement in two of the four industries (TRANS & ELEC).[10] Two mechanisms can explain this observation. First, regions in East Germany are able to catch-up to regions in the West. Second, regions in East Germany show lower mean innovation efficiency, which might make it easier to achieve higher rates of improvement. While there is some empirical support for the first argument (see, e.g., Fritsch and Graf, 2010), the second cannot be ruled out.

With the exception of INSTR, all industries' rates of change are significantly positive spatially correlated 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

For the second-stage regression all industry-specific data is pooled to increase the number of observations, which is necessary because the use of rates of change is reducing the number of observational periods from five to four. In a first model the change in efficiency is related to the control variables. Given the high correlation between HIGH and GDP as well as between ENG and NAT (see Table 6 in the Appendix), GDP and NAT are excluded because of their relatively smaller

[10] The t.test as well as a Wilcoxon test are significant at the 0.10 level.

relevance. All control variables are log transformed because they are measured at different scales and show a positive skew. The dependent variable, change in innovation efficiency, is also log transformed because of its strongly skewed distribution. Differences between industries and regions are accounted for with the fixed effects estimation.[11]

As previously pointed out, the dependent variable is plagued by spatial correlation. In a standard fixed effects panel regression this translates into spatially correlated error terms.[12] A BSJK conditional LM (C.1) test reveals that this should be taken into account (Baltagi et al., 2007).[13] Accordingly, a spatial panel fixed effects model is used for the second-stage regression (see, e.g., Elhorst, 2009).

Regional patent statistics often exhibit significant distortion and fluctuation at the lower bound (Buerger et al., 2010). This means that for regions with few patents, patent growth rates and change in innovation efficiency are strongly variable. This distortion may bias the estimations because regions with few patent numbers represent the majority of observations: the median of the industry specific patent output is 5.36, while the mean is 23.21. Two subsamples are therefore created. One includes all regions with less the mean patent output (752 industry-specific regions) and the second covers all regions with more than the mean patent output (238 industry-specific regions). The splitting yields two advantages. For the first subsample (above mean) distorted rates of change are rare making the estimations more reliable. Second, it can be analyzed how subsidies related to innovation efficiency change in the most innovative regions (large innovation capacities) as compared to the majority of regions with little innovation activities in a particular industry (low innovation capacities).

5.3 Regional characteristics and innovation efficiency

As compared to the use of a two and a four-year time lag between subsidies and change in innovation efficiency the results are most robust using a three-year time lag. Therefore, these are used in the following.[14]

- Table 7 about here -

- Table 9 about here -

- Table 8 about here -

[11]A Hausman test confirms this approach. The test statistics are: χ^2: 61.21***.

[12]Moran's I statistic for the regression's residuals: 0.03**.

[13]The test statistic is: LM=12.63***.

[14]The results for the 2nd and 4th lag scenario can be obtained from the author upon request.

The results of the regression analyses are presented in Table 7 (all regions), in Table 8 (large innovation capacities), and in Table 9 (low innovation capacities). With the exception of the models for regions with large innovation capacities, *lambda* is positive significant in all models indicating that spatial autocorrelation is primarily relevant for regions with low innovation capacities. Accordingly, these are characterized by high inefficiencies, extremely fluctuating rates of change, and they tend to be geographically clustered.

Meeting the expectations, high levels of innovation efficiency in $t-1$ are negatively associated with efficiency improvements in the subsequent period. The finding might reflect a technical artifact because less efficient regions can improve their efficiency by larger extents than regions already highly efficient.[15]

The degree of specialization and the degree of diversification obtain negative significant coefficients in all models. Accordingly, being over-diversified as well as being too specialized lowers regional innovation efficiency, which confirms the findings by Fritsch and Slavtchev (2008).

In the models on the basis of all regions, the share of highly educated employees (HIGH) shows a significant positive coefficient, which is not observed in the models for the two subsamples, though. This positive impact of highly qualified employment on innovation is also well documented in the literature (see, e.g., Rodriguez-Pose, 1999).

In the models for all regions and those with large innovation capacities, the presence of institutes belonging to the Fraunhofer Society is negatively associated to innovation efficiency improvement. The finding clearly contradicts the expectations but may have a simple explanation. Institutes belonging to the Fraunhofer Society are strongly concentrated in the South West of Germany and primarily located in regions with strong patenting and innovation activities. In fact, FHG is correlated to PAT with 0.49^{***}. The variable is therefore likely to capture some portions of the negative association between total patent output and efficiency change. Support for this argument is found in the models for regions with low innovation capacities in which the variable remains insignificant.

The analyses reveal furthermore that increasing numbers of engineering graduates improves innovation efficiency in regions that already have a good innovation capacity. The investigation thereby adds to the long queue of studies attributing positive effects to universities for regional innovation activities (see, e.g., Jaffe, 1989).

By and large the control variables show coherent coefficients indicating that the empirical approach is well specified and thereby suitable for analyzing the role of R&D subsidies.

[15] Again, the findings do not imply a convergence process because trends in efficiency change are eliminated by the fixed effects estimation.

5.4 The impact of R&D subsidies

Some cooperation and network variables are strongly correlated, which prevent their simultaneous inclusion in one model. Therefore, different regression models are presented that test the four hypotheses. As expected, for regions with large innovation capacities, a larger number of significant coefficients are found, which is probably a result of the smaller disturbance in the dependent variable.

According to the **hypothesis 1**, cooperative R&D subsidies are expected to have stronger positive effects than non-cooperative subsidies. In line with this, the amount of non-cooperative subsidies (gSUM) does not gain significance in any model. In contrast, for regions with large innovation capacities, change in cooperative subsidies (gCSUM) obtains a positive significant linear and a negative significant squared term (Table 8). It suggests that two different patterns exist at the extremes of the variable's distribution. The positive linear term indicates that innovation efficiency can be improved by expanding cooperative subsidies. It is however crucial that the expansion is only moderate in magnitude. The significance of the squared term indicates that strong positive or negative disturbance in cooperative subsidies reduces innovation efficiency. When excluding regions with negative gCSUM the significance of the squared term vanishes, which indicates that these negative effects are primarily induced by strong reductions in cooperative subsidies. Accordingly, for regions with large innovation capacities **hypothesis 1** is confirmed. In this respect, it is interesting to ask if the negative effects are related to the reduction in the monetary amounts of cooperative subsidies or to the simultaneous lowering of the number of cooperation links. It speaks for the first that low levels of subsidies are associated with weak innovation performance (see, e.g., Guellec and van Pottelsberghe de la Potterie, 1997) and accordingly, a reduction to sub-optimal levels may lower innovation efficiency. Moreover, strong declines in the number of subsidized links are captured by $gIND\_DEG^2$ and $gDEG^2$. These remain however insignificant, which suggests that negative effects are primarily related to the monetary side.

Hypothesis 2 puts forward that subsidizing intra-regional cooperation is a proper way of stimulating regional innovation efficiency. To test this hypothesis the variable gS_INTRA has been created reflecting the change in the share of subsidized intra-regional cooperation. In the models for all regions and those with low innovation capacities, the variable's coefficient is positive and gains significance when the squared term (gS_INTRA^2) is included as well (Table 7 and Table 9). Again, this points towards the existence of different patterns at the extremes of gS_INTRA's distribution, with small values of gS_INTRA representing moderate change and large values capturing drastic change. Since gS_INTRA is not significant in the models for regions with large innovation capacities (Table 8) the results can be interpreted the following. For regions with low innovation capacities, high intra-regional cooperation intensities in $t-1$ tend to be followed by a reduction in t (correlation between the two variables is $r = -0.35^{***}$). The reason for this is that in these regions frequently only a single organization is engaged in a cooperative project. Any change (termination of the project or the start of a new one) induces the share of intra-regional cooperation to fluctuate strongly. According to the insignificant squared term, the analysis fails to deliver a clear relationship in these instances. However, these fluctuations need to be controlled for (by including the squared term) to reveal the significance of moderately changing shares of intra-regional cooperation.

The results imply that increasing the share of intra-regional cooperation reduces regional innovation efficiency, which means that **hypothesis 2** has to be rejected. Actually, the contrary of the hypothesis seems to hold: Since growing shares of intra-regional cooperation correspond to relative reductions in inter-regional cooperation, expanding the latter tends to improve innovation efficiency.[16] This is the case for regions with low innovation capacities, which are most likely rural regions. A potential explanation for this can be that these regions are characterized by a lack of intra-regional potential cooperation partners, which forces firms to seek partners outside their region. In line with this Meyer-Krahmer (1985) reports that firms in rural regions perceive the lack of complementary knowledge in their region as "locational disadvantage" (p. 531). Engaging in inter-regional cooperation represents the only way accessing a wider range of knowledge assets and cooperation partners. Accordingly, to secure their innovation performance firms must connect to "global pipelines of knowledge" (Bathelt et al., 2004). Once a firm is linked to these pipelines it may become a 'gate keeper' for other regional firms, which eventually stimulates the performance of the entire region (Graf, 2010). In this respect, links to universities and research institutes might be especially important because these are rarely located in rural regions.

The findings for the two different types of network centrality measures (degree and betweenness centrality) are compared to assess **hypothesis 3**. No statistical significances are observed for either variable in the models including regions with low innovation capacities (Table 7 and Table 9). In contrast, in the models for regions with large innovation capacities (Table 8) gIND_DEG obtains a negative significant coefficient. However, this is only if gIND_W_BETWEEN is simultaneously included. The latter's coefficient is positive significant. A region's network centrality is consequently related to two opposing effects. Advancing degree centrality tends to reduce innovation efficiency, while improving on betweenness fosters innovation efficiency. The findings clearly confirm **hypothesis 3**. It is interesting that gIND_DEG is based on the unweighted network and gIND_W_BETWEEN is

[16] The data at hand includes primarily German subsidies, which do not cover inter-national cooperation activities.

based on the weighted network, while their counterparts in the respective other networks remain insignificant. This implies that negative effects are related to the number of regions organizations are linked to and not to their total number of links (as captured by gIND_W_DEG). The latter may include multiple links to the same region. An explanation might therefore be that in each industry only a limited number of regions exist that offer valuable knowledge assets. Once regional organization have established at least one link to each of these, connecting to further regions does not yield any benefits. The negative coefficient rather suggests that in these cases negative effects prevail. These might be induced by a loss of competitiveness caused by too extensive knowledge sharing. This remains however speculative and needs to be addressed by future research. Nevertheless, the negative impact of high degree centrality meets previous findings in the literature. For instance, Broekel et al. (2010) empirically demonstrate a negative relationship between high levels of inter-regional cooperation and regional innovation efficiency. Using firm level data Fornahl et al. (2010) furthermore report that firms' patent performance is reduced if they are located in regions whose organizations engage in many inter-regional cooperation.

For gIND_W_BETWEEN to increase, it is necessary that the intensity of interaction between regions changes. In this sense, it matters with which regions new links are established. The positive coefficient for betweenness centrality suggests that it is particularly beneficial for a region to improve its (indirect) access to more distant parts of the network, an issue that is related to **hypothesis 4**.

In **hypothesis 4** it is put forward that subsidizing R&D cooperation is helpful if these give access to related competences and knowledge. To shed light on this, network variables are compared that are based on two distinct types of networks, which reflected different degrees of knowledge relatedness. While this is a rather rough approach, the analyses still reveal that in models for all and for small regions (see Table 7 and Table 9) gS_INTRA is negatively significant while its industry-specific counterpart gIND_S_INTRA remains insignificant. It implies that positive effects are related to relative increases in inter-regional cooperation. The significance of gS_INTRA and the insignificance of gIND_S_INTRA, which is solely based on intra-industrial cooperation, suggest that inter-regional cooperation need to include universities, associations, and research institutes as these are included in the network underlying gS_INTRA. Since this observation holds primarily for regions with low innovation capacities implying that for these regions access to (potentially unrelated) variety seems to be of greater relevance (see Table 9). Accordingly, **hypothesis 4** has to be rejected for regions with low innovation capacities. A reasonable explanation might be again the lack of potent cooperation partners in these regions.

Somewhat different results are observed for regions with large innovation capacities

(Table 8). Here, the significant network variables gIND_DEG and gIND_W_BETWEEN reflect the intra-industrial (firm-only) network. The network effects are therefore solely restricted to cooperation connecting firms with similar competences and knowledge. It can be argued that the positive coefficient of betweenness centrality represents the idea of 'related variety', i.e. it is not access to variety per se what matters for innovation but connecting to complementary and related knowledge (Frenken et al., 2007). Betweenness centrality increases when a region improves in connecting to distant parts of the network. By this means, it advances its (indirect) access to distinct knowledge bases and the variety of knowledge in the network. In the present case, this applies however only to the variety of knowledge within the intra-industrial network, which is obviously more related to firms' knowledge base (in this particular industry) than the variety within the inter-industrial and inter-sectoral network. Betweenness centrality in the later network, gW_BETWEEN, remains insignificant, though. In this sense, **hypothesis 4** is confirmed for regions with large innovation capacities. Accordingly, it is "not so much the quantity of contacts and intensity of knowledge exchanges that matters for [...] success, but rather the type of knowledge exchanged, and how that matches the existing knowledge base " (Fornahl et al., 2010, p. 6). For policy this means that cooperative R&D subsidies need to be granted in a way that organizations are linked with backgrounds in related fields.

To summarize these findings, **hypothesis 1** and **hypothesis 3** are confirmed for all regions. **Hypothesis 2** is not only rejected but evidence is found that points towards the opposite than the hypothesis claims. **Hypothesis 4** is confirmed for regions with large innovation capacities. For regions with low innovation capacities it is rejected.

6 Discussion and conclusion

The study showed that R&D subsidies are a suitable policy measure for stimulating regional innovation efficiency. It provided empirical evidence that policy can help regions with low innovation capacities (rural regions) by subsidizing inter-regional cooperation involving partners with varying industrial and sectoral backgrounds. In contrast, regions with large innovation capacities (urban regions) are best supported with continuous and moderately increasing grants for cooperative projects. The choice of cooperation partners is also crucial in this respect inasmuch as cooperative R&D subsides need to establish inter-regional links between organizations with related knowledge and skills.

While the study can be seen as complementary (regional) approach to firm-level studies, it highlights that there is more to R&D subsidies than just the monetary benefits. Interestingly, non-cooperative subsidies have not been found to impact regional innovation efficiency, which has similarly been by reported by Fornahl et al. (2010) concerning firms' patenting activities. However, this differentiation between cooperative and non-cooperative R&D subsidies is rarely being made in studies investigating subsidies' effects. Even more important, with respect to the data used in this paper, non-cooperative subsidies still account for about seventy percent of all granted projects and the sum spend for non-cooperative subsidies is about five-times larger than what is invested into cooperative projects. However, while influential, cooperative subsidies are not solely beneficial but may induce negative effects as well. In this respect, the present study calls for more attention on this subject in future research.

The latter point particularly applies to the impact of R&D subsidies on regional innovation performance. Although panel data was used, the empirical analyses cover only a limited time period. The emergence and evolution of regional innovation structures are long-term processes that may encompass different phases (Rees, 1979). Varying types of support programs might be crucial at particular phases flanking these developments. In light of the importance of informal networks in the early stages of technology evolution (Niosi and Banik, 2005) a greater importance can be assigned to policies focusing on intra-regional network building in these phases. In later stages, the prevention of lock-ins might be the crucial issue (Grabher, 1993), which rather requires the support of inter-sectoral and inter-regional cooperation.

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

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A Appendix

Industries	Technological fields*	NACE**
Chemistry (CHEM)	TF5, TF12, TF13, TF14, TF15	DG24, DI26
	TF24, TF25	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 1: Definition of industries

	CHEM	TRANS	ELEC	INSTR
Firms	198	136	294	363
Projects	$1,439$	946	1544	$3,968$
Grants	$1,642$	995	1717	$4,751$
% of coop. proj.	$> 9\%$	$> 5\%$	$> 15\%$	$> 22\%$
% of intra-regional links	$> 29\%$	$> 34\%$	$> 25\%$	$> 27\%$

Table 2: Descriptives subsidies data

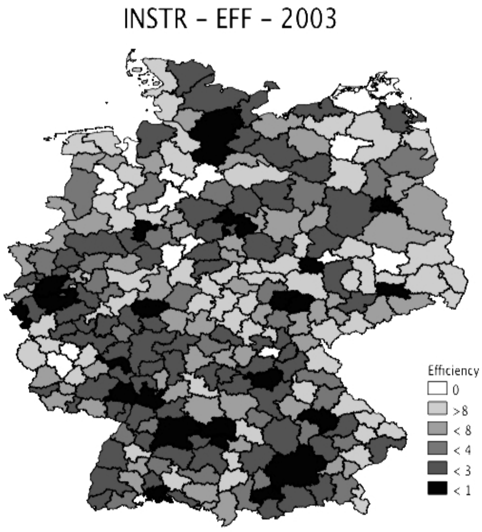

Figure 1: Efficiencies of German LMR INSTR

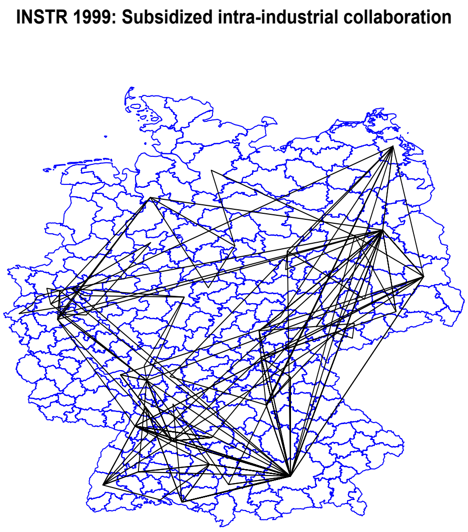

Figure 2: Subsidized cooperation network INSTR

	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
pool log(gEFF)	0.03**	0.03**	0.03**	0.03**

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

Table 3: Test for spatial autocorrelation

	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
total growth	1.01	1.09	1.27	1.04

Table 4: Mean growth rates - industry-specific

	mean	**sd**	**median**	**min**	**max**	**range**	**skew**
gEFF	1.43	3.15	1.01	0.04	174.93	174.89	43.00
EFF	-8.82	28.10	-2.95	-419.51	-0.10	419.41	-9.04
POP	878.33	1299.23	268.50	40.00	8495.00	8455.00	2.96
HIGH	11.77	10.68	7.90	2.50	85.40	82.90	3.13
GDP	39.20	32.71	25.60	12.20	279.40	267.20	3.60
EMPL	105921.79	138941.32	64774.00	15700.00	1139100.00	1123400.00	4.60
SPEC	1.04	1.48	0.61	0.00	18.44	18.44	5.58
FHG	32.15	124.49	0.00	0.00	1051.00	1051.00	5.11
MPG	51.03	255.52	0.00	0.00	3574.00	3574.00	10.14
HELM	87.86	469.58	0.00	0.00	4151.00	4151.00	6.72
LEIB	37.82	160.96	0.00	0.00	1478.00	1478.00	6.27
FIRMS	49.66	71.60	30.00	1.00	888.00	887.00	5.46
DIV	0.88	0.91	0.58	0.01	6.21	6.19	2.44
$\sum$ R&D	446.83	1450.09	89.00	1.00	31243.00	31242.00	11.26
$\sum$ PATS	23.21	86.96	5.36	0.00	1811.93	1811.93	13.53
ENG	140.65	153.22	102.05	8.36	1412.79	1404.42	4.88
NAT	114.89	133.45	73.89	4.36	1127.67	1123.31	3.69
gSUBS	0.24	2.41	0.00	-13.57	15.37	28.95	1.35
gSUM	0.23	2.34	0.00	-14.11	15.37	29.49	1.45
gCSUM	0.10	1.90	0.00	-13.31	14.66	27.97	1.10
gDEGREE	0.05	0.55	0.00	-3.56	3.81	7.36	1.35
gW_DEGREE	0.04	0.53	0.00	-4.32	5.41	9.72	1.69
gINTRA	0.02	0.32	0.00	-3.14	4.84	7.98	2.71
gSHARE_INTRA	0.02	0.42	0.00	-3.37	3.37	6.73	1.75
gIND_DEGREE	0.02	0.28	0.00	-2.56	2.40	4.96	0.71
gW_IND_DEGREE	0.02	0.30	0.00	-2.71	2.56	5.27	0.76
gIND_BETWEEN	0.04	0.60	0.00	-7.34	7.23	14.58	4.17
gW_IND_BETWEEN	0.03	0.66	0.00	-6.42	6.73	13.14	2.16
gIND_INTRA	0.02	0.25	0.00	-2.20	1.95	4.14	1.22
gIND_SHARE_INTRA	0.02	0.40	0.00	-2.20	2.20	4.39	1.00

Table 5: Descriptives

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)gEFF													
(2) EFF	0.04**												
(3) POP	−0.05***	0.1***											
(4) HIGH	−0.04**	0.05***	0.74***										
(5) GDP	−0.04***	0.11***	0.8***	0.85***									
(6) EMPL	−0.05***	0.1***	0.76***	0.7***	0.69***								
(7) SPEC	−0.03**	0.05***	0.01	−0.01	0.07***	−0.01							
(8) FHG	−0.03*	0.06***	0.4***	0.48***	0.4***	0.62***	0.02						
(9) MPG	−0.02	0.05***	0.41***	0.57***	0.54***	0.64***	0	0.58***					
(10) HELM	−0.02	0.05***	0.22***	0.24***	0.22***	0.37***	−0.02	0.31***	0.34***				
(11) LEIB	−0.02	0.02	0.27***	0.3***	0.16***	0.52***	−0.05***	0.44***	0.29***	0.25***			
(12) FIRMS	−0.05***	0.11***	0.61***	0.62***	0.62***	0.73***	0.08***	0.45***	0.52***	0.3***	0.32***		
(13) DIV	0	−0.08***	0.22***	0.36***	0.1***	0.27***	−0.07***	0.16***	0.19***	0.11***	0.46***	0.16***	
(14) R&D	−0.03*	0.05***	0.39***	0.42***	0.47***	0.52***	0.4***	0.42***	0.41***	0.14***	0.13***	0.35***	0.05***
(15) PAT	−0.03	0.07***	0.42***	0.51***	0.54***	0.57***	0.18***	0.49***	0.55***	0.21***	0.14***	0.45***	0.05***
(16) ENG	−0.04**	0.11***	0.53***	0.7***	0.74***	0.68***	0.03*	0.53***	0.58***	0.3***	0.19***	0.64***	0.05***
(17) NAT	−0.05***	0.12***	0.56***	0.73***	0.74***	0.69***	0.02	0.56***	0.64***	0.32***	0.26***	0.63***	0.13***
(18) EAST	0.03**	−0.23***	−0.12***	0.22***	−0.17***	−0.05***	−0.15***	0.01	−0.01	−0.06***	0.22***	−0.06***	0.54***
(19) gSUBS	−0.01	0	0.03*	0.04**	0.02	0.02	0	0.03*	0	0.01	0.01	0	0.01
(20) gSUM	−0.01	−0.01	0.03**	0.05***	0.02	0.02	0	0.03	0	0	0.01	0	0.02
(21) gCSUM	0	0.04**	0.03**	0.05***	0.04**	0.07***	0	0.06***	0.04**	0.04**	0.06***	0.05***	0.01
(22) gDEG	−0.01	0.01	0.04***	0.05***	0.03*	0.06***	0	0.06***	0.02	0.07***	0.04***	0.04***	0
(23) gWDEG	−0.01	0.02	0.05***	0.07***	0.05***	0.07***	0.01	0.09***	0.05***	0.07***	0.07***	0.07***	0.03*
(24) gINTRA	−0.01	0.01	0.06***	0.09***	0.06***	0.08***	0	0.1***	0.07***	0.08***	0.09***	0.09***	0.04**
(25) gSINTRA	−0.01	0.01	0.02	0.03*	0.01	0.03*	0	0.04**	0.02	0.05***	0.03**	0.03**	0.03**
(26) gIND_DEG	0	0.03**	0.03**	0.06***	0.04**	0.07***	0.01	0.08***	0.05***	0.04***	0.05***	0.06***	0.01
(27) gIND_WDEG	0	0.03**	0.04***	0.06***	0.04***	0.08***	0.01	0.1***	0.07***	0.05***	0.07***	0.08***	0.01
(28) gIND_BET	0	0.02	0.06***	0.07***	0.07***	0.07***	0.01	0.08***	0.07***	0.03*	0.07***	0.06***	0.01
(29) gIND_WBET	0	0.01	0.05***	0.07***	0.06***	0.05***	0.01	0.07***	0.06***	0.02	0.06***	0.06***	0.01
(30) gIND_INTRA	0	0.04**	0.04***	0.07***	0.05***	0.09***	0	0.1***	0.08***	0.05***	0.07***	0.08***	0.02
(31) gIND_SINTRA	0	0.03**	0	0.02	0.01	0.04**	−0.01	0.05***	0.03	0.03*	0.03*	0.02	0.01

	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
(4) R&D													
(4) PAT	0.84***												
(4) ENG	0.55***	0.63***											
(4) T	0.49***	0.58***	0.87***										
(4) EAST	−0.11***	−0.1***	−0.17***	−0.16***									
(4) gSUBS	0.03**	0.03*	0.03*	0.03**	0.02								
(4) gSUM	0.03**	0.03*	0.03*	0.03*	0.02	0.82***							
(4) gCSUM	0.05***	0.08***	0.07***	0.06***	−0.01	0.37***	0.08***						
(4) gDEG	0.04***	0.06***	0.06***	0.06***	−0.01	0.62***	0.39***	0.59***	1***				
(4) gWDEG	0.06***	0.09***	0.08***	0.08***	0.01	0.13***	0.21***	0.3***	0.39***	1***			
(4) gINTRA	0.07***	0.11***	0.11***	0.1***	0.02	0.11***	0.19***	0.25***	0.32***	0.91***	1***		
(4) gSINTRA	0.03*	0.04***	0.03**	0.03**	0.02	0.14***	0.22***	0.22***	0.29***	0.77***	0.8***	1***	
(4) gIND_DEG	0.06***	0.09***	0.08***	0.07***	0	0.3***	0.07***	0.8***	0.57***	0.32***	0.28***	0.16***	1***
(4) gIND_WDEG	0.06***	0.09***	0.08***	0.09***	0	0.29***	0.07***	0.78***	0.56***	0.33***	0.29***	0.15***	0.98***
(4) gIND_BET	0.08***	0.11***	0.09***	0.08***	0	0.03*	0.04**	0.11***	0.16***	0.15***	0.16***	−0.02	0.38***
(4) gIND_WBET	0.07***	0.1***	0.08***	0.08***	0	0.06***	0.03**	0.19***	0.22***	0.17***	0.17***	0.02	0.49***
(4) gIND_INTRA	0.06***	0.1***	0.09***	0.09***	0	0.3***	0.07***	0.81***	0.55***	0.32***	0.29***	0.16***	0.93***
(4) gIND_SINTRA	0.03*	0.05***	0.04**	0.04**	0	0.33***	0.06***	0.87***	0.53***	0.25***	0.21***	0.19***	0.81***
	27	28	29	30									
(4) gIND_DEG	0.37***												
(4) gIND_WBET	0.45***	0.74***											
(4) gIND_INTRA	0.94***	0.38***	0.37***										
(4) gIND_SINTRA	0.77***	0.07***	0.11***	0.87***									

Table 6: Correlation table

Dep. var: log(gEFF), all regions, balanced panel: n=990, T=4, N=3960								
Model	1	2	3	4	5	6	7	8
lambda	96.822 ***	96.734 ***	98.287 ***	98.821 ***	99.369 ***	100.094 ***	99.346 ***	98.957 ***
log(EFF_{t-1})	-1.115 ***	-1.115 ***	-1.114 ***	-1.114 ***	-1.115 ***	-1.115 ***	-1.115 ***	-1.115 ***
log(POP)	-0.004	-0.004	0.02	-0.024	-0.017	-0.001	-0.008	-0.024
log(HIGH)	1.699 **	1.697 **	1.696 **	1.708 **	1.688 **	1.701 **	1.718 **	1.709 **
log(EMPL)	-0.131	-0.13	-0.139	-0.135	-0.141	-0.14	-0.14	-0.141
log(SPEC)	-0.158 **	-0.158 **	-0.157 **	-0.16 **	-0.158 **	-0.158 **	-0.158 **	-0.158 **
log(FHG)	-0.054 *	-0.054 *	-0.054 *	-0.054 *	-0.056 *	-0.055 *	-0.055 *	-0.056 *
log(MPG)	0.054	0.054	0.056	0.055	0.06	0.062	0.062	0.064
log(HELM)	-0.869	-0.87	-0.826	-0.862	-0.8	-0.854	-0.992	-0.914
log(LEIB)	-0.053	-0.053	-0.054	-0.055	-0.053	-0.055	-0.056	-0.056
log(FIRMS)	-0.011	-0.011	-0.014	-0.016	-0.016	-0.017	-0.019	-0.019
log(DIV)	-0.367 ***	-0.367 ***	-0.371 ***	-0.368 ***	-0.368 ***	-0.372 ***	-0.374 ***	-0.373 ***
log(ENG)	-0.09	-0.089	-0.086	-0.087	-0.088	-0.085	-0.08	-0.079
2001	-0.029	-0.029	-0.029	-0.028	-0.028	-0.028	-0.028	-0.029
2002	0.005	0.005	0.005	0.007	0.007	0.007	0.007	0.007
2003	0.041	0.042	0.041	0.043	0.043	0.042	0.043	0.04
gSUBS		0.000						
gSUM			-0.001	0.000	0.002	0.002	0.003	0.002
$gSUM^2$				0.000	0.000	0.000	0.000	0.000
gCSUM			0.004	0.006	0.007	0.007	0.001	0.005
$gCSUM^2$				-0.001	0	-0.001	0.000	0.000
gDEG							-0.014	
gS_INTRA					-0.031	-0.037 *	-0.035 *	-0.037 *
gS_INTRA^2						0.009	0.009	0.009
gIND_DEG							0.011	0.017
gIND_DEG^2							-0.014	-0.025
gIND_BETWEEN							0.003	
gIND_W_BETWEEN								0.001
gIND_W_BETWEEN^2								0.003
gIND_S_INTRA							0.034	
gIND_S_INTRA^2							0.00	
R^2	0.619	0.619	0.62	0.62	0.62	0.62	0.62	0.62

Table 7: Determinants of innovation efficiency growth, all regions

Dep. var: log(gEFF), large regions, balanced panel: n=238, T=4, N=952									
Model	1	2	3	4	5	6	7	8	9
lambda	11.812	11.697	12.438	13.431	13.232	14.281	12.362	13.984	14.284
log(EFF_{t-1})	-1.051 ***	-1.05 ***	-1.048 ***	-1.05 ***	-1.051 ***	-1.051 ***	-1.051 ***	-1.052 ***	-1.052 ***
log(POP)	0.82	0.816	0.858	0.864	0.875	0.84	0.879	0.836	0.798
log(HIGH)	1.215	1.221	1.242	1.288	1.254	1.24	1.259	1.241	1.227
log(EMPL)	0.003	0.003	-0.012	0.02	0.012	0.016	0.038	0.055	0.063
log(SPEC)	-0.113 *	-0.112 *	-0.105	-0.118 *	-0.114 *	-0.115 *	-0.113 *	-0.116 *	-0.115 *
log(FHG)	-0.059 ***	-0.059 ***	-0.059 ***	-0.057 ***	-0.059 ***	-0.06 ***	-0.056 ***	-0.058 ***	-0.056 ***
log(MPG)	0.042	0.041	0.044	0.043	0.044	0.044	0.046	0.046	0.046
log(HELM)	-0.371	-0.368	-0.304	-0.295	-0.224	-0.159	-0.236	-0.095	-0.095
log(LEIB)	-0.046	-0.046	-0.048	-0.048	-0.05	-0.05	-0.048	-0.049	-0.048
log(FIRMS)	0.009	0.008	0	0.007	0	0.002	-0.007	-0.004	-0.005
log(DIV)	-0.293 *	-0.295 *	-0.303 *	-0.305 *	-0.318 *	-0.302 *	-0.336 **	-0.301 *	-0.309 *
log(ENG)	0.298 ***	0.297 ***	0.303 ***	0.296 ***	0.292 ***	0.296 ***	0.293 ***	0.309 ***	0.303 ***
2001	0.087 ***	0.087 ***	0.088 ***	0.088 ***	0.087 ***	0.088 ***	0.085 ***	0.086 ***	0.086 ***
2002	0.111 ***	0.11 ***	0.109 ***	0.111 ***	0.11 ***	0.112 ***	0.108 ***	0.11 ***	0.11 ***
2003	0.129 ***	0.129 ***	0.129 ***	0.13 ***	0.13 ***	0.132 ***	0.126 ***	0.128 ***	0.129 ***
gSUBS		0.001							
gSUM			-0.001	0	0.001	0.001	0.001	0.001	0.001
$gSUM^2$				0.000	0.000	0.000	0.000	0.000	0.000
gCSUM			0.005	0.008 **	0.009 ***	0.012 **	0.009 **	0.016 ***	0.016 ***
$gCSUM^2$				-0.001 ***	-0.001 **	-0.001 *	-0.001 ***	-0.001 **	-0.001 *
gS_INTRA					-0.018	-0.019	-0.016	-0.018	-0.018
gS_INTRA^2					-0.003	-0.003	-0.003	-0.003	-0.002
gIND_DEG						-0.03		-0.069 *	-0.072 *
$gIND\_DEG^2$						0.003			0.003
gIND_W_BETWEEN							0.015	0.022 **	0.025 **
$gIND\_W\_BETWEEN^2$							-0.001		-0.002
R^2	0.58	0.58	0.581	0.585	0.586	0.586	0.587	0.588	0.588

Table 8: Determinants of innovation efficiency growth, large regions

Dep. var: log(gEFF), small regions, balanced panel: n=752, T=4, N=3008								
Model	1	2	3	4	5	6	7	8
lambda	66.307 ***	66.341 ***	67.009 ***	67.424 ***	67.311 ***	66.714 ***	64.691 ***	66.069 ***
log(EFF_{t-1})	-1.117 ***	-1.117 ***	-1.117 ***	-1.117 ***	-1.116 ***	-1.116 ***	-1.117 ***	-1.116 ***
log(POP)	-1.102	-1.099	-1.091	-1.128	-1.12	-1.096	-1.073	-1.105
log(HIGH)	1.705	1.698	1.695	1.687	1.65	1.671	1.642	1.673
log(EMPL)	-0.073	-0.069	-0.076	-0.082	-0.087	-0.083	-0.081	-0.09
log(SPEC)	-0.166 **	-0.166 **	-0.166 **	-0.166 **	-0.166 **	-0.165 **	-0.16 **	-0.163 **
log(FHG)	-0.078	-0.078	-0.078	-0.078	-0.078	-0.081	-0.08	-0.08
log(MPG)	0.059	0.06	0.06	0.059	0.069	0.083	0.089	0.093
log(HELM)	-2.548	-2.54	-2.537	-2.553	-2.5	-2.595	-2.729	-2.656
log(LEIB)	-0.072	-0.073	-0.073	-0.074	-0.066	-0.069	-0.076	-0.07
log(FIRMS)	-0.022	-0.021	-0.024	-0.025	-0.024	-0.023	-0.033	-0.032
log(DIV)	-0.357 **	-0.359 **	-0.361 **	-0.359 **	-0.355 **	-0.364 **	-0.36 **	-0.363 **
log(ENG)	-0.261	-0.26	-0.258	-0.258	-0.261	-0.259	-0.248	-0.253
2001	-0.079 **	-0.079 **	-0.078 **	-0.077 **	-0.077 **	-0.078 **	-0.077 **	-0.078 **
2002	-0.055	-0.055	-0.054	-0.052	-0.051	-0.051	-0.052	-0.05
2003	-0.019	-0.019	-0.019	-0.017	-0.017	-0.019	-0.016	-0.018
gSUBS		-0.002						
gSUM			-0.002	0	0.001	0.002	0.004	0.002
$gSUM^2$				0.000	0.000	-0.001	0	-0.001
gCSUM			0.004	0.005	0.006	0.005	-0.02	-0.01
$gCSUM^2$				0.000	0.000	0	0.001	0.000
gDEG							-0.032	
gS_INTRA					-0.04	-0.059 *	-0.053	-0.065 *
gS_INTRA^2						0.022	0.023	0.023
gIND_DEG							0.089	0.129
gIND_DEG^2							-0.038	-0.058
gIND_BETWEEN							-0.009	
gIND_W_BETWEEN								-0.023
gIND_W_BETWEEN^2								0.007
gIND_S_INTRA							0.097	
gIND_S_INTRA^2							-0.02	
R^2	0.623	0.623	0.623	0.623	0.623	0.624	0.624	0.624

Table 9: Determinants of innovation efficiency growth, small regions