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An investigation of the relation between cooperation and the innovative success of German regions

Tom Broekel* and Matthias Buerger** and Thomas Brenner***

Abstract. Concepts like regional innovation systems, innovative milieu, and learning regions emphasize the positive contribution of intra-regional cooperation to firms' innovation performance. Despite substantial numbers of case studies, the quantitative empirical evidence for this claim is thin. Using data on the co-application and co-invention of patents for 270 German labor market regions the study shows that intra-regional cooperation intensity and regional innovation efficiency are associated. In contrast to the negative influence of inter-regional cooperation, medium levels of intra-regional cooperation stimulate regional innovation efficiency.

JEL codes: O18, R11, O31

Keywords: regional innovation efficiency, cooperation intensity, collaboration, regional cooperation

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I Introduction

It is consensus that firms do not innovate in isolation. Rather they are embedded into knowledge networks and sectoral innovation systems (Camagni, 1991; Cooke et al., 1997; Malerba, 2002; De Propris, 2002). An essential part of this embeddeness is related to firms' engagement in R&D cooperation, which represents a substantial vehicle for knowledge spillovers (Ponds et al., 2010). In line with this, there is strong empirical evidence that cooperation fosters firms' innovation performance (see, e.g., Boschma and ter Wal, 2007; Powell et al., 1996; Uzzi, 1996).

Most of the empirical work concentrates on the firm level when investigating the relationship between cooperation and innovation performance. However, innovation processes and knowledge networks can show a regional focus and even build the basic structures of regional systems of innovation (Asheim and Isaksen, 2002; Cooke et al., 1997). Accordingly, it can be argued that varying levels of regional cooperation intensity translate into inter-regional differences in innovation performance (Aydalot and Keeble, 1985; Camagni, 1991; Florida, 1995).

It has been shown empirically that regional levels of cooperation intensity differ systematically between regions (Cantner and Meder, 2008). Similar applies to regional innovation efficiency (Fritsch and Slavtchev, 2006). Therefore, the present paper focuses on the question that has been put forward in a similar way by Fritsch (2004): Do regional cooperation intensities relate to regional innovation efficiency? Despite the many studies dealing with such issues, which are based primarily on qualitative approaches (see, e.g., Isaksen, 2005), the quantitative empirical evidence is still inconclusive. While some authors do not find any relationship between regional cooperation and innovative activity (e.g., Fritsch 2004; Fritsch and Franke, 2004), others find positive (Ibrahim et al., 2009) as well as negative effects of regional levels of cooperation intensity (Broekel and Meder, 2008). However, a major drawback of these studies is that they are often restricted to few regions or a single industry. The present paper overcomes these shortcomings by drawing on a new dataset that comprises data for twenty-two manufacturing industries in 270 German regions over a period of seven years. In particular, patent data is used to construct measures of regional cooperation intensity.

The remainder of the paper is structured as follows. The theoretical foundations of the paper are presented in the next section alongside with an overview on the empirical literature. The methodology is pointed out in section three. Section four introduces the dataset and explains in detail how the variables are constructed. The results are presented in section five. Section six concludes and puts the analysis into perspective.

II Collaborative invention

Theoretical issues

The literature on innovation processes including systems of innovation, innovation networks, and open innovation models stress the importance of external knowledge transferred to the firm through diverse channels (Nelson, 1993; Chesbrough, 2008). Such knowledge can be obtained by acquisition from appropriate markets, by integrating those actors who possess the relevant know-how, or by performing collaborative research projects. The present paper concentrates on the latter mode where two or more actors join in formal or informal agreements on inventive and innovative activities.

There are different incentives to engage in cooperation projects. For instance, actors share costs and risks of innovation projects inasmuch “the costs for capital investment, such as laboratories, office space, equipment, etc. are shared between the partners” (Hagedoorn, 2002 p.479). In addition, collaborative innovation projects yield access to external know-how (Teece, 1986), which in turn (as a complement to internal resources) is crucial for the generation of new knowledge (Desrochers and Leppälä, 2010). Accordingly, there is a general consensus in the literature that collaborative R&D projects help improving a firm’s innovative capabilities (Faems et al, 2005).

However, the relationship between cooperation and innovation performance is not quite as simple. Cooperation does not turn out to be beneficial per se. While collaborative agreements are costly in both establishment and maintenance the outcome of cooperative projects is uncertain a priori (Bleeke and Ernst, 1993). Furthermore, cooperative and cheating (free riding) profits are equally affected by knowledge spillovers, i.e. knowledge flows a firm cannot control. While spillovers potentially facilitate cooperation they “may also make cheating more profitable”

(Kesteloot and Veugelers, 1995 p.653). Not surprisingly, failure rates of 50-60% for strategic alliances are mentioned in the literature (Kogut, 1988; Dacin et al., 1997). Thus the choice of the right partner is one of the most important factors for successful cooperation (Fornahl et al., 2010).

In recent years the geographic component of cooperation activities has drawn much attention especially from Economic Geographers. On the one hand, some regions realized an outstanding innovation performance owed to their distinct regional cooperation culture and intra-regional learning processes (Aydalot and Keeble, 1985; Saxenian, 1994; Asheim and Isaksen, 2002). Concepts such as 'innovative milieus' (Camagni, 1991), 'learning regions' (Florida, 1995), and 'regional innovation systems' (Cooke, 1992) build on this finding.

On the other hand, too much emphasis on intra-regional cooperation and networking may result in a situation of over-embedded actors, which is a well-known issue in network research. Such situation is characterized by inappropriate and redundant relations amongst actors once embeddedness exceeds a certain threshold level (Granovetter, 1985; Uzzi, 1996). The network can become too close and too rigid and "the firms in the network may become sealed off from the market as they begin to trade with a confined set of network partners" which makes it hard for new ideas to enter the network (Uzzi, 1996 p.684). Social aspects such as obligation and friendship between the network partners can "stifle effective economic action" (Uzzi, 1997 p.59)

In the context of economic geography such overembeddedness may be fuelled by a regional bias, which the actors in a region are exposed to in their search for external knowledge (Broekel and Binder, 2007). As a consequence new developments and innovations from outside the region can be missed - a situation which potentially lowers a region's innovation performance (Camagni, 1991; Grabher, 1993). Broekel and Meder (2008) refer to such situations as 'regional over-embeddedness'. Regional over-embeddedness is closely related to, however not to be mistaken for, a regional lock-in situation. The latter is characterized by regional actors incapable of leaving an old and pursuing a new development trajectory. It is thus a dynamic concept while regional over-embeddedness describes a regional knowledge network at a particular moment in time.

The opposite to a situation of regional over-embeddedness can be described as a situation in which the regional actors are highly connected to partners located in other regions (or even other countries) but are insufficiently linked amongst each other. Too strong external linkages (global pipelines) dominating the local milieu can be a reason for the segmentation among regional actors and a quietening of local buzz (Bathelt et al., 2004; Storper and Venables, 2004). In that case the firms are isolated or under-embedded in the region, which Bathelt et al. (2004) characterize as a 'hollow cluster'. Additionally, this situation is detrimental to innovation performance as the firms do not take advantage of geographic proximity to other regional actors, which is however argued to facilitate inter-organizational learning processes, development of trust, and the exchange of non-codifiable knowledge (Bathelt et al., 2004, Ibrahim et al., 2009, Storper and Venables, 2004).

In the following the term 'supra-regional over-embeddedness' will be used to describe a situation in which regional actors excessively engage in inter-regional cooperation but at the same time lack sufficient intra-regional linkages (Broekel and Meder, 2008). Both situations regional as well as supra-regional over-embeddedness affect regional innovation performance in a negative way since firms need both 'local buzz' and 'global pipelines' in order to perform well (Bathelt et al., 2004).

Findings from the empirical literature

The literature comprises numerous studies aiming at exploring the relevance of collaboration for the generation of new knowledge and innovation at the firm level (Tether, 2002; Laursen and Salter, 2004) and its effects on firm performance (Powell et al., 1996; Uzzi, 1996; Faems et al., 2005; Tsai, 2009). A frequent finding in most of these studies is that intensive cooperation raises firms' innovation performance. However, Uzzi (1996) also finds evidence for over-embeddedness situations.

Beyond these studies there is an increasing interest in the role that the geography of knowledge networks plays in this regard (e.g., Boschma and ter Wal, 2007). Investigations into the relationship between firm characteristics and the dependence on intra- and inter-regional collaboration show that collaborative agreements are most beneficial for knowledge intensive firms if regional and inter-regional partner are engaged (Arndt and Sternberg, 2000). Sternberg (1999 p. 538) concludes that small and medium sized firms "profit more from intraregional linkages than large firms do."

However, firm-level approaches are not the only option when investigating regional phenomena. Regional innovation systems, regional over-embeddedness (regional lock-ins), and supra-regional over-embeddedness refer to the collective behaviour of regional actors and thus can also be captured using a regional framework (Broekel and Meder, 2008). Accordingly, applying a regional approach (using regionalized data), though not unproblematic in general (Maskell, 2001, Giuliani, 2005), can be regarded an acceptable option when approaching regional phenomena. Moreover, it allows considering a larger number of regions for which firm-level data is usually not available.

Studies explicitly considering this regional perspective mostly approach those phenomena in a qualitative way. While some of these studies find positive effects of regional cooperation on innovation activities (e.g., Saxenian, 1994; Edquist et al., 2000; Asheim and Isaksen, 2002) others also confirm the existence of regional lock-in situations (Grabher, 1993; Hassink, 2007; Cho and Hassink, 2009).

However, quantitative evidence on the relationship between regional cooperation patterns and innovation performance is scarce. Fritsch (2004) exploits data on firms from eleven European regions, though his results do not back the expectation that cooperation or a certain cooperative attitude were conducive to innovative activity. Similar results are obtained by Fritsch and Franke (2004) investigating three German regions. Broekel and Meder (2008), instead, draw on a data set on German labor market regions and the Electrics & Electronics industry. Their findings indicate the existence of positive as well as negative effects of cooperation, i.e. an inverted u-shaped relationship between the regional cooperation intensity and regional innovation performance. In addition, there is a substantial literature analyzing the relevance of (regional) knowledge spillovers. While cooperation is an essential part of the spatial spillover argument, studies in this field do not explicitly include measures for the levels of (intra- or inter-) regional cooperation intensity. These are rather 'hidden' inside the spatial weights used to model interactions between regions (see, e.g., Ponds et al., 2010).

Thus, the empirical findings are not as unanimous as the theoretical argumentation and the qualitative evidence. Therefore, this paper contributes to the literature by empirically investigating the relationship between regional cooperation behavior and regional innovation performance using a unique data set on 270 German regions and multiple industries.

III Methodology

Since the works of Griliches (1979) and Jaffe (1989) regional innovation performance is commonly assessed using a knowledge production function framework (KPF). On this basis, the innovation performance of regions can be perceived as the efficiency with which knowledge inputs are transformed into innovation outputs (Brenner and Broekel, 2010; Fritsch, 2000, 2003; Fritsch and Slavtchev, 2008).[1] With a similar methodological set-up as Fritsch and Slavtchev (2008), we analyze the effect of cooperation on this regional innovation efficiency by estimating the regional innovation efficiency in a first step. In a second step, the obtained efficiency scores are related to a range of regional control variables and the variables approximating regional cooperation intensities in a regression framework.

In contrast to parametric approaches used to estimate regional innovation efficiency (see, e.g., Fritsch and Slavtchev, 2008), we follow the suggestions by Bonaccorsi and Daraio (2006) to use nonparametric techniques for the estimation of innovation efficiency at the regional level. This yields a number of advantages. For example, nonparametric techniques do not require the specification of parametric models (and error terms), which significantly reduces the danger of model misspecification. Moreover, such approaches allow the relationship between knowledge inputs and innovative outputs to vary between regions. Hence, they do not assume the existence of a universal knowledge production function and account for the uniqueness of regional innovation systems. From a practical perspective they also allow the simultaneous consideration of multiple (innovation) output indicators and do not require choosing a particular distribution of the efficiency scores (see, e.g., Coelli and Perleman, 1999).

For this paper we employ the *robust* version of the traditional Data Envelopment Analysis (called *convex order-m* in the following) as presented in Daraio and Simar (2005), which is non-deterministic and thereby less sensitive to noise and outliers in

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[1] Of course, we acknowledge that regions do not transform knowledge inputs into innovation output. In this sense, regional innovation efficiency refers to the regionally aggregated innovation efficiency of firms and other organizations located within a particular region.

the data (see also Daraio and Simar (2007) for more details). Practically, we examine for each region whether there is any region (as well as any linear combination of the observed (knowledge) input x (innovation) output combinations) among *m* randomly drawn regions (including the same region) that has equal or less inputs (*X*) and achieves higher levels of output (*Y*). In other words, a region is benchmarked against the expected maximal value of output of *m* randomly drawn regions with equal or less levels of input (output-oriented order-m frontier).[2]

In practice, we first have to estimate the non-convex order-m efficiency measure. Non-convex means that a region is compared to "real" observations only, while linear combinations of observed input and output relations are ignored. Economically, this means that no substitutive relationships are assumed to exist between the considered input and output dimensions, i.e. an actor cannot compensate a high value in one input dimension with a low value in another input dimension. The non-convex order-*m* measure can be computed in the following way: $Y_1,...,Y_m$ are *m* random observations[3] (regions) drawn from the conditional distribution function of *Y* given $X \leq x_0$, i.e. only regions with equal or less inputs than region (x_0,y_0) are considered. The output-oriented order-m efficiency measure $\tilde{\lambda}_m(x_0,y_0)$ is defined for region (x_0,y_0) as

$$\tilde{\lambda}_m(x_0,y_0) = \max_{i=1,\dots,m}\{\min_{j,\dots,q}(\frac{Y_i^j}{y_0^j})\} \tag{5}$$

with $Y_i^j(y_0^j)$ being the *j*th component of Y_i (of y_0 respectively). Note that $\tilde{\lambda}(x_0,y_0)$ is a random variable because the Y_i regions against which (x_0,y_0) is compared, are randomly drawn. In order to obtain the final $\hat{\lambda}_m(x_0,y_0)$, Cazals et al. (2002) proposes a simple Monte-Carlo algorithm with $\tilde{\lambda}_m(x_0,y_0)$ being estimated B times, where B is large (B=200). The order-*m* efficiency measure of region (x_0,y_0) is then defined as

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[2] One may also ask by how much the input factors have to be reduced for a region to become best practice given a certain output level (input-orientation). We argue that the output-orientation is more appropriate because our aim is to identify obstacles that hinder regions in achieving "maximal" innovation output (see Broekel and Brenner, 2007).

[3] *m* can be seen as a trimming parameter, which defines the estimation's sensitivity to statistical noise in the data. We achieve the best results with *m=50*, which implies that about ten percent of the observations show efficiency values less than one (see for more details Bonaccorsi et al. (2005))

$$\hat{\lambda}_m(x_0,y_0) = E[\tilde{\lambda}_m(x_0,y_0) | X \le x_0] = \frac{1}{B}\sum_{b=1}^{B}\tilde{\lambda}_m^b(x_0,y_0). \qquad (6)$$

However, in the context of our paper, a convex concept of efficiency might be more appropriate because in the later analyses the relations between the output indicators are clearly substitutive[4]. According to Daraio and Simar (2005) a convex order-m efficiency measure ($\lambda_m^C(x,y)$) is obtained by projecting all empirical observations on the above estimated non-convex order-*m* frontier and solving the following program:

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

with $\hat{Y}^{\delta}_{m,i} = \hat{\lambda}_m(x_i, y_i) * y_i$ being the previously estimated order-*m* output efficient level of region *i*.

The result of this efficiency analysis is a measure of relative efficiency of each region under the assumption of global convexity and potential statistical noise in the data. In the context of this paper, it indicates by how much the innovative output of a region has to increase in order for that region to become best practice (efficient) given its level of knowledge inputs. It is denoted by EFF in the remainder of the paper.

In order to test regional variables influencing this efficiency, in the second stage the estimated efficiency scores are used as dependent variables in a regression framework. As they are not truncated, continuous, and always positive a standard (panel) regression is appropriate.

IV Data and construction of variables

Regional units, knowledge inputs and innovative output

For the empirical analyses, we utilize data on German labor market regions[5] (LMR), which are formed by aggregation of the 439 German NUTS-3-regions. These regions

[4] We use only a single knowledge input variable, which is why only the output side is relevant.

[5] The definition of labor market regions used here follows that of the Joint Task "Improvement of the Regional Economic Structure" (see Eckey et al., 2007).

have been successfully used in similar studies (see, e.g., Buerger et al., 2010). The German Institute for Labor and Employment (Institut für Arbeit und Beschäftigung, IAB) defines the 270 German labor market regions that reflect the spatial dimension of labor mobility in Germany. About half of all job changes of highly educated people take place within labor market regions (Haas, 2000). Most of the university graduates also find their first job within the labor market region their university is located in (Mohr, 2002). Moreover, they are also likely to correspond to spatial constraints in firms' search for cooperation and knowledge exchange partners (Broekel and Binder, 2007). Hence, a significant portion of firm-spanning innovation processes as well as the geographically bounded effects of the technological infrastructure are likely to be captured by this level of spatial disaggregation.

In a common fashion, we use firms' R&D employees as approximation of employed firm-level knowledge inputs. Data on R&D employees is obtained from the German labor market statistics provided by the German Federal Employment Agency. It covers all employees subject to social insurance contribution. The R&D personnel is defined as the sum of the occupational groups agrarian engineers, engineers, physicists, chemists, mathematicians, and other natural scientists (Bade, 1987).

Patent applications are used as indicators of a region's innovation output. It is also used to model cooperation activities. It is taken from the German Patent and Trademark Office (DPMA) and covers all German patent applications within the period from 1999 to 2005.

In order to regionalize the patent data the inventor principle is applied, i.e. each patent is assigned to the labor market region where its inventor is located. In the case an invention was developed by multiple inventors from different regions, the patent is equally assigned to all regions.

Definition of industries

It is well known that the importance of patents for protecting innovations varies significantly between industries (Arundel and Kabla, 1998). Accordingly, when relating patent information to R&D activities significant inter-industrial differences have to be taken into account concerning the productivity of R&D employees and patent propensity. This is problematic in as much as the R&D employees are organized according to the international NACE classification[6], while the patent data is organized by the IPC (international patent classification) codes. We rely on the concordance developed by Schmoch et al. (2003) that relates the two classifications. More precise, we use the 44 sectoral fields defined therein. A number of IPCs are related to each sectoral field. As patent applications frequently feature more than one IPC class they are divided by the number of IPCs and the according shares are attributed to the corresponding NACE industries.

Moreover, Schmoch et al. (2003) provide the propensities with which each NACE industry patents into a particular sectoral field. The number of regional R&D employees for each sectoral field is estimated using these propensities as weighting scheme.

Lastly, we aggregate the R&D employment of those sectoral fields that are defined by three-digit NACE codes to the level of two-digit NACE codes. This is motivated by the need to have a sufficient number of patents in many regions, which is essential for the construction of the collaboration measures. However, the differences between these three-digit NACE industries as highlighted by Schmoch et al. (2003) are taken into account. Although, we sum up the employees of the respective three-digit NACE codes to form a single knowledge input variable, we consider these differences on the output side. More precise, we make use of the possibility to consider multiple output variables in the previously described efficiency analysis. Each of the sectoral fields that is related to a particular 2-digit NACE code industry becomes a separate output variable in the efficiency analysis, i.e. the efficiency analysis is based on a single input (sum of R&D employees in 3-digit NACE industries belonging to one 2-digit industry) but multiple output variables (patent classes assigned to a 2-digit NACE code industry). In the end, we construct data sets for 22 industries, which correspond to the sectoral fields of Schmoch et al. (2002) aggregated to 2-digit NACE code industries. However, only 15 industries have at least one region with 5 or more patents. As our collaboration measures are based on patent data, a minimum of 5 (or even 10) patents per region and industry should be used (see next subsection). Accordingly, we restrict the analysis to these 15 industries (for the list of considered industries see Table 2 in the Appendix). As usual in the literature, a time lag of two years is assumed between the two (Fritsch and Slavtchev, 2008).

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[6] Nomenclature Generale des Activites Economiques dans I`Union Europeenne (NACE).

Construction of the cooperation measures

A crucial aspect in this study is to differentiate between collaborative and non-collaborative inventions. A collaborative invention is referred to as an invention, which is an outcome of research efforts by more than one actor. Patent data provides information on both the applicants (typically firms) and the inventors (typically individuals) (Breschi and Lissoni, 2003). Using this information inter-organizational cooperation can be defined as the case in which two or more organizations jointly apply for a patent (Cantner and Meder, 2007). In addition, one may also use the information on the inventors to construct measures of cooperation at the level of individuals, i.e. cooperation as indicated by multiple inventors (Ejermo and Karlsson, 2006). Both measures have interesting meanings, which is why they are simultaneously used in this paper. It has to be pointed out, however, that it is not possible to link a particular inventor to a specific applicant (organization). Accordingly, if multiple inventors are mentioned in a patent it is not possible to identify intra- or inter-organizational cooperation at the inventor level. For this reason, we perceive patents with multiple inventors and a single applicant not as cooperative per se. However, we will use this inventor-related information to gain important insides on the inter-regional orientation of regional innovation activities.

On the basis of this data the following measures are defined capturing different dimensions of regional cooperation intensity:

COOP: For the first variable we use information on co-applications, which implies that inter-organizational cooperation activities are in the foreground. To account for regional organizations' general cooperation propensity the variable COOP is defined as the regional share of collaborative patents (patents with at least two applicants) in total patent applications.

INTRA: A second variable focuses on the intensities of intra-regional cooperation activities. The variable INTRA is defined as the share of intra-regional cooperation patents in total cooperation patents. Again, we use information on patent co-applications. Accordingly, intra-regional cooperation show as patents with applications from the same region, while inter-regional cooperation are characterized by at least two applications from different regions.

INTER_INV: The third variable aims at capturing the degree of regional actors' "outward orientation". More precise, it approximates their embeddedness into inter-regional knowledge relations. However, this does not necessarily mean that these relations cross organizational borders, i.e. we also consider intra-organizational (though, still inter-regional) knowledge links. By utilizing information on co-inventorship the variable INTER_INV is constructed as the share of regional patents with (at least two) inventors from at least two regions. It indicates the presence of linkages to actors (which may or may not be part of the same firm, though) located outside the considered region.

For the main variables of interest squared versions are included to check for potential non-linear effects. To reduce multicollinearity, the variables are de-meaned before being squared. Again, we consider a two-years time lag to the R&D data as we do for the patent data used to construct the innovative output.

Control variables

The literature discusses and tests a great number of regional characteristics that are associated with high regional innovation performance (see, e.g., Broekel and Brenner, 2010). In this study, we consider the regional characteristics most commonly put forward in the literature in order to control for their influence on regional innovation efficiency.

Agglomeration and urbanization economies are frequently shown to enhance firms' innovation propensity (Greunz, 2004). The advantages of urbanization are among others rich local labor markets and a well-developed non-technological infrastructure. In a common fashion we approximate urbanization advantages by population density (POP) and the gross-domestic product (GDP).

Industrial agglomeration is also argued to stimulate knowledge exchange and spillovers (Rigby and Essletzbichler, 2002), which in turn foster innovation performance. The variable SPEC depicts the specialization of a region with respect to a particular industry (the 15 considered industries). It is estimated as the location coefficient based on industries' employment numbers. To capture the presence of an industry in absolute terms (Brenner, 2004), we include the number of employees in the considered industry as well (EMPL).

Also the availability of highly qualified human capital plays a significant role for firms. Given a surplus in demand, some R&D projects cannot be started or require more time than expected if the available workforce does not show the right qualifications. Following Weibert (1999) we approximate the availability of highly qualified human capital by the share of employees with high qualifications (HIGH). The data used to construct EMPL and HIGH are taken from the German statistical office.

Universities and technical colleges ("Fachhochschulen") are amongst the most important elements of regional innovation systems. They primarily provide human capital and a wide range of services to regional firms (see, e.g., Blind and Grupp, 1999). More important in the context of this paper is their contribution to regional patent output and their impact on regional collaboration behavior. Concerning the latter, universities often establish cooperation with spatially more distant partners and play a role as gatekeepers to national and global knowledge networks (Graf, 2009; Graf and Henning, 2009). In contrast, technical colleges tend to specialize in the same area as the regional economy (Beise and Stahl, 1999) making them an easily accessible and valuable collaboration partner for regional firms.

Similarly public funded research institutes impact the regional innovation system and engage in patenting activities. This especially concerns the 'big four' institutions in Germany: the Helmholtz Association, the Max Planck Society, the Fraunhofer Society and the Leibnitz Association.

We approximate these organizations' influence by the number of their patents. The information is obtained from the German "Patentatlas", which provides disaggregated information on the patenting activities of firms, private persons, and public science organizations (universities and research institutes) at the regional level (Greif et al., 2006). Disaggregated into 31 technological fields this data is available for the relevant period of time. Taking into account technological differences we construct 31 variables each representing the share of patents from public research organizations from a particular technological field in the total number of regional patents (see for more information Greif et al., 2006). They are denoted by "TF" followed by the corresponding number of the technological field.[7]

From the same source we obtain the share of regional patents that are applied for by private persons. These may be private individuals who dedicate their spare time to innovative activity. Until 2002 also university professors had the right to apply for a patent in their own name even if the underlying invention was developed as part of their professional activities at universities (e.g., Bielig and Haase, 2004). To take this into account we create a single variable (PRIVATE) that indicates the share of patents applied for by private inventors.

V Results

Regional innovation efficiency

The main objective of the paper is the analysis of the relationship between regional levels of cooperation intensity and regional innovation efficiency, which is why we only briefly discuss the obtained efficiency results in the following. A region is deemed to be efficient if its efficiency score is below or equal to one. The mean of the efficiency scores is about 10. However, we restrict the sample to regions with at least five patents because only these are used in the second stage regression. The mean in the restricted sample decreases to 2.34. It implies that in average regions need to increase their innovation output to 234 percent of the actual value to become efficient. At first sight this values appears to be very large. However, it is relatively small compared to similar studies (see, e.g., Broekel and Meder, 2008). The reason for the relatively lower mean efficiency is a result of the restriction of the sample, whereby most extreme values are excluded. The latter tend to be found for regions with few R&D employees and marginal patent numbers.

An industry comparison (see Table 3 in the Appendix) on this basis reveals significant differences whereby I10.16 (Chemicals) show the lowest mean efficiency (0.99) and I42 (Motor vehicles) the highest (4.42).[8] It is also interesting to compare the studied

[7] The ideal set-up would have been to create a single variable summing the public patents for the IPCs assigned to each of the 15 industries considered in the paper. However, given the data at hand this is not possible.

[8] I7 (Paper) actually has the lowest mean efficiency but too few observations to be meaningfully considered.

industries considering the share of regions that are found to be efficient. Among those regions with at least 5 patents this share ranges from 8% for industry I42 (Motor vehicles) to 62% for industry I10.16 (Chemistry).

In general, many efficient regions correspond to the "usual suspects". For example, in the optics and precision instruments industry (I37.41) Munich, Stuttgart, and Erlangen show efficiency scores well below one. Regarding motor vehicles (I42) the same applies to the regions of Munich (headquarter of BMW) and Stuttgart (headquarter of Daimler and Porsche).[9] However, there are also regions, such as Wolfsburg (headquarter of VW), that are found to be inefficient. Figure 3 in the Appendix exemplarily shows the spatial distribution of innovation efficiency for I37.41 (Optical and precision instruments) in 2001. It indicates that the efficiency scores might be spatially correlated. For this reason we estimate the spatial correlation using Moran's I. Table 2 in the Appendix shows the results for all industries and years, which confirm the presence of spatial autocorrelation in a significant number of instances.

In order to obtain some knowledge about whether the spatial distribution of efficiency scores is stable in time, we calculate the temporal autocorrelation of the efficiency scores. The autocorrelation is found to be around r=0.85 and highly significant. Hence, the innovation efficiency of German labor market regions is relatively stable but not fixed over time. The changes of innovation efficiency in time are, at least, much smaller than the differences of this efficiency between regions. In a next step, we turn towards the explanation of this inter-regional variation in innovation efficiency with a special focus on the relation to regional cooperation intensities.

Regional cooperation and innovation efficiency

Given the regional nature of our approach and the need for a minimum number of patent applications in each industry and region our sample for each industry is limited. Therefore, we pool the data for all industries in the following analysis, implicitly assuming that a similar relationship exists between cooperation and innovation efficiency in all considered industries. This yields more observations and, hence, statistically more reliable results.

[9] Please note once more that the patent scores are distributed by inventor residence, which is why "headquarter" effects should be of minor relevance.

In addition, most variables are used in logarithmic scale because they have very different sizes and their distributions are positively skewed. Note however that our model does not correspond to a classic production function approach because the dependent variable is an efficiency estimate. Figure 1 and Figure 2 in the Appendix show the transformation's effect on the dependent variable, which afterwards is characterized by a nearly perfect normal distribution. To allow for an easier interpretation, the transformed dependent variable is multiplied by -1 implying that larger scores indicate higher efficiency.

We do not logarithmize the main variables of interest, i.e. INTER_INV, COOP, and INTRA for two reasons. Firstly, they are estimated as shares meaning that they are already bound to the interval from zero to one. Secondly, we want to test for non-linear relationships (squared versions), which is problematic for logarithmized variables.

The first (baseline) model is defined by relating the dependent variable to the control variables, i.e. the variables referring to cooperation intensity are not considered. A Hausman test[10] suggests using a fixed effects model. Using a fixed effects model is well fitting in the context of the paper because the regional (fixed) effects approximate omitted variables, which are most likely region-specific characteristics. This approach also controls for most structural differences between regions that are also known to influence regional innovation efficiency, e.g. if the region is located in East or West Germany or whether it has a specific industrial structure (see, e.g., Fritsch and Slavtchev, 2008).

We pointed out above that the dependent variable is troubled by spatial dependency, which translates into spatially correlated residuals in a standard panel regression model.[11] A Baltagi, Song, Jung, and Koh conditional LM tests (C.1) adds more support for the use of regression models that take into account the spatial structure of the dependent variable (Baltagi et al., 2007).[12]

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[10] For the data with a minimum of 5 patent applications the following statistics are obtained: Hausman test: Chisq: 307.07, df=5, p-value=2.2e-16. Similar values are obtained for the data with a minimum of 10 patent applications. The results can be obtained upon request from the authors.

[11] For example, the test statistics are: I=0.117*** (minimum 5 patents) and I=0.09*** in 1999.

[12] The test statistics are: LM=30.01*** (minimum 5 patents) and LM=12.75*** (minimum 10 patents).

Accordingly, a spatial (error) panel fixed effects model is used for the second-stage regression (see, e.g., Elhorst, 2009).

The determinants of innovation efficiency

Table 5 (five patents minimum scenario MIN5) and Table 6 (ten patents minimum scenario MIN10) in the Appendix depict the results of the second stage regressions. For each of the samples the relationships are relatively stable concerning different model specifications. For instance, the spatial parameter *lambda* is significant in all models, which underlines the relevance of spatial dependencies.

However, some differences exist between the two scenarios in particular with respect to the importance of patents from public actors. In Scenario MIN5 the technological fields TF12, TF19, TF22, and TF23 gain significance, while the same applies to TF18, TF19, TF21, TF23, and TF27 in scenario MIN10. Only TF19 ("paper") and TF23 ("machine tool engineering") appear to be significant in both scenarios. The reasons for these differences are the varying degrees of spatial concentration, which make the variables sensitive to restricting the sample to regions with at least ten patents. It moreover indicates (with the exception of TF19 and TF23) that these relationships are not very robust. This becomes obvious in scenario MIN10 where the coefficient for TF18 ("textiles") turns out to be negative significant, which clearly runs against previous expectations. Apparently, a high share of textile's patents from public research organizations is associated with lower efficiency scores.

In contrast, TF19 and TF23 confirm the importance of public research activities either as direct contributions to regional patent output or by stimulating influence on firms' innovation activities. In this respect our study supports similar findings in the literature (Fritsch and Slavtchev, 2007a).

With respect to the other control variables, population density (POP) is positive significant in the first model in scenario MIN5. It loses its significance when the collaboration variables are considered, which might suggest that a relationship exists between urbanization and collaboration intensity. The correlation between COOP and POP is however only 0.009^{***} giving little support for this hypothesis. The low relevance of population density contradicts the findings by Fritsch and Slavtchev (2008). Similar applies to GDP, which is not significant in all models and scenarios. Most likely, estimating the innovation efficiency in an industry-specific manner controls for their effects. In contrast to Fritsch and Slavtchev (2008) and their (economy-wide) aggregated data, potential differences in the industrial structure between rural and urban regions do not impact our results.

The most important determinant of regional innovation efficiency is a region's degree of specialization in a particular industry. In line with the findings of Feldman and Audretsch (1999) we find innovation efficiency and the degree of specialization to be negatively related. As we do not include a measure of diversification the inverse of the specialization measure might capture also the presence of related industries, i.e. the degree of specialization might represent the absence of diversification, which has frequently found to positively impact innovation activities (see, e.g., Greunz, 2004).[13]

The share of patents from private inventors is not significant in all models. This is somewhat surprising as this number should be particularly high in regions with many small firms since the owners of small firms frequently apply for the patents themselves rather than on behalf of the firm (Greif and Schmiedl, 2002). While young and small firms are often argued to be more innovative (Frenkel and Schefer, 1998) we do not find a positive firm size effect.

Lastly, we observe the year dummy for 2001 positive significant, which is likely to capture the effect of the dot.com bubble leading to an increasing innovation (patenting) efficiency of R&D in particular from 2000 to 2001.

To conclude this section, the results for the control variables are well in line with existing studies suggesting that our models are well specified and reliable.

Cooperation intensity and innovation efficiency

The coefficient for INTER_INV is negative and significant in all models and specifications. This means that the share of patents with at least one inventor from another region is negatively related to regional innovation efficiency. Or in other words, regions in which inventors frequently form teams with inventors from other regions are less innovative than regions with lower levels of inter-regional co-inventorship. The squared version of this variable is not gaining significance suggesting the existence of a log-linear relationship between regional innovation efficiency and INTER_INV.

The results reveal a similar relationship for a region's cooperation propensity. When included without its squared term, COOP shows a significantly negative correlation to

[13] We also included a squared version of SPEC but did not obtain significant results.

regional innovation efficiency in all models. Accordingly, higher shares of cooperative patents (more than one application) are negatively related to innovation efficiency. Against previous expectations and contrasting the results by Broekel and Meder (2008) we do not observe an inverted 'U' relationship within the relevant range. The coefficient for the squared term of COOP is significantly negative but the coefficient for the linear term remains negative as well, although it looses its significance. Hence, especially high values of COOP seem to be associated with lower efficiency.

Keeping in mind that the dependent variable is positively correlated with the regions' total innovative output but negatively with cooperation (see Table 5 in the Appendix) one might draw the following conclusion. Regions with high innovative output are likely to be amongst the more efficient regions, which according to our results show a lower share of cooperative patents. It, thus, should be acknowledged that this relationship might as well be impacted by the presence of large firms, which compared to smaller firms are shown to be, on average, less prone to co-patenting (Giuri and Mariani, 2005). However, the employed fixed effects regression should capture most of this relation.

So far, we do not distinguish between intra- and inter-regional cooperation, which may however yield different effects (see, e.g., Bathelt et. al. 2004, Ibrahim et al., 2009). For this reasons, we include the variable INTRA into the analysis, which approximates the share of intra-regional cooperation. In scenario MIN5 the variable's linear term is negatively associated with innovation efficiency. Once included, the squared term of INTRA becomes negative and significant with the linear term loosing significance. This already suggests that especially high values of INTRA are associated with lower efficiency scores. In scenario MIN10, the linear term becomes positive significant with its squared version being significantly negative. In other words, we find an inverted 'U' relationship between the intensity of intra-regional cooperation and regional innovation efficiency for regions with substantial numbers of patents.

As a first contribution to the literature our study clearly reveals a significant relationship between regional levels of cooperation intensity and regional innovation performance, which contradicts the findings of e.g., Fritsch (2004) and Fritsch and Franke (2004). In contrast to their findings, our study supports the quantitative-empirical results of Broekel and Meder (2008) and Ibrahim et al. (2009) as well as qualitative evidence (Asheim and Isaksen, 2002).

Summarizing the findings for the three variables, we find that the share of (inter-organizational) cooperation (COOP) is significantly negative in all models. Taken together with the inverted 'U' relationship found for the share of regional cooperation (INTRA), the analyses highlights that in particular inter-regional cooperation is associated with low innovation efficiency. This holds for inter-organizational cooperation (COOP) as well as links between individual inventors, which are potentially part of the same organization (INTER_INV). Accordingly, if regional actors are well embedded into inter-regional (global) pipelines of knowledge this does not boost their innovation efficiency. The results rather suggest that the development of “local buzz”, i.e. strong connections between regional actors, stimulates innovation efficiency. However, the inverted-U relationship of INTRA (in Scenario MIN10) means that having only connections within the region is also not favorable for high innovation efficiency. Accordingly, our results confirm the “local buzz” and “global pipeline” argument by Bathelt et al. (2004) and provide support for the rather positive perception of high intra-regional cooperation intensities found in the literature (see, e.g., Asheim, 2001; Ibrahim et al., 2009). In addition, the results show that the existence of “regional over-embeddedness” situations is not particular to the Electrics and Electronics industry confirming the argument of Broekel and Meder (2008). Our study shows that regional over-embeddedness situations (corresponding to high INTRA values) are associated with low innovation efficiency. Unfortunately, missing the data we cannot test if the association is induced by lacking rivalry (Porter, 1990), the discrimination of new ideas (Uzzi, 1996), or the wrong choice of cooperation partners (Fornahl et al., 2010).

More common, however, are situations in which regional actors fail to develop sufficient intra-regional linkages while having significant relations to actors located outside their region. Broekel and Meder (2008) label this pattern as “supra-regional overembeddedness”. In our analysis, this translates into high values of COOP and low values of INTRA, which we accordingly find associated with below average innovation efficiency. Hence, there seems to be a trade-off between the levels of intra- and inter-regional cooperation. Compared to the study by Broekel and Meder (2008) we show that these patterns seem to be fairly general and exist in more than one particular industry. There is still an ongoing debate about the exact mechanisms making regional cooperation activities more beneficial than inter-regional ones (see, e.g., Asheim and Isaksen, 2002; Ibrahim et al., 2009; Storper and Venables, 2004). Regarding the data our results primarily relate to formal cooperation. However, beyond this the assessment does not allow making any inference about the relevance of these mechanisms, which is why we refrain from speculating about the causal mechanisms.

Another immediate question in this context is what exactly causes the observed inter-regional variations in cooperation behavior? Mayer-Krahmer (1985) argues that a firm's location inside or outside an agglomeration can be an important aspect. He found that firms with high levels of outward orientation are more likely to be found in agglomerations, while small levels of outward orientation are observed in rural areas. He puts forward that firms in regions with few potential cooperation partners (as it is the case in rural areas) perceived the lack of knowledge in their region as "locational disadvantage" (p. 531). In order to overcome this disadvantage they may be forced to engage more frequently in external cooperation. These links however lack the benefits of geographical proximity resulting in lower innovation efficiencies.[14] We find support for this argument in so far as INTER_INV is negative correlated with the measures of agglomeration and urbanization approximated by the absolute number of employees in the industry (EMPL) and population density (POP), respectively (see Table 5).

VI Conclusions

The analyses provided new evidence on the relationship between regional levels of cooperation and regional innovation efficiency. In contrast to previous studies, the data set employed in the present paper comprises information on fourteen 2-digit manufacturing industries in 270 regions within a period of seven years. This allows overcoming major drawbacks in related studies, which are often restricted to a few regions or a single industry.

[14] For an overview and a critical discussion on the relationship between different forms of proximity and innovation see Boschma, 2005.

One of the most important shortcomings of the present study is however the use of patent data to construct regional cooperation intensities. The determinants of firms' engagement in cooperation in general and cooperative patenting in particular are manifold (see, e.g., Cassiman and Veugelers, 2002; Leiponen and Byma, 2009; Negassi, 2004). Amongst these firm, industry, and technology specific determinants are surely the most crucial ones. However, the measures constructed from patent data are only used to compare regions in this study. In order to be visible in our results, these factors must have a non-random spatial distribution otherwise they are captured by the random components in the analyses. The industrial structure is primarily known to vary systematically between regions in a non-random way (Ellison and Glaeser, 1997). This is taken into account by estimating the regional innovation efficiency separately for 15 industries and applying the second stage fixed effects regression, though. We are therefore confident that our approach captures the effects of a regional cooperation culture, which we show is influencing regional innovation efficiency.

While simulating intra-regional cooperation seems to be the preferred way to foster regional innovation it is essential for policy to balance the efforts. Too intense intra-regional cooperation and the absence of non-regional linkages are significant obstacles to high innovation performance. Against this background initiatives aiming at stimulating innovation performance by encouraging or subsidizing cooperation activities, should be carefully designed to meet the needs of regional actors. Stimulating the wrong type of cooperation (intra- or inter-regional) may not only yield ineffective efforts, but can even lead to inferior situations. Accordingly, our analyses enjoin to carefully rethink the unconditional promotion of innovative cooperation projects. Policy measures, such as the German PRO INNO program, designed to encourage individual cooperative innovation projects are found to be highly successful at the firm level (e.g., Lo et al., 2006). This can be expected as long as firms themselves take care to have a well-balanced set of collaborations. However, given their embeddedness into various types of knowledge networks and innovation systems, the program's stimulus might influence network density and, thus, have (negative and positive) effects on directly supported as well as cooperating firms. Taking this inter-relatedness of firms and its consequences into account in the design of (regional) innovation policies seems to be a major challenge for the future.

	mean	*sd*	*median*	*min*	*max*	*skew*	*kurtosis*
EFF	2.34	2.5	1.66	0.06	49.75	6.98	98.82
POP	1552.72	1797.44	986	74	8495	1.81	3.12
GDP	54.85	46.23	46.3	12.7	279.4	2.63	8.37
HIGH	16.09	14.58	11.5	2.4	85.4	2.55	8.26
EMPL	182563	217921	106953	20500	1139100	2.75	7.5
SPEC	1.28	1.39	0.93	0.05	20.66	6.41	64.16
PRIVATE	0.26	0.12	0.25	0.02	1	1.54	3.49
INTRA	0.02	0.05	0	0	0.6	4.33	26.79
COOP	0.05	0.08	0.03	0	1	3.9	28.46
INTER_INV	0.62	0.21	0.65	0	1	-0.76	0.6
EAST	0.07	0.25	0	0	1	3.51	10.31
TF1	0.02	0.09	0	0	1	8.24	79.84
TF2	0.01	0.07	0	0	1	10.11	113.88
TF3	0.01	0.05	0	0	1	14.41	264.62
TF4	0.04	0.1	0	0	1	5.28	36.17
TF5	0.05	0.15	0	0	1	4.27	20.22
TF6	0.06	0.13	0	0	1	3.79	18.52
TF7	0.04	0.13	0	0	1	4.69	26.42
TF8	0.03	0.11	0	0	1	5.79	39.53
TF9	0.01	0.06	0	0	1	14.77	247.2
TF10	0.01	0.04	0	0	1	14.06	300.14
TF11	0.01	0.05	0	0	0.83	10.77	149.37
TF12	0.08	0.18	0	0	1	3.25	11.28
TF13	0.08	0.18	0	0	1	3.14	11.01
TF14	0.06	0.18	0	0	1	3.48	12.56
TF15	0.05	0.16	0	0	1	4.42	20.65
TF16	0.11	0.21	0	0	1	2.48	6.23
TF17	0.08	0.19	0	0	1	3.24	10.55
TF18	0.02	0.11	0	0	1	6.99	53.57
TF19	0.01	0.1	0	0	1	7.97	69.69
TF20	0.01	0.03	0	0	0.71	12.42	218.95
TF21	0.01	0.09	0	0	1	10.06	105.59
TF22	0.02	0.07	0	0	1	6.69	56.56
TF23	0.02	0.06	0	0	1	7.38	79.83
TF24	0.02	0.07	0	0	1	7.16	68.79
TF25	0.02	0.13	0	0	1	6.47	42.94
TF26	0.07	0.12	0.02	0	1	3.16	13.72
TF27	0.02	0.09	0	0	1	7.9	76.25
TF28	0.04	0.14	0	0	1	5.61	33.62
TF29	0.04	0.18	0	0	1	4.5	19.28
TF30	0.05	0.11	0.01	0	1	4.27	25.03
TF31	0.03	0.1	0	0	1	6.46	48.48

Statistics based on pooled observations (n=5870) over all industries and years.

Table 1: Descriptives

Industry code	Industry description
I1	Food, beverages
I2	Tobacco products
I3	Textiles
I4	Wearing apparel
I5	Leather articles
I6	Wood products
I7	Paper
I8	Publishing, printing
I9	Petroleum products, nuclear fuel
I10.16	Chemicals
I17	Rubber and plastic products
I18	Non-metallic mineral products
I19	Basic metals
I20	Fabricated metal products
I21.27	Machinery
I28	Office machinery and computers
I29.33	Electrics
I34.36	Electronics
I37.41	Optics and precision instruments
I42	Motor vehicles
I43	Other transport equipment
I44	Furniture, consumer goods

Table 2: Industries

Table Industry	Obs. p.a. min 5 pat	Mean (EFF), min 5 patents	Share of efficient (min 5 pats)	Share of efficient (all)	Moran I 1999	Moran I 2000	Moran I 2001	Moran I 2002	Moran I 2003
I1	6	1.08	0.55	0.03	-	-	-	-	-
I2	0								
I3	0								
I4	0								
I5	0								
I6	0								
I7	5	0.69	1	0.24	-	-	-	-	-
I8	0								
I9	0								
I10.16	99	0.99	0.62	0.21	-0.016	0.013***	-0.131*	0.049	0.018
I17	78	2.03	0.13	0.23	0.023	0.100***	0.058	0.028	-0.044
I18	49	1.91	0.09	0.02	0.255***	0.087	0.251***	0.023	-0.051
I19	29	1.18	0.46	0.03	0.043	0.110*	-0.024	0.003	-0.127
I20	89	2.32	0.11	0.03	-0.050	0.053	0.045	0.000	0.111***
I21.27	218	1.47	0.40	0.29	0.058*	0.018	0.130***	0.082**	0.101***
I28	40	2.87	0.08	0.03	-0.004	0.085*	0.099*	0.030	-0.066
I29.33	90	1.09	0.55	0.17	-0.075	-0.008	0.006	-0.016	-0.071
I34.36	92	2.84	0.14	0.05	-0.009	0.069*	0.024	0.037	0.104**
I37.41	147	2.13	0.27	0.15	0.168***	0.075**	0.047	0.050	0.047
I42	113	4.49	0.08	0.03	0.188***	0.132***	0.204***	0.112***	0.205***
I43	23	1.46	0.35	0.02	-0.023	-0.017	-0.009	0.022	0.228***
I44	39	1.67	0.16	0.02	-0.009	0.069*	0.024	0.037	0.104**
Pooled					0.341***	0.344***	0.344***	0.359***	0.365***

Table 3: Spatial correlation of dependent variable

	EFF	PAT	POP	GDP	HIGH	EMPL	SPEC	PRIVATE	INTER_INV
PAT	0.21***								
POP	0.11***	0.27***							
GDP	0.15***	0.36***	0.78***						
HIGH	0.17***	0.37***	0.77***	0.92***					
EMPL	0.16***	0.37***	0.74***	0.66***	0.69***				
SPEC	0	0.17***	-0.05***	0.03*	-0.02	-0.08***			
PRIVATE	-0.11***	-0.07***	-0.04***	-0.13***	-0.09***	-0.2***	-0.04***		
INTER_INV	-0.11***	-0.07***	-0.04***	-0.13***	-0.09***	-0.2***	0.04**	0.01	
COOP	-0.05***	-0.07***	0.09***	0.04**	0.1***	0.1***	-0.11***	0	-0.02
INTRA	-0.02	-0.06***	-0.05***	-0.03*	-0.05***	0	0	0.1***	-0.24***
TF12	0.02	0.03*	0.03	-0.02	0.1***	0.08***	-0.07***	-0.09***	-0.01
TF18	0	0.01	-0.03*	-0.04**	0.1***	-0.01	-0.05***	-0.03*	0.02
TF19	0.01	0.03**	0.03*	0.02	0.06***	0.05***	-0.02	-0.04**	-0.02
TF21	0.03*	0.01	0.03*	-0.03*	0	0.11***	-0.04**	-0.01	-0.03
TF22	0.01	-0.01	0.02	-0.05***	0.09***	0.05***	-0.06***	-0.07***	0.03*
TF23	-0.03*	-0.01	0.02	-0.05***	0.07***	0.02	-0.05***	0.02	0.06***
TF27	0	-0.02	0.03*	-0.05***	0.03*	0.02	-0.07***	0.03**	0.02
	COOP	INTRA	TF12	TF18	TF19	TF21	TF22	TF23	
INTRA	-0.03*								
TF12	0.11***	-0.03*							
TF18	0.12***	-0.03*	0.24***						
TF19	0.03	-0.03	0.11***	0.1***					
TF21	0.03*	-0.01	0.08***	-0.01	-0.02				
TF22	0.06***	-0.06***	0.26***	0.36***	0.3***	-0.03			
TF23	0.08***	-0.05***	0.19***	0.29***	0.08***	0.02	0.27***		
TF27	0.08***	-0.03*	0.1***	0.13***	0.03	0.04**	0.16***	0.21***	

Table 4: Correlation of variables

Table 5: Determinants of efficiency, minimum 10 patent applications

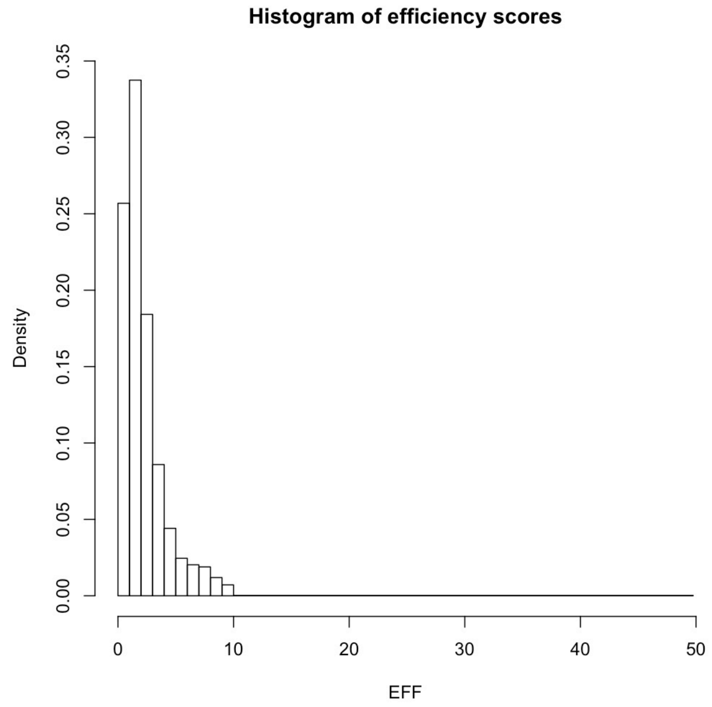

Figure 1: Histogram of efficiency scores

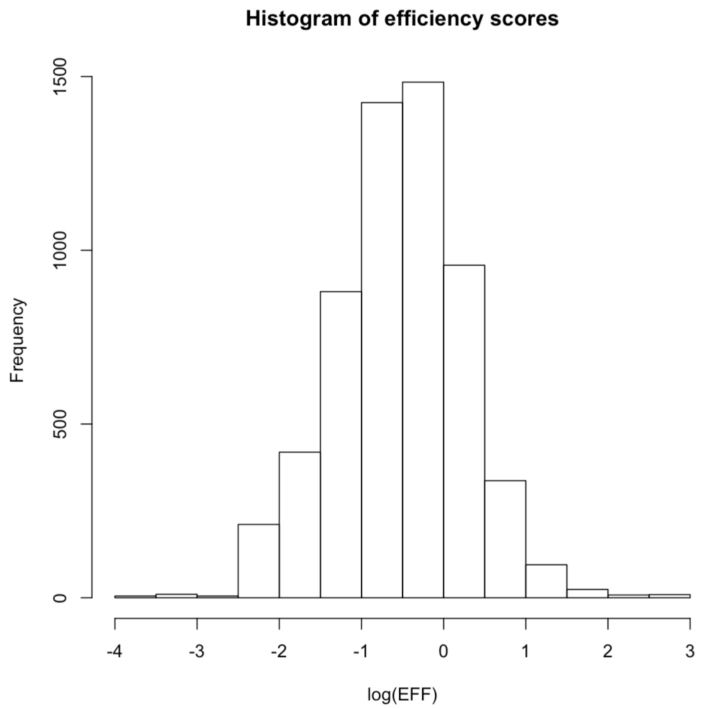

Figure 2: Histogram of logged efficiency scores

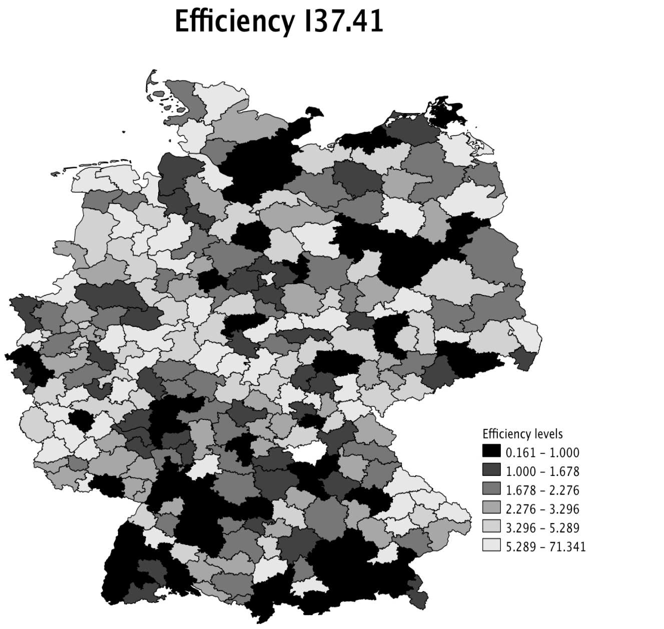

Figure 3: Efficiency of German LMR for I37.41 in 2001

Dep. EFF	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
lambda	105.57***	111.66***	110.99***	111.69***	111.83***	113.12***	109.43***
Log(POP)	1.545*	1.278	1.253	1.250	1.259	1.330	1.322
Log(GDP)	-0.257	-0.271	-0.248	-0.246	-0.221	-0.225	-0.220
Log(HIGH)	-0.232	-0.197	-0.203	-0.202	-0.185	-0.188	-0.196
Log(EMPL)	0.089	0.080	0.080	0.081	0.081	0.080	0.062
Log(SPEC)	-0.295***	-0.314***	-0.319***	-0.319***	-0.318***	-0.319***	-0.331***
TF1	-0.007	-0.001	0.001	0.004	0.003	0.000	-0.007
TF2	0.028	0.048	0.047	0.045	0.046	0.048	0.052
TF3	0.056	0.065	0.062	0.058	0.059	0.060	0.055
TF4	-0.025	0.018	0.019	0.022	0.023	0.020	0.021
TF5	-0.068	-0.074	-0.073	-0.073	-0.073	-0.072	-0.074
TF6	-0.074	-0.102	-0.103	-0.102	-0.102	-0.096	-0.091
TF7	-0.015	-0.025	-0.024	-0.022	-0.023	-0.026	-0.013
TF8	0.086	0.123	0.123	0.122	0.123	0.121	0.117
TF9	-0.030	-0.047	-0.045	-0.052	-0.052	-0.059	-0.045
TF10	0.134	0.061	0.065	0.070	0.072	0.052	0.079
TF11	-0.046	-0.003	-0.012	-0.015	-0.013	-0.014	-0.014
TF12	0.080*	0.084*	0.085*	0.088*	0.087*	0.089*	0.094*
TF13	-0.014	-0.002	-0.004	-0.005	-0.005	-0.006	-0.006
TF14	-0.046	-0.034	-0.035	-0.035	-0.034	-0.036	-0.030
TF15	-0.046	-0.043	-0.043	-0.044	-0.044	-0.046	-0.041
TF16	0.013	0.004	0.005	0.004	0.004	0.004	-0.001
TF17	0.047	0.048	0.048	0.048	0.048	0.047	0.039
TF18	-0.081	-0.115	-0.105	-0.109	-0.109	-0.103	-0.100
TF19	0.132**	0.142**	0.142**	0.140**	0.140**	0.140**	0.133**
TF20	0.108	0.080	0.096	0.090	0.093	0.085	0.093
TF21	0.060	0.046	0.045	0.044	0.044	0.047	0.044

TF22	0.289*	0.296*	0.287	0.284	0.283	0.287	0.277
TF23	0.458***	0.411***	0.391***	0.387***	0.385***	0.383***	0.392***
TF24	-0.007	-0.010	-0.001	0.003	0.004	0.009	0.006
TF25	0.013	0.013	0.014	0.015	0.016	0.015	0.017
TF26	0.058	0.070	0.072	0.073	0.073	0.080	0.066
TF27	0.194	0.192	0.197	0.197	0.197	0.200	0.175
TF28	-0.043	-0.010	-0.006	-0.001	-0.001	0.004	-0.005
TF29	-0.024	-0.022	-0.017	-0.017	-0.017	-0.016	-0.012
TF30	-0.059	-0.048	-0.055	-0.054	-0.054	-0.054	-0.047
TF31	-0.063	-0.064	-0.068	-0.071	-0.071	-0.078	-0.082
y2000	0.014	0.017	0.019	0.019	0.016	0.017	0.020
y2001	0.068***	0.077***	0.078***	0.077***	0.075***	0.075***	0.082***
y2002	0.010	0.023	0.026	0.025	0.018	0.019	0.030
y2003	0.015	0.030	0.031	0.030	0.028	0.028	0.030
PRIVATE	0.140	0.139	0.139	0.141	0.140	0.139	0.136
INTER_INV		-0.613***	-0.596***	-0.611***	-0.605***	-0.610**	-0.605***
COOP			-0.346***	-0.345***	-0.346***	-0.064	-0.742***
INTRA				-0.031**	-0.031*	-0.025	-0.045
$(\text{INTER\_INV})^2$					-0.069		
COOP^2						-2.373**	
INTRA^2							-0.005***
Total sum of squares:	2117.44	2117.44	2117.44	2117.44	2117.44	2117.44	2117.44
Residual sum	269.462	258.499	257.817	257.399	257.389	256.884	253.742
F-statistic	1.66	4.27	4.28	4.18	6.04	7.72	5.57
DF	2819	2818	2817	2816	2815	2814	2815
R2	0.873	0.878	0.878	0.878	0.878	0.879	0.88

Table 6: Determinants of efficiency, minimum 5 patent applications

Dep. EFF	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*	*Model 7*
lambda	54.267***	63.533***	61.944***	62.087***	61.938***	62.189***	60.004***
Log(POP)	0.409	0.283	0.290	0.339	0.265	0.317	0.364
Log(GDP)	0.168	0.229	0.228	0.214	0.221	0.186	0.205
Log(HIGH)	-0.125	-0.115	-0.118	-0.124	-0.110	-0.109	-0.111
Log(EMPL)	0.073	0.084	0.082	0.083	0.087	0.084	0.074
Log(SPEC)	-0.293**	-0.356***	-0.358***	-0.365***	-0.357***	-0.355***	-0.365***
TF1	-0.129	-0.115	-0.113	-0.107	-0.113	-0.109	-0.123
TF2	0.085	0.078	0.071	0.069	0.069	0.069	0.085
TF3	0.293	0.264	0.279	0.264	0.254	0.260	0.277
TF4	-0.142	-0.128	-0.132	-0.127	-0.130	-0.130	-0.127
TF5	0.025	0.022	0.018	0.020	0.021	0.020	0.022
TF6	0.007	-0.005	-0.004	-0.011	-0.012	-0.014	-0.001
TF7	0.058	0.060	0.046	0.055	0.053	0.056	0.070
TF8	0.034	0.032	0.024	0.031	0.032	0.030	0.026
TF9	-0.020	-0.019	-0.017	-0.016	-0.015	-0.011	-0.010
TF10	-0.240	-0.325	-0.296	-0.319	-0.326	-0.331	-0.270
TF11	-0.178	-0.166	-0.147	-0.164	-0.159	-0.159	-0.160
TF12	0.018	0.015	0.008	0.009	0.008	0.008	0.018
TF13	0.023	0.034	0.031	0.033	0.035	0.033	0.035
TF14	-0.038	-0.041	-0.036	-0.039	-0.036	-0.038	-0.031
TF15	-0.084	-0.096	-0.090	-0.093	-0.091	-0.091	-0.089
TF16	-0.040	-0.049	-0.047	-0.047	-0.046	-0.046	-0.045
TF17	0.052	0.048	0.048	0.049	0.049	0.049	0.048
TF18	-0.235***	-0.215	-0.236	-0.232***	-0.235	-0.234***	-0.222***
TF19	0.181***	0.191	0.192	0.188***	0.192	0.190***	0.173***

TF20	-0.020	-0.025	-0.064	-0.039	-0.034	-0.029	-0.032
TF21	0.132*	0.118*	0.108*	0.108*	0.111*	0.109*	0.113*
TF22	0.121	0.121	0.100	0.115	0.118	0.119	0.114
TF23	0.350*	0.341*	0.349*	0.339*	0.344*	0.346*	0.362*
TF24	-0.053	-0.007	-0.042	-0.030	-0.029	-0.034	-0.014
TF25	0.009	0.023	0.021	0.027	0.028	0.025	0.019
TF26	-0.036	0.006	-0.004	0.001	-0.001	0.000	-0.004
TF27	0.321***	0.305***	0.310***	0.308***	0.310***	0.307***	0.261**
TF28	-0.050	-0.012	-0.022	-0.014	-0.014	-0.014	-0.021
TF29	-0.032	-0.028	-0.036	-0.031	-0.029	-0.030	-0.022
TF30	-0.143	-0.157	-0.137	-0.142	-0.146	-0.143	-0.148
TF31	-0.091	-0.098	-0.091	-0.093	-0.096	-0.093	-0.095
y2000	0.004	-0.001	0.000	0.000	-0.002	-0.001	0.003
y2001	0.073**	0.079***	0.079***	0.082***	0.080***	0.082***	0.087***
y2002	0.037	0.044	0.046	0.049	0.042	0.043	0.053
y2003	0.009	0.023	0.024	0.027	0.023	0.025	0.027
PRIVATE	0.139	0.139	0.138	0.137	0.140	0.137	0.136
INTER_INV		-0.672***	-0.655***	-0.649***	-0.635***	-0.647***	-0.642***
COOP			-0.370*	-0.393*	-0.395*	-0.098	-0.855***
INTRA				0.016	0.016	0.017	0.075***
$(INTER\_INV)^2$					-0.237		
$COOP^2$						-2.931*	
$INTRA^2$							-0.440***
Total sum of squares:	946.782	946.782	946.782	946.782	946.782	946.782	946.782
Residual sum	118.5	114.06	113.99	113.79	113.72	113.50	111.97
F-statistic	1.76	3.40	3.34	3.33	3.28	3.37	3.91
DF	1627	1626	1625	1624	1.623	1623	1623
R2	0.875	0.880	0.880	0.880	0.880	0.880	0.882

Table 7: Determinants of Efficiency, minimum 10 patent applications

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