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What determines the efficiency of regional innovation systems?

Michael Fritsch^{‡*} & Viktor Slavtchev[‡]

March 2007

Abstract

We assess the efficiency of regional innovation systems (RIS) in Germany by means of a knowledge production function. This function relates private sector research and development (R&D) activity in a region to the number of inventions that have been registered by residents of that region. Different measures and estimation approaches lead to rather similar assessments. We find that both spillovers within the private sector as well as from universities and other public research institutions have a positive effect on the efficiency of private sector R&D in the respective region. It is not the mere presence and size of public research institutions, but rather the intensity of interactions between private and public sector R&D that leads to high RIS efficiency. We find that relationship between the diversity of a regions' industry structure and the efficiency of its innovation system is inversely u-shaped. Regions dominated by large establishments tend to be less efficient than regions with a lower average establishment size.

JEL-classification: O31, O18, R12

Keywords: Knowledge, innovation, technical efficiency, spillovers, patents, regional analysis.

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1. Introduction

Inventions and innovations are not evenly distributed in space but tend to be clustered in certain locations (Feldman, 1994; Paci and Usai, 1999, 2000; Moreno, Paci and Usai, 2005). One main reason for this phenomenon is that a number of inputs, which are crucial for innovative activities, are not available to the same degree at all locations. Another reason may be that there are differences with regard to the 'quality' or 'efficiency' of regional innovation systems (RIS) leading to different levels of innovative output even if the inputs are identical. The available empirical evidence for such differences in RIS efficiency is, however, sparse and not at all convincing. We still know only rather little about the conditions that are conducive or unfavorable for innovation activity and how policy could help to improve the functioning of RIS. Moreover, it is not clear how to assess the efficiency of regional innovation processes.

This paper elaborates on the determinants of the efficiency of RIS. We first introduce two different measures for RIS efficiency, which are both based on the concept of a knowledge production function (section 2), and describe the spatial distribution of efficiency among the German planning regions (section 3). Section 4 discusses the possible determinants of the efficiency of RIS. The results of multivariate regression analyses of the impact of different factors on the efficiency of RIS are presented in section 5. Finally, we draw conclusions for further research (section 6).

2. Assessing the efficiency of RIS

Our understanding of the efficiency of RIS¹ corresponds to the concept of technical efficiency as introduced by Farrell (1957). Farrell regards an economic unit as being inefficient if it fails to generate the maximum feasible output from a given set of inputs. Reasons for technical inefficiency can be manifold and comprise all sorts of mismanagement such as inappropriate work organization and improper use of technology, scarcity of inputs as well as X-inefficiency as exposed by Leibenstein's (1966) seminal work. Applying this definition to the concept of a regional innovation system means that a region is technically efficient if it is able to produce the possible maximum of innovative output from a given amount of innovative input. Accordingly, a RIS is regarded as technically inefficient if its output falls below the maximum possible value.

In this paper, we use the concept of a knowledge production function (KPF) for assessing the technical efficiency of regional innovation systems. The basic hypothesis behind the KPF is that inventions do not completely 'fall from heaven' but result predominantly from respective R&D activities. According to Griliches (1979) and Jaffe (1989), who assume a Cobb-Douglas type function for the relation between input and output, the KPF can be expressed as

$$(1) \quad Y_i = A_i X_i^{\beta_i} .$$

Y_i denotes the innovative output of a region i , and X_i is a set of inputs.

$A_i = \alpha e^{-u_i}$ is an inefficiency parameter, with α as a constant term, which is

¹ A regional innovation system is commonly understood as a set of all those local actors, formal institutions and other organizations, which jointly or individually contribute to the generation, use, accumulation and diffusion of knowledge and technologies (Asheim and Gertler, 2005; Cooke, Uranga and Etxebarria, 1997).

common for all regions, while $u_i \in [0;1]$ denotes the technical inefficiency of a certain region i .

To estimate a KPF, we employ the number of disclosed patent applications by regional inventors as an output variable of the regional innovation processes. The information on the regional patent applications is currently available on a yearly basis for the period from 1995 to 2000 (Greif and Schmiedl, 2002). As an input for the innovation process, we use the number of R&D employees in the private sector (*R&D*). This information is taken from the establishment file of the German Social Insurance Statistics (*Statistik der sozialversicherungspflichtig Beschäftigten*) as described and documented by Fritsch and Brixly (2004). Employees are classified as working in R&D if they have a tertiary degree in engineering or in natural sciences.

In an earlier analysis of the knowledge sources of innovation for West German districts² (*Kreise*) with the number of patent applications as the dependent variable, we found a dominant effect for the number of private sector R&D employees in the region (Fritsch and Slavtchev, 2007a, c). The same result holds if the German planning regions (*Raumordnungsregionen*) are chosen as the spatial unit of analysis as is the case in this study. Further knowledge sources that had a significant effect on innovative output of a region were spatial knowledge spillovers from adjacent regions as well as from the research at universities. In order to assess the efficiency of RIS, we include only the regional private sector R&D employment as an explanatory variable into the knowledge production function and omit other input variables. This is done for two reasons. First, as we only have a small number of observations per region, there are only limited degrees of freedom left to include more explanatory variables. Second, knowledge spillovers from

² The German districts (*Kreise*) coincide with the NUTS-3 regional classification.

other sources, for example public research institutions, may have a considerable impact on the productivity of private sector R&D employees or, in other words, are a determinant of the efficiency of RIS and should, therefore, not be used for its measurement. Moreover, public research institutions are an important element of public policy for influencing the quality of RIS.

When relating knowledge input to innovative output, we have to assume that there is a time lag. The main reason is that R&D activity requires time for attaining a patentable result. Moreover, patent applications are published only about twelve to eighteen months after submission. This is the time necessary for the patent office to verify whether an application fulfils the basic preconditions for being granted a patent and to complete the patent documents (Greif and Schmiedl, 2002). Therefore, a time lag between innovative inputs and output of at least two years should be assumed.³ However, because reliable data on R&D employment in East Germany are only available for the years 1996 onwards, we reduce the time lag between R&D input and the patent application to a period of one year in order to have more observations and degrees of freedom. Hence, the R&D output for the 1997-2000 period is related to R&D input between 1996 and 1999. This appears justified because there are no great fluctuations of both innovation input and innovation output over these years. Moreover, the differences between the estimated parameters of a KPF with a time lag of one year and with a time lag of three years are negligible.⁴

³ Assuming such a time lag also helps to avoid potential problems of endogeneity between R&D inputs and output. Fritsch and Slavtchev (2007a, b), in their analysis for Germany, use a time lag of three years between patent applications and innovative input. Fischer and Varga (2003) use a two-year lag and Ronde and Hussler (2005) link the number of patents between 1997 and 2000 to R&D efforts in 1997. Acs, Anselin and Varga (2002) report that US innovation records in 1982 result from inventions made 4.3 years prior.

⁴ Bode (2004) also uses a time lag of one year when relating patent output to R&D employment across German planning regions.

The spatial framework used for the analysis of the efficiency of RIS are the 97 German planning regions (*Raumordnungsregionen*). The main advantage of using planning regions is that they are functional units that account for travel to work areas, and they include at least one core city as well as its surroundings.⁵ This is particularly important because the patents in our database are assigned to the inventors' residence; thus, they would not be related to the location of the respective R&D activity if the place of employment and the place of the inventor's residence would be located in different regions (Deyle and Grupp, 2005). Choosing planning regions as spatial units of analysis may largely avoid such spatial distortions. For historical reasons, the cities of Berlin, Hamburg and Bremen are defined as planning regions even though they are not functional economic units. In order to avoid possible distortions, we merged these cities with adjacent planning regions (Berlin with the region of Havelland-Flaeming, Hamburg with the region of Schleswig-Holstein South and Bremen with Bremerhaven and Bremen-Umland). Hence, the estimation approach applied in this paper is based on observations for 93 regions over 4 years.

From the perspective of the KPF, there are two possible reasons why a region's innovative output is lower than the highest possible level. The first reason is due to a relatively low value of the slope parameter β_i , which can be interpreted as the marginal patent productivity of private sector R&D employees. A second reason could be differences in the level of the function with a given slope. Such differences reflect the various levels of R&D output with a certain input in terms of average productivity and would correspond with different values of the constant term of the function. According to these two types of differences, we apply two approaches for assessing the efficiency of RIS.

⁵ For this definition of the planning regions, see Federal Office for Building and Regional Planning (*Bundesamt für Bauwesen und Raumordnung, BBR*) (2003).

To estimate the productivity of RIS in terms of the marginal return to R&D input, we include a binary dummy variable for each region that is multiplied with the respective number of private sector R&D employees. The constant term A is assumed to be identical for all regions. Hence, the equation (1) can be rewritten as

$$(2) \quad \text{Number of patents}_i = A \prod_i R \& D \text{ priv}_i^{\beta_i},$$

with β_i as a measure of the marginal productivity of private sector R&D employment in the i^{th} region ($i = 1, \dots, 93$). If the constant term A is not significantly different than zero (see table A1 in the Appendix), marginal productivity equals average productivity. Based on the estimated values for the marginal productivity of private sector R&D, we define the efficiency of a certain region as the quotient of the estimated in that particular region and the maximum estimated value, i.e.,

$$(3) \quad TE_i = \beta_i / \max \beta_i.$$

Accordingly, at least one region is assumed to be fully efficient. We label this approach as (quasi) ‘deterministic’ because it implies that all deviations from the maximum value are due to inefficiency and, therefore, neglects the possibility that values could be affected by measurement errors or by random disturbances.⁶ As the number of patents that have been applied for by regional residents is whole-numbered information⁷ and cannot be less than

⁶ Hence, there is the danger that an extremely high output value, which is due to stochastic disturbances, is wrongfully taken as the benchmark for the measurement of efficiency.

⁷ If a patent has more than one inventor, the patent is divided by the number of inventors and the respective shares are assigned to the regions in which the inventors have their residence. Therefore, in event that the inventors are located in different regions, the number of patents per region may not always be whole-numbered. To adjust the information on the number of patents to the assumptions of the negative-binomial procedure, these numbers have been rounded up.

zero, we apply a negative-binomial regression as estimation technique (Greene, 2003, 931-939). Due to the insufficient length of the time series (four years), applying a panel regression technique appears inappropriate, and the data are, therefore, pooled. However, in order to partly relax the assumption of independent observations for a particular planning region, we adjust the standard error for intragroup correlation by clustering the observations for each region. Applying such a clustering procedure is equivalent to the White-corrected standard error in the presence of heteroscedasticity (White, 1980).

According to the second approach, the produced output may fall systematically below the maximum, not because of lower marginal output elasticities of the factors of production ($\beta_i = \beta, \forall i$), but rather because of a lower level of the function. Thus, the knowledge production function can be expressed as

$$(4) \quad \text{Number of patents}_i = \alpha R \& D \text{priv}_i^\beta e^{-v_i} e^{u_i},$$

where v_i denotes effects of the region-specific environment on innovative output and u_i represents the stochastic error term. Therefore, a RIS achieves its maximum feasible output if, and only if, it is fully efficient ($v_i = 0$). The value of v_i provides a measure for the deviation of observed output from the possible maximum. In contrast to the deterministic approach, v_i can be interpreted as a measure for the average productivity and not for the marginal productivity of a RIS. The approach is called stochastic frontier approach (SFA) because it allows for stochastic disturbances. This implies that extreme values are not necessarily taken as the benchmark for the measurement of efficiency. The yearly data for the regions are pooled together, and the technical efficiency is computed as the average value of the four observations per region. A general precondition for the estimation of a stochastic frontier function is a negative skewness of residuals (Schmidt and

Lin, 1984). In order to separate the impact of technical inefficiency v_i from the general stochastic effects u_i , an a priori assumption about the distribution of technical inefficiency is necessary. In contrast to u_i , which is always assumed to be independently $N(0; \sigma_u^2)$ distributed, several specifications for the inefficiency term v_i are possible: v_i can be assumed to be independently and exponentially distributed with variance σ_v^2 , or independently and half-normally $N^+(0; \sigma_v^2)$ distributed, or independently $N^+(\mu; \sigma_v^2)$ distributed with a truncation point at 0. Due to the fact that the choice of the distributional assumption is a priori not clear, we report the results of the different alternatives in order to demonstrate the robustness of the results. All models are estimated by a maximum likelihood procedure. In order to be compatible with the calculation of technical efficiency according to the (quasi) deterministic approach (e.g., equation (3)), the values of technical efficiency from equation (4) are transformed in the following way

$$(5) \quad TE_i' = e^{-v_i} / \max e^{-v_i} .$$

The results are reported in table A1 in the Appendix.

3. The distribution of RIS efficiency

There are considerable differences between the values of technical efficiency for the German planning regions. The efficiency levels estimated by means of a stochastic frontier function show a rather wide spread with the least efficient region attaining only 9.8 percent of the highest value (table 1 and figure 1). As compared to the quasi deterministic approach, the stochastic frontier method leads to a much more differentiated assessment of RIS efficiency (see Fritsch and Slavtchev, 2006, for detailed discussion). The greater dispersion of efficiency estimates derived on the basis of a stochastic frontier approach indicates that innovation systems differ more with respect to their average productivity than by marginal productivity of R&D input.

Table 1: Descriptive statistics for the distribution of technical efficiency in German planning regions^a

No.	Variable	Mean	Median	Minimum	Maximum	Standard deviation	Pearson correlation coefficient		
							1	2	3
1	TE _i (quasi deterministic) ^b	0.837	0.870	0.529	1.00	0.115	1.00		
2	TE' _i (SFA, half-normal) ^c	0.558	0.607	0.100	1.00	0.265	0.98	1.00	
3	TE' _i (SFA, truncated normal) ^c	0.585	0.650	0.105	1.00	0.270	0.98	0.99	1.00
4	TE' _i (SFA, exponential) ^c	0.619	0.706	0.113	1.00	0.275	0.98	0.99	0.99

^a Number of observations (regions) = 93.

^b According to equation (3).

^c According to equation (5).

The spatial distribution of the technical efficiency of RIS according to the different approaches is, however, rather similar. The Pearson correlation coefficients between the efficiency values estimated by the different approaches are about 0.98 (table 1). The spatial distribution of the efficiency values (figure 1) suggests that regions with similar values of technical efficiency tend to be clustered in space. Planning regions with the highest values of technical efficiency are located in the south, in the west and in the center of the country. None of the planning regions in the north or in the east of Germany fall into this category. In particular, the values for the technical efficiency of RIS tend to be relatively high in larger, densely populated areas such as Munich, Stuttgart, Cologne and Frankfurt. The Berlin region, which has a position in the middle range of the efficiency ranking, is an exception in the East German innovation landscape. Regions with relatively low values for the efficiency of their innovation system are entirely located in the north and in the east. Generally, location in border regions seems to be unfavorable. Regions with moderate values of technical efficiency are found to be located predominantly in the center of the country; thus, this separates the west from the east as well as the south from the north. The distribution of RIS efficiency

across the regions indicates that the German innovation system is spatially divided into different regimes with diverging levels of performance.

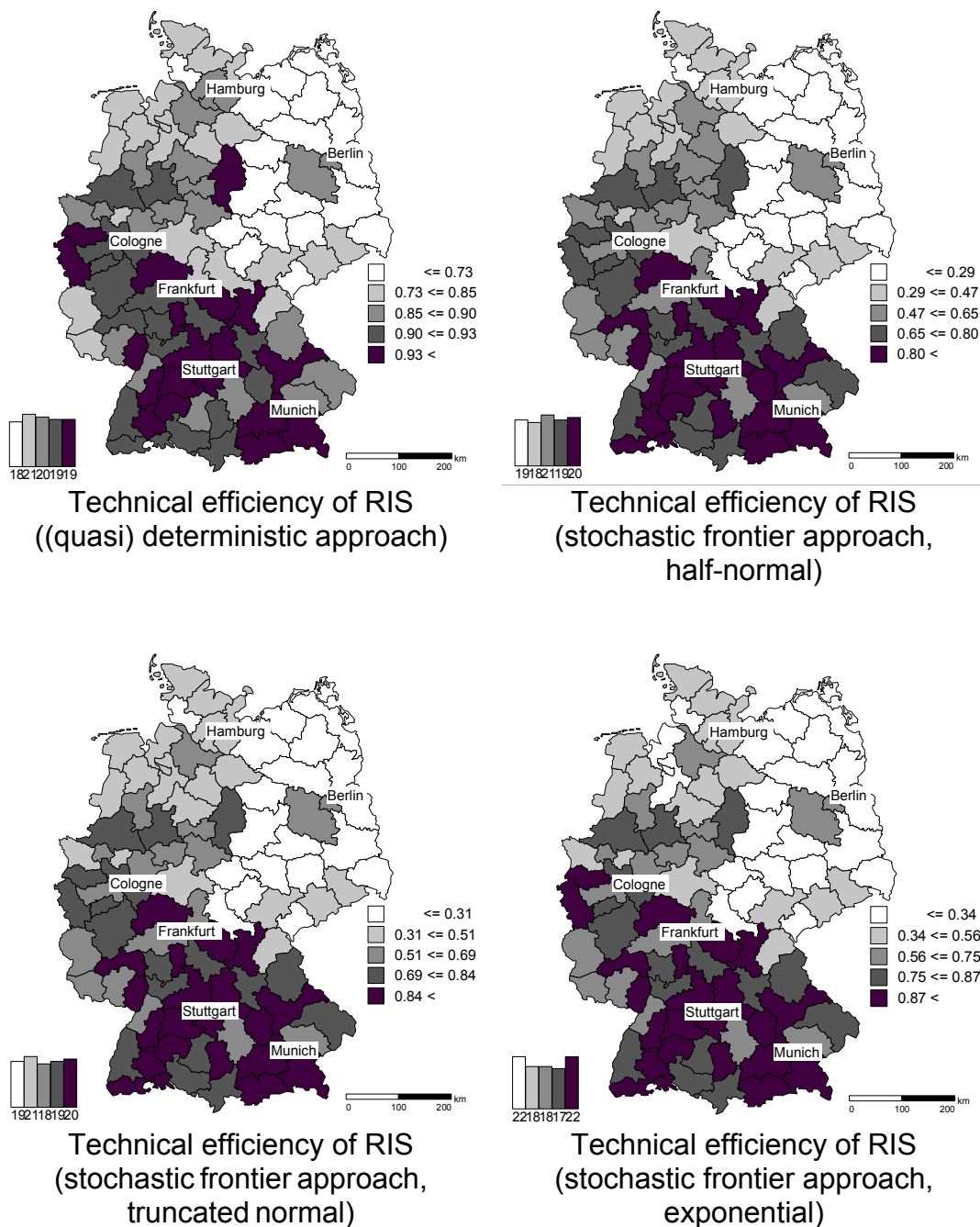


Figure 1: The spatial distribution of technical efficiency of RIS in Germany

4. Possible determinants of efficiency of RIS

The factors that determine the efficiency of RIS can be manifold. It is plausible to assume that the ability of private sector R&D employees to produce innovative output may depend on the availability and the quality of knowledge and other innovative inputs in the region. Given that innovation processes are characterized by a pronounced division of labor⁸, one may expect that the efficiency of a RIS depends on how intensely the regional knowledge base is exploited and further developed through the interaction of regional agents. The efficiency of RIS may, therefore, be strongly influenced by the level and the quality of interaction and exchange between its different elements and the respective knowledge flows (spillovers). This interaction may be critically dependent on the availability of potential cooperation partners in the region such as other private firms working in the respective technological field, public research institutes as well as suppliers of innovative inputs. Therefore, the density and industrial composition of the regional actors, the accessibility of the region as well as the technological, industrial and institutional infrastructure (e.g., the 'networks') may play an important role.⁹ The interaction between the different elements of RIS generates partly self-enforcing systemic effects that may result in specific knowledge as well as specific technologies and methods of problem solving

⁸ Arora and Gambardella (1994); Arora, Gambardella and Rullani (1997); Arora and Gambardella (1998), Cockburn et al., (1999); Arora, Fosfuri and Gambardella (2001).

⁹ The assertion of such a positive impact of interaction and exchange between regional actors on innovation activity constitutes a main hypothesis in the literature on industrial districts (cf. Porter, 1998, and the contributions in Pyke, Beccatini and Sengenberger, 1990), innovation networks (cf. Camagni, 1991; Grabher, 1993) and "innovative milieux" (Crevoisier, 2004; Ratti, Bramanti and Gordon, 1997). In this literature, it is argued that regional differences in cooperation behavior are, to a considerable degree, responsible for differences with regard to innovation activity, particularly the efficiency of R&D. One main reason given for such a positive effect is that the cooperation between actors may work as an important medium for knowledge spillovers. Knowledge spillovers play a significant role in recent approaches to growth theory (cf. Krugman, 1991; Romer, 1994) as well as in the concept of (national or regional) innovation systems (cf. Lundvall, 1992; Nelson, 1993; Edquist, 1997; Cooke, Uranga and Etxebarria, 1997).

(Gertler, 2003), which can be expected to affect the workability of the system (Leydesdorff and Fritsch, 2006).

We assume that the amount of knowledge spillovers within the private sector is related to the number of R&D employees in this sector. The larger the number of R&D employees is, the greater the opportunity to find a suitable partner for cooperation and knowledge exchange is. The indicator for knowledge spillovers within the private sector is the share of R&D employment in that sector (*R&D*). Employees are classified as working in R&D if they have a tertiary degree in engineering or in natural sciences. This information is taken from the establishment file of the German Social Insurance Statistics (*Statistik der sozialversicherungspflichtig Beschäftigten*), as described and documented by Fritsch and Brixey (2004).

The knowledge that is generated and accumulated by the universities may constitute a basic precondition for private sector R&D activities (Jaffe, 1989). However, in order to become effective, this knowledge has to spill over. The ways in which such knowledge transfers occur are manifold.¹⁰ In particular, the direct channels for transfer of academic knowledge such as R&D cooperation with private sector firms or the provision of innovation related services play a major role for private sector innovative activities (Mansfield and Lee, 1996; Fritsch and Slavtchev, 2007a, c). The impact of universities on innovative performance of private sector firms may differ considerably according to the quality of a university's research and the intensity in which the university interacts with the firms (e.g., Feldman and Desrochers, 2003; Mansfield and Lee, 1996; Fritsch und Slavtchev, 2007a, c). In order to test the impact of universities for the performance of the private sector, we introduce the amount of external research funds that the universities gain from private firms (*ER-PRIV*). Universities' external funds

¹⁰ See Varga (1998) for an overview of the transfer channels of knowledge from universities to the private sector.

can be regarded as an indicator of the amount and the quality of the research (Hornbostel, 2001). The main reason is that universities' funding from external sources occurs predominantly by means of some competitive procedure and is, therefore, largely dependent on the quality of the research conducted. In particular, the funds from private firms are well suited to indicate the relevance of academic research for commercial applications as well as the intensity of university-industry linkages, which may be characterized by pronounced knowledge spillovers (Fritsch and Slavtchev, 2007a, c). In order to avoid possible scale effects of large universities, which are likely to attract larger amounts of external funds from private firms, we use the average amount of external funds from private sector firms per university professor.¹¹ Previous empirical analyses of university-industry cooperation show that a high share of private sector cooperation partners tends to be located in the region of the respective university (Beise and Stahl, 1999; Fritsch, 2003).

Non-university public research institutions such as the Max-Planck-Society (*MPG*) and the Fraunhofer-Society (*FhG*) may also have a positive effect on the technical efficiency of private sector R&D employees. Unfortunately, we do not have information about the external research funds of these institutes available; thus, we introduce the regional number of institutes in our analysis.

As far as a technology is unique in the sense that the transfer and the application of respective knowledge requires specific skills or a specific common language, the occurrence of knowledge spillovers depends critically on the degree of technological similarity between the parties (Jaffe, 1986; Nadiri, 1993). Therefore, we introduce the technological proximity between public and private sector R&D as a measure of correspondence and potential

¹¹ All university related information is own preparation of data from the German University Statistics.

interplay of the regional actors in the innovation process (*PROXTECH*). The technological proximity between public and private sector R&D is measured as the degree of congruence between the technological fields of the patent output of public research institutions (PAT_{ACAD}) and private sector firms (PAT_{PRIV}):¹²

$$(8) \quad PROXTECH_i = \frac{PAT_{ACAD_i} * PAT_{PRIV_i}}{|PAT_{ACAD_i}| * |PAT_{PRIV_i}|}$$

This index can assume values between one and zero. The larger the value is, the closer the technological proximity between public and private sector R&D is and the greater the possibilities for cooperation and occurrence of knowledge spillovers should be.

The service sector may provide important support for the R&D activities in diverse ways such as counseling, technical services, provision of venture capital, etc. One could, therefore, expect a positive impact of the share of the regional service sector (*SERVICES*) on RIS efficiency. On the other hand, a high share of the service sector in the region may have a negative effect due to the relatively low propensity to patent in this sector.

A large body of empirical literature shows that economies external to the firms may be conducive to their innovative activities (see Fritsch and Slavtchev, 2007b, for a more detailed discussion). On the one hand, it is argued that the geographical concentration of firms belonging to the same industry may constitute an advantage by creating a large pool of common knowledge and other inputs or by allowing for a high degree of labor division within the region. Such effects are labeled *Marshall-Arrow-Romer* (MAR)

¹² See Greif and Schmiidl (2002) for the definition of the 31 technological fields.

externalities¹³ (Glaeser et al., 1992). On the other hand, the exchange of complementary knowledge between agents of different industries may also stimulate the generation of new ideas. Thus, a broader variety of economic activities can play an important role for innovative activities (*Jacobs'* externalities according to Jacobs, 1969). To account for the effects of industrial diversity or concentration, we include the industrial diversity index (*DIVERSITY*). It is calculated as the inverse value of the Gini coefficient based on the number of employees in 58 different industries. The larger this value is, the higher the degree of industrial diversity is.

Population density (number of inhabitants in the region per squared kilometer, *POPDENS*) is a measure, not only of the effects of urbanization economies on RIS performance, but can also be regarded as a catch-all variable for diverse types of unobserved region-specific influences. Literature suggests that high population density should be conducive to innovation activity because it is related to intensive contacts and cooperation (see Feldman, 2000, and Fritsch, 2000, for an overview). We, therefore, expect a positive sign for this variable. The average number of employees per establishment (*SIZE*) is supposed to capture the effects of establishment size.¹⁴ According to a number of previous empirical studies, the number of patents per employee is higher in smaller firms than in large firms (see Cohen and Klepper, 1996, for a discussion); therefore, we expect a negative sign. Two binary dummy variables are supposed to capture additional unobserved effects of a location in West Germany (*WEST*) and in the periphery (*PERIPHERY*). We expect a positive sign for a location in West Germany due to the generally weaker performance of the economy in the

¹³ Based on Marshall (1890), Arrow (1962) and Romer (1986).

¹⁴ Data on population density are taken from Federal Office for Building and Regional Planning (*Bundesamt für Bauwesen und Raumordnung, BBR*). Data on employment and the number of establishments in the region are taken from the establishment file of the German Social Insurance Statistics.

Eastern part of the country, which became rather obvious in the assessment of RIS efficiency as shown in figure 1. Given that a location in the periphery is unfavorable for innovation activity due to relatively large geographical distance to other actors, we expect a negative sign for this variable.

Table 2: Definition of variables and expected sign of coefficient

<i>Variable</i>	<i>Operational definition</i>	<i>Expected sign</i>
R&D	Share of R&D employees in the private sector; <i>source</i> : Social Insurance Statistics.	+
ERF-PRIV	External research funds per university professor (including <i>Fachhochschulen</i>) in 1,000s of Euro; <i>source</i> : University Statistics.	+
MPG	Number of institutes of the Max Planck Society; <i>source</i> : <i>Bundesministerium für Bildung und Forschung</i> (2004).	+
FhG	Number of institutes of the Fraunhofer Society; <i>source</i> : <i>Bundesministerium für Bildung und Forschung</i> (2004).	+
PROXTECH	Correspondence of the technological fields of public and private sector R&D; <i>source</i> : own calculation based on Patent Statistics (Greif and Schmiedl, 2002).	+
DIVERSITY	Index of the diversity of industry structure in the region; <i>source</i> : own calculation based on Social Insurance Statistics.	+ / -
POP DENS	Population density; <i>source</i> : <i>Bundesamt für Bauwesen und Raumordnung</i> .	+
SERVICES	Employment share in the service sector; <i>source</i> : Social Insurance Statistics.	-
SIZE	Average number of employees per establishment; <i>source</i> : Social Insurance Statistics.	-
WEST	Dummy variable for location in West Germany (yes=1; no=0)	+
PERIPHERY	Dummy for location of a planning region at the border of the country (yes=1; no=0)	-
TRANSPORT	Employment share in the service sector; <i>source</i> : Social Insurance Statistics.	?
ELECTRICAL	Employment share in the service sector; <i>source</i> : Social Insurance Statistics.	?
OPTICS	Employment share in the service sector; <i>source</i> : Social Insurance Statistics.	?
CHEMICALS	Employment share in the service sector; <i>source</i> : Social Insurance Statistics.	?

Table 3: Descriptive statistics for independent variables

<i>Variable</i>	<i>Mean</i>	<i>Median</i>	<i>Minimum</i>	<i>Maximum</i>	<i>Standard deviation</i>
TE' (quasi deterministic)	0.84	0.87	0.53	1.00	0.11
TE' (SFA, half-normal)	0.56	0.78	0.10	1.00	0.26
TE' (SFA, truncated normal)	0.58	0.65	0.10	1.00	0.27
TE' (SFA, exponential)	0.62	0.71	0.11	1.00	0.27
R&D (ln)	0.02	0.02	0.01	0.04	0.01
ERF-PRIV	11.06	7.20	0.00	97.07	14.74
MPG	0.86	0.00	0.00	12.00	1.84
FhG	0.85	0.00	0.00	10.00	1.76
PROXTECH	0.62	0.66	0.20	0.84	0.14
DIVERSITY	1.50	1.50	1.31	0.18	0.08
POPDENS	336.99	180.67	53.43	3,886.29	507.56
SERVICES	0.32	0.31	0.22	0.52	0.06
SIZE	13.20	13.31	8.53	18.27	1.70
TRANSPORT	0.04	0.03	0.01	0.03	0.04
ELECTRICAL	0.04	0.03	0.00	0.23	0.02
OPTICS	0.01	0.01	0.00	0.12	0.01
CHEMICALS	0.02	0.01	0.00	0.06	0.02

^a Number of observations (regions) = 93.

^b Pearson correlation coefficient of logarithmic values.

As the propensity to patent the results of R&D may differ between the industries (if there are, for example, alternative ways to appropriate the returns of R&D), efficiency of RIS may be subject to industry specific effects. In order to control for the impact of regional specialization in certain industries with a relatively high level of patenting, we include the share of employees in transportation engineering (TRANSPORT), in electrical engineering (ELECTRICAL), in measurement engineering and optics (OPTICS) as well as in chemistry (including biochemistry) (CHEMICALS) into

our model. These are, according to Greif and Schmiedl (2002), the technological fields with the highest share of patent applications in Germany.¹⁵ Table 2 gives an overview on the definition of variables and respective data sources. Descriptive statistics for the variables used in the analysis are provided in table 3. Table A3 in the Appendix shows the correlations between the variables.

For estimating the model, we transform the dependent as well as the independent variables into log-values because of a better fit with the distributional assumptions of the estimation procedure. Another advantage of logging both sides of the equation is that the estimated coefficients can be regarded as elasticities that can be directly compared with each other. In order to assess the presence and the importance of interdependences between the geographical units of investigation, we have carried out several diagnostic tests (Moran's I, LM-Error, robust LM-Error, LM-Lag and robust LM-Lag) for such spatial dependences. These tests indicate the presence of spatial dependence that takes the form of a spatial autoregressive process in the error term. Therefore, we apply a spatial error model

$$(9) \quad Y = X\beta + \varepsilon ,$$

where $\varepsilon = \lambda W\varepsilon + \mu$, λ denotes the spatial autoregressive parameter, μ denotes a homoscedastic and uncorrelated error term, and W row standardized spatial weights matrix based on a first order contiguity (Anselin, 1988; Anselin and Bera, 1998). The relative importance of different determinants is calculated by applying a robust variance-covariance estimator (White, 1980).

¹⁵ In the period 1995-2000, about 9.6 percent of all patent applications have been submitted in the field of transportation engineering, 13 percent in electrical engineering and 7.4 percent in measurement engineering/optics (Greif and Schmiedl, 2002).

5. Empirical results

The impact of different determinants on the technical efficiency of RIS according to the (quasi) deterministic approach is reported in table 4. With respect to the stochastic frontier approach, there are three particular forms that refer to different assumptions about the distribution of the inefficiency term: half-normal distribution, normal distribution with a truncation point at zero and exponential distribution. The results for the most common case of a half-normal distribution are reported in table 4. Tables A4 and A5 in the Appendix present the estimates of determinants of RIS that refer to the truncated normal distribution and the exponential distribution, respectively.

The share of private sector R&D employment (*R&D*) has a pronounced positive impact on the technical efficiency of RIS. The estimated coefficient provides clear evidence for the relevance of scale economies, i.e., an increase of the share of private sector R&D employment at a certain location can lead to higher efficiency of innovation processes. Obviously, high R&D intensity at a certain location may stimulate knowledge spillovers between actors. However, if more measures for regional specialization in certain industries are included (models 2-8), the impact of the share of R&D employment becomes slightly weaker. This holds particularly for the share of regional employment in electrical engineering (*ELECTRICAL*). The average amount of external research funds from private sector sources per university professor (*ERF-PRIV*) has a positive impact on the efficiency of RIS. This suggests that the intensity of university-industry linkages, as indicated by the money paid by private firms, is conducive to regional innovation activity. Substituting *ERF-PRIV* by other university related indicators such as the number of academic personnel shows hardly any statistically significant impact for such a variable and results in a considerable reduction of the log-likelihood of the model. These results clearly confirm previous findings for the role of academic research on innovation activity in Germany (Fritsch and

Table 4: Determinants of the technical efficiency of RIS (quasi deterministic approach)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	-0.004 (0.01)	0.002 (0.01)	-0.054 (0.18)	-0.051 (0.18)	-0.092 (0.35)	-0.551 (1.31)	-0.566 (1.16)	-0.378 (0.97)
R&D [ln]	0.087** (3.36)	0.082** (3.24)	0.074** (2.96)	0.080** (3.21)	0.074** (3.00)	0.074** (2.71)	0.065** (2.86)	0.070** (2.90)
ERF-PRIV [ln]	0.025** (2.87)	0.025** (2.89)	0.024* (2.56)	0.024** (2.89)	0.025** (2.94)	0.023* (2.25)	-	-
MPG [ln]	-	-	-	-	-	-	0.031* (2.45)	-
FhG [ln]	-	-	-	-	-	-	0.023* (1.98)	-
PROXTECH [ln]	-	-	-	-	-	-	-	0.091** (2.59)
DIVERSITY [ln]	-	-	-	-	-	2.363* (2.44)	3.794* (2.51)	1.778 (1.87)
DIVERSITY ² [ln]	-	-	-	-	-	-2.577* (2.29)	-4.273* (2.33)	-2.108 (1.85)
POPDENS [ln]	0.081** (4.82)	0.080** (4.77)	0.073** (4.86)	0.079** (4.76)	0.079** (4.69)	0.067** (3.79)	0.049** (2.89)	0.055** (3.26)
SERVICES [ln]	-0.281** (5.31)	-0.270** (4.76)	-0.261** (4.86)	-0.270** (5.04)	-0.282** (5.48)	-0.244** (4.81)	-0.273** (5.55)	-0.215** (4.59)
SIZE [ln]	-0.317** (3.344)	-0.319** (3.50)	-0.296** (3.16)	-0.292** (3.24)	-0.296** (3.54)	-0.274** (2.96)	-0.222** (2.60)	-0.227** (2.74)
WEST	0.257** (8.32)	0.253** (8.36)	0.232** (8.00)	0.248** (7.76)	0.247** (6.98)	0.203** (5.84)	0.214** (7.88)	0.216** (6.66)
PERIPHERY	-0.017 (1.07)	-0.018 (1.11)	-0.012 (0.77)	-0.015 (0.95)	-0.015 (0.95)	-0.016 (1.00)	-0.009 (0.69)	-0.009 (0.62)
TRANSPORT [ln]	-	0.006 (0.65)	-	-	-	-	-	-
ELECTRICAL [ln]	-	-	0.034* (2.11)	-	-	0.030* (1.99)	0.028* (1.98)	0.027 (1.92)
OPTICS [ln]	-	-	-	0.015 (1.31)	-	-	-	-
CHEMICALS [ln]	-	-	-	-	0.008 (0.86)	-	-	-
λ	0.468** (3.50)	0.474** (3.54)	0.360* (1.96)	0.451** (3.33)	0.484** (3.71)	0.257 (1.03)	0.117 (0.40)	0.254 (1.12)
Log likelihood	125.739	125.880	128.268	126.554	126.249	130.041	132.678	132.116
Wald ($\lambda=0$)	12.220	12.516	3.842	11.100	13.785	1.051	0.158	1.247
LM-Error ($\lambda=0$)	8.890	9.008	3.951	9.190	9.253	1.294	0.222	1.461

Notes: Absolute value of robust z-statistics in parentheses; * significant at 5% level; ** significant at 1% level. Critical value for the Wald test-statistic and LM-Error with one degree of freedom is 3.48 ($p = 0.05$); spatial weights are row-standardized: W is 1st order contiguity matrix.

Table 5: Determinants of the technical efficiency of RIS (stochastic frontier approach, half-normal distribution)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.043 (0.04)	0.049 (0.04)	-0.062 (0.05)	-0.117 (0.11)	-0.235 (0.22)	-0.113 (0.10)	-0.562 (0.52)	0.143 (0.14)
R&D [ln]	0.249* (2.39)	0.247* (2.33)	0.226* (2.11)	0.233* (2.30)	0.215* (2.07)	0.237* (2.10)	0.213* (2.25)	0.230* (2.20)
ERF-PRIV [ln]	0.054* (2.81)	0.054** (2.81)	0.050* (2.48)	0.052** (2.83)	0.055** (2.86)	0.051* (2.47)	-	-
MPG [ln]	-	-	-	-	-	-	0.109* (2.25)	-
FhG [ln]	-	-	-	-	-	-	0.099* (2.01)	-
PROXTECH [ln]	-	-	-	-	-	-	-	0.240* (1.98)
DIVERSITY [ln]	-	-	-	-	-	0.443 (0.59)	0.648 (0.83)	-0.111 (0.15)
POPDENS [ln]	0.280** (3.99)	0.279** (3.95)	0.253** (3.75)	0.272** (3.92)	0.276** (3.89)	0.247** (3.49)	0.191** (3.00)	0.214** (3.02)
SERVICES [ln]	-1.242** (5.85)	-1.233** (5.48)	-1.190** (5.57)	-1.207** (5.63)	-1.245** (6.00)	-1.178** (5.74)	-1.304** (6.30)	-1.059** (5.33)
SIZE [ln]	-1.425** (4.15)	-1.428** (4.20)	-1.364** (3.92)	-1.338** (3.96)	-1.358** (4.33)	-1.366** (3.95)	-1.214** (3.70)	-1.197** (3.71)
WEST	1.165** (9.97)	1.161** (9.90)	1.092** (9.33)	1.136** (9.38)	1.134** (8.39)	1.059** (7.66)	1.122** (10.44)	1.091** (8.31)
PERIPHERY	-0.107 (1.62)	-0.107 (1.62)	-0.093 (1.41)	-0.100 (1.53)	-0.100 (1.54)	-0.101 (1.51)	-0.082 (1.33)	-0.076 (1.15)
TRANSPORT [ln]	-	0.006 (0.16)	-	-	-	-	-	-
ELECTRICAL [ln]	-	-	0.112* (1.97)	-	-	0.106* (1.96)	0.106* (1.96)	0.106* (1.99)
OPTICS [ln]	-	-	-	0.053 (1.21)	-	-	-	-
CHEMICALS [ln]	-	-	-	-	0.024 (0.73)	-	-	-
λ	0.463** (3.41)	0.464** (3.41)	0.353 (1.76)	0.444** (3.22)	0.477** (3.67)	0.320 (1.38)	0.211 (0.83)	0.295 (1.29)
Log likelihood	-1.966	-1.958	-0.343	-1.303	-1.654	-0.158	1.993	-0.652
Wald ($\lambda=0$)	11.623	11.630	3.082	10.345	13.433	1.894	0.691	1.670
LM-Error ($\lambda=0$)	7.887	7.880	3.145	7.992	8.109	2.256	0.981	2.095

Notes: Absolute value of robust z-statistics in parentheses; * significant at 5% level; ** significant at 1% level. Critical value for the Wald test-statistic and LM-Error with one degree of freedom is 3.48 ($p = 0.05$); spatial weights are row-standardized: W is 1st order contiguity matrix.

Slavtchev, 2007a and c). A positive impact can also be found for non-university public research establishments as indicated by the number of research institutes of the Max-Planck Society (*MPG*) and of the Fraunhofer Society (*FhG*) (model 7). These results suggest that there are knowledge spillovers from both types of research, basic research that is conducted at the Max-Planck-Institutes, and from more applied research carried out by the Fraunhofer Society, which increase the technical efficiency of a RIS.¹⁶ Regions with a high efficiency of innovation activity are characterized by pronounced technological proximity between public and private R&D as measured by the *PROXTECH*-variable (model 8)¹⁷. A possible explanation for this finding is that the knowledge exchange between the two sectors might become more intensive as public and private research is in similar technological fields.

The positive sign for the industrial diversity index (*DIVERSITY*) in models 6-8 suggests the presence of *Jacobs'* externalities. This means that the efficiency of innovation activity increases with the variety of industries in the region and that interaction of actors with different knowledge endowments stimulates the generation of new ideas rather than specialization. However, the negative sign for the squared value of the diversity index indicates a nonlinear relationship that has the shape of an inverse 'U'. This pattern implies that there exists an optimum degree of industrial diversity and that a further increase beyond this level has an unfavorable effect. Obviously, both extremes – broad diversity as well as narrow specialization – are not conducive to the performance of a RIS. The results suggest that both *Marshall* and *Jacobs'* type externalities affect the efficiency of regions in

¹⁶ The variable for the external research funds from the private sector per university professor (*ERF-PRIV*) has been excluded here due to pronounced multicollinearity problems if the number of Max Planck (*MPG*) and of Fraunhofer institutes (*FhG*) are contained in the model.

¹⁷ The variables *ERF-PRIV* as well as *MPG* and *FhG* are excluded here due to multicollinearity problems.

producing innovative output. This confirms previous results of Paci and Usai (1999, 2000), who use the *Herfindahl* index as a measure of industrial diversity, and it also parallels the findings of Greunz (2004), who tests the impact of the industrial structure on innovation in European regions by means of Gini coefficients. However, no such effect of industrial diversity on the efficiency of RIS can be found for the efficiency estimates by means of a stochastic frontier approach (table 5 as well as tables A4 and A5 in the Appendix). A possible explanation for the non-significance of the DIVERSITY-variable in the analyses, which use the efficiency estimates derived from a stochastic frontier approach, could be the wider spread of the efficiency values. Obviously, the effects of industrial diversity are captured by the other variables included in the model. The significant positive value of the coefficient for the spatial error component (λ) indicates that there are spatial dependences between neighboring regions.

The positive coefficient for population density (*POP DENS*) indicates the presence of urbanization economies. This suggests that densely populated regions provide a variety of opportunities for interaction, rich supplies of inputs as well as a comprehensive physical and institutional infrastructure that is advantageous for innovation activity.

The coefficient for the share of service sector employment (*SERVICE*) indicates a negative impact on the efficiency of a RIS. This means that despite their supporting function, resources allocated to the service sector are less efficient in terms of patenting than in manufacturing. As indicated by the significantly negative coefficient for average firm size (*SIZE*), patenting efficiency tends to be lower in regions that are characterized by a high share of large establishments. This result is in line with other studies, which find that the number of patents per unit of R&D input is higher in the smaller firms than in larger ones (Acs and Audretsch, 1990; Cohen and Klepper, 1996). According to the positive and highly significant coefficient of the dummy variable for a location in West Germany (*WEST*), innovation activities in

regions located in the western part of the country are more efficient than in East Germany. This result suggests that there are still considerable differences in the efficiency of the innovative process in the two parts of the country even after the reunification in 1990. There are at least two possible explanations for this difference. First, a relatively pronounced industrial monostructure¹⁸ and a concentration on less innovative industries may cause a technological shortfall of East Germany. Second, and probably most important, catching up can only be possible in a relatively long run if current technological skills and innovative performance are subject to a path dependent process. The estimated coefficient for the dummy variable for regions located in the periphery of Germany is not statistically significant.

Of the different variables for regional industry specialization, only the regional employment share in the electrical engineering industry (ELECTRICAL) proves to have a significant effect on the efficiency of a RIS. To control for the industry structure in the region appears important for at least two reasons. Firstly, introducing the share of the electrical engineering industry significantly increases the log likelihood of the model. Secondly, the parameter of spatial dependence λ becomes insignificant if a control for the size of this industry in the region is included.

6. Summary and conclusions

The objective of this paper was to provide an answer to the question about what determines the differences in the efficiency of RIS. For this purpose, we first introduced alternative measures for the technical efficiency of RIS based on the concept of a KPF. These approaches for assessing the efficiency of

¹⁸ The average value of industrial diversity is 1.527 for West Germany and 1.404 for East Germany. Significantly less industrial variety in the eastern part of the country is confirmed by two-sample mean comparison tests ($p=0.0000$).

RIS led to quite comparable results. Particularly, the spatial distribution of efficiency estimates turned out to be rather similar.

We have found a number of factors that have an effect on the efficiency of RIS. Our results suggest that both knowledge spillovers within the private sector as well as between public research institutions (universities as well as non-university research institutes) and actors in the private sector have a positive impact on private sector innovation activities. The presence and the interaction of universities and other public research institutes with private sector firms also proved to be conducive. This effect is, particularly, high if the technological fields of research pursued in public research institutes correspond to those of innovation activity in the private sector. We find that the relationship between industry concentration and efficiency of innovation activity is inversely u-shaped, indicating the relevance of *Jacobs'* as well as *Marshall-Arrow-Romer-externalities*. Obviously, neither a broad variety of industries nor narrow specialization is favorable for the performance of RIS. Population density has a positive effect on innovation performance indicating that R&D expenditure is more productive in agglomerations than in rural areas. The negative effect of the employment share in the service sector and of the average establishment size corresponds with the relatively low number of patents per R&D employee in the service industries and in larger firms, which has been found in other empirical studies. RIS in West Germany are considerably more efficient than those in the eastern part of the country even after controlling for all other influences that have a significant effect. There is no indication for lower efficiency of innovation activities in regions located at the periphery of the country. All in all, our results are consistent with the view that the performance of RIS is strongly influenced by the level and the quality of interaction and exchange between their different elements. To put it differently, a pronounced division of innovative labor leads to relatively high efficiency.

Our results raise some important questions for further research. A main issue in this respect is the ways of knowledge transfer between the different actors that need to be further illuminated. A policy that aims at improving the efficiency of RIS should be able to identify the most relevant ways of knowledge transfer and needs information on how such knowledge transfer can be stimulated. What stimulates knowledge spillovers and the division of innovative labor between the elements of a RIS? What are the impediments in this respect? Lastly, regarding the role of industrial specialization for innovation, more information about the role of the industrial structure of a region for the efficiency of innovation activity would be helpful in order to derive reasonable policy implications. The low efficiency of RIS in East Germany indicates that there may be a considerable degree of path-dependency that shapes the performance of these regions. This implies that it may take quite a long time until a policy, which aims at improving the performance of RIS, produces significant results.

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Appendix

Table A1: The distribution of technical efficiency in the German planning regions

Planning Region		(Quasi) Deterministic Approach				Stochastic Frontier Approach								
Code	Name	Estimated production elasticity ^a		TE ($\beta_i / \max \beta_i$)		TE (half-normal) ^b			TE (truncated normal) ^b			TE (exponential) ^b		
		Value (β_i)	Std. error	Value	Rank	e^{-v_i}	TE _i '	Rank	e^{-v_i}	TE _i '	Rank	e^{-v_i}	TE _i '	Rank
1	Schleswig-Holstein North	0.5685	0.3012	0.7307	75	0.3223	0.3502	69	0.3421	0.3712	70	0.3771	0.4094	69
2	Schleswig-Holstein South-West	0.5412	0.2919	0.6957	80	0.2560	0.2782	75	0.2713	0.2944	75	0.2976	0.3230	75
3	Schleswig-Holstein Central	0.6104	0.2408	0.7846	67	0.3119	0.3389	71	0.3323	0.3606	71	0.3636	0.3946	71
4	Schleswig-Holstein East	0.5991	0.2639	0.7702	70	0.3280	0.3564	68	0.3490	0.3786	68	0.3832	0.4160	68
5 & 6	Schleswig-Holstein South & Hamburg	0.6657	0.1995	0.8557	55	0.3894	0.4231	61	0.4174	0.4528	61	0.4551	0.4940	61
7	Western Mecklenburg	0.4634	0.2534	0.5957	88	0.1080	0.1174	90	0.1140	0.1237	90	0.1227	0.1332	90
8	Central Mecklenburg/Rostock	0.5163	0.2524	0.6637	84	0.1610	0.1750	83	0.1705	0.1850	83	0.1847	0.2005	83
9	Western Pomerania	0.4479	0.2558	0.5758	91	0.0984	0.1070	92	0.1038	0.1127	92	0.1116	0.1211	92
10	Mecklenburgische Seenplatte	0.4119	0.2737	0.5294	93	0.0917	0.0996	93	0.0965	0.1047	93	0.1038	0.1127	93
11 & 13 & 15	Bremen & Bremerhaven & Bremen-Umland	0.6123	0.2170	0.7871	66	0.2682	0.2914	74	0.2861	0.3104	74	0.3110	0.3376	74
12	East Frisian	0.5866	0.2777	0.7541	71	0.3221	0.3499	70	0.3423	0.3714	69	0.3764	0.4085	70
14	Hamburg-Umland-South	0.6778	0.2669	0.8712	46	0.5920	0.6432	41	0.6291	0.6825	41	0.6823	0.7406	41
16	Oldenburg	0.6008	0.2683	0.7722	69	0.3407	0.3702	65	0.3625	0.3933	65	0.3985	0.4326	65
17	Emsland	0.5823	0.2705	0.7485	72	0.3008	0.3268	72	0.3197	0.3469	72	0.3508	0.3808	72
18	Osnabruck	0.6767	0.2550	0.8699	48	0.5643	0.6132	46	0.6013	0.6524	46	0.6546	0.7106	46
19	Hanover	0.6691	0.2136	0.8601	53	0.4388	0.4768	57	0.4699	0.5099	57	0.5141	0.5580	57
20	Suedheide	0.6290	0.2780	0.8085	65	0.4358	0.4735	58	0.4642	0.5037	59	0.5126	0.5565	58
21	Luneburg	0.5726	0.3003	0.7360	73	0.3321	0.3609	66	0.3527	0.3826	67	0.3886	0.4218	66
22	Brunswick	0.7250	0.2178	0.9319	18	0.7046	0.7656	25	0.7343	0.7967	27	0.7673	0.8329	31
23	Hildesheim	0.6713	0.2566	0.8629	50	0.5448	0.5919	48	0.5804	0.6297	48	0.6320	0.6860	48
24	Göttingen	0.6817	0.2601	0.8762	45	0.5965	0.6482	40	0.6354	0.6894	40	0.6908	0.7498	40
25	Prignitz-Obehave	0.4859	0.2630	0.6246	87	0.1410	0.1532	85	0.1490	0.1617	85	0.1613	0.1751	85
26	Uckermark-Barnim	0.4542	0.2716	0.5838	90	0.1223	0.1329	89	0.1291	0.1401	89	0.1396	0.1516	89
27	Oderland-Spree	0.4899	0.2574	0.6298	86	0.1400	0.1521	86	0.1481	0.1606	86	0.1602	0.1739	86
28	Lusatia-Spreewald	0.5389	0.2314	0.6928	81	0.1605	0.1744	84	0.1702	0.1847	84	0.1839	0.1996	84
29 & 30	Havelland-Flaeming & Berlin	0.6833	0.1915	0.8783	44	0.4413	0.4795	56	0.4739	0.5142	56	0.5165	0.5607	56
31	Altmark	0.4247	0.3065	0.5459	92	0.1332	0.1447	88	0.1404	0.1523	88	0.1525	0.1655	87
32	Magdeburg	0.5550	0.2300	0.7134	78	0.1820	0.1977	80	0.1932	0.2096	80	0.2091	0.2270	80
33	Dessau	0.4634	0.2474	0.5956	89	0.1028	0.1117	91	0.1085	0.1178	91	0.1166	0.1265	91
34	Halle/Saale	0.5604	0.2273	0.7204	77	0.1859	0.2020	79	0.1975	0.2143	79	0.2138	0.2321	79

35	Muenster	0.7112	0.2255	0.9142	31	0.6687	0.7266	34	0.7086	0.7689	34	0.7533	0.8177	34
36	Bielefeld	0.7150	0.2233	0.9191	28	0.6835	0.7427	32	0.7218	0.7831	32	0.7633	0.8286	32
37	Paderborn	0.6673	0.2556	0.8578	54	0.5265	0.5720	50	0.5622	0.6100	50	0.6179	0.6707	50
38	Arnsberg	0.6692	0.2516	0.8603	52	0.5253	0.5708	52	0.5608	0.6085	51	0.6147	0.6672	51
39	Dortmund	0.6403	0.2276	0.8231	58	0.3690	0.4010	64	0.3941	0.4276	64	0.4316	0.4685	64
40	Emscher-Lippe	0.6768	0.2413	0.8701	47	0.5360	0.5824	49	0.5727	0.6214	49	0.6264	0.6800	49
41	Duisburg/Essen	0.6714	0.2077	0.8631	49	0.4334	0.4709	59	0.4644	0.5039	58	0.5079	0.5513	59
42	Düsseldorf	0.7335	0.1964	0.9429	12	0.7352	0.7988	21	0.7710	0.8366	21	0.8018	0.8703	22
43	Bochum/Hagen	0.7171	0.2215	0.9218	26	0.6928	0.7527	30	0.7312	0.7934	29	0.7716	0.8376	27
44	Cologne	0.7018	0.2008	0.9021	38	0.5584	0.6068	47	0.5992	0.6501	47	0.6507	0.7063	47
45	Aachen	0.7237	0.2235	0.9302	19	0.7336	0.7971	22	0.7688	0.8342	22	0.8025	0.8711	21
46	Bonn	0.7149	0.2418	0.9190	29	0.7158	0.7778	24	0.7500	0.8138	24	0.7875	0.8549	23
47	Siegen	0.7049	0.2571	0.9061	35	0.6955	0.7557	29	0.7304	0.7925	30	0.7716	0.8375	28
48	Northern Hesse	0.6353	0.2399	0.8166	62	0.3795	0.4124	62	0.4050	0.4395	62	0.4445	0.4825	62
49	Central Hesse	0.7282	0.2366	0.9361	15	0.7758	0.8430	15	0.8040	0.8723	15	0.8301	0.9011	15
50	Eastern Hesse	0.6306	0.2843	0.8107	64	0.4529	0.4922	54	0.4823	0.5233	54	0.5319	0.5773	54
51	Rhine-Main	0.7107	0.1920	0.9136	32	0.5851	0.6358	42	0.6278	0.6811	42	0.6773	0.7352	42
52	Starkenburger	0.7185	0.2141	0.9235	25	0.6858	0.7452	31	0.7260	0.7877	31	0.7674	0.8330	30
53	Northern Thuringia	0.5008	0.2697	0.6437	85	0.1659	0.1803	82	0.1756	0.1905	82	0.1907	0.2070	82
54	Central Thuringia	0.5658	0.2296	0.7274	76	0.1984	0.2156	78	0.2109	0.2288	78	0.2286	0.2481	78
55	Southern Thuringia	0.5698	0.2540	0.7324	74	0.2475	0.2689	76	0.2629	0.2853	76	0.2869	0.3115	76
56	Eastern Thuringia	0.6349	0.2354	0.8161	63	0.3698	0.4018	63	0.3947	0.4282	63	0.4327	0.4697	63
57	Western Saxony	0.5347	0.2171	0.6874	83	0.1333	0.1449	87	0.1415	0.1535	87	0.1519	0.1649	88
58	Upper Elbe Valley / Eastern Ore Mountains	0.6387	0.2132	0.8210	59	0.3316	0.3603	67	0.3544	0.3846	66	0.3865	0.4195	67
59	Upper Lusatia-Lower Silesia	0.5356	0.2440	0.6885	82	0.1753	0.1905	81	0.1859	0.2017	81	0.2014	0.2187	81
60	Chemnitz-Ore Mountains	0.6087	0.2254	0.7825	68	0.2767	0.3007	73	0.2950	0.3200	73	0.3213	0.3487	73
61	South West Saxony	0.5520	0.2446	0.7096	79	0.2016	0.2191	77	0.2140	0.2322	77	0.2325	0.2524	77
62	Middle Rhine-Nahe	0.7033	0.2385	0.9040	37	0.6535	0.7101	35	0.6920	0.7509	35	0.7385	0.8017	35
63	Trier	0.6370	0.2847	0.8189	61	0.4755	0.5166	53	0.5065	0.5496	53	0.5597	0.6076	53
64	Rhine-Hesse-Nahe	0.7220	0.2427	0.9281	22	0.7487	0.8136	19	0.7785	0.8447	19	0.8098	0.8790	19
65	Western Palatinate	0.6619	0.2659	0.8508	56	0.5262	0.5718	51	0.5608	0.6085	52	0.6146	0.6671	52
66	Rhine Palatinate	0.7339	0.2229	0.9434	11	0.7843	0.8522	12	0.8119	0.8809	12	0.8355	0.9069	12
67	Saar	0.6591	0.2354	0.8473	57	0.4511	0.4902	55	0.4821	0.5231	55	0.5289	0.5741	55
68	Upper Neckar	0.7084	0.2137	0.9106	33	0.6265	0.6808	38	0.6672	0.7239	38	0.7146	0.7757	38
69	Franconia	0.7292	0.2348	0.9373	14	0.7783	0.8457	13	0.8063	0.8749	13	0.8319	0.9030	13
70	Middle Upper Rhine	0.6975	0.2158	0.8966	40	0.5732	0.6228	44	0.6128	0.6649	44	0.6636	0.7203	44
71	Northern Black Forest	0.7631	0.2490	0.9809	3	0.8971	0.9747	3	0.9023	0.9790	3	0.9051	0.9825	3
72	Stuttgart	0.7556	0.1869	0.9713	5	0.8362	0.9086	8	0.8552	0.9280	8	0.8664	0.9405	8
73	Eastern Wuertemberg	0.7631	0.2459	0.9809	4	0.8941	0.9715	4	0.9000	0.9765	4	0.9033	0.9805	4
74	Danube-Iller (BW)	0.6950	0.2373	0.8934	41	0.6085	0.6612	39	0.6460	0.7010	39	0.6945	0.7539	39

75	Neckar-Alb	0.7295	0.2390	0.9377	13	0.7781	0.8455	14	0.8047	0.8731	14	0.8303	0.9013	14
76	Black Forest-Baar-Heuberg	0.7498	0.2501	0.9639	7	0.8674	0.9425	5	0.8782	0.9529	5	0.8864	0.9622	6
77	Southern Upper Rhine	0.7141	0.2344	0.9180	30	0.7020	0.7628	26	0.7391	0.8019	25	0.7789	0.8455	25
78	High Rhine-Lake Constance	0.7226	0.2397	0.9288	20	0.7541	0.8193	18	0.7854	0.8522	18	0.8162	0.8859	18
79	Lake Constance-Upper Swabia	0.7198	0.2282	0.9253	23	0.7170	0.7791	23	0.7516	0.8155	23	0.7875	0.8548	24
80	Bavarian Lower Main	0.7254	0.2604	0.9324	17	0.7916	0.8601	11	0.8162	0.8856	11	0.8403	0.9121	11
81	Wurzburg	0.7083	0.2495	0.9105	34	0.6978	0.7582	28	0.7319	0.7942	28	0.7715	0.8375	29
82	Main-Rhone	0.7531	0.2603	0.9681	6	0.8666	0.9417	6	0.8775	0.9521	6	0.8867	0.9625	5
83	Upper Franconia-West	0.7407	0.2558	0.9521	8	0.8393	0.9120	7	0.8553	0.9280	7	0.8694	0.9437	7
84	Upper Franconia-East	0.6377	0.2599	0.8197	60	0.4287	0.4658	60	0.4571	0.4960	60	0.5035	0.5466	60
85	Upper Franconia-North	0.6868	0.2669	0.8828	43	0.6326	0.6874	37	0.6710	0.7281	37	0.7230	0.7848	37
86	Industrial Region Central Franconia	0.7167	0.2021	0.9213	27	0.6463	0.7023	36	0.6878	0.7463	36	0.7323	0.7949	36
87	Augsburg	0.7281	0.2885	0.9360	16	0.8134	0.8839	9	0.8324	0.9032	9	0.8531	0.9260	9
88	Western Central Franconia	0.6910	0.2305	0.8883	42	0.5762	0.6261	43	0.6154	0.6678	43	0.6683	0.7254	43
89	Ingolstadt	0.7189	0.2545	0.9240	24	0.7599	0.8257	17	0.7901	0.8573	17	0.8205	0.8907	17
90	Regensburg	0.7354	0.2384	0.9453	10	0.7983	0.8674	10	0.8212	0.8910	10	0.8427	0.9148	10
91	Danube-Forest	0.6984	0.2658	0.8978	39	0.682	0.7411	33	0.7181	0.7792	33	0.7629	0.8281	33
92	Landshut	0.6713	0.2702	0.8629	51	0.5724	0.6220	45	0.6090	0.6608	45	0.6636	0.7203	45
93	Munich	0.7379	0.1868	0.9485	9	0.7396	0.8036	20	0.7748	0.8407	20	0.8035	0.8722	20
94	Danube-Iller (BY)	0.7223	0.2578	0.9285	21	0.7731	0.8401	16	0.8005	0.8686	16	0.8284	0.8992	16
95	Allgaeu	0.7041	0.2612	0.9051	36	0.6993	0.7599	27	0.7350	0.7975	26	0.7772	0.8437	26
96	Oberland	0.7779	0.2693	1.0000	1	0.9203	1.0000	1	0.9216	1.0000	1	0.9213	1.0000	1
97	Southeast Upper Bavaria	0.7723	0.2441	0.9927	2	0.9093	0.9881	2	0.9126	0.9902	2	0.9135	0.9916	2

^a Results of robust negative-binomial regression. Estimated intercept = -0.0225 with a robust standard error = 2.0049 (level of significance = 0.99). Log pseudo-likelihood = -1,749.860.

^b Average efficiency per region in 1997-2000.

Table A2: The stochastic frontier estimation statistics

	Dependent variable: number of patents (ln)		
	half-normal	truncated normal	exponential
<i>R&D</i> (ln)	0.800 (0.032)	0.798 (0.030)	0.802 (0.029)
Intercept	-0.394 (0.281)	-0.424 (0.266)	-0.522 (0.259)
Observations	372	372	372
Log likelihood	-344.336	-342.712	-346.759
Wald chi2(1)	610.97	691.91	746.22
Prob>chi2	0.000	0.000	0.000
ln σ_v^2	-3.527 (0.334)		-3.116 (0.260)
ln σ_u^2	0.151 (0.094)		-0.624 (0.135)
σ_v	0.171 (0.029)		0.211 (0.027)
σ_u	1.079 (0.051)		0.732 (0.049)
σ	0.193 (0.106)		0.580 (0.068)
λ	6.291 (0.068)		3.476 (0.066)
LR-test ($\sigma_u = 0$)			
Chibar2(01)	76.64		71.80
Prob>chibar2	0.000		0.000
μ		-1.164 (1.067)	
ln σ		0.711 (0.395)	
ilgtgamma		4.054 (0.454)	
σ^2		2.036 (0.804)	
γ		0.983 (0.008)	
σ_u^2		2.001 (0.802)	
σ_v^2		0.035 (0.010)	
Ho: no inefficiency			
z		-5.755	
Prob<=z		0.000	

Table A3: Correlation between variables

No.	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	TE' (quasi deterministic)	1.00															
2	TE' (SFA, half-normal)	0.98	1.00														
3	TE' (SFA, truncated normal)	0.98	0.99	1.00													
4	TE' (SFA, exponential)	0.98	0.99	0.99	1.00												
5	R&D	0.21	0.08	0.08	0.07	1.00											
6	ERF-PRIV	0.24	0.17	0.18	0.18	0.28	1.00										
7	MPG	0.14	0.04	0.05	0.05	0.44	0.40	1.00									
8	FhG	0.16	0.08	0.08	0.08	0.48	0.38	0.43	1.00								
9	PROXTECH	0.58	0.47	0.48	0.48	0.30	0.34	0.27	0.27	1.00							
10	SERVICES	0.09	0.03	0.04	0.05	0.33	0.39	0.49	0.36	0.15	1.00						
11	SIZE	0.07	-0.03	-0.03	-0.02	0.60	0.30	0.34	0.24	0.19	0.14	1.00					
12	POPDENS	0.44	0.33	0.34	0.34	0.55	0.37	0.53	0.42	0.47	0.54	0.56	1.00				
13	TRANSPORT	0.38	0.39	0.38	0.38	0.11	0.06	-0.12	-0.04	0.15	-0.07	0.07	0.07	1.00			
14	ELECTRICAL	0.67	0.65	0.65	0.64	0.26	0.10	0.05	0.12	0.43	-0.05	0.16	0.26	0.23	1.00		
15	OPTICS	0.43	0.44	0.43	0.43	0.10	-0.01	0.07	-0.03	0.31	-0.06	-0.14	0.05	0.09	0.42	1.00	
16	CHEMISTRY	0.51	0.47	0.47	0.48	0.35	0.15	0.24	0.15	0.22	0.34	0.07	0.42	0.08	0.16	0.17	1.00
17	DIVERSITY	0.68	0.68	0.69	0.69	-0.05	0.01	-0.12	-0.12	0.48	-0.11	-0.04	0.17	0.11	0.57	0.42	0.33

Table A4: Determinants of the technical efficiency of RIS (SFA, truncated normal distribution)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.042 (0.04)	0.047 (0.04)	-0.073 (0.06)	-0.112 (0.10)	-0.234 (0.23)	-0.132 (0.12)	-0.620 (0.59)	0.111 (0.11)
R&D [ln]	0.242* (2.35)	0.240* (2.29)	0.218* (2.08)	0.226* (2.26)	0.207* (2.05)	0.230* (2.08)	0.203* (2.20)	0.221* (2.18)
ERF-PRIV[ln]	0.055** (2.94)	0.055** (2.94)	0.052** (2.61)	0.053** (2.97)	0.056** (2.99)	0.053** (2.60)		
MPG [ln]							0.109* (2.28)	
FhG [ln]							0.101* (2.00)	
PROXTECH [ln]								0.244* (1.99)
DIVERSITY [ln]						0.504 (0.68)	0.702 (0.92)	-0.070 (0.09)
POPDENS [ln]	0.276** (3.94)	0.276** (3.91)	0.250** (3.77)	0.269** (3.88)	0.272** (3.83)	0.244** (3.49)	0.188** (3.07)	0.211** (3.03)
SERVICES [ln]	-1.196** (5.60)	-1.188** (5.26)	-1.146** (5.32)	-1.162** (5.39)	-1.198** (5.76)	-1.132** (5.54)	-1.253** (6.12)	-1.008** (5.14)
SIZE [ln]	-1.387** (4.11)	-1.388** (4.16)	-1.324** (3.89)	-1.304** (3.92)	-1.319** (4.29)	-1.327** (3.94)	-1.163** (3.66)	-1.149** (3.68)
WEST	1.152** (9.94)	1.149** (9.86)	1.079** (9.32)	1.125** (9.36)	1.122** (8.41)	1.042** (7.67)	1.107** (10.55)	1.076** (8.36)
PERIPHERY	-0.103 (1.59)	-0.104 (1.60)	-0.090 (1.38)	-0.097 (1.51)	-0.097 (1.52)	-0.099 (1.50)	-0.079 (1.31)	-0.073 (1.12)
TRANSPORT [ln]		0.005 (0.14)						
ELECTRICAL [ln]			0.112* (1.97)			0.106 (1.94)	0.104* (1.96)	0.105* (1.96)
OPTICS [ln]				0.050 (1.16)				
CHEMICALS [ln]					0.024 (0.75)			
λ	0.456** (3.30)	0.457** (3.29)	0.343 (1.70)	0.440** (3.13)	0.470** (3.54)	0.304 (1.29)	0.200 (0.80)	0.285 (1.25)
Log likelihood	-0.147	-0.141	1.556	0.458	0.179	1.803	3.976	1.202
Wald ($\lambda=0$)	10.866	10.844	2.883	9.812	12.561	1.671	0.640	1.575
LM-Error ($\lambda=0$)	7.661	7.646	3.079	7.814	7.896	2.105	0.929	2.029

Notes: Absolute value of robust z-statistics in parentheses; * significant at 5% level; ** significant at 1% level. Critical value for the Wald test-statistic and LM-Error with one degree of freedom is 3.48 ($p = 0.05$); spatial weights are row-standardized: W is 1st order contiguity matrix.

Table A5: Determinants of the technical efficiency of RIS (SFA, exponential distribution)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.014 (0.01)	0.017 (0.02)	-0.117 (0.11)	-0.141 (0.13)	-0.247 (0.25)	-0.188 (0.18)	-0.746 (0.74)	0.026 (0.03)
R&DD [ln]	0.222* (2.21)	0.221* (2.16)	0.197* (1.96)	0.206* (2.12)	0.190* (1.96)	0.211* (2.00)	0.175* (2.01)	0.198* (2.08)
ERD-PRIV [ln]	0.056** (3.04)	0.056** (3.05)	0.052** (2.72)	0.054** (3.09)	0.057** (3.10)	0.054** (2.71)		
MPG [ln]							0.106* (2.28)	
FhG [ln]							0.106* (2.07)	
PROXTECH [ln]								0.246* (1.99)
DIVERSITY [ln]						0.590 (0.82)	0.774 (1.06)	-0.008 (0.01)
POPDENS [ln]	0.267** (3.82)	0.267** (3.80)	0.242** (3.76)	0.261** (3.78)	0.263** (3.70)	0.235** (3.45)	0.181** (3.15)	0.203** (3.03)
SIZE [ln]	-1.324** (4.04)	-1.325** (4.08)	-1.261** (3.84)	-1.245** (3.85)	-1.260** (4.21)	-1.264** (3.91)	-1.085** (3.60)	-1.077** (3.63)
SERVICES [ln]	-1.124** (5.21)	-1.120** (4.92)	-1.077** (4.95)	-1.091** (5.03)	-1.127** (5.37)	-1.061** (5.26)	-1.174** (5.89)	-0.932** (4.89)
WEST	1.132** (9.93)	1.130** (9.83)	1.057** (9.28)	1.106** (9.35)	1.103** (8.50)	1.014** (7.65)	1.082** (10.70)	1.051** (8.42)
PERIPHERY	-0.098 (1.57)	-0.098 (1.57)	-0.085 (1.36)	-0.091 (1.49)	-0.092 (1.50)	-0.095 (1.51)	-0.074 (1.31)	-0.067 (1.08)
TRANSPORT [ln]		0.003 (0.08)						
ELECTRICAL [ln]			0.112* (2.10)			0.105 (1.91)	0.099* (1.97)	0.102* (1.96)
OPTICS [ln]				0.047 (1.13)				
CHEMICALS. [ln]					0.023 (0.75)			
λ	0.437** (3.01)	0.437** (3.00)	0.318 (1.53)	0.423** (2.89)	0.450** (3.23)	0.268 (1.11)	0.177 (0.72)	0.261 (1.15)
Log likelihood	3.171	3.173	5.028	3.748	3.491	5.391	7.743	4.685
Wald ($\lambda=0$)	9.072	9.017	2.349	8.371	10.431	1.241	0.517	1.328
LM-Error ($\lambda=0$)	6.979	6.962	2.763	7.194	7.199	1.725	0.779	1.803

Notes: Absolute value of robust z-statistics in parentheses; * significant at 5% level; ** significant at 1% level. Critical value for the Wald test-statistic and LM-Error with one degree of freedom is 3.48 ($p = 0.05$); spatial weights are row-standardized: W is 1st order contiguity matrix.