Determinants of the efficiency of regional innovation systems

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Abstract

This paper analyzes differences in the efficiency of regional innovation systems (RIS). Alternative measures for the efficiency of RIS based on the concept of a knowledge production function are discussed. The empirical findings suggest 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. It is the intensity of interactions between private and public sector R&D that leads to high efficiency. Regions dominated by large establishments tend to be less efficient than regions with a lower average establishment size.

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Contents

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). Possible reasons for this phenomenon are regional differences in the availability and the quality of local inputs as well as geographically bounded knowledge spillovers (GREUNZ, 2003; FRITSCH and SLAVTCHEV, 2007, 2008). A further reason may be that locations differ with regard to the 'quality' or the 'efficiency' of regional innovation systems (RIS) leading to different levels of innovative output even if the inputs are identical in quantitative as well as in qualitative terms. 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 RIS[1] 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 analyzing the relationship between input and output of the innovation process that is essential 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) $$Y_i = A_i X_i^{\beta_i} .$$

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

Our measure for innovative output is based on the number of disclosed regional patent applications in the years 1995 to 2000. This data has been provided by the German Patent Office (*Deutsches Patent- und Markenamt*) as published in GREIF and SCHMIEDL (2002). A patent application indicates that an invention has been made that extends the existing knowledge pool. However, a number of limitations of the number of patents as a measure of innovative output should be mentioned. First, patents reflect an invention which is not necessarily transformed into an innovation, i.e. a new production technology or a product new to the market. Second, rather products than processes apply for patent (COHEN, NELSON and WALSH 2000). Third, as there are other possibilities to appropriate the benefits of an invention (cf. COHEN, NELSON and WALSH 2002), the number of patents may underestimate the actual innovative output.

The German Patent Office provides information on the number of regional patent applications in 31 different technological fields and from three distinct sources: private companies, public research and private persons. However, although the classification in different technological fields is based on the International Patent Classification (IPC)[2], the level of aggregation into technological fields does not allow to assign patent applications to R&D activities in a certain industry or in a certain academic discipline. As this paper focuses on the efficiency of private R&D only corporate patent applications are analyzed in this paper, i.e. patent applications by public research institutions or private persons are omitted.[3] The patent applications are assigned to the region in which the inventor has his residence.[4]

As a proxy for the input to the innovation process in the private sector, we use the number of R&D employees in this sector (*R&D*). This information is taken from the establishment file of the German Social Insurance Statistics (*Statistik der sozialversicherungspflichtig Beschaeftigten*) as described and documented by FRITSCH and BRIXY (2004). Employees are classified as working in R&D if they have a tertiary degree in engineering or in natural sciences. Only the regional private sector R&D employment is included as an explanatory variable into the knowledge production function while other input variables are omitted. The reason is that private sector R&D employees appear the only factor that directly impacts the innovative output in that sector. Knowledge spillovers from adjacent regions or spillovers from other sources such as public research institutions may also make a considerable contribution to the innovation process in the private sector, however, their impact is rather indirect in nature**,** mainly through the private sector R&D employees.[5]

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.[6] 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.[7]

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.[8] 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 do not coincide (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 or output elasticity 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 (for further discussion see KALIRAJAN and SHAND, 1999).

The first approach relies on the idea of regional differences in the slope of the knowledge production function. To estimate the specific productivity of each region in terms of the marginal return to R&D input, we include a binary dummy variable for each region, D_i ($D_i = 1$ if $i = i$, otherwise 0), 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) $$\ln(Number\ of\ patents_i) = \ln A + \sum_i \beta_i * D_i * \ln(R\&D\ priv_i) + \varepsilon_i ,$$

with β_i as a measure of the output elasticity of private sector R&D employment in the i^{th} region (*i = 1, …, 93*). Based on the estimated values for the output elasticity of private sector R&D, we define the efficiency of a certain region as the quotient of the observed output of a particular region and the maximum possible value, i.e.,

(3) $$TE_i^{DET} = \exp\left(\ln\left(Number\ \ of\ \ patents_i\right) - \left(\ln A + \beta_{\max} * \ln\left(R\,\&\,D\ \ priv_i\right) + \varepsilon_i\right)\right),$$

where $\beta_{\max} = \max_i\{\beta_i\}$ is the maximum estimated output elasticity of R&D input. Accordingly, at least one region is assumed to be fully efficient. We label this approach as 'deterministic' because it implies that all deviations from the maximum value are due to inefficiency and neglects, therefore, the possibility that values could be affected by measurement errors or by random disturbances.[9] The output elasticity of private sector R&D is estimated by means of a negative binomial regression technique (GREENE, 2003, 931-939). Due to the relatively short length of the time series (four years) the data are pooled.

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

(4) $$Number\ \ of\ \ patents_i = \alpha\ \ R\,\&\,D\,priv_i^{\beta}\ e^{-v_i}\ e^{u_i}\ ,$$

where v_i denotes effects of the region-specific environment on innovative output and u_i represents the stochastic error term. The technical efficiency of a region can, therefore, be calculated as

(5) $$TE_i^{SFA} = e^{-v_i}\ .$$

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. This type of approach is called stochastic frontier function (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, and the technical efficiency is estimated as the average value per region. 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. The general assumption in this respect is that the distribution of technical efficiency has a negative skewness (SCHMIDT and LIN, 1984), i.e. that most regions are clustered close to the efficiency frontier. 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 estimate the efficiency measure according all three alternatives in order to check the robustness of the results. Table A1 in the Appendix provides descriptive statistics of private sector R&D input and output used to estimate the efficiency of RIS.

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 both approaches, the deterministic frontier function and the stochastic frontier function show a wide spread with the least efficient region attaining only 6.7 and 9.9 percent of the highest value (table 1 and figure 1). As compared to the stochastic frontier method, the deterministic approach leads to a slightly more differentiated assessment of RIS efficiency. However, the spatial distribution of the technical efficiency of RIS according to the different approaches is virtually identical. The Pearson correlation coefficients suggest almost perfect correlation between the efficiency values estimated by the different approaches (table 1).

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

No.	*Variable*	*Mean*	*Median*	*Min.*	*Max.*	*Std. Dev.*	*Pearson correlation coefficient* 1	2	3
1	TE_i^{DET}	0.434	0.452	0.067	1.000	0.203	1.000		
2	TE_i^{SFA} (half-normal)	0.514	0.558	0.091	0.920	0.244	0.987	1.000	
3	TE_i^{SFA} (truncated normal)	0.539	0.599	0.097	0.922	0.249	0.981	0.999	1.000
4	TE_i^{SFA} (exponential)	0.571	0.651	0.104	0.921	0.253	0.969	0.995	0.998

Note: Number of observations (regions) = 93.

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, separating the west from the east as well as the south from the north. This indicates that the German innovation system is spatially divided into different regimes with diverging levels of performance.

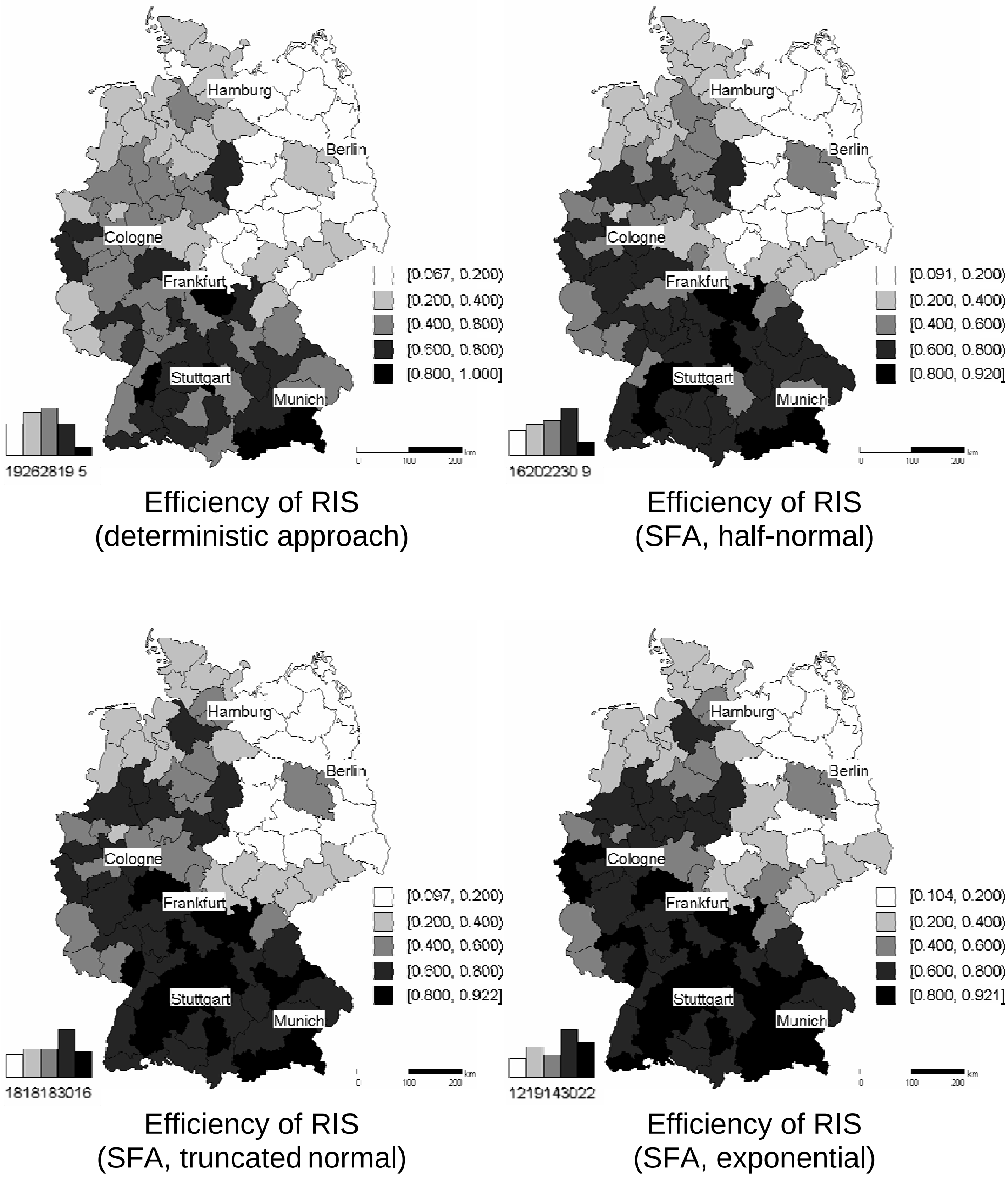

Figure 1: The spatial distribution of efficiency of RIS in Germany

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 labor[10], 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 and services. 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.[11] 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 (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*).

The knowledge that is generated and accumulated by universities may constitute a basic precondition for private sector R&D activities (JAFFE, 1989). However, since universities are non-profit organizations, they can hardly market the results of their own R&D in terms of new products or technologies. For this reason, their knowledge has to spill over to other actors (e.g. private companies) in order to become commercially effective. The ways in which such knowledge transfers occur can be manifold (see

VARGA, 1998, for an overview). In particular, 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; COHEN, NELSON, and WALSH 2002). However, 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 and SLAVTCHEV, 2007, 2008). In order to test the impact of universities for the performance of the private sector, we introduce the amount of third-party funds that the universities gain from private firms (*TPF-PRIV*). Universities' third-party funds in general can be regarded as an indicator of the amount and the quality of the research. The main reason is that the allocation of universities' third-party funds is usually based on some competitive procedure and is, therefore, largely dependent on the quality of the research conducted. According to HORNBOSTEL (2001), there is a distinct correspondence between indicators that are based on third-party funds and bibliometric indicators for high quality research such as SCI publications. Funds from private sector firms, in particular, can be regarded compensation for academic R&D or for other services. Hence, these revenues are well suited to indicate the relevance of academic research for commercial applications as well as the intensity of university-industry linkages, which may lead to pronounced knowledge spillovers (FRITSCH and SLAVTCHEV, 2007, 2008).

Although we have no detailed information about the location of the private firms that cooperate with the universities, one can assume that, in most cases, universities and the cooperating private firms are co-located in the same planning region (FRITSCH and SCHWIRTEN, 1999).[12] In order to avoid possible scale effects of large universities, which are likely to attract larger amounts of third-party funds from private firms, we use the average amount of third-party funds from private sector firms per university professor.

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 third-party 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 strength 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 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}):[13]

$$(6) \qquad PROXTECH_i = \frac{PAT_{ACADi} * PAT_{PRIV\,i}'}{\left|PAT_{ACADi}\right| * \left|PAT_{PRIV\,i}\right|}\,.$$

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. This is particularly true for knowledge intensive business services, which in some cases have been even associated with the emergence of high-tech regions such as Silicon Valley and Route 128

(SAXENIAN, 1985; DORFMAN, 1983). According to FELDMAN and FLORIDA (1994), the presence of business services at certain location also indicates relatively well developed infrastructure that may be beneficial for innovation. 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 (GREIF and POTKOWIK, 1990; BODE, 2004).

Population density (number of inhabitants in the region per squared kilometer, *POPDEN*) 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). One could, 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. 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, a negative sign could be expected. 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 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

Variable	*Operational definition*	*Expected sign*
R&D	Share of R&D employees in the private sector; *source:* Social Insurance Statistics.	+
TPF-PRIV	Third-party funds per university professor (including *Fachhochschulen*) in 1,000s of Euro; *source:* German University Statistics.	+
MPG	Number of institutes of the Max Planck Society; *source:* BUNDESMINISTERIUM FUER BILDUNG UND FORSCHUNG (2004).	+
FhG	Number of institutes of the Fraunhofer Society; *source:* BUNDESMINISTERIUM FUER BILDUNG UND FORSCHUNG (2004).	+
PROXTECH	Correspondence of the technological fields of public and private sector R&D; *source:* own calculation based on Patent Statistics (GREIF and SCHMIEDL, 2002).	+
POPDEN	Population density; *source*: BUNDESAMT FUER BAUWESEN UND RAUMORDNUNG - BBR.	+
SERVICES	Employment share in the service sector; *source:* Social Insurance Statistics.	+ / -
SIZE	Average number of employees per establishment; *source*: Social Insurance Statistics.	-
WEST	Dummy 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 transportation engineering; *source:* Social Insurance Statistics.	+
ELECTRICAL	Employment share in electrical engineering; *source:* Social Insurance Statistics.	+
OPTICS	Employment share in optics and measurement engineering; *source:* Social Insurance Statistics.	+
CHEMICALS	Employment share in chemistry; *source:* Social Insurance Statistics.	+

Table 3: Descriptive statistics for independent variables

Variable	*Mean*	*Median*	*Min.*	*Max.*	*Std. Dev.*
R&D	0.019	0.016	0.006	0.044	0.008
TPF-PRIV	11.062	7.195	0.000	97.067	14.735
MPG	0.860	0.000	0.000	12.000	1.839
FhG	0.849	0.000	0.000	10.000	1.763
PROXTECH	0.623	0.659	0.200	0.837	0.139
SERVICES	0.321	0.312	0.220	0.523	0.056
SIZE	13.204	13.308	8.529	18.266	1.696
POPDEN	336.990	180.675	53.425	3,886.292	507.559
TRANSPORT	0.043	0.031	0.010	0.226	0.037
ELECTRICAL	0.035	0.029	0.004	0.123	0.023
OPTICS	0.009	0.005	0.002	0.055	0.009
CHEMISTRY	0.017	0.010	0.001	0.180	0.023

Note: Number of observations (regions) = 93.

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.[14] 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 A2 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. Important 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

(7) $Y = X\beta + \varepsilon$,

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).

5. Empirical results

The impact of different determinants on the efficiency of RIS according to the deterministic and the stochastic frontier approach are 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. However, since the efficiency measures obtained according to all the three approaches are almost perfectly correlated (see table 1), we compare the deterministic frontier only to the stochastic frontier approach with half-normal distribution.[15]

The share of private sector R&D employment (*R&D*) has a pronounced positive impact on the 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, 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 third-party funds from private sector sources per university professor (*TPF-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 for university R&D, is conducive to regional innovation activity. Substituting *TPF-PRIV* by other university related indicators such as the number of academic personnel shows hardly any statistically significant impact for the respective 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 SLAVTCHEV, 2007, 2008).

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*). 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 as typically carried out by the institutes of 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.[17] A possible explanation for this finding is that the knowledge exchange between the two sectors might become more likely as public and private research is in similar technological fields.

Table 4: Determinants of the efficiency of RIS

	Technical efficiency according to the deterministic frontier approach, TE_i^{DET}							Technical efficiency according to the stochastic frontier approach, TE_i^{SFA}						
Intercept	0.074	0.091	-0.036	-0.130	-0.191	-0.360	0.192	-0.040	-0.034	-0.145	-0.200	-0.319	-0.518	0.038
	(1.321)	(1.305)	(1.361)	(1.268)	(1.205)	(1.283)	(1.262)	(1.152)	(1.141)	(1.171)	(1.115)	(1.050)	(1.095)	(1.062)
R&D [ln]	0.307**	0.302**	0.279*	0.286**	0.274*	0.259*	0.286*	0.249*	0.247*	0.226*	0.233*	0.215*	0.203*	0.233*
	(0.112)	(0.113)	(0.116)	(0.108)	(0.115)	(0.105)	(0.111)	(0.104)	(0.106)	(0.107)	(0.101)	(0.104)	(0.094)	(0.100)
TPF-PRIV [ln]	0.051*	0.051*	0.046*	0.048*	0.052*			0.054**	0.054**	0.050*	0.052**	0.055**		
	(0.022)	(0.022)	(0.023)	(0.021)	(0.022)			(0.019)	(0.019)	(0.020)	(0.018)	(0.019)		
MPG [lm]						0.112*							0.107*	
						(0.054)							(0.049)	
FhG [ln]						0.104*							0.099*	
						(0.049)							(0.050)	
PROXTECH [ln]							0.295*							0.275*
							(0.142)							(0.128)
POPDEN [ln]	0.317**	0.316**	0.286**	0.306**	0.314**	0.232**	0.245**	0.280**	0.279**	0.253**	0.272**	0.276**	0.203**	0.214**
	(0.076)	(0.076)	(0.075)	(0.075)	(0.076)	(0.069)	(0.079)	(0.070)	(0.071)	(0.067)	(0.069)	(0.071)	(0.059)	(0.071)
SERVICES [ln]	-1.367**	-1.344**	-1.300**	-1.318**	-1.371**	-1.460**	-1.172**	-1.242**	-1.233**	-1.190**	-1.207**	-1.245**	-1.327**	-1.054**
	(0.230)	(0.245)	(0.228)	(0.230)	(0.227)	(0.243)	(0.212)	(0.212)	(0.225)	(0.214)	(0.214)	(0.207)	(0.228)	(0.197)
SIZE [ln]	-1.615**	-1.621**	-1.545**	-1.499**	-1.552**	-1.431**	-1.392**	-1.425**	-1.428**	-1.364**	-1.338**	-1.358**	-1.230**	-1.196**
	(0.399)	(0.393)	(0.411)	(0.386)	(0.362)	(0.401)	(0.388)	(0.344)	(0.340)	(0.349)	(0.338)	(0.313)	(0.334)	(0.323)
WEST	1.253**	1.244**	1.170**	1.214**	1.224**	1.242**	1.159**	1.165**	1.161**	1.092**	1.136**	1.134**	1.165**	1.084**
	(0.129)	(0.129)	(0.130)	(0.133)	(0.153)	(0.103)	(0.129)	(0.117)	(0.117)	(0.117)	(0.121)	(0.135)	(0.092)	(0.116)
PERIPHERY	-0.113	-0.114	-0.097	-0.104	-0.106	-0.079	-0.085	-0.107	-0.107	-0.093	-0.100	-0.100	-0.072	-0.078
	(0.073)	(0.073)	(0.073)	(0.072)	(0.073)	(0.070)	(0.073)	(0.066)	(0.066)	(0.066)	(0.065)	(0.065)	(0.063)	(0.066)
TRANSPORT [ln]		0.014							0.006					
		(0.043)							(0.037)					
ELECTRICAL [ln]			0.125			0.131	0.118			0.112			0.116	0.105
			(0.075)			(0.072)	(0.078)			(0.066)			(0.061)	(0.067)
OPTICS [ln]				0.072							0.053			
				(0.050)							(0.044)			
CHEMICALS [ln]					0.023							0.024		
					(0.040)							(0.033)		
λ	0.485**	0.487**	0.379*	0.462**	0.498**	0.287	0.319	0.463**	0.464**	0.353	0.444**	0.477**	0.264	0.288
	(0.129)	(0.129)	(0.195)	(0.133)	(0.126)	(0.232)	(0.214)	(0.136)	(0.136)	(0.201)	(0.138)	(0.130)	(0.225)	(0.212)
Squared corr.	0.80	0.80	0.82	0.81	0.80	0.84	0.83	0.82	0.82	0.84	0.82	0.82	0.85	0.84
Log likelihood	-12.79	-12.76	-11.19	-11.83	-12.57	-9.07	-11.02	-1.97	-1.96	-0.34	-1.30	-1.65	1.59	-0.66
Wald (λ=0)	14.07	14.26	3.74	12.15	15.59	1.52	2.23	11.62	11.63	3.08	10.35	13.43	1.38	1.85
LM-Error (λ=0)	8.69	8.72	3.39	8.73	8.78	1.86	2.46	7.89	7.88	3.15	7.99	8.11	1.83	2.25

Notes: Robust standard errors 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. Number of observations (regions) = 93.

The positive coefficient for population density (*POPDEN*) 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. This confirms previous results of BODE (2004), who found negative impact of service-manufacturing ratio on regional innovation output. 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 monostructure[18] 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.

Control for the local presence of industries with relatively high patent intensity provides evidence which may increase the efficiency of the region provides evidence for positive impact (at 10 percent significance level) only with respect to electrical engineering (*ELECTRICAL*). Nevertheless, 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 goodness of fit (squared correlation, 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 is to provide an answer to the question about what determines the differences in the efficiency of RIS. For this purpose, we first introduce alternative measures for the efficiency of RIS based on the concept of a KPF. These approaches for assessing the efficiency of RIS lead to virtually identical results. Particularly, the spatial distribution of efficiency estimates turns out to be very 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. Population density has a positive effect on innovation performance indicating that R&D activity 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 patent intensity 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: Descriptive statistics of private sector R&D output and input

Variable	Obs.	Mean	Median	Minimum	Maximum	Standard Deviation
PAT_{PRIV}	372	291.465	165.950	1.500	3,143.322	408.519
R&D	372	6,674.016	3,690.000	649.000	48,968.000	8,724.051

Note: Number of observations = 372.

Table A2: Correlation between variables

No.	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	TE_i^{DE} [ln]	1.000														
2	TE_i^{SFA} (half-normal) [ln]	0.998	1.000													
3	TE_i^{SFA} (truncated normal) [ln]	0.996	0.999	1.000												
4	TE_i^{SFA} (exponential) [ln]	0.993	0.998	0.999	1.000											
5	R&D [ln]	0.092	0.075	0.077	0.071	1.000										
6	TPF-PRIV [ln]	0.153	0.165	0.175	0.184	0.284	1.000									
7	MPG [ln]	0.047	0.042	0.047	0.050	0.439	0.396	1.000								
8	FhG [ln]	0.084	0.075	0.080	0.083	0.483	0.377	0.427	1.000							
9	PROXTECH [ln]	0.473	0.471	0.475	0.478	0.296	0.340	0.265	0.271	1.000						
10	SERVICES [ln]	0.026	0.027	0.037	0.049	0.327	0.387	0.488	0.356	0.150	1.000					
11	SIZE [ln]	-0.033	-0.032	-0.026	-0.024	0.604	0.302	0.341	0.244	0.193	0.142	1.000				
12	POPDEN [ln]	0.328	0.327	0.336	0.343	0.549	0.372	0.528	0.420	0.472	0.538	0.563	1.000			
13	TRANSPORT [ln]	0.387	0.385	0.384	0.382	0.112	0.059	-0.121	-0.035	0.151	-0.072	0.069	0.066	1.000		
14	ELECTRICAL [ln]	0.651	0.646	0.645	0.641	0.260	0.103	0.050	0.124	0.429	-0.053	0.163	0.262	0.229	1.000	
15	OPTICS [ln]	0.453	0.438	0.432	0.425	0.097	-0.013	0.072	-0.030	0.309	-0.059	-0.142	0.049	0.090	0.415	1.000
16	CHEMISTRY [ln]	0.465	0.468	0.473	0.476	0.351	0.149	0.237	0.151	0.220	0.344	0.066	0.421	0.075	0.157	0.169

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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).

2. This classification is provided by the *World Intellectual Property Organization* (WIPO).

3. Patent applications by private companies account on the average for about three fourth of all patent applications.

4. If a patent has more than one inventor, the count is divided by the number of the inventors involved and assigned to the place of inventor's residence with the respective share on that patent. Hence, the number of regional patents may not always be a whole number.

5. For example, COHEN, NELSON and WALSH (2002) as well as SCHARTINGER, SCHIBANY and GASSLER (2001) provide evidence for the greater importance of indirect and informal university-industry linkages (e.g. information trading) as compared to direct channels of knowledge transfer such as licenses, prototypes, etc.

6. Assuming such a time lag also helps to avoid potential problems of endogeneity between R&D inputs and output. FRITSCH and SLAVTCHEV (2007, 2008), 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.

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

8. For this definition of the planning regions, see Federal Office for Building and Regional Planning (BUNDESAMT FUER BAUWESEN UND RAUMORDNUNG - BBR, 2003).

9. 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.

10. ARORA and GAMBARDELLA (1994); ARORA, GAMBARDELLA and RULLANI (1997); ARORA and GAMBARDELLA (1998), COCKBURN ET AL., (1999); ARORA, FOSFURI and GAMBARDELLA (2001).

11. 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 interaction 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 interaction 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

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of (national or regional) innovation systems (cf. LUNDVALL, 1992; NELSON, 1993; EDQUIST, 1997; COOKE, URANGA and ETXEBARRIA, 1997).

12. Based on a survey of about 2,300 private enterprises in Germany, BEISE and STAHL (1999) found that about 60 percent of the firms that had introduced university-based innovations were located at a distance of up to 100 km from the particular knowledge source. When technical colleges were the source of knowledge the figure was about 80 percent. Similar finding are provided by econometric studies on the spatial scope of university-industry linkages. By using third-party funds from private firms as an indicator for university-industry linkages, FRITSCH and SLAVTCHEV (2007, 2008) found spillovers from universities at a distance of up to 50 km. Because most universities in Germany are located in relatively large cities which are usually considered core of a planning region these results suggest that the large majority of universities' private-sector cooperation partners should be sited in the same planning region.

13. See GREIF and SCHMIEDL (2002) for the definition of the 31 technological fields.

14. 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).

15. The results for the truncated normal distribution and the exponential distribution differ only slightly from those for the half-normal distribution and are, therefore, not reported here.

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

17. When the impact of *PROXTECH* is analyzed, *TPF-PRIV*, *MPG* and *FhG* are excluded from the model. The reason is that *PROXTECH* measures the potential knowledge spillovers between all kinds of public research institutions and the private sector. Hence, the effects of universities and institutes of the Max-Planck- or Fraunhofer-Society are already included.

18. Two sample mean comparison test suggests significantly (p=0.000) less industrial diversity in East Germany (1.404) than in West Germany (1.527).