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Industry Specialization, Diversity and the Efficiency of Regional Innovation Systems

Michael Fritsch [a,b] and Viktor Slavtchev [a]

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Abstract

Innovation processes are characterized by a pronounced division of labor between actors. Two types of externality may arise from such interactions. On the one hand, a close location of actors affiliated to the same industry may stimulate innovation (MAR externalities). On the other hand, new ideas may be born by the exchange of heterogeneous and complementary knowledge between actors, which belong to different industries (Jacobs' externalities). We test the impact of both MAR as well as Jacobs' externalities on innovative performance at the regional level. The results suggest an inverted u-shaped relationship between regional specialization in certain industries and innovative performance. Further key determinants of the regional innovative performance are private sector R&D and university-industry collaboration.

Keywords: Innovation, technical efficiency, patents, agglomeration concentration, specialization, diversity, regional analysis.

JEL-classification: O31, O18, R12

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1. Industry specialization and innovation activity

Innovating firms are no isolated, self-sustained entities but rather are highly linked to their environment. This embeddedness can have a considerable effect on innovation processes, and it is not very far-fetched to assume that not all kinds of environment are equally well suited for a certain type of research and development (R&D) activity. There are two prominent hypotheses that pertain to the sectoral structure of the regional environment. One of these hypotheses states that the geographic concentration of firms that belong to the same industry or to related industries is conducive to innovation. The other hypothesis assumes that it is the diversity of industries and activities in a region, not the concentration of similar industries that has a stimulating effect.

In this paper we test these two hypotheses by linking sectoral specialization of a region to the performance of the respective regional innovation system (RIS). The next two sections elaborate on the theoretical background of the two hypotheses and review the empirical evidence attained thus far. Section 4 introduces our concept of efficiency of the RIS and section 5 deals with data and measurement issues. We then give an overview on the efficiency of German RIS (section 6) and investigate the relationship between sectoral concentration and the RIS efficiency (section 7). The final section (section 8) concludes.

2. Why should sectoral specialization of a region stimulate or impede innovation: theoretical background

Innovation activity is characterized by interaction and transfer of knowledge between people and institutions. It can be regarded as a collective learning process. The main actors involved in this learning process are private firms, customers, universities and other public research institutions, technology transfer bureaus, industry associations as well as public policy. If these actors are located in the same region they participate in the same RIS.

The specialization of a certain region in a particular industry is believed to be conducive to innovation activities of firms affiliated with this industry for a number of reasons. Accordingly, the co-location of a large number of firms that are operating in similar technological fields may induce localization advantages because:

- the aggregate demand of a relatively large amount of firms of an industry may result in a pool of regional workforce with certain industry specific skills that can be utilized by all firms belonging to that particular industry and located in the region (Marshall, 1890; Ellison and Glaeser, 1999);
- this aggregate demand of the regional firms can also induce a rich regional supply of other relevant inputs such as specialized business services, banks and credit institutions or certain kinds of infrastructure (Bartelsman, Caballero and Lyons, 1994);
- the sectoral specialization of a region may stimulate R&D cooperation between the firms which are sharing the same knowledge base and thus may promote a high level of knowledge spillovers (Mowery, Oxley and Silverman, 1998);
- tacit knowledge and geographically bounded knowledge spillovers may be conductive for local collective learning processes (Lawson and Lorenz, 1999; Maskell and Malmberg, 1999).

These benefits of specialization within a certain industry are external to the firm belonging to that industry but remain largely internal to the particular region. Such effects that result from the specialization of regional economic activities in the same industry are labeled *Marshall-Arrow-Romer* externalities[1] (MAR externalities) according to the authors who have created this concept (Glaeser et al., 1992).

However, the concentration of several firms of the same industry in a region can also be disadvantageous if it leads to *lock-in* effects. Such

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[1] Based on Marshall (1890), Arrow (1962) and Romer (1986).

lock-in effects may occur if the specialization of the regional knowledge and resources deter the emergence and evolution of other technological fields (Grabher, 1993). In particular, specialization may hamper the exchange between heterogeneous actors with different, but complementary types of knowledge. As argued by Jacobs (1969), many ingenious ideas are born in the exchange process which occurs between different fields of knowledge. In economic terms, this means that diversity may lead to advantages of innovation activity which are comprised of different technological fields. Hence, it may be the industrial variety in a region that is conducive to innovation activity. Such economies are external to the firms and industry but internal to the respective geographical location. Moreover, as pointed out by Jacobs (1969), these effects can be expected to be greater in densely populated regions. Therefore, regions with diverse kinds of activities and a high degree of agglomeration, particularly cities, may have a comparative advantage over less densely populated areas which are usually characterized by a lesser variety of actors, institutions and industries. Such effects of industrial diversity are also labeled *Jacobs'* externalities. However, as Henderson (1997) showed for the USA, agglomerations and cities not only tend to be more diversified but also more specialized in certain industries.

3. Empirical evidence

The answer to the question if specialization or diversity in a region is conducive to innovation activity is still largely unclear. For example, Glaeser et al., (1992) found that diversity rather than regional specialization had a positive impact on employment growth in US-American cities in the 1956-1987 period. This study is, however, not directly linked to innovative activities. Feldman and Audretsch (1999) analyzed the effect of sectoral specialization on innovative output on the basis of innovation counts which were attributed to four-digit SIC industries at the city level. They found that innovative output of an industry tends to be lower in cities which are specialized in that particular industry. This result supports the idea that diversity rather than specialization plays a major role (Jacobs, 1969). In an earlier study for the USA, the authors found that the spatial concentration of certain industries (MAR-externalities) is not an important determinant for explaining innovative output (Audretsch and Feldman, 1996a, b). Obviously, Jacobs' thesis seems to hold for the US and can, according to Duranton and Puga (2000), be regarded as a stylized fact.

Many of the respective studies for European regions explicitly tested for both types of externalities. Paci and Usai (2000a) provide clear evidence for a significantly positive relationship between sectoral specialization and innovative output at the level of European NUTS-1 regions. The authors conclude that innovations simply occur in locations with pronounced manufacturing activities. However, there are typically a number of different knowledge sources (e.g., universities and other public R&D labs) and other supporting facilities in such locations that are not included in their analyses. In the case of Italy, Paci and Usai (1999, 2000b) found evidence for both, Jacobs' externalities as well as MAR externalities. With respect to the latter, the authors conclude that innovative activities in a certain industry, as measured by the number of patents, tend to be higher in geographic locations which are specialized in that particular industry. In a more recent study, Greunz (2004) tested the impact of sectoral specialization on the number of patents at the level of European NUTS-2 regions and clearly confirmed these results. Van der Panne and van Beers (2006) argue that MAR and Jacobs' externalities may both be relevant for innovation; however, they are at different stages of the process. According to their analysis for the Netherlands, MAR externalities have stronger positive effects in the early phases of innovation activity while Jacobs' externalities are more supportive for the marketing of an innovation.

Overall, previous analyses could not provide an unambiguous answer to the question whether sectoral specialization or diversity in a region stimulates innovation activities. In contrast to previous studies which focused on the impact of MAR- and Jacobs-externalities on the number of innovations or patents, we use the efficiency of RIS in generating new knowledge as a performance indicator. Moreover, our analysis focuses not only on the role of specialization or diversity but it also accounts for other key determinants of the efficiency of RIS.

4. Assessing the efficiency of RIS

The term efficiency is used in a variety of ways. Our understanding of the efficiency of RIS corresponds to the concept of technical efficiency as introduced by Farrell (1957). Technical efficiency is defined as the generation of a maximum output from a given amount of resources. A firm is regarded as being technically inefficient if it fails to obtain the possible maximum output. Reasons for technical inefficiency can be manifold and comprise all kinds of mismanagement such as inappropriate work organization and improper use of technology (Fritsch and Mallok, 2002), bottlenecks in regard to certain inputs as well as X-inefficiency as exposed by Leibenstein's (1966) seminal work. Applying that definition to the concept of RIS means that a region is technically efficient if it is able to produce a possible maximum of innovative output from a given amount of innovative input. Accordingly, the inefficiency of a RIS results from the failure to meet the best practice of conducting innovation activity.

Our measure of efficiency is based on a regional knowledge production function that describes the relationship between innovative input and output (Griliches, 1979; Jaffe, 1989). The basic hypothesis behind the knowledge production function is that inventions do not 'fall from heaven' but result predominantly from systematic R&D efforts, i.e.,

(1) $R\&D \text{ ouput} = f(R\&D \text{ input})$.

Adopting the Cobb-Douglas form of a production function, the basic relationship between regional R&D output and input can be written as

(2) $R\&D \text{ ouput} = A * R\&D \text{ input}^{\beta} * e^{\varepsilon}$,

with the term A representing a constant factor, β providing the elasticity by which R&D output varies with the input to the R&D process and ε as an additional *iid* distributed statistical noise component.

The output of the R&D process for regions may differ because of two reasons: the output elasticity of R&D input, β, and the constant term, A. The output elasticity may be interpreted as a measure of the marginal productivity or efficiency of the input to the innovation process. If, for example, the quality of inputs to the R&D process is improving or if spillovers from the R&D activities of other actors in the region become more pronounced, the input elasticity of R&D output may increase. Differences between regions in regard to the constant term indicate higher innovative output at any level of input. Such differences in the constant term may be explained by all kinds of characteristics of RIS that influence average productivity of R&D input but do not necessarily affect marginal returns. An illustrative example of such differences that only pertain to the average productivity of R&D input and not to marginal productivity could be innovations that are not entirely based on current R&D but also on the existing stock of 'old' knowledge. Moreover, the presence of informal networks and 'milieux' may mainly affect average productivity. Due to the fact that, in practice, we are only able to assess the relevant knowledge stock rather incompletely, differences in regard to the constant term may also reflect a misspecification or incomplete measurement of the input variable. We, therefore, restrict ourselves here to the assessment based on the marginal productivity of R&D input. Analyses of the two measures show that they lead to a quite similar assessment of the quality of RIS (Fritsch and Slavtchev, 2006). Based on the estimates of the marginal productivity of R&D input in each region, the efficiency E_r of the region r is then calculated as

$$E_r = \left(\hat{\beta}_r / \max \hat{\beta}_r\right) * 100 \ [\%]. \tag{3}$$

According to this approach, at least one region will meet the benchmark value and the remaining regions will have efficiency values between 0 and 100 percent of this benchmark value.

5. Data and measurement issue

In this study we use the number of disclosed patent applications as an indicator for the innovative output of the regional innovation processes. Information on the yearly number of disclosed patent applications is available for the 1995 to 2000 period from Greif and Schmiedl (2002). A patent application indicates that an invention has been made which extends the existing pool of economically relevant knowledge. However, using patents as an indicator for new knowledge has some shortcomings (Brouwer and Kleinknecht, 1996; Acs, Anselin and Varga, 2002; Griliches, 1990). On the one hand, patents may underestimate the output of R&D activity as the results of basic research cannot be patented in Germany. The actual R&D output may also be overestimated in the case of blocking patents, which are typically applied around one core invention in fairly new technological fields, where there may be many potential applications which are not yet known. Although patents have some shortcomings, this paper follows previous studies in this field, thus, assuming that patents are appropriate indicator of innovative output.

A patent is assigned to the region in which the inventor has his main residence. 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 of the inventors being located in different regions, the number of patents per region may not always be a whole number. We have rounded up the number of patents per region assuming that innovations are randomly occurring discrete events that typically follow a Poisson distribution. Hence, econometric methods that account for the discrete nature of the dependent variable appear more appropriate than the least square estimation technique, which is based on the assumption of a normal distribution of the residuals. However, as the distribution of patent records shows pronounced skewness to the left (overdispersion), we apply negative-binomial regression as an estimation technique for assessing the efficiency of RIS.[2]

In an analysis of the knowledge sources of innovation for West German districts[3] (*Kreise*) as well as for the German planning regions (*Raumordnungsregionen*) 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, 2005, 2007). Further knowledge sources that had a significant effect on innovative output of a region were the number of R&D employees in adjacent regions indicating the presence of spatial knowledge spillovers as well as the amount of external research funds attracted by public research institutions. In this paper, we omit other input variables and limit the analysis to the number of private sector R&D employees as the main knowledge source in the knowledge production function. The main reason for this approach is that knowledge spillovers from adjacent regions as well as the presence of public research institutions can be regarded as determinants of the efficiency of private sector R&D input and should, therefore, not be used for measuring it. The number of R&D employment in the private sector stems from the German Social Insurance Statistics (*Statistik der sozialversicherungspflichtig Beschäftigten*) 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.

The estimation of a knowledge production function at the level of planning regions (table 1) shows a strong impact of the number of private sector R&D employees on the number of patents. The production elasticity of private sector R&D employment is 0.885

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[2] See Greene (2003, 931-939). As we find at least one patent per year for each district in our data, the problem of having “too many zero values” does not apply.

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

indicating that an increase of R&D employment by one percent leads to an increase in the number of patents of nearly 0.89 percent. According to the constant term of the model, there are only 0.17 patents in the average planning region per year that cannot be attributed to private sector R&D efforts as measured by R&D employment.

Table 1: The knowledge production function

Variable	
Private sector R&D employees (ln)	0.885**
	(0.051)
Intercept	-1.773**
	(0.441)
N	388
Alpha	0.365
	(0.045)
Wald χ^2 (1)	306.46**
Log pseudo likelihood	-2,466.15
Pseudo R^{2adj}	0.916

Results of robust (cluster) negative-binomial regression; robust standard error in parentheses; ** statistically significant at the 1% level.

When relating knowledge input to innovation output we have to assume that there is a time lag between the respective indicators for two reasons. Firstly, R&D activity requires time for attaining a patentable result. Secondly, 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 (Greif and Schmiedl, 2002). Thereafter, each patent application has to be disclosed (Hinze and Schmoch, 2004). Hence, at least two or three years should be an appropriate time lag between input and output of the R&D process.[4]

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[4] Fritsch and Slavtchev (2005, 2007) relate patenting activities in West Germany between 1995 and 2000 to R&D activities three years ago. Acs, Anselin and Varga (2002) report that US innovation records in 1982 resulted from inventions that had been made 4.3 years earlier. Fischer and Varga (2003) used a two year lag between R&D efforts and patent counts in Austria in 1993. Ronde and Hussler (2005) linked the innovative output, the number of patents between 1997 and 2000, to R&D efforts in 1997.

However, because reliable data on R&D employment in East Germany are only available for the years 1996 onwards, a time lag of two or three years would lead to too few observations per region for estimating a region-specific effect. In order to have more observations available, we reduce the time lag between R&D input and the patent application to a period of one year.[5] In other words, R&D output in the period 1997-2000 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 the years. Moreover, the differences between an estimated knowledge production function with a time lag of one year and with a time lag of three years are negligible (Fritsch and Slavtchev, 2005, 2007).

The spatial pattern to be used for the analysis is given by the 97 German planning regions.[6] The spatial concept of planning regions focuses on commuter distances; therefore, they account for travel to work areas and are well suited to represent functional spatial economic entities. In general, planning regions consist of several districts and include at least one core city as well as its surroundings. 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 create functional units, we merge these cities with adjacent planning regions for the analysis. Berlin was merged with the region Havelland-Flaeming, Hamburg with the region Schleswig-Holstein South, Bremen with Bremerhaven and with the region Bremen-Umland. Hence, the estimation approach applied in this paper is based on observations for 93 regions over 4 years.

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

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

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

which is multiplied with the respective number of private sector R&D employees. This dummy variable assumes the value one for the respective region and otherwise has the value zero. The constant term, A, is assumed to be the same for all regions. Hence, the equation (2) can be rewritten as

$$(4) \qquad Patents_r = A\prod_r R\&D\ priv_r^{\beta_r} * e^{\varepsilon_r},$$

with β_r as a measure of the marginal productivity of private sector R&D employment in the r^{th} region ($r = 1, ..., 93$). In order to partly relax the assumption of independency of the observations for a particular planning region, we adjust the standard error for intragroup correlation by clustering the observations for each region. Applying the clustering procedure is equivalent to a White-corrected standard error in the presence of heteroscedasticity (White, 1980). The efficiency measure is computed according to equation (3). The results are reported in table A1 in the Appendix.

6. The distribution of RIS efficiency across German regions

There is a wide dispersion of technical efficiency of RIS among the planning regions that reflects the marginal productivity of R&D input. The values for technical efficiency range between 53 and 100 per cent, meaning that productivity of private R&D input in the best practice region is about twice the productivity in the least efficient region (see table A1 in the Appendix as well as Fritsch and Slavtchev, 2006, for details).

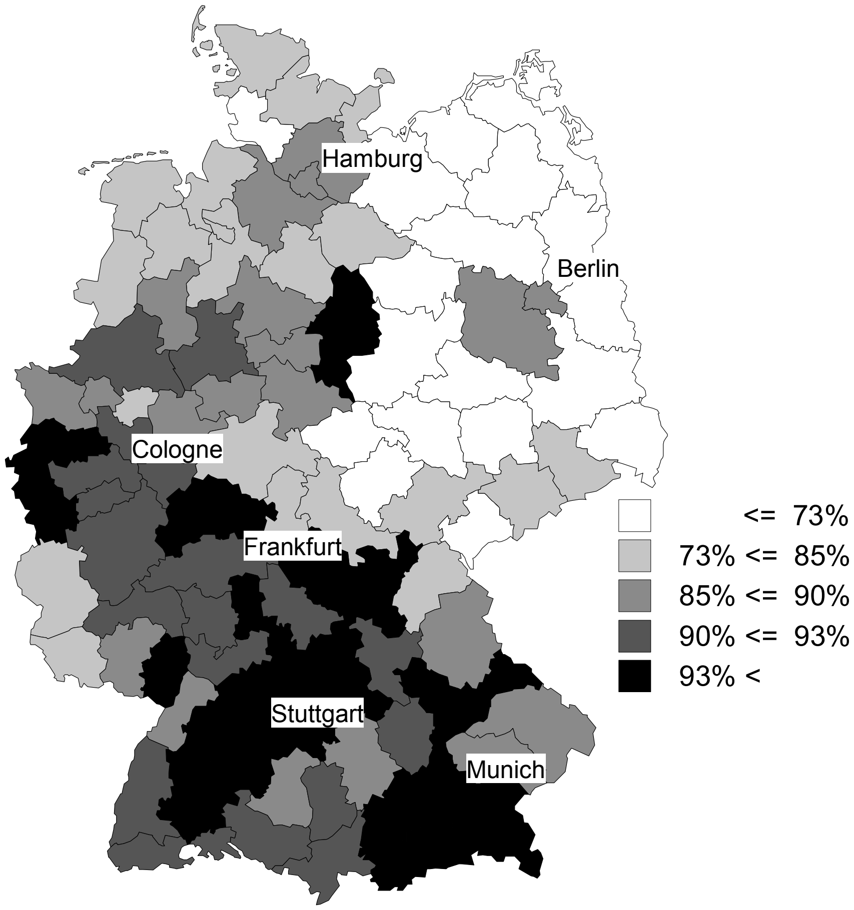

Figure 1: The distribution of efficiency of RIS in German planning regions

Generally, the values for the technical efficiency of RIS tend to be higher in regions with large, densely populated agglomerations such as Munich, Stuttgart, Cologne and Frankfurt. The lowest efficiency estimates are found for regions in the northeast such as “Mecklenburgische Seenplatte,” “Vorpommern” and “Altmark” located in eastern Germany, the former German Democratic Republic (GDR). The Berlin region, showing a relatively high RIS efficiency, is an exception in the East German innovation landscape. The relatively low values for technical efficiency in East Germany indicate that the RIS in this part of the country is rather inefficient. Most of the regions with a relatively high level of technical efficiency of RIS are located in the southern and in the western part of the country. We find evidence for spatial clustering of regions with similar levels of RIS efficiency (see Fritsch and Slavtchev, 2006, for details). This indicates that some of the determinants of the efficiency of RIS apply to larger geographical units than planning regions.

7. Sectoral concentration and the efficiency of RIS

To estimate the relative impact of different determinants of the technical efficiency of RIS a robust OLS cross-section regression technique was applied. Although the main focus of this study is on the relationship between sectoral concentration in a region and marginal productivity of R&D employment, a number of further important determinants of RIS efficiency as well as a number of control variables are included. Table 2 gives an overview on the definition of variables and respective data sources. Descriptive statistics presented in table 3 and table 4 show the regression results. Correlation coefficients for the relationship between the variables are given in table A2 in the Appendix.

Table 2: Definition of variables and data sources

Variable	Description	Definition	Source
Patents	Number of disclosed patent applications in the region, 1997-2000		German Patent and Trademark Office (*DPMA*)
$R\&D_{PRIV}$	Number of private sector R&D employees in the region, 1996-1999	Number of employees with tertiary degree in engineering and natural sciences in the region	German Social Insurance Statistics
Efficiency of RIS	Marginal productivity of private sector R&D employees in the region, 1997-2000	See section 4	See section 4
$R\&D_{PRIV}$ [share]	Share of private sector R&D employees in the region, 1996-1999 average	Number of employees with tertiary degree in engineering and natural sciences in the region / Number of employees in the region	German Social Insurance Statistics
SERVICES	Service sector relative size in the region, 1996-1999 average	Share of employment in services in the region divided by the share of employment in services in the entire economy. This index is standardized in [-1;1] according to Paci and Usai (1999).	German Social Insurance Statistics
POPden	Population density in the region, 1996-1999 average	Number of inhabitants per km^2	Federal Office for Building and Regional Planning
∅ FSIZE	Average firm size in the region, 1996-1999 average	Number of employees in the region / Number of firms in the region	German Social Insurance Statistics
ERF_{IND} per Professor	Universities external research funds per professor in the region, 1996-1999 average	Volume of external research funds, that universities in the region gain from private sector actors [1,000 Euro] / Number of professors at universities in the region	German University Statistics available at the Federal Statistical Office
DIV	Regional index of industrial diversity, 1996-1999 average	Inverse of the Donaldson-Weymark relative S-Gini coefficient on basis of 58 industries (industrial classification WZ58)	German Social Insurance Statistics
TRANSPORT_ENG	Share of employment in transportation engineering in the region, 1996-1999 average	Number of employees in transportation engineering in the region / Number of regional employees	German Social Insurance Statistics
ELECTR_ENG	Share of employment in electrical engineering in the region, 1996-1999 average	Number of employees in electrical engineering in the region / Number of regional employment	German Social Insurance Statistics
OPTICS	Share of employment in measurement engineering and optics in the region, 1996-1999 average	Number of employees in measurement engineering and optics in the region / Number of regional employees	German Social Insurance Statistics
CHEMISTRY	Share of employment in chemistry in the region, 1996-1999 average	Number of employees in chemistry in the region / Number of regional employees	German Social Insurance Statistics
Dummy West	Region located in West Germany	Regions in former German Federal Republic = 1; regions in former GDR and Berlin = 0	
Dummy South	Region located south of Frankfurt (Main)	Regions located south of Frankfurt (Main) = 1, otherwise dummy = 0	
Dummy Periphery	Region located at the border of Germany	Regions located at the border of Germany = 1, otherwise dummy = 0	

Table 3: Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max	Median
Patents [a]	372	395.50	508.60	11.778	3,652.7	245.75
$R\&D_{PRIV}$ [a]	372	6,674.0	8,724.1	649.00	48,968	3,690.0
Marginal productivity of $R\&D_{PRIV}$ [$\hat{\beta}$]	93	0.6513	0.0893	0.4119	0.7779	0.6768
Efficiency of RIS [%]	93	83.717	11.480	52.941	100.00	87.005
$R\&D_{PRIV}$ [Share]	93	0.0223	0.0089	0.0089	0.0528	0,0200
ERF_{IND} per Professor	93	11.062	14.735	0	97.067	7.1950
DIV	93	1.4979	0.0825	1.3076	1.6785	1.5023
TRANSPORT_ENG	93	0.0428	0.0375	0.0096	0.2259	0.0308
ELECTR_ENG	93	0.0354	0.0233	0.0038	0.1227	0.0292
OPTICS	93	0.0086	0.0086	0.0022	0.0553	0.0055
CHEMISTRY	93	0.0167	0.0227	0.0009	0.1795	0.0100
∅ FSIZE	93	13.204	1.6957	8.5294	18.2661	13.308
SERVICES	93	-0.0481	0.0818	-0.2255	0.1999	-0.0556
POPden	93	336.99	507.56	53.425	3,886.29	180.67

[a] Pooled yearly values.

A significantly positive impact on technical efficiency of RIS can be found for the share of private sector R&D employment. The estimated coefficient provides clear evidence for scale economies. This means that an increase of the share of private sector R&D employment at a certain location may make innovation processes more efficient. The sources of such scale economies could be increasing opportunities for a division of innovative labor that is related to a high level of knowledge spillovers. However, if more detailed measures for regional specialization in R&D intensive industries are included (models 4-8), the impact of the share of R&D employment becomes somewhat weaker or is no longer statistically significant (model 8).

The average amount of external research funds from private sector sources per university professor has a positive impact on the efficiency of RIS. This suggests that the intensity of university-industry linkages is conducive to the efficiency of regional innovation activity presumably as a result of the knowledge flows that are indicated by the money that private firms pay for the R&D that the universities perform for them.

Table 4: Determinants of efficiency of RIS

	Dependent variable: Efficiency of RIS [equation (3)]							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$R\&D_{PRIV}$ [Share] (ln)	0.026*	0.048*	0.067**	0.066**	0.056**	0.064**	0.060*	0.028
	(2.21)	(2.62)	(2.89)	(2.79)	(2.44)	(2.69)	(2.60)	(1.19)
ERF_{IND} per professor (ln)	0.022*	0.012	0.015**	0.015**	0.014*	0.015**	0.015*	0.016*
	(1.99)	(1.92)	(2.65)	(2.67)	(2.54)	(2.65)	(2.63)	(2.62)
DIV (ln)		8.540**	4.210*	4.027*	3.884*	4.216*	4.130*	3.306*
		(3.71)	(2.54)	(2.45)	(2.51)	(2.54)	(2.45)	(2.05)
DIV^2 $(ln)^2$		-8.760**	-4.727*	-4.449*	-4.425*	-4.755*	-4.646*	-3.730
		(2.97)	(2.31)	(2.19)	(2.33)	(2.33)	(2.22)	(1.88)
TRANSPORT_ENG (ln)				0.008				0.012
				(0.80)				(1.25)
ELECTR_ENG (ln)					0.023*			0.032*
					(1.96)			(2.48)
OPTICS (ln)						0.005		0.005
						(0.46)		(0.49)
CHEMISTRY (ln)							0.005	0.013
							(0.61)	(1.37)
∅ FSIZE (ln)	-0.441**	-0.224*	-0.248**	-0.253**	-0.244**	-0.239**	-0.234**	-0.206**
	(2.98)	(2.03)	(2.89)	(2.99)	(2.84)	(2.81)	(2.86)	(2.67)
SERVICES	-0.637**	-0.239	-0.473**	-0.453**	-0.436**	-0.468**	-0.478**	-0.401**
	(3.10)	(1.42)	(5.26)	(4.97)	(4.68)	(5.12)	(5.36)	(4.46)
POPden (ln)	0.137**	0.064**	0.069**	0.070**	0.068**	0.069**	0.068**	0.065**
	(4.65)	(3.51)	(4.63)	(4.61)	(4.93)	(4.61)	(4.37)	(4.53)
Dummy West (1 = yes)			0.155**	0.147**	0.148**	0.154**	0.150**	0.122**
			(5.92)	(5.65)	(5.62)	(5.86)	(5.08)	(3.81)
Dummy South (1 = yes)			0.080**	0.078**	0.074**	0.080**	0.081**	0.069**
			(5.23)	(4.98)	(4.98)	(5.15)	(5.31)	(4.49)
Dummy Periphery (1 = yes)			-0.028*	-0.029*	-0.023	-0.027*	-0.027*	-0.019
			(2.04)	(2.11)	(1.72)	(1.98)	(1.96)	(1.46)
Intercept	4.845**	2.811**	3.837**	3.869**	3.856**	3.807**	3.799**	3.783**
	(10.94)	(4.79)	(9.02)	(9.25)	(9.79)	(9.18)	(8.90)	(10.16)
R-squared	0.33	0.66	0.86	0.86	0.86	0.86	0.86	0.87
R-squared adj.	0.29	0.63	0.84	0.84	0.85	0.84	0.84	0.85
F	5.40	44.60	61.08	57.19	58.01	54.52	59.00	52.62
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Results of OLS, Huber-White estimation. Robust t-statistics in parentheses; * significant at 5% level; ** significant at 1% level. Number of observations (regions): 93.

The industrial diversity index is the inverse value of the Gini coefficient calculated on the basis of the number of employees in 58 different industries. The positive sign for the industrial diversity index (models 2-8) suggests that the efficiency of regional 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. The results favor

Jacobs' externalities. However, the negative sign for the squared value of the diversity index indicates a nonlinear relationship with the efficiency of the RIS that has the shape of an inverse 'U' which is truncated close behind the maximum value. Indeed, the same pattern can be directly observed in the data (figure 2)[7]. This pattern implies that an optimum degree of industrial diversity exists and that a further increase beyond this level has an unfavorable effect. Obviously, both extremes broad diversity as well as narrow specialization may be unfavorable for the performance of a RIS. Even after introducing a number of additional variables in order to control for further effects, the estimated pattern for industrial diversity remains remarkably stable.

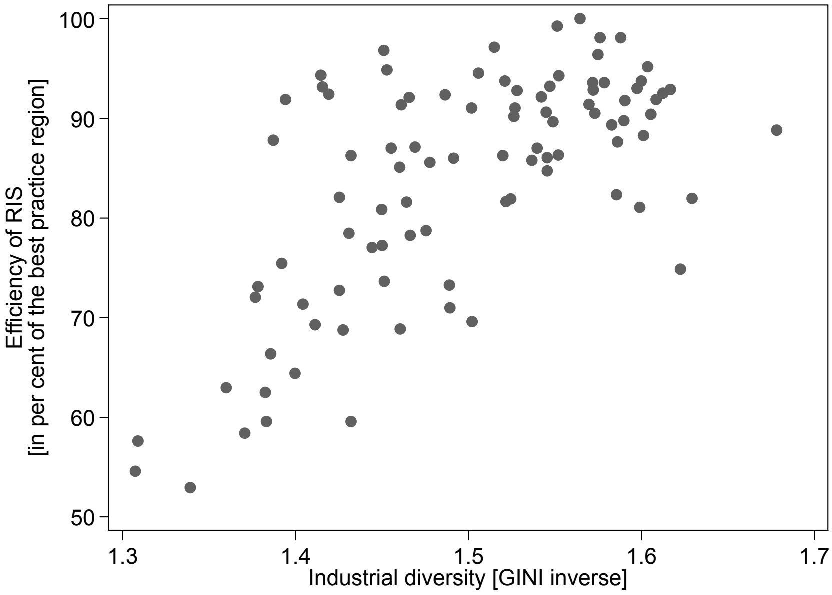

Figure 2: Industrial variety and technical efficiency of RIS at the level of the German planning regions

Our results suggest that externalities of both Marshall and Jacobs' type affect the efficiency of regions in producing innovative output. This

[7] High values indicate high levels of industry diversification.

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confirms previous results of Paci and Usai (1999, 2000b), who used the Herfindahl index as a measure of industrial diversity, and it also parallels the findings of Greunz (2004), who tested the impact of the industrial structure on innovation in European regions by means of Gini coefficients.

In order to control for the relative impact of regional specialization in certain industries with a relatively high level of patenting, we include the share of employees in the transportation engineering, electrical engineering, measurement engineering and optics. These are, according to Greif and Schmiedl (2002), the technological fields in which most of the patent applications in Germany are generated.[8] Due to the fact that the available data do not allow the identification of the exact number of employees in the biochemical industry, which is another field with a relatively high share of patenting, we include the percentage of people employed in chemistry as indicator for the region's specialization in that particular sector. However, only regional specialization in electrical engineering seems to have an effect on the efficiency of RIS. 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 (KIBS), which also may produce and diffuse knowledge that is crucial for innovation processes (Muller and Zenker, 2001; Anselin, Varga and Acs, 2000). One could, therefore, expect a positive impact of the share of the regional service sector on RIS efficiency. However, a high share of the service sector in the region may have a negative effect on the number of regional patents due to the relatively low propensity to patent in this sector. Hence, the overall effect of services on the efficiency of RIS is a priori not clear. In order to test the impact of the service supply in a region on the marginal patent

[8] In the 1995-2000 period 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).

productivity of the private sector R&D, we include the relative size of that sector (in terms of employment) into the model (SERVICES). Our results indicate that the share of the service sector has a negative impact on the efficiency of RIS. This means that despite their supporting function resources allocated to the service sector are less efficient in terms of patenting. This corresponds to the relatively low share of patents in services.

As indicated by the significantly negative coefficient for average firm size, the patenting efficiency tends to be lower in regions that are dominated by industries in which economies of scale play an important role. This confirms 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).

The positive coefficient for population density indicates the presence of urbanization economies. This suggests that a location in a densely populated region which provides a variety of opportunities for interaction in addition to often abundant supplies of input as well as a rich physical, institutional and communication infrastructure may be advantageous for innovation activity.

The results of the analysis also suggest that regions located in the West Germany as well as in the South of the country are more efficient in producing innovative output per unit innovative input than regions located in the North and in the East of the country. Regions located in the periphery tend to be relatively inefficient in comparison to the non-peripheral areas. However, if the share of employment in electrical engineering is included (model 5 and 8), the estimated coefficient for location in the periphery becomes statistically insignificant indicating that this industry is not present in this spatial category. The dummy variables for location in the western and in the southern part of Germany remain quite robust providing clear evidence for the presence of region-specific factors which are not captured by the other variables.

8. Conclusions

This paper investigated the effect of a region's specialization in certain industries on the efficiency of RIS in producing knowledge. Our answer to the question "Is regional specialization in a certain industry conducive to the performance of RIS in terms of efficiency?" is "Yes, but only to a certain degree." In fact, the data suggest that the relationship between sectoral specialization and the performance of RIS has the form of an inverse 'U'. This means that if a certain level of specialization is reached any further concentration in the respective industry tends to be unfavorable for the efficiency of RIS. A high concentration as well as great diversity of the sectoral structure in a region is associated with a relatively low level of RIS efficiency. The results suggest that a region's specialization in a certain industry may increase the efficiency of the region in producing innovative output. However, this does not hold for all industries but seems to be the case for high-tech manufacturing industries such as electrical engineering.

The results of this paper raise some important questions for further research. First, the determinants of knowledge spillovers within the private sector as well as the industry-universities relationships should be more illuminated as such interchanges seem to be conducive to the regional innovative performance. Second additional research is required in order to answer the question about what are the forces drawing the industrial structure of regions. Moreover, regarding the positive impact of industrial diversity on innovation, more information about the ways in which knowledge spills over between industries should be helpful in order to derive reasonable policy implications.

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Appendix

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

Planning region		Estimated production elasticities		Technical efficiency [%]	Rank
Code	Name	$\hat{\beta}$	robust std. error	$\frac{\hat{\beta}}{\max\hat{\beta}} * 100$	
1	Schleswig-Holstein North	0.5685	0.3012	73.07	75
2	Schleswig-Holstein South-West	0.5412	0.2919	69.57	80
3	Schleswig-Holstein Central	0.6104	0.2408	78.46	67
4	Schleswig-Holstein East	0.5991	.0.2639	77.02	70
5 & 6	Schleswig-Holstein South & Hamburg	0.6657	0.1995	85.57	55
7	Western Mecklenburg	0.4634	0.2534	59.57	88
8	Central Mecklenburg/Rostock	0.5163	0.2524	66.37	84
9	Western Pomerania	0.4479	0.2558	57.58	91
10	Mecklenburgische Seenplatte	0.4119	0.2737	52.94	93
11 & 13 & 15	Bremen & Bremerhaven & Bremen-Umland	0.6123	0.2170	78.71	66
12	East Frisian	0.5866	0.2777	75.41	71
14	Hamburg-Umland-South	0.6778	0.2669	87.12	46
16	Oldenburg	0.6008	0.2683	77.22	69
17	Emsland	0.5823	0.2705	74.85	72
18	Osnabruck	0.6767	0.2550	86.99	48
19	Hanover	0.6691	0.2136	86.01	53
20	Suedheide	0.6290	0.2780	80.85	65
21	Luneburg	0.5726	0.3003	73.60	73
22	Brunswick	0.7250	0.2178	93.19	18
23	Hildesheim	0.6713	0.2566	86.29	50
24	Gottingen	0.6817	0.2601	87.62	45
25	Prignitz-Obehavel	0.4859	0.2630	62.46	87
26	Uckermark-Barnim	0.4542	0.2716	58.38	90
27	Oderland-Spree	0.4899	0.2574	62.98	86
28	Lusatia-Spreewald	0.5389	0.2314	69.28	81
29 & 30	Havelland-Flaeming & Berlin	0.6833	0.1915	87.83	44
31	Altmark	0.4247	0.3065	54.59	92
32	Magdeburg	0.5550	0.2300	71.34	78
33	Dessau	0.4634	0.2474	59.56	89
34	Halle/Saale	0.5604	0.2273	72.04	77
35	Muenster	0.7112	0.2255	91.42	31
36	Bielefeld	0.7150	0.2233	91.91	28
37	Paderborn	0.6673	0.2556	85.78	54
38	Arnsberg	0.6692	0.2516	86.03	52
39	Dortmund	0.6403	0.2276	82.31	58
40	Emscher-Lippe	0.6768	0.2413	87.01	47
41	Duisburg/Essen	0.6714	0.2077	86.31	49
42	Düsseldorf	0.7335	0.1964	94.29	12
43	Bochum/Hagen	0.7171	0.2215	92.18	26
44	Cologne	0.7018	0.2008	90.21	38
45	Aachen	0.7237	0.2235	93.02	19
46	Bonn	0.7149	0.2418	91.90	29
47	Siegen	0.7049	0.2571	90.61	35
48	Northern Hesse	0.6353	0.2399	81.66	62
49	Central Hesse	0.7282	0.2366	93.61	15
50	Eastern Hesse	0.6306	0.2843	81.07	64
51	Rhine-Main	0.7107	0.1920	91.36	32
52	Starkenburg	0.7185	0.2141	92.35	25
53	Northern Thuringia	0.5008	0.2697	64.37	85
54	Central Thuringia	0.5658	0.2296	72.74	76
55	Southern Thuringia	0.5698	0.2540	73.24	74
56	Eastern Thuringia	0.6349	0.2354	81.61	63

57	Western Saxony	0.5347	0.2171	68.74	83
58	Upper Elbe Valley / Eastern Ore Mountains	0.6387	0.2132	82.10	59
59	Upper Lusatia-Lower Silesia	0.5356	0.2440	68.85	82
60	Chemnitz-Ore Mountains	0.6087	0.2254	78.25	68
61	South West Saxony	0.5520	0.2446	70.96	79
62	Middle Rhine-Nahe	0.7033	0.2385	90.40	37
63	Trier	0.6370	0.2847	81.89	61
64	Rhine-Hesse-Nahe	0.7220	0.2427	92.81	22
65	Western Palatinate	0.6619	0.2659	85.08	56
66	Rhine Palatinate	0.7339	0.2229	94.34	11
67	Saar	0.6591	0.2354	84.73	57
68	Upper Neckar	0.7084	0.2137	91.06	33
69	Franconia	0.7292	0.2348	93.73	14
70	Middle Upper Rhine	0.6975	0.2158	89.66	40
71	Northern Black Forest	0.7631	0.2490	98.09	3
72	Stuttgart	0.7556	0.1869	97.13	5
73	Eastern Wuertemberg	0.7631	0.2459	98.09	4
74	Danube-Iller (BW)	0.6950	0.2373	89.34	41
75	Neckar-Alb	0.7295	0.2390	93.77	13
76	Black Forest-Baar-Heuberg	0.7498	0.2501	96.39	7
77	Southern Upper Rhine	0.7141	0.2344	91.80	30
78	High Rhine-Lake Constance	0.7226	0.2397	92.88	20
79	Lake Constance-Upper Swabia	0.7198	0.2282	92.53	23
80	Bavarian Lower Main	0.7254	0.2604	93.24	17
81	Wurzburg	0.7083	0.2495	91.05	34
82	Main-Rhone	0.7531	0.2603	96.81	6
83	Upper Franconia-West	0.7407	0.2558	95.21	8
84	Upper Franconia-East	0.6377	0.2599	81.97	60
85	Upper Franconia-North	0.6868	0.2669	88.28	43
86	Industrial Region Central Franconia	0.7167	0.2021	92.13	27
87	Augsburg	0.7281	0.2885	93.60	16
88	Western Central Franconia	0.6910	0.2305	88.83	42
89	Ingolstadt	0.7189	0.2545	92.40	24
90	Regensburg	0.7354	0.2384	94.53	10
91	Danube-Forest	0.6984	0.2658	89.78	39
92	Landshut	0.6713	0.2702	86.29	51
93	Munich	0.7379	0.1868	94.85	9
94	Danube-Iller (BY)	0.7223	0.2578	92.85	21
95	Allgaeu	0.7041	0.2612	90.51	36
96	Oberland	0.7779	0.2693	100.00	1
97	Southeast Upper Bavaria	0.7723	0.2441	99.27	2

Results of robust (cluster) negative-binomial regression.

Table A2: Correlation of variables

	Variable	1	2	3	4	5	6	7	8	9	10	11
1	Patents [a]											
2	$R\&D_{PRIV}$ [a]	0.92										
3	Efficiency of RIS		1.00									
4	$R\&D_{PRIV}$ [Share]		0.22	1.00								
5	SERVICES		0.08	0.44	1.00							
6	POPden		0.17	0.38	0.47	1.00						
7	∅ FSIZE		0.08	0.58	0.19	0.46	1.00					
8	ERF_{IND} per professor		0.23	0.33	0.20	0.04	0.20	1.00				
9	DIV		0.66	-0.09	-0.12	-0.05	-0.05	0.10	1.00			
10	TRANSPORT_ENG		0.29	0.12	-0.12	-0.05	0.16	0.13	-0.05	1.00		
11	ELECTR_ENG		0.55	0.26	-0.11	0.02	0.18	0.21	0.44	0.06	1.00	
12	OPTICS		0.34	0.02	-0.19	-0.08	-0.11	-0.04	0.31	0.00	0.36	1.00
13	CHEMISTRY		0.31	0.23	0.17	0.09	-0.01	-0.08	0.07	0.04	-0.08	0.02

[a] Pooled yearly values.