Ann Reg Sci (2010) 45:87–108
DOI 10.1007/s00168-009-0292-9

SPECIAL ISSUE PAPER

How does industry specialization affect the efficiency of regional innovation systems?

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Received: 23 January 2009 / Accepted: 23 January 2009 / Published online: 22 February 2009

Abstract This study analyzes the relationship between the specialization of a region in certain industries and the efficiency of the region in generating new knowledge. The efficiency measure is constructed by relating regional R&D input and output. An inversely u-shaped relationship is found between regional specialization and R&D efficiency, indicating the presence of externalities of both Marshall and Jacobs' type. Further factors influencing efficiency are externalities resulting from high R&D intensity of the local private sector as well as knowledge from local public research institutions. The impact of both the specialization and the additional factors is, however, different for regions at different efficiency levels.

JEL Classification O31 · O18 · R12

1 Introduction

The supposition that agglomerations are well suited for innovation activities has a long tradition in economics and economic geography. The idea behind this conjecture is

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rather simple. First, innovative activities may be stimulated by the easy availability of inputs that is typical for agglomerated regions. Second, innovating firms are not isolated, self-sustained entities but rather are highly linked to their environment. Accordingly, innovative processes are characterized by pronounced degrees of labor division and knowledge flows so that spatial proximity to other innovating actors is important. Therefore, a certain degree of agglomeration or clustering of innovators within a particular area should be conducive to innovation activities (Porter 1998). In particular, there are two prominent hypotheses that pertain to the industry structure of the regional environment. One of these hypotheses states that the geographic concentration, i.e., the co-localization of firms that belong to the same industry or to related industries is conducive to innovation. Another hypothesis assumes that it is the diversity of industries and activities in a region, not the concentration in a certain industry that has a stimulating effect.

In this study, we test these two hypotheses by linking industry specialization of a region to its innovative performance. The next two sections elaborate on the theoretical background of the two hypotheses (Sect. 2) and review the empirical evidence attained thus far (Sect. 3). Section 4 introduces our concept of efficiency of a region in generating new knowledge, and Sect. 5 deals with data and measurement issues. We then give an overview on the efficiency of German regions (Sect. 6) and investigate the role of industry specialization (Sect. 7). Section 8 concludes.

2 Why should industry specialization of a region stimulate or impede innovation?

Innovation activity is characterized by interactions and flows of knowledge between actors and institutions. It can be regarded as a collective learning process taking place in a system of interconnected actors. The efficiency of the system may, therefore, be influenced by both the availability of actors as well as by the intensity of interaction and the respective knowledge flows. Interactions of a particular kind can occur between all the elements (or actors) constituting the system such as innovating private firms, public research institutes, suppliers of innovative inputs and services as well as public policy. For instance, the importance of backward and forward linkages has been pointed out by Kline (1985) and Kline and Rosenberg (1986), while Hippel (1986) and Urban and Hippel (1988) have referred particularly to the importance of lead users for inducing innovation. Hence, the density and industrial composition of the regional actors, the accessibility of the region as well as the technological, industrial, and institutional infrastructure may play an important role. Accordingly, differences in the socio-economic conditions that shape the creation of knowledge may lead to diverging innovative performance across regions (Cooke et al. 1997). Moreover, the interactions between the different elements of a regional innovation system (RIS) generate partly self-enforcing systemic effects that may result in region specific knowledge as well as in specific technologies and methods of problem solving (Gertler 2003), which can be expected to affect the workability of the system (Leydesdorff and Fritsch 2006).

The specialization of a certain region in particular industries, typically measured by the co-location of a larger number of firms operating in similar or related technological fields is believed to be conducive to innovation activities of these firms since:

- 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, financial institutions or certain kinds of infrastructure (Bartelsman et al. 1994);
- the industry specialization of a region may stimulate intensive knowledge flows between the firms which are sharing the same technological base (Mowery et al. 1998; Beaudry and Breschi 2003);
- geographically bounded knowledge flows 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 made this concept popular (Glaeser et al. 1992).

However, the concentration of firms of the same industry in a region can also be disadvantageous if it leads to lock-in effects. Such lock-in effects may occur if the specialization of the regional knowledge and resources deter the emergence and evolution of other fields of innovation (Grabher 1993). In particular, narrow technological specialization may hamper the creation of novel knowledge. As argued by Jacobs (1969), many ingenious ideas are born in the exchange process that occurs between different fields of knowledge. This means that diversity may lead to advantages for innovation activity which are comprised of different, but complementary technological fields. Hence, it may be the industrial variety in a region that is conducive to innovation activity. Such effects of industrial variety are also labeled Jacobs' externalities and are supposed to be external to the firms and industries 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. Henderson (1997) shows for the USA that although a number of certain industries tend to be concentrated in agglomerations and large cities, these locations still remain more diversified.

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

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

that diversity rather than regional specialization has a positive impact on employment growth in US-American cities. The study was, however, not directly linked to innovative activities. Feldman and Audretsch (1999) analyzed the effect of industry specialization on innovative output on the basis of innovation counts, which were attributed to four-digit SIC industries at the city level. The authors 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. In other studies for the USA, Audretsch and Feldman (1996a,b) found that the geographical concentration of production is not a sufficient determinant for explaining the geographical concentration of innovative output. 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) provided clear evidence for a significantly positive relationship between industry specialization and innovative output at the level of European NUTS-1 regions. The authors conclude that innovations 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 laboratories) and other supporting facilities in such locations that are not included in their analysis. 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 relationship between industry specialization and the number of patents at the level of European NUTS-2 regions and confirms these results. There is also some evidence from other European countries. For the Netherlands, van Oort (2002) and Ouwersloot and Rietveld (2000) found positive relationship between regional diversification and innovation in manufacturing industries. Also for the Netherlands, van der Panne (2004) identifies a positive relationship between regional specialization and the probability of firms to announce a new product, while diversification was insignificant. For Sweden, Andersson et al. (2005) conclude that there is a negative relationship between regional diversity and the innovative performance of firms. Also studies at the firm level provide ambiguous evidence (Baptista and Swann 1998; Beaudry and Breschi 2003).

Overall, previous analyses do not provide an unambiguous answer to the question whether industry specialization or diversity in a region stimulates innovation activities. In contrast to previous studies that focus on the impact of MAR- and Jacobs'-externalities on the number of innovations or patents, we use the efficiency of regions 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 (1966) seminal work. Applying this definition to a regional concept 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 region results from the failure to meet the best practice of conducting innovation activity.

We assume that inventions do not come out of thin air but result predominantly from systematic R&D efforts, i.e.,

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

Adopting the Cobb-Douglas form of a production function (Griliches 1979; Jaffe 1989), the basic relationship between regional R&D output and input can be written as

$$\text{R\&D output}_r = A_r \times \text{R\&D input}_r^{\beta_r}, \tag{2}$$

where the term A represents a constant factor, β denotes the output elasticity of the input to the R&D process and r is a regional index.

The output of the regional R&D process may differ because of two reasons: the output elasticity of R&D input, β_r, and the constant term, A_r. For example, an increase in the quality of inputs to the R&D process or more pronounced spillovers from the R&D activities of other actors in the region may lead to a rising output elasticity of R&D. 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 a region that influence average productivity of R&D input but do not necessarily affect marginal productivity. Since, 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 innovative performance of regions (Fritsch and Slavtchev 2006).[2] Based on the estimates of the output elasticity of R&D input in each region, the efficiency E_r of the region r is then calculated as

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

[2] See Fritsch and Slavtchev (2009a) for an alternative approach.

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% of this benchmark value.[3]

5 Data and measurement issues

In this study, we use the number of disclosed corporate patent applications as an indicator of the innovative output of regions. The patent applications are assigned to the main residence of inventors. Information on the yearly number of disclosed patent applications is available for the 1995–2000 period from Greif and Schmiedl (2002). A patent application indicates that an invention has been made which is expected to have some economic value. However, using patents as an indicator of new knowledge has some shortcomings (Brouwer and Kleinknecht 1996; Acs et al. 2002; Griliches 1990). On the one hand, patents may underestimate the output of R&D activity for several reasons. One of these reasons is that the results of basic research cannot be patented in Germany. Moreover, firms may not file all of their inventions for patenting or, in some cases, do not patent at all (Cohen et al. 2000). In this context, it is well known that firms tend to patent product innovations rather than process innovations. On the other hand, the actual R&D output may also be overestimated on the basis of patent data in the event that the firms file blocking patents, which are typically applied around one core invention in a fairly new technological field and where there may be many potential applications which are not yet known. Although patents as an indicator of innovation have such shortcomings, we follow previous studies by assuming that patents are the best indicator of innovative output that is currently available.

Studies that analyze the innovation output of private firms at a regional level typically consider, in addition to corporate R&D inputs, also a number of variables for determinants external to the firm such as university research, policy measures and regional characteristics (Fritsch and Slavtchev 2007, 2009b for details). The typically applied equation (cf. Eq. 2) does not actually indicate how firms internally innovate but rather implicitly assumes that such variables have direct impact on corporate innovation output. In our study we consider the number of private sector R&D employees as the main knowledge input. We thereby assume that other factors such as public research, interregional spillovers, etc. which might be important for the innovative activities of local firms do not impact regional innovative output directly but rather operate through the local private sector R&D employees. Information on the number of R&D employment in the private sector stems from the German Social Insurance Statistics (Statistik der sozialversicherungspflichtig Beschaeftigten) as described and documented by Fritsch and Brixy (2004). Employees are classified as working

[3] However, as we consider that differences in the innovative performance of regions are only due to regional differences in the output elasticity of R&D input, our measure of efficiency slightly differs from Farell's original concept (see for discussion Kalirajan and Shand 1999).

in R&D if they have a tertiary degree and are employed as engineers or as natural scientists.[4]

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 (Griliches 1979). Secondly, patent applications are disclosed only about 12–18 months after submission (Greif and Schmiedl 2002). This is the time necessary for the patent office to verify whether an application fulfills the basic preconditions for being granted a patent. The patent application has to be disclosed 18 months after submission (Hinze and Schmoch 2004). Hence, at least 2–3 years should be an appropriate time lag between input and output of the R&D process.[5] However, since reliable data on R&D employment in East Germany are only available for the years 1996 onwards, a time lag of 2 or 3 years would result in too few observations per region for estimating a region-specific efficiency. In order to have more observations available, we reduce the time lag between R&D input and the patent application to a period of 1 year.[6] In other words, R&D output in the period from 1997 to 2000 is related to R&D input between 1996 and 1999.

The spatial pattern used for the analysis is given by the 97 German planning regions.[7] The spatial concept of planning regions considers 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 study is based on observations for 93 regions over 4 years.

To estimate the efficiency of regions, we include a binary dummy variable for each region, D_r, which is multiplied with the respective number of private sector R&D employees. As this dummy variable assumes the value one for the respective region and otherwise has the value zero, the estimation of the region specific efficiency measure, β_r, can be done by using only one equation. The constant term, A_r, is assumed

[4] Private sector employees with tertiary degree working as engineers or as natural scientists are only a proxy for the actual R&D employees. However, this measure is highly correlated with the actual R&D employees of private sector firms (about 0.95). Unfortunately, the actual number of private sector R&D employees is not publicly available for the period of investigation in this study.

[5] Fritsch and Slavtchev (2006, 2007) relate patenting activities in West Germany to R&D activities 3 years ago. Acs et al. (2002) report that US innovation records in 1982 resulted from inventions that had been made 4.3 years earlier. Fischer and Varga (2003) use a 2-year lag between R&D efforts and patent counts in Austria in 1993. Ronde and Hussler (2005) link the innovative output, the number of patents between 1997 and 2000, to R&D efforts in 1997.

[6] Bode (2004) also uses a time lag of 1 year when relating patent output to R&D employment across German planning regions.

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

to be the same for all regions ($A_r = A$). Hence, after taking logarithms of both sides, the Eq. 2 can be rewritten as

$$\ln\left(\text{Number of patents}_r\right) = \ln A + \sum_r \beta_r \times D_r \times \ln\left(\text{R\&D priv}_r\right) + \varepsilon_r, \qquad (4)$$

where β_r is a measure of the output elasticity of private sector R&D employment in the rth region ($r = 1, \ldots, 93$). The output elasticity of R&D in the region, β_r, is estimated by means of robust negative-binomial regression technique.[8] The data have been pooled. The efficiency measure, E_r, is then computed according to Eq. 3. The results are reported in Table 4 in the Appendix.

6 The distribution of efficiency across German regions

There is a wide dispersion of RIS efficiency among the planning regions. The values for efficiency are within the range between 53 and 100%, meaning that productivity of private R&D input in the best practice region is about twice the productivity in the least efficient region (Fig. 1).

Generally, the efficiency values tend to be higher in regions with large, densely populated agglomerations such as Munich, Stuttgart, Cologne, Frankfurt, and Hamburg. The lowest efficiency estimates are found for regions in the northeast such as “Mecklenburgische Seenplatte”, “Vorpommern”, and “Altmark” located in East Germany, the former German Democratic Republic. The Berlin region, showing a relatively high efficiency, is an exception in the East German innovation landscape. The relatively low efficiency values in East Germany indicate that the innovation processes in this part of the country tend to be rather inefficient. Most of the relatively efficient regions are located in the southern and in the western part of the country. This suggests that the German innovation system is spatially divided into different regimes.

7 Industry specialization and the efficiency of RIS

To estimate the relative impact of different determinants of the efficiency of RIS, a robust OLS cross-section regression technique can be applied. A critical assumption of such an empirical approach is that whatever the sources of efficiency are, they operate identically in all regions whether they are highly efficient or not. However, the relative importance of the possible determinants of RIS’s efficiency may differ for regions at different efficiency levels. We, therefore, apply simultaneous quantile regressions for analyzing this question. Differences in the effects between regions imply that the respective policy recommendations may only hold for certain types of regions.

[8] See Greene (2003), pp 931–939. We find at least one patent per year for each region in our data; thus, the problem of having “too many zero values” does not apply. In the presence of over dispersion, i.e., the pronounced skewness to the left of the distribution of patent records, the negative binomial estimation technique is strongly favored over Poisson regression technique.

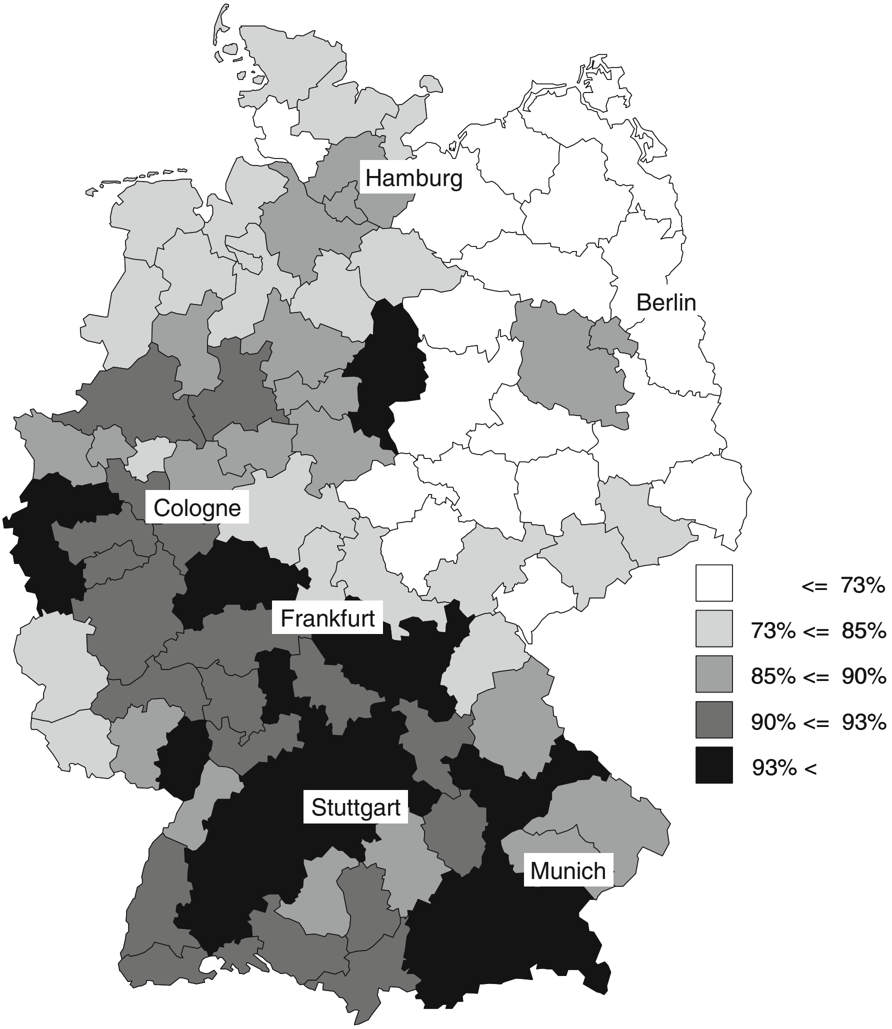

Fig. 1 The distribution of efficiency in German planning regions

Quantile regression was originally discussed in Koenker and Bassett (1982) and Rogers (1993) as a robust regression technique alternative to OLS. This technique differs from OLS in the estimation of the coefficients of the equation as it minimizes the sum of absolute error values rather than the sum of squared errors. More important for the problem here is that the coefficients can be estimated for a particular point q in the distribution of the dependent variable:

$$Q_q(y) = \alpha_q + \beta_{q,1}x_1 + \cdots + \beta_{q,n}x_n. \tag{5}$$

Thus, assertions for different stages on the efficiency scale can be made. Although the estimated coefficients refer to a particular point in the distribution, all observations are used in calculating the coefficients for that particular quantile. For example, concerning median regression all residuals become equally weighted; while when fitting the qth quantile, negative residuals are weighted by $2(1-q)$ and positive residuals by $2q$. Here we apply a simultaneous quantile regression technique. The difference to a standard quantile regression is that the equations are estimated simultaneously and an estimate of the entire variance–covariance matrix is obtained by bootstrapping (Gould 1992). A main advantage of this method is that the estimated coefficients can be easily compared across equations (quantiles).

Although the main focus of this study is on the relationship between industry specialization in a region and productivity of R&D employment, a number of further important determinants of efficiency as well as a number of control variables are included. Table 1 gives an overview on the definition of variables and respective data sources. Descriptive statistics are presented in Table 2 while Table 3 shows the regression results. Correlation coefficients for the relationship between the variables are given in Table 5 in the Appendix.

A significantly positive impact on efficiency of RIS can be found for the share of private sector R&D employment. The estimated coefficient provides evidence for scale economies. This means that an increase in the share of private sector R&D

Table 1 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&DPRIV	Number of private sector R&D employees in the region, 1996–1999	Number of employees with tertiary degree working as engineers or natural scientists in the region	German Social Insurance Statistics
Efficiency	Efficiency of RIS, 1997–2000 average	See Eq. 3	See Eq. 3
R&DPRIV (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
TPFIND per professor	Universities third-party funds from private companies per professor in the region, 1996–1999 average	Volume of third-party 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
Ø 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
POPden	Population density in the region, 1996–1999 average	Number of inhabitants per km^2	Federal Office for Building and Regional Planning

Table 1 continued

Variable	Description	Definition	Source
SERVICES	Share of regional employment in services, 1996–1999 average	Number of regional employees in services/overall regional employment	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
DIV	Regional index of industrial diversity, 1996–1999 average	Inverse of the Donaldson-Weymark relative S-Gini coefficient on basis of employment in 58 industries (industrial classification WZ58)	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 Periphery	Region located at the border of Germany	Regions located at the border of Germany = 1, otherwise dummy = 0	

Table 2 Descriptive statistics

Variable	Observations	Mean	Median	Standard deviation	Minimum	Maximum
Patents[a]	372	395.50	245.75	508.60	11.778	3,652.7
R&DPRIV[a]	372	6,674.0	3,690.0	8,724.1	649.00	48,968
Marginal productivity of R&DPRIV ($\hat{\beta}$)	93	0.6513	0.6768	0.0893	0.4119	0.7779
Efficiency (%)	93	83.717	87.005	11.480	52.941	100.00
R&DRIV (share)	93	0.0223	0.0200	0.0089	0.0089	0.0528
SERVICES	93	0.3208	0.3118	0.0560	0.2203	0.5227
POPden	93	336.99	180.67	507.56	53.425	3,886.29
Ø FSIZE	93	13.204	13.308	1.6957	8.5294	18.2661
TPFIND per professor	93	11.062	7.1950	14.735	0	97.067
DIV	93	1.4979	1.5023	0.0825	1.3076	1.6785
ELECTR_ENG	93	0.0354	0.0292	0.0233	0.0038	0.1227

[a] Pooled yearly values

employment at a certain location may make innovation processes more efficient. Such scale economies could result from increasing opportunities for R&D cooperation and networking that are associated with intensive knowledge flows between actors and,

Table 3 Determinants of efficiency

	Dependent variable: efficiency $\left[\ln\left(100 \times \hat{\beta}/\max\hat{\beta}\right)\right]$ Simultaneous quantile regressions (2,500 bootstrap replications)[a]						
	Q5	Q15	Q20	Q30	Q40	Q50	Q60
R&DPRIV (share) (ln)	0.062 (1.10)	0.084* (1.98)	0.095* (2.25)	0.091* (2.35)	0.107** (2.88)	0.107** (2.85)	0.097* (2.50)
TPFIND per professor (ln)	0.022* (2.00)	0.018* (1.97)	0.015 (1.85)	0.015* (1.97)	0.010 (1.14)	0.012 (1.38)	0.019* (2.16)
Ø FSIZE (ln)	−0.295 (1.52)	−0.349* (2.18)	−0.255 (1.86)	−0.325* (2.27)	−0.302* (2.36)	−0.349** (2.85)	−0.307* (2.54)
POPden (ln)	0.074** (3.03)	0.071** (3.33)	0.050* (2.48)	0.066** (3.28)	0.052* (2.32)	0.056* (2.25)	0.058* (2.24)
SERVICES (share) (ln)	−0.419** (3.69)	−0.339** (3.62)	−0.252** (2.82)	−0.207* (2.49)	−0.209* (2.51)	−0.234** (2.70)	−0.225* (2.45)
ELECTR_ENG (share) (ln)	0.069* (2.40)	0.036 (1.63)	0.036 (1.76)	0.024 (1.19)	0.018 (0.87)	0.020 (0.86)	0.021 (0.80)
DIV (ln)	−0.327 (0.75)	0.154 (0.45)	0.377 (1.46)	0.489* (2.00)	0.579* (2.17)	0.643* (2.23)	0.555* (1.99)
DIV^2 (ln)							
Dummy West (1 = yes)	0.233** (3.59)	0.225** (4.45)	0.215** (4.60)	0.201** (4.97)	0.228** (5.69)	0.212** (4.98)	0.207** (4.45)
Dummy Periphery (1 = yes)	0.018 (0.60)	0.008 (0.32)	−0.009 (0.37)	−0.018 (0.82)	−0.027 (1.17)	−0.042 (1.70)	−0.040 (1.66)
Intercept	4.285** (7.14)	4.510** (8.56)	4.469** (8.91)	4.596** (9.91)	4.657** (11.44)	4.726** (12.52)	4.623** (12.71)
$R^{2\text{pseudo}}/R^{2\text{adj.}}$	0.73	0.70	0.70	0.66	0.62	0.57	0.51
Percentile value	4.087	4.244	4.291	4.371	4.442	4.466	4.503

Table 3 continued

	Dependent variable: efficiency $\left[\ln\left(100 \times \hat{\beta}/\max \hat{\beta}\right)\right]$ Simultaneous quantile regressions (2,500 bootstrap replications) [a]				OLS, robust covariance matrix estimator [b]	
	Q70	Q80	Q85	Q95		
R&DPRIV (share) (ln)	0.108** (2.66)	0.070 (1.52)	0.078 (1.58)	0.016 (0.25)	0.097** (4.17)	0.090** (4.04)
TPFIND per professor (ln)	0.016* (2.04)	0.009 (0.89)	0.007 (0.62)	−0.005 (0.35)	0.019* (2.51)	0.017* (2.07)
Ø FSIZE (ln)	−0.279* (2.28)	−0.270* (2.11)	−0.302* (2.42)	−0.249* (1.96)	−0.316** (3.41)	−0.288** (3.06)
POPden (ln)	0.062* (2.54)	0.060* (2.63)	0.055* (2.51)	0.032 (1.28)	0.064** (4.46)	0.060** (3.69)
SERVICES (share) (ln)	−0.302** (3.26)	−0.235* (2.53)	−0.214* (2.31)	−0.112(0.93)	−0.259** (5.00)	−0.250** (4.80)
ELECTR_ENG (share) (ln)	0.021 (0.80)	0.055* (2.25)	0.053* (2.33)	0.033 (1.41)	0.035* (2.41)	0.035* (2.39)
DIV (ln)	0.333 (1.39)	−0.064 (0.18)	0.009 (0.02)	−0.462 (1.00)	0.375* (2.17)	2.763* (2.35)
DIV^2 (ln)						−2.967* (2.03)
Dummy West (1 = yes)	0.186** (3.99)	0.172** (4.12)	0.172** (4.35)	0.166** (4.42)	0.197** (7.35)	0.191** (7.08)
Dummy Periphery (1 = yes)	−0.025 (1.11)	−0.021 (1.03)	−0.035 (1.65)	−0.002 (0.09)	−0.022 (1.57)	−0.020 (1.39)
Intercept	4.614** (12.29)	4.685** (11.06)	4.846** (11.29)	4.953** (12.59)	4.624** (16.33)	4.093** (9.81)
$R^{2\text{pseudo}}/R^{2\text{adj.}}$	0.47	0.42	0.41	0.42	0.81	0.82
Percentile value	4.521	4.533	4.540	4.579		

Number of observations: 93
* Statistically significant at the 5% level, ** statistically significant at the 1% level
[a] Bootstrap t-statistics in parentheses
[b] Robust t-statistics in parentheses

therefore, may lead to a relatively high level of productivity. However, as indicated by the quantile regressions, this pertains mainly to regions with a medium level of efficiency since regions at both ends of distribution do not seem to benefit from such positive externalities.

The average amount of third-party funds from private sector firms per university professor (TPFIND) has a positive impact on the RIS efficiency. Universities' third-party funds in general can be regarded as an indicator of the quality of their 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 as compensation for academic R&D or for other services that universities perform for private companies. Hence, these revenues are well suited to indicate the relevance of academic research for commercial applications as well as the intensity of formal university–industry linkages (Fritsch and Slavtchev 2007, 2009b). 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. Overall, the results for TPFIND suggest that the intensity of knowledge flows from universities due to formal university–industry linkages (e.g., R&D contracts) is conducive to the efficiency of local corporate innovation activity. According to the quantile regressions, such a positive impact of university–industry relations on the efficiency of RIS is found for regions at the lower end and at the upper mid-range of the efficiency distribution. The impact of the intensity of university–industry interactions is less pronounced and becomes insignificant for regions with efficiency values belonging to the upper end of the distribution.

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. Considering the quantile regression approach, we find that the efficiency increases with industrial variety only for regions with relatively low efficiency up to the median value. According to Table 3, the estimated coefficients for industrial diversity are not statistically significant for relatively less efficient regions as well as for regions at the upper end of the distribution. This pattern suggests that the impact of the industrial diversity differs for regions at different efficiency levels (Fig. 2).

The OLS approach also provides evidence for nonlinear relationship between the degree of industrial diversity and the innovative performance of a region when introducing the inverse of the Gini coefficient and its squared value.[9] The positive sign for the industrial diversity index 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 (Jacobs' externalities). However, the negative sign for the

[9] No relationship of third or higher polynomial order can be found between the degree of industrial diversity and efficiency. Furthermore, there is no significant relationship of second or higher polynomial order between any other explanatory variables and the efficiency.

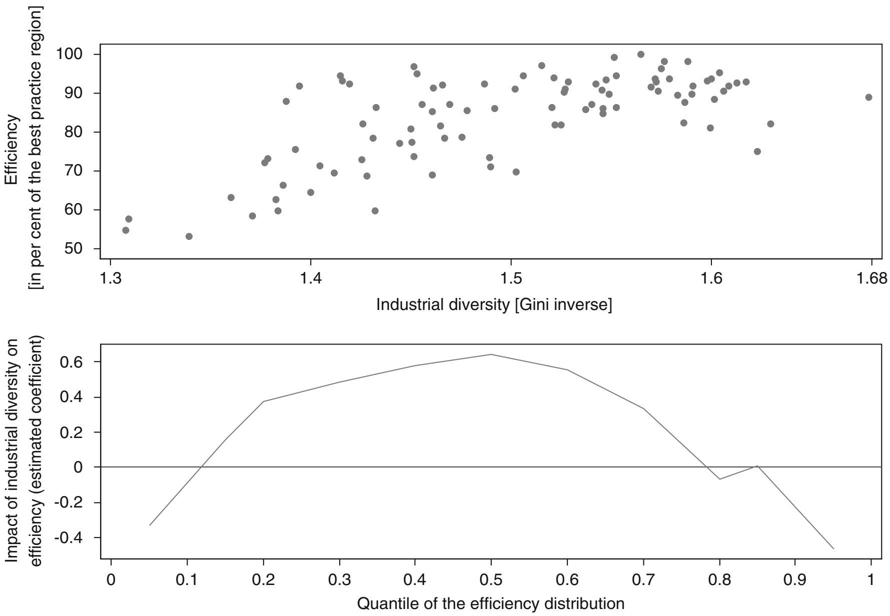

Fig. 2 Industrial variety and efficiency at the level of the German planning regions

squared value of the diversity index indicates a nonlinear relationship with the efficiency that has the shape of an inverse "U" that is truncated close behind the maximum value. Indeed, the same pattern can be directly observed in the data (Fig. 2).[10] 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 of the extremes, broad diversity as well as narrow specialization, may be unfavorable for the performance of a region. Even after introducing a number of additional variables in order to control for further effects, the estimated pattern for industrial diversity remains remarkably stable.

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

Because the specialization of a region in a certain industry with a relatively high level of patenting may significantly influence its innovative output and, therefore, the efficiency, a control for such industry-specific effects appears appropriate. Therefore, we account for the share of employees in the transportation engineering, electrical engineering, measurement engineering and optics, and chemistry, biochemistry inclusively. These are, according to Greif and Schmiedl (2002), the technological fields

10 High values of the Gini coefficient indicate high levels of industry diversification. Such an inverse "U"-shaped relationship between industrial diversity and efficiency may cause the insignificant coefficient estimated by means of quantile regression approach at the upper end of the distribution.

in which most of the patent applications in Germany are generated.[11] However, only regional specialization in electrical engineering appears to have a significant effect on RIS efficiency. The OLS approach as well as the quantile regressions suggest that there is a concentration of electrical engineering industry in high efficiency regions. The estimates for transportation engineering, measurement engineering, and optics as well as for chemistry are not statistically significant and, therefore, are not reported here.

Since firms in different industries tend to differ with respect to their minimum efficient size, we include the average firm size in the region in order to control for further industry-specific effects that are yet not captured. As indicated by the significantly negative coefficient for average firm size, efficiency of innovation activity tends to be lower in regions that are dominated by large scale industries. This confirms other studies which suggest that the number of patents per unit of R&D input is higher in smaller firms than in larger ones (Acs and Audretsch 1990; Cohen and Klepper 1996).

Another common assumption in the innovation literature is that services, particularly knowledge intensive business services (KIBS), may produce and diffuse knowledge that is crucial for innovation processes (Muller and Zenker 2001; Anselin et al. 2000). In order to test the impact of the service supply in a region on the efficiency, we include the size of that sector (in terms of employment) into the model. However, our results indicate that the share of the service sector always has a negative impact on the efficiency of regions. This suggests that despite their supporting function, resources allocated to the service sector are less productive in terms of patenting (Bode 2004). This corresponds to the relatively low share of patents in services.

The positive coefficient for population density indicates the presence of urbanization economies. This means that densely populated regions provide a variety of opportunities for interaction in addition to often abundant supplies of input as well as a rich physical and institutional infrastructure, which may be advantageous for economic and innovation activity (Ciccone and Hall 1996; Crescenzi et al. 2007; Carlino et al. 2007).

The results of the analysis provide robust evidence that regions located in the western part of Germany are more efficient than regions located in the eastern part of the country. This suggests the presence of further region-specific factors (e.g., organization of the R&D process, institutions, etc.) which also influence the efficiency of the R&D processes. The statistically insignificant coefficient for the dummy variable for location at the periphery indicates that such regions do not tend to be relatively inefficient in comparison to the non-peripheral areas.

8 Conclusions

This study investigates the effect of a region's specialization in certain industries on its efficiency in producing knowledge. Our answer to the question "Is regional special-

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

ization in a certain industry conducive to the innovative performance of regions?" is "Yes, but only to a certain degree". In fact, the analysis suggests that the relationship between specialization and the performance of a region has the form of an inverse "U". This means that the more a region specializes, the lesser contributes any further specialization to its efficiency.

The results of the quantile regressions indicate that the impact of different factors that determine the efficiency of RIS may not be identical at all levels of efficiency. In our analysis this pertained particularly to industrial diversity, to the amount of private sector R&D, and to the intensity of university–industry knowledge transfer (as indicated by universities third-party funds from private sector firms). These results imply that there are no one-size-fits-all policy recommendations for stimulating the innovative performance in all kinds of regions. Clearly, policy should be well aware of regional idiosyncrasies and should properly account for region-specific factors.

The results of this study 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 interactions seem to be conducive to the regional innovative performance. Second, additional research is required in order to answer the question about what the forces are that determine the industrial structure of regions. Moreover, regarding the role of industrial diversity for innovation, more information about the ways in which knowledge spills over between industries should be helpful in order to derive reasonable policy implications.

Appendix

Table 4 The distribution of efficiency in the German planning regions

Planning region		Estimated production elasticities		Efficiency (%)	Rank
Code	Name	$\hat{\beta}_r$	Robust std.error	$\frac{\hat{\beta}_r}{\max \hat{\beta}_r} \times 100$	
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 and 6	Schleswig-Holstein South and 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 and 15	Bremen and Bremerhaven and Bremen-Umland	0.6123	0.2170	78.71	66
12	East Frisian	0.5866	0.2777	75.41	71

Table 4 continued

Planning region		Estimated production elasticities		Efficiency (%)	Rank
Code	Name	$\hat{\beta}_r$	Robust std. error	$\frac{\hat{\beta}_r}{\max \hat{\beta}_r} \times 100$	
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 and 30	Havelland-Flaeming and 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	Duesseldorf	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

Table 4 continued

Planning region		Estimated production elasticities		Efficiency (%)	Rank
Code	Name	$\hat{\beta}_r$	Robust std. error	$\frac{\hat{\beta}_r}{\max \hat{\beta}_r} \times 100$	
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

Table 4 continued

Planning region		Estimated production elasticities		Efficiency (%)	Rank
Code	Name	$\hat{\beta}_r$	Robust std. error	$\frac{\hat{\beta}_r}{\max \hat{\beta}_r} \times 100$	
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. Estimated INTERCEPT = −0.0225, robust standard error = 2.0049. Log pseudolikelihood = −1,749.86

Table 5 Correlation of variables

	Variable	1	3	4	5	6	7	8	9
1	Patents[a]								
2	R&DPRIV[a]	0.92							
3	Efficiency		1.00						
4	R&DPRIV (share)		0.22	1.00					
5	SERVICES		0.08	0.44	1.00				
6	POPden		0.17	0.38	0.47	1.00			
7	Ø FSIZE		0.08	0.58	0.19	0.46	1.00		
8	TPFIND 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	ELECTR_ENG		0.55	0.26	−0.11	0.02	0.18	0.21	0.44

[a] Pooled yearly values

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