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MEASURING THE QUALITY OF REGIONAL INNOVATION SYSTEMS: A KNOWLEDGE PRODUCTION FUNCTION APPROACH

MICHAEL FRITSCH
Technical University Bergakademie Freiberg, Faculty of Economics and Business Administration, Freiberg, Germany, fritschm@vwl.tu-freiberg.de

This article deals with applying the knowledge production function approach to the measuring and the comparison of the quality of regional innovation systems. It is argued that an embeddedness in a well-functioning innovation system should result in a relatively high propensity to innovate and a high productivity of efforts in research and development (R&D). Based on data for eleven European regions, the author has found a number of such statistically significant differences between the manufacturing firms in these regions. Interregional differences in the productivity of R&D activities correspond to some degree with a center-periphery paradigm, which can be found in the literature. Obviously, there exist considerable agglomeration economies that are conducive to R&D activities.

LOCATION AND RESEARCH AND DEVELOPMENT ACTIVITIES

The notion of a regional innovation system is based on the assumption that location and spatial proximity matter for innovation activities (Cooke, Uranga, and Etxebarria 1997; Cooke 1998). There have been a number of approaches to investigate the impact of regional conditions on the innovation of research and development (R&D) activities of private firms empirically. However, most attempts that tried to find significant regional difference with regard to innovation activities have more or less failed.[1] There are several possible reasons that may be responsible for such a result. One main obstacle for an empirical investigation into regional differences of R&D activities could be the lack of appropriate data. Another shortcoming is unclear methodology with regard to the assessment of effects of location. In many cases, multivariate models for the impact of a number of factors on innovation activities are specified more or less ad hoc, with regional dummies included as a measure of regional effects. The test statistics for these regional dummy variables then stand for the significance of a locational effect.

In this contribution, an approach to measure the quality of a regional innovation system on the basis of knowledge production functions will be discussed. By applying this approach to data for eleven European regions, it will be shown that statistically significant differences in the quality of regional innovation systems exist that have an impact on the efficiency of R&D activities. In the next section, the basic hypothesis concerning the impact of the regional innovation system on R&D is presented in some detail. The third section then deals with the measurement of the quality of a regional innovation system by a knowledge production function. It follows a brief description of the database of the empirical analysis (fourth section). Estimation results are presented in the fifth section and, finally, some conclusions are drawn (final section).

DIFFERENCES IN THE WORKABILITY OF REGIONAL INNOVATION SYSTEMS

In recent years, the system of innovation approach has been increasingly applied to the analysis of innovation activities in both a national and a regional context (Cooke 1998; Lundvall 1992; Edquist 1997). The system of innovation approach emphasizes the importance of labor division for innovation processes and tries to account for the contributions of the different actors or institutions to innovation output. Regional systems of innovation may constitute an adequate approach for the analysis of innovation activities if spatial proximity matters, and the effect of certain influences is limited to a particular region. The main groups of actors in a region that may have an impact on the innovation activities of a firm are other private firms, public research institutions, supportive services, and the regional workforce. A key hypothesis in the systems of innovation literature states that it is not the mere presence of such actors or institutions—the elements of the innovation system— that has an effect on the division of innovative labor in a region. Rather, it is the interaction, the density, and the quality of the network between these elements that is decisive for the impact of location in a certain region on innovation activity.

Relationships with other actors may affect R&D activities of a certain firm or research institution in a number of ways. One form of such influences is knowledge spillovers, that is, the flow of relevant knowledge from other actors that may be associated with all kinds of interaction. One important medium for such spillovers of knowledge may be the labor market, particularly the inflow of workers from education institutions (e.g., universities) into private firms and the fluctuation of employees between different employers. Other possible media for knowledge spillovers are cooperative relationships, publications, and purchased goods and services. A further important effect of relationships with other actors that may be conducive to R&D can be a high level of outsourcing and division of innovative labor. Such a relatively high degree of labor division constitutes an important attribute of many so-called industrial districts, a certain kind of regional innovation system that has been extensively dealt with in the literature.[2] Division of innovative labor may allow those firms that are members of the network to benefit from the advantages of market allocation as compared to the internal provision of the different elements of an R&D process within a hierarchy.[3] Therefore, one can expect relatively high productivity of R&D activities if they are characterized by a high degree of interaction and specialization.

Because in most cases contracts on R&D activities cannot be completely specified, the respective relationships represent more than just impersonal "spot-market" interaction and may necessitate face-to-face contacts from time to time (see Nohria and Eccles 1992). Spatial proximity may, therefore, be very conducive to such forms of interaction. Intensive contacts between the actors involved in a division of innovative labor may stimulate a high level of knowledge spillovers between these actors. Because outsourcing certain tasks of the innovation process necessitates the availability of suppliers that are able to fulfill these tasks, a rich supply of complementary firms and research institutions in the region may be rather conducive to R&D. Another element of a location that may be highly relevant for innovation activities is a diversified labor market that provides appropriate qualifications. For these reasons, a basic hypothesis in the respective literature suggests that the level, as well as the success or efficiency, of R&D activity is higher in the center than in more remote areas or in regions characterized by a relatively low degree of agglomeration, the periphery (for a brief overview, see Fritsch 2000).[4]

All of these influences can stimulate innovation activities in two ways. One effect may be that the availability of inputs makes certain innovation projects possible that would otherwise not be started or accomplished. Therefore, a well-working innovation system should be characterized by a relatively high share of innovating firms and a relatively high level of R&D output in these firms. A second possible effect of a local environment is that it stimulates a high degree of labor division in the field of innovation activities resulting in a relatively high efficiency or productivity of innovation processes.

The Knowledge Production Function

The concept of a knowledge production function has been introduced by Griliches (1979) for measuring the contribution of R&D and knowledge spillovers to productivity growth. The basic assumption states that the output of the innovation process represents a result of R&D capital or investment, that is,

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

Taking the Cobb-Douglas production function as a framework, the basic relationship is

$$\text{R\&D output} = a\ \text{R\&D input}^{b}, \tag{2}$$

with the term a representing a constant factor and b giving the elasticity by which R&D output varies in relation to the input to the R&D process. If the elasticity value equals 1, a 100 percent increase in R&D expenditure would lead to a doubling of innovative output. An elasticity value lower than 1 indicates that innovative output does not rise in proportion to R&D input. Taking the natural logarithms of both sides leads to

$$\ln \text{R\&D output} = \ln a + b \ln \text{R\&D input}. \tag{3}$$

This equation can be estimated by standard regression methods.

The slope of the knowledge production function represents the output elasticity of R&D input. This elasticity may be interpreted as a measure of the productivity of the inputs to the innovation process, indicating the efficiency of R&D activities and thereby the quality of the innovation system in a region. In particular, this elasticity should increase as the quality of inputs to the R&D process is improving and as the spillovers stemming from the R&D activities of other actors in the region (whether they are public research institutions or private sector firms) become more pronounced. Differences in output elasticities between regions indicate the effects of locational conditions not explicitly accounted for in the empirical model on the efficiency of R&D processes. For example, if variables for regional spillover pools or for cooperation with other firms or institutions are included in the model, the output elasticity measures those influences that are not explained by these variables (see Fritsch and Franke 2000 for examples). Thus, differences of output elasticities between regions signify diverging locational conditions for R&D, but they tell us nothing about the causes of these effects. All we know in this respect is that the differences do not result from the variables in the empirical model. However, one can investigate the causes for interregional differences by including respective variables. Note that the output elasticity is dimensionless and cannot, therefore, be affected by a difference of price levels between the regions or by the exchange rates in case of an international comparison.

The constant term of the knowledge production function has the same dimension as the indicator of R&D output. If the success of R&D activities is measured in real terms (e.g., number of patents, number of new products), the estimates for the constant are also unaffected by the exchange rates or the differences in price levels so that a comparison between regions can neglect such factors. The interpretation of the constant term, however, is somewhat delicate. If the number of innovations is used as an indicator for the success of R&D activities, the constant term denotes how many innovations have been generated without a corresponding R&D input during the period in which R&D input was measured. Assuming that the generation of an innovation necessitates some R&D input, there are two possible explanations for the existence of a positive constant term. One explanation could be that the respective innovation was completely the result of knowledge spillovers from other sources, without any R&D effort on the part of the firm that is supposed to have generated it. In this case, the constant term of the knowledge production function represents those innovations that are "falling from heaven" on a certain firm. A second possible explanation has to do with the measurement of the input to the innovation process. The key input factor to this process, knowledge, is cumulative in character, so that innovation is based on a stock of knowledge capital. In practice, we can measure this knowledge stock only incompletely. The best that we might know is the R&D effort, that is, the investment into the knowledge stock within a certain time period. In many data sets available for an empirical analysis of innovation activities, we cannot be entirely sure if R&D investment is properly defined and relates to that part of the knowledge stock that was relevant for the innovation output measured. Moreover, information on an R&D investment that was made long ago is hardly available. Therefore, a positive constant term of the knowledge production function may be an indication that the innovation was not based on current R&D investment but on the existing stock of "old" knowledge, which could not be measured. In this case, the constant term of the knowledge production function represents a misspecification of the input variable.

As long as the data underlying an interregional comparison of knowledge production functions are comparable and have about the same bias, the differences of the absolute term of the knowledge production function may be seen as an indication of how much the innovation output is based on an older stock of knowledge. Therefore, if innovation activities are path dependent, a relatively low value of the constant term can be expected if the respective technological paradigm is relatively young.[5] This is to the extent that not much old knowledge exists that is relevant for innovation activities along the new path or if the technological path has been changed recently. The latter example is the case for the postsocialist countries of Eastern Europe, in the course of their transformation to a market economy (see Fritsch and Werker 1999 for a detailed exposition). These factors may also explain differences of the constant term between knowledge production functions for certain industries.

Database and Indicators

The empirical analyses reported here are based on data gathered by sending questionnaires to manufacturing enterprises in eleven European regions. This inquiry was carried out in two phases between 1995 and 1998 and resulted in approximately 4,300 usable questionnaires, which constitute the data set. The questions concentrated on innovation-related issues but also raised some general information on each enterprise such as the number of employees, the amount of turnover, characteristics of the product program, and so forth (for a more detailed description of the data set, see Sternberg 2000).

Four of the eleven regions (see Figure 1) in which the inquiry was carried out are dominated by large cities of international importance. These regions are Barcelona, Rotterdam, Stockholm, and Vienna, with the two latter cities serving as national capitals. Two of the regions in our sample, Saxony and Slovenia, have been under socialist regime until 1990-91 and are faced with the need to more or less completely reorganize their innovation system. Baden, one of the two West German regions in the sample, is said to have a relatively well-functioning innovation system (Cooke 1996; Heidenreich and Krauss 1998). In Hanover, the other West German region, there is a relatively high share of large-scale industries (e.g., automobiles, steel), while the proportion of employment in new innovative industries is comparatively low. The French border region of Alsace, which is adjacent to the Baden region in Germany, represents a relatively rural area. The second French region, Gironde, has a significant share of employment in high-tech industries that are well-integrated into the global division of labor. Finally, South Wales represents an old industrialized region that has experienced a considerable employment shift from old declining industries to new high-tech industries in recent years (cf. Cooke 1998). Due to the great variety with regard to economic development and locational conditions of the regions in our sample, we may expect that if location matters for R&D, we should find corresponding differences in the data.[6] Applying a center-periphery paradigm (cf. Differences in the Workability of Regional Innovation Systems section) to this set of regions, Barcelona, Rotterdam, Stockholm, and Vienna can be classified as centers, while Alsace, Gironde, Saxony, Slovenia, and South Wales may represent the periphery.

Our data set provides two indicators for the output volume of R&D activities: the number of new products introduced in the three preceding years and the number of inventions registered for patenting during the same time period. However, attempts to estimate models with the number of new products as a dependent variable have led to rather poor results for most of the regions. In many cases, not only was the share of explained variance rather low, but also the whole model proved not to be statistically significant at the .05 level. Apparently, the number of new products is not a good measure for the volume of R&D output. The analysis has, therefore, been limited to the number of inventions registered for patenting, which serves as the indicator for the output of R&D activities. R&D expenditures in the preceding three years[7] and the number of R&D personnel at the beginning of this three-year period have been used as alternative measures of R&D input. Because R&D expenditure includes inputs to the R&D process that are purchased from other firms, it represents a more comprehensive measure than the number of R&D personnel.

To avoid the problem of having too many zero values in the model,[8] the estimations were restricted to those enterprises that had registered at least one invention for patenting during the preceding three years. A patent is only granted for a significant invention that is new on a worldwide scale. For this reason, counting only firms that have patent applications in the sample implies that the estimations are based solely on information from enterprises that are performing near the technological frontier. This approach has the great advantage that the output of the innovation process is somewhat standardized and that innovation processes of about the same

FIGURE 1. The Spatial Framework Analysis

level of novelty are compared. Six dummies control for the influence of the different industry sectors the firms belong to. Therefore, interregional differences of output elasticities found in the analysis should not be a result of diverging industry structures.

Estimation Results

Interregional differences of knowledge production functions have been investigated in two ways. In a first approach, the model was estimated for each of the regions separately. Comparing the estimated coefficients allows for the identification of differences with regard to innovation activities between the regions. In a second approach, all regions were included in one model, with dummy variables testing for regional deviations. A main difference between these two approaches concerns the industry dummies that are included to control for sector effects. When running the model for each of the regions separately, the industry dummies represent the influence of affiliation to a particular industry on innovation activities in a certain region. These industry effects may deviate between the regions. However, if all regions are included in one model, it is implicitly assumed that the industry effects are identical in all of the regions. In such an approach, the results for regional dummy variables may be influenced by diverging effects of affiliation to a certain industry in the regions under inspection. This could provide an explanation for differences in the assessment of the regional impact on innovation activities attained by the two approaches applied. A main practical advantage of an empirical model that includes information for more than one region over estimating models for the individual regions is that fewer cases are needed to attain a statistically significant estimate for the regional impact. The reason is that in a model for more than one region, the observations of a certain region are less needed for estimating the industry effects compared to assessing these impacts for each region separately. This is due to the fact that in a multiregion approach, the coefficients for industry dummies can be estimated using the information from the other regions. Therefore, this type of test is statistically more efficient than estimating a separate model for each region.

Table 1 depicts the constant terms and the coefficients for the output elasticity of R&D input in the different regions, which was calculated by running the model for each region separately. Because the dependent variable of the model, the number of patents, has the character of a count variable, negative-binomial regression has been applied as the estimation procedure. Using this method implies the hypothesis that the number of patents is generated by a Poisson-like process. Compared to a Poisson regression, negative binomial regression is based on somewhat more general assumptions and allows for a greater variance than is assumed for a true Poisson process (Green 1997, 931-39). As an example of the output of the complete model, the coefficients for the region of Saxony are given in the table in the appendix. Baden serves as the reference region for testing for significance of differences of the estimated elasticities, as well as of the constants of the regressions. Unfortunately, no statistically significant estimates of a region-specific knowledge production function could be found for Gironde or Slovenia, presumably due to the relatively small number of observations that our sample provides for these regions.[9]

Looking first at the elasticities based on R&D expenditure, the values range between 0.35 and 0.62, indicating that a certain increase in R&D input leads to a less than proportionate rise in R&D output. The lowest value of the output elasticity with regard to R&D expenditure is found in South Wales. In contrast, three of the four regions in our sample dominated by large cities (Barcelona, Stockholm, and Vienna) have relatively high estimated values of the elasticities. That the estimate for Baden is in the upper range of values confirms assessments found in the literature that characterize the innovation system in this region as relatively well

TABLE 1. Estimates of the Constant Term and of Output Elasticity of Research and Development (R&D) Input in the Different Regions

	Number of Patents with Regard to R&D Expenditure				*Number of Patents with Regard to R&D Employment*			
	Constant	t-*value*	*Elasticity*	t-*value*	*Constant*	t-*value*	*Elasticity*	t-*value*
Barcelona	1.14*/-	(2.11)	0.62**/-	(8.35)	0.92*/-	(2.22)	0.58**/-	(6.27)
Rotterdam	1.45**/-	(6.44)	0.43**/-	(4.92)	0.46-/-	(1.86)	0.53**/*	(5.38)
Stockholm	1.82**/-	(11.06)	0.52**/-	(9.98)	0.51*/-	(2.41)	0.61**/-	(10.42)
Vienna	2.01**/-	(6.51)	0.59**/-	(5.19)	0.65-/-	(1.55)	0.57**/-	(3.62)
Alsace	1.02**/**	(4.41)	0.41**/-	(6.19)	0.57*/-	(2.17)	0.39**/*	(6.01)
Baden	1.75**/-	(11.45)	0.49**/-	(7.68)	0.66**/-	(3.21)	0.49**	(8.96)
Gironde	ns				ns			
Hanover	1.67**/-	(8.11)	0.43**/-	(8.00)	0.65**/-	(2.84)	0.40**/**	(7.56)
Saxony	1.62**/-	(10.24)	0.42**/-	(7.84)	0.39*/-	(1.99)	0.44**/*	(7.90)
Slovenia	ns				ns			
South Wales	1.80**/-	(5.15)	0.35**/-	(5.15)	0.60-/-	1.90)	0.51**/*	(3.38)

Note: The asterisk(s) before the slash denote(s) if the coefficient is significantly different from zero; the asterisk(s) after the slash indicate(s) if the coefficient is significantly different from the values for Baden (χ^2 test). Asymptotic *t*-values of the coefficient appear in parentheses. ns = no statistically significant estimate of the model could be attained.
**p* = .05. ***p* = .01.

functioning or efficient (see, for example, Heidenreich and Krauss 1998). Apparently, the pattern of estimated coefficients for the output elasticities of R&D input corresponds to some degree with a center-periphery pattern of R&D productivity, indicating relatively favorable locational conditions for innovation activities in the agglomerations. However, none of the calculated elasticities differ from the value for Baden on the .05 level of significance. Yet, if South Wales is taken as a reference, then the elasticities for Barcelona and Vienna prove to be higher at the .05 significance level.

The estimates of output elasticities based on R&D employment as a measure of input fall in about the same range (between 0.39 and 0.61; see Table 1) as the estimates based on R&D expenditure. Compared to the elasticities estimated using R&D expenditures as an indicator for R&D input, some differences in the results can be found (particularly for Rotterdam, Stockholm, and South Wales), but for most of the regions, the estimates attained with the two alternative input measures lie relatively close together. Again, the overall pattern of the estimates for the different regions corresponds to some degree with a center-periphery hypothesis of locational conditions for R&D activity. For the estimates of output elasticities based on R&D employment, there are a number of statistically significant differences when compared to the value for Baden. While the output elasticity for Rotterdam is significantly higher than for Baden, the values for Hanover, Alsace, and Saxony turn out to be significantly lower.

We also find a number of differences between the regions with regard to the constant term of the model (see Table 1). In the estimates based on R&D expenditure as a measure of R&D input, however, these differences may be influenced by the exchange rates that were applied for converting the original values into a common currency. The respective results are, therefore, dubious. Indeed, the regional pattern of the estimates for the constant term based on R&D expenditure differs considerably from the pattern attained when using R&D employment as a measure of the input to the innovation process. In the estimations with R&D employment, we find the by far lowest value of the constant term for Saxony. This indicates a relatively poor ability of firms to exploit a longer existing knowledge stock. This may be explained with the more or less complete reorganization of the innovation system in this former socialist region. Even more important, a considerable part of the knowledge stock generated under socialist regime had to be depreciated in the last years because it proved to be no longer useful in the framework of an open market economy (cf. Fritsch and Werker 1999). Although the highest estimate for the constant term by far is found for the enterprises in Barcelona when using R&D employment as input indicator, there is no clear pattern according to a center-periphery paradigm.[10] This conclusion also holds for the results based on R&D expenditure as a measure for innovative input, where we find the highest estimates of the constant term for Vienna and Stockholm (but also for South Wales and Baden) and a relatively low value for Barcelona.

In the integrated model for all the regions, two types of regional dummy variables were included to test for differences compared to establishments in the region of Baden (Table 2). Dichotomous variables that had the value 1 if the respective firm was located in a certain region and the value 0 if not indicated differences with regard to the constant term of the knowledge production function. The coefficients for an interaction of these dummies with a firm's R&D input (R&D expenditure or R&D employment, respectively) reflect differences of the slopes of the knowledge production function pointing to a diverging output elasticity or productivity of innovation processes. As in the separate estimates for each of the single regions, six sector dummies control for industry-specific effects. On the basis of this approach, which includes all regions into one model, significant estimates for Gironde and Slovenia could also be attained. Looking first at the coefficients for divergent output elasticities of R&D input, the highest value is found for Vienna. While the elasticities for Rotterdam and for Stockholm are not significantly different from the value of Baden (the reference region), the coefficient for Barcelona estimated on the basis of R&D employment as an input measure indicates a significantly lower productivity than in Baden. Relatively low values of the output elasticity of R&D input are also found for Gironde and Slovenia, the two regions for which no significant estimate of a region-specific knowledge production function could be attained. For many of the other regions, the regional dummies for differences of R&D output elasticities have a negative sign, indicating a lower productivity of R&D activities than in Baden. However, these differences are not statistically significant. As could have been expected, the estimates of the interaction dummies based on R&D expenditure differ to some extent from the estimates using R&D employment as indicator for R&D input; yet, these differences are within reasonable limits. The estimates of the regional output elasticities of R&D input generated on the basis of one model, including all regions, differ somehow from the coefficients R&D attained with separate models for the individual regions. However, the regional pattern of the results remains about the same. Locations in a large agglomeration appear to be conducive to R&D activities as compared to less densely populated or more peripheral regions.

Looking at the estimates for the dummies that indicate interregional differences with regard to the constant term of the knowledge production function, the deviation between the coefficients based on the two measures for R&D input is somewhat higher. A relatively large divergence between the two types of estimates is found in the cases of Vienna, Gironde, Alsace, and Slovenia. A main cause for these discrepancies may be respective variation with regard to price levels and exchange rates that influence the estimates using R&D expenditure as a measure of input. Because an interregional comparison of R&D employment is not directly affected by such factors, the estimates of the constant-term dummies based on employment figures may be considered more reliable. Looking at the respective estimate, the significantly lower value of the constant term for Saxony may be seen as a reflection of necessary depreciations of old knowledge capital in the transformation process.

TABLE 2. Results of Negbin-Regressions of a Knowledge Production Function with Regional Dummy Variables

	Number of Patents with Respect to R&D Expenditure		*Number of Patents with Respect to R&D Employment*	
Constant	1.83**	(15.78)	0.79**	(5.14)
R&D expenditure (ln)	0.51**	(7.44)	—	
Number of R&D employees (ln)	—		0.50**	(9.46)
Industry dummies				
Food, beverages, tobacco	0.59	(1.83)	0.51	(1.46)
Textiles, clothing, leather	–0.18	(0.045)	–0.35	(1.01)
Wood, paper, printing, publishing	–0.21	(1.33)	–0.09	(0.60)
Mineral oil, chemicals, rubber, plastics, stone, and so on	0.16	(1.27)	0.37**	(3.12)
Metal products, recycling	0.44**	(3.15)	0.67**	(4.87)
Mechanical engineering, vehicles	0.15	(1.38)	0.17	(1.66)
Regional dummies for absolute term				
Barcelona	0.58**	(3.48)	0.56**	(2.83)
Rotterdam	–0.15	(0.71)	–0.39	(1.41)
Stockholm	–0.34*	(2.31)	–0.66**	(2.92)
Vienna	0.04	(0.23)	–0.57	(1.82)
Alsace	–0.52*	(2.29)	–0.06	(0.20)
Gironde	–0.77*	(2.20)	0.49	(1.42)
Hanover	–0.07	(0.51)	–0.03	(0.14)
Saxony	–0.30*	(2.10)	–0.61**	(2.91)
Slovenia	–0.82**	(3.48)	0.02	(0.06)
South Wales	0.03	(0.12)	–0.13	(0.37)
Regional dummies for R&D elasticity				
Barcelona	–0.10	(1.11)	–0.20*	(2.20)
Rotterdam	–0.07	(0.55)	0.05	(0.36)
Stockholm	0.01	(0.18)	0.14	(1.54)
Vienna	0.20*	(2.10)	0.48**	(4.11)
Alsace	–0.07	(0.50)	–0.12	(0.95)
Gironde	–0.61**	(5.77)	–0.56**	(3.53)
Hanover	–0.12	(1.41)	–0.13	(1.68)
Saxony	–0.07	(0.74)	–0.01	(0.09)
Slovenia	–0.43**	(3.37)	–0.40**	(2.84)
South Wales	–0.14	(1.15)	0.02	(0.10)
α	.73**	(16.71)	.73**	(16.62)
Pseudo R^2	.134		.127	
Probability χ^2	0.00		0.00	
Number of cases	705		707	

Note: Asymptotic *t* values of the coefficient appear in parentheses.
$^*p = .05$. $^{**}p = .01$.

However, plausible explanations for the other significant constant-term dummies appear to be more difficult to find.

CONCLUSION

This contribution has demonstrated the application of the knowledge production function approach for measuring the quality of regional innovation systems. The main idea was that the output elasticity of R&D input, the slope of the knowledge production function, can be interpreted as a measure for the productivity of innovation activities and that this productivity is affected by region-specific conditions. Output elasticity, as a measure for the productivity of R&D effort, has the advantage of being dimensionless. If the analysis is based on monetary figures (e.g., R&D expenditure), the estimates for output elasticity should not, therefore, be influenced by interregional differences in price levels or if regions in different currency areas are included by the underlying exchange rate. The estimates based on data for eleven European regions revealed significant differences with regard to R&D productivity between manufacturing firms in these regions. In accordance with a number of theoretical models and the hypotheses that can be found in the literature, output elasticity of R&D input in manufacturing establishments tended to be relatively high in the center as compared to the periphery. Obviously, there exist considerable agglomeration economies, which are conducive to R&D activities. However, relatively high values of output elasticity of R&D activities with regard to R&D input could also be found for some less urbanized regions, indicating that a certain degree of agglomeration does not constitute a necessary condition for R&D activity to be conducted productively.

A number of statistically significant differences could also be found with regard to the constant term of the knowledge production function. Assuming that an innovation necessitates at least some R&D input, this constant term represents an error in the measurement of the input to R&D activities. If information on R&D input included in the analysis is restricted to a more recent period of time, then the absolute term of the knowledge production function may represent the importance of older knowledge for the output of the innovation process. In this case, relatively high depreciations of knowledge capital caused by a change of the technological path, for example, should lead to a relatively low value of the absolute term of the knowledge production function. This is indeed what could be found for the two regions in the sample that have been under socialist regime until the late 1980s, Saxony and Slovenia. These two regions are now faced with the necessity of adjusting their innovation system to the demands of a market economy.

In total, we may conclude that the knowledge production function is a quite useful approach for comparing the quality of regional innovation systems in providing a simple measure for the productivity of R&D activities. However, innovation processes are quite complex and cannot be comprehensively assessed with a single indicator. Therefore, not only one indicator but a whole number of measures should be applied when comparing innovation activities between regions.[11] Among such a group of measures, output elasticity of R&D input can be relatively interesting.

Because the estimates for this measure are limited to information on innovating firms, indicators for the propensity to innovate might be a good complement.

APPENDIX
NEGATIVE BINOMIAL REGRESSIONS FOR THE NUMBER OF PATENTS IN MANUFACTURING ENTERPRISES LOCATED IN SAXONY

	Number of Patents with Respect to R&D Expenditure		*Number of Patents with Respect to R&D Employment*	
Constant	1.62**	(10.34)	0.39*	(1.99)
R&D effort (ln)	0.42**	(7.84)	—	
Number of R&D employees at the beginning of designated period (ln)	—	—	0.44**	(7.90)
Industry dummies				
Food, beverages, tobacco	–0.58	(1.11)	–0.57	(0.92)
Textiles, clothing, leather	–0.86	(0.74)	–1.03	(1.24)
Wood, paper, printing, publishing	–0.42	(1.04)	–0.44	(1.05)
Mineral oil, chemicals, rubber, plastics, stone, etc.	0.14	(0.63)	0.23	(1.00)
Metal products, recycling	–0.50	(0.20)	0.22	(0.01)
Mechanical engineering, vehicles	0.12	(0.65)	0.22	(1.14)
α	.33**	(5.02)	.32**	(4.73)
Adjusted R^2	.114		.128	
Probability χ^2	0.00		0.00	
Number of cases	135		118	

Note: Asymptotic *t*-values of the coefficient appear in parentheses.
$*p = .05$. $**p = .01$.

NOTES

1. See, for example, Alderman and Fischer (1992); Brower, Budil-Nadvornikova, and Kleinknecht (1999); Kleinknecht and Poot (1992); Davelaar (1991); Davelaar and Nijkamp (1989); Meyer-Krahmer (1985); and Pfirrmann (1994). For a brief review of the evidence, see Fritsch (2000).

2. See, for example, Marshall (1920) and the contributions in Pyke, Becattini, and Sengenberger (1990).

3. For a detailed account of the different advantages that may emerge from an increased division of innovative labor, see Fritsch (2001).

4. In a broad sense, a region in the center may be defined as an easily accessible location characterized by a relatively high density of population and economic activity. It has a relatively high rank in the spatial hierarchy. In contrast, regions in the periphery are lacking these properties. They are characterized by relatively low density, poor accessibility, and rank relatively low in the spatial hierarchy.

5. Accordingly, a relatively low value for the absolute term of the knowledge production function can be expected for those industries that follow a relatively new technological path or paradigm, for which the relevant stock of older knowledge is relatively small. The conditions for innovation processes in such industries are also characterized as an entrepreneurial regime. See Winter (1984) and Audretsch (1995) for details.

6. For an overview of economic conditions and innovation activities in the different regions, see Fritsch (2000).

7. The original responses have been converted into the European Currency Unit, but as already mentioned, this should not affect the comparison of elasticities according to the approach chosen here.

8. A distribution of observations that is characterized by a relatively large number of cases at one end violates basic assumptions underlying most standard estimation procedures.

9. The estimates for Gironde were based on data for thirteen R&D expenditures and eleven R&D employment enterprises, respectively, with at least one patent application during the respective time period. The estimates for Slovenia were based on thirty-one and thirty-five cases, respectively.

10. In the estimations based on R&D employment as a measure of innovative input, none of the constant terms were significantly different from the value for Baden. However, statistically significant differences of constant terms can be found if relatively extreme values are compared, for instance, those found for Saxony and Barcelona.

11. See Fritsch (2000) for a more detailed comparison of innovation activities in the regions under inspection here.

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