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May 2008

Abstract
This paper reviews approaches used for evaluating the performance of local or regional innovation systems. This evaluation is performed by a benchmarking approach in which a frontier production function can be determined, based on a knowledge production function relating innovation inputs and innovation outputs. In analyses on the regional level and especially when acknowledging regional innovation systems those approaches have to take into account cooperative invention and innovation – the core of the innovation system approach. To make these interactive effects visible, a method is suggested to identify the relative regional impact on cooperative innovative activities.

JEL: O3, R11, C2, C6

Keywords: benchmarking, regional innovation systems, frontier function approaches

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1. Introduction

The discussion of innovation systems in general and of local or regional systems in particular focuses on collective invention and collective innovation. The core of the concept is interactive learning, exchange of know-how and cooperative invention and innovation respectively. To put it rather general, in the context of innovation systems interactive learning and cooperation is not discussed on the level of bilateral relationships between actors but in the context of a system of actors. Such systems can nicely be described by networks of interacting actors, in a direct but also in an indirect way.

Obviously the interaction of actors and the involved exchange of knowledge aim at generating new ideas, to introduce them into the market (innovation) and to earn appropriate profits. Hence, actors invest in those activities and attempt to earn at least those investment and some profit. To evaluate those activities several routes can be taken.

First, we can distinguish whether we want to evaluate

(i) the individual performance of actors with respect to other network actors or those outside the network;
(ii) the network in a region in comparison to other networks located in other regions;
(iii) an industry related network in comparison to the networks belonging to other industries;
(iv) in a broader view, the region compound of one or several networks (RIS) compared to other regions;
(v) in a broader view, an industry with one or several networks (SIS) with respect to other industries;
(vi) an industry (or the respective network) located in a certain region compared to the same industry located in other regions.

Take here as an example a biotech firm integrated in a network belonging to a specific regional innovation system (RIS) or to a specific sectoral innovation system (SIS). The evaluation can be performed only with respect to the biotech firm ((i) above); it can be extended to the level of the

biotech-network where a comparison to biotech networks in other regions ((ii) above) or to networks belonging to other industries or technologies ((iii) above) is accomplished; in a further step the level of regions can be addressed where each region may consist of the biotech network but also other networks ((iv) above); equivalently, a comparison can be made between the biotech industry and other industries each one compounding several networks ((v) above); finally, the biotech industry of a certain region can be compared with the biotech industry in other regions ((vi) above). Obviously, in evaluating the RIS performance or the SIS performance one assumes that there are externalities from respective networks to other, non-network actors also belonging to the RIS or SIS respectively.

Second, the performance measurement can look at the various stages of the innovation process. Hence, the output of the processes of generating new knowledge can be measured at the stage of invention as number of new ideas, at the stage of innovation as the sales or the profits reaped by new ideas, or in a more indirect way as productivity improvement or growth rate.

Third, the evaluation may be performed by taking one of those units (one actor, one network, one region, one industry) and track it over time; alternatively evaluation may be accomplished on a comparative basis in the sense of benchmarking.

On the basis of these possible ways of evaluation, in the following a benchmarking approach is introduced, considering the regional dimension and addressing several stages in the innovation process. Hence, from the possible cases above, (ii), (iii) and (vi) are pursued. The principle starting point is a production function approach in the sense that actors invest resources into invention and innovation in order to generate new ideas and to economize on them. This production function approach will be applied in a way that it can be used for benchmarking regional invention or innovation performance. For that, several issues will be addressed:

(i) Methods of the parametric frontier function approach
(ii) Methods of the non-parametric frontier function approach
(iii) Method to disentangle several technological and regional factors on the success of interactive learning and cooperative invention/innovation.

With the purpose of introducing several methods that are able to compare local innovation systems by their performance, the following notation for regions, innovative output, innovative inputs, technologies / sectors is used:

Number of regions:	$R:\ k=1,...,r$
Quantity of innovation (R&D) inputs	$X:\ z=1,....,x$
Number of technologies / sectors	$F:\ j=1,....,f$
Number of innovations:	$N:\ i=1,....,n$

The paper is structured as follows: Section 2 introduces approaches labelled parametric frontier estimation and reports on most recent results when applied to the performance of regions in Germany. In section 3 an alternative non parametric approach is introduced. Here again most recent empirical results pertaining to Germany are presented. The issue of disentangling several impact factors on the performance of regional innovation systems is addressed in section 4. Section 5 concludes and suggests further research to be done.

2. Parametric frontier estimation of the knowledge production function approach

Fritsch & Slavtchev (2007) apply a knowledge production function approach to arrive at a measure for the efficiency of regional innovation systems. Hence, the efficiency they calculate is a technical efficiency in the sense of Farell (1957).

The knowledge production function relates the output of innovative activities N which is considered new knowledge to the input X used to produce this knowledge. That relationship looks like:

$$N = f(X) \tag{1}$$

The function f governs this relationship and can be for example written in a Cobb-Douglas way:

$$N = a \cdot X^{b} \tag{2}$$

This formulation b is the elasticity by which N varies with respect to the variation of X; in principle it allows for constant (b =1), increasing (b >1) and decreasing returns to scale (b <1). a represents a constant factor and be interpreted as an indicator for productivity of the knowledge production function; a higher a at the same level of R&D input allows for a higher R&D output.

This knowledge production function can be transformed logarithmically leading to the linear relationship:

$$\ln N = \ln a + b \cdot \ln X \tag{3}$$

Here knowledge production is dependent on a basis productivity a and a marginal productivity b.

This relationship can be estimated by standard techniques:

$$\ln N_k = \ln a + b \cdot \ln X_k + \varepsilon_k \qquad (4)$$

Here, the index k represents regions and the error term ε_k which is normally distributed, $\varepsilon_k \sim N(0;\sigma^2)$. Estimating (4) leads to an average knowledge production function. However, this does not allow taking into account systematic differences between the regions. For accomplishing that a frontier function has to be estimated. The frontier function is the function used by the best-practice observation. To determine this function a couple of approaches are available. In principle one distinguishes between parametric and non-parametric methods. In this section the parametric approach is discussed, the non-parametric in the following one. Within the group of parametric frontier function concepts one distinguishes further deterministic and stochastic approaches.

Deterministic frontier function

A minor modification for the error term in estimation equation above allows applying this function as a benchmark for comparison of the observations. The modification constrains the error term to take only values larger one, $u \geq 0$. This constraint can be used in two ways:

First, it is assumed that all observations produce with the same average marginal productivity b and differ in a. This implies that for the constant term a one computes in a first step the maximum value in the sample, $a^{\max}$. The regression equation than reads:

$$\ln N_k = \ln a^{\max} + b \cdot \ln X_k - u_k \quad , \; u_k \geq 0 \qquad (5)$$

This implies that the average production function is shifted towards the highest possible a assuming that there are no further stochastic effects (noisy, measurement error, etc. are involved. This procedure is called COLS (Corrected ordinary least squares).

From that, in a second step, the differences in a among the regions can be determined. For the best performing observation / region k^* one estimates a best-practice productivity of the knowledge production function of $\ln \hat{a}_{k^*} = \ln a^{\max}$. For all other regions k one estimates a below-best practice productivity of $\ln \hat{a}_k = \ln a^{\max} - u_k$. As one is interested in the relative distance of each region from the best-practice region the ratio of the below best-practice productivity and the best-practice productivity is of interest:

$$TE_k^a = \frac{\hat{a}_k}{a^{\max}} = \frac{\exp(\ln \hat{a}_k)}{\exp(\ln a^{\max})} = \exp\left(\frac{\ln \hat{a}_k}{\ln a^{\max}}\right)$$
$$= \exp(\ln \hat{a} - \ln a^{\max}) = \exp(\ln a^{\max} - u_k - \ln a^{\max}) \quad (6)$$
$$= \exp(-u_k)$$

This ratio takes values out of the interval $[1;0)$ where 1 refers to the best-practice region and lower values indicate the efficiency level of the respective region. The less that value the less efficient or productive the respective region in transforming X into N.

As an alternative one forces a to take the average value and the marginal productivity b to vary:

$$\ln N_k = \ln a + b_k \cdot \ln X_k - u_k \quad , \; u_k \geq 0 \quad (7)$$

For the best-practice region one then gets $\hat{b}_{k^*} = b^{\max}$ and for the below best-practice regions one gets $\hat{b}_k$. For the efficiency one calculates:

$$TE_k^b = \exp\left(\frac{\hat{b}_k}{\hat{b}_{k^*}}\right) \quad (8)$$

Stochastic frontier function approach

The stochastic approach flows in principle the deterministic approach but does not assume that there are no further stochastic effects (noise, measurement error, etc.) involved. Hence the error term in the equation to be estimated consist of two parts, a systematic deviation $u_k \geq 0$ and a normally distributed stochastic term $\varepsilon_k \sim N(0, \sigma^2)$. The equation then reads:

$$\ln N_k = \ln a + b^{\max} \cdot \ln X_k + \varepsilon_k - u_k \quad , \; u_k \geq 0 \quad (9)$$

The efficiency of a region in transforming X into N is here given by

$$TE_k^s = \exp(-u_k) \quad (10)$$

For the efficiency parameter $u_k \geq 0$ several assumptions with respect to its distribution can be made, (i) half normally distributed, (ii) normally trunctated, and (iii) exponential.

Results

The frontier approach just introduced has been applied by Fritsch & Slavtchev (2007) using data for Germany. They use patent and R&D data on the regional level where for the regions a structure based on the 93 RORs ("Raumordnungsregionen") is applied. With respect to the cases introduced in section 1 here case (iii) is addressed. Figure 1 summarizes the results where always another form of the frontier function has been applied. The darker the colour of the respective area is the higher is the efficiency computed.

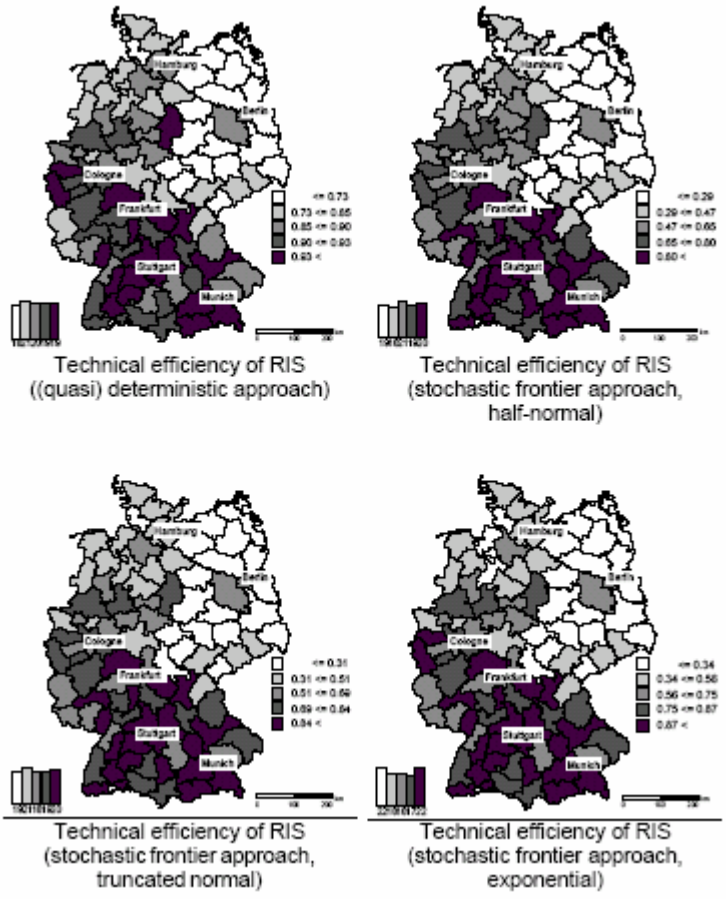


Figure 1: Fritsch & Slavtchev (2007): The spatial distribution of technical efficiency of Regional Innovation Systems in Germany

Independent of the method applied, quite obviously for Germany there is a West-East as well as a South-North decline.

3. Non parametric frontier function approach

Another route to perform a benchmarking analysis for regions or RIS is to again estimate a frontier function but to go without the assumption that this function is parametrically given. Hence no ex-ante specification of the functional relationship is required. For that case non-

parametric approaches are available. Brenner & Brökel (2007 a,b) as well as Bernard & Cantner (1999) apply this non-parametric frontier function approach to evaluate the performance of regions, the former for a specific sector in Germany and the latter for France.

For this approach one principally can distinguish between convex methods like DEA (data envelopment analysis) (Charnes, Cooper, Rhodes 1978) or non-parametric frontier function analysis (Färe, Grosskopf, Lovell 1994) and non-convex ones like FDH (free disposal hull) (Tulkens 1993). Both are based on Farell's concept of efficiency (Farell 1957). Convexity implies here substitutability among the inputs as well as among the outputs.

Non-parametric Frontier Analysis
The Non-parametric Frontier Analysis method assumes a relationship between innovation output and the z different innovation inputs as follows

$$p \cdot N = \sum_z q_z \cdot X_z \tag{11}$$

A benchmark is performed by computing for each region a productivity index under the constraint the productivity index of each of the regions is not larger than one:

$$\begin{aligned} &\max h_o = \frac{p_o \cdot N_o}{\sum_z q_{zo} \cdot X_{zo}} \\ &s.t. \qquad \frac{p_o \cdot N_k}{\sum_z q_{zo} \cdot X_{zk}} \leq 1 \quad , \quad \forall k \in \{1,...o,...,K\} \end{aligned} \tag{12}$$

This problem can be solved by transforming it into a linear form by the Charnes-Cooper Transformation (Charnes & Cooper 1962). Transforming the resulting problem in a further step into its dual formulation leads to:

$$\begin{aligned} \min_{\theta,\boldsymbol{\lambda}} \quad & \theta \\ & \mathbf{N}\boldsymbol{\lambda} \geq N_o \\ & \theta\mathbf{X}_o - \mathbf{X}\boldsymbol{\lambda} \geq \mathbf{0} \\ & \boldsymbol{\lambda} \geq \mathbf{0} \end{aligned} \tag{13}$$

The interpretation of this so-called input-oriented version of the DEA is as follows: states the level θ onto which all inputs of the region under consideration have to be reduced proportionally in order to become best-practice. The parameters in the $1 \times k$ vector λ indicate to what degree each of the R regions serves as a benchmark for the region under consideration, region k. By

computing this efficiency index a frontier function is determined which envelops all the observations most closely. This frontier function serves as a benchmark for the regions whereby regions are compared by all means only with part of the frontier. By this regions are only compared with regions structured in a more similar way. The vector λ contains this information.

There is also an output oriented version of this problem. The interpretation there runs as follows: the efficiency parameter determined indicates onto what percentage level ϕ the region under consideration has to increase its outputs given the inputs in order to become best practice. The respective model for region k reads as follows:

$$\begin{array}{lrcl} \max\limits_{\phi,\boldsymbol{\lambda}} & \phi & & \\ \text{s.t.} & \mathbf{X}\boldsymbol{\lambda} & \leq & \mathbf{X}_o \\ & \phi N_o - \mathbf{N}\boldsymbol{\lambda} & \leq & \mathbf{0} \\ & \boldsymbol{\lambda} & \geq & \mathbf{0} \end{array} \tag{14}$$

Here again an enveloping frontier is determined which serves as yardstick for each of the regions, although as above only partially taking into account structural differences. The efficiency measure in this case is

$$TE_k^{no} = \phi \tag{15}$$

Order m-method

An extension of the non-parametric frontier function approach has been applied by Brenner & Brökel (2007b) as well as by Brökel & Meder (2008), the order-*m* approach.

The order-*m* approach follows a slightly different philosophy than the other no-parametric methods. Instead of comparing a certain region with all other regions only a sub-sample is chosen. By this biases are avoided which result from extreme observations or outliers. For an output oriented version of the approach the following procedure is chosen. First, there is randomly drawn a sub-sample of m observations which only have to satisfy the condition that those regions do not use more of the inputs $\mathbf{X}_z$ than the region o under consideration. Those regions have the innovation inputs and outputs $(\mathbf{X}_1, N_1),...,(\mathbf{X}_m, N_m)$. It has to hold $\mathbf{X}_k \leq \mathbf{X}_o$, $k = 1,...,m$. The measure computed is then the distance between N_o and an order-*m* frontier function set up by $N_1,...,N_m$:

$$\tilde{\omega}_m(\mathbf{X}_o, N_o) = \max_{k=1,...,m}\left\{\frac{N_k}{N_o}\right\} \tag{16}$$

The order-*m* efficiency measure is the expected value of $\tilde{\omega}$:

$$\omega_m(\mathbf{R}_o, N_o) = E\left[\tilde{\omega}_m(\mathbf{R}_o, N_o) \middle| \mathbf{R} \leq \mathbf{R}_o\right] \tag{17}$$

Usually, to compute this expected value a Monte-Carlo approximation with about 200 replications is run. A further problem is the determination of *m*. The larger *m* the less we have the case that observation lie outside the frontier implying an efficiency score less than 1. One has to test here at what m the appearance of this case goes down significantly.

The efficiency measure then reads as

$$TE_k^{mo} = \omega_{m,k} \tag{18}$$

Results

Brenner & Brökel (2007b) apply the order-m approach for analysis a specific industry, the electrics and electronics industry. Hence, from the cases suggested in section 1 they address case (vi). Brenner & Brökel (2007b) use as inputs R&D employees as well as data on regional and interregional factor endowments; as research outputs are proxied by patent applications in several technology fields related to the industry under consideration.

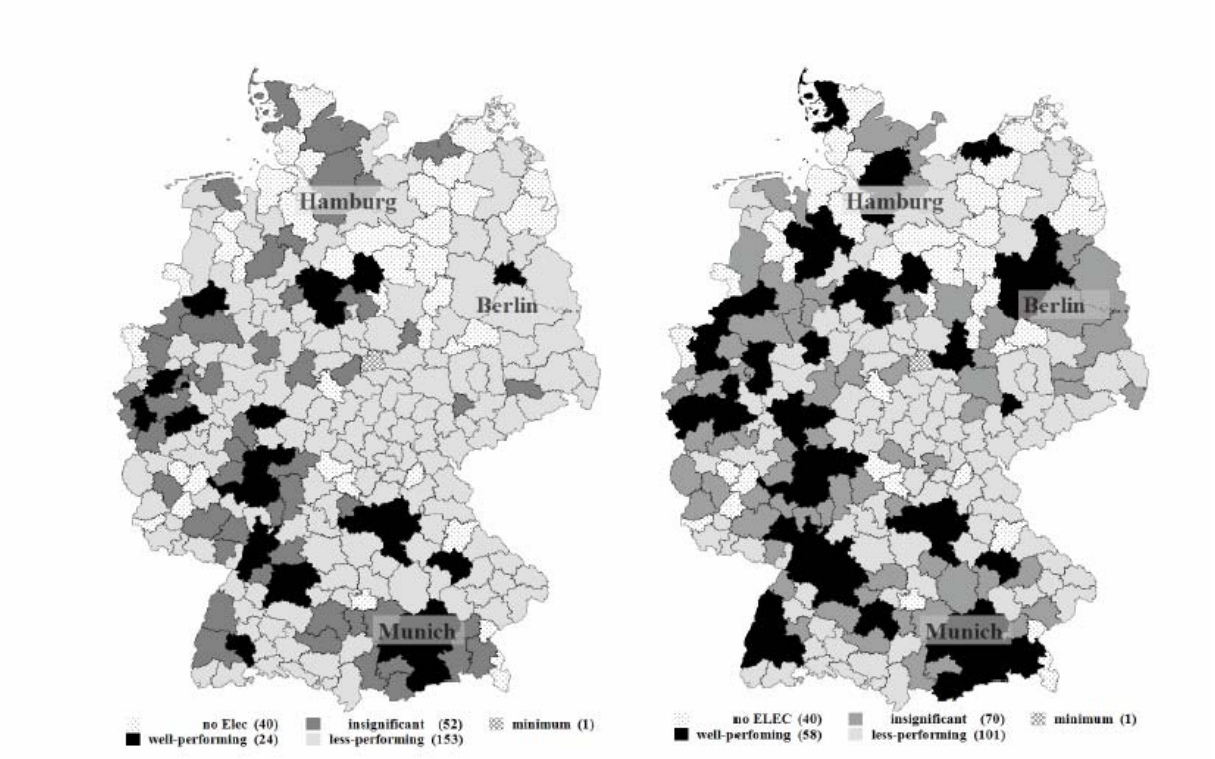


Figure 2: Brökel & Brenner (2007): Regional Efficiency of German electrics and electronics industry measured by the order-m approach with only R&D input (left-hand figure) and with several additional inputs (right-hand figure)

Two different designs are investigated. The first approach takes into account R&D employees as only input and various outputs. And an alternative design considers on the input side additional regional endowment factors. The benchmark used in the first case is the number of R&D employees, in the second case the number of R&D employees and the regional factors. For the regional dimension they use the 270 labour market regions.

The results are summarized in figure 2. There obviously is to be observed some difference between the results of the first and the second design. Efficiency in general increases if more input factors are used which is due to the fact that in the multi-input case those regions with the lowest level in one input are automatically best-practice.

Those differences can be used in both designs to classify regions with respect to their efficiency class. Broekel & Brenner (2007) use this classification to interpret the kind and level of innovative activities of the electric and electronics sector on the regional level.

4. Disentangling several impact factors on the performance of regional innovation systems

Cantner & Meder (2008a) argue that looking at actors engaged in interactive learning and knowledge exchange one observes that those actors are member of several overlapping networks or innovation systems. So for example a biotech-firm may be member of the national system of innovation of the country it has its headquarter and of other countries' national innovation systems with its subsidiaries; it may be member of the technology systems relevant to the technologies the firm runs; and it may be member of regional or local innovations systems each one distinguished by its regional demarcation, may that be determined politically, geographically or by the separation between rural and urban areas.

If one looks now at the performance of actors located in a certain region and compares that performance with that of actors located in other regions the question arises whether performance differences can be attributed to the region of ´location itself or whether effects from the membership to other innovations systems are responsible. In this case we can consider a certain region as a place where several innovation systems overlap. By the degree that different regions experience different degrees of overlap it is not at all obvious whether regional differences in cooperative innovation are regionally determined or by the particular overlap structures.

On this background Cantner & Meder (2008a) suggest a method which allows separating technological and regional effects on cooperative innovation. Hence they consider a region as place where several technological or sectoral systems overlap. Cooperative innovation observed in a certain region can now be related to the various technological or sectoral systems to which actors in that region belong and possibly to a certain region specific effect. The analysis is

performed on the basis of the assumption that all actors are affected by innovation systems of a higher level by the same degree[1] the national system of innovation in the same way and there is no additional differential influence of lower level innovation systems[2].

The analysis requires several types of information about innovations: (1) the actor(s) involved in generating an innovation, (2) the region(s) those actors are located in, and (3) the technology field(s) an innovation belongs to. With (1) we cover the issue of cooperative vs. non-cooperative innovations, with (2) we take into account the regional dimension, and with (3) we have at hand information about the technological dimension.

For these three categories we introduce a formal representation. First, we take into account N innovations indexed by $i = 1,...,n$. The technological space within which innovations are created is F with different technologies indexed by $j = 1,..., f$. Here it is entirely possible that an innovation i is related to more than one of the j technologies. The spatial dimension of innovative activities is represented by the regions R indexed by $k = 1,..., r$. Here it is also possible that the R&D activities for innovation i have taken place in more than one of the k regions. This is the case whenever innovation i is the result of a cooperation between actors located in different regions. However, we will observe a spatial distribution of innovation i also in the case where the innovative actors belong to different branches of the same firm which are located in different regions. To distinguish between both possibilities we take into account information on whether an innovation i has been developed in cooperation or not.

The relationship between innovations, technological field, spatial distribution and cooperative innovation are formalized as follows. The assignment of all innovations n to the technological fields f is are summarized in matrix $\mathbf{A}$. $\mathbf{A}$ is a $n \times f$ matrix with a typical element:

$$a_{ij} = \begin{cases} 1 & \textit{if } i \textit{ is related to } j \\ 0 & \textit{otherwise} \end{cases} \tag{19}$$

The spatial distribution of innovations n is represented by the matrix $\mathbf{B}$. $\mathbf{B}$ is a $n \times r$ matrix with a typical element:

$$b_{ik} = \begin{cases} 1 & \textit{if } i \textit{ has been developed by actors located in region } k \\ 0 & \textit{otherwise} \end{cases} \tag{20}$$

[1] Here one may think of the national system of innovation of the country the region is located in, as well as other national innovation systems which affect actors by the way of subsidiaries located abroad.
[2] With respect to regional systems one may think of systems on the sub-regional level such as urban systems; with respect to technology systems or sectoral systems on can think of those systems defined on a more fine classification.

A spatial distribution of an innovation i occurs whenever different research groups cooperated in a R&D project resulting in innovation i. Whether these research groups work for different economic actors (e.g. firms or universities) is indicated in vector $\boldsymbol{\gamma}$. $\boldsymbol{\gamma}$ is a vector of length n with a typical element:

$$\gamma_i = \begin{cases} 1 \ \textit{if i has been developed by more than one actor} \\ 0 \ \textit{otherwise} \end{cases} \tag{21}$$

In addition and as a variant to general cooperative innovation we suggest a vector $\tilde{\boldsymbol{\gamma}}$ which contains information about cooperative innovation taking place within a region. This vector is again of length n with a typical element:

$$\tilde{\gamma}_i = \begin{cases} 1 \ \textit{if i has been developed by more than one actor, all located in the same region} \\ 0 \ \textit{otherwise} \end{cases} \tag{22}$$

Given this information a method is proposed able to identify regional effects on cooperative behaviour by separating technological effects. Hence, the first step is to account for the technological effects.

The technological dimension of cooperative innovation

The first step focuses on the technological dimension of innovation. The aim is to indicate the propensity of cooperative innovation for each of the technologies. Since innovations regularly are related to several technologies one needs to know to what degree an innovation i is related to each of the f technologies. Hence, for each innovation i we determine weights with respect to each of the f technologies.

Matrix $\mathbf{A}$ which contains the unweighed values is the starting point. Dividing each element a_{ij} of row i by the sum of all elements $\sum_{h=1}^{f} a_{ih}$ just leads to the weights required. Matrix $\mathbf{A}^w$ contains these weights. It is a $n \times f$ matrix with a typical element:

$$a_{ij}^w = \frac{a_{ij}}{\sum_{h=1}^{f} a_{ih}} \tag{23}$$

The sum of the elements of row i in matrix $\mathbf{A}^w$ is equal to one. We here assume that all technologies related to innovation i show the same weight. In order to distinguish between innovative and cooperative activities among technologies, each row i of matrix Aw is multiplied

with the corresponding value i of vector $\boldsymbol{\gamma}$. The result is a matrix $\mathbf{A}^{wc}$ comprising only the technology weights of cooperative innovations. $\mathbf{A}^{wc}$ is a $n \times f$ matrix with a typical element:

$$a_{ij}^{wc} = \frac{a_{ij} \cdot \gamma_i}{\sum_{h=1}^{f} a_{ih} \cdot \gamma_i} \tag{24}$$

Matrices $\mathbf{A}^{w}$ and $\mathbf{A}^{wc}$ are now used to determine average cooperation behaviour for each technology. For that we sum up the elements of each column (technology field) in $\mathbf{A}^{w}$ and $\mathbf{A}^{wc}$. In the former case we get an account of the number of innovations related to technology j, in the latter case of the number of related cooperative innovations in that technology. The ratio of both magnitudes indicates the propensity of cooperative innovation in technology j. The ratios of all the technologies are included in vector $\mathbf{p}^{c}$.[3]3 It is a vector of length f with a typical element:

$$p_j^c = \frac{\sum_{i=1}^{n} a_{ij}^{wc}}{\sum_{i=1}^{n} a_{ij}^{w}} \tag{25}$$

At this point, however, one has to be careful in interpreting this ratio as a purely technological effect. Since the cooperative innovations considered are affected by both technological as well as regional effects the ratio computed contains the specific technology based propensity to cooperate as well as an average influence of regional effects. Equivalently to the procedure above one can restrict the analysis to cooperative innovation taking place only within the region. For that each row i of matrix $\mathbf{A}^{w}$ is multiplied with the corresponding value $\tilde{\gamma}_i$ of vector $\tilde{\boldsymbol{\gamma}}$. The result is a matrix $\tilde{\mathbf{A}}^{wc}$ comprising only the technology weights of cooperative innovations which have taken place within regions. Using now matrices $\tilde{\mathbf{A}}^{w}$ and $\tilde{\mathbf{A}}^{wc}$ we can compute the propensity of cooperative innovation represented by vector $\tilde{\mathbf{p}}^{c}$ which does not only comprise the technological effects but also the average intra-regional effect.

The regional dimension of cooperative innovation

The second step focuses on the regional distribution of innovation in general and of cooperative innovation in particular. Equivalent to the procedure above, the weights are to be determined by which an innovation i is related to regions k where the actors innovating i are located. Matrix

[3] We assume that there is at least one innovation in each technology. Therefore, we do not distinguish several cases in equation 7.

$\mathbf{B}$ contains the unweighed relationships. Dividing each element of row i by the sum of all elements of row i delivers the respective weights; here to each region related to innovation i the same weight is assigned. Matrix $\mathbf{B}^w$ contains the results. It is a $n \times r$ matrix with a typical element:

$$b_{ik}^w = \frac{b_{ik}}{\sum_{l=1}^{k} b_{il}} \tag{26}$$

Multiplying each element b_{ik}^w of matrix $\mathbf{B}^w$ by the element i of vector $\boldsymbol{\gamma}$ leads to the spatial distribution of the cooperative innovations. The resulting matrix is $\mathbf{B}^{wc}$. It is a $n \times r$ matrix with a typical element:

$$b_{ik}^w = \frac{b_{ik} \cdot \gamma_i}{\sum_{l=1}^{k} b_{il} \cdot \gamma_i} \tag{27}$$

Matrix $\mathbf{B}^{wc}$ contains information about the regional distribution of cooperative innovation independent of whether the cooperation is within the region or between different regions. Using $\tilde{\boldsymbol{\gamma}}$ instead of leads to a matrix $\tilde{\mathbf{B}}^{wc}$ which contains information on cooperative innovations internal to the region.

The expected value of regional cooperative innovation

In a third step, an indicator is computed stating the expected number of cooperative innovations in a region k. For this index we take into account the technology specific propensity for cooperative innovation of the previous section which contains also the average regional effect. We start by computing the number of innovations of technology j in region k. The respective numbers are stated in a matrix $\mathbf{C}$ with r rows (regions) and f columns (technology fields). This $r \times f$ matrix $\mathbf{C}^w$ contains information about the number of innovations that have been developed in technology j by actors from region k. $\mathbf{C}^w$ is computed by:

$$\mathbf{C}^w = \mathbf{B}^{w'} \cdot \mathbf{A}^w \tag{28}$$

$\mathbf{B}^{w'}$ is the transposed matrix $\mathbf{B}^w$. $\mathbf{C}^w$ is used to create an indicator of what we call the "expected number of cooperative innovations" (e_k^c) of region k. It indicates how many cooperative innovations are to be expected in region k taking into account the technology specific

propensities for cooperative innovation p_j^c. Vector $\mathbf{e}^c$ contains the expected cooperation values for all regions k. It is a vector of length r with a typical element:

$$e_k^c = \sum_{j=1}^{f} c_{kj}^w \cdot p_j^c \tag{29}$$

Observed and expected number of regional cooperative innovation

Were cooperative innovations within a region solely affected by technological determinants (and an average regional effect) - implying that there are no differential regional effects on cooperative innovation - the observed number of cooperative innovations has to be identical to the expected number. In order to test for this, in a final step for each region r the ratio between observed and expected cooperative innovations is determined. For that one computes the column sum of elements of matrix $\mathbf{B}^{wc}$. This just leads to number of all cooperative innovations observed in each region. For each region we take this sum and divide it by the respective expected number of cooperative innovations e_k^c. The region specific ratios are contained by vector $\mathbf{v}$. It is a vector of length r with a typical element:

$$v_k = \frac{\sum_{i=1}^{n} b_{ik}^{wc}}{e_k^c} \tag{30}$$

This ratio takes values out of $(0;\infty)$. At a value of 1 the number cooperative innovations observed in a region is just equal to the expected number. A ratio different from 1 indicates that there exists a differential regional effect above or below the average regional effect. Regional cooperative innovation above (below) the average is indicated by a ratio larger (less) than 1. Using instead of $\mathbf{B}^{wc}$ the matrix $\tilde{\mathbf{B}}^{wc}$ one achieves at a vector $\tilde{\mathbf{v}}$ which contains the ratio of observed intra-regional cooperations to the expected ones. The interpretation is equivalent to the one above. The difference is that there regional effects on cooperative innovation in general are identified whereas here regional effects on intra-regional cooperation are looked at.

Results

Cantner & Meder (2008b) apply the method introduce to data from German regions from 1999 to 2002. Innovations (inventions) are proxied by patent applications, cooperative patents account for cooperative innovative activities, for the regional dimension is the 97 ROR are used. The assignment of patents to regions is accomplished by using the inventors' addresses. As here the regional networks of innovative actors are identified, the benchmarking runs as in case (ii) suggested in section 1.

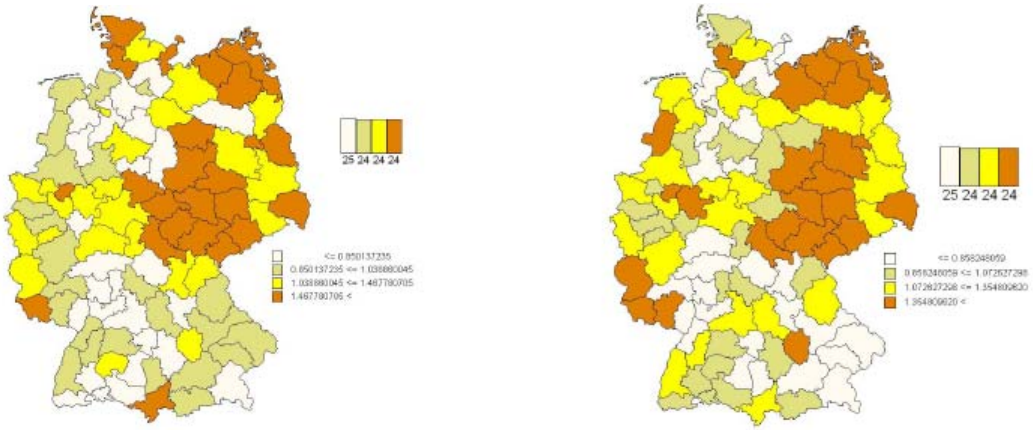


Figure 3: Cantner & Meder (2008a): RRI Index for German regions 1999 (left-hand figure) and 2002 (right-hand figure)

Figure 3 contains the results. Here, the darker the colour of a region the more does the observed number of cooperative innovation exceed the expected number and, hence, the stronger is the regional impact on cooperative innovation. The two figures belong to the years 1999 and 2002. There obviously is not much change in the relative regional impact over time. Clearly, the RRI index is much higher in east compared to west regions. There also is a slight decline of this index from the North to the South.

5. Conclusion and outlook

This paper summarizes several approaches to be used evaluating the performance of local or regional innovation systems. Here a benchmarking approach has been chosen. For that frontier production function can be determined, here on the basis of a knowledge production function relating innovation inputs and innovation outputs. Applying regression techniques allows estimating frontier functions, applying non-parametric methods leads to frontier function which do not imply that all observations apply the parametrically same production function. For analyses on the regional level and especially with a focus on regional innovation systems those approaches only indirectly take into account cooperative invention and innovation – the core of the innovation system approach. To make these interactive effects more visible one has to look specifically on the level, the influence and the effects of cooperative innovation activities. Here, the general problem arises that it is not at all obvious whether these effects are caused by regional or be technological determinants. To disentangle this, a method has been suggested to identify the relative regional impact on cooperative innovative activities.

The benchmarking approaches as well as the method to identify regional effects in a local or regional innovation system are only a first step in understanding the performance and performance differences of regions or regional innovation systems. The results obtained have to

be explained in a second step. For this approaches will be used which allow explaining the various TE_k indices as well as the RRI_k index. Partly the literature stated in this paper already pursued in this direction.

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