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## Measuring regional innovativeness: a methodological discussion and an application to one German industry

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# JENA ECONOMIC RESEARCH PAPERS



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## **Measuring Regional Innovativeness A Methodological Discussion and an Application to One German Industry**

by

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# MEASURING REGIONAL INNOVATIVENESS

## A Methodological Discussion and an Application to One German Industry

13th September 2007

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### **Abstract**

The regional or national innovation performance has been repeatedly measured in the literature; but it has so far not been discussed what this means, especially in relation to a region. What is the contribution of a region to innovation output? The usual approaches implicitly assume that higher innovation outputs per inhabitant, employee, or R&D employee can be assigned to a region. We argue that more insights are gained if we distinguish between various mechanisms that influence the innovation activities in a region. Different analyses need to be conducted, using different variables and including different local factors. Furthermore, we see no justification for using a linear dependence of innovation activity on the number of inhabitants or employees as a benchmark for performance. We use a method that takes into account these arguments and apply it to the Electrics & Electronics industry in Germany.

**JEL-classification:** R11, R15, O31

**Keywords:** Regional innovation performance, regional innovativeness, non-parametric performance analysis, measurement of regional innovativeness

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## 1 Introduction

The regional or national innovation performance has been repeatedly investigated in the literature (see, e.g., Nijkamp and Kangasharju (1997); Kostianen (2002a,b); Oinas and Malecki (2002)). There has been much discussion about the ‘right operationalization of innovativeness, but little about what innovation performance means in the context of regions or nations. It is implicitly assumed that regions with a higher innovation output (e.g., a higher number of patents), or higher innovation inputs (e.g., large spendings on R&D) are more innovative. Often these measures are corrected for the size of the spatial units (e.g., by dividing them by the number of inhabitants).

The aim of this paper is twofold. First, to discuss extensively how innovation performance can be measured and what it means to measure the innovation performance of a spatial unit in a specific way; second, in addition to referring to the literature, to apply various measurements to one industry in order to show how the results differ and how these differences can be used to gain additional insights.

In order to shed light on the issue of how innovation performance can be measured, the paper provides discussions about the meaning of innovation performance, the definition of benchmarks, the inclusion of local resources and its implications for the results, and the question of whether industries should be studied separately. Basically all these issues are related to what is to be measured as innovation performance.

To achieve the second aim, the industry chosen will be analyzed and subjected to various measurements. In addition, references to the literature are made. The literature dealing with analyses of regional innovation performance is rather scarce. To the author’s knowledge there are few conceptual works, such as, e.g., Gracia et al. (2005), and several empirical approaches, as, e.g. Fritsch (2000, 2002, 2003); Fritsch and Slavtechev (2006). Fritsch also discusses what innovation performance on a regional level means and why it is worthwhile to analyze it. In particular, he considers the implications of the differences in innovation performance. Therefore, we refrain from discussing this further and refer the reader to the papers of Fritsch (2000) and Gracia et al. (2005).

In empirical terms, our paper differs from the approaches in the literature especially in four respects: First, we analyze total innovation output as well as the innovation output of one industry in order to determine differences between industries. Second, we do not restrict our analysis by assuming a linear dependence of innovation output on resources, such as the number of inhabitants, as a way to establish an adequate benchmark for judging the performance of a region. Furthermore, and in contrast to Fritsch’s work (2000, 2002, 2003 and 2006), we do not rely on the ‘knowledge production function’ framework with its assumption of specific functional relationships between the regional resources and the innovative output. Third, in contrast to these works, our approach incorporates multiple outputs that account for some diversity on the output side. Fourth, and most importantly in the context of the above discus-

sion, we extend the approaches of Fritsch (2003) and Fritsch and Slavtechev (2006). Whereas they use total R&D investments and total R&D employment as single input variables, respectively, we include a wide range of input variables modeling the regional resource endowment. We conduct two analyses, one that includes a number of local resources beyond R&D employment and one that does not, providing us with more detailed information about why some regions are more innovative than others.

The paper proceeds as follows: Section 2 contains a detailed discussion of the issues involved in measuring the innovation performance of regions. The approaches taken are described in Section 3 which also contains a description of the data used. The results of the empirical study that compares different performance measures are presented and discussed in Section 4. Section 5 concludes.

## **2 Theoretical considerations on the innovation performance of spatial units**

In recent years the innovation performance of different sets of regions or nations has been the subject of an increasing amount of research. The usual approach is to define one index or a number of indices that represent the innovation output of the spatial unit considered. Most commonly, patents are used as approximations for the number of innovations generated within a region (see, e.g., Feldman, 1994; Feldman and Florida, 1994; Fritsch, 2002). To capture the size of regions, many approaches use criteria, such as patents per inhabitants (Stern et al., 2002) or patents per employee (Bode, 2004).

As stated, measuring the innovation performance of spatial units, has raised a number of questions that have not been sufficiently answered in the literature. To remedy this, our focus will be on four questions: what does innovation performance mean (Section 2.1); how should the benchmark to evaluate the innovation performance of spatial units be defined (Section 2.2); do we have to take characteristics of the regions into account (Section 2.3); and is innovation performance a general characteristic or is it specific to industry (Section 2.4).

### **2.1 Definition of innovation performance**

A common approach to such a definition is to count the number of patents per inhabitants (see, e.g., Audretsch, 1998; Stern et al., 2002). What is measured is the average performance of each inhabitant of a region rather than the performance of the region as a whole. However, not all inhabitants have the same opportunities or interest to contribute to the innovation or patent output of a region or nation. This raises two questions: what does performance mean, and what is the unit of analysis? The common approach would provide the following answers: first, performance is simply measured in terms of the number of innovations per inhabitant,

and, second, the unit of analysis is the individual aggregated to the regional or national level. If the region or nation were taken as units of analysis, there would seem to be no reason for dividing the patent numbers by the number of inhabitants, assuming that performance is still defined in terms of what is generated. Thus we could formulate a second approach that for each spatial unit simply counts the total number of innovations. But the problem with this is that the measure depends strongly on how the unit of analysis is defined. Especially, if units vary in size, it is unclear what the measure indicates. If the units are similar in size, the results are easier to interpret, but do not provide information about the causes for different innovation outputs. Although this is a valuable option, we will not investigate it here. We aim for further insights into why regions perform differently with respect to their innovation output.

We therefore return to the more common approach, which is to measure innovation output per inhabitant or R&D employee. As stated above, the result can be interpreted as the average performance of an inhabitant or R&D employee in the spatial unit studied. However, many authors seem to have a different interpretation in mind: the measured innovation performance as a characteristic of the region or nation, which is considered as the unit of analysis. However, this changes the definition of performance defining the latter being generated in relation to the resources available. From here it is a small step to interpreting the innovation process as a production process, implying that there are resources (e.g., inhabitants or different types of knowledge) that are transformed into output (innovations by a spatial unit (e.g., a nation, a region, a group of researchers, or a firm) (on this issue see also Bonaccorsi and Daraio, 2006). Fritsch (2003), and Fritsch and Slavtchev (2006), for example, use the term 'efficiency' for the measured innovation performance. In contrast to production processes, however, output is stochastic and not deterministic.

To shed some light on what is at stake, we take the perspective of a spatial unit as the unit of analysis and discuss what factors influence the innovation output measured for such a unit of analysis. Output is given by the total number of innovations that originate from a region or nation, usually measured in the form of patents. The question arises as to what a region contributes to explain innovation output. Assigning a performance measure to a spatial unit means attributing a better or worse performance to this unit. Four different kinds of characteristics or circumstances in the spatial units may have an influence:

**Fixed characteristics of the spatial unit:** Examples are geographic size, and location as well as natural resources. These characteristics are given and do not change on the time scale that is relevant here.

**Characteristics of the population within the spatial unit:** Examples are population number, population density, spatial structure of settlement (urban or rural areas), and culture. These characteristics are influenced by the 'fixed characteristics of the spatial unit,' but 'historical events' may also matter. They are likely to change relatively slowly.

**Policy settings and activities in the spatial unit:** Examples are tax policies, regulations, infrastructure and public research. Policies in a spatial unit are influenced by the population characteristics, especially culture, but also by population density. At the same time, they also influence population changes, probably more slowly. They are also influenced by the fixed characteristics of the spatial unit.

**Economic activities in the spatial unit:** Examples are industrial structure, number of firms, number of employees, and characteristics of the firms such as their R&D intensity. Economic activities interact with population characteristics - again economic activities probably change faster than population characteristics - and similarly with policy settings. Furthermore, economic activities are influenced by the fixed characteristics of the spatial unit, especially natural resources and geographic location. Historical events and path dependencies might also matter.

Considering the innovation output generated in a spatial unit, two elements mentioned above are important: the firms in the spatial unit, especially their R&D activity, and the public research conducted. These two actors are responsible for most innovations (some innovations are generated by private individuals / persons). If a study is restricted to patents that are gained by firms, only the former element matters. However, the other elements listed above also have some effect. On the one hand they influence what and how many firms are located in the spatial unit. On the other hand they influence the ability of these firms to generate innovations, e.g. through the provision of public support, an adequate infrastructure, or research institutes as cooperation partners and knowledge sources.

We restrict our discussion to innovations generated by firms, as we do in our study below. An inclusion of innovations generated by public research and private activities would make an interpretation more difficult. Focusing on firm innovations merely allows for depicting the influences as done in Figure 1. The interaction between the four boxes – ‘unit characteristics’, ‘population characteristics’, ‘policy settings and activities,’ and ‘economic activity’ – determines the ‘economic activity’ within the spatial unit and its R&D activity. However, the status of one box is not completely determined by the status of the other boxes. Multiple equilibria might exist due to path dependence, and on account of ‘historical events’, the whole system keeps evolving. This is shown by the influence of ‘historical events’ and the circular arrows. The ‘economic activity’ generates innovations (thick arrow), in which it is influenced in its potential by the other three boxes, ‘unit characteristics’, ‘population characteristics’, and ‘policy settings and activities.’ Furthermore, innovation generation is a stochastic process, which is indicated by ‘random events.’

Of course, the innovation output of a spatial unit may also have an impact on the ‘population characteristics’, ‘policy settings and activities,’ and especially ‘economic activity.’ This impact is ignored here as in every study of the innovation performance of spatial units we know of. Furthermore, all elements depicted in Figure 1 might be influenced by events and situations

outside a region. Examples are neighboring regions with their characteristics and inherent dynamics or the world market. These influences are ignored here for the sake of simplicity.

Figure 1 – including these simplifications – helps to interpret the different approaches used to measure the innovation performance of spatial units. A measure of innovation performance that is based on counting all innovations generated in a spatial unit simply measures the innovation output and treats all interactions in Figure 1 as a black box. Hence it attributes everything, including ‘historical events’ with their dynamic and random events to the spatial unit.

Using the ratio of innovations per inhabitant means that all arrows in Figure 1 pointing to the box ‘population characteristics’ are excluded from the analysis. The ‘population characteristics’, specifically population size, are considered as given characteristics of a spatial unit. All interactions between the boxes ‘population characteristics’ and ‘innovation output’ in Figure 1 are attributed to the spatial unit as performance measure. This means that the performance measure includes the effects of ‘historical events’, ‘unit characteristics’, ‘policy settings and activities,’ and ‘population characteristics’ (except population size) on ‘economic activity’, the effects of ‘unit characteristics’, ‘policy settings and activities,’ and ‘population characteristics’ other than population size on the ability of firms to innovate, and the effect of ‘random events.’ Using the ratio of innovations per R&D employee means that all arrows

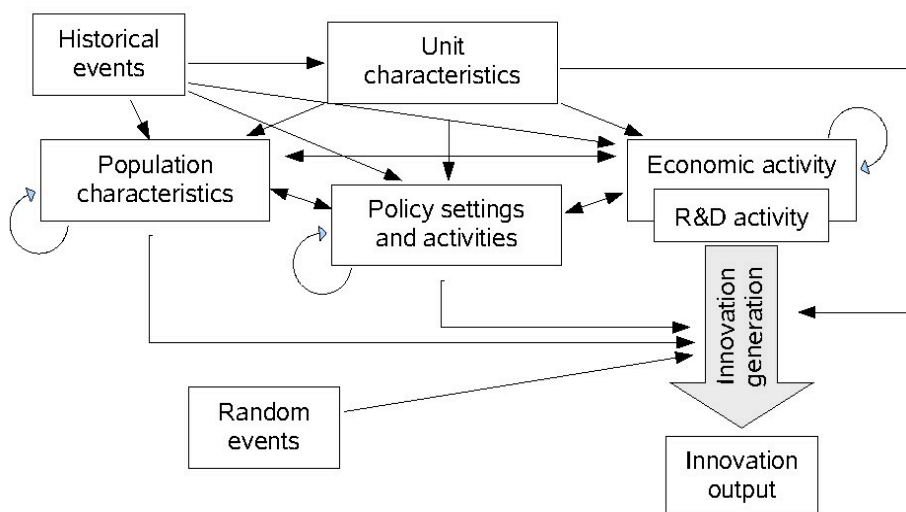


Figure 1: Regional interactions that cause the innovation output of a region.

in Figure 1 pointing to the box ‘economic activity’ are excluded from the analysis. ‘Economic activities,’ in the form of R&D employment, are considered as given characteristics of a spatial unit. All interaction between the boxes ‘economic activity’ and ‘innovation output’ in Figure 1 are defined as performance of the spatial unit. This means that the performance measure



includes the effects of ‘unit characteristics’, ‘policy settings and activities,’ ‘population characteristics’, and ‘economic activities’ (other than R&D employment) on the ability of R&D employees to innovate and the effect of ‘random events.’

The approach we use below includes a number of variables that represent parts of ‘unit characteristics’, ‘policy settings and activities,’ ‘population characteristics’, and ‘economic activities’. This is explained in detail in Section 2.3. Using this approach implies that we exclude the variables considered in the study from those factors that are attributed to the spatial unit as performance measure. Moreover, the approach that we use statistically accounts for the effects of ‘random events.’ In this way, we are able to narrow down the number of effects that our performance measure represents a sum of. However, which effects are excluded and how much the analysis is narrowed down depends on the research question under review. We will show how the analysis can be focused and how the results of different approaches can be interpreted. Besides different approaches offer different insights, so that a joined application of them will increase our understanding of the processes underlying innovation performance. It should be noted that such a discussion also relates to the use of *partial* or *total* factor productivity measures. Clearly, simple input / output ratios as e.g., patents per inhabitants may be considered as partial factor productivity measures. In contrast, the inclusion of additional regional factors implies that this investigation aims is to estimate a total factor productivity measure. On this issue, see also Bonaccorsi and Daraio (2006) who provide a more detailed discussion. Whether a partial factor productivity is to be estimated or an attempt made to calculate a total factor productivity is up to the researcher. However, it should be pointed out that the estimation of a total factor productivity might be problematic because in contrast to classic production processes, this would make it much more unlikely to identify *all* factors that contribute to regional innovation processes.

## **2.2 The benchmark for the evaluating innovation performance of spatial units**

Using an approach that does not only consider the innovation output of a spatial unit but also includes characteristics, e.g. the number of R&D employees, implies that only the same spatial units with respect to the considered characteristics can be directly compared. We argued above that these characteristics have an impact on the innovation output of the spatial unit. Hence, spatial units with a different endowment in terms of these characteristics can be expected to generate a different number of innovations. To compare such units, we have to define a benchmark assumption. The implicit assumption in an approach that calculates the number of innovations per inhabitant or R&D employee is that innovation output should increase linearly with the number of inhabitants or R&D employees. Although in the case of these two groups a linear dependence seems to be an adequate assumption, it need not necessarily hold (evidence that rejects such a linear assumption is provided in Brenner and

Greif, 2006).

Alternatively, the benchmark can be based on a frontier that is estimated by a regression approach (Fritsch, 2002; Fritsch and Slavtechev, 2006). In this case some flexibility with respect to the functional form of the dependence is implemented. However, the type of functional dependence (in the case of Fritsch (2002); Fritsch and Slavtechev (2006) a log-linear function is assumed) is restricted in such an approach. Thus a benchmark assumption is still made about how many innovations a spatial unit should generate given its endowments. This assumption has to be justified.

As another alternative method, the non-parametric frontier approach, which is explained and used below, allows to calculate a benchmark for each spatial unit without any assumption about the functional form of the dependence between the considered variables and the innovation output, besides the assumption that this dependence is continuous. This means we only assume that spatial units that are characterized by similar endowments should also have a similar innovation output and that inputs are freely disposable. This is to be an unproblematic assumption, because it seems unlikely that the innovation potential of a spatial unit jumps up at certain values of the endowment variables. For a discussion about advantages and disadvantages of the different approaches see also Bonaccorsi and Daraio (2006).

A problem that should be mentioned in this context is the fact that the innovation output is a random variable (Nelson, 1982; Simonton, 2003). It is undetermined whether a certain innovation will be generated even though all necessary resources are in place. The quality and quantity in which the resources are available influence the likelihood of innovations to be created. However, they do not determine the number of innovations that are generated in a given period of time. The randomness of the innovation numbers hits the calculation of innovation performance at two points. First, the benchmark is calculated on the basis of spatial units that perform best. Spatial units with a positive fluctuation in the considered period of time might increase this benchmark beyond the value that can be expected in the long-run. This problem can be cured by using a random frontier approach. Second, random effects also impact the performance measure for each spatial unit. Hence, the performance measure is only an estimate. Arguing that certain spatial units are better or worse than others or basing policy activities on such an estimate is dangerous. Therefore, we calculate confidence intervals and base our interpretations on these intervals instead of the estimates.

### **2.3 Resources in the regional innovation process**

As mentioned above, local factors can be expected to influence the number of innovations generated in a spatial unit. Most works on innovation performance in the literature control for the size of the spatial unit in terms of inhabitants (e.g. Paci and Usai, 2000; Stern et al., 2002), some control for the number of R&D employees (Fritsch, 2002, 2003). Many additional factors also influence the number of innovations generated in a spatial unit - as shown in

Figure 1. There is no general solution to the question of which resources should be included. However, this determines the results and their meaning. A study of innovation performance should clearly state the aim of the approach taken, the consequences of this aim for the choice of the resources to be included, and a respective interpretation of the results.

Figure 1 helps in interpreting the different approaches to measure innovation performance of spatial units. Whatever local resource or factor we include in the measurement of innovation performance implies that we exclude from the analysis all arrows in Figure 1 pointing to the respective box, while measuring all arrows and combinations of arrows that run between this box and that of 'innovation output'. This leads to four insights. First, including different factors implies measuring different effects and local influences. Second, the more factors are included that have a direct or quite direct impact on the innovation output, the easier it becomes to assign the measure of innovation performance to one or several influences. Third, three fundamental factors are not determined by other factors: 'unit characteristics', 'historical events' and 'random events.' Fourth, some factors are difficult or impossible to exclude. For example, 'random effects' affect the innovation generation and cannot be excluded. 'Historical events' can only be excluded if all variables they influence, namely 'population characteristics,' 'policy settings and activities,' and 'economic activity,' are included in the measurement.

As a consequence, some theoretical considerations are necessary to make choices regarding the local resources to be included in the measurement of innovation performance. There are three options:

**Option A:** No local resource is included, implying that the measurement of innovation performance represents a mixture of all influences that are depicted in Figure 1. The fundamental factors - 'unit characteristics,' 'historical events,' and 'random events' - can be conceived as ultimately causal in this option.

**Option B:** All final resources are included, i.e., those aspects of 'population characteristics,' 'policy settings and activities,' and 'economic activity' that influence innovation output directly. If one succeeded in including all important factors, the innovation output could be completely determined except for the influence of 'random events'. If these were considered as proposed above, the resulting innovation measure would not contain any information.

**Option C:** Some factors are included in the analysis while others are excluded. This implies that by excluding some influences, others can be examined. For example, if the number of R&D employees is included, the influence of all other variables can be examined, especially 'population characteristics,' 'policy settings and activities,' and other economic activity measures as long as they are not determined by the number of R&D employees. These variables can again be explained by 'unit characteristics' and 'historical events'. However, such an approach would only measure the influence of 'unit characteristics'

and ‘historical events’ that is not already reflected in the number of R&D employees.

We choose Option C. This implies that more discussion is necessary on the variables that are included in the analysis. We argue that R&D employees are the dominating source for the generation of innovations, especially if these are measured by patents that are filed by firms - as we do here (see Fig. 1). Taken to the extreme, it might be argued that only R&D employees generate innovations. This implies the following:

**Assumption 1:** R&D employees are necessary for the innovation process and are not substitutable by local factors.

This assumption is justified by the twofold role played by R&D employees: On the one hand they can be regarded as an important ‘transformation unit’ in innovation processes transforming available resources into innovation output. On the other hand they approximate the firm’s internal resources that are invested in innovation processes.

In light of this argument, Option A can be reinterpreted. This approach provides us with information as to whether a spatial unit can attract more R&D employees, more innovative R&D employees, and/or whether it can provide them with resources increasing their innovativeness. Measuring innovation output in terms of patents per R&D employee (example of Option C) still mixes two different effects: first, spatial units provide different resources – ‘population characteristics’ and ‘policy settings and activities’ – which make R&D employees in these units more or less innovative, and second, different industries with a different innovativeness of their R&D employees are located in different spatial units.

In order to further reduce what is measured, additional factors can be included in this approach. Candidates are all local resources assumed in the literature to influence innovation activities in a spatial unit. Before discussing the factors included here, we have to determine their mathematical form. We make the following assumption (see Fig. 1):

**Assumption 2:** All resources (factors) affect firms’ innovation processes through R&D employees. This means that they do not generate innovations themselves but influence the generation capabilities of R&D employees.

By allowing regional factors to take effect only through the R&D employees their role as ‘transforming units’ is taken into account. Furthermore, Assumption 2 implies that local resources do not directly impact on the innovation output of spatial units but modulate the output generated by R&D employees. In the common regression analysis this is a controversial issue because through fixing the regression function assumptions are made about how different factors interact to generate innovation output (see for a detailed discussion Broekel and Brenner, 2005). In a non-parametric approach, such as the one used here, this is less an issue because no functional form of the interaction between factors is assumed. Even so, the choice of the input variables in such an approach has an impact on the outcome of using the method.

Assumptions 1 and 2 imply that local factors have no independent effect on the innovation output of a spatial unit and hence seem inadequate to be used as independent inputs in a non-parametric frontier approach. We do not know the functional form of their impact on innovation output. The simplest assumption, given Assumption 2, is that innovation output depends on the multiplication of each local factor with the number of R&D employees (see Broekel and Brenner (2005) for a detailed discussion). Therefore, we use variables that are defined as the multiplication of a local factor with the number of R&D employees as input variables in the performance analysis below. The approach chosen, nevertheless, still allows to represent any kind of dependence.

### 2.4 Industry specificity

Above we argued that R&D employees are responsible for generating innovations. Therefore, the number of R&D employees is used as a basic resource in the generation of innovations in many approaches and in most analyses here. However, not all R&D employees show the same probability of generating innovations. This depends, for example, on the individual characteristics of employees, the strategy of the firm, and the industry in which the firm is active. We discuss here the measure of the innovation performance of a spatial unit. In each unit, there are usually a number of firms with many R&D employees. These employees' or firms' characteristics will, therefore, only play a role if there are factors that attract firms or employees with certain characteristics to specific spatial units. While some effects of this kind can be expected, we know from empirical studies of the distribution of industries in space (see Ellison and Glaeser, 1997) that spatial units are characterized by highly different industrial structures.

For one thing, these differences in industrial structure refer to different types of industries and rates of innovation. In addition, the ways in which innovations become effective in industries also differ. Pavitt (1984) shows how innovation processes differ between manufacturing industries and how this affects their relations to other actors and institutions. The industrial dimension also plays a crucial role in empirical research because of its effect on the innovation measure. Commonly used proxies for innovations (most importantly patents) capture innovations to a varying extent for manufacturing industries (see, e.g., Arundel and Kabla, 1998). Hence, when using patents as a measure of innovations the observed variance in regional innovativeness can be biased by the industrial structure of the a region. If the innovation performance of spatial units is measured without including the industrial structure, the result will in a significant part represent the industrial structure in the spatial units.

There are in principle three ways in which the industrial component can be accounted for. First, it can be considered as a factor, being part of 'economic activity' in Figure 1. This would, however, lead to the problem that the industrial structure of a spatial unit could only be measured by a large number of variables. Second, one could try to weight the different

industries and sectors with respect to their presence in the region and construct a single ‘weighted’ innovativeness index. To the authors knowledge this has not been done so far. Third, regional innovativeness can be examined separately for different industries (see, e.g., Broekel and Brenner, 2005; Brenner and Greif, 2006). Such an industry specific approach is used here.

The main disadvantage of such an approach is that unless the weighting problem in the aggregation of a number of measures of industry specific innovativeness is solved, it is not possible to obtain a single measure of regional innovativeness that controls for industrial structure effects. Another disadvantage is of a practical nature. One has to ensure that the proxy for industry specific resources (e.g. R&D employment) corresponds to the industry specific output measures (e.g. patents). Thus, in contrast to the over-all innovativeness approach, in an industry specific approach the data needs to be of better quality.

It might be argued that the potential to attract innovative industries to a region is part of its innovation performance. However, according to the literature on spatial concentration (e.g., Fujita et al., 1999) industries might agglomerate in one region even if regions are identical. The industrial structure in a region is strongly influenced by historical developments, chance, and self-reinforcing dynamics and does not necessarily reflect specific regional resources.

### 3 Employed method and data

The theoretical discussion above has shown that there is no correct or optimal way to measure the innovation performance of spatial units. Different approaches have different advantages and disadvantages. More important, different approaches measure different things, and measuring innovation performance in different ways provides us with additional information about the causes of the different performances of various spatial units. In light of the two aims of this paper, as stated above four different approaches are taken here:

**Analysis 1:** First, we use a simple and common approach, which is to measure innovations per R&D employees. The total of all patents is divided by the total number of R&D employees. This is done for each region.

**Analysis 2:** In order to account for the industrial structure in each region, Analysis 1 is repeated, considering only the R&D employees in a specific industry and the patents in the technological category corresponding to this industry. This requires finding a match between an industrial class and a technological category and will be discussed below (Section 3.1).

**Analysis 3:** Again only industry specific data is used. In contrast to Analysis 2, the non-parametric frontier approach is used showing a number of differences in comparison with Analysis 2. First, Analysis 3 is not based on the assumption of a linear dependence of

the innovation output on the number of R&D employees, which is implicitly used in Analysis 2. Second, in Analysis 3, confidence intervals are calculated, so that random effects are accounted for and do not determine the outcome. Third, the use of this method allows to consider the effects other industries have which also patent into the same technological category.

**Analysis 4:** Finally, we study how results change if that factors representing local endowments are included in the analysis. Therefore, Analysis 3 is repeated including a number of local variables. The non-parametric frontier analysis allows for including additional variables in the performance measurement. The variables used are discussed below (Section 3.2).

Some aspects regarding the approaches taken need to be explained in more detail. These are the data used (Section 3.1), the data on resources included in Analysis 4 (Section 3.2), and the non-parametric frontier method used in Analyses 3 and 4 (Section 3.3).

### 3.1 Empirical data on patents and R&D employees

The 270 German labor market regions were chosen as unit of analysis, because they seemed to fit best to the theoretical arguments of a regional dimension of innovation processes (see, e.g., Broekel and Binder, 2007). As is common in innovation research the innovative output is approximated by patent applications. The data on the latter is published by the *Deutsches Patent- und Markenamt (German Patent and Trademark Office)* in Greif and Schmiedl (2002). Applications by public research institutes, such as universities and other research institutes (e.g. Max Planck Society) as well as those by private inventors are not included (as discussed in Section 2.3). In Analysis 1 the total number of patent applications for one region is used as published in Greif and Schmiedl (2002).<sup>1</sup>

As discussed above, we assume R&D employees to be the most important input variable. Data on R&D employees is obtained from the German labor market statistics. The R&D employees are defined as the sum of the occupational groups of agrarian engineers (032), engineers (60), physicists, chemists, mathematicians (61) and other natural scientists (883) (Bade, 1987, p. 194ff.).

An industry specific analysis requires the definition of an industry that, as in the present context, covers both the input and the output sides. In other words, our industry specific input data (R&D employees) need to reflect those firms' inputs for which we refer to the patent applications in Greif and Schmiedl (2002). This is an important point because these applications are classified according to 31 technological fields (TF). In contrast, our industry specific input variables (most importantly R&D employment) are organized according to the

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<sup>1</sup> Note that we use the up-to-date definition of labor market regions in contrast to an older definition in Greif and Schmiedl (2002).

German Industry Classification ('Deutsche Wirtschaftszweig Klassifikation') which is the German equivalent of the international NACE classification. Both, the technological fields classification by Greif and Schmiedl (2002) and the German Industry Classification, cannot be matched straightforwardly.

We use the concordance between these two classifications as developed by Broekel (2007). This defines five 'sectors' for which it is possible to assign a number of technological fields defined by Greif and Schmiedl to a number of industries defined by the German Industry Classification (for further details, see Broekel, 2007).

In this paper, we concentrate only on one 'sectors': the Electrics & Electronics industry, which is denoted as ELEC in the following.<sup>2</sup> Its definition in terms of included technological fields and industries is presented in Table 4.

In the following ELEC serves as an example for the construction of industry specific measures. Though this does not apply to all industries, in the case of ELEC, patenting represents an important protection mechanism for property rights (Arundel and Kabla, 1998). It ensures that the output measure captures most innovations in this industry. In order to reduce the effect of random events and year specific effects, all variables are estimated as averages of the years 1999 and 2000. Accordingly, the industry had 671,162 employees (representing 2 % of the total employment), 169,715 of whom were R&D employees located in Germany (representing approx. 25 % of this industry's workforce). On the output side this industry accounted for about 6,200 patent applications (approx. 21 % of total patent applications). These figures clearly show that ELEC is a highly research intensive industry.

### 3.2 Resources in the region

In Analysis 4 regional factors are included that are likely to influence the innovation output of a region. As discussed in Broekel and Brenner (2005), a large number of (regional) variables have been put forward in regional studies as potential influences on the innovativeness of firms. Although researchers have not yet a consensus as to the 'definitely' important factors, some 'core' factors are commonly employed in such analyses. Most of them were proposed by Feldman and Florida (1994) who defined a region's 'technological infrastructure' and by Griliches (1979) and Jaffe (1989) in their seminal works. Following this research, we define a 'German regional technological infrastructure' as consisting of factors with a purely regional effect and factors with an inter-regional effect. The first set of factors is argued to affect firms' innovation activities only if these are located in the same region. In contrast, the effects on firms' innovativeness of inter-regional factors are locally bounded to a lesser extent. Firms might benefit from the presence of these factors in a neighboring region.<sup>3</sup> In total, nine re-

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<sup>2</sup> Please note that the terms 'sector' and 'industry' can be arbitrarily used in this context. For the sake of readability we only use the term 'industry' in the remainder of this paper.

<sup>3</sup> All variables are only briefly presented due to space limitations. A more detailed description and literature references of most of the employed variables can be found in Broekel and Brenner (2005).



gional input variables are included in Analysis 4. They are summarized and their data sources are given in Table 5.

In order to account for urban agglomeration advantages the population density is used (POP\_DEN). The financial situation of the region as well as its economic activity is approximated by the gross domestic product (GDP) per capita. Furthermore, the literature highlights the importance of business services (see e.g. Feldman, 1994) so that the variable SERVICE has been added. This represents the number of employees in industry KA74 (according to WZ03). In a common fashion we compute the influence of SERVICE by using the Revealed Symmetric Comparative Advantage (RSCA) as defined by Laursen (1998).

The potential impact of the share of employees with high qualifications (EMP\_HIGH) is also considered because it is an often used measure for the quality of local human capital (Weibert, 1999).

As a proxy for a region's over-all endowment with private research facilities we computed the RSCA for total R&D employment with respect to over-all employment (ALL\_RD). In contrast to public research institutes, which are said to have an inter-regional spill-over effect (see next section), we assume the spill-over potential of ALL\_RD to be regionally bounded.

Another industry specific variable accounts for the specialization of a region in ELEC. It is approximated by the RSCA of the employees of ELEC and is added as variable ELEC\_RSCA. In adding ELEC\_RSCA as an input we follow Henderson et al. (1995) in assigning a positive impact to a region's degree of specialization in ELEC on firms' innovativeness. However, other studies find that industrial diversity, rather than specialization, fosters firms innovation processes (see e.g. Feldman and Audretsch, 1999; Fritsch and Slavtechev, 2007). Certainly, this point needs to be investigated further in future research.

These six variables are argued to affect only firms located in the same region. The factors presented below are regionally less bounded, requiring so that some additional discussion. The literature shows that university graduates who are thought to be important for firms' innovativeness do not stay in the region where they obtained their degree (Mohr, 2002). Furthermore, it is argued in the literature that knowledge transfers can be regionally bounded (Broekel and Binder, 2007). This regional local nature of R&D knowledge spill-overs is empirically confirmed by e.g., Bottazzi and Peri (2003). In the case of public research institutes Beise and Stahl (1999) show that firms' tend to name those institutes more often that are located close by.

In order to assign adequate shares of such interregional resources to the regions in which they are effective, we use a hyperbolic distribution procedure. As regards the graduates we define two parameters that determine the former's likelihood to move to a certain location.<sup>4</sup> First, the distance to the university where they graduated, and, second, the population in the graduates' likely region of destination. Two assumptions can be made: the greater the distance to

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<sup>4</sup> The same was done for the estimation of the spill-overs of public research.

their home university the less likelihood there is that graduates moves to that region; and the larger the population in the region of destination, the higher is the likelihood that graduates move there.

A hyperbolic function is assumed to calculate the probability of the move.<sup>5</sup> The parameters of the function are fitted by a maximum likelihood calculation, using geographic coordinates and population counts for 8.196 German five digit postal code areas. For this calculation, we used empirical findings from the literature on the mobility of graduates (see Legler et al., 2001; Mohr, 2002)<sup>6</sup>.

To control for size effects regarding a region's industry endowment, the distributed graduate counts are entered in the analysis as ratios of the region's total employment. For technological innovations, graduates of engineering and natural science faculties of technical colleges and universities are of special interest and have been included as variables GRAD\_ENG and GRAD\_NAT.

Similar to universities, public research institutes are important actors in innovation processes (Nicolay and Wimmers, 2000). Beise and Stahl (1999) show that a significant part of their influence operates inter-regionally. While their research output is highly codified (Schibany and Scharfetter, 2001) and only weakly affected by geographic distance, their employees' mobility which constitutes an important mechanism for knowledge transfer is clearly spatially restricted (Witt and Zellner, 2005). Thus we argue that these positive effects on firms' innovativeness decreases with a growing distance.

In order to approximate these institutes influence, the structural factor SCIENCE is constructed. It is defined as the sum of the number of employees working at different regional (public) research institutes. Included are the 'big four' institutions in Germany: the *Helmholtz Association of German Research Centers*, the *Max Planck Society*, the *Fraunhofer Gesellschaft* and the *Leibnitz Association*.<sup>7</sup>

Again, we assume that the influence of the public research institutes decreases hyperbolically with growing distance, as described. Assigned to postal codes the employees of these institutes are distributed via the same procedure as the graduates. The relevant parameters for the distribution procedure are calculated by using the findings of Beise and Stahl (1999). Table 3 summarizes the distribution parameters. SCIENCE is also computed as a ratio of total employment to control for differences in the regions' size.

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<sup>5</sup> We also estimated exponential and linear distributions, but found the hyperbolic distribution to be best fitting to empirical patterns as e.g. found in Beise and Stahl (1999) and Mohr (2002).

<sup>6</sup> Because the mobility data is only available separately for the graduates of technical colleges and universities, we had to weight them with their shares in the total numbers and sum them for the analysis of each subject. Furthermore, note that the  $\alpha$  value which determines the slope of the hyperbolic function is estimated by using the combined data for 1999/2000 because no year specific data on the mobility parameters is available.

<sup>7</sup> All institutes are included in this number, even those that are not technologically relevant such as institutes doing research on language or history.

### 3.3 A method to calculate innovation performance

The advantages and disadvantages of the different methods to calculate the innovation performance of spatial units have been discussed extensively above. In Analyses 1 and 2 we use the standard approach: dividing the number of patents by that of R&D employees. In Analyses 3 and 4 we use a non-parametric method, which is described in detail in the following.

Recent developments have improved the statistical foundation of non-parametric approaches for performance analyses, so that the robustness of the estimates is no longer limited. We use (and present) the robust non-parametric approach based on the order- $m$  frontier concept by Cazals et al. (2002). In addition the outlier detection procedure by Simar (2003) is used beforehand in order to identify the most extreme observations. These are then checked manually if they can be considered as outliers, and if so, are excluded. Finally, the impact of sampling error on the performance estimates is evaluated by calculating confidence intervals.

The most common non-parametric performance analyses, as e.g., the Data Envelopment Analysis (DEA) and the Free Disposal Hull (FDH) are based on the performance concept of Farrell (1957). Thereby, an efficiency analysis compares the actual output of a unit with the maximal output estimated by a production function. The *best-practice* units of a comparison group are used as reference for the evaluation of each unit. The main advantages of such non-parametric approaches are that no ex-ante specification of a functional form is needed, and only very few further assumptions need to be made.<sup>8</sup>

Before the method is introduced in more detail, some specifications have to be made in advance. In the context of this paper an output oriented version of the method seems to be the appropriate choice for the following reason: we intend to measure the ‘extra’ output of the units caused by regional factors that are not included in the analysis. This seems to be modeled more appropriately by the output-oriented version.

The order- $m$  frontier approach might be seen as a robust version of the FDH approach.<sup>9</sup> But in contrast to the traditional FDH, the idea behind the order- $m$  approach is to compare a unit’s input-output relation not to the complete population of units, but rather to a (conditionally) randomly drawn sub-sample. The advantage of such an approach is that it avoids that exceptionally well-performing regions (outliers in the statistical sense) dominate all comparisons (Cazals et al., 2002). The argument is that there might be regions that for some reasons, perform exceptionally well, for example because of random effects. These regions would become benchmarks for many other regions. The order- $m$  approach implies that the randomness of the performance in other regions is taken into account. The output-oriented order- $m$  frontier represents the expected maximally achievable output-level among  $m$  units that are drawn randomly (with replacement) from the population of all units that show at

<sup>8</sup> For an introduction see Scheel (2000); Daraio and Simar (2007).

<sup>9</sup> Thus the order- $m$  approach shares some of the characteristics of the FDH approach, e.g., variable returns to scale (see Cazals et al., 2002).

maximum the input level of the considered unit  $i$ .  $m$  might be considered a “trimming” parameter.

We refrain from presenting the complete model of the order- $m$  approach and only present a brief version of our estimate. For a detailed presentation see Simar and Wilson (2006). The main idea is simple: for a multivariate case consider  $(x_0, y_0)$  as the inputs and outputs of the unit of interest.  $(X_1, Y_1), \dots, (X_m, Y_m)$  are the inputs and outputs of  $m$  randomly drawn units that satisfy  $X_i \leq x_0$ .  $\tilde{\lambda}_m(x_0, y_0)$  measures the distance between point  $y_0$  and the order- $m$  frontier of  $Y_1, \dots, Y_m$ . It can be written as:

$$\tilde{\lambda}_m(x_0, y_0) = \max_{i=1, \dots, m} \left\{ \min_{j=1, \dots, q} \left( \frac{Y_i^j}{y^j} \right) \right\} \quad (1)$$

with  $Y_i^j$  ( $y_0^j$ ) as the  $j$ th component of  $Y_i$  (of  $y_0$  respectively). The order- $m$  efficiency measure of unit  $(x_0, y_0)$  is defined as

$$\lambda_m(x_0, y_0) = E[\tilde{\lambda}_m(x_0, y_0) | X \leq x_0] \quad . \quad (2)$$

The obtained performance measure represents the radial distance of the unit to the order- $m$  frontier. It converges for  $\lim_{m \rightarrow \infty}$  and  $\lim_{n \rightarrow \infty}$  toward the traditional FDH efficiency measure, where  $n$  is the total number of units. It has “several desirable properties” (Wheelock and Wilson, 2003), such as root- $n$  consistency, low sensitivity to noise in the data and the absence of the “curse of dimensionality” (see, e.g., Cazals et al., 2002; Wheelock and Wilson, 2003). This makes it a very attractive tool especially when the sample size is small (which is certainly given when analyzing regions). In order to calculate the order- $m$  frontiers Cazals et al. (2002) suggest to employ a Monte-Carlo approximation with 200 replications which is followed here. An open issue is the choice of parameter  $m$ . The literature does not yet provide a definite rule on how to choose the value of  $m$ . “Experience has shown that in many applications, qualitative conclusions are little affected by particular choices of  $m$ , provided the values of  $m$  are somewhat less than the sample size,  $n$ ” (Simar and Wilson, 2006, p. 78). Here we follow Bonaccorsi et al. (2005) in setting the level of robustness to ten percent, i.e. ten percent of the units are outside the frontier. In the following estimations this corresponds to a value of  $m = 90$  and is used as parameter value throughout the paper.

Note that the order- $m$  performance measure takes a value of one (less than one) for all regions that perform as predicted by (better than) the estimated frontier. The larger the performance measure is for a region, the less well this region performs. In contrast to traditional non-parametric performance estimators its score can drop below one for efficient units in the output-oriented case. The reliability of this estimate can be increased by a beforehand outlier detection procedure and the estimation of confidence intervals which is presented next.

For non-parametric efficiency analysis there are a number of methods for detecting outliers,

e.g., Wilson (1993, 1995); Simar (2003). We find Simar (2003) most convincing and best fitting to this context. The approach by Simar (2003) is based on the order- $m$  concept introduced above and fairly easy to implement. The basis of this approach is the estimation of input- as well as output-oriented order- $m$  performance scores. In contrast to the order- $m$  model presented above, Simar (2003) suggests to employ a ‘leave-one-out’ approach which is equivalent to the ‘super-efficiency’ concept of Andersen and Petersen (1993): During the estimation the unit of interest is excluded from the reference set. The calculations are conducted for different values of  $m$ . A unit is a potential outlier if its super-efficiency input order- $m$  efficiency measures are greater than one plus a certain threshold  $\alpha$  (in case of the output orientation, respectively, if the efficiency score is smaller than one minus  $\alpha$ ). This is underpinned if the unit’s input or output levels are close to the boundary of the data set. Note, however, that the researcher still has to take a close look at the data, in order at some point on excluding this unit from the relevant data set.

While the outlier-detection is conducted ex-ante to the robust performance analysis, we also estimate confidence intervals afterwards. The properties of the order- $m$  approach allow for using a simple naive bootstrap procedure to estimate them (Simar and Wilson, 2006). Thus we repeatedly apply the performance analysis to ‘pseudo’ data sets which are created by drawing identical, uniform and with replacement from the original data set.<sup>10</sup> The obtained scores are sorted in increasing order, subsequently the  $(\frac{\alpha}{2} * 100)$  percent of the elements at either end of the sorted lists are deleted. The new endpoints define the corresponding confidence intervals. We chose  $\alpha = 0.05$ .

The outlier-detection procedure as well as the estimation of confidence in combination with the robust non-parametric performance estimation seem to be a powerful tools for our approach. They allow using the strength of non-parametric frontier estimation and at the same time provide a very robust statistical foundation.

## 4 Results for the different regional innovativeness measures

### 4.1 Innovations per R&D employment (Analyses 1 and 2)

In Section 2.1 we suggested to use patent numbers per R&D employee as a (very) simple measure. In Analysis 1 all patents and all R&D employees are used. In Analysis 2 an industry specific approach is taken as argued in Section 2.4. The results of the two analyses are given in Figures 2 and 3. As we have argued in Section 2.4, the results of Analysis 1 are strongly biased by the industrial structure. This becomes obvious, for example, when comparing the obtained ratios: In 2000 the ratio for the tenth best region (Ludwigshafen with 5.87 patent

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<sup>10</sup> Following Hall (1986) we use 1000 replications for the estimation.

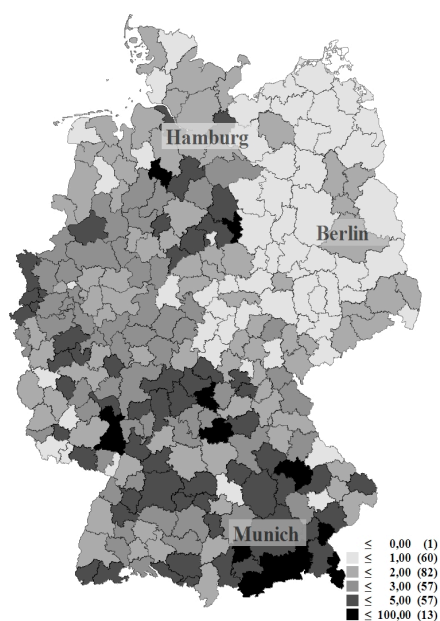


Figure 2: Analysis 1

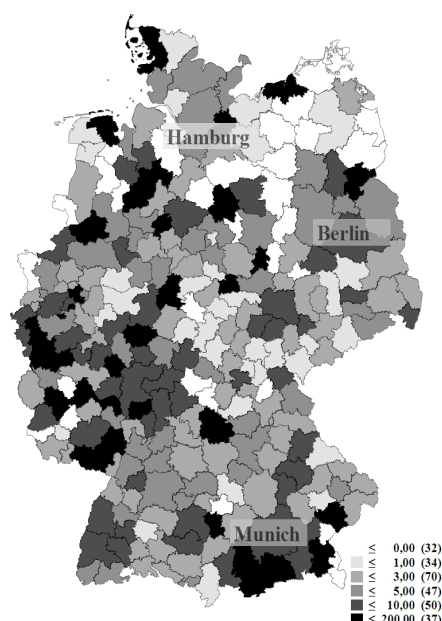


Figure 3: Analysis 2

applications per 100 R&D employees) is less than one third of the ratio of the best region (Helmstedt, 19.1 patent applications per 100 R&D employees). This means that the tenth best region performs not even one third as well as the best region. It is doubtful that such a measure represents innovative performance adequately. For example, the reason for the good performance of Helmstedt is the region's strong position in the transport industry including car manufacturing. This is a rather innovative and patent intensive industry. Because of its strong specialization the total measure is largely dominated by this industry.

Such a bias is avoided in Analysis 2. In contrast to Analysis 1 the patent application data is disaggregated for a single industry. However, setting up a correct specification of the industry specific input and output data set is problematic (see Broekel, 2007). The problem lies in the fact that a common innovation measure consists of patents which are classified by technological fields, e.g. the International Patent Classification (IPC) or, in our case, those proposed in Greif and Schmiedl (2002). In contrast most input variables are classified by industry classifications, as NACE. Thus the explanatory power of this measure depends strongly on the correct assignment of input to output data. We use the concordance by Broekel (2007) and concentrate on the R&D employees of industries DL30, DL31, and DL32, which represent the Electrics & Electronics industry (Broekel, 2007). On the output side, we use the patent application data of those technological fields that this industry patents into (see Section 3.1 for more details). These are TF27, TF28, TF29, TF30, and TF31.

The concordance by Broekel (2007) works fairly well for regions with substantial numbers of R&D employees in ELEC, but fails if only few ELEC R&D employees are present in a region. In these regions, the presence of R&D employees in other industries that patent into

the same technological field might strongly disturb the calculated performance. Therefore, we concentrate on regions with five or more ELEC R&D employees. The industry specific innovativeness measure for ELEC is given by

$$RI_r^{ELEC} = \frac{\sum(R\&D_{DL30}, R\&D_{DL31}, R\&D_{DL32})}{\sum(TF27, TF28, TF29, TF30, TF31)} . \quad (3)$$

Figure 3 shows the industry specific patent applications per 100 R&D employees scores for the German labor market regions. Similar to Analysis 1, the variance in this measure is quite large. The tenth best region's measure (Wolfsburg, 26.34) is less than 17 percent of that of the best region (Düren, 162.04). Again, this seems to be an inadequate representation of innovative performance. However, this problem may well be related to outliers because the tenth best score is about 70 percent of the fifth best measure (Landsberg, 36,82). Hence, this performance measure seems to react quite sensitively to outliers.

Apart from the variance of the values, which is still strong, a comparison between Figures 2 and 3 shows that the distribution of innovative performance changes visibly when it comes to industry specific data. Figure 2 shows the (usually found) distribution with a higher performance in the south of Germany and a very weak performance in former East Germany. Especially the latter disappears in relation to industry specific data. The former East Germany seems to perform less well in terms of a patents per R&D employees measure because it has less R&D employees in patent intensive industries. If only one patent intensive industry is considered, however, well-performing regions are also found in that part of Germany. The importance of the industrial structure is underpinned when comparing the scores of Analyses 1 and 2 with Spearman's rank correlation coefficient. It turns out that both scores are only correlated with +0.296\*\*<sup>11</sup>

To summarize, we find that a simple single input - single output measure (as Analysis 1 and 2) is easy to compute. The resulting index is, however, strongly biased by the industrial structure (Analyses 1) and the insufficient incorporation of other industries' effects on the output measure (Analyses 2). Furthermore, in Section 2 we argued that there are a number of disadvantages in using such a simple measure. Especially, it provides no information about why certain regions perform better than others. In addition, this performance measure is based on the assumption that innovation output should increase linearly with the number of R&D employees. This is a plausible assumption if R&D employees are employed in different firms. An increase of R&D employees in one firm, though, might, have different implications.

<sup>11</sup>\*\* indicate significance at the level of 0.01. Note, that the Spearman's rank correlation coefficient is used throughout the paper because most variables (including the performance scores) are not normally distributed.

## 4.2 Single-input, multi-output performance analysis (Analysis 3)

Analysis 3 takes some of these disadvantages into account. Especially, the assumption of a linear relationship is omitted. In addition, the different technological fields are treated as different output categories. As a first step, we consider all five technological fields as output variables that Broekel (2007) has assigned as being relevant to the Electrics & Electronics industry (TF27, TF28, TF29, TF30, TF31). Similar to Analysis 2, the R&D employment of the Electrics & Electronics industry is constructed as input by summing the R&D employment of industries DL30, DL31, and DL32 to a single variable RD\_ELEC. The non-parametric frontier analysis is used as described in Section 3.3.

Since we evaluate the performance of industry ELEC, all regions with no R&D employees or no output in ELEC are excluded to begin with, namely 23 out of the 270 labor market regions. In order to keep those regions in the analysis that do not show a positive value in all output variables, and to avoid distortion in the estimation, we follow Bonaccorsi and Daraio (2007) by adding a constant value of 0.01 to all input and output variables. Note that this has not effect on the obtained performance score because of the analyses' invariance to linear transformations. As in Analysis 2, we concentrate on regions with five or more R&D employees in ELEC. This excludes a further 16 regions. One of the regions (Schwandorf) is excluded because of data inconsistencies (zero employees in ELEC, but positive R&D employment (269)). This leaves us with a sample of 230 regions.

After the data has been prepared accordingly we check the correlation structures of the input and output variables, because the correlation structure affects the estimated efficiency scores (Smith, 1997). Variables that are correlated with 0.9 or above are excluded. Such a strong positive correlation is observed between the output variables TF27 and TF30 as well as between TF28 and TF31. Furthermore, TF29 shows many zero observations. Compared to the average of 1999 and 2000 it accounts for only 59 patent applications. In order not to lose the information of the output measures, we sum the number of the patent applications of those technological fields (except for TF29) that are correlated with 0.9 or above. The patent applications of TF29 are added to the output variable with which it correlates most strongly. In the end, we are left with two output variables TF28\_31 (sum of TF28 and TF31) and TF27\_29\_30 (sum of TF27, TF29, and TF30).

The final data set consists of 230 regions, one input and two output variables. These are summarized in Table 6. The correlation analysis is followed by the outlier detection analysis, which did not indicate the existence of any 'not-normal' observations. The performance analysis described in Section 3.3 provides a confidence interval for the performance measure for each region. This measure is given in form of the inverse of the ratio between a region's output and the output that could be reached given the inputs of the region (Farrell-measure). This ratio is an empirical estimate. For this reason we do not present the obtained ratios for each region in the following analysis but use the 0.95 confidence intervals (see Section 3.3). This



allows us to detect regions for which we can significantly state that they are as good as could be – calling them significantly well-performing – and regions for which we can significantly state that they do not reach the performance level that would be possible – calling them significantly less-performing –, given the R&D employees present in the regions. Twenty-five regions are significantly well-performing, while 153 are significantly less-performing. For 52 regions no significant results are obtained. The results are shown in Figure 4.

Comparing the results of Analyses 2 and 3, some differences can be observed. Not all the regions found to be significantly well-performing according to Analysis 3 performed also well in Analysis 2, and regions found to be significantly less-performing according to Analysis 3 do not always perform averagely or below according to Analysis 2. For example, Berlin, identified in Analysis 3 as well-performing, shows a ratio between patent application and 100 ELEC R&D employees of only 3.77 (Analysis 2). On average, this ratio is about 6.93. Similar results can be observed for Stuttgart, Erlangen and Nürnberg. In contrast, Oldenburg shows a very high ratio in Analysis 2 (9.37) but is identified as less-performing in Analysis 3.

These distortions demonstrate one of the strengths of the chosen approach: it is less sensitive to outliers because regions are only compared to similar regions, i.e. those showing at most the same input level as the unit under consideration. In addition, the unfolding of the output data into two different technologies and the non-parametric character of Analysis 3 seem to have an effect on the results. For example, it seems that the consideration of variable (especially non-increasing) returns to scale is important. However, this remains speculative for the time being and needs further investigation in future research.

Despite these differences, the performance scores of Analyses 2 and 3 are correlated at  $r = -0.727^{**12}$ .

What is striking, is that especially large agglomerations like Munich, Berlin, Frankfurt am Main, and Stuttgart are identified as efficient. There are two possible explanations for this finding. First, we might interpret this as an indication of the impact of agglomeration advantages (see, e.g., Audretsch, 1998; Feldman, 1994; Cooke et al., 1997). Second, this could be an outcome of the employed concordance between industry specific data and patent application data. We know of several other industries patenting into the technological fields serving as output variables in this investigation; on this, see Section 3.1 and Broekel (2007).

Since in this analysis the R&D employees of these industries are not considered as inputs, we can expect a higher performance in regions where these industries show an above average presence. Of the industries whose firms patent into one of the technological fields considered as outputs in this analysis, DL33 is the most important one (see Tables 4 and 5 in Broekel, 2007). The correlation coefficient between the performance score of Analysis 3 and the R&D employees of DL33 shows only a weak relation of  $-0.479^{**}$ . Thus, we can not neglect an influence on the performance results of other industries whose R&D employees are not considered

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<sup>12</sup> Please note, that in Analysis 3 inefficiency is indicated by large efficiency scores.

here, but this effect does not seem to be predominant.

The important step taken in Analysis 3, however, is that in addition to assigning a performance estimate to each region, a confidence interval is calculated for this estimate. This allows to distinguish between regions that might perform as well as possible given their endowment (here the number of R&D employees) and regions for which we can state on a significance level of 5% that they perform less than others with similar endowments. In this way, Analysis 3 accounts for the random effects that influence the innovation output of a region. It avoids assigning high performance measures to regions because of random effects. A more conservative approach is taken here which only classifies regions into three categories. What can be stated with certainty is that regions in the first category (significantly well-performing) are performing better than regions in the last category (significantly less-performing).

### 4.3 Innovation performance including regional factors (Analysis 4)

The procedure for the multi-input, multi-output measure that includes the effect of regional factors is similar to the one just presented (Analysis 3). Regions with less than five R&D employees in ELEC and zero values in the output measures are again excluded. A constant of 0.01 is added to all other variables. The outlier detection procedure is repeated. Again, it does not show any critical cases, leaving 230 regions to be evaluated.

In contrast to Analysis 3, variables that approximate the regional and inter-regional factor endowment are included in Analysis 4. As discussed in Section 2.3 all factors are multiplied by the number of R&D employees of ELEC. As a by-product this raises the correlation between the output and input variables (because the R&D employees are highly correlated with the corresponding patent data). This increases the stability and robustness of the results (Smith, 1997) and reduces the effect of variables not included in the analysis (Smith, 1997; Ruggiero, 2005). Thus, while the model becomes more realistic, its statistical properties are enhanced as well.

In Analysis 4 the output variables are the same as in Analysis 3, TF28\_31 (sum of TF28 and TF31) and TF27\_29\_30 (sum of TF27, TF29, and TF30). On the input side the nine local resource variables (see Section 3.2), multiplied by the number of R&D employees of ELEC, are considered (see Table 6). Again, the correlation structure is checked and highly correlated variables are excluded. From the variables that are correlated with 0.9 or above with each other the variable with less theoretical relevance is excluded. The strong correlation (above 0.9) of the specialization measure ELEC\_RSCA with the presence of total R&D personnel in the region (ALL\_RD), the size of the service sector (SERVICE), and the GDP is possibly a result of the concentration of R&D facilities in urban areas. We keep ELEC\_RSCA in the analysis because it is the most industry specific measure of the four variables.

In addition, the graduates of engineering faculties (GRAD\_ENG) are strongly correlated with the graduates of natural & science faculties (GRAD\_NAT) and the staff of public research

institutes (SCIENCE). The reason for this is their concentration in urban areas as well as the effect of the hyperbolic distribution method which distributes these variables similarly across regions. Because most ELEC R&D employees are engineers by training (98.5% according to German labor market statistics), GRAD\_ENG serves as an approximation for the impact of the public research and education infrastructure. Hence, GRAD\_NAT and SCIENCE are not considered.

Altogether four variables are obtained on the input side and two on the output side. They are summarized in Table 6.

The results of Analysis 4 are presented as those of Analysis 3 (see Fig. 5). Fifty-eight regions are significantly well-performing, 101 regions are significantly less-performing and for 70 regions no significant results are found. Generally the results are not too different from those in Analysis 3. The Spearman rank correlation coefficient of +0.890\*\* indicates a (very) strong similarity between the results, possibly because of the multiplication of the regional variables with the number of ELEC R&D employees. This homogenizes their structure and reduces the likelihood to observe substantial changes between the results of the two analyses. Hence, it may be appropriate to lower the strong assumption of non-substituability of the R&D employees in future research. In Analysis 3, the benchmark is created by using other regions with

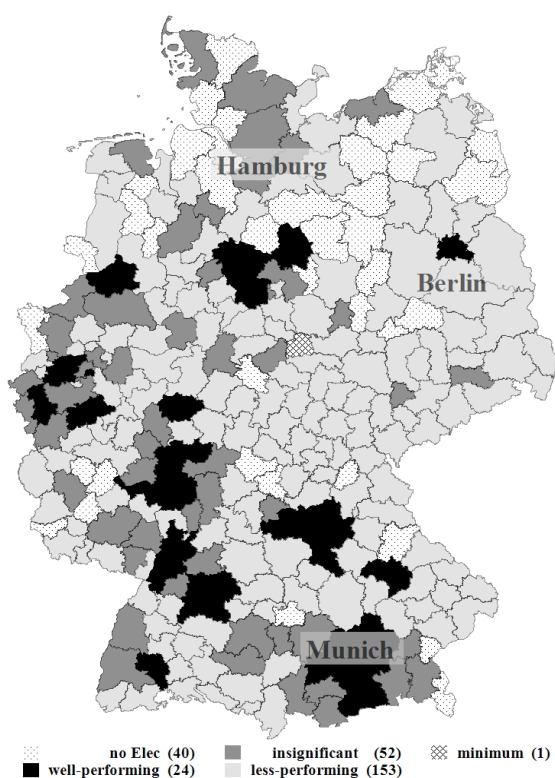


Figure 4: Analysis 3

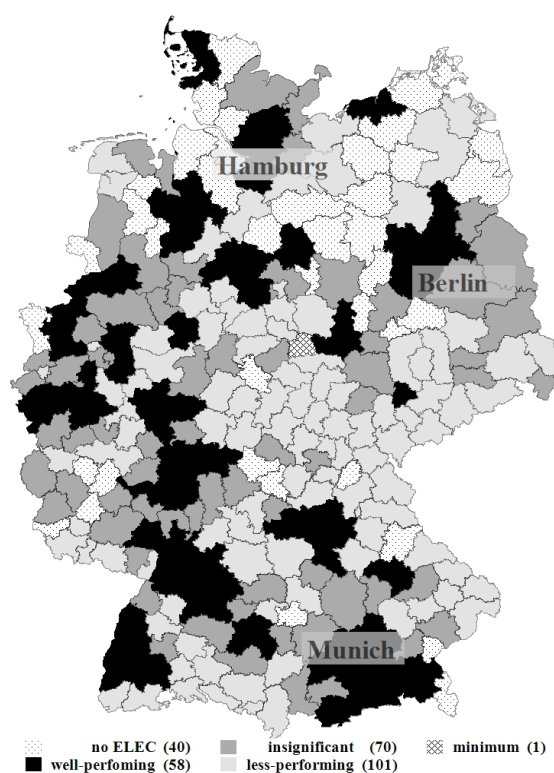


Figure 5: Analysis 4

similar numbers in R&D employment<sup>13</sup>. In Analysis 4 the same type of analysis is conducted as in Analysis 3, but with a benchmark defined by R&D employment numbers and available resources.

All regions with the minimum value in at least one input are automatically declared well-performing (efficient). This is a result of the employed method and the chosen orientation (output orientation). The number of such regions will tend to increase as more input factors are considered. However, the strong impact of ELEC R&D employment on the input variables (because of multiplication) reduces this effect substantially. Thus in Analysis 3 and 4 we found only one region with the minimum input, it is the same region in both analyses, Nordhausen, with a minimum of R&D employment in ELEC. It is not considered as an efficient region in the following and listed in brackets in Table 1.

Again, mainly agglomerations are found to be well-performing. Moreover, the presence of industry DL33 in a region, which is the most important other industry that patents into the technological fields used as outputs here and whose R&D employees are not considered as inputs, seems to have an influence on the obtained performance scores. They are correlated with this industry's R&D employment at  $-0.461^{**}$ .

The differences between Analysis 3 and 4 provide additional insights. Combining these analyses, we obtain nine different possible results for each region (see Table 1). Five of the nine cells in Table 1 represent cases in which the status of a region's performance score changes from significant to insignificant and vice versa. This is true for cells **D**, **B**, **E**, **H** and **F**. These cases are not discussed further because they might be a result of a statistical error. Hence four interesting cases with significant results are left for discussion. The first group of regions, cell

		<b>Analysis 4</b>		
		Well-performing	Insignificant	Less-performing
<b>Analysis 3</b>	Well-performing	<b>A</b> 24 (1)	<b>B</b> 1	<b>C</b> 0
	Insignificant	<b>D</b> 27	<b>E</b> 25	<b>F</b> 0
	Less-performing	<b>G</b> 8	<b>H</b> 44	<b>I</b> 101
Number of regions with minimum input in parentheses.				

Table 1: Number of regions and their performance in Analyses 3 and 4 in 2000.

**A**, is found to be well-performing in both analyses. Remember, that the performance measure is calculated by comparing the region's output with the best performing other regions that show similar inputs. The best performance is taken as a benchmark. A performance is implicitly defined as 'standard' if it is at least not significantly below that level. Regions that are found to be well-performing in both analyses are in line with this standard. No deviation from what could potentially be reached has to be explained. With 24 regions a considerable number of well-performing regions are found in both analyses.

<sup>13</sup> This is done by the order- $m$  frontier method in a complex but statistically sound way.

Next 101 regions are found that are less-performing according to both analyses, cell **I**. These regions have a lower innovation output than others with a similar number of R&D employees. This implies that R&D employees are less innovative in these regions. One explanation that comes immediately to mind is that the local circumstances might be less favorable in these regions. However, they are also found to be less-performing in Analysis 4. Apparently the local resources, at least those included in this analysis, do not explain the weak performance of these regions. Other causes could be non-measurable local factors, such as culture or networks, and the presence of specific firms that have a lower probability to patent their innovations.

There are eight regions that are found to be less-performing in Analysis 3 and well-performing in Analysis 4, cell **G**. The two analyses differ only with respect to the inclusion of additional input variables in Analysis 4: the regional factors multiplied by the number of ELEC R&D employees (the R&D employees in ELEC are excluded instead). The result can be interpreted as follows: these regions have a low innovation output (number of patent applications) with respect to the number of R&D employees located in it. This means that these R&D employees are not very innovative. However, a region performs well if the performance measure is a result of the availability of various (beneficial) resources in the region. The comparatively low innovativeness of the R&D employees is thus well explained by a comparatively low endowment with resources. We can state that these regions perform comparatively weak in terms of innovation output because they do not have sufficient resources at their disposal.

Finally, we find no well-performing regions in Analysis 3 that are less-performing according to Analysis 4, cell **C** which is no surprise. As stated in Section 2.3, the more factors that are involved in the generation of innovations are included in an approach, the easier it becomes to explain the variance in the innovation output. All innovation performance measures are based on the difference between the explained output and the real output. Hence, if we include an increasing number of variables in our analysis, we can expect that an increasing number of regions will show an output consistent with the benchmark and can, thus be classified as well-performing.

Regions that are found to be well-performing on account of the inclusion of additional factors are relevant for understanding the reasons underlying the innovative performance of regions. It is shown that an additional factor can be responsible for their under-performance. In the case of Analysis 4, which includes a number of additional factors, eight such regions are found. However, there are further regions that change from being insignificant (Analysis 3) to being significantly well-performing (Analysis 4) (cell **D**:27) or from being significantly less-performing (Analysis 3) to being insignificant (Analysis 4) (cell **H**:44). Altogether there are 71 regions that show such a result. Only one region that moves though insignificantly in the opposite direction (cell **B**:1), demonstrates that the shift toward a better performance in Analysis 4 can not be explained entirely as statistical artifacts.

From this we can conclude that the difference between the potential and actual innovation

output of a number of regions can be explained fully or partly by the local variables that are included in Analysis 4. This shows the strength of the approach taken in Analyses 3 and 4. Through the inclusion of different factors it has been possible to analyze how these factors contribute to explaining the innovation output of regions. We could even detect which factors are crucially relevant in which regions.

## 5 Conclusions

This paper's contribution is twofold: first, an extensive discussion of how innovation performance is, can, or should be measured and, second a method that can be used to measure innovation performance and examine the factors that influence innovation output has been presented. In the literature, innovation performance is usually equated to innovation output or innovation output per inhabitant, employee, or R&D employee. This raises the question of what performance means in the context of innovation and how it should be measured, a question that is widely ignored in the literature.

We argue that performance is measured in relation to a benchmark and that the benchmark represents what the researcher assumes to be normal, standard or optimal. Different benchmarks can be used because there is no theoretical argument that disallows to deduce only one correct benchmark. It should be noted, however, that each benchmark entails a number of assumptions. These concern the unit of analysis, of whether the benchmark is the same for all industries, of whether it should be defined in relation to the resources of each unit, and the question of the functional form of the relationship between resources and innovation output in the benchmark case. Each of these topics has been discussed in this paper.

We further argue that industries should be studied separately and that functional forms should not be fixed, implying a non-parametric approach. Most importantly, however, we argue that the simultaneous application of several measures that are based on the inclusion of more or less, resources provides additional information about the causes underlying the innovation performance of spatial units.

In order to pursue an approach using such various measures, a method is proposed here based on the robust non-parametric performance analysis that usually serves to calculate the efficiency of production units. We have applied this method to the German Electrics & Electronics industry. This has allowed us to distinguish three types of regions: those that perform well; those that perform weakly, but whose weak performance can be explained by the availability of local resources; and those that perform weakly without our method being able to explain their performance. This categorization is statistically significant and is not based on any assumption about the functional form that describes the relationship between resources and innovation output.

This paper describes only a first application of the method we propose. More information

about the causes of performance can be obtained by doing the calculation on different sets of resources. Other industries should also be studied to learn more about the innovation performance in different industries. We see this paper as a starting point of a promising line of research.

## Appendix

Distance	< 50km #	50 < 200km #	Share 1999	Share 2000
GRAD_ENG (university)	48.8%	29.8%	41.6%	40.7%
GRAD_ENG (tc)	42.3%	35.5%	58.4%	59.3%
GRAD_NAT (university)	61.2%	14.9.9%	89.7%	89.8%
GRAD_NAT* (tc)	45.4%	36.0%	10.3%	10.2%

\* No data available, the shares of all technical graduates taken together are used.  
 # Data based on Legler et al. (2001) but adjusted for inner Germany mobility

Table 2: Graduates Mobility

Spill-over source	Empirical values		Estimation		$\alpha$
	< 50km	200km <	< 50km	200km <	
GRAD_ENG	45,1%	33,1%	44.70%	34.35%	1.4851
GRAD_NAT	60.0%	17.0%	56.34%	29.29%	1.6358
SCIENCE #	36.0%	34.0%	34.82%	37.36 %	1.3197

Estimation based on sum of 1999 and 2000 data.  
 # Numbers are approximated from data in Beise and Stahl (1999).

Table 3: Range of spill-overs of R&D institutes, hyperbolic distribution

Technological fields of Greif and Schmiedl (2002)	NACE industries
TF27, TF28, TF29, TF30, TF31	DL31, DL32, DL30

Table 4: Definition of the Electrics & Electronics industry according to Broekel (2007)



Variable	Description
RD_ELEC	R&D employees of industries DL30, DL31,L32
EMP_HIGH	Share of employees with high qualification
GDP	Gross domestic product per inhabitant
ELEC_RSCA	Revealed symmetric comparative advantage (RSCA of DL32)
POP_DEN	Inhabitants per <i>kilometer</i> <sup>2</sup> land area
SERVICE	RSCA of WZ03' category 74: 'other business activities' (business services) industry
ALL_RD	RSCA of total R&D employment
GRAD_ENG	Engineering graduates per employee
GRAD_NAT	Natural and science graduates per employee
SCIENCE	Researchers at public research institutions per employee
TF27	Patent applications in technological field 27, from Greif and Schmiedl (2002)
TF28	Patent applications in technological field 28, from Greif and Schmiedl (2002)
TF29	Patent applications in technological field 29, from Greif and Schmiedl (2002)
TF30	Patent applications in technological field 30, from Greif and Schmiedl (2002)
TF31	Patent applications in technological field 31, from Greif and Schmiedl (2002)
TF28_31	Sum of TF28 and TF31
TF27_29_30	Sum of TF27, TF29, and TF30
All shares refer to total employment	

Table 5: Variables, estimation base, and sources

Variable	Analysis 3	Analysis 4
Output		
TF28_31	×	×
TF27_29_30	×	×
Input		
EMP_HIGH		×
GDP		—
ELEC_RSCA		×
POP_DEN		×
SERVICE		—
ALL_RD		—
GRAD_ENG		×
GRAD_NAT		—
SCIENCE		—
× indicates inclusion		
— exclusion because of correlation		

Table 6: Variables and their employment

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