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Thomas Brenner & Tom Broekel

Utrecht University
Urban & Regional research centre Utrecht

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METHODOLOGICAL ISSUES IN MEASURING INNOVATION PERFORMANCE OF SPATIAL UNITS

Thomas Brenner and Tom Broekel*

Philipps University Marburg, Germany
and
Utrecht University, The Netherlands

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Abstract

Measuring the innovation performance of regions or nations has been repeatedly done in the literature. What is missing in the literature is a discussion of what innovation performance of a region means. How do regions or nations contribute really to the innovation output of firms? And how can this contribution be investigated in an empirically sound way? We argue that while the literature offers many suggestions, their theoretical foundation is often weak and the underlying assumptions are rarely discussed. In this paper, we systematize various mechanisms by which spatial units influence firms' innovation activities. On the basis of this, common innovation performance measures and analyses are discussed and evaluated. It is concluded that there is no general best way of measuring the innovation performance of spatial units. In fact, the most interesting insights can be obtained using a multitude of different approaches at the same time.

Keywords: innovation performance, regional innovativeness, innovation generation, regional innovation system, national innovation system

JEL codes:: R11, R15, O31

*Corresponding author: Thomas Brenner, Philipps University Marburg, Deutschhausstr. 10, 35032 Marburg, Germany. *Phone*: +49 6421 28 24211. *E-mail*: thomas.brenner@staff.uni-marburg.de

1 Introduction

The innovation performance of regions or nations has repeatedly been investigated (see, e.g., Nijkamp and Kangasharju, 2001; Kostiainen, 2002a,b; Oinas and Malecki, 2002). The literature contains a lot of discussion about the right operationalisation of innovations, but little discussion about what innovation performance means in the context of regions or nations. It is often implicitly assumed that regions showing higher innovation output (e.g. a higher number of patents) or higher innovation inputs (e.g. large spending on R&D) are more innovative. Measures that are used for capturing inter-regional and inter-national differences in this context are furthermore corrected for the size of the spatial units (e.g. by dividing them by the inhabitants number). However, the underlying assumptions and meanings of these approaches to the measurement of spatial units' innovativeness are little discussed.

This paper provides a fundamental and comprehensive discussion of what innovation performance could mean and how it can and should be measured in the context of spatial units. We argue that there is no best way for such a measurement. Instead, there are different ways how innovation performance can be defined and corresponding ways of measurement. In order to interpret the results of these different measurement procedures, we require an understanding of the mechanisms underlying innovation activities within a spatial unit.

In this context, we systematize the various mechanisms through which spatial units contribute to firms' innovation performance. By doing so a comprehensive overview of the various mechanisms and processes is provided, which is so far missing in the existing literature.

To this end, we first discuss theoretically how the characteristics and history of spatial units influence the generation of innovations within this unit. We consider in this analysis historical events, interactions between the various characteristics of the region, and self-augmenting processes. We find that there are two fundamentally different ways in which local characteristics influence innovation generation: the unit's characteristics attract more or less innovative activities and innovation generators to the spatial unit and the unit's characteristics make innovation activities more or less effective. Different measures are needed to detect these two kinds of contributions of spatial units to the innovation output of actors located within.

On the basis of this understanding, the most commonly applied measures of innovation performance in the literature are examined. It is shown that they measure quite different things. Furthermore, in the case of some measurements it is important which local characteristics are included. In some cases the results are blurred or, at least, made more diffuse, when multiple characteristics are simultaneously investigated.

This leads to the final aim of this paper: Inferring some recommendations about a number of issues that are connected to the measurement of innovation performance. These issues are the question of whether to analyze the whole economy together or industries separately and the choice of variables included in the analysis.

The paper proceeds as follows. In Section 2 a detailed discussion is provided of how characteristics of the spatial unit influence the innovation output. From this a conceptual model of the innovation generation in spatial units is inferred and two fundamental mechanisms are detected. The various approaches applied in the literature are evaluated on the basis of the previously developed concept in Section 3. Section 4 provides a discussion on two important issues in the context of measuring innovation performance. Section 5 concludes.

2 Innovation generation in spatial units

In a first step, in this section, we develop a detailed picture of the various ways in which a spatial unit influences the innovation output generated within this unit. There is an extensive literature discussing the influence of certain geographical factors on innovation generation. It is also theoretically discussed and empirically studied why and how these factors influence innovations activities within spatial units. Examples of such theoretical discussions and empirical estimations of the relevant local factors can be found in the classical works by Jaffe (1989), Feldman and Florida (1994), and Anselin et al. (1997), and the more recent contributions by Weibert (1999) and Broekel and Brenner (2005). These studies focus however on a particular empirical model and do not provide an overview of different approaches. They also do not discuss in detail what innovation performance means and on which basis to compare spatial units in this respect.

In the literature the term 'innovation performance' is not precisely defined in the context of spatial units. There are many papers that measure the innovation performance of regions or nations but most of them simply use output measures, such as patent numbers, or a mixture of measures. A detailed theoretical discussion of how to approach such is missing (see however Carlsson et al., 2002). In economics, performance is usually defined as the achievements in comparison to the costs, or more generally as the produced outputs in comparison to the used inputs. In the context of spatial units and the innovation generation therein, the question arises of what are the inputs and what is the contribution of the spatial unit.

Therefore, we start our analysis with a reflection on the performance of firms and how this can be transfered to the innovation generation in spatial units (Section 2.1). Then, the various kinds of impacts of the spatial unit on the innovation processes are described in Section 2.2. In Section 2.3 meaningful distinctions between the types of mechanisms are developed. Finally, in Section 2.4, on the basis of the structure developed we set up a mathematical model that describes the impact of a spatial unit on the innovation activity therein.

2.1 The production allegory

When accessing the economic performance of firms the output is set into relation with the invested input. For example, firms' performance is seldom compared in absolute terms but rather in relative terms, e.g. on the basis of the return on investment or turnover growth. No one would argue that a large multinational electronic producer is outperforming the local electronics manufacturer because it managed to increase its turnover by another billion while the local manufacturer grew only by thousand Euros in the same time period. However on the basis of the return of investment a comparison is commonly accepted. For example, the multinational may have managed to boost its return on investment to seven percent while the local electronics manufacturer achieved ten percent. The latter can clearly be regarded as outperforming the first.[1]

Interestingly the same does not always hold when talking about innovativeness. Here frequently the absolute number of innovations determines the perceived image of firms, regions, and nations. For instance, if the multinational company applies for a thousand patents and the local electronic store for a single one, often the first is perceived as being more innovative. That the multinational may have invested ten-thousand times the efforts of the local manufacturer is hereby neglected. A reason can probably be found in the positive connotation of innovations, i.e. it seems consensus that it is normatively desirable to maximize the number of innovations. Hence, the positive image assigned to technological progress seems to bias peoples' perception.

However, when looking from an economic stand point at innovation processes it is clear that innovations do not "fall from heaven" but that creative actors and certain resources are needed for their creation (Nelson, 1959). Frequently, the allegory of production processes is used in this context. In fact, this allegory is the basis for the famous *knowledge production function* approach by Griliches (1979). It has to be pointed out that as a main difference innovation processes are by their very nature non-deterministic while production processes are largely deterministic. This is commonly acknowledged and implies that a different terminology might be more adequate: Instead of production *inputs* we will speak of *(input) factors* and for *output* we use *innovation output*. Hence, corresponding to this view innovations are results of economic activities that involve creative actors and scarce resources, i.e. it is costly for actors to innovate. In this, innovation processes are similar to standard production processes. Nevertheless, besides their non-deterministic character, it is worthwhile to review some further characteristics of production processes and discuss them with respect to their applicability to innovation processes.

In production processes resources are commonly exhausted when transformed into output. At least, during the processes they cannot be used otherwise. Undoubtedly, the same holds for innovation processes. Man- (or better brain-) power as well as certain equipment are needed for creating innovations. In industrial set-ups this involves laboratories, testing facilities, engineering software, and so on. Of course, actors' time and the equipment could be used differently implying the presence of depreciation and opportunity costs. However, there are also input factors that are frequently included in the analysis of innovation processes, such as urbanisation, that are not exhausted or could have been "used" otherwise. Especially on the level of spatial units it is obvious that not all characteristics are exhausted during or exclusive for particular innovation processes. Factors, such as urbanization, might be regarded as a certain 'organizational principle' that effects the working conditions of actors. In addition, it might be a public good, i.e. with no rivalry and exclusivity in use. However, this

[1] Only when scale effects are absent.

already shows that the production allegory has its limitations in the context of innovation processes. Furthermore, there is an important distinction between inputs and external factors in production theory (see Banker and Morey, 1986). While the first are under control of the unit investigated, the later are not. In contrast to firms, spatial units are no organizations that have a clear centralized governmental structure. This implies that no factor is really under control and hence, a separate treatment of the two does not seem to be helpful. In contrast, it is discussed below that there are input factors in innovation processes that have different functional meanings, which could be used for classification. By making use of the production allegory, firms' innovation performances can be estimated by setting the innovative output into relation with the input factors. Of course, this requires that the efforts put into innovation processes and the obtained innovative output can be quantified and valued.[2] A clear quantification of the input factors is, especially in the case of a spatial unit, difficult.
Given the strong normatively motivated aim to increase innovativeness, it is essential to gain a deeper understanding of innovation processes. From the above it becomes already obvious that for achieving this the production allegory has its limitations. Nevertheless, many researchers make use of it for investigating the innovation performance of spatial units and we think, they do so rightly. However, it has to be carefully applied and researchers need to be highly aware of what they are actually measuring when applying this concept. While using the terms 'innovation output' and '(input) factors' in the following, we will repeatedly come back to the issue behind this.

2.2 Mechanism and dependencies

In order to be able to structure the different mechanisms influencing the innovation generation in a spatial unit, we have to identify all mechanisms first. We start with identifying the factors that influence the innovation output of such a unit. The output is given by the total number of innovations that originate from actors located in a spatial unit. We might now ask what does the region provide or contribute to the explanation of this innovation output. Four different kinds of characteristics of or situations in the spatial units might have an influence here:

Fixed characteristics of the unit: Examples are the geographic profile, the geographic location, and natural resources. These characteristics are given and do not change on the time scale that is relevant here. In the literature there are no studies that report a direct impact of this kind of factors on the innovation activity, but these factors influence other factors, especially the question of what kind of industries are active in a certain region or nation. For example, the relevance of natural resources is repeatedly discussed in the literature on clusters and spatial concentration of industries (see, e.g., Ellsion and Glaeser, 1999).

Characteristics of the population within the spatial unit: Examples are the population size, the population density, the spatial structure of settlement (cities or rural areas), and culture. These characteristics are influenced by the fixed characteristics of the unit, but historical events also

[2] We refrain from discussing the exact measurability of these.

matter. They change quite slowly. Several studies in the literature find an influence of these factors on the innovation activities in regions or nations. For example, it is repeatedly found that innovation activities are more frequent in cities (Feldman and Audretsch, 1999). Culture is also found to play a role (Saxenian, 1998). In particular, in empirical approaches it is often controlled for the population size of the spatial unit. Implicitly this assumes that it is related to the innovation activities, i.e. it is argued that more people generate more innovations (see, e.g., Audretsch, 1998).

Policy settings and activities in the spatial unit: Examples are tax policies, regulations, education, transportation infrastructure, public research, and specific policy measures. The policy in a spatial unit is influenced by population characteristics, particularly culture, but also by population density. Policy settings are also influenced by the fixed characteristics of the spatial unit. Furthermore, the specific history of the spatial unit might influence the policy setting. Finally, policy often reacts to the economic development in the spatial unit. At the same time, it also influences population changes and impacts on the economic development. Empirical studies find that policy settings and activities, especially education and public research, have a strong impact on innovation activities (Jaffe, 1989; Feldman, 1994). Public research can even be seen as an actor that generates innovations, although the economic definition of innovations requires a successful use of the invention on the market, which is rarely done by public research institutes and universities.

Economic activities in the spatial unit: Factors of this kind are, for example, the industrial structure, the number of firms, the number of employees, and characteristics of the firms, such as their size and R&D intensity. The economic activities interact with the population characteristics - economic activities probably change faster than population characteristics - and 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 also matter. The empirical literature provides plenty of evidence for an impact of the economic activities on the innovation activities in a spatial unit (Bode, 2004; Greunz, 2004; Broekel and Brenner, 2005). Most innovations are conducted by firms, especially by their R&D employees. It is also found that the size and the industrial characteristics of the firms matter for their innovation generation.

Considering the innovation output of a spatial unit, we find three kinds of actors that produce this output: firms with their R&D activities, public research, and private people. In Germany 83.5% of the patents have been applied for by firm in 2005. Public research has contributed 3.5%. The remaining 13% of the patents have been applied for by private persons, many of them owning a firm but intending to keep the rights on the innovation independent from the firm (Greif et al., 2006). Patents are a limited measure for innovation activities because many innovation activities are not patented and many inventions are patented but never reach the market. Nevertheless, the above numbers give

us an impression of which are the crucial actors generating innovations, namely private firms.
However, all other factors listed above are also important for the innovation generation process. They support the innovation generation. For example, specific policy measures might offer firms additional financial resources to conduct innovation projects. Other firms and public research institutes might act as cooperation partners in innovation projects. Cultural aspects and education also influence the ability of actors within a spatial unit to cooperate and innovate. Hence, the other factors that are listed above enlarge the input factor set available for innovation processes or enable actors to use the given input factors more effectively.
Besides all the above influences, we have to keep in mind that generating innovations is a process that cannot be completely planed. Sometimes fortune makes one innovation processes more successful than another. This implies for modelling innovation generation that there is a certain degree of randomness involved.
Putting all the above discussed arguments together, we can draw a model of the innovation generation within a spatial unit. This is done in Figure 1. We draw this model in order to get an overview on all relevant processes and to be able to structure the processes in the next section.

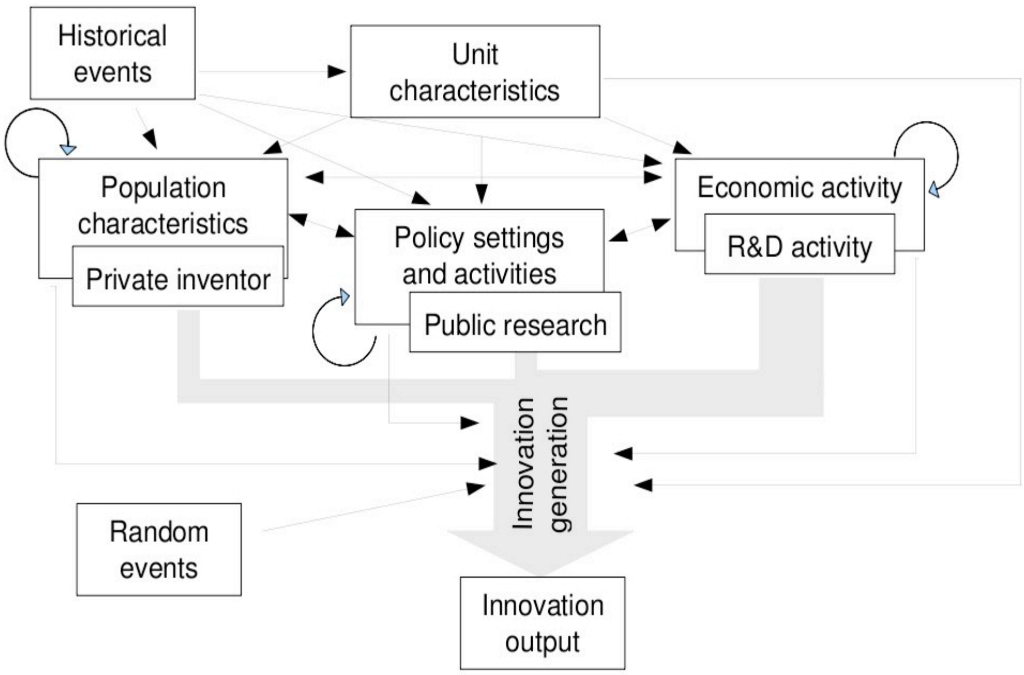

Figure 1: Interactions that cause the innovation output of a spatial unit.

We neglected one kind of interaction in Figure 1: The innovation activity within a spatial unit has also effects on the other factors. For example, a high innovation output can lead to an increase in economic activity over time and will make the region attractive for people to move there. For the sake of simplicity we leave this feedback processes aside and neglect all causal relations from the innovation activity on any of the other local factors. However, we acknowledge that these relations exist and shape the system over time.

2.3 Structure of innovation generation

In a next step, we identify a number of structurally different mechanisms in the above model (see Figure 1). To this end we simplify the model, focusing on the roles that various factors play. There are three fundamentally different roles.

First, there are factors that actively generate innovations. These are namely R&D employees in firms[3], researchers in public research facilities, and private inventors. This means that not the whole system, which is depicted in Figure 1, is actively generating innovations. A spatial unit contains a limited number of actors that generate innovations. Patent statistics show that firms dominate this generation, while within firms R&D employees are responsible for most innovation activities. In the following we denote all people actively involved in the generation of innovations the *innovation generators* and shorten them in mathematical equations by G.

Second, most factors in our model have an effect on the innovation generation process, depicted in Figure 1 by an arrow ending at the 'innovation generation'. For example, cultural attitudes in a spatial unit can make innovation generation more or less effective. The transportation infrastructure can also support innovation processes. Furthermore, all innovation generators in a spatial unit have an impact on the ability of other innovation generators to produce innovations because they can provide relevant knowledge and possibilities for cooperation. Hence, all factors but historical events[4] might influence the innovation generators in their activities. We call these factors the *innovation facilitators* and shorten them in mathematical equations by F. By using the term 'facilitators' we take the perspective of the innovation generators. For them all factors in the region that are not their own characteristics are some kind of externalities. From the perspective of the spatial unit, these factors would be rather called 'input factors' or 'resources'.

Third, all factors of the system interact, as depicted in Figure 1 by the arrows between all the boxes. Through their interactions and in combinations with historical events they shape the structure and content of the spatial unit. This historical process has self-reinforcing characteristics and involves social, economic, and institutional developments. It determines the state of a spatial unit, including all characteristics but the fixed characteristics.

This interactive process is too complex for a representation in a simple mathematical model. It can only be understood comprehensively with the help of case studies. In this theoretical paper we use a number of assumption to simplify the problem and make some structural statements. The first set of assumptions regards the development of the factors. In general, culture develops very slowly. Population characteristics, such as the number of inhabitants, their social status and qualification,

[3] Usually R&D employees are responsible for the generation of innovation, but sometimes other employees in firms generate innovations as well.

[4] The term 'historical events' refers here to events that change permanently the situation in a spatial units. Hence, they impact on innovation processes indirectly via this change in the situation and characteristics of a spatial unit. Inventions and innovations are not considered historical events.

and the population density, change slowly in comparison to economic activities. The same holds for public institutions and general policy settings: Firms move - and are established or closed down - quicker than public institutions. This holds even more so for research activities within firms.
Thus, we might assume that in the short run the number of innovation generators - mainly R&D activity in firms - in a spatial unit is strongly influenced by the state of the other factors. Of course, in the medium and long run their presence feeds back on the other factors. Hence, all factors in a spatial unit have, besides their role as innovation facilitators, a second role: They attract or distract innovation generators to or from the spatial unit. We call the factors involved in this role the *innovation attractors* and shorten them by A. Historical events have this role as well as all the characteristics of the spatial unit in Figure 1. This holds also for the innovation generators, whose number might make the spatial unit attractive for further innovation generators.
Most factors are at the same time innovation facilitators and innovation attractors. The distinction made here is not based on the characteristics of the factors but on their functional meaning. For example, researcher are usually at the same time innovation generators (producing innovations), innovation facilitators (contributing to the innovation ability of firms by providing them with scientific knowledge), and innovation attractors (making the spatial unit attractive for firms because of the potential for cooperation). The insight that the same factors have different functional meanings is important for empirical analyses because it implies that measuring the importance of a factor does not necessarily tell us something about which of its functions is relevant. Figure 2 depicts the functional structure of a spatial unit in the context of innovation generation.

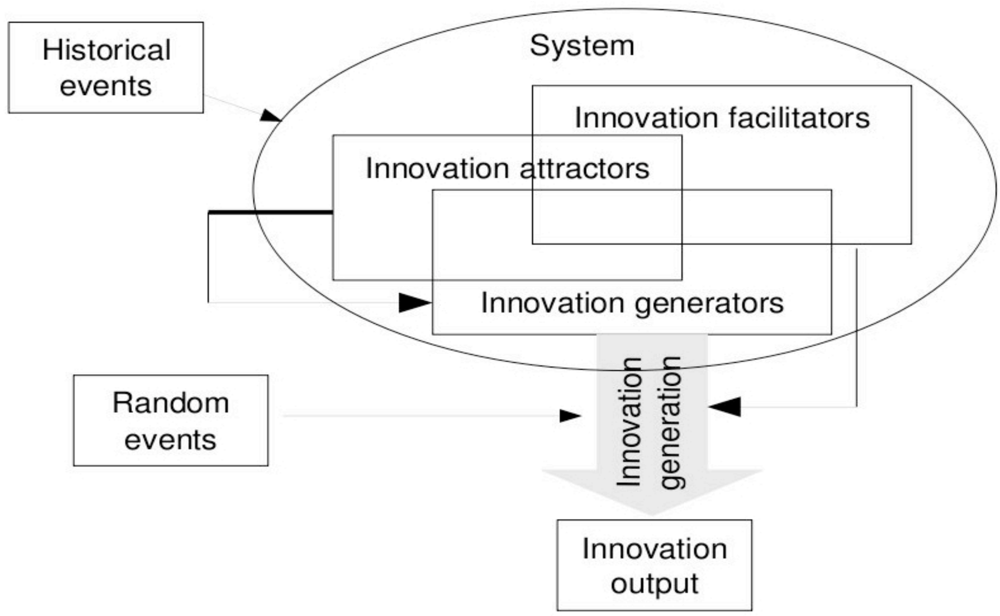

Figure 2: Interactions that cause the innovation output of a spatial unit.

2.4 Mathematical formulation

The aim of this paper is to discuss how the innovation performance of a spatial unit can be measured meaningfully. Such a measurement requires a mathematical definition, which can serve as basis for empirical approaches. In a first step, in order to evaluate the multitude of measures used in the literature, we transform the above model (see Figure 2) into a mathematical formulation.

Above we have defined the variable G, which represents the number of innovation generators in the spatial unit. Let us start the discussion with the consideration of one specific innovation generator (e.g., a R&D worker in a firms of a specific industry). Let us denote the number of innovations that this innovation generator produces in a given period of time by η. The value of η depends on the characteristics of this innovation generator and on other characteristics and factors in the spatial unit. Furthermore, fortune plays a role in innovation processes. This implies a random element in the innovation output of an innovation generator.

In order to represent the impact of individual characteristics in the mathematical formulation, we write η as a function of c, a variable that stand for all relevant individual characteristics. Furthermore, the innovation facilitators, F, within the spatial unit support the innovation generators in their innovation activity. Hence, η depends on the presence of innovation facilitators, F. Finally, in order to consider the random element, η is declared to represent the average innovation output of an innovation generator, and not the realised output.

As a result we can write the average innovation output of one individual i located in the spatial unit s by

$$E(I_i) = \eta_i(c_i, F_s) \ , \tag{1}$$

where I_i denotes the innovation output of individual i and $E()$ stands for the expected or average value in a certain time period. The functional dependence of the innovation output on the innovation facilitators might differ between innovation generators.

In order to obtain an equation for the spatial unit we have to sum the expected values, $E(I_i)$ for all innovation generators. There are G_s innovation generators within the spatial unit s. This number depends on the innovation attractors, A_s. Hence, G_s is a function of A_s. We obtain for the expected number of innovations $E(I_s)$ in the spatial unit:

$$E(I_s) = \sum_{i=1}^{G_s(A_s)} \eta_i(c_i, F_s) \ . \tag{2}$$

We might use an additional assumption to simplify the mathematical formulation: If all innovation generators have the same individual characteristics and the same innovation generation function, $\eta_i = \eta$, we can write:

$$E(I_s) = \eta(c_s, F_s) \cdot G_s(A_s) \ . \tag{3}$$

The innovation output is, in this case, given by a binomial distribution with the number of trials given by $G_s(A_s)$ and the probability given by $\eta(c_s, F_s)$. This is an approximation and does not hold especially if we consider innovation generators with a different background (researcher in firms or public institutions and private persons) or innovation generators in different industries and technologies (this issue is taken up in Section 4.1). Nevertheless, we use the assumption of identical innovation generators most of the time in the rest of the paper and refer to this assumption as *Identity Assumption*.

The exact form of the two functions $\eta(c_i, F_s)$ and $G_s(A_s)$ and the factors that are involved can only be investigated empirically. We discuss the empirical measurement in the next section. Here, we focus on the discussion of what innovation performance of a spatial unit might mean. We argue that different views can be taken and justified. These views are presented in the following.

Approach A: Output measurement

First, the above model shows that the innovation output in a spatial unit is the result of a complex structure of interactions and dependencies. The spatial unit is involved in several ways: attracting innovation activities and supporting their effectiveness. Hence, we might argue that the innovation output is finally the result of what a spatial unit offers. As a consequence, we can measure the innovation performance of a spatial unit by its innovation output. This implies that we treat all the interactions depicted in Figure 1 as a black box and focus on the final outcome. We call this approach the 'Output measurement' in the following.

Approach B: Efficiency measurement

Second, we might argue that the current state of the spatial unit is the result of a historical process. This also holds for the number of innovation generators that are present in the region. We could then focus on the current contribution of the spatial unit, namely its innovation facilitating function. This would mean that we focus on the term $\eta_i(c_i, F_s)$ and within this term especially on the dependence of η on F_s. In such an approach, we define the innovation performance of a spatial unit by the contribution of this unit to the innovation efficiency of the innovation generators present in the unit. Empirically we would have to measure the number of innovation generators, mainly the R&D employees or activities in firms, with their individual characteristics, such as firm size or industry, and relate this to the innovation output. According to this approach a comparison of regions is done on the basis of the innovation output that is generated in relation to the presence of innovation generators. We call this approach the 'Efficiency measurement' in the following.

Approach C: Attraction measurement

Third, we might argue that the main contribution of the spatial unit to the innovation output is found in its ability to attract innovation activity to the region. This is confirmed by the strong correlation between research expenditures or employees and innovation output. It might be argued that η does not vary a lot between spatial units. The number of innovation generators, G_s, is the variable that varies most between spatial units. As a consequence, measuring G_s and the impact of the region on G_s, denoted by $G_s(A_s)$, would be the way to measure innovation performance. We call this approach the 'Attraction measurement' in the following.

Approach D: Selected facilitation impact

Fourth, we might focus on the facilitation impact of a one or a few local factors F_s^*. For example, one might be interested in the effects of universities in a spatial region but not in the contributions of public research institutes. For such a set-up it is necessary that the number of innovation generators, G_s as well as all facilitators, $\hat{F}_s = F_s \setminus F_s^*$, whose effects are not to be analyzed are part of the input factor set. In this case the measure will contain fluctuation as well as the effect of the not included facilitators. There are two major problems to this approach, though. Firstly, what facilitators are to be analyzed and secondly, how to account for the effects of all other facilitators. While the first problem depends on the aim of the study the second problem can only partly be dealt with by including a great number of facilitators. Therefore, we argue that this approach is only attractive for very particular problems or for testing the sensitivity of the results obtained with Approach B (see, e.g., Broekel and Meder, 2008).

For all four approaches good argument are put forward above. The adequate choice depends on the intention of the analysis. The model and discussion above provide one important insight in this context: There are two fundamentally different ways in which characteristics of the spatial unit influence the innovation output. On the one side the characteristics of the spatial unit attract more or less innovation activity to the region. On the other side the characteristics of the spatial unit influence the effectiveness of these innovation activities. Innovation performance of a spatial unit can be measured by measuring both effects together (Approach A), measuring only the impact on the effectiveness (Approach B, D), or measuring only the attracting effect (Approach C).

3 Usual approaches and their meaning

Above we identified the various functional meanings of the spatial unit and its characteristics in the innovation generation process. We found that, measuring the innovation performance of a spatial unit might mean different things. Four fundamentally different approach are possible. They are outlined above. In this section we discuss the approaches that are used in the literature and put them into the picture set up above.

Subsequently, we examine five approaches: total innovation output (Section 3.1), innovations per inhabitant or R&D employee (Section 3.2), Regional Innovation Scoreboard (Section 3.3), R&D employees' innovation efficiency (Section 3.4), and region-oriented innovation efficiency (Section 3.5).

3.1 Total innovation output

The innovation performance of different sets of regions or nations has been subject to an increasing amount of research in recent years. The usual approach is to define one or a number of indices that represent the innovation output of the considered spatial unit. Most commonly patents are used as approximations for the number of innovations created. Putting such an approach into the picture outlined in Section 2 it becomes clear that it treats the spatial unit as a black box. All interactions within this black box – within the region or nation – are not considered in detail but only in the outcome they jointly cause. The focus is on the total amount of innovations that this black box is able to generate.

This corresponds to what is called the Output measurement (Approach A) above: Regions are ranked according to the total number of innovations that are generated by their actors. It combines measuring the impact of the spatial unit on attracting activity, especially innovation activity, to the unit and the impact of the spatial unit on attracting and developing helpful circumstances within the unit. Furthermore, all historical effects are included as well as the randomness of the innovation process itself. This implies that such an approach assigns the effect of historical events on the innovativeness of a spatial unit to this unit. Cluster theory tells us that historical events can trigger very different dynamics in regions with the same initial conditions (e.g., Fujita et al., 1999). These different developments will show up as differences in the innovation output of regions. If the innovation performance of a spatial unit is measured by its total innovation output, such historically triggered developments are included in the measurement. If the time period of measurement is short, fluctuations in the innovation output matter and might disturb the measuring of innovation performance.

The advantage of this approach is its simplicity. Everything that happened to and happened within the spatial unit is included and the final impact on the innovative activity of all factors, features and developments is measured.

3.2 Innovations per inhabitant

A common approach to measure innovation performance is to count the number of patents per inhabitants (Greif and Schmiedl, 2002; Stern et al., 2002; Greif et al., 2006). This means that what is measured is not the performance of the region but the average performance of each inhabitant in a region. In other words, the performance is measured as the number of innovations conducted by a person and the unit of analysis is the individuum, which is then aggregated to the regional or national level. In this sense Stern et al. (2002) argue that relating the innovative output to the number of inhabitants of a spatial unit provides insights on the "total innovation output relative to total inputs which *could* be devoted to innovation" (p. 912). However, not all inhabitants have the same opportunities or interest to contribute to the innovation or patent output of a region or nation. This is acknowledge by Stern et al. (2002) as well. They point out that R&D productivity rather corresponds to the relation between the number of R&D employees (or similar variables approximating firms' investments into R&D) within the spatial unit to the innovative output. This is also done in the literature and will be discuss in the next subsection. A very similar measure are patents per worker, which is used by Bode (2004). Because almost the same argumentation as for innovations per inhabitant applies to this measure we will not discuss this approach separately.

Lets put this approaches into the framework developed in Section 2. Using innovations per inhabitant means that all arrows in Figure 1 that run into the box 'population characteristics', or more precisely into the part 'population size' of this box, are excluded from the analysis. The population size is considered as the given characteristics of a spatial unit. Innovation performance is measured in relation to this characteristic.

Mathematically we obtain according to Equation (3):

$$\frac{E(I_s)}{p_s} = \eta(c_s, F_s) \cdot \frac{G_s(A_s)}{p_s} \tag{4}$$

if we denote the population size in the spatial unit s by p_s. We might assume that the number of innovation generators in a spatial unit is proportional to the population size, meaning $G_s(A_s) = p_s \cdot G_{0,s}(A_s^{(-p)})$ where $G_{0,s}$ denotes the number of innovation generators per inhabitant and $A_s^{(-p)}$ stands for all innovation attractors besides the population size. In this case we obtain a meaningful measure

$$\frac{E(I_s)}{p_s} = \eta(c_s, F_s) \cdot G_{0,s}(A_s^{(-p)}) \ . \tag{5}$$

However, this measure is based on the product of all facilitating impacts of all local factors on the innovation generation and the attracting impacts on the share of innovation generators in the population of all factors except population size. It seems difficult to justify why only population size is taken out of the equation and why only its attracting impact and not its facilitating impact is excluded. The situation is even more complicated if the relationship between population size and innovation generators is not linear. This is very like because private as well as public R&D employees are concentrated in (big) cities (see, e.g., Rosenbloom, 2004). Hence, innovations per inhabitant measures represent, as shown in Equation (4), the multiplication of the share of innovation generators in the population with their average innovation output. This does not correspond to any of the above mentioned Approaches A,B,C, or D.

Furthermore, using innovations per inhabitants as measure of innovation performance, bears the problem that if measured within a short period of time it includes random effects. Spatial units might be measured to be more or less innovative dependent on short-run fluctuations.

3.3 Regional Innovation Scoreboard

The Regional Innovation Scoreboard measures the innovativeness of regions in Europe with an index that is based on 25 variables (see EIS, 2006). These variables represent a number of different aspects, such as education, R&D resources, and innovation output values. All these aspects are claimed, probably rightly so, to be connected to innovation activity.

If we put this approach into the picture developed above, it becomes unclear what the Regional Innovation Scoreboard measures. It combines all kinds of variables, variables that represent innovation facilitators and attractors, variables that represent mainly innovation generators and variables that represent the innovation output. A weighted average of these variables is claimed to approximate the innovativeness of regions.

From the perspective of our framework the interesting aspect in this measure is that it is the only one that includes measures of the number of innovation generators. The existence of innovation generators, e.g. the R&D employees or the highly educated population, is seen as part of the innovativeness of a region. This is in line with our Approach C, which focuses on the ability of a spatial unit to attract innovation generators. It might be argued that innovation generators differ not much in their average innovation output. Such a claim is supported by the high correlation between patents and R&D employment (Greif and Schmiedl, 2002). Hence, it might be argued that what we measure, even if we take the innovation output, is mainly the ability of a spatial unit to attract or produce innovation generators. In such a view the Regional Innovation Scoreboard can be seen as a trial to find and add many proxies for this ability of regions to establish innovation generators in the region. However, the Regional Innovation Scoreboard is not explicit on this.

Of course, this view becomes problematic if innovation generators differ in their ability to generate innovations. This is especially the case for R&D employees from different industries. Innovation processes differ strongly between industries. Hence, independent of the innovation output measure the average innovation output per R&D employees differs strongly between industries. The above argument that innovation generators and innovation output are strongly correlated does not hold if different industries are involved. This is further discussed in Section 4.1.

3.4 R&D employees' innovation efficiency

Recently, another innovation performance measure has become popular: the so called "innovation efficiency" approach (see, e.g., Fritsch, 2003; Fritsch and Slavtchev, 2006). Innovation performance is defined as the relation between the generated innovative output and the invested efforts. The approach takes up the production analogy and sees innovation processes as being very similar to production process, meaning that there are resources that are transformed by a unit (e.g. a nation, a region, or a firm) into output (innovations). Fritsch (2000, 2003); Fritsch and Slavtchev (2006); Broekel and Brenner (2007); Broekel (2008) define innovation efficiency as the relation between the innovative output and the number of R&D employees in a spatial unit.

There are two approaches in the literature how the innovation efficiency of a spatial unit is measured. While Broekel and Brenner (2007); Broekel (2008) estimates the innovation efficiency non-parametrically and industry-specific, Fritsch (2003) and Fritsch and Slavtchev (2006) take total regional R&D employment as input factor.

For the latter two studies this means that all arrows in Figure 2 running into the box 'economic activity' are excluded from the analysis. The economic activities, in the form of R&D employment, are considered as the given characteristics of a spatial unit. Everything that happens between the economic activities, especially the R&D employment, and the innovation output in Figure 2 is defined as the performance of the spatial unit. Such a view becomes interesting if we can approximate the number of innovation generators by the number of R&D employees. Above we have stated that most innovations are conducted by firms. Thus, the number of R&D employees, denoted by r_s in the following, might well represent a good approximation for G_s, which is the only factor considered in the knowledge production function (KPF). This leads to

$$\frac{E(I_s)}{KPF(r_s)} \approx \eta(c_s, F_s) \ . \tag{6}$$

Hence, accepting R&D employment as an approximation for the number of innovation generators implies that the relation between the number of innovations and the number of R&D employees measures the innovation performance of the innovation generators in the spatial unit, including all facilitating effects of the local factors on the innovation generation. This corresponds to what we declared the Efficiency measurement (Approach B) above.

However, for the implementation of the innovation efficiency approach Fritsch and Slavtchev rely on the *knowledge production function* concept. It was introduced by Griliches (1979) and has become very popular. Here the economic efforts or *input factors* are set into a pre-defined functional relationship with the innovative *output*. Similar to traditional efficiency (productivity) measures Fritsch and Slavtchev (2006) proposed the use of parametric production frontier approaches (deterministic as well as stochastic) for estimating regional innovation efficiencies. The Efficiency measurement approach that is defined above would be based on measuring

$$\frac{E(I_s)}{G_s(A_s)} = \eta(c_s, F_s) \ . \tag{7}$$

Let us assume that the number of R&D employees is a good approximation for the number of innovation generators: $r_s \approx G_s$. Then, we obtain

$$\frac{E(I_s)}{r_s} \approx \frac{E(I_s)}{G_s(A_s)} = \eta(c_s, F_s) \ . \tag{8}$$

The difference to the above Equation (6) lies in the fact that the knowledge production function (KPF) is estimated with a given functional form in order to minimise the fluctuations of $\eta(c_s, F_s)$ between the spatial units. However, the R&D employees function also as innovation facilitators and are, therefore, part of F_s. The approach based on the knowledge production function includes this facilitating effect into the efficiency measurement.

Another problem with this approach are the assumptions made with respect to the error term in the knowledge production function. If the distribution of the error term is not specified correctly the resulting measures will include portions of the fluctuation inherent to innovation processes. Sensitivity analyses with respect to the chosen distributions are necessarily. The non-parametric approach by Broekel and Brenner (2007) and Broekel (2008) is naturally less troubled by this problem.

Another problem related to the use of the knowledge production function/frontier approach arises when more than one variable is used to approximated the innovation generators. This is the case if different types of R&D employees are considered that show varying innovation propensities (see, e.g., Broekel, 2008). In this case the approach becomes more complex and we might face a situation in which the knowledge production function is not correctly specified. The mathematical structure of the dependence of the innovation output on the various innovation generators is fixed in the knowledge production function approach before the coefficients are estimated. If this structure is not in line with the real structure, the resulting equation cannot be simplified and it is unclear what is obtained.

To sum up, it is very important that the knowledge production function is correctly specified. This is particularly true for the distribution of the error term. Studies that use non-parametric techniques for the estimation of the innovation efficiency get around the problem of misspecifying the functional relationship. However this applies only to the specification of the mathematical function. Misspecifications with respect to the considered variables still exist. In order to correspond to the Efficiency measurement proposed above, no function should be defined and the innovation output should simply be divided by the R&D employment. If this employment is a good approximation of the number of innovation generators, the resulting measures show differences between spatial units with respect to the innovation facilitating factors.

3.5 Regional innovation efficiency

In some of the analyses conducted by Broekel and Brenner (2007) and Broekel and Meder (2008) the innovation efficiency concept is extend. Their "region-oriented innovation efficiency" approach considers not solely innovation generators on the input side of the efficiency analyses. In addition, variables are included that represent population characteristics (e.g., population density) as well as policy settings and activities (e.g., graduates of engineering faculties).

In this case the innovation output I_s of a spatial unit is related to a potential output that is given as a function of the various factors. Mathematically it can be written as

$$\frac{E(I_s)}{IPF(F_s, A_s, G_s)} \tag{9}$$

where IPF denotes the innovation production function that depends on all these kinds of factors, meaning the innovation facilitators, the innovation attractors and the innovation generators. With respect to the interpretation of the results we can distinguish two cases.

First, let us assume it is possible to empirically include all relevant factors. Furthermore, let us assume that the innovation production function is correctly specified. In this case, the innovation production function should match the right-hand side of Equation (3). Hence, we obtain as a measure for the innovativeness of a spatial unit:

$$\frac{E(I_s)}{IPF(F_s, A_s, G_s)} = \frac{\eta(c_s, F_s) \cdot G_s(A_s)}{IPF(F_s, A_s, G_s)} = 1 \; . \tag{10}$$

Equation (10) represents the average expectation. If we measure the innovation output for a limited period of time, the results will contain fluctuation and our measure will represent solely these fluctuations.

Second, we might face the situation that the innovation production function is correctly specified but that not all relevant factors can be measured and included in the empirical approach. In this case the innovation production function is based only on some innovation facilitators, attractors and generators, denoted here by F_s^*, A_s^* and G_s^*, respectively. Let us denote the other innovation facilitators, attractors and generators, by $\hat{F}_s$, $\hat{A}_s$ and $\hat{G}_s$, respectively. We obtain

$$\frac{E(I_s)}{IPF(F_s^*, A_s^*, G_s^*)} = \frac{\eta(c_s, F_s^*, \hat{F}_s) \cdot \left(G_s^*(A_s^*, \hat{A}_s) + \hat{G}_s(A_s^*, \hat{A}_s) \right)}{IPF(F_s^*, A_s^*, G_s^*)} . \tag{11}$$

If either all innovation generators or no innovation generators are included and if the impacts of the innovation facilitators and innovation attractors are multiplicative, we obtain a result that can be well interpreted. Let us, for example, assume multiplicative impacts and all innovation generators included ($G_s^* = G_s$ and $\hat{G}_s = 0$). Then, we obtain mathematically

$$\frac{E(I_s)}{IPF(F_s^*, A_s^*, G_s)} = \frac{\eta(c_s, F_s^*, \hat{F}_s) \cdot G_s(A_s^*)}{IPF(F_s^*, A_s^*, G_s)} = \tilde{\eta}(c_s, \hat{F}_s) \tag{12}$$

where $\tilde{\eta}$ denote the multiplicative part of this variable that are explained by the factors that are explicitly included. The impact of the innovation attractors, A_s, disappears in Equation (12) because the innovation attractors have no direct impact on the innovation output. Hence, if all innovation generators are included in a innovation production function as input factors, the innovation attraction does not play a role.

In this case, the approach measures the facilitating contribution of the excluded factors on the innovation output. From the perspective of our framework (Section 2) this corresponds to Approach D. Such an approach builds on many assumptions. Most importantly, the effects of the innovation facilitators and innovation attractors need to be multiplicative. Second, the innovation production function (IPF) needs to be specified correctly. Third, the innovation generators have to be identical in their ability to generate innovation (Identity assumption). Fourth, fluctuation needs to be accurately considered. These are strong assumptions. In particular the danger of misspecifying the IPF, which results in non-meaningful results seems to prohibit parametric approaches. Non-parametric frontier approaches similar to those used by Broekel and Brenner (2007) and Broekel and Meder (2008) avoid, at least, this problem. They allow not to specify the functional form of the IPF as well as as specific distribution of the fluctuation ex-ante. However, they also rely on the assumption of multiplicative effects and the assumption of identical innovation generators. If these assumptions are not given, the interpretation is less straight-forward, although the result has still something to do with the impacts of the excluded factors. Naturally it is important for the interpretation of the results that not all relevant factors are included.

4 Issues in measuring innovation performance

The above approach and its discussion lead to two important questions in the context of measuring the innovation performance of spatial units: How to deal with industry differences and which local factors should be included in the measurement?

4.1 Industry differences

Above four different ways of measuring the innovation performance of spatial units have been discussed. Approach B is based on measuring the average innovation output, η, of the innovation generators, G_s. In Approach A, which is based on the innovation output of the spatial unit, the value of η plays also an important role for the outcome of the measurement. If all innovation generators are approximately the same, η reflects the innovation facilitating effects of the spatial unit. However, if innovation generators are different, η depends crucially on the effect that some spatial units might be able to attract more innovative innovation generators than other spatial units. This messes up the differentiation between innovation facilitation and innovation attraction effects.

Different industries are characterised by very different types and rates of innovation. Furthermore, the ways in which innovations become affective in industries differs. Pavitt (1984) shows how innovation processes differ between manufacturing industries and how this takes effect on the industries relation to other actors and institutions. The industrial dimension plays a crucial role in empirical research as well because it has an effect on the innovation measure. Commonly used proxies for innovations (most importantly patents) capture innovations with a varying extent for manufacturing industries (see, e.g., Arundel and Kabla, 1998). Hence, innovation generators from different industries have a different average innovation output, η. This implies that the simplification from Equation (2) to Equation (3) is not correct. If we denote industries by j and assume that all innovation generators within an industry are of the same type – meaning with the same average innovation output – , we should write:

$$E(I_s) = \sum_j \eta_j(c_j, F_s) \cdot G_{s,j}(A_s) \ . \tag{13}$$

It might be argued that the ability to attract innovative industries to a region is part of the innovation performance of a region. However, the literature on spatial concentration (e.g., Fujita et al., 1999) shows that 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.

There are two ways to deal with this situation empirically. First, one could try to weight the different industries and sectors present in the spatial unit according to industry-specific average innovation output and construct a single 'weighted' innovativeness index. Mathematically, this means that we separate the impacts of the industry and the spatial unit on the average innovation output of an innovation generator from each other. To this end, we define: $\eta_j(c_j, F_s) = \hat{\eta}_j(c_j) \cdot \tilde{\eta}(F_s)$. Of course, whether the two impacts can be separated in this way is not clear. If such a separation is possible, we obtain

$$E(I_s) = \tilde{\eta}(F_s) \cdot \sum_j \hat{\eta}_j(c_j) \cdot G_{s,j}(A_s) \ . \tag{14}$$

In this case Approach B can be used to identify the impact of the innovation facilitators.

Second, the innovation performance of spatial units can be examined for each industry separately (see, e.g., Broekel and Brenner, 2005; Brenner and Greif, 2006). This would imply that the innovation generators and the innovation output are identified for one industry at a time only. Assuming that within an industry innovation generators produce on average the same innovation output, all four approaches can be used. Approach A leads to a comparison of spatial units according to their innovation output in a specific industry. Approach B and D estimate the innovation facilitating impact (or parts of it) of the spatial unit. And Approach C measures the ability of the spatial unit to attract innovation activity in the specific industry.

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

4.2 Choice of factors

Some of the approaches used in the literature include one or a number of local input factors in the analysis. This is done in two ways. First, local factors are included to correct for the size of the spatial units, as done in the approach based on innovations per inhabitant (Section 3.2). Second, an approach similar to the measurement of firm performance is taken in which innovation output is related to (input) factors (Section 3.4 and Section 3.5).

In both cases the inclusion of factors is problematic. The problem is not just about the choice of the considered input factors but also impacts the interpretation of spatial units innovation performance. The mathematical formulation has shown that four approaches are possible (Approaches A, B, C and D). Approaches A and C compare spatial units with respect to the presence of either innovation output or innovation generators. Of course, each of these values might be measured in relation to a factor, e.g. per inhabitant. However, this means that we exclude the indirect impact of the spatial unit via this factor. For the example of measuring innovations per inhabitant, it means that the effect of a spatial unit's attractiveness causing people to move from outside to this spatial unit and, thus, attracting innovation generators to the unit is neglected. In the Approaches A and C it seems difficult to justify such an inclusion.

The aim of traditional firm performance analyses is to identify ways how the output can be increased

with constant inputs or decreasing inputs holding output constant. The same might be applied to analyzing spatial units' innovation performances. However, in the case of production the inputs that a firm utilises can be related to respective costs. These inputs are bought by the firm and the performance is seen as what the firm is able to make out of them. The situation is different in the case of a spatial unit. There are no inputs bought from the outside. If all (input) factors are included, the innovation output should be completely explained as discussed above. Hence, it is not clear which factors should be included and which factors should not be included. This is particularly relevant for Approach D.
Only in Approach B a clear answer can be given. This approach interprets the performance of the spatial unit as its facilitating effect on the innovation generators. Hence, the innovation generators are the input factors. The more innovation generators are present within the spatial unit the higher should the innovation output be. However, the spatial unit may make the innovation generators to perform better or worse. This is what is measured in Approach B.

5 Conclusions

The innovation performance of spatial units is repeatedly measures in the literature. This paper examines the usual approaches and discusses the question of what innovation performance could and should mean in the context of spatial units. The basis for this discussion is an understanding of the various ways in which a spatial unit contributes to the innovations generated therein.
We find that two kinds of influences can be distinguished: an attracting effect and a facilitating effect. First, the characteristics of a spatial unit attract innovative activities more or less to the spatial unit. Second, the characteristics of a spatial unit may support the innovative activity that takes place within the unit and, thus, make the innovation generators more effective. Many characteristics have both effects at the same time. This complicates the measurement of the contribution of local factors to the innovation output.
For measuring the innovation performance of spatial units we infer four possible approaches. First, the complete impact of the spatial unit might be measured by measuring the total innovation output. In such an approach both effects, the attracting and the facilitating effect, are measured jointly. Second, the ability of the spatial unit to attract innovative activity to the unit can be measured. In this approach the number of innovation generators or the innovation expenditures are measured. Third, the ability of the spatial unit to facilitate innovation processes and make them more effective can be measured. In such an approach the innovation output is related to the number of innovation generators. Fourth, the analysis might focus on the effect of one or a few specific factors, examining only their facilitating impact.
Furthermore, we argue that, especially in the first, third and fourth approach, it is important to measure the innovation performance for different industries separately. Otherwise we mix the ability of a spatial unit to attract specific industries with its ability to support innovation activities.

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