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The Dependence of Innovativeness on the Local Firm Population - An Empirical Study of German Patents

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ABSTRACT Local clusters of firms are repeatedly related to a high level of innovativeness in the literature. The underlying argument is that firms that are co-located with other firms of the same industry undertake more innovation than 'lonely' firms. This argument is tested here for four industries in Germany. To this end, three different theoretical models are developed that represent different assumptions about the innovativeness in local clusters. The empirical evidence for these models is compared. The results show that the innovativeness of firms indeed depends on the existence of other firms in the same region. However, the dependence is not necessarily of the kind usually assumed. Furthermore, it depends on the industry studied.
KEYWORDS: innovations, spillovers, patents, economies of location.

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1. Introduction

The importance of spillovers for the innovativeness of firms has been repeatedly addressed in the recent literature (see, e.g., Branstetter 1998 for an overview). There is strong evidence of the beneficial impact of spillovers on the innovativeness of firms (see, e.g., Porter 1994, Grupp 1996, and Blind & Grupp 1999). Furthermore, there is evidence of local boundedness of spillovers (see, e.g., Jaffe, Trajtenberg & Henderson 1993 and Anselin, Varga & Acs 1997). This implies that firms benefit from the co-location with other firms. The more other firms are located in the same region, the more innovative is a firm, on average.

A similar argument is put forward in the literature on industrial districts, local clusters and the likes. It is argued that local clusters exist or emerge because spillovers make the firms in these clusters more innovative (see, e.g., Morgan 1997 and Brenner 2000). A higher innovativeness of firms within agglomerations attracts further firms to these locations and increases or stabilises the difference between clusters and other locations. This implies that innovations should occur much more frequently in local clusters than in other places (see, e.g., Beaudry & Breschi 2000 and Greif 2001b). If the firms benefit from each other in such clusters, the number of innovations should increase more than linearly with the size of the firm population in a region.

In the empirical literature on spillovers two types of dependence of the innovation output on the co-location with other firms are studied. First, whether research conducted by other firms in the same region increases the innovativeness of a firm is examined (see, e.g., Jaffe, Trajtenberg & Henderson 1993 and Anselin, Varga & Acs 1997). This is done in the form of a regression assuming a linear relationship. Second, the innovativeness of firms is often explained on the basis of several impacts including the number of firms that are located in the same region (see, e.g., Acs, Audretsch & Feldman 1994, Audretsch 1998, Koschatzky 1998, Shefer & Frenkel 1998 and Fritsch & Franke 2000). Again a linear regression is used in all these approaches.

This paper aims to identify the exact structure of the dependence between the innovations conducted in a region, measured by the number of patents, and the number and size of the firms located there. The theoretical analysis of local self-augmenting processes shows that the number of innovations in a region has to increase more than linearly with the number of firms or employees there if this effect contributes to the existence and emergence of local industrial clusters (this analysis is conducted in Brenner 2001). Hence, it is important to know the exact relationship between innovations and the number of firms or employees in a region.

This relationship might not be identical for all types of industries. Therefore, four different industries are studied here. The results are compared in order to identify differences and general elements of the relationship between innovations and the firm population. The four industries that are examined are chemicals, vehicles, electrics and instruments.

The paper proceeds as follows. In the next section the basic theoretical considerations are presented, and the regression equations that are used in the empirical analysis are developed, described and discussed. Section 3 contains a description of the data that are used in the empirical study. The results of the empirical analysis are given in Section 4. They are also discussed in this section, particularly with respect to their implications for the understanding of the existence and emergence of local clusters. Section 5 concludes.

2. Theoretical considerations

The regressions that are conducted in the literature usually try to explain the innovativeness of firms as the dependent variable. Here, the question of what makes firms more or less innovative is transferred to the region. The innovation output of a region is chosen as the dependent variable that is to be explained. This means that we study the question of what characterises innovative regions. The main focus is on the question of how the number of firms and employees in a region is related to the region's innovativeness.

However, the innovativeness of regions is very much related to the innovativeness of the firms therein. The innovativeness of regions is measured by the number of patent applications made within the region. More than 90% of all the patents studied originate from firms. Therefore, a high innovativeness of a region is mainly caused by a high innovativeness of the firms therein.

The main difference to the studies in the literature is that we study the functional form of the relationship between the number of patents and the number of firms or employees in a region. If firms would be independent with respect to their innovative success, twice as many patents should come from a region that contains twice as many firms. Two arguments in the literature suggest a different feature. On the one hand, it is argued and empirically shown that firms benefit from spillovers if they are co-located (see, e.g., Jaffe, Trajtenberg & Henderson 1993, Anselin, Varga & Acs 1997, and Orlando 2000). On the other hand, the literature on local clusters repeatedly signifies the high innovativeness of the firms in such clusters (see, e.g., Greif 2001a). Both arguments might be related because spillovers represent one of the mechanisms within local clusters that are responsible for their success (see Brenner 2000).

However, a somewhat different argument is put forward in the literature on innovative milieux. There, the symbiosis between firms is seen as a major cause for the innovativeness of regions (see Camagni 1995). This symbiosis between firms might have different causes. Spillovers might occur in the form of knowledge flows or the movement of employees from one to another firm. Furthermore, the existence of other innovative firms in a region might cause a positive attitude towards innovations in the local population. Firms might also benefit from a high number and quality of services and public research in the region that might be caused by the large number of firms in the region. Finally, local cooperation, for example, in the form of joint R&D, might increase innovativeness.

Hence, there are several reasons for a region with many firms or employees in a particular industry to become especially innovative with respect to this industry. The approach that is taken here is not able to distinguish between these reasons. We aim to test whether the number of firms and employees in an industry and region is indeed related to the innovativeness of this region, and we aim to examine the functional form of this relationship.

To this end, several assumptions about the effect of spillovers and synergies on the innovativeness of the firms in a region are formulated. Mathematical representations of these assumptions are set up and tested empirically. We start with two basic assumptions about the synergies in regions. These will be formulated and discussed separately below.

2.1. Linear dependence

Let us start with the assumption that no synergies between firms take place. This means that the innovation output of each firm is independent of its co-location with other firms. In such a case the number of innovations undertaken in a region should increase linearly with the number of firms located there. The shape of the dependence of the number of innovations on the number of employees is less clear. Many empirical studies have been conducted that examine the innovation output of firms dependent on their size (see, e.g., Audretsch & Acs 1991, Bertschek & Entorf 1996, Arbanitis 1997, Blind & Grupp 1999, and Brouwer & Kleinknecht 1999). The results vary. Some studies find linear or less than linear dependencies, while other studies find u-shaped dependencies. Since we do not use any information about the size distribution of firms in the analysis in this paper, we are not able to include such dependencies in the analysis. Therefore, we assume that if no synergies between firms take place, the number of innovations depends also linearly on the number of employees in the region.

This linear dependence is used as a benchmark here. Therefore, no model is set up that represents the linear dependence. However, it is clear that if we find a linear dependence in the analysis below, this can be interpreted as a lack of local synergies between firms.

2.2. Non-linear dependence

Spillovers are assumed to have a linear impact on the innovation output of firms in the literature (see, e.g., Henderson & Cockburn 1996). This means that an additional firm in a region adds to the innovation output in this region in the form of its own innovations and in the form of additional innovations by the already existing firms. The first effect leads to a linear increase of the innovativeness of the region. The second effect leads to a quadratic increase of this innovativeness because the more firms that already exist in the region the more firms there are that can benefit from the spillovers from the new firm. In the same vein, the additional firm also benefits from the existence of the other firms. This benefit is higher, the more other firms already exist.

To describe these effects mathematically, let us assume that each firm is of the same size and has the same innovativeness. The number of innovations conducted by a firm is given by a basic rate of innovations, which is independent of the co-location with other firms, and a rate of innovations caused by spillovers. The latter one is assumed to increase linearly with the number of other firms that are located in the region. If $n_f(r)$ firms are located in region r, the number of other firms is $n_f(r) - 1$. The basic rate of innovations is denoted by b and the number of innovations caused by spillovers from each of the other firms is denoted by s. Thus, the number of innovations, I_f, conducted by one firm is given by

$$I_f = b + s \cdot (n_f(r) - 1) \ . \tag{2.1}$$

The number of innovations, $I(r)$, undertaken in a region, r, that contains $n_f(r)$ firms is given by

$$I_{qu,f}(r) = b \cdot n_f(r) + s \cdot n_f(r) \cdot (n_f(r) - 1) = \alpha \cdot n_f(r) + \beta \cdot n_f(r)^2 \tag{2.2}$$

where the index qu signifies the fact that this function has a quadratic form.

There are two factors that might make the quadratic form inadequate. The first is that firms of different sizes might have different impacts on the number of innovations that are conducted in a region. The second is that the benefits from spillovers might not increase linearly with the number of firms in the region.

Brenner (2001) even argues that if local industrial clusters emerge, the benefit from co-location has to increase more than linearly with the number or size of the co-located firms. The existence of local industrial clusters (see Brenner 2003 for an empirical study) demonstrates that such benefits exist. There might be different causes for such benefits. Examples are the cooperation between firms, the joint development of an adequate local labour force, the influence on politics, and the co-evolution of service firms (see Brenner 2000 for a detailed discussion of the different potential causes). Hence, the exact dependence of the innovativeness of firms on the number or size of co-located firms cannot be predicted empirically.

However, the arguments above imply that the number of innovations conducted in region, r, increases more than quadratically with the number or size of firms in this region. There are many possible ways to formulate such a dependence. We use a flexible form here that includes the benchmark assumption of a linear dependence as well as the quadratic form above and also offers the possibility of synergies that increase more than linearly. A power function has all these characteristics. Two alternative models are used: one with a dependence on the number of firms and one with a dependence on the number of employees. They are given by

$$I_{pow,f}(r) = \alpha \cdot n_f(r)^\beta \tag{2.3}$$

in the case where the number of firms is the independent variable, and by

$$I_{pow,e}(r) = \alpha \cdot n_e(r)^\beta \tag{2.4}$$

when the independent variable is the number of employees in the industry and region. The parameter, α, denotes the strength of the increase of the innovativeness, while the parameter, β, denotes the functional form of the dependence in this case. If synergies take place and lead to a higher level of innovativeness of firms, β can be expected to be larger than 1. If synergies play a role for the emergence of local industrial clusters, β can be expected to be larger than 2. The functional form is depicted for $\beta = 0.5$ and $\beta = 3$ in Figure 1.

2.3. Additional effect of clustering

In addition to the models above, a second method for modelling local synergies is tested here. This second approach is also related to the existence of local industrial clusters and assumes that most of the innovations in an industry are conducted within local clusters. These local clusters are characterised by a large number of firms or employees in the industry under consideration. This implies that there are a few regions with a high number of firms or employees, the so-called local clusters, that are characterised by a high number of innovations. In all other regions the innovation rate is comparatively low.

The difference between these two types of regions is assumed to effect not only the total number of innovations in the regions but also the relative number of innovations. This means that the firms or employees in the local clusters are more innovative than those located in the other regions. No speculations about the reasons for this difference are put forward here. It is simply assumed that local industrial clusters have some characteristics that increase the innovativeness of firms and/or employees.

Mathematically, such an assumption can be represented by a step function (see Figure 1). Such a function is given by

$$I_{step,f}(r) = \frac{\alpha \cdot n_f(r)}{1 + \exp[\beta \cdot (-n_f(r) + \eta)]} \tag{2.5}$$

if the number of firms is used as the independent variable and by

$$I_{step,e}(r) = \frac{\alpha \cdot n_e(r)}{1 + \exp[\beta \cdot (-n_e(r) + \eta)]} \tag{2.6}$$

if the number of employees is used as the independent variable. The parameter, α, denotes the number of innovations per firm or employee within local clusters, while the parameters, β and η, determine the impact of local clusters on the innovativeness in regions. β can be expected to be negative if the assumptions outlined above hold. η can be expected to be positive. Its value determines how many firms or employees have to accumulate in a region before the synergies between them become effective, while β determines how abrupt the innovativeness changes if the number of firms or employees exceeds η.

Above it is assumed that the more firms local clusters contain the more innovative are these firms. Alternatively it can be assumed that that each firm contributes, on average, the same amount of innovations to the level of innovativeness of a region. However, once the number of firms or employees exceeds a certain value,

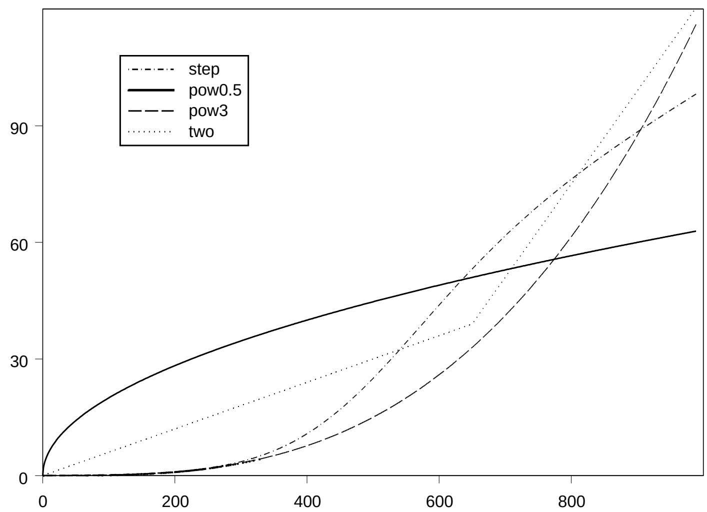

Figure 1: Examples of the three functions that are fitted to the empirical data: A step function, a power function with $\beta = 0.5$, a power function with $\beta = 3$ and a two-parts function.

the amount changes. Hence, firms in clusters would be more innovative than firms outside of clusters, but the level of innovativeness would not increase unlimited.

This can be mathematically formulated by a function that contains two parts. It is modelled here by

$$I_{two,f}(r) = \alpha \cdot n_f(r) + \begin{cases} \beta \cdot (n_f(r) - \eta) & \text{if} \quad n_f(r) > \eta \\ 0 & \text{if} \quad n_f(r) \leq \eta \end{cases} \tag{2.7}$$

if the number of firms is used as the independent variable and by

$$I_{two,e}(r) = \alpha \cdot n_e(r) + \begin{cases} \beta \cdot (n_e(r) - \eta) & \text{if} \quad n_e(r) > \eta \\ 0 & \text{if} \quad n_e(r) \leq \eta \end{cases} \tag{2.8}$$

if the number of employees is used as the independent variable. The parameter, α, denotes the number of innovations per firm or employee in regions with no cluster. The parameter, β, denotes the additional innovations per firm or employee once the critical value is exceeded. The parameter, η, denotes the critical value of the number of firms or employees that distinguishes regions with clusters from those regions without a cluster. Both modellings of the cluster effect are tested empirically below.

2.4. Type of region

The functions above describe the number of innovations depending on the number of firms or employees in the industry under consideration. Usually a constant is added to such regression functions. However, it is a well known fact that large cities are more innovative than rural areas (see, e.g., Koschatzky 1998 and Fritsch & Franke 2000). Therefore, we add a constant to the above function that is different for different kinds of regions.

Three types of regions are distinguished in correspondence with the usual classification of regions in Germany. The kinds of regions are regions that contain agglomerations (*Agglomerationsräume*), called type A here, regions with cities (*verstädterte Räume*), called type B here, and rural areas (*ländliche Räume*), called type C here (the definitions and the classification of regions are taken from INKAR 2000).

In addition to the regression parameters, α and β, three further parameters are introduced: γ_A, γ_B and γ_C. The regression function reads

$$I(r) = I_{F,D}(r) + \gamma_A \cdot T_A(r) + \gamma_B \cdot T_B(r) + \gamma_C \cdot T_C(r) \tag{2.9}$$

where F stands for 'pow', 'step' and 'two', D for 'f' or 'e' and $T_A(r)$, $T_B(r)$ and $T_C(r)$ are dummies that characterise the type of the region. They are defined as

$$T_A(r) = \begin{cases} 1 & \text{if} \quad \text{region } r \text{ is of type A} \\ 0 & \text{if} \quad \text{region } r \text{ is not of type A} \end{cases} \tag{2.10}$$

and accordingly for the types B and C.

All other potential factors that influence the innovativeness of regions are ignored here. The analysis that is conducted here focuses on the question of whether and to what extent an agglomeration of firms or employment in a region increases the number of innovations that are conducted there.

3. Data

Two sources of data are used here. The first source provides data on the number of firms and employment in each 3-digit industry and each administrative district in Germany. In addition, data on the number of patents originating from each of the regions in Germany and belonging to 4 types of technologies are used. Both sources are described separately below. Finally, how they are matched with respect to the different classifications of the industries on which they are based is explained.

3.1. Data on the spatial distribution of firms and employees

The data on the spatial firm distribution, which is used here, has been collected by the *Bundesanstalt für Arbeit*. It contains the number of firms and employees for each 3-digit industry (according to the WZ93-classification[1]) and each of the 441 administrative districts ('Landkreise' and 'kreisfreie Städte') in Germany. The data is recorded for the 30th of June 1999.

Neither the industrial nor the regional units for which this data is provided seem to be adequate for the study conducted here. Patents are recorded on the basis of technologies instead of industries. Therefore, we study only four classes of industries that can be efficiently matched to a respective classification of technology in the patent statistics. These industries are chemicals, vehicles (including ships and aircrafts), electrics and instruments & optics. For each of these industries the data for all 3-digit industries that belong to the industry under consideration is aggregated.

Furthermore, the patent data shows that the inventor and the applicant of a patent are, in almost all cases, located in the same region if *Raumordnungsregion*en[2] are used as regional units (see, e.g., Greif & Schmiedl 2002). Hence, this regional unit seems to be adequate for the study conducted here. There are 97 such regions defined in Germany. They are based on considerations about economic functions of a region, e.g., the commuting of workers.

Each of the 441 administrative districts can be unambiguously assigned to one *Raumordnungsregion*. Hence, the data used here can be easily aggregated to the level of these regions. The regional units are the 97 *Raumordnungsregionen*, which are denoted by r ($\in \{1, 2, ..., N_r(t)\}$, $N_r(t) = 97$). The number of firms in each region, r, is denoted by $n_f(r)$[3]. The number of employees in region, r, is denoted by $n_e(r)$.

[1] 'WZ93' stands for the classification of industries (*Wirtschaftszweige*) that was established in Germany in 1993 and is used by the *Bundesanstalt für Arbeit* since 1996.

[2] *Raumordnungsregionen* are regions in German that typically consist of a major city and its surround. There are 97 such regions defined in Germany. They come most nearest to what is defined in other countries as labour market areas. At the same time administrative borders are respected by the definition of *Raumordnungsregionen*, so that each *Raumordnungsregion* consists of a number of complete administrative districts

[3] The *Bundesanstalt für Arbeit* records all employees. Each employee is assigned to

3.2. Patent data

Since patents go on from the beginning of innovations and accompany their development and application, the patent system provides a suitable instrument for monitoring and analysing innovative potentials and activities. The actual relationship between patents and innovations has been exemplified in empirical investigations (see Greif & Potkowik 1990 and Greif 2001a, and the literature cited therein). This applies also to spatial analyses: spatial and factual differentiation of patent activities show corresponding relations to innovations.

The subject matter of this study is patent applications of domestic origin in Germany. These are patent applications with the German Patent Office and those with the European Patent Office excluding double counting.

The spatial arrangement of patent applications relates to the residence of inventors. The 97 *Raumordnungsregionen* in which Germany is divided are taken as spatial units. In all probability, the place of residence and the work place of an inventor are located within the same region. Therefore, on this spatial level economic and patent data can be connected in a suitable way.

Patent applications published in 1998 are taken as the basis for this study. This makes them temporally close to the economic data of June 1999 described above. Since patent applications are of short-term and medium-term stability in volume as well as in spatial and sectoral structure, they harmonize with economic data even in greater temporal differences (see Greif 1998).

Corresponding to the object of the study, patent applications are broken down according to categories of patent applicants. For this purpose patent applications of firms are relevant. Such a differentiation is not performed by the Patent Office. Therefore, the data has be analysed and classified. Equally, not provided by the Patent Office is a differentiation of patent applications according to sectors of the economy. The available factual subdivisions relate to technical areas as defined by the International Patent Classification. This technical classification does not allow conclusions on sectors of the economy.

To solve this unsatisfactory situation, a concordance system between the Inter-

a working place, called *Betrieb*. The economic unit '*Betrieb*' is defined according to economic considerations and location. Each *Betrieb* is assigned to an industry. If a firm has several branches in different municipalities, each branch is defined as a *Betrieb*, while production sites in the same municipality are counted only once. We use the number of *Betriebe* as the number of firms here. Firms that are run without employees by the owner only are not counted.

national Patent Classification and the German system of classifying sectors of the economy has been created (see Greif & Potkowik 1990). With the aid of this concordance system technological and economic facts can be linked, and consequently economic statistics can be connected with patent statistics. The instrument developed permits detailed observation of innovations in individual fields of technology or sectors of the economy. Since the two classifications that are brought together are very different in their construction, some areas exist where it is not possible to produce a workable connection.

For this study sectors of the economy were selected whose connection to patent classes by means of the concordance system is efficient, and which are provided with a sufficient numerical quantity to ensure a reliable analysis. In this way the following industries were selected and their economic and patent data connected and analysed: chemicals, vehicles, electrics and instruments & optics.

4. Analysis

The 3 models, the power function, the step function and the two-parts function, outlined above have been developed to describe the innovation activity in regions and industries. They are mathematically given by Equation (2.9). Each of them is examined with the help of regression analysis for each industry and for the numbers of firms and employees separately. In total 24 regression analyses are conducted.

The regressions are conducted using GLS estimates according to the Levenberg-Marquardt method. In the case of the function with two parts, this method always converges. In the case of the step function and the power function the convergence is problematic because of the high values of the number of employees. Therefore, the numbers are normated such that the average number of firms or employees in a region is one. As a consequence, the Levenberg-Marquardt method always converges. The parameters are then recalculated for the real numbers of firms and employees.

In addition, a linear regression with the three dummy variable, T_A, T_B and T_C, is conducted. This is mainly done to obtain a comparative residual so that the contributions of the different functions to the prediction of the number of patents in a region can be estimated. The results for all regressions are given in Table 1. Various aspects of these results are discussed below.

First, the regression parameters that are related to the types of regions are discussed. Then, we check whether the numbers of firms or employees are more adequate to describe the innovativeness of regions. Subsequently, we compare the regression results for the three different functional forms that are used. Different assumptions are made in the different modelling approaches. Thus, the validity of the different assumptions can be tested to some extent. Finally, the values of the parameters fitted to the empirical data are discussed. In particular, how the results can be interpreted in the context of the relevance of spillovers and synergies for the existence and emergence of local industrial clusters will be discussed.

4.1. Innovativeness in cities

It is usually claimed that large cities are more innovative than the countryside. This is confirmed by the analysis conducted here. The constant, γ_A, in the regression functions is much higher than the constants, γ_B and γ_C. The difference is statistically significant for nearly all regression. This result is clearly observable if only the dummies γ_A, γ_B and γ_C are used to explain the number of patents. However, it is also obtained in addition to the fact that the higher number of firms in larger cities increases the number of innovations there. Concerning the best fits for each studied industry γ_A is significantly greater than γ_B and γ_C for each of the industries.

A comparison between regions of type B and regions of type C shows a much smaller and always insignificant difference. While agglomerations produce between 29 and 69 patents more than regions with cities (only considering the best fits for each industry), regions with cities cause only up to 17 patents more than rural areas and in one case they cause even less patents. Hence, agglomerations seem to benefit very much from increased innovativeness while regions with cities benefit only slightly compared to rural areas.

Furthermore, the effect is greatest in the case of chemical while it is approximately of the same size in the cases of vehicles and electrics and smallest in the case of instruments & optics. The differences for the best fit in each industry are given in Table 2.

4.2. Firms, employees and local innovativeness

The regression results give no clear answer to the question of whether local innovativeness depends on the number of firms or employees in a region. In the case of vehicles the result is clear: a much smaller value of the residual is obtained for the regression with the number of employees. Employees matter much more than firms in this industry. A plausible explanation for this result is the dominance

industry	#	model	α	β	η	γ_A	γ_B	γ_C	residual
chem.	-	-				**113**	21	10	82.1
	firms	power	6.4 E-8	**4.5***		**82**	14	7.4	69.6
		step	1.5	-19	0.01	42	-27	-19	74.8
		two	**0.67**	**8.1**	**99**	**63**	-5.6	-3.8	**68.3**
	empl.	power	**0.50**	0.99		45	-30	-22	74.7
		step	**0.005**	2660	1.2	**85**	6.6	6.4	76.3
		two	**0.01**	**-0.01**	**22500**	**61**	-5.7	-6.9	71.5
vehicle	-	-				**104**	43	16	114
	firms	power	**2.2 E-7**	**4.3***		**59**	27	12	92.8
		step	1.6	28	0.01	7.6	-7.1	-11.3	104
		two	0.44	**7.5**	**97**	48	14	2.0	92.8
	empl.	power	1.3 E-8	**2.1***		**69**	**25**	7.6	**61.0**
		step	0.007	45000	2.1 E-5	**59**	20	1.3	66.0
		two	0	**0.01**	**24600**	**70**	**26**	4.4	61.5
elect.	-	-				**109**	31	14	97.1
	firms	power	0.61	0.97		33	-18	-19	91.2
		step	**0.43**	15	0.02	48	-2.4	-3.1	91.7
		two	0.36	0.20	93	44	-5.7	-7.8	91.6
	empl.	power	1.3 E-6	**1.8**		**70**	22	6.0	**87.5**
		step	**0.005**	**4680**	0.02	**58**	13	-2.4	89.0
		two	0.03	-0.03	282	39	-9.6	-21	89.2
instr.	-	-				**58**	21	7.8	40.8
	firms	power	0.004	**1.5**		**30**	6.7	-1.3	35.4
		step	0.19	287	0.002	26	3.0	-4.4	35.6
		two	0.02	0.14	165	**32**	9.9	1.6	35.5
	empl.	power	**0.0006**	**1.2**		**32**	3.1	-2.2	**34.7**
		step	**0.005**	**3590**	0.006	**36**	6.9	1.1	34.9
		two	0.004	0.001	2910	**31**	1.3	-3.6	35.0

Table 1: Regression results. Parameters that differ from zero on a significance level of 0.05 are given in bold letter. If the parameter β in the power function is greater than one on a significance level of 0.05, it is highlighted by '*'. The smallest residual that is obtained for each industry is also highlighted in bold letters.

of a few, very large firms. These large firms are especially dominating patenting in this industry.

For the other three industries the values of the residuals differ only slightly between the regressions based on firm numbers and the regressions based on em-

industry	$\gamma_A - \gamma_B$	$\gamma_A - \gamma_C$	$\gamma_B - \gamma_C$
chemicals	69	67	-2
vehicles	44	61	17
electrics	48	64	16
instruments & optics	29	34	5

Table 2: Differences between the parameters γ_A, γ_B and γ_C.

ployment numbers. In the case of chemicals the smallest residual is obtained using firm numbers. In the case of electrics and instruments & optics the smallest residuals are obtained using employment numbers. Hence, the number of firms seems to be slightly more important in the case of chemicals, while the number of employees is more decisive for the innovativeness of a region in the cases of electrics and instruments & optics. However, the differences are very small.

Therefore, the results for both numbers are discussed together below. Only in the case of vehicles are the results for the firm numbers ignored.

4.3. Adequateness of the models

Comparing the regression results for the different models, two fact shows up unambiguously: First, the step function nearly always explains the number of patents in regions worst and never explains the number of patents best. Hence, the assumptions underlying the step function are contradicted by the analysis. Second, the power function nearly always explains the number of patents in regions best and never explains them worst. In addition, the power function contains one parameter less than the other functions, so that it should be expected to be less able to fit the empirical data. Therefore, the empirical study shows that the most adequate model of all studied models is the power function. This seems to hold independent of the industry, although the patents in chemistry are slightly better explained using a function with two parts.

This can be summed up as follows. The hypothesis of a non-linear increase in innovativeness with the number of firms or employees is confirmed. The hypothesis of a clear difference between clusters and other regions is rejected.

4.4. Spillovers, synergies and clustering

The power function, which is confirmed by the above results, has been chosen to allow over-linear as well as under-linear dependencies of the number of patents on the numbers of employees or firms. The parameter β in Equations (2.3) and (2.4) determines the shape of the function. For $0 < \beta < 1$, the slope of the function decreases, which is called under-linear. For $\beta > 1$ the slope of the function increases, which is called over-linear.

Above it has been argued that if no local synergies occur, the number of patents should, on average, increase linearly with the number of firms and employees. This implies a value of $\beta = 1$. If spillovers take place, which cause a benefit for the firms that increases linearly with the number of firms, a value of $\beta \approx 2$ has been predicted above. Finally, it has be argued that $\beta > 2$ has to be satisfied if local synergies cause the emergence of local industrial clusters.

In the cases of chemicals and vehicles we obtain values of 4.5 (for the number of firms) and 2.1 (for the number of employees), respectively. Both values are significantly above 1 and in the case of chemicals the value is even significantly above 2. Thus, it can be concluded that local synergies exist in these industries. Firms seem to benefit from having other firms in the same location. They even seem to benefit from each additional firm in the same region more than from the previous additional firm. This means that the synergies from co-location increase with the number of firms/employees in a region.

In the cases of electrics and instruments & optics, $\beta = 1.8$ and $\beta = 1.2$, respectively, are obtained. Again an over-linear dependence between the number of patents and the number of employees seems to describe reality best. However, for these industries the values of β are not significantly higher than 1 and they are also smaller than 2. This means that it seems to be likely that spillovers also play a role in these industries but that it cannot be proved that spillovers occur. Furthermore, they seem not to be strong enough to cause the emergence of local industrial clusters according to the theoretical argument in Brenner 2001. There might be other synergies that show different characteristics. In the case of innovations, however, we can state that local synergies increase with the number of firms or employees for all industries - with significant increases for chemicals and vehicles. However, a functional dependence $\beta > 2$ that should cause the emergence of local clusters can only be proved for chemicals.

This has implications for the explanation of the existence of local industrial clusters. Brenner (2001) has argued theoretically that some synergies that increase with the number of firms or employees are a necessary condition for the existence of local industrial clusters. Such synergies have been called self-augmenting there. Different causes for such synergies might exist. It is, however, necessary that their addition is of sufficient strength (see Brenner 2001).

The analysis conducted in this paper identifies one source of such self-augmenting synergies for the chemicals industry: synergies with respect to the innovativeness of firms. However, in the case of vehicles, electrics and instruments & optics the results are less clear. The value of β is neither significantly above nor significantly below 2. It is shown in the literature that, at least, for some sub-industries local clusters exist (see Brenner 2003). Three interpretation can be put forward. First, the real value of β might be greater than 2 and the local clusters are caused by spillovers. Second, the various sub-industries might differ in their characteristics. In some of them the spillovers are strong enough to cause local clusters while in others spillovers are weak. The analysis conducted here measures an average value of β which is near to the critical value. Third, there might be other sources of local self-augmenting synergies that cause clustering in these sub-industries.

5. Conclusions

This paper analyses the relationship between the number of firms and employees and the number of patent applications in a region. Several assumptions about the mechanisms behind this relationship are proposed. They are formulated mathematically and tested empirically.

Besides the fact that large cities are much more innovative than other regions, we obtain several results about the dependence of local innovativeness on the number of firms and employees. First, a situation in which the innovativeness of firms is independent of their co-location is rejected. Hence, it is shown that co-location matters. Second, the assumption that a certain threshold of the number of firms or employees exists that separates innovative regions from non-innovative regions is rejected.

It is found that a power function describes the relationship between the number of firms or employees and the number of patents most adequately. However, the four industries that are studied differ with respect to the shape of this function. In two industries, namely chemicals and vehicles, the function is over-linear. This means that firms increasingly benefit from synergies with other firms the more other firms there are located in the same region. In the other two industries, namely electrics and instruments & optics, the results are not significant. Although an over-linear dependence between the number of employees and the number of patents is found, this finding is not significant.

In the context of research into local industrial clusters these results are very informative. To understand why, when and where local clusters emerge, local synergies between firms have to be understood in detail. These synergies have to increase with the number of firms or employees in the region to cause a self-augmenting process that leads to clustering (see Brenner 2001). The study conducted here has shown that only in the chemicals industry such synergies can be proved to exist with respect to the innovativeness of firms. Hence, spillovers and other kinds of synergies that result in a higher innovativeness might explain clustering in some industries but not in others. Similar studies on other factors of local synergies have to be conducted to obtain a complete picture of local clustering.

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