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THE REGIONAL DIMENSION OF SECTORAL INNOVATIVENESS

AN EMPIRICAL INVESTIGATION OF TWO SPECIALISED SUPPLIER AND TWO SCIENCE-BASED INDUSTRIES[*]

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Abstract. The aim of this paper is to test how geographical and technological proximity relate to a particular industry's innovative output. Two mechanisms are therefore tested, i.e. agglomeration economies and the regional exploitation of technological proximity. A new dataset is applied, which includes German patent applications from within the period 1995 to 2006. Four industries are considered, two of which are science-based, whereas the remaining two are specialised supplier industries. While diversity is associated with high innovative output in the specialised supplier industries, the results for specialisation are mixed. However, all industries seem to benefit, at least to a certain degree, from the regional re-combination of their own technologies with those of specific key industries.

JEL codes: O18, R11

Keywords: Innovation, Proximity, Diversity

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I Introduction

The concept of collective invention was coined by Allen (1983) when he observed that innovative actors do not generate new ideas in isolation, but in contact with other actors. This contact provides the exchange of information and knowledge that is required for the generation of new ideas. Hence, knowledge possessed by one actor influences the knowledge generation of other actors – the so-called technological externalities are at work.

Different types of such externalities have been identified and empirically investigated. While some industries seem to benefit from a large regional variety of different sectors, others appear to be more reliant on the regional concentration of firms in their own sector.

The ways these externalities contribute to innovation, growth and welfare are all based on the concept of collective invention and they have been developed further elsewhere. There has been a discussion of the institutional framing within which these externalities are transmitted and the concept of innovation systems as just one of these infrastructures. These systems have been investigated on the national level (Freeman 1988, Nelson 1992, Lundvall 1992) and have also been identified on a more disaggregated level, most prominently from the regional point of view (Cooke 1992).

Another set of disciplines interested in the flow of knowledge with respect to type and intensity is the so-called technology-flow analysis (Scherer 1982, Meyer-Krahmer and Wessels 1989, Cantner and Hanusch 1999). Studies herein identified which sectors of an economy are more closely related to these flows and which are more independent. The potential for cross-fertilization of knowledge has been a major target of this kind of research.

This paper not only investigates which type of agglomeration economies is conducive to different industries' innovative activity but it also aims to find out whether the regional exploitation of technological proximity to certain key industries helps foster innovative output for a particular industry. A new dataset is employed covering all German patent applications within the period from 1995 to 2006.

The remainder of the paper is structured as follows. Section two provides some theoretical considerations on the topic. Section three concentrates on measurement issues and introduces the dataset applied. In section four, the characteristics of the considered industries are highlighted. The estimation framework used to test the hypotheses is explained in section five. Hereafter, the empirical findings are presented and discussed in section six. Section seven highlights the conclusions and puts this analysis into perspective.

II Geographical and Technological Proximity

Agglomeration Externalities

One of the most prominent issues addressed in Regional Economics is the role that geographical distance (or proximity) plays in the exchange of knowledge and inter-organisational learning processes. The observation that innovative activity tends to be clustered geographically (see e.g. Jaffe, 1989; Audretsch and Feldman, 1996; Breschi 1999) triggered a raft of research into the investigation of the causes and effects of such agglomeration. Since the seminal work of Glaeser et al. (1992), a huge body of empirically-dominated literature has developed on the topic. Basically one can distinguish between two different types of externalities that have been identified in playing a role in this respect, viz. (i) localisation economies and (ii) urbanisation economies. Both concepts are based on the idea that firms may benefit from being closely located to one another. However, they differ in terms of the importance of industry concentration and the local variety of industries.

Localisation economies, first stressed by Marshall (1890), refer to the spatial concentration of a single industry. The driving forces that help describe this concept are labour market pooling, input-output linkages, and intra-industry knowledge spillovers, all of which allow firms in specialised regions to be more productive and efficient than their counterparts in less specialised urban or rural areas. By adding Arrow’s (1962) formalization of learning and Romer’s (1986) contributions regarding the impact of dynamic knowledge accumulation, Glaeser et al. (1992) coined the term Marshall-Arrow-Romer (MAR) externalities. This concept claims that the local concentration of an industry promotes innovation within this very industry, as it eases the transmission of knowledge and information, the imitation of products and processes, as well as inter-firm employee mobility (Saxenian, 1994).

While localisation economies deal with a single industry and only indirectly refer to other industries via buyer-supplier relations, the concept of urbanisation economies follows a different line of reasoning. It refers to urban size and local variety of industries. The literature sometimes further discriminates between urbanisation economies as such and Jacobs externalities (see e.g., Frenken et al., 2007).

Accordingly, urbanisation economies reflect benefits for an industry stemming from a large urban region itself. This concept is not primarily related to industrial composition. It prefers to depict the fact that large cities are likely to host universities, extramural research institutes, and other knowledge-generating organisations. However, it does not only refer to the economic character of such institutions but also to social, political and cultural aspects (Frenken et al., 2007).

Jacobs externalities, instead, are economies external to the firm stemming from the local variety of sectors (Jacobs, 1969). This variety is supposed to positively affect the generation of innovations in two (similar) ways. First, it is the recombination of knowledge from different industries that leads to important and radical innovations. Consequently, the likelihood for new product combinations is supposed to be higher in regions with a large variety of sectors. Second, firms in different industries may face similar (technological) problems. In this case, solutions developed in one industry might be adopted in another one without major difficulties. Hence, the more diverse the local knowledge base is, the higher the chance for knowledge spillovers (Neffke et al., 2008).

In this respect, Frenken et al. (2007) distinguish between related and unrelated variety. The authors argue that unrelated variety may slow down unemployment growth as it serves as protection against external asymmetric demand shocks. Related variety, in contrast, is said to stimulate Jacobs externalities and thus foster economic growth and employment.

While empirical studies consistently agree that knowledge spillovers are geographically-bounded (Anselin et al., 1997; Feldman and Audretsch, 1999), the empirical results regarding the causes of such externalities are less unanimous. Amongst the approaches that use some kind of a production function to analyse the impact of agglomeration economies on innovation, are the results that vary from positive and significant to insignificant or even negative and significant (see Beaudry and Schiffauerova, 2009 for an overview).

Van der Panne and van Beers (2006), for example, find positive effects of MAR externalities but none from Jacobs externalities. In contrast, the results by Feldman and Audretsch (1999) back up Jacobs' diversity theory but only provide little support for the specialisation thesis. Greunz (2004, p. 584) reports: "whatever the investigated model, diversity influences innovation more than specialisation." For Italian districts, Paci and Usai (2000) report that the innovative activity of a local industry is positively affected by both types of externalities with Jacobs externalities being more powerful in high technology industries located in metropolitan regions.

Recently, some attempts have been made to link the influence of agglomeration economies to a corresponding stage in an individual industry's life cycle. Henderson et al. (1995) already presented their results against the background of product cycles. Jacobs externalities, they argue, are particularly important to attract newer high-tech industries. Localisation economies, in contrast, should gain importance when it comes to retaining traditional manufacturing industries. Neffke et al. (2008) offer theoretical considerations and empirical evidence for this relationship. Hence the predominantly young firms in the early stages of the industry life cycle (ILC) compete on the basis of individual characteristics and the quality of their products but not so much on price. Accordingly, these early stages are characterised by radical innovations since a 'dominant design' has not yet emerged (Abernathy and Utterback, 1978). This, in turn, implies that sources of information for further inventions may often come from outside the industry as firms seek a variety of knowledge in order to offer an improved product to the customer. Therefore, immature industries should disproportionately benefit from inter-industry knowledge spillovers and thus from Jacobs externalities. As industries mature, the competition will be more and more based on price. Accordingly, MAR externalities are likely to gain importance as they are associated with cost savings (Neffke et al., 2008).

Unfortunately, reliable information on the industries' individual stages within their life cycles is not easily available. Moreover, the use of NACE industry codes at a 3-digit level in the present study disallows the identification of a single industry life cycle as the industries at this level of aggregation are far too heterogeneous. It can be argued, however, that an industry's affinity for a certain type of agglomeration externality is not only determined by the life cycle but also by its inherent innovation characteristics. Pavitt (1984) delivers a description of sectoral technological trajectories and, based thereon, develops his renowned taxonomy. He distinguishes between 'supplier-dominated', 'scale-intensive', 'specialised suppliers', and 'science-based' industries. Recent studies confirmed the validity of this taxonomy (e.g. Archibugi, 2001; de Jong and Marsili, 2006) but at the same time, point out that it is "applicable at the firm rather than at the industry-level" (Leiponen and Drejer, 2007 pp. 1233/1234). Hence an industry cannot be completely characterised by this classification but the respective firm characteristics can be considered as prevalent.

For the purpose of the analysis in this paper, two categories of industries gain importance, i.e., science-based industries and specialised suppliers. In a science-based industry, new technologies typically originate from the R&D activities of firms in that very industry, "based on the rapid development of the underlying sciences in the universities and elsewhere" (Pavitt, 1984, p.362). Pavitt goes on to mention that the innovative firms in these industries have "little incentive to look for innovative opportunities beyond their principal sector" and that it is "difficult for firms outside the sectors to enter them" due to the use of sophisticated technologies (Pavitt, 19984 p.362). This suggests that the science-based industries are less dependent on knowledge from a large variety of other industries and, if at all, are rather prone to localisation economies.

On the contrary, a significant contribution to the innovative output of the specialised supplier firms comes from users and other firms outside their principal sector (Pavitt, 1984). Moreover, these firms concentrate their innovative activities on product innovations which are meant to be used in other sectors. Pavitt (1984, p.359) also mentions that "Such suppliers … provide their large customers with specialised knowledge and experience as a result of designing and building equipment for a variety of users, often spread across a number of industries." This crucial role of a variety of industries, in turn, points at the relative importance of Jacobs externalities in these industries. This is, however, not to say that these industries would not, at the same time, benefit from localisation economies. From Pavitt's taxonomy, one cannot presume that a certain degree of sectoral specialisation providing for intra-industry knowledge spillovers would not be beneficial for a certain type of industry. Based on these sectoral characteristics, the first two hypotheses are extracted:

> Hypothesis 1: A high degree of regional diversity is associated with a high innovative output of the specialised supplier but not of the science-based industries.

> Hypothesis 2: Specialisation is positively related to innovation in both types of industries.

Technological Re-Combinations

It should be acknowledged that the sole focus of the relevance of geographical proximity or co-location for the exchange of knowledge is not undisputed. In the 1990s, the French School of Proximity Dynamics began to criticise such a one-dimensional view on proximity. Ever since, it has been argued that proximity encompasses several different dimensions (Rallet and Torre, 1999; Torre and Gilly, 2000). In this respect, it is often distinguished between organisational and geographical proximity (e.g. Torre and Rallet, 2005). Boschma (2005) even proposes five different forms, i.e. cognitive, organisational, social, institutional and geographical proximity.

Besides geographical proximity, which has already been addressed, the cognitive dimension is of special importance for the purpose of this paper. Cognitive proximity consists of an overlap in the actors' knowledge bases. Learning processes always require a certain degree of mutual understanding between those involved. Consequently, the cognitive dimension of proximity determines the probability that the knowledge of two industries could potentially be combined. Hence a realised re-combination of technologies from different industries in a region may be regarded as a case in which the regional actors actually exploit this cognitive proximity.

Regarding the causes of such re-combinations, one can highlight three potential mechanisms, viz. (i) inter-industry cooperation or spillovers, (ii) input-output linkages, and (iii) intra-firm knowledge flows within highly diversified firms. The notion of inter-industry knowledge spillovers is the most popular mechanism and forms the underlying idea of what has been introduced as Jacobs externalities above. The second mechanism is straightforward as well, i.e., technological recombination may occur because a firm from industry *j* operates as a supplier to industry *i*. The third plausible explanation is not external to the firm but can be regarded as an inter-industry knowledge flow as well. Consider a large corporation with different departments operating in different industries. Such a firm may be able to effectively combine its resources from different departments to come up with a new invention.

It has already been pointed out that specialised supplier industries are likely to benefit from inter-industry knowledge spillovers. Moreover, buyer-supplier relations by definition form a crucial vehicle of knowledge transfer in these industries. Hence it is straightforward to assume that these industries would benefit from the regional exploitation of technological proximity to other industries, i.e. from technological re-combinations. Alternatively, for the science-based industries, intra-firm knowledge flows are a more plausible mechanism in this respect. Indeed Pavitt (1984, p. 364) points out that "… large, diversified firms make a bigger contribution to innovations by science-based firms, than to those by specialised equipment suppliers." Hence for both types of industries, there is reason to anticipate the appearance of technological recombination. Therefore the third hypothesis to be tested is framed as:

> Hypothesis 3: The regional exploitation of technological proximity to certain industries is positively associated with the innovative output of both, science-based and specialised supplier industries.

III Data and Measurement issues

The present study is based on German patent data for the period from 1995 to 2006 which is taken from the German Patent and Trade Mark Office (DPMA). Regarding the regional dimension, this data can be assigned to 97 Raumordnungsregionen (ROR) representing German planning regions. Employment data is obtained from the German labour market statistics and refers to all employees subject to social insurance contribution in the year 1999. Control variables describing the regions are taken from the German statistical office and refer to the year 2000.

Patent data is used to determine the innovative output of an industry. The authors are well aware of the pitfalls and drawbacks of such data as have been intensively discussed in the literature (e.g., Encaoua et al., 2006). However, it provides unique information on the quantity, the regional dimension and technological aspects of inventions. All German patent applications within the period from 1995 to 2006 will be considered as long as they allow for the localisation of its inventors. Unfortunately, no reliable data is available on a regional basis for the period before 1995 due to a change in German postal codes and a reshaping of postal code areas after the German reunification. To the authors' knowledge there is no such thing as a simple matching procedure which would allow anyone to relate old postal codes to new ones.

For the purpose of this study, it is necessary to relate the patent applications to the respective industries and regions so that each patent application can be described in a two-dimensional space. For this purpose, it is necessary to define the size of a region. In doing so, the paper follows Fritsch and Franke (2004) by opting for German Planning Regions (ROR) to describe regions above local and below federal units. On this basis, each patent application is assigned to the planning regions in which its inventors were identified.

To relate the patent applications to the respective industries, the most common way is based on the IPC classes assigned to each patent. Using a concordance developed by Schmoch et al. (2003), these classes can be related to the NACE industry codes on a 3-digit level. All in all, this concordance covers forty-three industries of the manufacturing sector, whereas each IPC class is attributed to only one single industry.

In order to test Hypothesis 1, it is necessary to assess a region's variety of industries, i.e. the potential for Jacobs externalities. To capture such diversity, an inverse Herfindahl index will be used as is frequently done in the literature (e.g. Combes, 2000). This measure is based on the local employment shares of all sectors K, except the one considered, i.e. industry i:

$$DIV_{-i,r} = \frac{1/\sum\limits_{\substack{k=1 \\ k \neq i}}^{K} \left(\frac{Emp_{k,r}}{Empl_r - Empl_{i,r}} \right)^2}{1/\sum\limits_{\substack{k=1 \\ k \neq i}}^{K} \left(\frac{Empl_k}{Empl - Empl_i} \right)^2}$$

where $Empl_r$ and $Empl$ indicate total employment while $Empl_{i,r}$ and $Empl_i$ denote sectoral employment in region r and Germany, respectively. The variable $DIV_{-i,r}$ reaches its maximum whenever all industries except for the one considered exhibit the same size in the region.

To assess an industry's degree of regional concentration, the production structure specialisation index ($SPEC_{i,r}$) is computed (see Table 2). This coefficient indicates the relative size of an industry in the region compared to the national average (see, e.g., Feldman and Audretsch, 1999). It is formally defined as:

$$SPEC_{i,r} = \frac{Empl_{i,r} \ / \ Empl_r}{Empl_i \ / \ Empl} \ ,$$

This index is made symmetric by applying the same transformation as in Dalum et al. (1999):

$$\frac{SPEC_{i,r}-1}{SPEC_{i,r}+1}$$

The values of the normalized specialization index range from -1 to 1. In this respect zero indicates that the regional employment share of an industry equals the industry's average employment share in Germany.

While the literature on agglomeration economies suggests a positive relationship between spatial co-location and the innovative activity of industries, the proximity literature additionally proposes a supportive role of the cognitive dimension of proximity. This cognitive or technological proximity is argued to be a prerequisite for the recombination of knowledge from different industries. In keeping with the literature, the present study also aims at assessing the effects stemming from the regional exploitation of technological proximity to other industries.

industry *i*	key industries	NACE code
basic chemical	pharmaceuticals	24.4
	rubber and plastic products	25
	non-metallic mineral products	26
	non-specific purpose machinery	29.2
	special purpose machinery	29.5
signal transmission, telecommunications	office machinery and computers	30
	electric distribution, control, wire, cable	31.2, 31.3
	electronic components	32.1
	measuring instruments	33.2
	motor vehicles	34
medical equipment	basic chemical	24.1
	pharmaceuticals	24.4
	non-specific purpose machinery	29.2
	special purpose machinery	29.5
	measuring instruments	33.2
optical instruments	office machinery and computers	30
	signal transmission, telecommunications	32.2
	television and radio receivers, audiovisual electronics	32.3
	medical equipment	33.1
	measuring instruments	33.2

Table 1: The key industries of the investigated sectors

In this sense, the paper draws on the technology flow analysis which attempts to find out how technological knowledge generated in one sector of an economy flows to other sectors with the purpose of being used there. Several ways on how to measure the direction and "quantity" of knowledge flows have been developed (for an overview see Cantner and Hanusch 1999). In this paper, a method is applied which belongs to the class of disembodiment approaches (meaning there is no specific material carrier of knowledge such as goods or investment goods). Here, the proximity or the distance of actors in the technological space is considered as the main determinant for knowledge to spill over from one actor to another. Jaffe (1986), and his predecessor Scherer (1982), introduced this approach into the literature investigating the technology flows between sectors for the US. Relying on the basic idea of this approach, a comparative measure will be developed that accounts for the regional recombination of technologies of any pair of industries.

Given the restriction of only ninety-seven observations (corresponding to the spatial units), one must refrain from considering all possible combinations of the forty-four industries. Thus for each industry *i* only those five industries shall be considered with whose technologies *i*'s own technologies are most frequently combined with. In each case, these five industries roughly account for 2/3 of industry *i*'s overall re-combinations which, in turn, account for up to 50% of *i*'s overall patents. Hence these five industries can be regarded as some of *i*'s technologically (or cognitively) most proximate industries. This is why they are referred to as its key industries in the following. Table 1 presents an overview about all these industries.

As mentioned above, such re-combinations of the industries' know-how are based on a certain degree of cognitive proximity which is typically measured at the national level thus accounting for direct as well as indirect linkages between the industries. In the literature, this is frequently done using a cosine index (e.g. Engelsman and van Raan, 1992; Breschi et al., 2003; Cantner and Meder, 2008) which takes the following form:

$$Cosine_{i,j} = \frac{\sum_{k=1}^{K} App_{i,k} \cdot App_{j,k}}{\sqrt{\sum_{k=1}^{K} App_{i,k}^2}\sqrt{\sum_{k=1}^{K} App_{j,k}^2}},$$

where $App_{i,k}$ is the number of patents which are based on technologies of both, industry *i* and *k*. The question here, however, is how this cognitive proximity between two industries is exploited at the regional level. In other words, how related two industries are in terms of direct re-combinations of their technologies in a certain region. To quantify this relationship the cosine index is restricted to only direct linkages (re-combinations) and is calculated for each region separately. The resulting variable takes the innovative activity of both industries in the region into account and is defined as:

$$Recomb_{i,j,r} = \frac{App_{i,r} \cdot App_{j,i,r} + App_{i,j,r} \cdot App_{j,r}}{\sqrt{App_{i,r}^2 + App_{i,j,r}^2}\sqrt{App_{j,i,r}^2 + App_{j,r}^2}}.$$

Here $App_{i,r}$ denotes industry *i*'s patents and $App_{i,j,r}$ captures the patents describing re-combinations of technologies from industry *i* and *j* in region *r*. The variable $Recomb_{i,j,r}$ does not capture the technological proximity between industry *i* and *j* but rather indicates how it is exploited in the region. Hence it is a relative measure of re-combinations of technologies of both industries that have actually been realised in a certain region *r*. The index is standardised in a way that it takes a value of unity whenever there is a perfect overlap between the patenting activities of both industries and zero if there is no overlap at all.

Such re-combinations must not be regarded as Jacobs externalities per se since one cannot distinguish between regional effects and effects across regional boundaries. Certainly one of the patent's inventors is registered in the region under consideration. What is not known, however, is whether the knowledge of both or just of one industry stems from this very region. Therefore in section II the sources for such re-combinations were identified as (i) inter-industry cooperation or spillovers, (ii) input-output linkages, and (iii) intra-firm knowledge flows within diversified firms.

A few control variables have to be included in order to account for regional and industry-specific characteristics. The regional size of an industry will be regarded as one of the main predictors of its innovative output in the region in absolute terms. The variable $Employment_{i,r}$ captures the number of industry *i*'s employees in region *r* and therewith the size of the industry.

Following Feldman and Audretsch (1999, p.415), population is understood as a 'crude but useful measure of the size of the geographic unit'. In order to account for the fact that regions are not homogeneous in size, the variable $population\ density_r$ will be included for each planning region. It is defined as the number of inhabitants per sq km of settlement and traffic area (INKAR, 2002). Since the size of the industry is already controlled for, a positive coefficient indicates benefits from an urban environment as such. In other words, this variable captures what was labelled as urbanisation economies above.

Differences in the regions' economic performance may influence an industry's innovative potential. To account for such differences, the variable GDP_r, which is specified as a region's gross domestic product per 1,000 inhabitants, is added to the model.

There is a whole strand of literature dedicated to the impact of public research on regional development (e.g., Dahlstrand, 1999; Fritsch and Schwirten, 1999). In keeping with this literature, the presence of universities and technical colleges shall be controlled for by the number of their graduates in the region holding a degree in natural sciences or engineering ($Graduates_r$).

Last but not least, $Other\ Patents_r$ is a control for the overall innovativeness of a region covering the innovative output of all other industries except for the industry under consideration.

IV The industries

The present study surveys four 3-digit industries, i.e. *basic chemical* (NACE 24.1), s*ignal transmission/telecommunications* (NACE 32.2), *medical equipment* (NACE 33.1), as well as *optical instruments* (NACE 33.4). Considering product innovations, Arundel and Kabla (1998) report a patent propensity rate for the whole chemical sector (ISIC 24) of 57.3%, 46.6% for communication equipment (ISIC 32) and 56.4% for precision instruments (ISIC 33). Based on their results, patents can be regarded as a decent indicator for product innovations in the four industries. In doing so, an implicit assumption is made, i.e., that all innovations are homogeneous in their impact. This assumption, as unrealistic as it may be, underlies most of the studies that use some measure of innovative activity (Feldman and Audretsch, 1999).

As was pointed out in section two, the industries may differ in their dependence on agglomeration economies according to their idiosyncratic innovation characteristics. Pavitt's taxonomy was introduced as a way of classifying the industries respectively. According to Pavitt (1984, p. 362), "science-based firms are to be found in the chemical and the electronic/electrical sectors." Thus in the following, the industries *basic chemical* (*BC*) and s*ignal transm./telecom.* (*STT*) will be considered 'science-based' industries. Instead Pavitt (1984) characterises instrument engineering firms as specialised suppliers, which is why the remaining two industries *medical equipment* (MDE) and *optical instruments* (OI) will be regarded as belonging to this category (Pavitt, 1984).

$SPEC_{i,r}$	basic chemical	signal transm./ telecom.	medical equipment	optical instruments
Mean	-0.4243	-0.3887	-0.0710	-0.3048
Std Dev	0.4654	0.4922	0.2462	0.4524
Min	-0.9825	-1.0000	-0.4776	-1.0000
Max	0.9196	0.7213	0.8066	0.9391
Gini*	0.4459	0.4418	0.1381	0.3520
Obs	97	97	97	97

* Gini coefficients obtained from 100 bootstrap replications and multiplied by n/(n-1) to get unbiased estimates (cf. Dixon 1987)

Table 2: Production structure specialisation indices for 1999

According to hypothesis 1, only *medical equipment* and *optical instruments* should benefit from a large local variety of industries, i.e. Jacobs externalities. In contrast, it is hard to make any predictions as to which industry is more likely to benefit from MAR externalities (hypothesis 2). In this regard, it is worth considering the industries' degree of spatial concentration. From Table 2, one can easily see that the science-based industries show the highest degree of agglomeration. Regarding the specialisation index ($SPEC_{i,r}$), both industries, *basic chemical* and *signal* *transm./telecom.*, not only exhibit the lowest mean values of all four industries but also the highest standard deviation. Accordingly, the Gini coefficient of inequality on the specialisation coefficients is largest for both specialised supplier industries. However, they are followed closely by *optical instruments*. Only the spatial distribution of medical equipment seems to be rather homogeneous.

For the recombination of technologies from different industries, three potential causes were identified, i.e. (i) inter-industry cooperation and knowledge spillovers, (ii) buyer-supplier relations, as well as (iii) large diversified firms. The first two were already argued to be likely mechanisms of technological recombination in the specialised supplier industries, *medical equipment* and *optical instruments*. As Pavitt (1984) points at the importance of large, diversified firms in the science-based industries, intra-firm knowledge flows must be regarded a potential mechanism of technological re-combinations in the *basic chemical* and *signal transm./telecom.* industry. This view is supported by the findings of Malerba and Orsenigo (1995, p. 57), who report that “chemicals and electronics have the characteristics of the 'Schumpeter Mark II' model”, i.e. innovation in these industries is dominated by large firms.

V Estimation framework

In order to test the hypotheses put forward in section II, a model will be estimated in which the dependent variable is the number of patent applications that are attributed exclusively to the industry under consideration. Hence all patents describing re-combinations of this industry’s technologies with those of others are excluded from the left-hand side of the equation. On average, these re-combinations account for around forty to fifty percent of an industry’s overall innovative output. This procedure ensures that contributions from outside the respective industry to its own innovative output are not part of the dependent variable. That way the focus is on the sole innovative output of the considered industry. Hence all patents that contribute to the $Recomb_{i,j,r}$ variables only appear on the right-hand side of the equation. This model is then estimated separately for each of the four industries described above (Models 1 to 4). Table 3 shows some descriptive statistics for the dependent variables.

In order to test hypothesis H1, the variable $DIV_{-i,r}$ serves as an explanatory variable covering the effects from a region’s variety of industries, i.e., the potential for Jacobs externalities. The variable $SPEC_{i,r}$ is used to test for MAR externalities. The five $Recomb_{i,j,r}$ variables are included to capture the effects stemming from the regional exploitation of the cognitive proximity to the five key industries. The $Employment_{i,r}$ variables control for the presence and size of the industry under consideration and that of the respective five key industries. $Other\ Patents_r$ is a control for the overall innovativeness of a region covering the innovative output of all other industries except for the industry under consideration. The variables GDP_r, $Density_r$, and $Graduates_r$ serve as region specific controls. Tables A1 to A4 in the appendix show the correlation matrices for all variables and each industry.

Patents of	Mean	Std Dev	10%	25%	Median	75%	90%	Min	Max	Obs
basic chemical	600.1	1074.3	53.6	94.0	236.0	449.0	1290.2	19	5799	97
signal transm./telecom.	352.6	698.7	31.4	77.0	166.0	404.0	663.2	2	6064	97
medical equipment	288.8	367.1	41.6	66.0	156.0	349.0	633.8	9	2427	97
optical instruments	131.6	192.1	12.6	27.0	65.0	144.0	312.6	2	1324	97

Table 3: Descriptive statistics on the dependent variables.

Some of the employment variables are significantly correlated with each other and/or with some of the control variables. To deal with problems arising from multicollinearity and thus to assess the robustness of the results, different versions of each model will be estimated. Version (a) only includes the two variables capturing MAR and Jacobs externalities, the number of employees of the industry under consideration as well as the region-specific controls. Instead of $SPEC_{i,r}$ and $DIV_{-i,r}$ (b) contains the $Recomb_{i,j,r}$ variables while all of these variables jointly enter into model version (c) which additionally includes *Other Patents*$_r$. The Employment figures of the five key industries only appear in model version (d). Since the number of explanatory variables in this last version (d) is rather high compared to the number of observations, this model version shall merely be regarded as a robustness check. Moreover, one must admit that the number of graduates is highly correlated with population density. However, the main results are robust enough to omit either one or the other variable.

The dependent variable is a non-negative integer which shows a Poisson-like distribution. Hence, applying simple OLS estimation cannot be an appropriate solution. To account for the highly skewed distribution of a limited dependent variable, a Poisson regression seems to be better suited. Yet the authors refrain from this option and rather rely on negative binomial regressions which use a different probability model allowing for more variability in the data (Greene, 2003). This method has been used frequently in other studies on related topics (e.g., del Barrio-Castro and Garcia-Quevedo, 2005; Ponds et al., 2009). As the time span for which the innovations are observed is rather long there are no zero values in any of the regions. Hence the problem of having a distribution with too many observations at one end does not occur.

Since this is a plain cross section analysis, causal relationships cannot be addressed. Instead the results shall be interpreted in terms of correlations reflecting regularities or general patterns, as may be observed in the regional distribution of an industry's innovative activity.

VI Results

In this section, the results from the negative binomial regressions are presented with respect to the hypotheses put forward in section II. As mentioned earlier, four models are estimated, i.e., one for each industry. The exhaustive results can be found in Tables A5 to A8 in the appendix. The results for the science-based industries are found in table A5 (with models 1a-d) for *basic chemical* (*BC*) and in table A6 (with models 2a-d) for *signal transm./telecom.* (*STT*). Tables A7 (models 3a-d) and A8 (models 4a-d) display the results for the specialised supplier industries, i.e *medical equipment* (*MDE*) and *optical instruments* (*OI*).

Agglomeration Economies

To begin with, the results support hypothesis 1 for which the variable of note is $DIV_{-i,r}$. In line with hypothesis 1, the regression results do not reveal any relationship between general industrial diversity and the innovative output in the science based industries. In model 1a and 2a, the coefficients for $DIV_{-i,r}$ are not significant at any reasonable level. Adding more explanatory variables in the following models, 1b-d and 2b-d do not change anything in this regard.

Nevertheless, for *basic chemical*, it should be mentioned that the coefficient for diversity gains little significance in model 1c (but only at the 10% level). However, significance again disappears as soon as the employment figures of the five key industries are added in model version 1d. The coefficients for three of these employment variables are positive and significant. Apparently spatial co-location with *pharmaceuticals* (*PHA*), *Non-Metallic Mineral Products* (*NMM*), and *Special Purpose Machinery* (*SPM*) but not general sectoral diversity is associated with high innovative output of *basic chemical*. Accordingly, the results hint at the importance of regional knowledge transfers between *basic chemical* and those three industries. Interestingly, the three industries are not generally co-located with *basic chemical* as the correlations in Table A1 reveal.

Neither in the case of *signal transm./telecom.* (*STT*) is diversity correlated with the industry's innovative activity in any of the model specifications. Nor are the employment figures of the five key industries. Only for employees in *Office Machinery/Computers* (*OMC*), do the results in model 2d reveal a negative correlation with the industry's (*STT*) patents. As the employment in *OMC* and *STT* are positively correlated amongst each other, this result might indicate that manufacturing of both industries is co-located while R&D is not. The fact that the coefficient for *STT*'s own employment remains insignificant also suggests a strong division between R&D and manufacturing. On the other hand, *OMC*'s employment is highly correlated with the regions' overall innovativeness (*OtherPatents$_r$*) which raises concerns about multi-collinearity. Overall, the results show that the industry neither benefits from geographical proximity to a large variety of other industries nor to certain technologically similar industries.

The picture is a different one for the specialised suppliers, i.e. *medical equipment* (*MDE*) and *optical instruments* (*OI*). For *MDE*, the coefficient for industrial diversity is positive and highly significant in all specifications of model 3. Still after the re-combination variables are simultaneously included with the region's overall innovativeness (model 3c), and the presence of the five key industries is controlled for (model 4d), the coefficient remains significant. Moreover, the regional size of the *measuring instruments* industry (*MSI*) is positively related to *medical equipment*'s own innovative output. Hence the industry seems to benefit from geographical proximity to a large variety of industries in general and to *MSI* in particular.

For *optical instruments* (*OI*), the coefficient for diversity in model version 4a is positive but exhibits only a low significance level. However, once the regional innovativeness is controlled for and the re-combination variables are included (model 4c), the coefficient gains significance which is maintained in model 4d. Hence the *optical instruments* industry indeed seems to benefit from a large regional variety of other industries. At the same time, the geographical proximity to the five key industries turns out to be irrelevant. The coefficients for employment in *signal transm./telecom.* (*STT*) are even negative and significant. However, this should not be overrated due to high correlations with the regions' overall innovativeness (*Other Patents$_r$*) and the other region specific controls and the resulting concerns about multi-collinearity.

These first findings distinctly coincide with the industries' characteristics as reported in Pavitt (1984). Hypothesis 1 stated that the specialised suppliers but not the science-based industries benefit from the geographical co-location with a large variety of other industries and appears to be valid.

Regarding specialisation, the results are mixed. Hypothesis 2 does not make any assumptions about which industry is more likely to draw advantages from being located in a highly specialised region. Nevertheless, one would expect those industries to benefit relatively more from MAR externalities which are already more concentrated.

Surprisingly this is not the case. Indeed a high degree of specialisation is associated with a lot of innovative activity in *basic chemical*, which is one of the two most agglomerated industries. The coefficient is always positive and significant in the respective specifications of model 1. The fact that the region's overall innovativeness (*Other Patents$_r$*) does not seem to play a role further underlines the importance of specialisation. The industry seems to be most innovative in specialised regions irrespective of how innovative the other industries in the same regions are.

However, for *signal transm./telecom.* and for *optical instruments*, both of which are relatively agglomerated in geographical terms, the degree of specialisation is not related to the industries' patents. In contrast, the innovative output of the industry with the most even distribution over space, i.e. *medical equipment*, appears to be higher in specialised regions. The respective coefficients are positive and highly significant in all specifications of model 3 in which the variable is included. As has been shown above the industry benefits from Jacobs externalities at the same time. Apparently, an industry does not necessarily need to be highly concentrated in a few regions to benefit from MAR externalities. Firms in the *medical equipment* industry rather seem to benefit from being located in relatively moderate specialised regions that also exhibit a certain degree of diversity. The results confirm the validity of hypothesis 2 since specialisation is associated with high innovative output in one specialised supplier as well as in one science based industry.

Besides testing for MAR and Jacobs externalities, the study also controls for effects stemming from an urban environment as such, i.e. pure urbanisation economies. As it turns out, *basic chemical* seems to benefit from an urban surrounding as indicated by the positive and significant coefficient for the variable *population density*$_r$. Hence, all other things being equal, the industry is more innovative in urban compared to more rural areas. The same holds true for optical instruments. As in the case of *basic chemical*, the respective coefficient for *population density*$_r$ is positive and highly significant in all specifications of the model.

Technological Re-Combinations

The other major focus of this paper is on the relationship between an industry's innovative output and the regional exploitation of technological (or cognitive) proximity to its five key industries. Therefore, versions b to d of each model include the re-combination variables with these industries. As put forward in hypothesis 3, both types of industries, science-based and specialised suppliers, are likely to benefit from such technological re-combinations.

With respect to *basic chemical*, the re-combination of its own technologies with those of *pharmaceuticals* (PHA), *rubber and plastic products* (RPP), and *non-metallic mineral products* (NMM) appears to be advantageous. The respective coefficients are positive and highly significant in model version 1b. Simultaneously controlling for agglomeration economies in model 1c and for geographical co-location with the respective industries in model 1d does not change the sign of the coefficients nor their significance.

As already mentioned above, the industry also benefits from spatial co-location with *pharmaceuticals* and *non-metallic mineral products*. Accordingly, the *basic chemical* industry seems to benefit from both geographical proximity and the regional exploitation of technological proximity to these two industries. Hence the relationship between these industries shows a distinct regional dimension.

Regarding *signal transm./telecom.* (STT), the re-combination variables with *office machinery and computers* (OMC) and *electronic components* (EC) show positive and significant coefficients in all versions of model 2 in which they are included (2b-d). The coefficient for re-combinations with *measuring instruments* (MSI) is positive but significant only at the 10% level. It has already been mentioned that the industry does not benefit from co-location with any of the considered industries. Accordingly, the regional exploitation of technological proximity to *OMC* and *EC* is associated with a higher innovative output for *signal transm./ telecom.* whereas the sole presence of the industries does not hold any benefits per se.

Concerning technological re-combinations in the *medical equipment* industry, the only positive correlation found pertains to *measuring instruments* (MSI). The coefficient for the re-combination variable is always positive and highly significant. Again this seems to be a distinct regional effect as the industry also benefits from co-location with this industry.

For the *optical instruments* industry, the only re-combination variable with a highly significant coefficient belongs to the industry *television, radio receivers, and audiovisual electronics* (TVA). While the coefficient is insignificant in model 4b, it gains significance at the 5% level once agglomeration economies and the region's overall innovativeness is controlled for (model 4c and 4d). At the same time, *TVA*'s own employment in the region is not related to *optical instruments*' innovative output. In other words the pure co-location of both industries does not hold benefits for optical instruments but the regional exploitation of technological proximity between them does.

Further Findings

Pavitt (1984, p. 362) argues that the science-based industries depend "… on the rapid development of the underlying sciences in the universities and elsewhere." In line with this argument, the results reveal a significant correlation between the number of graduates from universities and technical colleges and the innovative output of both science based industries. Regarding *basic chemical*, the coefficient for $graduates_r$ is positive and highly significant in specifications a to c of model 1 whereas in model 1d, it is significant but at the 10% level. One reason therefore might be that the graduates are significantly correlated with a number of employment variables. For *signal transm./telecom.*. the same coefficient is positive and significant in all specifications of model 2. This result underlines the importance of geographical proximity to public research facilities for these industries. The same relationship is found for the *optical instruments* industry showing that the industry not only depends on the local presence of a large variety of industries but also benefits from spatial co-location with universities.

Interestingly, in the case of *signal transm./telecom.* and *medical equipment* industry employment does not really add much to the explanatory power of the respective model. One may conclude that there is a spatial division between manufacturing and R&D in these industries.

VII Conclusion

In which way geographical and technological proximity influence the innovative activity of a certain industry is subject to an ongoing debate in regional science. The aim of this paper was to add to the understanding of these processes by asking whether the geographical proximity to a variety of sectors or the regional exploitation of technological proximity to certain key industries matters for an industry's own innovative output. Patent data are used as an indicator for an industry's innovations but also provide information on the mutual use of technologies from different industries.

According to the Pavitt taxonomy, the paper differentiates between two science-based (*basic chemical* and *signal transmission/telecommunications*) and two specialised supplier industries (*medical equipment* and *optical instruments*). Negative binomial regressions are applied to estimate a model in which the dependent variable is the innovative output of the respective industry. All in all, four of these models were estimated, i.e. one for each industry.

The results confirm previous expectations based on the industries' innovation characteristics. Neither of the science-based industries benefit from Jacobs externalities whereas spatial co-location to universities appears to be advantageous for both of them. The innovative output of *basic chemical* is largest in regions specialised in the industry and regions with a high population density. In contrast, none of these variables seems to play a role in the *signal transm./telecom*. industry. The *medical equipment* industry derives advantages from both, MAR and Jacobs externalities, whereas only the latter can be applied to the other specialised supplier industry, *optical instruments*. Moreover, all industries benefit from the regional exploitation of technological proximity to certain key industries.

Based on a cross-section of regions, the study cannot solve any issues of causality. However, the observed correlations are in line with the theoretical considerations based on the industries' characteristics as reported by Pavitt (1984). In order to control for region-specific fixed effects and to gain deeper insights into the underlying dynamics, a panel data framework would be desirable for follow-up studies. Moreover, future work may focus on the mechanisms through which co-located firms of the same or different industries are linked. One interesting aspect to be explored in the future would be the relationship between diversity/specialisation and cooperation.

Appendix

	SPEC	DIV	Recomb PHA	Recomb RPP	Recomb NMM	Recomb NSP	Recomb SPM	Employment PHA	Employment RPP	Employment NMM	Employment NSP	Employment SPM	Employment BC	Other Patents	GDP	Pop. Density	Graduates
SPEC	1																
DIV	0.1283	1															
Recomb$_{PHA}$	0.2757*	-0.0451	1														
Recomb$_{RPP}$	0.3329*	0.1249	0.0528	1													
Recomb$_{NMM}$	0.4845*	0.1435	0.111	0.4209*	1												
Recomb$_{NSP}$	0.1402	0.1473	0.2492*	0.1779	0.1677	1											
Recomb$_{SPM}$	0.0622	-0.1359	0.1267	0.158	0.2397*	0.181	1										
Employment$_{PHA}$	0.1897	0.3191*	0.157	0.0776	0.2414*	0.2515*	-0.0263	1									
Employment$_{RPP}$	0.154	0.5397*	-0.0317	0.1567	0.1465	0.0759	-0.044	0.3391*	1								
Employment$_{NMM}$	0.0713	0.3326*	0.1047	0.2520*	0.1626	0.2211*	0.0548	0.1112	0.5122*	1							
Employment$_{NSP}$	0.1015	0.5208*	-0.042	-0.0416	0.0779	0.1098	-0.1031	0.3090*	0.6167*	0.1995	1						
Employment$_{SPM}$	0.1514	0.5468*	0.0402	0.0269	0.1486	0.0869	-0.1409	0.2634*	0.6329*	0.2525*	0.6824*	1					
Employment$_{BC}$	0.5905*	0.2065*	0.2619*	0.2642*	0.3804*	0.2644*	0.1724	0.1328	0.2323*	0.0536	0.1705	0.1942	1				
OtherPatents	0.1697	0.4445*	0.0505	0.0099	0.1435	0.1856	-0.1133	0.3968*	0.5936*	0.2160*	0.7952*	0.6738*	0.2672*	1			
GDP	0.1741	0.4371*	-0.0664	-0.1356	0.1156	0.0725	-0.2165*	0.3238*	0.3521*	0.0757	0.5058*	0.4687*	0.2085*	0.6067*	1		
Pop. Density	0.1637	0.4412*	0.1141	-0.0207	0.2119*	0.2644*	0.0224	0.5109*	0.3791*	0.1479	0.6478*	0.4663*	0.2643*	0.6007*	0.4611*	1	
Graduates	0.092	0.4314*	0.0776	0.0077	0.0807	0.1543	-0.0458	0.5533*	0.5252*	0.2155*	0.7018*	0.4895*	0.1171	0.7354*	0.4614*	0.7443*	1

BC = Basic Chemical; PHA = Pharmaceuticals; RPP = Rubber and Plastic Products; NMM = Non-Metallic Mineral Products; NSP = Non-Specific Purpose Machinery; SPM = Special Purpose Machinery; '*' indicates significance at the 5% level

Table A 1: Correlation Matrix *Basic Chemical*

	SPEC	DIV	Recomb OMC	Recomb EDC	Recomb EC	Recomb MSI	Recomb MV	Employment OMC	Employment EDC	Employment EC	Employment MSI	Employment MV	Employment STT	Other Patents	GDP	Pop. Density	Graduates
SPEC	1																
DIV	0.2794*	1															
Recomb$_{OMC}$	0.1954	0.2122*	1														
Recomb$_{EDC}$	-0.0256	0.128	0.12	1													
Recomb$_{EC}$	0.0029	0.2146*	0.1724	0.1475	1												
Recomb$_{MSI}$	0.1048	0.0568	0.1991	-0.0521	0.0986	1											
Recomb$_{MV}$	-0.0151	-0.1202	-0.1422	0.0058	0.2326*	0.2795*	1										
Employment$_{OMC}$	0.2010*	0.3024*	0.1399	0.0483	0.0911	0.0267	0.0551	1									
Employment$_{EDC}$	0.2519*	0.3993*	0.0909	-0.0163	0.1668	0.075	0.1108	0.5102*	1								
Employment$_{EC}$	0.2290*	0.3523*	0.2292*	0.1183	0.2087*	0.0161	0.1259	0.5238*	0.4612*	1							
Employment$_{MSI}$	0.3938*	0.4543*	0.0775	0.0844	0.0488	0.1108	-0.0462	0.4881*	0.5020*	0.4444*	1						
Employment$_{MV}$	0.2527*	0.0155	0.0739	-0.0046	0.0194	0.0987	0.2343*	0.6046*	0.5816*	0.4058*	0.3770*	1					
Employment$_{STT}$	0.6889*	0.2956*	0.1286	-0.0513	-0.0603	0.0081	0.0172	0.5080*	0.5604*	0.4188*	0.6394*	0.5801*	1				
OtherPatents	0.3771*	0.4121*	0.1249	0.0131	0.0676	0.0397	0.0467	0.7428*	0.7064*	0.6343*	0.7727*	0.7053*	0.7736*	1			
GDP	0.2577*	0.4093*	0.0495	0.2089*	0.1445	0.0934	0.1358	0.3693*	0.3364*	0.4043*	0.6338*	0.3776*	0.4213*	0.6093*	1		
Pop. Density	0.4524*	0.4065*	0.1536	0.0822	0.0135	-0.0541	-0.1433	0.3363*	0.4872*	0.3830*	0.6264*	0.3159*	0.6235*	0.6111*	0.4611*	1	
Graduates	0.4529*	0.4356*	0.0964	0.0973	-0.0177	-0.0509	-0.1075	0.5412*	0.4714*	0.5683*	0.6568*	0.4889*	0.6762*	0.7287*	0.4614*	0.7443*	1

STT = Signal Transmission/Telecommunications; OMC = Office Machinery/Computers; EDC = Electric Distribution, Control, Wire, Cable; EC = Electronic Components; MSI = Measuring Instruments; MV = Motor Vehicles; '*' indicates significance at the 5% level

Table A 2: Correlation Matrix *Signal Transmission/Telecommunications*

	SPEC	DIV	Recomb BC	Recomb PHA	Recomb NSP	Recomb SPM	Recomb MSI	Employment BC	Employment PHA	Employment NSP	Employment SPM	Employment MSI	Employment MDE	Other Patents	GDP	Pop. Density	Graduates
SPEC	1																
DIV	0.2172*	1															
$Recomb_{BC}$	0.0545	0.13	1														
$Recomb_{PHA}$	0.1479	0.0989	0.0774	1													
$Recomb_{NSP}$	0.1417	-0.0013	0.3765*	0.1717	1												
$Recomb_{SPM}$	-0.0841	-0.1215	0.1183	-0.2280*	0.0586	1											
$Recomb_{MSI}$	0.1061	0.0604	0.0484	-0.0252	0.0262	0.0738	1										
$Employment_{BC}$	-0.1577	-0.0103	0.3676*	-0.1076	-0.0084	0.118	0.0508	1									
$Employment_{PHA}$	0.1162	0.2952*	0.092	-0.1401	-0.055	0.0914	0.1029	0.1328	1								
$Employment_{NSP}$	0.1084	0.5171*	0.0765	-0.0628	-0.0541	-0.0118	-0.0568	0.1705	0.3090*	1							
$Employment_{SPM}$	0.1028	0.5380*	0.1785	-0.0471	-0.0767	-0.0569	-0.0359	0.1942	0.2634*	0.6824*	1						
$Employment_{MSI}$	0.1771	0.4613*	0.1009	-0.0481	-0.0196	0.0313	0.0531	0.1798	0.5284*	0.6624*	0.5566*	1					
$Employment_{MDE}$	0.6258*	0.4554*	0.1003	0.1201	0.005	-0.0275	0.0821	0.0984	0.3187*	0.5933*	0.5116*	0.6681*	1				
OtherPatents	0.0353	0.4154*	0.1312	-0.0537	-0.0748	0.0495	0.0293	0.3146*	0.4092*	0.7878*	0.6868*	0.7688*	0.5887*	1			
GDP	0.1873	0.4120*	0.0511	-0.0527	-0.0171	0.0028	0.0393	0.2085*	0.3238*	0.5058*	0.4687*	0.6338*	0.5019*	0.6081*	1		
Pop. Density	0.1059	0.4141*	0.2902*	-0.0761	0.0035	-0.0168	0.1565	0.2643*	0.5109*	0.6478*	0.4663*	0.6264*	0.6002*	0.6064*	0.4611*	1	
Graduates	0.0484	0.4442*	0.1026	-0.1728	-0.1226	0.0121	0.0597	0.1171	0.5533*	0.7018*	0.4895*	0.6568*	0.5764*	0.7320*	0.4614*	0.7443*	1

MDE = Medical Equipment; BC = Basic Chemical; PHA = Pharmaceuticals; NSP = Non-Specific Purpose Machinery; SPM = Special Purpose Machinery; MSI = Measuring Instruments; '*' indicates significance at the 5% level

Table A 3: Correlation Matrix *Medical Equipment*

	SPEC	DIV	Recomb OMC	Recomb STT	Recomb TVA	Recomb MDE	Recomb MSI	Employment OMC	Employment STT	Employment TVA	Employment MDE	Employment MSI	Employment OI	Other Patents	GDP	Pop. Density	Graduates
SPEC	1																
DIV	0.0914	1															
$Recomb_{OMC}$	0.1273	0.1715	1														
$Recomb_{STT}$	0.0716	-0.0317	0.0434	1													
$Recomb_{TVA}$	0.1866	-0.0784	0.3276*	0.1169	1												
$Recomb_{MDE}$	0.2451*	0.0101	-0.0778	-0.1652	0.0927	1											
$Recomb_{MSI}$	0.0461	-0.1019	-0.0594	0.1075	0.2074*	-0.0582	1										
$Employment_{OMC}$	0.1181	0.3054*	0.0872	0.1434	0.0244	-0.0187	-0.0622	1									
$Employment_{STT}$	0.1281	0.3127*	0.0193	-0.0093	-0.1167	-0.0307	-0.0646	0.5080*	1								
$Employment_{TVA}$	0.2725*	0.2385*	0.0366	0.0566	0.0055	0.0095	0.0558	0.4580*	0.4729*	1							
$Employment_{MDE}$	0.1786	0.4598*	0.0515	0.0249	-0.0184	0.1755	-0.0639	0.3676*	0.6018*	0.2874*	1						
$Employment_{MSI}$	0.2710*	0.4586*	0.1496	0.0361	-0.0146	0.0006	-0.0065	0.4881*	0.6394*	0.5307*	0.6681*	1					
$Employment_{OI}$	0.6432*	0.2254*	0.1229	0.0324	0.2802*	0.3494*	0.0853	0.2738*	0.2894*	0.2682*	0.2127*	0.3484*	1				
OtherPatents	0.2228*	0.4154*	0.0863	0.0394	-0.018	-0.0232	-0.0766	0.7465*	0.7707*	0.6134*	0.5957*	0.7726*	0.4196*	1			
GDP	0.1993	0.4128*	0.0851	0.0048	-0.0001	0.0344	-0.0992	0.3693*	0.4213*	0.3057*	0.5019*	0.6338*	0.2693*	0.6106*	1		
Pop. Density	0.0208	0.4149*	0.0987	0.0689	0.0237	-0.0402	0.0111	0.3363*	0.6235*	0.3579*	0.6002*	0.6264*	0.2160*	0.6091*	0.4611*	1	
Graduates	0.0239	0.4446*	0.0927	0.1243	-0.0512	-0.1301	0.0057	0.5412*	0.6762*	0.4225*	0.5764*	0.6568*	0.2310*	0.7337*	0.4614*	0.7443*	1

OI = Optical Instruments; OMC = Office Machinery/Computers; STT = Signal Transmission/Telecommunications; TVA = Television/Radio Receivers/Audiovisual electronics; MSI = Measuring Instruments; '*' indicates significance at the 5% level

Table A 4: Correlation Matrix *Optical Instruments*

Dependent Variable	Patent applications *Basic Chemical*											
Model	(1a)			(1b)			(1c)			(1d)		
	coef	z-stat	p-value	coef	z-stat	p-value	coef	z-stat	p-value	coef	z-stat	p-value
SPEC	0.7705	3.62	0.000	-	-	-	0.3534	1.86	0.063	0.3532	2.01	0.044
DIV	1.0077	1.41	0.158	-	-	-	1.1011	1.81	0.071	0.4522	0.71	0.476
$Recomb_{PHA}$	-	-	-	3.1864	4.36	0.000	3.2762	4.45	0.000	2.4230	3.38	0.001
$Recomb_{RPP}$	-	-	-	4.5159	3.33	0.001	3.9529	2.91	0.004	3.8814	3.03	0.002
$Recomb_{NMM}$	-	-	-	3.3713	3.65	0.000	2.9183	3.05	0.002	1.8464	2.07	0.039
$Recomb_{NSP}$	-	-	-	-0.2599	-0.25	0.800	-0.1165	-0.12	0.908	-0.7501	-0.76	0.445
$Recomb_{SPM}$	-	-	-	-1.2245	-0.78	0.436	-0.3864	-0.25	0.804	-0.1645	-0.11	0.912
$Employment_{PHA}$	-	-	-	-	-	-	-	-	-	0.0001	1.95	0.051
$Employment_{RPP}$	-	-	-	-	-	-	-	-	-	0.0000	-1.01	0.314
$Employment_{NMM}$	-	-	-	-	-	-	-	-	-	0.0001	2.68	0.007
$Employment_{NSP}$	-	-	-	-	-	-	-	-	-	-0.0001	-0.97	0.332
$Employment_{SPM}$	-	-	-	-	-	-	-	-	-	0.0001	2.03	0.043
$Employment_{BC}$	0.0001	2.75	0.006	0.0000	2.82	0.005	0.0000	1.63	0.104	0.0000	2.53	0.011
OtherPatents	-	-	-	-	-	-	0.0000	0.51	0.612	0.0000	0.67	0.502
GDP	0.0000	0.83	0.407	0.0000	1.60	0.110	0.0000	0.81	0.418	0.0000	0.54	0.592
Pop. Density	0.0005	2.59	0.010	0.0005	3.27	0.001	0.0004	2.73	0.006	0.0004	2.99	0.003
Graduates	0.0005	3.21	0.001	0.0004	3.56	0.000	0.0004	2.41	0.016	0.0002	1.68	0.093
cons	2.9451	5.23	0.000	1.3346	2.56	0.010	0.9849	1.49	0.136	1.7620	2.67	0.008
n	97			97			97			97		
Pseudo R^2	0.100			0.130			0.135			0.148		
Log-likelihood	-579.011			-559.645			-556.573			-548.591		

BC = Basic Chemical; PHA = Pharmaceuticals; RPP = Rubber and Plastic Products; NMM = Non-Metallic Mineral Products; NSP = Non-Specific Purpose Machinery; SPM = Special Purpose Machinery

Table A 5: NegBin regression results *Basic Chemical*

Dependent Variable	Patent applications of *Signal Transmission/Telecommunications*											
Model	(2a)			(2b)			(2c)			(2d)		
variable	coef	z-stat	p-value	coef	z-stat	p-value	coef	z-stat	p-value	coef	z-stat	p-value
SPEC	0.2888	1.19	0.232	-	-	-	0.3585	1.53	0.125	0.3079	1.37	0.171
DIV	0.0683	0.11	0.913	-	-	-	-0.8960	-1.51	0.131	-0.6218	-0.88	0.381
$Recomb_{OMC}$	-	-	-	3.1501	2.65	0.008	3.0191	2.78	0.006	3.3178	3.09	0.002
$Recomb_{EDC}$	-	-	-	-0.7442	-0.79	0.430	-0.2270	-0.25	0.805	-0.0075	-0.01	0.993
$Recomb_{EC}$	-	-	-	3.6479	2.78	0.005	3.3732	2.78	0.005	3.7556	3.12	0.002
$Recomb_{MSI}$	-	-	-	3.2796	1.93	0.054	2.9466	1.82	0.068	3.1900	1.93	0.054
$Recomb_{MV}$	-	-	-	-1.1923	-0.88	0.377	-1.8254	-1.33	0.182	-1.2026	-0.83	0.406
$Employment_{OMC}$	-	-	-	-	-	-	-	-	-	-0.0002	-2.48	0.013
$Employment_{EDC}$	-	-	-	-	-	-	-	-	-	-0.0001	-1.57	0.117
$Employment_{EC}$	-	-	-	-	-	-	-	-	-	0.0000	-0.46	0.643
$Employment_{MSI}$	-	-	-	-	-	-	-	-	-	0.0000	-0.67	0.505
$Employment_{MV}$	-	-	-	-	-	-	-	-	-	0.0000	-0.46	0.644
$Employment_{STT}$	0.0000	-0.05	0.958	0.0000	0.66	0.512	-0.0002	-1.56	0.118	-0.0002	-1.65	0.098
OtherPatents	-	-	-	-	-	-	0.0001	3.63	0.000	0.0001	4.42	0.000
GDP	0.0000	3.28	0.001	0.0000	2.83	0.005	0.0000	0.71	0.479	0.0000	0.41	0.684
Pop. Density	0.0003	1.79	0.074	0.0003	2.18	0.030	0.0002	1.70	0.090	0.0002	1.46	0.143
Graduates	0.0005	3.54	0.000	0.0006	4.32	0.000	0.0004	2.86	0.004	0.0005	3.17	0.002
cons	2.8195	4.84	0.000	1.6114	4.02	0.000	3.0974	5.13	0.000	2.8078	4.38	0.000
n	97			97			97			97		
Pseudo R^2	0.084			0.105			0.117			0.124		
Log-likelihood	-560.114			-546.994			-539.501			-535.300		

STT = Signal Transmission/Telecommunications; OMC = Office Machinery/Computers; EDC = Electric Distribution, Control, Wire, Cable; EC = Electronic Components; MSI = Measuring Instruments; MV = Motor Vehicles

Table A 6: NegBin regression results *Signal Transmission/Telecommunications*

Dependent Variable	Patent applications of *Medical equipment*											
Model	(3a)			(3b)			(3c)			(3d)		
variable	coef	z-stat	p-value	coef	z-stat	p-value	coef	z-stat	p-value	coef	z-stat	p-value
SPEC	0.8606	2.07	0.039	-	-	-	1.1868	2.88	0.004	1.0874	2.62	0.009
DIV	1.4890	2.84	0.005	-	-	-	1.2598	2.57	0.010	1.0661	1.98	0.048
$Recomb_{BC}$	-	-	-	1.3409	0.78	0.433	0.8945	0.57	0.566	1.3629	0.83	0.408
$Recomb_{PHA}$	-	-	-	0.9503	1.00	0.317	0.9300	1.04	0.297	0.9843	1.12	0.262
$Recomb_{NSP}$	-	-	-	-1.1048	-0.61	0.544	-1.4083	-0.85	0.395	-1.7038	-1.07	0.285
$Recomb_{SPM}$	-	-	-	0.2068	0.11	0.911	1.1537	0.70	0.485	0.8036	0.51	0.611
$Recomb_{MSI}$	-	-	-	2.7803	3.72	0.000	2.2030	3.04	0.002	2.2081	3.05	0.002
$Employment_{BC}$	-	-	-	-	-	-	-	-	-	0.0000	-0.03	0.977
$Employment_{PHA}$	-	-	-	-	-	-	-	-	-	0.0001	1.31	0.190
$Employment_{NSP}$	-	-	-	-	-	-	-	-	-	0.0000	0.00	1.000
$Employment_{SPM}$	-	-	-	-	-	-	-	-	-	0.0000	-0.34	0.736
$Employment_{MSI}$	-	-	-	-	-	-	-	-	-	0.0001	1.97	0.049
$Employment_{MDE}$	0.0002	1.48	0.139	0.0004	4.82	0.000	0.0001	0.78	0.436	0.0001	0.71	0.480
OtherPatents	-	-	-	-	-	-	0.0000	2.64	0.008	0.0000	1.67	0.095
GDP	0.0000	2.26	0.024	0.0000	2.28	0.022	0.0000	0.48	0.634	0.0000	0.06	0.949
Pop. Density	0.0003	2.43	0.015	0.0002	1.17	0.240	0.0002	1.54	0.124	0.0001	0.84	0.402
Graduates	0.0002	1.74	0.082	0.0003	2.21	0.027	0.0001	1.12	0.262	0.0001	0.87	0.383
cons	2.0040	4.49	0.000	2.5354	6.79	0.000	2.3005	4.72	0.000	2.6255	5.35	0.000
n	97			97			97			97		
Pseudo R^2	0.092			0.096			0.111			0.118		
Log-likelihood	-540.169			-537.838			-528.976			-524.927		

MDE = Medical Equipment; BC = Basic Chemical; PHA = Pharmaceuticals; NSP = Non-Specific Purpose Machinery; SPM = Special Purpose Machinery; MSI = Measuring Instruments

Table A 7: NegBin regression results *Medical Equipment*

Dependent Variable	Patent applications of *Optical Instruments*											
Model	(4a)			(4b)			(4c)			(4d)		
variable	coef	z-stat	p-value	coef	z-stat	p-value	coef	z-stat	p-value	coef	z-stat	p-value
SPEC	0.3792	1.68	0.092	-	-	-	0.3082	1.48	0.140	0.2095	0.98	0.327
DIV	1.0075	1.63	0.104	-	-	-	1.4025	2.35	0.019	1.2211	2.14	0.033
$Recomb_{OMC}$	-	-	-	-0.2401	-0.15	0.877	-0.6871	-0.47	0.637	-1.3263	-1.01	0.311
$Recomb_{STT}$	-	-	-	2.3565	1.34	0.181	2.3325	1.41	0.159	2.4638	1.63	0.104
$Recomb_{TVA}$	-	-	-	1.1110	1.54	0.124	1.4720	2.13	0.033	1.3454	2.10	0.036
$Recomb_{MDE}$	-	-	-	-0.0431	-0.03	0.973	-0.3221	-0.26	0.798	0.1962	0.15	0.880
$Recomb_{MSI}$	-	-	-	0.1150	0.09	0.926	0.3136	0.27	0.789	-0.1736	-0.16	0.873
$Employment_{OMC}$	-	-	-	-	-	-	-	-	-	-0.0002	-1.80	0.072
$Employment_{STT}$	-	-	-	-	-	-	-	-	-	-0.0003	-4.01	0.000
$Employment_{TVA}$	-	-	-	-	-	-	-	-	-	0.0000	0.25	0.804
$Employment_{MDE}$	-	-	-	-	-	-	-	-	-	0.0000	0.00	0.998
$Employment_{MSI}$	-	-	-	-	-	-	-	-	-	0.0001	1.64	0.100
$Employment_{OI}$	0.0005	2.77	0.006	0.0005	3.68	0.000	0.0003	1.98	0.048	0.0003	2.07	0.039
OtherPatents	-	-	-	-	-	-	0.0000	1.95	0.051	0.0001	2.78	0.005
GDP	0.0000	0.57	0.570	0.0000	1.39	0.166	0.0000	-0.46	0.646	0.0000	-1.43	0.153
Pop. Density	0.0004	2.56	0.010	0.0004	2.47	0.013	0.0003	2.08	0.037	0.0004	2.40	0.016
Graduates	0.0004	2.99	0.003	0.0005	3.34	0.001	0.0003	1.89	0.059	0.0005	3.25	0.001
cons	1.5329	2.80	0.005	1.5258	3.30	0.001	1.2845	2.18	0.029	1.5828	2.81	0.005
n	97			97			97			97		
Pseudo R^2	0.107			0.109			0.119			0.139		
Log-likelihood	-443.426			-442.451			-437.561			-427.517		

OI = Optical Instruments; OMC = Office Machinery/Computers; STT = Signal Transmission/Telecommunications; TVA = Television/Radio Receivers/Audiovisual electronics; MDE = Medical Equipment; MSI = Measuring Instruments

Table A 8: NegBin regression results *Optical Instruments*

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