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Innovation, spillovers, and university-industry collaboration:

An extended knowledge production function approach

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Abstract

This paper analyses the effect of knowledge spillovers from academic research on regional innovation. Spillovers are localized to the extent that the underlying mechanisms are geographically bounded. However, university-industry collaboration - as one of the carriers of knowledge spillovers - is not limited to the regional scale. Consequently, we expect spillovers to take place over longer distances. The effect of university-industry collaboration networks on knowledge spillovers is modelled using an extended knowledge production function framework applied to regions in the Netherlands. We find that the impact of academic research on regional innovation is mediated not only by geographical proximity but also by social networks stemming from collaboration networks.

Keywords: Knowledge production function, knowledge spillovers, university-industry collaboration, innovation, social networks

JEL-codes: C21, O18, O31, R11

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1. Introduction

Regional differences in the rate of innovation are currently an important topic in economic geography and in policy debates on regional development. The possible determinants of regional differences in innovation have been analysed in many studies over the years (see Döring and Schnellenbach 2006 for an overview). The presence of public research organisations such as universities is generally assumed to have a large impact on regional innovation due to localized knowledge spillovers resulting from their research. Within the literature, various empirical studies have suggested the presence of localized academic knowledge spillovers for the USA (Jaffe 1989, Anselin et al. 1997, Adams 2002) and various European countries (Florax 1992, Autant-Bernard 2001, Andersson et al. 2004, Fritsch and Slavtchev 2007). In line with these insights, many countries have implemented regional innovation policies based on the presence of universities and research institutes in a region.

Research on academic knowledge spillovers on the micro-level finds that the different mechanisms through which spillovers occur, are indeed localized to a large extent. Besides the importance of local labour markets and spin-off dynamics, studies have emphasized the role of networking between individuals and between organisations as a mechanism for knowledge spillovers. Informal networking often takes place at the regional level, and as a result, knowledge spillovers are localized to the extent that these networks are (Breschi and Lissoni 2003, 2006). Formal networks of research collaboration are an important mechanism of knowledge spillovers as well. However, empirical research on the geographical dimension of these networks has suggested that these are not limited to the regional scale. Rather, formal research collaboration occurs largely at the national or even the international scale (McKelvey et al. 2003, Ponds et al. 2007). As a result, knowledge spillovers through research collaboration are expected to occur over long distances. This implies that, especially in industries where formal research collaboration frequently occurs, the structure of collaboration networks needs to be taken into account to fully understand the impact of academic knowledge spillovers.

The goal of this paper is to analyse the relative importance of both collaboration networks and geographical proximity for academic knowledge spillovers and their effect on regional innovation. We propose a novel approach to measuring academic spillovers by incorporating the geographical structure of research collaboration networks between universities and industries into a regional knowledge production function framework. We cover seven science-based industries in the Netherlands, where academic research and university-industry collaboration are especially important. The paper is structured as follows. In the second section, we review the existing literature on academic knowledge spillovers and the roles of geographical proximity and collaboration networks. In the third section, we describe the data and our extended knowledge production function methodology. Section four discusses the econometric results, and section five concludes.

2. Academic knowledge spillovers and the role of geography and networks

Differences in innovative performance between regions are often explained by agglomeration economies, which are advantages that firms obtain from being located in a region with a geographical concentration of similar firms and of knowledge institutes. A key element in the concept of agglomeration economies are localized knowledge spillovers, which reflect the advantages firms can have in accessing knowledge that, intentionally or unintentionally, 'spills over' from other firms and knowledge institutes. The existence of localized knowledge spillovers is generally treated as one of the most important explanations for regional differences in innovation (Jaffe et al. 1993).[2] It is often argued that localized knowledge spillovers give rise to increasing returns, which further induce innovative activities to cluster within specific regions exhibiting these agglomeration economies. The importance of geographical proximity for knowledge spillovers for firms and organizations is also emphasized in concepts like regional innovation systems (Cooke et al. 1997) and learning regions (Morgan 1997).

The literature on knowledge spillovers pays special attention to the role of academic research institutes and especially universities (for recent examples, see Audretsch et al. 2005, Del-Barrio-Castro and Garcia-Quevedo 2005, Fritsch and Slavtchev 2007). Universities are assumed to be important sources of localized knowledge spillovers due to their explicit focus on the generation and diffusion of knowledge. Nonetheless, the importance of academic research for innovation differs strongly across industries (Klevorick et al. 1995, Cohen et al. 2002). The results of academic research are especially important for firms in the so-called science-based industries. The notion of science-based industries was introduced by Pavitt (1984) in his classification of industries based on differences in their sources of innovation and characteristics of the processes of

[2] There is a large body of literature on the issue of whether a specialized or diversified regional economic structure is more beneficial for the occurrence and magnitude of localized spillovers (see for an overview Rosenthal and Strange 2004). It is, however, beyond the scope of this paper to elaborate further on this.

innovation. Science-based industries, such as biotechnology and semiconductors, are characterized by the importance of scientific knowledge for their innovative activities. As a result, firms in these industries invest relatively heavily in R&D and collaborate intensively with academic organizations such as universities. Given the importance of scientific research, it can be assumed that the presence of knowledge spillovers from academic research is especially important for explaining regional differences in innovation in science-based industries.

Academic knowledge spillovers are localized to the extent that the mechanisms underlying such spillovers take place at the regional level. Within the literature, three major mechanisms of knowledge spillover have been distinguished. First, spin-offs form an important mechanism of commercialisation of academic knowledge. Spin-offs and start-ups tend to locate in proximity to the parent organization, resulting in a geographical concentration of these firms around universities and research institutes (Zucker et al. 1998, Klepper 2007). Second, by moving from one organisation to another, the knowledge embodied in individuals is transferred. Labour mobility can thus be considered another important mechanism of knowledge spillovers (Almeida and Kogut 1999). Since labour mobility is a regional phenomenon to a considerable extent, knowledge spillovers through labour mobility are often localized as well. Third, informal knowledge exchange is an important mechanism for knowledge spillovers (Breschi and Lissoni 2003, 2006, Singh 2005). Informal knowledge exchange often takes place through social networks, which are to a large extent localized as well.

Besides informal social networks, formal networks of research collaboration also form an important mechanism of knowledge spillovers. This is especially the case in science-based industries, where collaborative networks are considered to be crucial for innovation (Powell et al. 1996, Stuart 2000). Though research collaboration can be considered as simple co-production of knowledge where inputs are transformed into outputs, knowledge spillovers will occur as a by-product of such processes. Moreover, following the line of reasoning of Breschi and Lissoni (2003, 2006), collaborative research can lead to enduring social relationships between researchers over longer distances. As such, research collaboration is likely to lead to future spillovers in the sense that researchers who have collaborated in the past are likely to continue to exchange knowledge informally. This is especially important in science- and engineering-based industries where informal knowledge exchange is commonplace due to the professional norms of communities of engineers and researchers (Von Hippel 1994, Lissoni 2001). The importance of this form of knowledge exchange is apparent from the fact that collaboration is increasingly important within processes of knowledge creation in both academia (Wagner-Doebler 2001) and the private sector (Hagedoorn 2002). Here, we focus on university-industry collaboration as a channel for academic knowledge spillovers in science-based industries (Etzkowitz and Leydesdorff 1996).

Research on the geographical dimension of university-industry collaborations shows that these linkages are not limited to the regional level; rather, they occur mostly on the national or even the international scale (McKelvey et al. 2003, Ponds et al. 2007). These findings are in line with the increasing attention to the non-regional dimension of knowledge flows (Bunnell and Coe 2001, Faulconbridge 2006). Geographical proximity itself is neither necessary nor a sufficient condition for inter-organisational knowledge spillovers to occur (Boschma 2005). In the case of research in science-based industries, collaboration is more likely to be based on the presence of specific knowledge of potential partners than on geographical proximity (Moodysson et al. 2008).

Altogether, this body of literature argues that knowledge flows and knowledge spillovers can occur at different geographical scales**.** This implies that knowledge spillovers from universities can also occur over longer distances between regions. If this is the case, it is unlikely that the relationship between academic knowledge spillovers and regional innovation is fully captured by taking only the regional dimension of spillovers into account. Rather, if networks of formal research collaboration are an important mechanism of knowledge spillovers, it is necessary to include the structure of these networks when analysing academic knowledge spillovers. The objective of our empirical analysis is to capture and weight this effect of formal collaboration networks between university and industry, as a channel for academic knowledge spillovers, on regional innovation.

3. Research design

A large number of empirical studies on knowledge spillovers have been based on the application of a regional knowledge production function as introduced by Jaffe (1989), who analysed the presence of localized academic knowledge spillovers at the level of US states. In a regional knowledge production function framework, regional knowledge inputs (such as R&D expenditures) are expected to contribute to regional innovation output (such as number of patents or new products). Based on Jaffe's seminal contribution, various authors have refined this approach by using a smaller geographical scale (Audretsch and Feldman 1996) and distinguishing between different industries (Anselin et al. 2000). Whereas in an early stage most of this research was based on US data, more recent studies on European countries have produced similar findings.[3] Whereas the largest part of this research has focussed on the roles of different R&D inputs and the presence of knowledge spillovers for innovative output, several studies have tried to account for region-specific conditions that influence the innovative output as well (see, for example, Rodriguez-Pose and Crescenzi 2008, Crescenzi et al. 2008). It was found that conditions such as human capital or demographic structure significantly influence the innovative output. This suggests that there is a need to take these regional 'contextual conditions' into account within empirical studies of regional differences in innovation.

We test the importance of geography and collaborative networks for knowledge spillovers from academic research using an extended regional knowledge production function framework. The innovative output of a region depends on the size of its own private and university R&D expenditures and the size of such expenditures in other regions to the extent that these inputs are accessible to a region. We assume that external R&D can be accessed through localized mechanisms and through social relationships over longer distances stemming from formal research collaboration. This means that the size of these spillovers depends on the geographical distance to other regions in case of

[3] See, for example, Autant-Bernard (2001) for France, Fischer and Varga (2003) for Austria, Del Barrio-Castro and Garcia-Quevedo (2005) for Spain, and Fritsch and Slavtchev (2007) for Germany.

localized spillovers, and on the intensity of collaboration with universities in other regions in the case of spillovers from research collaboration. Maggioni et al. (2007) explored such an approach, but, in contrast to their study, we will include the two sources of spillovers simultaneously as independent variables.[4] Possible regional differences in conditions that might influence innovative output are taken into account in two different ways. Following Rodriguez-Pose and Crescenzi (2008), several variables that measure different technology-specific regional conditions are included in the first set of models. The second set of models includes regional fixed effects, which control for unobserved regional heterogeneity in factors (see Fritsch 2001 for a related approach) affecting innovation output in general. A third set of models includes both regional fixed effects and the variables measuring technology specific regional conditions.

3.1 Data

We analysed the relative importance of geography and networks for academic knowledge spillovers for seven science-based technologies in the Netherlands at the level of NUTS3 regions. Within the Netherlands, NUTS3 regions are defined as labour market regions or functional regions around a central city. Innovation at the regional level was measured by the average of the number patents applied for by firms at the European Patent Office between 1999 and 2001. Patents are one of the few innovation indicators that have a regional, temporal, and technological dimension, and are therefore often used in empirical studies. Nonetheless, the use of patents as indicators for innovation is not

[4] Previous studies by Greunz (2003) and Moreno et al. (2005) included technological proximity in the knowledge production function next to spatial proximity. Technological proximity matrices take into account to what extent two regions have similar technological specialisations. We do not include technological proximity because our analyses are carried out at the level of individual technologies.

undisputed. Most importantly, not all patents are innovations, and not all innovations are patented (on this topic, see Griliches 1990). Furthermore, the rate of patenting differs systematically between industries and technologies due to differences in the relative importance of patents as a means of appropriating an invention. The latter problem, however, is 'solved' by the focus on science-based technologies, where patents do form an important appropriating mechanism (Pavitt 1984).

We classified patents into technologies according to the IPC-technology concordance table developed by FHG-ISI, OST, and INPI.[5] To select science-based technologies, we followed Van Looy et al. (2003) and Verbeek et al. (2002), who used the relative number of citations in patents to the scientific literature as a measure of the interaction between science and technology (see also Schmoch 1997). The higher the share of citations to the scientific literature, the more science-based the technology is considered to be. The technologies with the most intensive interactions with science were *agriculture and food chemistry*, *biotechnology* and *organic fine chemistry* (three life-sciences based technologies), and *optics*, *information technology*, *semiconductors* and *telecommunications* (four physical science-based technologies). Appendix A shows the relevant scientific fields for each technology. Patents were assigned to the different NUTS3 areas based on the addresses of the inventors. Patents with multiple inventors were proportionally distributed across different regions.

[5] Fraunhofer-Institut für System- und Innovationsforschung in Karlsruhe, L'Observatoire des Sciences et des Techniques in Paris, and l'Institut National de la Propriété Industrielle in Paris.

Figures 1 and 2 show the geographical patterns of patents in one life-science technology (biotechnology) and one physical science-based technology (optics). Within biotechnology, some regions exhibit a relatively large number of patents. Besides the larger cities of Amsterdam and Utrecht, these are the regions of Leiden and Veluwe/Wageningen, two regions that host life-sciences clusters in the Netherlands, fuelled by the presence of their respective universities. In the case of optics, the relatively high number of patents in the Southern region of Eindhoven is striking. This is caused by the location of the research laboratories of Philips, a large multinational in electronics, and several related firms nearby.

Figures 1 and 2. Number of patents in biotechnology and telecommunications in NUTS3 regions in the Netherlands

Private and university R&D expenditures are used as indicators for knowledge inputs. Regional private R&D expenditures are measured by the sum of the private wages for R&D employees for each technology.[6] University R&D expenditures are only available for broad science fields as defined by the Ministry of Education and Science, which can be linked to either physical sciences or life sciences. Within both types of technologies, university R&D expenditures were assigned to each technology in proportion to its share

[6] Data on technology specific R&D wage sums at the regional level are provided by the Ministry of Economic Affairs and are based on information from the tax deduction scheme for R&D personnel. This measure overlooks R&D investments in capital, e.g. specific scientific equipment, leading to an underestimating of the total R&D expenditures for each technology. Nonetheless, it is reasonable to assume that this indicator forms a fair proxy for regional differences in R&D expenditures in general, since there is no specific reason to assume that the share of R&D expenditures dedicated to wages within a specific technology significantly differs across regions. By using technology dummies in the estimations, we control for the possible differences between technologies in the share of R&D expenditures dedicated to wages

of the total number of scientific publications in the life sciences or physical sciences.[7] In line with other studies (Fischer and Varga 2003, Fritsch and Slavtchev 2007), a time lag of three years between R&D expenditures and patenting is assumed. The R&D variables refer to the average value between the years 1996 to 1998.

In the first set of empirical models, three different variables have been included to account for technology-specific regional conditions that might influence the innovative output of regions next to R&D inputs and spillovers. To avoid endogeneity, all three variables refer to the year 1998. First, a dummy variable is included, which indicates the presence of a branch of the semi-public contract research organisation TNO in either the physical sciences or life sciences. TNO is a multi-branch organisation with the explicit goal to bridge scientific research and innovation activities in different industries. As such, TNO can be compared with the Fraunhofer Institute in Germany. Following insights from case studies using a regional innovation system approach (see e.g Cooke et al., 1998), the presence of a 'bridging' organisation such as TNO is expected to increase the size of the spillovers within a region. Based on the analysis of annual reviews and the corporate website, the activities of each TNO branch in the Netherlands were determined and related to one of the science-based technologies. Second, the size of the employment within industries related to the specific technologies has been included as an indicator for human capital. A higher stock of technology-specific human capital is assumed to increase innovative output (Rodriguez-Pose and Crescenzi 2008). The selection of the industries is based on the concordance table developed by Schmoch et al. (2003). Appendix B shows the relevant industries for each technology.

[7] See the appendix for the relevant scientific subfields for each technology.

Third, based on size of the employment and the number of firms per region in each of these industries, regional differences in the average firm size in the industries related to each technology are included. Following Bode (2004), one wish to control for regional differences in average firm size as firm size may systematically affect innovation output (compare Licht and Loz 1999 and Cohen and Klepper 1996).

3.2 Defining interregional spillovers

We expect academic knowledge spillovers to occur between regions through geographical proximity and/or research collaboration networks. Geographically localized knowledge spillovers from academic research are assumed to take place through various mechanisms, such as labour mobility or spin-offs. The occurrence of such spillovers is assumed to decay over geographical distance. A spatial weight matrix based on a distance decay function is assumed to reflect the geographical structure of these mechanisms.

The weight matrix for spillovers through research collaboration is based on the intensity of collaboration between universities (including academic hospitals) and firms for each pair of regions. We consider formal collaboration between universities and firms as a direct knowledge flow from academia to industry and consequently as a prime form of academic knowledge spillover. Co-publications are frequently used as an indicator of research collaboration (see, for example, Cockburn and Henderson 1998, Zucker et al. 1998, Wagner-Doebler 2001). The appearance of multiple authors and/or multiple organisations on a scientific publication can be used as an indicator of collaboration in the research leading to the knowledge that is published. Within science-based industries, firms are actively involved in scientific publishing (Rosenberg 1990). Therefore, co-publications with both an academic affiliation and a corporate affiliation can be considered meaningful indicators of university-industry collaboration. Since individuals and their affiliations are generally only mentioned on a publication after a substantial contribution, publications with multiple authors and multiple organisations are considered good indicators of collaborative research (for an extensive overview of these arguments, see Glänzel and Hubert 2004 and Katz and Martin 1997). Whereas (almost) all co-publications might be considered to represent some form of collaboration, not all collaboration in research ends up in a co-publication, and consequently, not all research collaboration is measured by co-publications. Laudel (2001) showed that this most often occurs in collaborative research between individual researchers within the same organisation. Research collaboration with other organisations, on the other hand, generally does lead to a joint publication (Laudel 2001). As such, publications with multiple organisations can be considered valuable indicators of collaborative research. The underlying assumption is that a co-publication reflects formal research collaboration between the organisations involved and that knowledge has been exchanged between these organisations. Next to this, collaborative research is assumed to form an indicator of spillovers through social relationships, resulting from the notion that researchers who have collaborated in the past are likely to continue to exchange knowledge and advice.

All publications between 1993 and 1995 with at least two addresses in the Netherlands were selected from Web of Science in the scientific fields that are relevant for each technology**.** Based on the address information of the organisations on a co-publication, each organisation was assigned to a NUTS3 region. This was done on the basis of full-counting, meaning that each pair of organisations on a co-publication was counted as a collaboration. By aggregating these collaborations, a matrix was constructed with the number of collaborations between each pair of regions as an indicator of the intensity of formal collaboration. Based on the names of the organisations on the publication, universities, firms, and governmental research organisations were distinguished. Collaborations between universities and firms were selected to create the university-industry collaboration weight matrix. This resulted in an asymmetric weight matrix (without values on the diagonal) for each technology, with directed relationships from regions with universities towards regions with firms collaborating with these universities. From now on, this matrix will be referred to as the network weight matrix. It must be noted, though, that this matrix consists strictly of bilateral relationships and cannot be considered a 'true' network in the sense that indirect relationships are also taken into account. The focus on the Netherlands implies that, although a considerable part of research collaboration occurs at the international level, international knowledge flows have been excluded from this analysis. This might lead to an underestimation of the role of research collaboration for knowledge spillovers which will be taken into account in the discussion of the results. The values of the interregional network weight matrix are based on co-publications from the years 1993 to 1995, whereas the R&D data are from the period of 1996-1998. As such, the network weight matrix is considered an indicator for the presence of social relationships between researchers in the period 1996-1998 based on collaborative research in the period 1993-1995.

As two examples, figures 3 and 4 show the geographical structure of interregional research collaboration between universities and firms in biotechnology and optics, respectively. In both technologies, university-industry research collaboration takes place between nearby regions and over longer distances. As a result, research collaboration cannot be attached to a specific geographical scale. Rather, Figures 3 and 4 show that it takes place at both the regional and national levels.

Figures 3 and 4. Geographical structure of interregional university-industry research collaboration in biotechnology and optics - 1993-1995

In the following, we use weighted R&D expenditures in other regions as an additional explanatory variable, rather then as a mean to deal with spatial autocorrelation. Nonetheless, the use of accessibility variables can eliminate the problem of spatial autocorrelation as well (see Andersson and Karlsson 2007). Such explanatory variables are also referred to as accessibility or connectivity measures (Anderson and Grasjo 2009) and indicate the potential of opportunities for interaction (Weibull 1976, 1980). High accessibility between two regions implies a high level of interaction opportunities and, consequently, a high level of potential spillovers between two regions. Accessibility measures for region i are generally based on the weighted average of variable x in all other regions j, where the weights are based on the size of the possible interaction between regions i and j. The size of the possible interaction is generally based on the physical distance between regions (see e.g., Andersson and Karlsson 2007), but can also be based on the structure of economic or functional relationships (see, for example, Boix and Trullen 2007).

Whereas the spatial weight matrix is clearly exogenous, the network weight matrix might exhibit a problem of potential endogeneity, as the geographical structure of collaboration is likely to be related to geographical patterns of patents. This problem is minimized in this study by using time lags; the network weight matrix refers to university-industry collaboration in 1993-1995, the R&D data are from 1996-1998, and patents are from 1999-2001.[8] The time lag is likely to be even larger since co-publications result from collaborative research done long before actual publication. Given the fact that the geographical structure of R&D and innovation is relatively stable over time, the network weight matrix might still suffer from potential endogeneity. This is a common problem with the use of actual data on spatial interaction patterns for the construction of the weight matrix. Yet, the use of these data has the clear advantage that it bears 'a direct relation with the theoretical conceptualisation of the structure of spatial dependence, rather than (…..) an ad hoc description of a spatial pattern' (Anselin 1988, pp. 20-21). Consequently, several empirical studies have used weight matrices in knowledge production function frameworks, which cannot be considered strictly exogenous. Peri (2005), for example, analysed the effect of knowledge flows on innovation output as measured by patents in European regions, while applying a weight matrix based on

[8] Instrumental variables reflecting network potentials between regions would be a more definite solution to this problem, but good instruments are difficult if not impossible to find. Labour mobility (in professions related to the separate industries studied) as an instrument for social networks is a preferred candidate, but data on this detailed level are not available. Within the literature on trade and economic growth (see for example Frankel and Romer 1999), geographical distance is often used as an instrument for patterns on trade between countries. However, as we are interested in separating localized knowledge spillovers from spillovers carried by university-industry collaboration, it is obvious that this cannot be used here.

interregional patent citations to capture interregional knowledge spillovers. Given the fact that the pattern of interregional patent citations is not independent of the regional pattern of patenting, the weight matrix cannot be considered exogenous (see also Peri 2005 p. 318 on this). Despite this drawback, Peri (2005) argues that the use of an actual indicator for knowledge spillovers (here patent citations) is to be preferred over the arbitrary assumption that knowledge spillovers are solely localized as is the case with the use of physical distance, or contiguity based weight matrices alone.

3.3 Empirical model

Based on these specifications of interregional knowledge spillovers, the following pooled cross-sectional spatial model is estimated:

$$\begin{aligned}\ln P_{i,k,t} &= \alpha_0 + \alpha_1 \ln RDp_{i,k,t-1} + \alpha_2 \ln RDu_{i,k,t-1} + \alpha_3 \ln\left(\sum W_{ij\_space} RDu_{j\neq i,k,t-1}\right) + \\ &\alpha_4 \ln\left(\sum W_{ij\_space} RDp_{j\neq i,k,t-1}\right) + \alpha_5 \ln\left(\sum W_{ij\_network,t-2} RDu_{j\neq i,k,t-1}\right) + \alpha_6 \ln X_{i,k,t-1} + \varepsilon\end{aligned} \quad (1)$$

where $P_{i,k,t}$ stands for economically valuable knowledge as measured by patent applications of firms in region *i* in technology *k* in the period of 1999-2001, and $RDp_{i,k,t-1}$ denotes the private R&D expenditures and $RDu_{i,k,t-1}$ the university R&D expenditures in the period of 1996-1998 in region *i* and technology *k*. Both private and university R&D expenditures in the other regions *j* are spatially lagged using a spatial weight matrix, W_{ij_space}. Furthermore, university R&D is lagged by the network weight matrix $W_{ij\_network,t-2}$, which denotes the spatial structure of university-industry collaboration in the years of 1993-1995. ε is a stochastic error term. The seven technologies have been pooled, leading to a total number of 280 observations consisting of 40 NUTS3 regions *i* times seven technologies *k*. Technology dummies have been included to control for possible differences in the rates of patenting between technologies. The variable $X_{i,k,t-1}$ in equation 1 refers to the technology-specific regional conditions that might affect the innovative output. The second set of models leaves out the variables for technology-specific regional conditions and includes regional fixed effects, which control for regional unobserved heterogeneity in conditions that influence the innovative output in general. The third set of models includes both the regional fixed effects and the technology-specific regional conditions.

In order to render the effects of different weight matrices comparable, it is necessary to standardize them. The choice of the method of standardisation is, from a theoretical point of view, far from arbitrary, since it implies a specific way of allocating the value of a variable (in this case, R&D spillovers) from one region to other regions (see Leenders 2002 and Abreu et al. 2005). The use of a row standardized weight matrix in this study implies that the lagged variable is the weighted average of R&D expenditures in neighbouring (defined by space or networks) regions. An increase of the number of neighbours *j* implies that the size of the spillovers that region *i* receives from each individual neighbour *j* automatically decreases. Conceptually, this suggests the presence of some form of limited absorptive capacity of region *i,* to the extent that the size of spillovers from region *j* is less if region *i* is connected or linked with more regions.[9]

[9] Suppose region X has two neighbours and region Y has four neighbours. Both regions X and Y are of equal size and have one common neighbour but do not share a common border with each other. This common neighbour Z has a university with a given amount of R&D expenditures and has only two neighbours, X and Y. By row standardizing the weight matrix, the region X with two regions would

Alternatively, it can be assumed that the size of the R&D spillovers received by region *i* from region *j* is related to the total number of neighbouring regions (defined by space or networks) with *j*. As such, an increase of the total number of neighbours *i* of the spillover generating region *j* implies a smaller total of spillovers received by each specific region *i*. In this case, column standardization of the weight matrices is more appropriate. Each cell value is divided by the sum of the column, and consequently, each column sums up to one. Within a column standardized weight matrix, the column sum of region *i* represents the effect of an increase or decrease in R&D expenditures in region *i* on all other regions *j* (see also Abreu et al. 2005). R&D spillovers from region *i* are in this case conceptualised as a pool of knowledge spillovers partly accessible to other regions *j*.[10] In this study, all models have been estimated with column-standardized and row-standardized lagged variables separately to check for the robustness of the results.

The network weight matrix, with firms in region *i* in the rows and universities in region *j* in the columns, is defined as follows in the case of column standardization:

$$W_{ij\_network\_column} = \frac{r_{ij}}{\sum_j r_{ij}} \qquad (2)$$

and as follows in the case of row standardisation:

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receive ½ (1/(1+1)) the value of the R&D expenditures in region Z. Compare this with region Y, which has four neighbours and consequently only receives ¼ (1/(1+1+1+1)) the value of the R&D expenditures in region Z. The overall size of the spillovers is ¾ of the original R&D expenditures.

[10] In the case of column standardisation, the sum of all knowledge spillovers always equals the initial amount of R&D expenditures Following the example in the previous footnote, column standardisation implies that regions X and Y both receive ½ (Z has two neighbours: 1 / (1+1)) the R&D expenditures of region Z.

$$W_{ij\_network\_row} = \frac{r_{ij}}{\sum_i r_{ij}} \quad (3)$$

where r_{ij} stands for the number of collaborations between firms in region i and a university in region j.

In a similar way, the spatial weight matrix that defines the allocation of knowledge spillovers from region j to region i is defined as:

$$W_{ij\_space\_column} = \frac{d_{ij}^{-1}}{\sum_j d_{ij}^{-1}} \quad (4)$$

in the case of column standardisation and as:

$$W_{ij\_space\_row} = \frac{d_{ij}^{-1}}{\sum_i d_{ij}^{-1}} \quad (5)$$

in the case of row standardisation. In both equation 4 and 5 d_{ij} stands for the average travel time between regions i and j. The maximum possible value of d_{ij} was set to 90 minutes because the size of spillovers through localized mechanisms is considered negligible beyond a travel time of 90 minutes by car. Van Ham et al. (2001), for example, pointed to the fact that in the Netherlands, labour markets (and labour mobility) are generally bounded by a travel time of 45 minutes.[11]

In equation (1), the dependent variable is log transformed because of the transformation of the production function. This raises the issue of dealing with regions with zero patents

[11] Next to this specification, several other specifications of the spatial weight matrix have been applied: first-order contiguity, inverse distance functions with other cut-off points (60 minutes and 120 minutes) and without cut-off points. The results presented later on are robust with regard to these different specifications.

since the log of zero is undefined. Adding a (small) value to each observation typically solves this problem. Alternatively, several empirical studies have applied a count data model in a knowledge production framework (e.g., Fritsch and Slavtchev 2007, Del Barrio-Castro and Garcia-Quevedo 2005). We apply both approaches in order to check for the robustness of the results. Patents are a good example of count data to which a Poisson model is typically applied (Hausman et al. 1984). However, we will make use of a negative binomial regression in order to correct for overdispersion. With the application of a negative binomial model, an extra variable *alpha* is introduced, which corrects for the overdispersion by adjusting the variance independently from the mean (Cameron and Trivedi 1998). Besides linear regression models with fixed effects, unconditioned pooled negative binomial models with direct estimation of fixed effects by including region dummies have been estimated (Allison and Waterman 2003).[12]

4. Results

The descriptive statistics are presented in Table C.1 in appendix C. It is clear that the distribution of patents is rather skewed. Table C.2a and C.2b in appendix C show the correlations of all independent variables. The low correlation between the spatially and network lagged university R&D indicates that there are clear differences between the

[12] Note that this variant of a fixed effects negative binomial model differs from the one suggested by Hausman et al. (1984), where fixed effects refer to the dispersion parameter alpha, which is the same for all elements in the same group. Since the main goal of applying fixed effects is to control for regional unobserved heterogeneity, the pooled negative binomial model with regional dummies, as suggested by Allison and Waterman (2003), is more appropriate.

structure of the spatial weight matrix and the network matrix, resulting in different footprints (and hence impacts) of academic knowledge spillovers.

Table 1 shows respectively the results of the negative binomial estimations with the variables measuring the technology-specific regional conditions, the results of the estimations with regional fixed effects and the results of the estimations combining regional fixed effects and technology-specific regional conditions. The first four models include the technology-specific regional variables, the models five till eight include regional fixed effects and models nine till twelve include both.[13] For each model the results are shown for the specification with row and column standardized weight matrices. The first, fifth and ninth model include only the intra-regional R&D expenditures and, in the case of the first and ninth model, the variables that denote the technology-specific regional conditions. In the second, sixth and tenth model, geographically localized R&D spillovers are included. Models three, seven and eleven include R&D spillovers stemming from university-industry research collaboration. Finally, the models four, eight and twelve include both types of interregional spillovers.

The first, fifth and ninth model is the basic knowledge production function including only intra-regional R&D expenditures. In both models university R&D has a positive and significant relationship with innovation, suggesting the presence of academic knowledge spillovers within the regions having a university, a finding that is in line with previous studies in European countries. Note that the positive relationship of private R&D cannot

[13] In order to analyze the sensitivity of the results to the influence of the Philips Corporation, the models for physical science-based technologies (such as telecommunication) have also been estimated excluding the patents owned by Philips. The results remain similar.

be interpreted as an indication of localized knowledge spillovers in the region, since we cannot distinguish between the internal R&D investments of a firm and possible spillovers from R&D investments of other firms located in the region.

Table 1. Regression results of negative binomial estimations

The other models include the variables that denote the presence of interregional spillovers. The main conclusion holds that collaborative networks between universities and firms form an important mechanism for academic knowledge spillovers, irrespective of the method of standardisation and model specification. With regard to geographically localized spillovers between regions, the results are less robust. In the first set models (include only the technology-specific regional variables) no significant relationship between the spatially lagged university R&D and innovation was found, suggesting the absence of localized, interregional academic knowledge spillovers. A significant and positive relation for spatial lagged private R&D is found, which can be interpreted as an indication of the existence of geographically localized interregional spillovers from private research. In case of the fixed-effect estimations, the outcomes are opposite. There seems to be a positive and significant relationship between localized academic knowledge spillovers and innovation. Moreover, the insignificant effects of spatially lagged private R&D expenditures suggest the absence of interregional knowledge spillovers from private R&D. These results appear to be robust across the different methods of standardisation. In the third type of models, including technology-specific regional variables and regional fixed-effects, spatially lagged university R&D expenditures have a significant positive effect whereas spatially lagged private R&D expenditures remain insignificant. This suggests that the different signs and significance levels of the spatially lagged R&D variables in the first set of models result from an underspecification of the models. This is likely to result from unobserved regional heterogeneity, which is not fully controlled for in the first four models presented in table 1. Given the fact that the fixed effects models control for this, it is reasonable to assume that these results are more reliable and the conclusions are therefore based primarily on the second and third set of models (respectively, models five till eight and nine till twelve).

As a further check on the robustness of the results, linear models with similar specifications has been estimated as well.[14] The results are shown in table 2 and reveal that the outcomes are similar with regard to the positive effect of network related R&D spillovers. Note that in case of column standardization, no significant effect of spatially lagged R&D expenditures could be found in most cases. Given the count data nature of the dependent variable, the results of the negative binomial estimations are however considered more reliable.

Table 2. Regression results of OLS estimations

Concerning the technology-specific regional conditions, the coefficients and significance levels are stable across the different specifications of the first set of negative binominal models estimated. The presence of a branch of TNO in the relevant technology fields has a positive relationship with innovative output, as does human capital. There is a negative

[14] One patent has been added to each region to avoid zeros (which cannot be log-transformed).

correlation between average firm size and innovative output, suggesting that innovation in science-based technologies is, on average, higher in regions with smaller firms. This is in line with the findings for Germany reported by Bode (2004). However, in the third set of models, which includes regional fixed effects as well, these variables become insignificant.

In order to control for possible autocorrelation, a modified version of Moran's I for count data models introduced by Lin and Zhang (2006) has been applied on the residuals. Whereas the models including no spillover variables and only the network-mediated spillovers exhibit significant levels of spatial autocorrelation this is not the case anymore with the inclusion of the variables that denote spillovers.[15] This result implies that our specification does not only capture geographically and network-mediated spillovers, but also, by doing so, effectively deals with spatial autocorrelation.

In sum, the robust results with regard to network-mediated spillovers indicate that collaborative networks between universities and firms form an important mechanism for academic knowledge spillovers in science-based industries. Given that these networks are not limited to the regional scale, knowledge spillovers are also not bounded to this scale; this implying that academic knowledge spillovers occur over longer distances as well. Geographically localized spillovers from academic research seem to occur as well, leading to the conclusion that academic knowledge spillovers occur at different geographical scales simultaneously, depending on the underlying spillover mechanisms.

[15] Results are available on request

5. Conclusions

Universities are generally seen as important factors influencing regional differences in innovation due to the occurrence of knowledge spillovers, which are assumed to be to a large extent geographically localized. Empirical studies on knowledge spillovers typically include spatially lagged variables to measure the effect of interregional knowledge spillovers on regional innovation. The underlying mechanisms of knowledge spillovers are not modelled explicitly; rather it is implicitly assumed that such spillovers are geographically localized. Although empirical studies at the micro-level have found that spillover mechanisms as labour mobility or spin-offs are indeed largely localized, this is not the case for research collaboration, which occurs over longer distances as well. The goal of this study was to empirically analyse the possible presence of knowledge spillovers stemming from university-industry research collaboration over longer distances, while controlling for the presence of localized spillovers. This is done by the estimation of a pooled cross-sectional version of a knowledge production function for seven science-based technologies in the Netherlands.

The results of this study suggest that academic knowledge spillovers occur through both geographically localized mechanisms and collaborative research over longer distances. In line with the arguments set out in the theoretical section, these findings imply the presence of knowledge spillovers from university R&D at multiple spatial scales. Knowledge spillovers resulting from research collaboration occur over longer geographical distances since geographical proximity is less important in the establishment of collaborative research networks in science-based industries. The presence of knowledge spillovers over shorter geographical distances are likely to result from spillover mechanisms as spin-off dynamics and labour mobility where geographical proximity plays a more important role.

On the one hand, these results reinforce the conclusions of existing empirical studies on the presence of localized knowledge spillovers from university research. On the other hand, these results also show that studies on localized knowledge spillovers neglect the presence of spillovers over longer distances. Possibly, this leads to an over-estimation of the importance of geography for academic knowledge spillovers. In order to analyze the impact of university research on regional innovation it is therefore necessary to take into account the presence of spillovers over longer distances as well.

The conclusions that can be drawn from this study lead to some tentative policy implications as well. Within the Netherlands, academic knowledge spillovers within science-based technologies cannot be attributed solely to one specific geographical scale. This implies that the often-mentioned idea of policymakers that a university can be regarded as a booster for regional development is at least incomplete. Although regions seem to benefit from the presence of a university, this is not a necessity, since knowledge spillovers occur over longer distances as well. Related to this is the notion that given the wide geographical range of academic knowledge spillovers, innovation policy measures trying to stimulate these spillovers should not focus on specific regions. Rather, the national or even international scale seems more appropriate for such policies.

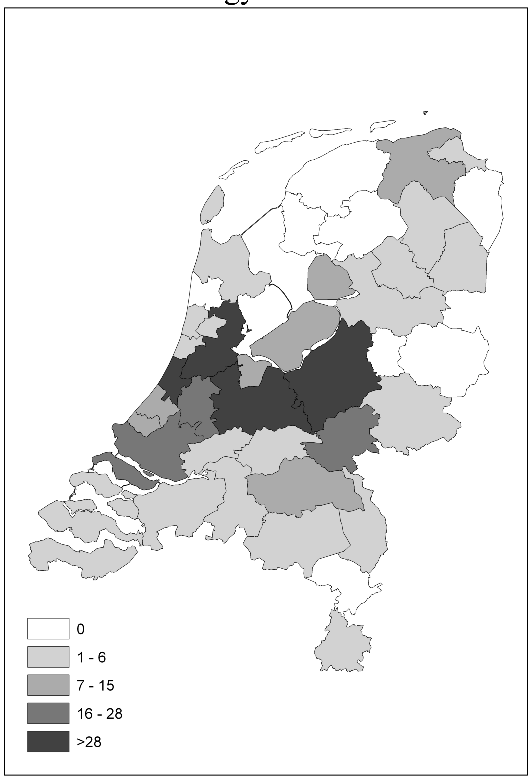
Importantly, our study has several limitations. First, the empirical study is based on pooled cross-sectional data. Although the time lags between the depended and independent variables lower the risk of endogeneity, future studies using panel data are necessary to come to more decisive conclusions. Second, this study focussed on science-based industries where research collaboration between universities and firms is a frequently occurring phenomenon. Given the fact that the importance of the different mechanisms of academic knowledge spillovers probably differs between industries, it would be interesting to see whether these conclusions hold for other industries as well. Third, this study focussed on the Netherlands solely. This implies that the possible effect of spillovers through international research collaboration is not taken into account, which is likely to be important as well. Especially since several studies have found empirical evidence for the presence of international knowledge spillovers (see e.g. Peri 2005), it is likely that the role of collaborative research as carrier of knowledge spillovers over longer distances is under-estimated.

This study included only one mechanism – collaborative research – explicitly, whereas other mechanisms were assumed to be fully captured by the spatially lagged variables. Future research in this area could further extend our framework by including additional weight matrices based on the actual geographical patterns of other mechanisms such as labour mobility flows, spinoff dynamics and inter-firm R&D alliances. Such a research program will shed light at the relative importance of the various mechanisms of knowledge spillovers at the different spatial scales at which these occur. A more systematic understanding of the mechanisms of knowledge spillovers can have fundamental implications for regional and innovation policy alike.

Tables and figures

Figure 1 and 2. Geographical patterns of patents in biotechnology and optics - 1999-2001

Biotechnology



Optics

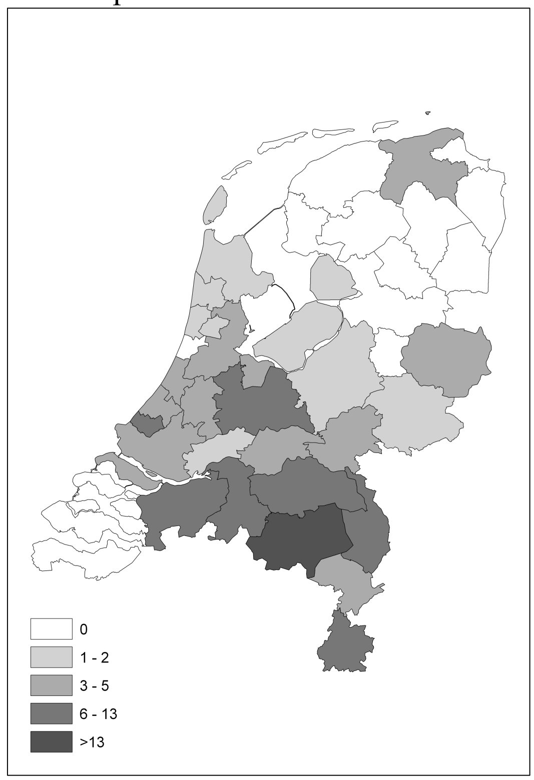


Figure 3 and 4. Geographical structure of interregional university-industry research collaboration in biotechnology and optics - 1993-1995

Biotechnology Optics

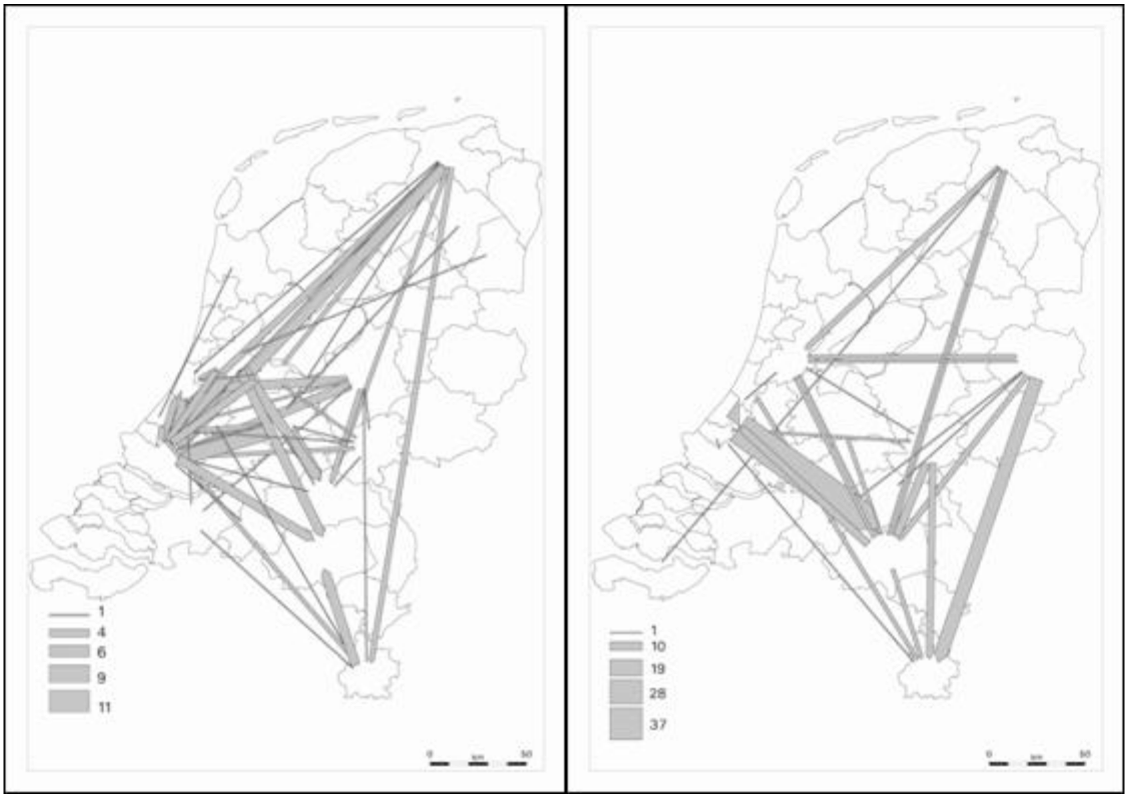


Table 1. Regression results of negative binomial estimations on regional patent intensity (standard errors in parentheses)

	Negative binomial regression including technology dummies and region-technology variables							Negative binomial regression including regional fixed effects and technology dummies						
	1	2		3		4		5	6		7		8	
Weight matrix	-	row	column	row	column	row	column	-	row	column	row	column	row	column
University R&D	0.142**	0.181**	0.164**	0.149**	0.166**	0.191**	0.193**	0.361**	0.442**	0.448**	0.369**	0.347**	0.450**	0.433**
	(0.048)	(0.052)	(0.050)	(0.048)	(0.048)	(0.051)	(0.050)	(0.069)	(0.072)	(0.087)	(0.068)	(0.083)	(0.071)	(0.085)
Private R&D	0.501**	0.474**	0.469**	0.434**	0.383**	0.403**	0.339**	0.350**	0.398**	0.395**	0.333**	0.314**	0.384**	0.360**
	(0.096)	(0.096)	(0.095)	(0.101)	(0.103)	(0.100)	(0.102)	(0.102)	(0.099)	(0.104)	(0.100)	(0.099)	(0.098)	(0.100)
W space university R&D		-0.015	-0.094			-0.003	-0.081		0.490**	0.519**			0.469**	0.514**
		(0.094)	(0.103)			(0.093)	(0.100)		(0.149)	(0.178)			(0.147)	(0.176)
W space private R&D		0.310**	0.365**			0.311**	0.378**		0.073	0.178			0.068	0.178
		(0.139)	(0.143)			(0.138)	(0.140)		(0.194)	(0.179)			(0.191)	(0.174)
W network university R&D				0.085**	0.151**	0.091**	0.162**				0.100**	0.115**	0.091**	0.117**
				(0.040)	(0.053)	(0.040)	(0.053)				(0.047)	(0.051)	(0.046)	(0.052)
Average firm size	-0.532**	-0.439**	-0.446**	-0.482**	-0.445**	-0.380*	-0.343*							
	(0.192)	(0.194)	(0.193)	(0.192)	(0.189)	(0.195)	(0.191)							
Human capital	0.591**	0.492**	0.498**	0.545**	0.511**	0.439**	0.404**							
	(0.148)	(0.151)	(0.150)	(0.148)	(0.147)	(0.152)	(0.150)							
TNO	1.018**	1.064**	1.051**	0.920**	0.736**	0.965**	0.752**							
	(0.265)	(0.263)	(0.261)	(0.266)	(0.276)	(0.264)	(0.272)							
Constant	-0.837**	-1.306**	-1.231**	-0.727**	-0.608**	-1.212**	-1.020**	-1.317	-2.523**	-3.899**	0.173	1.132**	-2.870**	-2.543**
	(0.251)	(0.309)	(0.301)	(0.253)	(0.257)	(0.309)	(0.299)	(1.049)	(0.842)	(1.025)	(0.517)	(0.479)	(0.865)	(0.951)
Alpha	0.885**	0.858**	0.850**	0.864**	0.840**	0.840**	0.807**	0.496**	0.448**	0.425**	0.471**	0.435**	0.427**	0.404**
	(0.117)	(0.113)	(0.113)	(0.115)	(0.113)	(0.111)	(0.108)	(0.077)	(0.072)	(0.069)	(0.075)	(0.067)	(0.071)	(0.066)
N	280	280	280	280	280	280	280	280	280	280	280	280	280	280
	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)
Max likelihood R2	0.687	0.695	0.695	0.692	0.695	0.700	0.705	0.774	0.784	0.808	0.777	0.803	0.787	0.811
Log likelihood	-621.26	-617.69	-617.31	-618.98	-617.30	-615.10	-612.58	-575.68	-569.29	-564.16	-573.43	-567.84	-567.37	-561.97

** indicates significance at 5% level, * indicates significance at 10% level

Table 1. Continued

	Negative binomial regression including regional fixed effects, technology dummies and region-technology variables						
	9	10		11		12	
Weight matrix	-	row	column	row	column	row	column
University R&D	0.328** (0.072)	0.412** (0.075)	0.414** (0.076)	0.344** (0.072)	0.322** (0.072)	0.429** (0.076)	0.411** (0.076)
Private R&D	0.337** (0.102)	0.388** (0.099)	0.386** (0.100)	0.318** (0.101)	0.300** (0.103)	0.373** (0.099)	0.352** (0.101)
W space university R&D		0.487** (0.151)	0.551** (0.191)			0.476** (0.150)	0.552** (0.189)
W space private R&D		0.064 (0.195)	0.169 (0.191)			0.052 (0.193)	0.158 (0.189)
W network university R&D				0.092* (0.048)	0.106* (0.059)	0.085* (0.047)	0.105* (0.058)
Average firm size	0.001 (0.256)	-0.169 (0.253)	-0.242 (0.259)	0.022 (0.253)	0.055 (0.255)	-0.142 (0.250)	-0.187 (0.258)
Employment	0.050 (0.203)	0.178 (0.200)	0.240 (0.205)	0.037 (0.201)	0.006 (0.202)	0.161 (0.198)	0.197 (0.204)
TNO	0.389 (0.276)	0.284 (0.270)	0.341 (0.272)	0.269 (0.280)	0.273 (0.281)	0.167 (0.275)	0.221 (0.279)
Constant	0.604 (0.612)	-1.446* (0.870)	-3.090** (1.110)	-1.890* (1.053)	-1.889* (1.053)	0.202 (0.474)	-2.149** (0.964)
Alpha	0.480** (0.076)	0.434** (0.072)	0.442** (0.072)	0.463** (0.075)	0.467 (0.075)	0.420** (0.071)	0.429 (0.070)
N	280 (7 x 40)	280 (7 x 40)	280 (7 x 40)	280 (7 x 40)	280 (7 x 40)	280 (7 x 40)	280 (7 x 40)
Max likelihood R2	0.776	0.786	0.785	0.779	0.779	0.788	0.788
Log likelihood	-574.24	-568.13	-568.49	-572.42	-572.64	-566.53	-566.87

** indicates significance at 5% level, * indicates significance at 10% level

Table 2. Regression results of OLS estimations on regional patent intensity (standard errors in parentheses)

	OLS regression							OLS regression including regional fixed effects and technology dummies						
	1	2		3		4		5	6		7		8	
Weight matrix	-	row	column	row	column	row	column	-	row	column	row	column	row	column
University R&D	0.155**	0.185**	0.168**	0.153**	0.160**	0.185**	0.187**	0.354**	0.393**	0.387**	0.353**	0.335**	0.392**	0.370**
	(0.032)	(0.034)	(0.034)	(0.032)	(0.031)	(0.034)	(0.032)	(0.050)	(0.051)	(0.053)	(0.049)	(0.050)	(0.051)	(0.053)
Private R&D	0.337**	0.314**	0.316**	0.289**	0.179**	0.262**	0.186**	0.232**	0.231**	0.235**	0.217**	0.205**	0.217**	0.208**
	(0.058)	(0.058)	(0.058)	(0.060)	(0.060)	(0.060)	(0.058)	(0.068)	(0.067)	(0.067)	(0.068)	(0.068)	(0.067)	(0.067)
W space university R&D		0.124	0.073			0.148	0.100		0.243**	0.191			0.242**	0.202
		(0.112)	(0.136)			(0.111)	(0.126)		(0.108)	(0.136)			(0.107)	(0.135)
W space private R&D		0.145	0.110			0.133	0.115		0.100	0.122			0.097	0.119
		(0.109)	(0.097)			(0.107)	(0.090)		(0.120)	(0.116)			(0.119)	(0.115)
W network university R&D				0.067**	0.153**	0.070**	0.153**				0.060*	0.100**	0.059*	0.103**
				(0.026)	(0.023)	(0.026)	(0.023)				(0.032)	(0.043)	(0.032)	(0.042)
Average firm size	-0.317**	-0.254**	-0.265**	-0.293**	-0.064	-0.228**	-0.187*							
	(0.111)	(0.112)	(0.113)	(0.110)	(0.132)	(0.111)	(0.106)							
Employment	0.326**	0.267**	0.281**	0.305**	0.099	0.245**	0.219**							
	(0.087)	(0.090)	(0.090)	(0.086)	(0.108)	(0.089)	(0.084)							
TNO	0.624**	0.568**	0.591**	0.546**	0.334*	0.480**	0.236							
	(0.176)	(0.176)	(0.176)	(0.177)	(0.174)	(0.177)	(0.173)							
Constant	-1.364**	-1.467**	-1.407**	-1.293**	-0.738	-1.402**	-1.064**	1.075**	-0.477	-0.326	1.038**	1.056**	-0.561	-0.434
	(0.360)	(0.359)	(0.363)	(0.357)	(0.734)	(0.355)	(0.342)	(0.138)	(0.375)	(0.420)	(0.138)	(0.137)	(0.376)	(0.418)
N	280	280	280	280	280	280	280	280	280	280	280	280	280	280
	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)	(7 x 40)
R2	0.598	0.610	0.607	0.608	0.660	0.620	0.661	0.507	0.526	0.525	0.530	0.550	0.548	0.562

** indicates significance at 5% level, * indicates significance at 10% level

Table 2. Continued

	including regional fixed effects, technology dummies and region-technology variables						
	9	10		11		12	
Weight matrix	-	row	column	row	column	row	column
University R&D	0.317** (0.054)	0.356** (0.055)	0.349** (0.056)	0.321** (0.053)	0.309** (0.053)	0.361** (0.055)	0.342** (0.056)
Private R&D	0.220** (0.068)	0.221** (0.067)	0.224** (0.068)	0.207** (0.068)	0.198** (0.068)	0.208** (0.068)	0.201** (0.068)
W space university R&D		0.237** (0.109)	0.207 (0.140)			0.239** (0.109)	0.217 (0.139)
W space private R&D		0.092 (0.123)	0.119 (0.120)			0.086 (0.123)	0.112 (0.119)
W network university R&D				0.055* (0.033)	0.090** (0.043)	0.054* (0.033)	0.091** (0.043)
Average firm size	0.021 (0.161)	-0.067 (0.163)	-0.080 (0.167)	0.023 (0.160)	0.039 (0.160)	-0.064 (0.162)	-0.063 (0.166)
Employment	0.017 (0.131)	0.077 (0.131)	0.092 (0.135)	0.019 (0.130)	0.004 (0.130)	0.079 (0.131)	0.080 (0.134)
TNO	0.377* (0.215)	0.343 (0.213)	0.385* (0.214)	0.318 (0.217)	0.292 (0.217)	0.284 (0.215)	0.298 (0.216)
Constant	0.521** (0.223)	-0.266 (0.393)	-0.270 (0.431)	0.495** (0.223)	0.541** (0.222)	-0.282 (0.391)	-0.259 (0.428)
N	280 (7 x 40)	280 (7 x 40)	280 (7 x 40)	280 (7 x 40)	280 (7 x 40)	280 (7 x 40)	280 (7 x 40)
R2	0.53	0.55	0.55	0.55	0.56	0.57	0.58

** indicates significance at 5% level, * indicates significance at 10% level

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Appendix A. The relevant science fields* for technological innovation in the seven selected technologies.

Agriculture & food chemistry

Biochemistry & Molecular Biology
Plant Sciences
Microbiology
Genetics & Heredity
Food Science & Technology
Agriculture Dairy & Animal Science
Nutrition & Dietetics

Biotechnology

Biochemistry & Molecular Biology
Microbiology
Genetics & Heredity
Immunology
Virology
Biophysics
Biotechnology & Applied Microbiology

Information technology

Electrical & Electronics Engineering
Computer Applications
Computer Cybernetics
Telecommunications
Acoustics

Optics

Optics
Electrical & Electronics Engineering
Applied Physics
Polymer Science

Organic fine chemistry

Biochemistry & Molecular Biology
Organic Chemistry
Pharmacology & Pharmacy
Immunology
Genetics & Heredity
Microbiology

Semiconductors

Electrical & Electronics Engineering
Physics Condensed Matters
Crystallography
Applied Physics
Nuclear Science and Technology
Material Science

Telecommunication

Electrical & Electronics Engineering
Telecommunications
Optics
Applied Physics
Computer Applications
Computer Cybernetics

* as defined by the Institute for Scientific Information (ISI).

Appendix B Linking technologies and industries

Technology	Industry	NACE
Agriculture and Foodchemistry	Food& Beverages	15
Biotechnology	Pharmaceuticals	24.4
Organic Fine Chemistry	Basic Chemicals	24.1
Information Technology	Office Machinery & Computers	30
Optics	Medical, precision and optical instruments	33
Semiconductors	Radio, television and communication equipment	32
Telecommunications	Radio, television and communication equipment	32

Based on Schmoch et al. 2003

Appendix C

Table C.1. Descriptive statistics

	N	Mean	Min.	Max.	Std. Dev.	Source	Unit of measurement
Patents (1999-2001)	280	11.19	0.00	912	67.81	European Patent Office – Patent Bulletins (www.epo.org)	absolute numbers
University R&D (ln) (1996-1998)	280	0.88	0.00	5.38	1.76	Association of universities in the Netherlands – VSNU (www.vsnu.nl)	R&D expenditures in million euro's
Private R&D (ln) (1996-1998)	280	1.77	0.00	5.55	1.14	Ministry of Economic Affairs – SenterNovem (www.senternovem.nl/wbso)	private R&D wages in million euro's
W space university R&D - column standardized (ln)	280	2.56	0.00	4.00	1.05	-	
W space university R&D - row standardized (ln)	280	2.66	0.00	4.07	1.08	-	
W space private R&D - column standardized (ln)	280	2.19	0.05	4.18	0.89	-	
W space private R&D – row standardized (ln)	280	2.25	0.16	4.47	0.84	-	
W network university R&D - column standardized (ln)	280	0.99	0.00	6.03	1.67	-	
W network university R&D - row standardized (ln)	280	1.40	0.00	5.38	2.13	-	
Human capital (ln) (1998)	280	5.76	0.00	9.29	2.30	National Statistical Office / CBS (www.cbs.nl)	Total regional employment in technology-related industry
Average firm size (ln) (1998)	280	2.93	0.00	5.92	1.46	National Statistical Office / CBS (www.cbs.nl)	Total employment divided by total number of firms in technology-related industry
TNO (dummy)	280	0.09				Own elaboration of annual reports (www.tno.nl)	Dummy

Table C.2a Correlation matrix – including column standardized variables

		1	2	3	4	5	6	7	8
1	University R&D	1.00							
2	Private R&D	0.44*	1.00						
3	W space university R&D - column standardized	-0.15*	0.10	1.00					
4	W space private R&D - column standardized	0.07	0.41*	0.59*	1.00				
5	W network university R&D - column standardized	0.37*	0.58*	0.09	0.19*	1.00			
6	Average firm size	0.10	0.24*	0.14*	0.15*	0.22*	1.00		
7	Employment	0.24*	0.46*	0.18*	0.30*	0.37*	0.83*	1.00	
8	TNO	0.43*	0.24*	-0.02	0.04	0.37*	-0.04	0.01	1.00

* indicates significance at 5% level

Table C .2b Correlation matrix – including row standardized variables

		1	2	3	4	5	6	7	8
1	University R&D	1.00							
2	Private R&D	0.44*	1.00						
3	W space university R&D – row standardized	-0.18*	0.09	1.00					
4	W space private R&D - row standardized	0.02	0.40*	0.49*	1.00				
5	W network university R&D - row standardized	0.35*	0.53*	0.05	0.17*	1.00			
6	Average firm size	0.10	0.24*	0.18*	0.17*	0.24*	1.00		
7	Employment	0.24*	0.46*	0.22*	0.32*	0.38*	0.83*	1.00	
8	TNO	0.43*	0.24*	-0.03	0.02	0.27*	-0.04	0.01	1.00

* indicates significance at 5% level