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The Geography of Knowledge Spillovers between High-Technology Firms in Europe

Evidence from a Spatial Interaction Modelling Perspective

Manfred M. Fischer[*+], Thomas Scherngell[+] and Eva Jansenberger[+]

Department of Economic Geography & Geoinformatics
Vienna University of Economics and Business Administration, Austria

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Abstract. The focus in this paper is on knowledge spillovers between high-technology firms in Europe, as captured by patent citations. High-technology is defined to include the ISIC-sectors aerospace (ISIC 3845), electronics-telecommunication (ISIC 3832), computers and office equipment (ISIC 3825), and pharmaceuticals (ISIC 3522). The European coverage is given by patent applications at the European Patent Office that are assigned to high-technology firms located in the EU-25 member states, the two accession countries Bulgaria and Romania, and Norway and Switzerland. By following the paper trail left by citations between these high-technology patents we adopt a Poisson spatial interaction modelling perspective to identify and measure spatial separation effects to interregional knowledge spillovers. In doing so we control for technological proximity between the regions, as geographical distance could be just proxying for technological proximity. The study produces prima facie evidence that geography matters. *First*, geographical distance has a significant impact on knowledge spillovers, and this effect is substantial. *Second*, national border effects are important and dominate geographical distance effects. Knowledge flows within European countries more easily than across. Not only geography, but also technological proximity matters. Interregional knowledge flows are industry specific and occur most often between regions located close to each other in technological space.

JEL Classification: O31, C21, R15, O52

Keywords: Knowledge spillovers, patent citations, high-technology, European regions, Poisson spatial interaction model

[*] Corresponding author, address for correspondence: Department of Economic Geography and Geoinformatics, Vienna University of Economics and Business Administration, Nordbergstr. 15, A-1090 Vienna.

[+] Manfred M. Fischer is Professor and Chair of Economic Geography at Vienna University of Economics and Business Administration, Austria. Thomas Scherngell and Eva Jansenberger are research assistants at the same institution.

1 Introduction

The last few years have witnessed an increasing interest in knowledge spillovers. Knowledge spillovers[1] may be defined to denote the benefits of knowledge to firms or individuals, not responsible for the original investment in the creation of this knowledge. There are two distinct types of knowledge spillovers: Spillovers embodied in traded capital or intermediate goods and services [so-called pecuniary externalities], and spillovers of the disembodied kind [non-pecuniary externalities]. This paper considers spillovers of the second type. Such spillovers arise when some of the R&D activities have the classic characteristic of a non-rivalrous good and cannot be appropriated entirely.

The importance of knowledge spillovers is widely recognised. Modern endogenous growth theory, for example, casts knowledge spillovers from investments in R&D as a central component in generating the increasing returns which sustain long-term growth (see, for example, Romer 1990). In these theories, it is typically assumed that knowledge spills over to other agents within the country, but not to other countries. Yet there is no good reason to believe that knowledge stops spilling over because it hits a national boundary.

The last few years have seen the development of a significant body of empirical research on knowledge spillovers. Empirical analysis of the externalities is usually carried out using the R&D expenditure that helps to create them, rather than the inventions themselves. Many different measurements[2] provide varied evidence of knowledge spillovers at the aggregate level. Most of the studies find some evidence for

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1 In this paper we use the notions knowledge spillovers and knowledge externalities interchangeably.

2 Various methods have been used in attempts to measure externalities. One calculates the elasticity of output with respect to R&D at various levels of aggregation. The R&D input to production is usually measured hereby as the stock of R&D, thus treating it as a normal input into current production. In the standard Cobb-Douglas form, this elasticity is the estimated exponential parameter on the R&D input. At the firm level, the elasticity with respect to the firm's internal stock of knowledge capital is expected to be smaller than the elasticity with respect to the entire stock [internal and external] that actually gets used by the firm. An increase in the measured elasticity of the knowledge stock is taken as evidence of a positive R&D spillover. Aside from conceptual problems this measurement approach requires that there be sufficient independent variation in inside and outside R&D to be able to separate their effects (Carlow and Lipsey 2002).

such spillovers, some do not (see Griliches 1995). Generally speaking, this research has shown that new technological knowledge spills over and complements R&D in some industries, especially in high-technology ones (see Bernstein and Nadiri 1988).

But the spatial range of such knowledge spillovers is greatly contested[3] (see Karlsson and Manduchi 2001). Several explanations have been offered for this lack of agreement, such as for example the notorious difficulty to measure knowledge spillovers. Indeed, Krugman (1991, p. 53) has argued that economists should abandon any attempts at measuring knowledge spillovers because "knowledge flows ... are invisible; they leave no paper trail by which they may be measured and tracked". The work of Jaffe, Trajtenberg and Henderson (1993), however, pointed to one important exception. They argued that spillovers of knowledge may well leave a paper trail in the citations to previous patents recorded in patent documents. Because patent documents contain detailed information about the technology of the patented invention, the inventor and his/her residence, the assignee (generally, the firm) that owns the patent rights, and citations to previous patents, these patent documents provide an important resource for analysing the geography of knowledge spillovers.

This paper follows Jaffe, Trajtenberg and Henderson (1993) to use patent citations as a proxy for knowledge spillovers[4]. The focus is on externalities within the high-technology sector[5]. The objective of the paper is to identify and measure those types of

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[3] Most studies identifying the spatial extent of knowledge spillovers are based on the Griliches-Jaffe knowledge production function model to measure knowledge spillovers, indirectly via effects on the output of the knowledge production function. Note, however, that this type of research is not without problems. The problems center around the question of whether the spatial units of observation are appropriately chosen, whether and how spatial effects are taken into account, how the output of the knowledge production process is measured, whether available measures actually capture the contribution of R&D spilled-over, how the spillover pools are constructed, and R&D capital deflated and depreciated. Despite these difficulties, there has been a significant number of reasonably well done studies (see, for example, Anselin, Varga and Acs 1997; Bottazzi and Peri 2003; Fischer and Varga 2003), all pointing in the direction that knowledge spillovers tend to be geographically bounded within the region of knowledge production.

[4] Jaffe, Trajtenberg and Henderson (1993) analysed patent citation data pertaining to domestic university and corporate patents to test the extent of localisation of knowledge spillovers by using a case-based matching approach. They left open, however, the issue of whether and to what extent border and distance effects influence knowledge externalities.

[5] Following Hatzichronoglou (1997) we define high-technology to include the ISIC-sectors pharmaceuticals (ISIC 3522), computers and office equipment (ISIC 3825), electronics-telecommunication (ISIC 3832), and aerospace (ISIC 3845).

spatial separation that tend to impede the likelihood of knowledge spillovers between regions in Europe[6]. In particular, we are interested in the questions whether or not knowledge – as captured by patented inventions – flows more easily within countries than between, and to what extent geographic distance between inventions has an influence on these knowledge flows. As we consider spatial separation effects to interregional spillovers in a multiregional setting it is important to control for technological proximity between regions as geographical distance could be just proxying for technological proximity.

In using patent citation data from the European Patent Office [EPO] this paper builds on recent work by Maurseth and Verspagen (2002), but departs from this prior analysis in four major aspects. *First*, it adopts a spatial interaction modelling perspective to identify and measure spatial separation effects, and develops the appropriate model specification to account for the integer nature of interactions in the given context. *Second*, we follow the paper trail left by individual patent citations in high-technology industries to track the individual flows within a discrete representation of space. This allows us to properly control for intrafirm patent citations[7]. *Third*, citations to a patent are counted for a window of five years to overcome at least partially the truncation bias that is due to the fact that we observe citations for only a portion of the life of an invention, with the duration of that portion varying across patent cohorts. *Finally*, the study extends the geographic coverage, essentially from the EU-15 to the EU-25 countries on the one side, and limits the context to the high-technology sector on the other.

The reminder of the paper is organised as follows. The section that follows explains in some more detail the nature of patents and patent citations, and briefly discusses how patent citations can be used as an indicator for knowledge spillovers. Section 3 elaborates on the patent citation data to be used in the study. In Section 4, we outline the spatial interaction modelling framework that is pertinent to the model development in this study. Section 5 develops a Poisson model specification that accommodates the true

6 We have chosen 188 regions (see Appendix A) that cover the EU-25 member countries (except Cyprus and Malta), the accession countries Bulgaria and Romania, and Norway and Switzerland.

7 Maurseth and Verspagen (2002) control for intraregional intrafirm, but not for interregional intrafirm patent citations. This is likely to generate errors due to the presence of multiregional firms in Europe.

integer nature of patent citation flows and derives maximum likelihood estimates of the model parameters. Section 6 generalises this model specification to allow for the overdispersion in the data by letting each pair's of regions Poisson parameter have a random distribution of its own. In Section 7 we present the estimation results of the basic Poisson spatial interaction model and its generalisation. We conclude with a summary and evaluation of our results in the final section.

2 Patents, Patent Citations and Knowledge Spillovers

A patent is a property right awarded to inventions for the commercial use of a newly invented device. An invention to be patented has to satisfy three patentability criteria. It has to be *novel* and *non-trivial* in the sense that it would not appear obvious[8] to a skilled practitioner of the relevant technology, and it has to be *useful*, in the sense that it has potential commercial value. If a patent is granted, an extensive public document is created. The document contains detailed information about the invention, the inventor, the assignee, and the technological antecedents of the invention. Because patents record the residence of the inventors they are an invaluable resource for studying how knowledge flows are affected by geography.

Patent related data, however, have two important limitations[9]. *First*, the range of patentable inventions constitutes only a subset of all R&D outcomes, and *second*, patenting is a strategic decision and, thus, not all patentable inventions are actually patented. As to the first limitation, purely scientific advances devoid of immediate applicability as well as incremental technological improvements which are too trite to pass for discrete, codifiable inventions are not patentable. The second limitation is rooted in the fact that it may be optimal for inventors *not* to apply for patents even though their inventions would satisfy the criteria for patentability (Trajtenberg 2001). Inventors balance the time and expense of the patent process, and the possible loss of

8 What is obvious or not can be very difficult to evaluate. Different national patent offices have taken different approaches to this problem. While, for example, among the European countries, in Germany the threshold is comparatively high, the requirements in the UK are much lower. In extreme cases, this may lead to a situation where a patent on a given subject is granted in one country, but not in another (Michel and Bettels 2001).

9 See Griliches (1990) for a more detailed discussion.

secrecy which results from patent publication, against the protection that a patent potentially provides to the inventor[10] (Jaffe 2000). Therefore, patentability requirements and incentives to refrain from patenting limit the scope of our analysis based on patent data.

Patent citations capture only those spillovers which occur between patented pieces of an invention, and, thus, underestimate the actual extent of knowledge spillovers. Other channels of knowledge transfers are not captured by patent citations, such as, for example, interfirm transfer of knowledge embodied in skilled labour; knowledge flows between customers and suppliers; knowledge exchange at conferences and trade fairs, etc. Thus, our study refers only to a very specific and limited form of interfirm knowledge flows.

It is also clear that patent citations not always represent what we typically think of as knowledge spillovers. Some citations may represent noise[11]. This is certainly the case for citations added by the patent examiner of which the citing inventor was unaware. This noise creates a bias against finding spillovers. Fortunately, Thompson (2003) illustrates that bias in this direction is a problem of power, which can be overcome with a sufficiently large sample size. His result also implies that patent citations are more indicative of patterns of knowledge flows at the level of organisations, industries and regions than at the level of individual patents (Jaffe, Fogarty and Banks 1998).

3 The Patent Citation Data and Some Descriptive Statistics

The European coverage in our study is achieved via European patent applications. By *European* patent applications we mean patents applied at the European Patent Office

[10] Though some firms may choose not to patent inventions, patenting in high-technology industries is commonly practiced and a vital part of maintaining technological competitiveness. High-tech firms use patents not only to protect the returns to specific inventions but also to block products of their competitors, as bargaining chips in cross-licensing negotiations, and/or to prevent or defend against infringement suits (Jaffe 2000, Almeida 1996).

[11] In the US, it is – in contrast to Europe – a legal requirement to supply a complete list of the state of the art, and non-compliance by the patent applicant can lead to subsequent revocation of the patent. Thus, applicants tend to quote each and every reference even if it is only remotely related to what is patented, rather than running the risk of filing an uncomplete list (Michels and Battels 2001).

[EPO][12] and assigned to organisations located in the EU-25 member states [except Cyprus and Malta], the two accession countries Bulgaria and Romania, and Norway and Switzerland. Our data source is the European Patent Office [EPO] database. This is a natural choice for the purpose of our study because patents from different national patent offices are not comparable to each other. There are different patenting costs, approval requirements, citation practices and enforcement rules across Europe.

The focus is on corporate patents in the high-technology sector. We used MERIT's concordance table (Verspagen, Moergastel and Slabbers 1994) between the four-digit ISIC-sectors and the 628 patent subclasses of the International Patent Code (IPC) classification[13] to identify such patents from the universe of European patent applications. Our core data set includes all the high-technology patents with an application date in the years 1985-2002, totalling 177,424 patents. Data on the inventor and his/her location, the assignee [that is, the legal entity that owns the patent rights, assigned to it by the inventor(s)], the time of application, the technology of the invention as captured by IPC codes, and EPO patent citations are the main pieces of information used from this file. We selected corporate patents, that is, patents assigned to non-government organisations located in Europe, since our interest is on interfirm research spillovers.

Patent citation is a phenomenon that derives from the relationship between two inventions or inventors as evidenced by a citing patent and a cited patent. The data on this relationship come in form of citations *made* [that is, each patent lists references to previous patents]. For identifying the citation flows we need a list of cited and citing patent applications. This requires in fact access to all citation data in a way that permits

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12 Patent protection in Europe can be obtained by filing national applications and European applications. This implies that patent data from the European Patent Office do cover only a subsample of patents applied for in Europe.

13 The IPC system is an internationally agreed, non-overlapping hierarchical classification system that consists of eight sections (first level), 118 classes (second level), 628 subclasses (third level), 6,871 (fourth level) main groups and 57,324 subgroups (fifth level) to classify inventions claimed in the patent documents. The concordance table assigns the technical knowledge in the patent subclasses to the ISIC-sector best corresponding to the origin of this knowledge. The patent subclasses associated with the four high-technology ISIC-sectors are outlined in Appendix B.

efficient search and extraction of citations not by the patent number of the citing patent but by the patent number of the cited patent.

While previous work indicates the usefulness of patent citations as an indicator for aggregate knowledge flows, it also highlights the need for careful attention to various biases that make their interpretation risky. In particular, the observation of citations is subject to a truncation bias because we observe citations for only a portion of the life of an invention, with the duration of that portion varying across patent cohorts. This means that patents of different ages are subject to different degrees of truncation. To overcome this problem at least in part we have identified all the pairs of cited and citing patents where citations to a patent are counted for a window of five years following its issuance. The analysis is, thus, confined to 1985-1997 in the case of cited patents while citing patents appearing in 1990-2002 are taken into account. Although the five-year horizon appears to be short, it does capture a significant amount of a typical patent's citation life[14].

Given our interest on pure externalities (that is, on interfirm knowledge spillovers), citations to patents that belong to the same assignee [so-called self-citations] were eliminated, resulting into 98,191 interfirm patent citations[15]. The elimination of self-citations – in this and all prior work – remains far from satisfactory. Although we have manually checked the sample for cases where company names are sufficiently similar to identify self-citations between parents and their subsidiaries, and joint ventures, this effect can only get us so far. One could presumably complete the process using directories of company ownership (such as Dun & Bradstreet's *Who owns Whom*). But, daunting as that task would be, one must then decide when a citation is a self-citation and when it represents a spillover. The judgement depends on the degree of interaction

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14 The mean citation lag of all citations in 1985-2002 is 4.62 years, with some sectoral differences: pharmaceuticals (4.4 years), computers and office equipment (4.4 years), electronics-telecommunication (4.7 years) and aerospace (5.4 years).

15 About one third of all patent citations are self-citations. Not surprisingly, the self-citation rate differs for the four-digit industry sectors. The rate is much higher in pharmaceuticals (78.6%) than in the other industries (electronics-telecommunications: 15.9%, computers and office equipment: 5.2%, and aerospace 0.2%). This corresponds well with what we know about this industry. Inventions are concentrated here in very large firms, and, thus, the likelihood that they will cite internally is higher.

taking place between related firms. This does not seem to be an operational criterion (Thompson 2003).

The spatial interaction modelling perspective we adopt in this study shifts attention from individual patent citations to interregional patent interactions or from the dyad "cited patent – citing patent" to the dyad "cited region – citing region". Accordingly, all citation data were aggregated into a region-by-region matrix (c_{ij}) where c_{ij} denotes the number of patent citations from region j (j=1, ..., J) to region i (i=1, ..., I). The rows of the matrix represent the regions of the cited patent [that is, the origins of spillovers] and the columns the regions of the citing patents [that is, the spillover absorbing regions]. The matrix is asymmetric in nature, that is, $c_{ij} \neq c_{ji}$.

We have chosen $I=J=188$ regions, generally NUTS-2 regions for the EU-15 countries[16] and NUTS-0 regions for the other countries. NUTS is an acronym of the French for the 'nomenclature of the territorial units for statistics', which is a hierarchical system of regions used by the statistical office of the European Community for the production of regional statistics. At the top of the hierarchy are the NUTS-0 regions (countries), below which are NUTS-1 regions (regions within countries) and then NUTS-2 regions (subdivisions of NUTS-1 regions).

In the case of cross-regional inventor-teams we have used the procedure of multiple full counting[17]. This procedure deviates from the USPTO [United States Patent and Trademark Office] practice to select first-named addresses only[18]. In order to clarify the difference between the two assignment procedures let us assume that patent A with three inventors in three different regions – say i, j and k – cites patent B with two inventors in two different regions, say s and t. In this case the USPTO practice would count only the cross-regional citation link A_i to B_s, while our procedure takes all six patent citation

[16] In some cases (Denmark, Greece, Ireland and Luxembourg) NUTS-0 regions are used as dictated by practical convenience. Details of the regional system are given in Appendix A.

[17] Note that full rather than fractional counting does justice to the true integer nature of patent citations, but gives the interregional cooperative inventions greater weight.

[18] This assignment rule has been a common approach because of programming ease.

links into account. Evidently, the USPTO procedure underestimates, our method overestimates knowledge spillovers.

Table 1: Descriptive Statistics on the Region-by-Region Citation Matrix

		Patent Citations				
	Number of Matrix Elements*	Number	Mean	Standard Deviation	Min.	Max.
All Elements	35,344	98,191	2.77	16.23	0	1,408
Intraregional Links	188	11,371	60.48	152.05	0	1,408
Interregional Links	35,156	86,820	2.46	11.14	0	351
Positive Interregional Links	11,468	86,820	7.57	18.49	1	351
National Interregional Links	3,952	25,341	6.41	20.02	0	351
International Interregional Links	31,204	61,479	1.97	9.31	0	290

* Elements of the region-by-region citation matrix

Table 1 provides some basic information about the region-by-region citation matrix. The (188, 188)-matrix contains 35,344 elements with a total of 98,191 citations between high-technology firms. The mean number of citations between any two regions (including intraregional flows) is 2.77, but the standard deviation is rather high. Interregional citations show a highly skewed distribution. About two thirds of all pairs (i, j; $i \neq j$) of regions [23,688 pairs] never cite each other's patents. The frequency of patent citations gradually declines for more intensive citation links. There are only 90 pairs of regions for which the number of citations is 100 or more. The average number of citations for all interregional pairs is 2.46 and the average for those that cite each other 7.57. Table 1 indicates that national patent citations are more frequent than international ones.

4 The Spatial Interaction Modelling Perspective

We adopt a spatial interaction modelling perspective to identify and measure spatial separation effects to interregional knowledge spillovers as captured by patent citations among high-technology firms. Mathematically, the situation we are considering is one of observations c_{ij} (i=1, ..., I=188; j=1, ..., J=188) on random variables, say C_{ij}, each of which corresponds to the interfirm transfer of knowledge from region i to region j. We are interested in models of the type

$$C_{ij} = \mu_{ij} + \varepsilon_{ij} \qquad i=1, ..., I; j=1, ..., J; i \neq j \qquad (1)$$

where the observed patent citation flows c_{ij} are independent Poisson variates with $\mu_{ij} = E[C_{ij}]$. The error ε_{ij} is noise, with the property $E[\varepsilon_{ij} \mid c_{ij}] = 0$ by construction. Note that this error term relates to a pair (i, j) of regions. We aim to develop appropriate models for the systematic part, μ_{ij}, of the stochastic relationship with other random variables which are the forecasts.

Spatial interaction models simultaneously incorporate the effect of origin and destination characteristics and separation. Mathematically, they may be written as

$$\mu_{ij} = A_i \; B_j \; F_{ij}(d_{ij}) \qquad i=1, ..., I; j=1, ..., J; i \neq j \qquad (2)$$

where μ_{ij} denotes the estimated knowledge flow from region i to region j. A_i represents a factor characterising the origin i of interaction, and B_j a factor characterising the destination j of interaction, while F_{ij} is a factor that measures separation from i to j. Origin and destination factors may be viewed as weights associated with origin and destination variables. Their classical specifications are given by power functions

$$A_i = A(a_i, \alpha_1) = a_i^{\alpha_1} \qquad i=1, ..., I \qquad (3)$$

$$B_j = B(b_j, \alpha_2) = b_j^{\alpha_2} \qquad j=1, ..., J \qquad (4)$$

where α_1 and α_2 are parameters to be estimated and a_i and b_j denote some appropriate origin and destination variables. The product $A_i B_j$ in (2) can be interpreted simply as the number of distinct (i, j)-interactions which are possible. In the current study a_i is measured in terms of the number of patents in the knowledge producing region i in the time period 1985-1997, and b_j in terms of the number of patents in the knowledge absorbing region j in the time period 1990-2002.

The separation function F_{ij} constitutes the very core of spatial interaction models. Hence, a number of alternative specifications of F_{ij} have been proposed. In this study we use the multivariate separation function

$$F_{ij} = F(d_{ij}, \boldsymbol{\beta}) = \exp\left[\sum_{k=1}^{K} \beta_k \; d_{ij}^{(k)}\right] \qquad i=1, ..., I; j=1, ..., J; i \neq j \qquad (5)$$

that provides a flexible representational framework for the purpose of our study. $d_{ij} = (d_{ij}^{(1)}, ..., d_{ij}^{(K)})$ denotes the K separation measures. β_k (k=1, ..., K) are unknown parameters.

Our interest is focused on K=4 measures: $d_{ij}^{(1)}$ represents geographic distance measured in terms of the great circle distance [in km] between the regions' economic centres, $d_{ij}^{(2)}$ is a dummy variable[19] that represents border effects measured in terms of the existence of country borders between i and j, while $d_{ij}^{(3)}$ is a dummy variable[20] that represents language barrier effects. As we consider the distance effect on interregional patent citations it is important to control for technological proximity between regions, as geographical distance could be just proxying for technological proximity. To do this we use the technological proximity index s_{ij} developed by Maurseth and Verspagen (2002). We divide the high-technology patents into fifty-five technological subclasses, following the International Patent Code (IPC) classification. Each region is then

[19] The dummy is set equal to zero for pairs of regions that are located within the same country, and to one otherwise.

[20] The language barrier dummy is set equal to zero for pairs of regions that share the same language, and one otherwise.

assigned a (55, 1)-'technology vector' that measures the share of patenting in each of the technological subclasses for the region. The technological proximity between two regions *i* and *j* is given by the uncentred correlation of their technological vectors. Two regions that patent exactly in the same proportion in each subclass have an index equal to one, while two regions patenting only in different subclasses have an index equal to zero. This index is appealing because it allows for a continuous measure of technological distance, namely $d_{ij}^{(4)} = 1 - s_{ij}$, and avoids the problem of defining technological distance between sectors.

Integrating (2)-(5) into (1) yields

$$C_{ij} = a_i^{\alpha_1} \, b_j^{\alpha_2} \, \exp\left[\sum_{k=1}^{K} \beta_k \; d_{ij}^{(k)} \right] + \varepsilon_{ij} \qquad i=1, ..., I; j=1, ..., J; i \neq j. \tag{6}$$

Fitting this model to the patent citation data is a question of estimating the unknown parameters α_1, α_2 and β_k (k=1, ..., K). At a first glance it is tempting to express (6) equivalently as a log-additive model of the form

$$\log C_{ij} = \alpha_1 \log a_i + \alpha_2 \log b_j + \sum_{k=1}^{K} \beta_k d_{ij}^{(k)} + u_{ij} \qquad i=1, ..., I; j=1, ..., J; i \neq j \tag{7}$$

with

$$u \sim N\left(0, \sigma^2\right) \tag{8}$$

and then proceed to estimate the parameters by ordinary least squares regression of the observations c_{ij} on a_i, b_j, and d_{ij}.

However, such an approach suffers from two major drawbacks. *First*, the regression produces estimates of the logarithms of μ_{ij}, not of the μ_{ij}'s themselves. The antilogarithms of these estimates are biased estimates of μ_{ij}. One of the effects of this is to underpredict large patent citations flows, and to underpredict the total flow (see Flowerdew and Aitkin 1982). *Second*, estimating the parameters by the ordinary log-additive regression model given by Equations (7)-(8) would only be justified statistically if we believed that flows C_{ij} were independent and log-normally distributed about their mean value with a constant variance. Such an assumption, however, is not valid since patent citation flows are discrete counts whose variance is very likely to be proportional to their mean value (see Bailey and Gatrell 1995, among others).

5 The Poisson Model Specification and Maximum Likelihood Estimation

Least squares and normality assumptions ignore the true integer nature of patent citations flows and approximate a discrete-valued process by an almost certainly misrepresentative continuous distribution (Fischer and Reismann 2002). To overcome this deficiency, it seems natural to assume that the C_{ij} given A_i, B_j and F_{ij} are *iid* Poisson distributed with density

$$f\left[C_{ij}=c_{ij}\left|A_i, B_j, F_{ij}\right.\right]=\frac{\exp\left(-\mu_{ij}\right)\mu_{ij}^{c_{ij}}}{c_{ij}\,!} \tag{9}$$

where the mean parameter μ [that is, the conditional expectation of (i, j) patent citations, given A_i, B_j, F_{ij}] is parameterised as

$$E\left[c_{ij}\left|A_i,\, B_j,\, F_{ij}\right.\right]=\exp\left[\log A(a_i,\alpha_1)+\log B(b_j,\alpha_2)+\log\, F\left(d_{ij},\boldsymbol{\beta}\right)\right] \tag{10}$$

with $d_{ij}=(d_{ij}^{(1)},...,d_{ij}^{(K)})$ and $\boldsymbol{\beta}=(\beta_1,\,...,\beta_K)$. Specification (10) is called the exponential mean function[21]. The model comprising (9) and (10) is referred to as the

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[21] The parameter $(\alpha_1, \alpha_2, \beta_1,\, ...,\beta_K)$ can be interpreted as elasticities.

basic *Poisson model specification*. Note that μ_{ij} is a deterministic function of A_i, B_j and F_{ij}, and the randomness in the model comes from the Poisson specification of c_{ij}.

Parameterisation (10) implies a particular form of heteroskedasticity, due to equidispersion or equality of conditional variance and conditional mean:

$$V\left[c_{ij}\left|A_i,\, B_j,\, F_{ij}\right.\right]=E\left[c_{ij}\left|A_i,\, B_j,\, F_{ij}\right.\right]=\mu_{ij}. \tag{11}$$

It also implies the conditional mean to have a multiplicative form given by

$$\begin{aligned}E\left[c_{ij}\left|A_i,\, B_j,\, F_{ij}\right.\right]&=\exp\left[\log A(a_i,\alpha_1)+\log B(b_j,\alpha_2)+\log\, F(d_{ij},\boldsymbol{\beta})\right]=\\&=A(a_i,\alpha_1)\,B(b_j,\alpha_2)\,F(d_{ij},\boldsymbol{\beta}).\end{aligned} \tag{12}$$

The Poisson specification of the spatial interaction model (6) shows some interesting advantages. *First*, it is analogous to the familiar econometric regression specification (7)-(8) in many ways. In particular, $E\left[c_{ij}\left|A_i,\, B_j,\, F_{ij}\right.\right]=\mu_{ij}$. Moreover, parameter estimation is straightforward and may be done by maximum likelihood. *Second*, the 'zero problem', c_{ij}=0, is a natural outcome of the Poisson specification. In contrast to the logarithmic regression specification there is no need to truncate an arbitrary continuous distribution. The integer property of the outcomes c_{ij} is handled directly.

Parameter Estimation

For notational economy, let us denote $\boldsymbol{\theta}$ the (K+2)-dimensional parameter vector $\left(\alpha_1,\alpha_2,\beta_1,\,...,\beta_K\right)=(\alpha_1,\alpha_2,\boldsymbol{\beta})$ that has to be estimated. The standard estimator for the model is the maximum likelihood estimator. The likelihood principle selects as estimator of θ the value which maximises the joint probability of observing the sample values c_{ij}. This probability, viewed as a function of parameters conditional on the data, is called the likelihood function and is denoted as

$$L(\theta) = \prod_{i=1}^{I} \prod_{\substack{j=1 \\ j \neq 1}}^{J} f\left[c_{ij} \middle| A_i, B_j, F_{ij}, \boldsymbol{\theta}\right] \tag{13}$$

where we suppress the dependence $L(\boldsymbol{\theta})$ on the data and have assumed independence over (i, j). Maximising $L(\boldsymbol{\theta})$ is equivalent to maximising the log-likelihood function (see Sen and Smith 1995)

$$\begin{aligned}
\mathcal{L}(\boldsymbol{\theta}) = \log L(\boldsymbol{\theta}) = & \sum_{i=1}^{I} \sum_{\substack{j=1 \\ j \neq i}}^{J} \left\{ -A(a_i, \alpha_1) B(b_j, \alpha_2) \exp[\boldsymbol{\beta}\, d_{ij}] + \right. \\
& \left. + c_{ij} [\log A(a_i, \alpha_1) + \log B(b_j, \alpha_2) + \boldsymbol{\beta}\, d_{ij})] - \log(c_{ij}\, !) \right\} = \\
& = \sum_{i=1}^{I} \sum_{\substack{j=1 \\ j \neq i}}^{J} \{ -A(a_i, \alpha_1)\, B(b_j, \alpha_2) \exp(\boldsymbol{\beta}\, d_{ij}) \} + \sum_{i=1}^{I} c_{i\bullet} \ \log A(a_i, \alpha_1) + \\
& + \sum_{\substack{j=1 \\ j \neq i}}^{J} c_{\bullet j} \ \log B(b_j, \alpha_2) + \sum_{k=1}^{K} \beta_k \left[d_{ij}^{(k)}\, c_{ij} \right] - \sum_{i=1}^{I} \sum_{\substack{j=1 \\ j \neq i}}^{J} \log(c_{ij}\, !)
\end{aligned} \tag{14}$$

where $c_{i\bullet} = \sum_{j=1}^{J} c_{ij}$ and $c_{\bullet j} = \sum_{i=1}^{I} c_{ij}$ .The partial derivatives of $\mathcal{L}(\boldsymbol{\theta})$ are:

$$\begin{aligned}
\frac{\vartheta \mathcal{L}(\boldsymbol{\theta})}{\vartheta \alpha_1} & = \sum_{j=1}^{J} \left\{ -B(b_j, \alpha_2) \exp\left[\boldsymbol{\beta}\, d_{ij}\right] + \frac{c_{ij}}{A(a_i, \alpha_1)} \right\} = \\
& = \left[c_{i\bullet} - \mu_{i\bullet} \right] A(a_i, \alpha_1)^{-1} \qquad \text{for } i = 1, ..., I
\end{aligned} \tag{15}$$

$$\begin{aligned}
\frac{\vartheta \mathcal{L}(\boldsymbol{\theta})}{\vartheta \alpha_2} & = \sum_{i=1}^{I} \left\{ -A(a_i, \alpha_1) \exp\left[\boldsymbol{\beta}\, d_{ij}\right] + \frac{c_{ij}}{B(b_j, \alpha_2)} \right\} = \\
& = \left[c_{\bullet j} - \mu_{\bullet j} \right] B(b_j, \alpha_2)^{-1} \qquad \text{for } j = 1, ..., J
\end{aligned} \tag{16}$$

$$\begin{aligned}
\frac{\vartheta \mathcal{L}(\boldsymbol{\theta})}{\vartheta \beta_k} & = \sum_{i=1}^{I} \sum_{\substack{j=1 \\ j \neq i}}^{J} \left\{ -d_{ij}^{(k)} A(a_i, \alpha_1)\, B(b_j, \alpha_2) \exp\left[\boldsymbol{\beta}\, d_{ij}\right] + c_{ij}\, d_{ij}^{(k)} \right\} = \\
& = \sum_{i=1}^{I} \sum_{\substack{j=1 \\ j \neq i}}^{J} d_{ij}^{(k)} \left[c_{ij} - \mu_{ij} \right] \qquad \text{for } k = 1, ..., K
\end{aligned} \tag{17}$$

with $\mu_{i\bullet} = \sum_{j=1}^{J} \mu_{ij}$ and $\mu_{\bullet j} = \sum_{i=1}^{I} \mu_{ij}$. Maximum likelihood estimates may be found by maximising $\mathcal{L}(\boldsymbol{\theta})$ directly using iterative procedures, usually gradient algorithms, such as Newton-Raphson. Alternatively, one could set the partial derivatives of $\mathcal{L}(\boldsymbol{\theta})$ [that is, Equations (15), (16) and (17)] equal to zero and solve the resultant equations:

$$\left.\begin{array}{l} \mu_{i\bullet} = c_{i\bullet} \text{ for } i=1, ..., I \text{ and } \mu_{\bullet j} = c_{\bullet j} \text{ for } j=1, ..., J, \text{ and} \\ \sum_{i=1}^{I} \sum_{\substack{j=1 \\ j\neq i}}^{J} d_{ij}^{(k)} \mu_{ij} = \sum_{i=1}^{I} \sum_{\substack{j=1 \\ j\neq i}}^{J} d_{ij}^{(k)} c_{ij} \qquad \text{for } k = 1,...,K. \end{array}\right\} \tag{18}$$

Convergence is guaranteed because the log-likelihood function is globally concave[22].

6 A Generalisation of the Poisson Spatial Interaction Model

The above Poisson model specification does not allow for individual (i, j)-effects, given the exogenous variables A_i, B_i, F_{ij}. The exogenous variables are assumed to summarise all individual deviations. Also, it is clear that the existence of fixed effects at the individual level of (i,j) pairs is likely to exist in interregional patent citation relationships. This individual effect problem can be partly solved[23] by introducing a heterogeneity term in the mean μ_{ij} of the Poisson distribution such that the multiplicative heterogeneity term $\exp(\xi_{ij})$ follows a gamma distribution with mean one and variance δ:

$$c_{ij} \sim \text{Poisson}\,(\mu_{ij}^{*}) \tag{19}$$

where

[22] The Hessian of the log-likelihood function is always negative. After estimation, the negative inverse of the estimated Hessian can be used for estimation of the asymptotic covariance matrix of the parameter estimates.

[23] Hausman, Hall and Griliches (1984) give results that are suggestive of ours, though pursuing a different specification in the context of the patents-R&D relationship.

$$\mu_{ij}^{*} = \exp\left[\log A(a_i,\alpha_1) + \log B(b_j,\alpha_2) + \log\ F(d_{ij},\boldsymbol{\beta}) + \xi_{ij}\right] = \\ = \exp\left[\log A(a_i,\alpha_1) + \log B(b_j,\alpha_2) + \log\ F(d_{ij},\boldsymbol{\beta})\right] \exp(\xi_{ij}) \tag{20}$$

and

$$\exp(\xi_{ij}) \sim \text{Gamma}\,(\delta^{-1},\delta). \tag{21}$$

If $\exp(\xi_{ij})$ is gamma distributed and independent of the explanatory variables, c_{ij} has a negative binomial distribution (Cameron and Trivedi 1998):

$$f\left[C_{ij} = c_{ij} \,\middle|\, A_i, B_j, F_{ij}, \delta\right] = \frac{\Gamma(c_{ij}+\delta^{-1})}{\Gamma(c_{ij}+1)\Gamma(\delta^{-1})} \left(\frac{\delta^{-1}}{\mu_{ij}+\delta^{-1}}\right)^{\delta^{-1}} \left(\frac{\mu_{ij}}{\mu_{ij}+\delta^{-1}}\right)^{c_{ij}} \tag{22}$$

where $\Gamma(.)$ is the gamma function and $\delta \geq 0$ the dispersion parameter. The larger δ is, the greater the dispersion. Specification (22) with (20)-(21) is referred to as the *heterogeneous Poisson model of interregional patent citations*. This modification leaves the mean unchanged, but changes the variance to

$$V(c_{ij}) = E\left\{V(c_{ij} \mid \mu_{ij}^{*})\right\} + V\left\{E(c_{ij} \mid \mu_{ij}^{*})\right\} = E(\mu_{ij}^{*}) + V(\mu_{ij}^{*}) = \mu_{ij}(1+\delta\,\mu_{ij}). \tag{23}$$

Thus, the model allows for overdispersion (that is, $\delta > 0$), with $\delta = 0$ reducing to the basic Poisson specification (9)-(10).

Estimation of the model may proceed with maximum likelihood. The log-likelihood function is

$$\log \mathcal{L}(\boldsymbol{\theta},\delta) = \sum_{i=1}^{I} \sum_{\substack{j=1 \\ j\neq i}}^{J} \left\{ \log\left[\frac{\Gamma(c_{ij}+\delta^{-1})}{\Gamma(\delta^{-1})}\right] - \log c_{ij}\,! - \right. \\ -(c_{ij}+\delta^{-1}) \log\left\{1 + \delta \exp\left[A(a_i,\alpha_1)\, B(b_j,\alpha_2)\, F(d_{ij},\boldsymbol{\beta})\right]\right\} + \\ \left. + c_{ij} \log\delta + c_{ij} \log\delta + c_{ij}\left[A(a_i,\alpha_1)\, B(b_j,\alpha_2)\, F(d_{ij},\boldsymbol{\beta})\right]\right\}. \tag{24}$$

7 Estimation Results

Table 2 reports the results from the estimation of the two Poisson spatial interaction model specifications [see Equations (9)-(10), and (22) with (20)-(21), respectively] by maximum likelihood, using Newton-Raphson. The maximum likelihood estimates of the basic Poisson spatial interaction model specification are given in the first column, those of the generalised Poisson model in the second. Standard errors are presented in brackets rather than *t*-statistics to allow comparison with the precision of the negative binomial maximum likelihood estimates in the second column. The reported standard errors all assume correct specification of the variance function. They are characterised by low significance levels.

Table 2: Estimation Results of the Poisson Spatial Interaction Model Specifications [N=35,156 observations; asymptotic standard errors in brackets]

Variable	Poisson Spatial Interaction Model	
	without Heterogeneity	with Heterogeneity
Log-Likelihood	-51,801.10	-37,235.05
{Corr (c_{ij}, predicted c_{ij})}^{2}	0.686	0.783
Wald Chi-Square (6)	307,522.81	30,552.12
Independent Variables		
Origin Variable [α_1]	0.833*** (0.002)	0.915*** (0.006)
Destination Variable [α_2]	0.858*** (0.002)	0.885*** (0.006)
Geographical Distance [β_1]	-0.270*** (0.005)	-0.321*** (0.014)
Country Border [β_2]	-0.050*** (0.007)	-0.533*** (0.046)
Language Barrier[β_3]	-0.238*** (0.014)	-0.031*** (0.043)
Technological Proximity [β_4]	0.928*** (0.032)	1.219*** (0.130)
Intercept	-10.278*** (0.051)	-10.881*** (0.124)
Dispersion Parameter (δ)	–	0.725 (0.014)

Note: All independent metric variables are expressed as natural logs in order to lessen the impact of outliers. The origin, destination and separation functions are specified as follows: $A(a_i, \alpha_i) = a_i^{\alpha_1}$, $B(b_j, \alpha_2) = b_j^{\alpha_2}$ and $F(d_{ij}, \boldsymbol{\beta}) = \exp(\sum_{k=1}^{K} d_{ij}^{(k)} \beta_k)$. a_i is measured in terms of patents (1985-1997) in the cited region *i*, b_j in terms of patents (1985-2002) in the citing region *j*, $d_{ij}^{(1)}$ representing geographic distance is measured in terms of the great circle distance [km] between the economic centres in *i* and *j*; $d_{ij}^{(2)}$ is a dummy that represents border effects [zero for pairs (*i*, *j*) that are located in the same country, one otherwise], $d_{ij}^{(3)}$ is a dummy that represents language barrier effects [zero for pairs (*i*, *j*) that share the same language, one otherwise]; $d_{ij}^{(4)} = 1 - s_{ij}$ where s_{ij} denotes technological proximity of regions i and j in a 55-dimensional technology space; *** denotes significance at the one percent level.

The estimated value of the dispersion parameter δ indicates that the basic Poisson model specification has to be rejected [H_0: δ=0, G^2 =29,256.6, p<0.01][24]. The rejection of this model version is due to the situation of overdispersion which is associated with unobserved heterogeneity among (*i*, *j*) pairs of regions. Therefore, the Poisson model specification with heterogeneity is preferred. The variance-mean equality assumption of the Poisson model is too restrictive to adequately describe the patent citation flows.

The parameters of the negative binomial distribution are estimated along with a large increase in the log-likelihood function compared to the Poisson model. The negative binomial parameter estimates are generally somewhat larger in magnitude than the basic Poisson ones, with the exception of the language dummy. But, since the negative binomial specification allows for an additional source of variance, the estimated standard errors are all larger, and therefore the conclusions to be drawn, while similar to those derived from the basic Poisson model specification, are less precise.

The Poisson spatial interaction model specification with heterogeneity yields highly significant effects. Both α-estimates are – in accordance with expectations – close to one[25]. Geographical distance between inventors has a strong and negative effect on the likelihood of high-technology patent citations. The parameter estimate, $\hat{\beta}_1 = -0.321$,

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24 The G-squared statistic is defined to be $\{\sum_{i=1}^{I}\sum_{\substack{j=1\\ j\neq i}}^{J}[c_{ij}\,\log(c_{ij}\,\hat{\mu}_{ij}^{-1}) - (c_{ij} - \hat{\mu}_{ij})]\}$ where $(c_{ij}\ \log c_{ij}) = 0$ if $c_{ij} = 0$ (see Bishop, Fienberg and Holland 1975).

25 Recall that the product of the origin and destination functions can be interpreted simply as the number of distinct (*i*, *j*)-interactions which are possible. The origin function is measured in terms of patents [1985-1997] in the knowledge producing region *i*, and the destination function in terms of patents [1985-2002] in the knowledge absorbing region *j*.

indicates that for any additional 100 km between regions i and j the (i, j)-mean patent citation frequency decreases by 27.5 percent. This suggests spillovers between high-technology firms are impeded by geographical distance.

Not only distance, but also border effects matter. The point estimate of the coefficient β_2 is nearly twice times as large as that of β_1, showing that border effects are more important than distance effects. Citing patents are much more likely to come from the same country as the cited patents. High-technology related knowledge flows much more easily within than between countries. This is a finding that corresponds well with the notion of national systems of innovation[26]. Note that language barriers though significant have only a rather small effect ($\hat{\beta}_3 = -0.031$) on interregional knowledge spillovers.

The variable technological proximity controls for spillovers that are stronger between technologically similar regions. The point estimate for the variable shows an effect that is about four times larger than the distance effect even though the estimate is not very precise. Interregional patent citation flows tend to follow particular technological trajectories as defined at the three-digit level of the IPC classification. This indicates that patent citation flows are industry specific and occur most often between regions not too far located from each other in technological space. Technological proximity matters more than geographical proximity.

8 Summary and Conclusions

A revival of interest in economic geography during the last decade has renewed efforts to consider knowledge spillovers as a geographical phenomenon. In adopting this view one is confronted with two challenges. The first is the notoriously difficult issue to measure knowledge spillovers and the second one the issue to model the geographic dimension of knowledge spillovers. In confronting the first challenge we used patent citations as proxy for knowledge spillovers and followed the paper trail left by patent

[26] See Fischer (2001) for a discussion of the concept of a system of innovation.

citations to track this specific type of knowledge flows within the high-technology sector across Europe. To address the second challenge we adopted a spatial interaction modelling perspective. This perspective shifted the focus of attention from individual to interregional patent citations, from the dyad "cited patent – citing patent" to the dyad "cited region – citing region".

The basic goal of this study has been to identify and measure spatial separation effects to interregional knowledge spillovers. In particular interest was focused on the following three questions: To what extent geographical distance has an impact on interregional knowledge spillovers? How important are national border effects as distinct from geographical distance? Do linguistic borders matter? We have used a Poisson spatial interaction model specification with heterogeneity to address these questions. It is important to note that in doing so we have controlled for technological proximity between regions, as geographical distance could be just proxying for technological proximity.

The previous section has produced prima facie evidence that knowledge spillovers are geographically localised. National borders have a negative impact on knowledge flows, and this effect is very substantial. Knowledge flows are larger within countries than between regions located in different countries. The results also indicate that geographical proximity matters, while also suggesting that these effects are much smaller than the border effects. Knowledge spillovers occur more often between regions that belong to the same country and are in geographical proximity. Technology proximity tends to overcome geographical proximity. Interregional knowledge flows seem to follow particular technological trajectories, and occur most often between regions that are located in technological space, not too far from each other.

The results support the conclusion that national and sectoral systems of innovation matter at least as far as high-technology firms are concerned. This is a conclusion that has important policy implications. European regional cohesion appears to be at stake, especially – but not exclusively – because of the localised nature of knowledge flows. The results also have important implications for modelling technological change and economic growth. They provide strong empirical support for the models of endogenous economic growth, such as Romer (1990), in which localised knowledge spillovers are simply assumed.

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Appendix A: List of Regions Used in the Study

Country	Nuts-Code	Region	Country	Nuts-Code	Region
Austria	AT11	Burgenland		DEB1	Koblenz
	AT12	Niederösterreich/Wien		DEB2	Trier
	AT21	Kärnten		DEB3	Rheinhessen-Pfalz
	AT22	Steiermark		DEC0	Saarland
	AT31	Oberösterreich		DED1	Chemnitz
	AT32	Salzburg		DED2	Dresden
	AT33	Tirol		DED3	Leipzig
	AT34	Vorarlberg		DEE1	Dessau
Belgium	BE10	Région Bruxelles-Capital		DEE2	Halle
	BE21	Antwerpen		DEE3	Magdeburg
	BE22	Limburg (B)		DEF0	Schleswig-Holst./Hamburg
	BE23	Oost-Vlaanderen		DEG0	Thüringen
	BE24	Vlaams Brabant	**Denmark**	DK00	Denmark
	BE25	West-Vlaanderen	**Estland**	EE00	Estland
	BE31	Brabant Wallon	**Finland**	FI13	Itä-Suomi
	BE32	Hainaut		FI14	Väli-Suomi
	BE33	Liège		FI15	Pohjois-Suomi
	BE34	Luxembourg (B)		FI16	Uusimaa
	BE35	Namur		FI17	Etelä-Suomi
Bulgaria	BG00	Bulgaria	**France**	FR10	Île de France
Czech Republic	CZ00	Czech Republic		FR21	Champagne-Ardenne
Germany	DE11	Stuttgart		FR22	Picardie
	DE12	Karlsruhe		FR23	Haute-Normandie
	DE13	Freiburg		FR24	Centre
	DE14	Tübingen		FR25	Basse-Normandie
	DE21	Oberbayern		FR26	Bourgogne
	DE22	Niederbayern		FR30	Nord - Pas-de-Calais
	DE23	Oberpfalz		FR41	Lorraine
	DE24	Oberfranken		FR42	Alsace
	DE25	Mittelfranken		FR43	Franche-Comté
	DE26	Unterfranken		FR51	Pays de la Loire
	DE27	Schwaben		FR52	Bretagne
	DE30	Berlin		FR53	Poitou-Charentes
	DE40	Brandenburg		FR61	Aquitaine
	DE71	Darmstadt		FR62	Midi-Pyrénées
	DE72	Gießen		FR63	Limousin
	DE73	Kassel		FR71	Rhône-Alpes
	DE80	Mecklenburg-Vorpommern		FR72	Auvergne
	DE91	Braunschweig		FR81	Languedoc-Roussillon
	DE92	Hannover		FR82	Provence-Côte d'Azur
	DE93	Lüneburg/Bremen	**Greece**	GR00	Greece
	DE94	Weser-Ems	**Hungary**	HU00	Hungary
	DEA1	Düsseldorf	**Ireland**	IE00	Ireland
	DEA2	Köln	**Italy**	IT11	Piemonte
	DEA3	Münster		IT12	Valle d'Aosta
	DEA4	Detmold		IT13	Liguria
	DEA5	Arnsberg		IT20	Lombardia

ctd.

	IT31	Trentino-Alto Adige		SE06	Norra Mellansverige
	IT32	Veneto		SE07	Mellersta Norrland
	IT33	Friuli-Venezia Giulia		SE08	Övre Norrland
	IT40	Emilia-Romagna		SE09	Småland med öarna
	IT51	Toscana		SE0A	Västsverige
	IT52	Umbria	**Switzerland**	CH00	Switzerland
	IT53	Marche	**United Kingdom**	UKC1	Tees Valley & Durham
	IT60	Lazio		UKC2	Northumberland & Wear
	IT71	Abruzzo		UKD1	Cumbria
	IT72	Molise		UKD2	Cheshire
	IT80	Campania		UKD3	Greater Manchester
	IT91	Puglia		UKD4	Lancashire
	IT92	Basilicata		UKD5	Merseyside
	IT93	Calabria		UKE1	East Riding & Lincolnsh.
	ITA0	Sicilia		UKE2	North Yorkshire
	ITB0	Sardegna		UKE3	South Yorkshire
Lithuania	LT00	Lithuania		UKE4	West Yorkshire
Luxembourg	LU00	Luxembourg		UKF1	Derbyshire & Nottingham
Latvia	LV00	Latvia		UKF2	Leicestershire
Netherlands	NL11	Groningen		UKF3	Lincolnshire
	NL12	Friesland		UKG1	Herefordshire
	NL13	Drenthe		UKG2	Shropshire & Staffordsh.
	NL21	Overijssel		UKG3	West Midlands
	NL22	Gelderland		UKH1	East Anglia
	NL23	Flevoland		UKH2	Bedfordshire & Hertford.
	NL31	Utrecht		UKH3	Essex
	NL32	Noord-Holland		UKI1/UKI2	London Region
	NL33	Zuid-Holland		UKJ1	Berkshire
	NL34	Zeeland		UKJ2	Surrey
	NL41	Noord-Brabant		UKJ3	Hampshire
	NL42	Limburg (NL)		UKJ4	Kent
Norway	NO00	Norway		UKK1	Gloucestershire
Poland	PL00	Poland		UKK2	Dorset & Somerset
Portugal	PT11/PT12/PT14/PT15	Portugal except Lisbon		UKK3	Cornwall
	PT13	Lisbon Region		UKK4	Devon
Romania	RO00	Romania		UKL1	West Wales
Slovakia	SK00	Slovakia		UKL2	East Wales
Slovenija	SI00	Slovenija		UKM1	North Eastern Scotland
Spain	ES11/ES12/ES13	Galicia/Asturias		UKM2	Eastern Scotland
	ES21	Pais Vasco		UKM3	South Western Scotland
	ES22/ES23/ES24	Aragón/La Rioja/Navarra		UKM4	Highlands and Islands
	ES30	Comunidad de Madrid		UKN0	Northern Ireland
	ES41	Castilla y León			
	ES42	Castilla-la Mancha	**Not included**	ES53	Baleares
	ES43	Extremadura		ES70	Canares
	ES51	Cataluña		FI20	Aland
	ES52	Comunidad Valenciana		FR83	Corse
	ES61	Andalucia		PT20	Acores
	ES62	Región de Murcia		PT30	Madeira
Sweden	SE01	Stockholm			
	SE02	Östra Mellansverige			
	SE04	Sydsverige			

Appendix B: Assignment of Patent Classes to the High-Technology Sector at the Four-Digit ISIC-Level

ISIC Category	Industry Sector	IPC Patent Class
3522	Pharmaceuticals	A61J, A61K, C07B, C07C, C07D, C07F, C07G, C07H, C07J, C07K, C12N, C12P, C12S
3825	Computers and Office Equipment	B41J, B41L, G06C, G06E, G06F, G06G, G06J, G06K, G06M G11B, G11C
3832	Electronics – Telecommunications	G08C, G09B, H01C, H01L, H01P, H01Q, H03B, H03C, H03D, H03F, H03G, H03H, H03J, H03K, H03L, H04A, H04B, H04G, H04H, H04J, H04K, H04L, H04M, H04N, H04Q, H04R, H04S, H05K
3845	Aerospace	B64B, B64C, B64D, B64F, B64G