Production of Knowledge and Geographically Mediated Spillovers from Universities

A Spatial Econometric Perspective and Evidence from Austria

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Abstract

The paper sheds some light on the issue of geographically mediated knowledge spillovers from university research activities to regional knowledge production in high tech industries in Austria. Knowledge spillovers occur because knowledge created by university is typically not contained within that institution, and thereby creates value for others.

The conceptual framework for analysing geographic spillovers of university research on regional knowledge production is derived from Griliches (1979). It is assumed that knowledge production in the high tech sectors essentially depends on two major sources of knowledge: the university research that represents the potential pool of knowledge spillovers and R&D performed by the high tech sectors themselves. Knowledge is measured in terms of patents, university research and R&D in terms of expenditures. We refine the standard knowledge production function by modelling research spillovers as a spatially discounted external stock of knowledge. This enables to capture intraregional and interregional spillovers. Using district-level data and employing spatial econometric tools evidence is found of university research spillovers that transcend the geographic scale of the political district in Austria. It is shown that geographic boundedness of the spillovers is linked to a decay effect.

JEL Classification: O31, H41, O40

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1. Introduction

Technology – in form of a new product or process – invariably combines codified information drawn from previous experience and formal scientific activity with uncodified knowledge that is industry-specific or even firm-specific, and shows some degree of tacitness. Following Polanyi (1967), tacitness refers to those elements of knowledge that persons have which are ill-defined, uncodified and which they themselves can not fully articulate and which differ from person to person, but which may to some degree be shared by collaborators who have a common experience. In most cases a piece of knowledge can be located between these two extremes. Knowledge is not created codified and is always at least partly tacit in the minds of those who create it. Codification is required because knowledge creation is a collective process that requires complex mechanisms of communication and transfer (Saviotti 1988). As tacit components – such as common practice based on modes of interpretations, perceptions and value systems – in the firm's knowledge base increase, knowledge accumulation becomes more experienced based. Such forms of knowledge can only be shared, communicated or transferred through network types of relationships (Fischer 2001). This kind of knowledge has to be carefully distinguished from information in the usual sense. It will often require more complex mechanisms of communication and transfer. It can more easily be appropriated privately and requires special learning processes.

Spillovers stem from specific features of knowledge. In particular, knowledge is a non-rivalrous and partially excludable good. Non-rivalry implies that a new piece of knowledge can be utilized many times and in many different circumstances, for example by combining with knowledge coming from another domain. Lack of excludability, on the other hand, implies that it is difficult for firms that have devoted resources to R&D fully to appropriate the benefits and prevent others from using the knowledge without compensation or with compensation less than the value of the knowledge (Teece 1986). While knowledge is subject to spillovers, however, it is only imperfectly excludable. With the use of patents or other devices such as secrecy knowledge producing firms capture at least part of the social benefits associated with the production of knowledge, and this is an incentive for their R&D investment (OECD 1992). The interest of users of knowledge (i.e. firms other than the knowledge producing firm) is thus best served if – once produced – knowledge is widely available and diffused at the lowest possible cost. This implies low appropriability for knowledge producers or – put another way – an environment rich in knowledge spillovers.

The term *spillover* is used in economics to capture the idea that some of the economic benefits of R&D activities accrue to economic agents other than the party that undertakes the research. Competing firms that initiate a successful innovation, and firms whose own research benefits from observation of the successes and failures of others' research efforts all garner such spillover benefits. These examples suggest that such spillovers are created by a combination of the new knowledge resulting from a R&D effort, and the commercialisation of the new technology in terms of a new product or process that is successfully implemented in the market place (Jaffe 1996). Research spillovers have been defined by Cohen and Levinthal (1989) to include any original valuable knowledge generated in the research process that becomes publicly accessible whether it be knowledge fully characterising an innovation or knowledge of a more intermediate nature. They have been also termed disembodied or *knowledge spillovers* to emphasize that they do not necessarily relate to knowledge embodied in machinery or equipment. Knowledge spillovers are an example of a positive externality. The concept of positive externalities is very closely related to the concept of public goods. In the limit the benefits of an activity may be so diffuse that no firm would undertake the activity on their own, such as national defense. R&D fall in an intermediate range in which the activity creates sufficient benefit to the party undertaking it that market forces generate some, but not enough of the activity.

Fundamental research of the quality and on the scale that can lead to major scientific advances takes place in relatively few firms. It calls for high thresholds of R&D investment and a corporate research environment conducive to developing and discussing ideas with other researchers. Knowledge developed within firms also raises proprietary issues. For such reasons, the advance towards reliable and public scientific knowledge primarily takes place within the institutions (universities, learned societies and academies) specially devised for the production of fundamental, general and public knowledge.

The majority of technological process innovations and most product innovations, especially in Pavitt's (1984) science-based industries, such as chemicals, biotechnology and electronics, do not occur without access to rather sophisticated forms of scientific knowledge. In this context the role of universities is crucial. Knowledge spillovers from university flow through a number of distinct channels. They occur when graduates who have the requisite levels of scientific and technological knowledge leave the university and take a job at a firm or start their own. They also occur between academic researchers and industry sector researchers – even without formal collaborative projects that bring the two together. In many technology-intensive industries, such as the computer industry or biotechnology industry, the research personnel of firms attend academic conferences, present academic papers and regularly engage in academic discussion with researchers in universities. It is also true that many industry sector researchers who do not attend academic conferences nevertheless follow the academic literature and receive spillovers from reading academic papers. It is moreover not uncommon for university professors to act as a formal consultant to individual firms.

The empirical studies in the literature on the phenomenon of knowledge spillovers from universities vary somehow in terms of research design, but they all find that investment in R&D made by private corporations and universities spills over for economic exploitation by third-party firms. The situation, however, is different in terms of the significance of a *local* geographic spillover effect. Overall considered, the evidence is either non-existent, weak or mixed, only pertaining to a few industrial sectors. Most of the US-American studies – with a few exceptions notably Anselin, Varga and Acs (1987) and Varga (1998) – use the idea suggested by Jaffe (1989) to utilize the product of the logarithm of state-level university expenditures with the logarithm of a geographic index. The latter is achieved as the uncentred correlation coefficient between university research and professional employees in R&D laboratories for the SMSAs in the state. The resulting index is rescaled so that its mean is zero. While the coincidence index may make intuitive sense, it is unrelated to the existing body of research on measures of spatial accessibility (see, for example, Frost and Spence 1995, Weibull 1976). In this study we utilize a measure of knowledge accessibility to overcome the above deficiency, a measure that is more tightly integrated with the existing body of spatial interaction theory and may enable to improve the results on analysing the phenomenon of geographically mediated knowledge spillovers from universities.

While the cost of transmitting information may be increasingly invariant to distance, presumably the cost of transmitting – particularly tacit – knowledge rises with distance. If knowledge spillovers are as important as much of the theoretical literature assumes (see, for example, Romer 1990, Krugman 1991a, b) suggests, then knowledge spillovers should be observed in the national innovation systems, especially in high technology industries where such spillovers are likely to play the most important role. The purpose of this contribution is to shed some light on this issue in Austria. The study is empirical in nature and has an explanatory dimension.

We consider two major sources of corporate knowledge production in the high technology sectors – R&D performed by the high technology sectors and the pool of university research for the high technology sectors – and model geographically mediated research spillovers as a spatially discounted external stock of knowledge within a knowledge production function framework as introduced by Griliches (1979). In the following section of the paper, we introduce the conceptual framework for analysing geographic knowledge spillovers, the formal model underlying the knowledge production function and the specification of the geographic scope of spillovers. We next briefly describe the variables and the data set and outline subsequently some methodological issues in specifying and estimating the model, before presenting the empirical results of our study. The paper concludes with a brief summary and evaluation of our findings.

2. The Conceptual Framework

Our interest is focused on regional corporate knowledge production in the high technology sectors in Austria as an aggregate, and on university research spillovers. Corporate knowledge is difficult to define and even more difficult to measure (see Radding 1998). In this study we follow Jaffe (1989) and others to use patents as a quantitative and rather direct indicator of invention to proxy the output of the knowledge production process. We are aware that the use of patent counts to identify the effect of spatially mediated spillovers is not without pitfalls. The use might be particularly sensitive to what Scherer (1983) has termed the propensity to patent. There is evidence that the propensity to patent does not appear to be invariant across industries (see, for example, Fischer, Fröhlich and Gassler 1994). For example, technology in the pharmaceuticals sector allows easy copying of newly developed drugs, and thus patent protection is essential. In other sectors, such as for example aerospace, the propensity to patent is typically smaller.

The existence of knowledge spillovers suggests that production of knowledge by a particular firm or industry not only depends on its own research efforts, but also on outside efforts or – more generally – on the knowledge pool available to it. Following the standard literature in the field (see Griliches 1979, Jaffe 1989), we assume that corporate knowledge production in the high technology sectors essentially depends on two major sources of knowledge: industrial R&D performed in the high technology sectors and academic basic research. Academic basic research, however, will not necessarily result in useful knowledge for every industry. But scientific knowledge from certain scientific fields or academic institutes is expected to be more important for high technology industries. In particular, the transfer sciences[1] tend to play a major role in bridging the gap between the type of knowledge produced by basic science and the type of knowledge needed by high tech firms in their knowledge producing activities. To capture the relevant pool of knowledge, scientific fields were assigned to relevant high technology sectors using the survey of industrial R&D managers by Levin et al. (1987).

Our conceptual framework for analysing geographic knowledge spillovers utilises the two factor Cobb-Douglas knowledge production function as introduced by Griliches (1979) and widely utilized in recent studies (see, for example, Audretsch and Feldmann 1994; Anselin, Varga and Acs 1997). The production function describes the relationship between various inputs and the output of the knowledge production process at the micro- or macro-level.

$$\boldsymbol{K} = a_0\, \boldsymbol{R}^{a_1}\, \boldsymbol{U}^{a_2}\, e \tag{1}$$

where ***K*** is measured in terms of patents as a proxy for new corporate knowledge generated by high tech firms, ***R*** is industry R&D and ***U*** university research [relevant for high technology industries] measured in terms of expenditures, with a_0 a constant, and a_1 and a_2 as associated parameters. e is a vector of stochastic error terms. If we would have had more and better data we could try a more complex description of the production process, using more general functional forms such as the CES or the translog, and using more parameters to be estimated.

Introducing a spatial dimension into the model, the knowledge production function reads in log-linear form as follows

$$\log K_i = a_0 + a_1 \log R_i + a_2 \log U_i + e_i \tag{2}$$

where $i = 1,..., N$ indexes the spatial unit of observation (political districts in Austria in this study). University research spillovers are modelled as an external stock of knowledge, represented by variable ***U***. It is assumed that these spillovers do not reach beyond the geographic boundaries of the spatial unit chosen. A positive and significant coefficient for a_2 indicates the presence of localised spatial spillovers from university research on regional knowledge production. The higher the value of this coefficient, the more intensive the effect of university-to-firm knowledge flows on regional knowledge production.

The above model appears to be unsatisfactory if the spatial range of interaction between industry R&D and university research reaches beyond the spatial unit where R&D is performed. To capture potential interregional knowledge spillovers that originate from universities outside the R&D district we introduce a measure of accessibility[2], A_i^U, to university knowledge for each industry R&D district i (i = 1,...,N) with respect to all university districts j ¹ i (j =1,..., $N_1 < N$) in the Austrian national innovation system:

$$A_i^U = \sum_{j \neq i} U_j \ d_{ji}^{-ß} \qquad (3)$$

where U_j is defined as before, d_{ji} is a measure of impedance from j to i or, in other words, the economic or technological distance from j to i as perceived by high technology industry located in i to get in touch with knowledge producers at university in j. In this study we use road distance as a crude proxy for d. $ß > 0$ is a parameter reflecting distance deterrence. Evidently, Equation (3) is closely related to accessibility indices derived from spatial interaction theory (see, for example, Weibull 1976). When an industry district i and an university district j coincide, no distance decay is applied to the ***U*** variable in order to avoid the familiar self-potential problem (see Frost and Spence 1995).

In a similar manner, the accessibility measure A_i^R may be introduced as

$$A_i^R = \sum_{j \neq i} R_j \, d_{ji}^{-ß} \tag{4}$$

to capture potential interregional knowledge spillovers between R&D laboratories located in districts i and j ¹ i. R_i is as before, d_{ji} is a measure of impedance, and $ß > 0$ is a distance deterrence parameter. Then the knowledge production function model becomes

$$\log K_i = a_0 + a_1 \log W_i + a_2 \log F_i + e_i \tag{5}$$

with

$$\log W_i = \log R_i + \log A_i^R \tag{6}$$

and

$$\log F_i = \log U_i + \log A_i^U \tag{7}$$

Model (5) – (7) may be *termed Basic Model for Regional Corporate Knowledge Production*. University research spillovers are modelled as a spatially discounted external stock of knowledge [see Equation (7)]. Variable F consists of two components. The first captures knowledge spillovers that do not reach beyond the geographic boundaries of the political district, and the second those that transcend the geographic scale of the political district. The accessibility measure assumes that these follow a clear distance decay pattern. A positive and significant coefficient for a_2

indicates the presence of localised geographic spillovers from university research on regional knowledge production. The higher the value of this coefficient, the more intense the effect of university-to-firm knowledge flows on regional knowledge production. By contrast, the lack of significance of a_2 would suggest that all knowledge production is generated internally to the high tech sectors, with or without cooperation between R&D laboratories [variable W in Equation (5)].

The lack of significance of a_2 in Equation (2) would suggest that all knowledge production is generated internally to the high tech sectors, that is exclusively through the variable log R_i. This does not exclude the presence of additional knowledge externalities of the Marshall-Arrow-Romer or the Isard-Jacobs type (see Glaser et al. 1992, Echeverri-Carroll and Brennan 1999, Karlsson and Manduchi 2001). Marshall-Arrow-Romer externalities promote knowledge spillovers across firms and, thus, stimulate knowledge production in that particular industry, while Isard-Jacobs externalities foster knowledge generation due to the diversity of knowledge resources located in the region. The exchange of complementary knowledge across diverse firms and economic agents leads to increasing returns to new economic knowledge.

Skilled workers endowed with a high level of human capital are a mechanism through which such knowledge externalities materialize. The concentration of skilled labour in one place facilitates intra-industry flows of information and knowledge because timeliness and face-to-face communication are important for generating new knowledge. To capture such externalities we add variable Z_i to Patent Equation (5) that measures the concentration of high technology employment in region i as a proxy for intra-industry information and knowledge exchange.

This leads to the following model which may be termed *Extended Model for Regional Corporate Knowledge Production*:

$$\log K_i = a_0 + a_1 \log W_i + a_2 \log F_i + a_3 Z_i + e_i \tag{8}$$

together with Equations (6)-(7). Z_i denotes the share of high technology employment in the national total; W_i, F_i, a_0, a_1, a_2, a_3 and e_i are in the same notation as above.

3. Data and Variable Definitions

One major issue to be confronted in implementing a model consisting of Equations (5)–(7) or (8) with (6)–(7) is identifying an appropriate unit of observation. The use of provinces as the unit of observation is conceptually problematic. Thinking of geographic spillovers as occuring similarly in Vienna and Carinthia, for example, strains credulity. There is no way around to utilize a finer spatial scale such as the scale of political districts, that is the finest spatial resolution at which the relevant data are available or may be estimated at least. The location of universities in only seven out of the 99 political districts, however, makes it difficult to estimate Equations (5)-(7) due to the very low degree of freedom. To overcome this problem the variables log W_i and log F_i in Equations (5) and (8), respectively, have to be replaced by variables such as

$$\log W_i = \log\left[R_i + A_i^R\right] \tag{6'}$$

and

$$\log F_i = \log\left[U_i + A_i^U\right] \tag{7'}$$

These variables represent those spatially discounted spillover pools that are associated with industrial R&D and university research in region i, respectively. Evidently in this way, the technical problem can be overcome but at the loss of a clear distinction between intra- and interregional spillovers.

Account of corporate patent applications has been used to construct the dependent variable in the geographic knowledge production functions [***K*** in Equation (5) and Equation (8)]. We obtained a tape from the Austrian Patent Office containing the following information: the exact application date, name of the assignee(s), address of the assignee(s) including the zip-code, name of the inventor(s), location of the inventor(s), one or more International Patent Classification (IPC) codes, an assignment code indicating whether the organisation is foreign or domestic and some information on the technology field of the patent application. Corporate patents were taken to be all patents that – based on their assignment code – were assigned by the applicant to either a domestic or foreign corporation located in Austria. An extensive effort was made to identify patent-applying subsidiaries. Several protocols were adopted to ensure that patents were in fact linked to the correct company or subsidiary. Postal code information made it possible to trace patent activity back to the region of knowledge production. In the case of multiple assignees we followed the standard procedure of proportionate assignment. Consequently, the dependent variable patent activity is a non-discrete variable and OLS rather than negative binomial regression seems to be an appropriate estimation approach.

At the sector of scale, the patent data were assigned to the two-digit International Standard Industrial Classification (ISIC) system. The absence of detailed R&D spending data at a more micro-level impedes to utilise the more appropriate three- and four-digit levels. The total for each political district that is used in the study is based on the application year 1993 rather than 1991, following Edwards and Gordon (1984) to assume a time lag between the time when a particular R&D project starts and the moment it leads to an invention.

Our interest focuses on the high technology sectors as an aggregate. Clearly, it is not unambiguous to determine the high technology sectors. A number of different classifications have been suggested in the literature (for example, Premus 1982, Malecki 1986, Glasmeier 1991), In general, the objective is to identify sectors dominated by the importance of non-routine functions, in contrast to standardised mass production. A number of criteria have been suggested in the literature, such as, for example, the percentage of scientists and engineers employed, and the number of innovations per employee. We considered patents in six ‘high technology’ sectors, broadly defined as Computers & Office Machines (ISIC 30); Electronics & Electrical Engineering (ISIC 31-32); Scientific Instruments (ISIC 33); Machinery & Transportation Vehicles (ISIC 29, 34-35); Oil Refining, Rubber & Plastics (ISIC 23, 25), and Chemistry & Pharmaceuticals (ISIC 24) in the International Standard Industrial Classification (ISIC) system. These six categories contain most of the three- and four-digit-ISIC sectors that are typically categorised as high technology sectors. But at the two-digit ISIC-level it is virtually impossible to designate industries as pure high technology. To the extent that the sectoral mix in these sectors shows systematic variation over space in its ‘pure’ high tech content, our results on the relationship between patents and research could be affected. But we are confident that we will be able to detect such systematic variations by means of careful specification tests for spatial effects (see Anselin 1988a).

We used the MERIT concordance table between patent classes (International Patent Classes, IPC) and industrial sectors (ISIC) to match the patent data with the two-digit ISIC codes that form the high technology sectors (Verspagen, Moergastel and Slabbers 1994). It assigns the technical knowledge in the patent classes to the industrial sector best corresponding to the origin of this knowledge. Knowledge on a machine for food processing, for example, will be assigned to machinery (ISIC 29) and not to the food sector. *Appendix A* gives the assignment of IPC patent classes to the high technology industry sectors.

The R&D expenditure figures for high technology firms [variable ***R*** in Equation (6')] are based on the definition of the Frascati/Oslo manual. They stem from a R&D survey carried out by the Austrian Chamber of Commerce in 1991. The questionnaire was sent to 5,670 manufacturing firms in Austria. The response rate was 34.04 percent. In the survey firms were questioned in a very conventional way about their R&D activities. The sample can be seen to cover nearly all firms performing R&D activities in Austria. The ZIP code has been used to trace R&D activities back to the origin of knowledge production. The expenditure data are broken down by the Industrial Classification System of the Chamber of Commerce. Unfortunately, this scheme can be converted to the International Standard Classification System only at the fairly broad two-digit ISIC-level.

Finally, we need data on the amount of university research relevant to the two-digit high-tech ISIC industries. There are great differences in the scope and commercial applicability of university research undertaken in different scientific fields. Academic research will not necessarily result in useful knowledge for every high tech industry. But scientific knowledge from certain scientific fields [especially the transfer sciences] is expected to be important for specific industries. To capture the relevant pool of knowledge scientific fields/academic disciplines are assigned to relevant industrial fields of the two-digit high tech ISIC industries using the survey of industrial R&D managers by Levin et al. (1987). For example, product innovation activities in drugs (ISIC 24) is linked to research in medicine, biology, chemistry and chemical engineering.

University research expenditure data disaggregated by scientific fields/ academic disciplines are not available in Austria, but they may be estimated roughly on the basis of two types of data provided by the Austrian Federal Ministry for Science and Research: *first*, national totals of university research expenditures 1991 disaggregated by broad scientific areas [natural sciences, technical sciences, social sciences, humanities, medicine, agricultural sciences], and, *second*, data on the number of professional researchers employed in 1991 [that is, university professors, university assistants and contract research assistants] disaggregated by scientific areas and political districts. University research expenditure disaggregated by scientific field/academic discipline and political district has estimated by the following procedure

$$R_{DP} = \frac{R_{AN}}{P_{AN}} P_{DP} \tag{9}$$

where R_{DP} stands for university research expenditure in a specific discipline/scientific field D and in political district P, R_{AN} for national research expenditure in a particular scientific area A, P_{AN} for the national total of professional researchers in scientific area A, and P_{DP} for the number of professional researchers working in university institutes belonging to discipline D and located in political district P. The assignment of academic disciplines/scientific fields to two-digit ISIC high technology industries is documented in *Appendix B*.

In the Extended Knowledge Production Function Model [see Equation (8) together with Equations (6') – (7')] the variable ***Z*** was added to account for intra-industry information and knowledge exchange in the high technology sectors. ***Z*** is operationalised as share of high technology employment 1991 in the national total. The Austrian Central Statistical Office was the source for this exogenous variable.

We use the Cobb-Douglas specification for the knowledge production function. The implied log-linear form [see Equations (5), (6')–(7') and Equations (6'), (7') and (8)] creates a particular sample selection problem in so far that only observations for which all the variables (dependent and independent) are non-zero can be utilised. Thus, our final data set only included those political districts for which there were patents and R&D expenditures available. The estimation was carried out on 72 out of 99 observational units for which data are complete. These samples districts represent 100 percent of the university research expenditures (1991); 93.3 percent of the industry R&D activities (1991) and 99.96 percent of the patent applications (1993) in the high tech sectors. The data and specifications used are listed in *Appendix C*.

4. Estimation Issues

When models such as (5) and (8) along with (6')–(7') are estimated for cross-sectoral data on neighbouring spatial units, the lack of independence across these spatial units may lead to spatial dependence [spatial autocorrelation] in the regression equations and, thus, cause serious problems in specifying and estimating the models. In the existing literature these effects are typically ignored with a few exceptions, most notably Anselin, Varga and Acs (1997, 2000). We assess these effects by means of a

Langrange Multiplier [LM] test using six different spatial weights matrices $\boldsymbol{W}$ that reflect different a priori notions on the spatial structure of dependence:

- the simple contiguity weights matrix [CONT],
- the inverse distance weights matrix [IDIS1],
- the square inverse distance weights matrix [IDIS2], and
- distance based matrices for 50 km [D50], 75 km [D75] and 100 km [D100] between the administrative centres of the political districts.

This test is used here to assess the extent to which remaining unspecified spatial knowledge spillovers may be present in the basic knowledge production function model and in its extended version. Spatial dependence can be incorporated in two distinct ways into the model: as an additional regressor in the form of a spatially lagged dependent variable $\boldsymbol{W}\,\boldsymbol{K}$, or in the error structure. The former is referred to as a *Spatial Lag Model* and the latter to as *a Spatial Error Model.* The Spatial Lag Model for Regional Knowledge Production can be expressed in matrix notation as

$$\boldsymbol{K} = r\,\boldsymbol{W}\,\boldsymbol{K} + \boldsymbol{X}\,a + x \tag{10}$$

where $\boldsymbol{K}$ is a (72,1)-vector of observations on the patent variable, $\boldsymbol{W}\,\boldsymbol{K}$ is the corresponding lag for the (72,72)-weights matrix $\boldsymbol{W}$, $\boldsymbol{X}$ is a (72,M)-matrix of observations on the explanatory variables, including a constant term [extended model: M = 4], with matching regression coefficients in the vector a. x is a 72 by 1 vector of normally distributed random error terms, with mean 0 and constant homoskedastic variance σ^2. r is the spatial autoregressive parameter. $\boldsymbol{W}\,\boldsymbol{K}$ is correlated with the disturbances, even when the latter are i.i.d. Consequently, the spatial lag term has to be treated as an endogenous variable and proper estimation procedures have to account for this endogeneity. Ordinary least squares will be biased and inconsistent due to the simultaneity bias.

The second way to incorporate spatial autocorrelation into the regression model for knowledge production is to specify a spatial process for the disturbance terms. The resulting error covariance will be non-spherical, thus ordinary least squares [OLS] while unbiased will be inefficient. Different spatial processes lead to different error covariances with varying implications about the range and extent of spatial interaction in the model (Anselin and Bera 1998). The most common specification is a spatial autoregressive process in the error terms that results into the following *spatial error model for regional knowledge production*

$$\boldsymbol{K} = \boldsymbol{X}\, a + x \tag{11}$$

with

$$x = l\, \boldsymbol{W}\, x + h \tag{12}$$

that is a linear regression with error vector x, where l is the spatial autoregressive coefficient for the error lag $\boldsymbol{W}\, x$. $\boldsymbol{X}$ is a 72 by M matrix of observations on the explanatory variables, a a M by 1 vector of regression coefficients. The errors x are assumed to follow a spatial autoregressive process with autoregressive coefficients, and a white noise error h.

The similarity between the Spatial Error Model (11) – (12) and the Spatial Lag Model (10) for knowledge production complicates specification testing in practice, since tests designed for a spatial lag specification will also have power against a spatial error specification, and vice versa. But as evidenced in a large number of Monte Carlo simulation experiments in Anselin and Rey (1991), the joint use of the Lagrange Multiplier tests for spatial lag and spatial error dependence suggested by Anselin (1988a, b) provides the best guidance for model specification. When both tests have high values indicating significant spatial dependence in the data, the one with the highest value [lowest probability] will indicate the correct specification. It is worthwhile to note that the conventional R^2 model performance measure is not applicable to the spatial lag and the spatial error models. Instead, an adjusted R^2 measure defined as the ratio of the variance of the predicted values over the variance of the observed values for the dependent variable can be used.

5. Empirical Results

Table 1 presents the results of the estimation of the cross-sectional regression of the geographic knowledge production function for 72 political districts in Austria and the distance friction parameter[3] b=2. All variables are in logarithms. In addition to the *Basic Model* [see Equations (5), (6')–(7')], reported in the first column of the table, we also estimated the *Extended Model* [see Equation (8) with Equations (6')–(7')] that includes a location quotient for high technology employment as a proxy for intra-industry information and knowledge exchange to capture additional knowledge externalities of the Marshall-Arrow-Romer or the Isard-Jacobs type [reported in column 2], and the *Spatial Error Model* that incorporates spatial dependence into the error structure of the knowledge production function [reported in column 3]. All estimation and specification tests were carried out with SpaceStat Software (Anselin 1995).

Locate Table 1 about here

An influence of W on patent activities at the district level indicates knowledge production internally to the high tech sectors including geographically mediated spillovers between R&D laboratories. We interpret an influence of F on patent activities at the district level as evidence of the existence of geographically mediated academic spillovers. All regressions yield highly significant and positive coefficients for both university research and industry R&D [at $p < 0.01$], confirming the results obtained in the US American studies mentioned above. The university research elasticities range in magnitude from 0.128 for the *Basic Model* to 0.130 for the *Spatial Error Model*. The university research effect is much smaller than the industry R&D effect. Knowledge externalities of the Marshall-Arrow-Romer or the Isard-Jacobs type are twice as important as industry R&D effects.

For all models, diagnostic tests were carried out for hetereoskedasticity, using the White (1980) test. In addition, specification tests for spatial dependence and spatial error were performed, utilising the Lagrange Multiplier test. The tests for spatial autocorrelation were computed for six different spatial weights matrices [CONT, IDIS1, IDIS2, D50, D75 and D100]. Only the results for the most significant diagnostic are reported in Table 1. No evidence of hetereoskedasticity was found, but the Lagrange

Multiplier test for Spatial Error Dependence shows a strong indication of misspecification.

The starting point of modelling was the basic model for knowledge production. It confirms the strong significance of university research and industry R&D spillovers as well as of additional externalities on the level of patent activity in the high tech sectors in a political district. There is a clear dominance of the coefficient of industry R&D over university research, indicating an elasticity that is about three times higher. There is no evidence of hetereoskedasticity, but the Lagrange Multiplier test for spatial error dependence strongly indicates misspecification of the model.

When the location quotient for high technology employment is added [see columns 2 and 3], the model fit increases from R^2 = 0.60 to R^2 = 0.70, with a positive and significant effect for the knowledge externalities of the Marshall-Arrow-Romer and Isard-Jacobs type. Industry R&D and geographically mediated university research spillovers remain positive and significant. But the addition of the variable causes the elasticity of both to drop more or less substantially: industry R&D elasticity from 0.402 to 0.211 and university research elasticity from 0.128 to 0.100. There is no evidence of hetereoskedasticity, but the Lagrange Multiplier test for spatial error dependence strongly indicates misspecification[4].

The correct interpretation should, thus, be based on the spatial error model that removes any misspecification in the form of spatial autocorrelation. The other results. are only reported for completeness sake. The significant parameter of the error term [l], the significant value of the Likelihood Ratio test in spatial error dependence as well as the missing indication for spatial lag dependence and heteroskedasticity (Breusch-Pagan test, see Breusch and Pagan 1979) are taken as evidence for the correctness of the model. There is little change between the interpretation of the model with and without spatial autocorrelation which is to be expected. The main effect of the spatial error autocorrelation is on the precision of the estimates, but in this case it is not sufficient to alter any indication of significance.

In sum, the maximum likelihood [ML]-estimates in column 3 of Table 1 can be reliably interpreted to indicate the influence of university research on patent activity in a political district, not only of university research in the district itself, but also in the surrounding districts. The geographic boundedness of university research spillovers is directly linked to a distance decay effect.

6. Conclusions

The research question of whether knowledge spillovers are bounded by geographical proximity or not has received increasing attention in recent years (see, for example, Jaffe 1989, Anselin, Varga and Acs 1997, 2000, Echeverri-Carrol and Brennan 1999, Karlsson and Manduchi 2001). There is general agreement that knowledge spills over, but substantial disagreement as whether such knowledge spillovers are geographically bounded or not (see Karlsson and Manduchi 2001). Indeed, the relationship between knowledge spillovers and space is extremely complex and only partially understood. This is partly due to the fact that knowledge spillovers are invisible and can be analysed only indirectly[5].

The key assumption we made in analysing the link between knowledge spillovers and corporate patent activity is that knowledge externalities are more prevalent in high technology industries where new technological and scientific knowledge plays a crucial role. Knowledge spillovers are captured by means of spatially discounted spillover pools and, moreover, by a proxy for intra-industry information and knowledge exchange.. Our empirical results clearly indicate the presence of geographically mediated knowledge spillovers from university that transcend the geographic scale of the political district in accordance with our conceptual framework. The results also demonstrate that such spillovers follow a clear distance decay pattern. But these externalities appear to be relatively small in comparison to the knowledge externalities of the Marshall-Arrow-Romer and Isard-Jacobs type. It is also important to emphasise that the statistical relationship is only suggestive. More detailed examination of university data will be required to determine if the university research spillover effects materialise in reality.

The findings are important in that they highlight the relevance of modelling knowledge spillovers in form of a spatially discounted external stock of knowledge. They also demonstrate the importance of carefully specifying spatial effects by employing spatial econometric tools. But, some cautionary remarks are in order as well. *First,* our analysis is limited by the use of a single cross-section. Unfortunately, there is no update of the 1991 industry R&D expenditure data for later points in time available, precluding an extension of the cross-sectional framework to incorporate the time dimension as well. *Second*, we have chosen to focus on those districts where patent activity and R&D research in the high tech sectors were observed. This leaves aside the issue of why certain locations have R&D and patent activity and others do not, especially when one of the two is present, but the other not. *Third,* we were forced to define the high tech sectors on the basis of two-digit ISIC industries. Many products manufactured by our high tech industries are medium- or even low-tech. This aggregation level, thus, masks considerable underlying heterogeneity and may be too crude to capture university research effects. *Finally,* it is worthwhile noting that the results will be partially affected by the chosen spatial scale of analysis. Political districts qualify as more appropriate spatial units of observation than provinces, but at the price that intra- and interregional university spillovers can not be separated anymore within our conceptual framework. No doubt, there is a need for studies that compare and carefully contrast results at different levels of spatial aggregation in an attempt to detect and measure the importance of knowledge spillovers.

7. Endnotes

1 The notion of transfer sciences involves a distinction between two classes of sciences: pure sciences and transfer sciences. Characteristics of pure sciences include the exploration of the boundaries of knowledge without concern for the practical implication of the findings. Transfer sciences share with the pure sciences a concern for predictive science, but otherwise they have rather different characteristics. Their activity is driven principally by the urge to solve problems. A large part of their findings comes from industry and their graduates are usually employed by industry (OECD 1992). The communities of scientists active in research are very close to the professions most concerned by application of their results. But it would be wrong to see them simply as applied science just downstream of fundamental science. Their bridging function does not imply that they are not fields or disciplines with their own organising principles. Transfer sciences may straddle the normal borders separating science and technology. Their boundaries are not always clear-cut. They are often multidisciplinary (for example, material science). Their analytical development largely reflects social and economic needs and their functions include those of any scientific discipline, namely creation, transmission and organisation of certain types of knowledge together with the aim of undertaking or improving technical projects (OECD 1992).

2 See Karlsson and Manduchi (2001) for a more comprehensive discussion of the issue of inter- and intraregional knowledge accessibility.

3 The distance friction parameter has been optimized for the *Basic Model*. The result achieved is in accordance with Sivitanidou and Sivitanides (1995). Note that the modelling results obtained are relatively insensitive to the choice of $\beta \in [1, ..., 4]$.

4 Exogeneity of R and U were also checked by applying the Durbin-Wu-Hausman test. The null hypothesis of exogeneity was not rejected ($p=0.22$) suggesting that the single equation estimation methods utilized are correct.

5 While Krugman (1991a, p.53) notes that knowledge spillovers leave no paper trail by which they may be measured and tracked, Jaffe, Trajtenberg and Henderson (1993, p.578) emphasize that knowledge flows do sometimes leave a paper trail, especially in the form of patented inventions.

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8. References

Acs Z.J., Audretsch D.B. and Feldman M.P. (1991): Real Effects of Academic Research: Comment, *American Economic Review* 81, 363-367

Anselin L. (1988a): *Spatial Econometrics: Methods and Models*, Kluwer, Boston

Anselin L. (1988b): Lagrange Multiplier Test Diagnostics for Spatial Dependence and Spatial Heterogeneity, *Geographical Analysis* 20, 1-17

Anselin L. (1995): SpaceStat Version 1.80 User's Guide, Regional Research Institute, West Virginia University, Morgantown [WV]

Anselin L. and Bera A. (1998): Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics. In: Ullah A. and Giles D. (eds.) *Handbook of Applied Economic Statistics*, 237-289, Marcel Dekker, New York

Anselin L. and Rey S. (1991): Properties of Tests for Spatial Dependence in Linear RegressionModels, *Geographical Analysis* 23, 112-131

Anselin L., Varga A. and Acs Z. (1997): Local Geographic Spillovers between University Research and High Technology Innovations, *Journal of Urban Economics* 42, 422-448

Anselin L., Varga A. and Acs Z. (2000): Geographic and Sectoral Characteristics of Academic Knowledge Externalities, *Papers in Regional Science* 79, 435-443

Audretsch D. B. and Feldman M. P. (1994) Knowledge Spillovers and the Geography of Innovation and Production, Discussion Paper no. 953, Centre for Economic Policy Research, London

Breusch T. and Pagan A. (1979): A Simple Test for Heteroskedasticity and Random Coefficient Variation, *Econometrics* 47, 1287-1294

Cohen W.M. and Lewinthal D.A. (1989): Innovation and Learning. The Two Faces of R&D, *Economic Journal* 99, 569-596

Echeverri-Carroll E.L. and Brennan W. (1999): Are Innovation Networks Bounded by Proximity? In: Fischer M.M., Suarez-Villa L. and Steiner M. (eds.) *Innovation, Networks and Localities*, 28-49, Spinger, Berlin, Heidelberg, New York

Edquist C. and Rees G. (2000): Learning Regions and Cities: Learning in Regional Innovation Systems – A Conceptual Framework, paper presented at the international workshop on *Knowledge, Complexity and Innovation Systems*, Vienna, July 1-3, 2000

Edwards K. and Gordon T. (1984): Final report. Characterization of Innovations Introduced on the U.S. Market in 1982. Prepared for the U.S. Small Business Administration. The Futures Group

Fischer M.M. (2001): Innovation, Knowledge Creation and Systems of Innovation, *Annals of Regional Science* 35 [in press]

Fischer M.M., Fröhlich J. and Gassler H. (1994): An Exploration into the Determinants of Patent Activities: Some Empirical Evidence for Austria, *Regional Studies* 28, 1-12

Frost M.E. and Spence N.A. (1995): The Rediscovery of Accessibility and Economic Potential: The Critical Issue of Self-Potential, *Environment and Planning* A27, 1833-1848

Glaeser E.L., Kallal H.D., Scheinkman J.A. and Schleifer A. (1992): Growth in Cities, *Journal of Political Economy* 100, 1126-1152

Glasmeier A. (1991): The High-Tech Potential. Economic Development in Rural America, Center of Urban Policy, New Brunswick [NJ]

Griliches Z. (1979): Issues in Assessing the Contribution of Research and Development to Productivity Growth, *Bell Journal of Economics* 10, 92-116

Jaffe A.B. (1989): Real Effects of Academic Research, *American Economic Review* 79, 957-970

Jaffe A.B. (1996): Economic Analysis of Research Spillovers. Implications for the Advanced Technology Program, Prepared for the Advanced Technology Program, Brandeis University and National Bureau of Economic Research

Jaffe A.B., Trajtenberg M. and Henderson R. (1993): Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations, *Quarterly Journal of Economics* 63(3), 577-598

Karlsson C. and Manduchi A. (2001): Knowledge Spillovers in a Spatial Context – A Critical Review and Assessment. In: Fischer M.M. and Fröhlich J. (eds.) *Knowledge, Complexity and Innovation Systems*, Springer, Berlin, Heidelberg, New York [forthcoming]

Krugman P. (1991a): Increasing Returns and Economic Geography, *Journal of Political Economy* 99 (3), 483-499

Krugman P. (1991b): *Geography and Trade*, MIT Press, Cambridge [MA]

Levin R.C., Klevorick A.K., Nelson R.R. and Winter S.G. (1987): Appropriating the Returns from Industrial Research and Development*, Brookings Papers on Economic Activity* 1987 (3), 783-820

Malecki E. (1986): Research and Development and the Geography of High-Technology Complexes. In: Rees J. (ed.) *Technology, Regions and Policy*, 51-74, Rowman & Littlefield, Totowa, NY

OECD (1992): Technology and Economy: The Key Relationships, Organisation for Economic Co-operation and Development, Paris

Pavitt, K (1984): Sectoral Patterns of Technical Change: Towards a Taxonomy, *Research Policy* 13, 343-373

Polanyi M. (1967): *The Tacit Dimension*, Doubleday Anchor, New York

Premus, R. (1982): Location of High Technology Firms and Regional Ecenomic Development, U.S. Government Printing Office, Washington [DC]

Radding A. (1998): *Knowledge Management: Succeeding in the Information-based Global Economy,* Computer Technology Research Corp., Charleston

Romer P. (1990): Endogeneous Technological Change, *Journal of Political Economy* 98, 72-102

Saviotti P.P. (1988): Information, Entropy and Variety in Technoeconomic Development, *Research Policy* 26, 843-856

Saxonian A. (1994): Regional Advantage - Culture and Competition in Silicon Valley and Route 128, Harvard University Press, Cambridge [MA]

Scherer F.M. (1983): The Propensity to Patent, *International Journal of Industrial Organisation* 1, 107-128

Sivitanidou R. and Sivitanides P. (1995): The Intrametropolitan Distribution of R&D Acitivities: Theory and Empirical Evidence, *Journal of Regional Science* 25, 391-415

Teece D.J. (1986): Profiting from Technological Innovation: Implications for Integration, Collaboration, Licensing and Public Policy, *Research Policy* 15, 285-305

Varga A. (1998): *University Research and Regional Innovation: A Spatial Econometric Analysis of Academic Technology Transfers*, Kluwer, Boston

Verspagen B., Moergastel T. and Slabbers M. (1994): MERIT Concordance Table: IPC-ISIC (rev.2), MERIT Research Memorandum 2/94-004, Maastricht Economic Research Institute on Innovation and Technology, University of Limburg

Weibull J. (1976): An Axiomatic Approach to the Measurement of Accessibility, *Regional Science and Urban Economics* 6, 357-379

White H. (1980): A Heteroskedastic-Consistent Covariance Matrix Estimation and a Direct Test for Hetereoskedasticity, *Econometrica* 48, 817-830

APPENDIX A Assignment of Patent Classes to the High Technology Sectors at the 2-Digit ISIC-Level

ISIC Category	Industry Sector	IPC Patent Classes
30	**Computers & Office Machinery**	B41J, B41L [50%], G06C, G06E, G06F, G06G, G06J, G06K, G06M, G11B, G11C
31-32	**Electronics & Electrical Engineering**	A45D [40%], A47J [80%], A47L [40%], A61H [30%], B03C, B23Q [10%], B60Q, B64F [20%], F02P, F21H, F21K, F21L; F21M, F21P, F21Q, F21S, F21V, F27B [10%], G08B, G08G, H01B, H01F, H01G, H01H, H01J, H01K, H01M, H01R, H01S, H01T, H02B, H02G, H02H, H02J, H02K, H02M, H02N, H02P, H03M, H05B, H05C, H05F, H05H, G08C, G09B [50%], 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
33	**Scientific Instruments**	A61B, A61C, A61D, A61F, A61G [90%], A61H [40%], A61L [60%], A61M, A61N, A62B [50%], B01L, B64F [10%], C12K [25%], C12Q, F16P [60%], F22B [20%], F22D [20%], F22G [20%], F22X [20%], F23N, F23Q [10%], F24F [20%], F41G, G01B, G01D, G01F [60%], G01H, G01J, G01K, G01L, G01M, G01N, G01P, G01R, G01S, G01T, G01V, G01W, G02B, G02C, G02F, G03B, G03C, G03D, G03G, G03H, G04B, G04C, G04F, G04G, G05B, G05C, G05D, G05F, G05G, G06D, G07B, G07C, G07D, G07F, G07G, G09G, G12B, G21F, G21G, G21H, G21K, H05G
29,34-35	**Machinery & Transportation Vehicles**	A01B, A01C, A01D, A01F, A01G [10%], A01J [80%], A01K [30%], A21B, A21C, A21D [30%], A22B [50%], A22C [70%], A23C[10%], A23G [10%], A23N, A23P, A24C, A24D [50%], A43D, A61H [30%], A62B [30%], B01B, B01D, B01F, B01J, B02B [50%], B02C, B03B, B03D, B04B, B04C, B05B [50%], B05C [95%], B05D, B05X [50%], B06B, B07B, B07C, B08B, B09B [25%], B22C [10%], B23Q [70%], B25J, B27J, B28B [60%], B28C [60%], B28D [70%], B29B [80%], B29C [80%], B29D [50%], B29F [80%], B29G [50%], B29H [50%], B29J [40%], B30B, B31B, B31C [90%], B31D [80%], B31F [80%], B41B, B41D, B41F, B41G, B42C [50%], B60C [20%], B65 B, B65C, B65G [40%], B65H, B66B, B66C, B66D, B66F, B66G, B67B [50%],B67C, B67D, C02F [30%], C10F, C12H, C12L, C12M, C13C, C13G, C13H, C14B [50%], C14C [50%],D01B [50%], D01C [50%], D01D [50%], D01F [50%], D01G [50%], D01H [50%], D02D, D02G [50%], D02H [50%], D02J [50%], D03D [50%],D03J, D04B [50%], D04C [50%], D04D [50%], D04G [50%], D04H [50%], D06C, D06F [70%], D06G, D06H [70%], D21F, D21G, E01B [50%], E01C [50%], E01H [80%], E02D [30%], E03B [30%], E04D [25%], E21B [45%], E21C, E21D [50%], F01B, F01C, F01D, F01K, F01L, F01M, F01N, F01P, F02B, F02C, F02D, F02F, F02G, F02K, F03B, F03C, F03D, F03G, F03H, F04B, F04C, F04D, F04F, F15B, F15C, F15D, F16C, F16J [80%], F16K, F16N, F16T, F23B, F23C, F23D, F23G, F23H, H23J, F23K, F23L, F23M, F23Q [60%], F23R, F24F [80%], F24J [30%], F25B, F25C, F25D, F25J, F26B, F27B [90%], F27D, F28B, F28C, F28D, F28G, F41A, F41B, F41C, F41D, F41F, F41H [50%], F42B, F42C, F42D [50%], G01F [40%], G01G, G21J

ctd.

23,25	**Oil Refining, Rubber & Plastics**	A47G [50%], A47K [40%], A61J [40%], A62B [20%], B29H [50%], B60C [80%], C10B, C10C, C10G, C10L, C10M, D06N [50%], F42D [50%]
24	**Chemistry & Pharmaceuticals**	A01M [20%], A01N, A61J [30%], A61K [95%], A61L [40%], A62D, B09B [75%], B27K [70%], B29B [20%], B29C [20%], B29D [50%], B29F [20%], B29G [50%], B29K, B29L, B41M [15%], B44D [50%], C01B, C01C, C01D, C01F, C01G, C02F [50%], C05B, C05C, C05D, C05F, C05G, C06B, C06C, C06D, C06F, C07B [95%], C07C [95%], C07D [95%], C07F [95%], C07G [95%], C07H [90%], C07J, C07K, C08B, C08C, C08F, C08G, C08H, C08J, C08K, C08L, C09B, C09C, C09D, C09F, C09G, C09H, C09J, C09K, C10H, C10J, C10K, C10N, C11B [50%], C11C [50%], C11D, C12D [90%], C12K [75%], C12N [80%], C12P [50%], C12R [10%], C12S, C14C [50%], E04D [25%], F41H [50%]

Note: The assignment is based on the MERIT concordance table (Verspagen, Moergastel and Slabbers 1994) between the International Patent Classification (IPC) and the International Standard Industrial Classification of all economic activities (ISIC-rev.2) of the United Nations. The percentages in brackets in the last column of the table give the share of the patents in the IPC-class assigned to the accessory ISIC-category if not all patents in the IPC-class are assigned to the corresponding ISIC-category. A percentage of 80%, for example, therefore means that all patents in the IPC-class are assigned to the corresponding ISIC-category

APPENDIX B Linking Scientific Fields/Academic Disciplines to the 2-Digit High Technology Sectors

ISIC Category	Industry Sector	Associated Scientific Fields/Academic Disciplines
30	Computers & Office Machinery	Fields connected with Information Technologies: Micro-Electronics, Automation and Robotics, Computer Sciences, etc.
31-32	Electronics & Electrical Engineering	Electrical Engineering, Micro-Electronics, Technical Mathematics, Automation and Robotics, Computer Sciences, etc.
33	Scientific Instruments	Engineering Fields such as Mechanical Engineering, Electrical Engineering, Micro-Electronics, Automation and Robotics, Technical Mathematics, Computer Sciences, Physics-Related Fields, Medicine-Related Fields, Biology-Related Fields, Materials Sciences, etc.
29,34-35	Machinery & Transportation Vehicles	Engineering Fields including Mechanical Engineering and Electrical Engineering, Heat Science, Thermodynamics, Material Sciences, Computer Sciences, Technical Mathematics, Astronomy, Transport Science
23,25	Oil Refining, Rubber & Plastics	Chemistry-Related Fields including Materials Sciences, Chemical Engineering and Care Chemistry except for certain sectors such as Quantum Chemistry, Biochemistry and Geochemistry
24	Chemistry & Pharmaceuticals	Chemistry-, Pharmaceuticals- and Medicine-Related Fields including Microbiology, Pharmaceutical Chemistry, Biochemistry, etc.

Source: On the basis of the survey of industrial R&D managers by Levin et al. (1987); only the most important academic disciplines [scientific fields] are listed

APPENDIX C Patent Applications (1993), Industry R&D (1991) and University Research (1991) for 72 Austrian Political Districts

Political District	Patent Applications [Variable *K*]	Industry R&D [Variable *R*]	University Research and Out-of-District Access to University Research [Variable *F*]
Eisenstadt-Umgebung	3.00	35.45	1.24
Neusiedl am See	3.00	7.29	1.38
Oberpullendorf	1.00	3.80	0.52
Klagenfurt (Stadt)	19.50	3.29	36.14
Villach(Stadt)	8.00	16.16	0.13
Hermagor	1.00	0.34	0.09
Sankt Veit an der Glan	1.00	3.16	0.26
Spittal an der Drau	4.00	0.41	0.10
Villach Land	6.50	35.01	0.14
Wolfsberg	2.00	6.24	0.35
Feldkirchen	2.00	0.35	0.20
Krems (Stadt)	2.50	17.74	0.71
Sankt Pölten (Stadt)	7.50	21.34	1.01
Waidhofen (Stadt)	3.00	6.60	0.31
Wiener Neustadt (Stadt)	5.00	14.24	1.65
Amstetten	16.00	87.49	0.37
Baden	27.50	360.98	4.80
Gänserndorf	3.00	14.33	3.19
Korneuburg	12.50	46.70	9.82
Mödling	22.40	213.57	12.97
Neunkirchen	10.00	61.54	1.01
Sankt Pölten (Land)	3.50	4.61	1.45
Scheibbs	1.00	4.98	0.42
Tulln	2.80	34.12	3.29
Waidhofen an der Thaya	1.00	1.20	0.28
Wiener Neustadt (Land)	6.60	11.75	1.55
Vienna-Umgebung	14.60	323.08	25.35
Linz (Stadt)	62.30	1144.26	218.16
Steyr (Stadt)	28.60	1123.43	0.36
Wels (Stadt)	12.50	30.87	0.44
Braunau am Inn	8.50	14.73	0.13
Gmunden	19.10	103.77	0.20
Grieskirchen	10.00	49.42	0.24
Kirchdorf an der Krems	12.30	7.21	0.25
Linz-Land	10.70	111.67	2.74
Perg	13.00	26.41	0.44
Ried im Innkreis	5.30	11.96	0.17
Rohrbach	3.00	3.11	0.22
Schärding	5.00	10.34	0.14
Steyr-Land	8.00	10.43	0.28
Vöcklabruck	43.80	318.82	0.20
Wels-Land	5.00	77.04	0.28
Salzburg (Stadt)	34.30	36.70	117.1
Hallein	8.10	107.28	0.53
Salzburg-Umgebung	23.80	20.92	0.70

ctd.

Zell am See	5.00	4.57	0.12
Graz (Stadt)	84.30	399.49	1195.15
Bruck an der Mur	4.30	9.17	1.09
Deutschlandsberg	5.50	93.80	0.97
Feldbach	1.00	2.08	0.81
Fürstenfeld	2.00	12.38	0.61
Graz-Umgebung	8.50	347.15	8.75
Hartberg	1.00	5.53	0.65
Judenburg	12.00	42.26	0.38
Knittelfeld	3.00	20.34	0.48
Leibnitz	4.00	2.23	1.09
Leoben	3.00	5.93	98.51
Liezen	4.00	25.22	0.22
Mürzzuschlag	1.00	9.84	0.55
Voitsberg	10.00	7.88	1.57
Weiz	4.00	123.45	1.68
Innsbruck-Stadt	9.00	5.54	852.03
Innsbruck-Land	29.40	39.07	8.38
Kitzbühel	7.00	15.91	0.18
Kufstein	9.00	329.98	0.25
Lienz	3.00	8.73	0.08
Schwaz	15.00	80.21	2.58
Bludenz	1.00	17.86	0.06
Bregenz	12.00	66.74	0.04
Dornbirn	11.00	146.49	0.04
Feldkirch	14.00	90.23	0.05
Vienna	383.70	6999.29	3345.06

Notes: Industry R&D and University Research were measured in terms of expenditures, all figures are in millions of 1991 ATS; Patent and industry R&D data refer to high technology industries; University research data include those academic institutes that are expected to be important for the high technology industries; Universities are located in seven political districts: Vienna hosting six universities, Graz (Stadt), Innsbruck (Stadt), Salzburg (Stadt), Linz (Stadt), Klagenfurt (Stadt) and Leoben; all the other political districts have only out-of-district access to university research.

Sources: Patent data were compiled from the Austrian Patent Office database; Industry R&D data were compiled from the 1991 Industry R&D Survey of the Austrian Chamber of Commerce; University research date were estimated on the basis of information provided by the Austrian Federal Ministry for Science and Research

Table 1 Regression results for log (Patent Applications) at the level of Austrian political districts (N = 72, 1993)

Model	Basic Model (OLS)	Extended Model (OLS)	Spatial Error Model (ML)
Constant	0.608*** (0.182)	3.741*** (0.783)	3.315*** (0.764)
Log W	0.402*** (0.504)	0.211*** (0.065)	0.213*** (0.064)
Log F **[University Research Spillover]**	0.128*** (0.040)	0.100*** (0.037)	0.130*** (0.037)
Log ***Z***		0.512*** (0.125)	0.438*** (0.121)
Spatial Autoregressive Coefficient l			0.366* (0.190)
Adjusted R^2	0.598	0.672	0.699
Multicollinearity Condition Number	3.978	21.341	21.341
White Test for Heteroscedasticity	3.210	8.839	
Breusch-Pagan Test for Heteroscedasticity			2.277
Likelihood Ratio Test for Spatial Error Dependence			2.863 (D100)
Lagrange Multiplier Test for Spatial Error Dependence	10.092 (D100)	3.444 (D100)	
Lagrange Multiplier Test for Spatial Lag Dependence	0.551 (D50)	0.889 (D75)	0.382 (IDIS2)

Notes: Estimated standard errors in parentheses; critical values for the White statistic respectively 5 and 9 degrees of freedom are 11.07 and 16.92 (p = 0.05); critical value for the Breusch-Pagan statistic with 3 degrees of freedom is 7.82 (p = 0.05); critical values for Lagrange Multiplier Lag and Lagrange Multiplier Error statistics are 3.84 (p = 0.05) and 2.71 (p = 0.10); critical value for Likelihood Ratio-Error statistic with one degree of freedom is 3.84 (p=0.05); spatial weights matrices are row-standardized: D100 is a distance-based contiguity for 100 kilometers; D75 a distance-based contiguity for 75 kilometers; D50 a distance-based contiguity for 50 kilometers; IDIS2 inverse distance squared; only the highest values for a spatial diagnostics are reported; * denotes significance at the 10 percent level, ** significance at the 5 percent level and *** significance at the one percent level

[2] See Karlsson and Manduchi (2001) for a more comprehensive discussion on the issue of intern- and intraregional knowledge accessibility
[3] The distance friction parameter has been optimized for the Basic Model. The result achieved is in accordance with Sivitanidou and Sivitanides (1995). Note that the modelling results obtained are insensitive to the choice of $\beta \in [1, ...,4]$.

[5] While Krugman (1991a, p.53) notes that knowledge spillovers leave no paper trail by which they may be measured and tracked, Jaffe, Trajtenberg and Henderson (1993, p.578) emphasize that knowledge flows do sometimes leave a paper trail, especially in the form of patented inventions.