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Spatial knowledge spillovers and university research: Evidence from Austria

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Abstract. This paper provides some evidence on the importance of geographically mediated knowledge spillovers from university research activities to regional knowledge production in high-technology industries in Austria. Spillovers occur because knowledge created by universities has some of the characteristics of public goods, and creates value for firms and other organisations. The paper lies in the research tradition that finds thinking in terms of a production function of knowledge useful and looks for patents as a proxy of the 'output' of this process, while university research and corporate R&D investment represent the 'input' side. We refine the classical regional knowledge production function by introducing a more explicit measure to capture the pool of relevant spatial academic knowledge spillovers. A spatial econometric approach is used to test for the presence of spatial effects and – when needed – to implement models that include them explicitly. The empirical results confirm the presence of geographically mediated university spillovers that transcend the spatial scale of political districts. They, moreover, demonstrate that such spillovers follow a clear distance decay pattern.

JEL classification: O31, H41, O40

1. Introduction

Innovation activities involve the use, application and transformation of scientific and technical knowledge in the solution of practical problems. Much of the essential knowledge in this process is specialised and resides in tacit form within experienced researchers and engineers. Tacitness refers – as Dosi (1988, p. 1126) suggested on the basis of earlier insights by Polanyi (1967) – to "those

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elements of knowledge, that persons have, which are ill-defined, uncodified, and which they themselves cannot articulate, and which differ from person to person, but which to some degree be shared by collaborators who have a common experience". This kind of knowledge has to be carefully distinguished from information in the usual sense that is factual, while knowledge is characteristically complex and aims to discover the *why* (procedural knowledge) and *how* (skills and competences).

Knowledge has some of the characteristics of public goods. It is widely considered to be a partially excludable and non-rivalrous good (see Romer 1990). Non-rivalry implies that a novel piece of knowledge can be utilised many times and in many different circumstances without reducing its value. Knowledge is only imperfectly excludable and, thus, subject to spillovers. One might view knowledge spillovers as leaks, but in reality they are the sine qua-non condition for the development of knowledge and economic growth (OECD 1992; Romer 1990). Following Cohen and Levinthal (1989, p. 571) we define knowledge spillovers to include "any original, valuable knowledge generated in the research process which becomes publicly accessible, whether it be knowledge fully characterising an innovation, or knowledge of a more intermediate nature".

In this paper we will concentrate on knowledge spillovers[1] that originate from university research. There are numerous channels through which knowledge might spread to firms. It may seep into the public domain in publications or public presentations of various types (university seminars, academic conferences etc.). It may travel with graduates who take a job at a firm or start their own. It may also be uncovered through reverse engineering and other purposive search processes. The extent to which knowledge flows through these different channels depends upon the capability of the recipient (especially, his/her absorptive capacity), the nature of the knowledge itself (for example, whether it is tacit or codified), and other factors that bring academic and industry sector researchers together (Geroski 1995). If knowledge is essentially tacit, then it can not be transferred by ways other than personal interaction, and geographical distance matters. Thus, the creation of knowledge is a process that is essentially localised.

Since knowledge spillovers are not directly observable, systematic evidence on the extent and importance of such spillovers is difficult to come by. In recent years various attempts have started to document the effect of academic knowledge spillovers on corporate R&D in manufacturing industry, almost exclusively in a US American context. Research by Nelson (1986); Mansfield (1991, 1995); Jaffe (1989); Adams (1990, 1993); Acs et al. (1992, 1994), and others has found that university research has substantial effects on technological change in important segments of the economy[2]. Using state-level patent and innovation data, respectively, Jaffe (1989), Acs et al. (1992) and others have added an important spatial dimension to the discussion by illustrating that the effects not only differ by industries, but also increase with geographic proximity.

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[1] More precisely on 'pure' knowledge spillovers in contrast to rent spillovers that are closely linked to knowledge embodied in traded capital or intermediated goods.

[2] Most have used the production function approach inspired by Griliches (1979) and Jaffe (1989), some (see, for example, Bernstein and Nadiri 1988) the cost function approach to estimate the effects of spillovers. The disadvantage of the latter approach is the required use of prices.

These and many other studies that followed[3] did find a strong and positive relationship between patenting or innovative activity, and university research and corporate R&D at the state level in the US. The situation, however, is different in terms of the significance of *local* geographic spillover effects. Overall considered the evidence is non-existent, weak or mixed, and only pertaining to a few individual sectors (see, for example, Anselin et al. 2000). This lack of evidence contradicts the strong findings in micro-level studies (see, for example, Mansfield 1995; Jaffe et al. 1993).

The objective of this paper is to shed some further light on the issue in an Austrian context. The study lies in the research tradition inspired by Griliches (1979) and Jaffe (1989), but departs from previous research in two major respects. *First*, it is based on a much finer, and thus, more appropriate spatial scale than most previous studies to capture interactions between universities and high-technology based firms. *Second*, we specify the relevant potential of spillovers in form of spatially discounted pools of knowledge. The specification makes use of accessibility measures derived from established principles in spatial interactions theory[4]. A spatial econometric approach is implemented both by testing for the presence of spatial effects and – when necessary – by implementing models that incorporate them explicitly. In the remainder of the paper we first introduce the conceptual framework in Sect. 2. Next we briefly describe the variables and the data sets (Sect. 3), then outline subsequently some methodological issues in specifying and estimating the model (Sect. 4) and finally present the results obtained (Sect. 5). The paper concludes with a brief evaluation of the results associated with some hints for future research activities.

2. The knowledge production function

We adopt the view that finds thinking in terms of a production function of knowledge congenial and useful, and looks for patents or innovations to serve as a proxy of the 'output' of this process, while university research and commercial R&D represent the 'input' side. Less 'neoclassical' oriented economists might deny the usefulness of this view or the simplifications on which this view is based. But we believe that the importance and extent of academic knowledge spillovers can be best discussed in the context of an empirically useful regional variant of the knowledge production function.

The basic model relates the output of the process, the increment of economically valuable technological knowledge (say, K), in region i $(i = 1, \ldots, N)$ to research and development inputs. Regional knowledge production may be seen to depend on two major sources[5]: University research,

[3] For a survey of the literature see Karlsson and Manduchi (2001).

[4] See Frost and Spence (1995) for a recent review of spatial accessibility measures.

[5] The main institutions created by Western Society to meet the purpose to generate fundamental, general and public knowledge have been its universities and learned societies. Fundamental research of the quality and on the scale comparable to these institutions calls for high thresholds of R&D investment and a corporate research environment conducive to developing and discussing ideas freely with other research workers. Knowledge development within firms also raises proprietary issues. Thus, some sort of division of labour has been developed between university research on the one side and industry R&D on the other (see OECD 1992).

say U, and commercial research and development, say R, located in region i. Inventive inputs have generally been treated as measured by the resources invested in them, most often research and development expenditures. The underlying assumption in general (see, for example, Anselin et al. 1997 and many others) is to assume that research and development expenditures will lead to immediate inventive results. Because the production of useful knowledge takes time, we depart from this common practice and assume a time lag between the investment and the yield of results. Thus, our basic regional knowledge production function is given in general form as

$$K_{i,t} = f(U_{i,t-q}, R_{i,t-q}) \quad \text{for } i = 1, \ldots, N \tag{1}$$

where the subscripts i and t refer to region i and time t, respectively. q denotes the time shape of the lag between research investment and invention results. $U_{i,t-q}$ and $R_{i,t-q}$, represent university research and industry R&D investments, respectively. We may call this equation – more precisely f – the *classical regional knowledge production function.*

Of course, this formulation is rather simplistic and is based on several simplifying assumptions, either explicit or implicit. For example, implicit is the assumption that the production of knowledge of 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 within the region. It is assumed that knowledge generated in universities spills over to the generation of economically valuable technological knowledge by firms. Moreover, generally the assumption is made that the variable U represents the local pool of potential university spillovers. Knowledge tacitness is the reason for the local dimension of spillovers.

The model is comparative-static in nature and abstracts from some important dynamic issues. In particular, there are long, variable, and uncertain lags in the interval between the start of a research activity and generating useful knowledge. The implicit assumption of a stable relationship between the input of the production process (U and R) and its output (in terms of K) may be defended on the perception that science progresses in general by a sequence of marginal improvements rather than through a series of discrete, essentially sporadic breakthroughs (see, for example, Kamien and Schwartz 1982; Rosenberg 1976). Assumptions about the properties of f – such as diminishing returns to research expenditures or economies of scale and economies of scope – imply restrictions on the relationship between (U, R) and K.

The increment to useful knowledge arising from R&D and university research is likely to depend upon a number of further factors including a host of variables related to the institutional and management environment within which the resources are deployed. We may broaden model (1) by including these additional influences represented by a vector of variables, Z_i, that reflects these additional influences. Thus

$$K_{i,t} = f(U_{i,t-q}, R_{i,t-q}, Z_{i,t-q}) \quad \text{for } i = 1, \ldots, N. \tag{2}$$

The problem of modelling regional knowledge production is much more complicated when we realise that different amounts of knowledge from different regions may spill-in. There are different approaches to the construction of spillover stocks or pools. We utilise the approach where every possible pair of regions is treated separately, and the relevant stock of non-local spillovers for the receiving region is constructed specifically for it, using its distance from the $N-1$ spilling regions as a weight. There is a wide choice of possible weights. We use a spatial accessibility measure to induce a distance metric[6].

To simplify notation, let us denote

$$U'_{t-q} = (U_{1,t-q}, \ldots, U_{N,t-q}) \tag{3}$$

$$R'_{t-q} = (R_{1,t-q}, \ldots, R_{N,t-q}) \tag{4}$$

and

$$D_{i\bullet} = (d_{i,1}^{-\gamma}, \ldots, d_{i,i-1}^{-\gamma}, 0, d_{i,i+1}^{-\gamma}, \ldots, d_{i,N}^{-\gamma}) \quad \text{for } i = 1, \ldots, N \tag{5}$$

where d_{ij} represents the average geographic distance from the spilling region j $(j \neq i)$ to the receiving region i. $\gamma > 0$ is a distance decay parameter. Then we can define the spatially discounted pool of non-local university spillovers as

$$S^U_{i,t-q} = D_{i\bullet} U_{t-q} \quad \text{for } i = 1, \ldots, N \tag{6}$$

and the spatially discounted pool of non-local industry R&D spillovers as

$$S^R_{i,t-q} = D_{i\bullet} R_{t-q} \quad \text{for } i = 1, \ldots, N. \tag{7}$$

This yields the following regional knowledge production function in general form:

$$K_{i,t} = f(U_{i,t-q}, S^U_{i,t-q}, R_{i,t-q}, S^R_{i,t-q}, Z_{i,t}) \quad \text{for } i = 1, \ldots, N \tag{8}$$

that will enable us to capture intra- and interregional knowledge spillovers of two types, those originating from university research and those from industrial R&D.

In order to implement model (8) we need to specify the functional form of f. For the purpose of this study we have taken the Cobb-Douglas version which can be written in logarithmic form as

$$\log K_{i,t} = \alpha_0 + \alpha_1 \log U_{i,t-q} + \alpha_2 \log S^U_{i,t-q} + \alpha_3 \log R_{i,t-q} + \alpha_4 \log S^R_{i,t-q} + \alpha_5 \log Z_{i,t} + \varepsilon_i \tag{9}$$

where $K_{i,t}$, $U_{i,t-q}$, $S^U_{i,t-q}$, $R_{i,t-q}$, $S^R_{i,t-q}$, and $Z_{i,t}$ are defined as above; $\alpha_1, \ldots, \alpha_5$ are the parameters of interest; α_0 is a constant term and ε_i a stochastic error term. Model (9) has some attractive features. Aside from being easy to estimate, the α are estimates of the elasticities of the increment of economically valuable technological knowledge, $K_{i,t}$, with respect to changes in the respective variables, and these elasticities are constant. But this tractability comes at some cost. The knowledge production function imposes a constant, unitary

[6] See, for example, Frost and Spence (1995).

elasticity of substitution between all input pairs in addition to the constant output elasticities noted above.

We interpret an influence of $U_{i,t-q}$ on $K_{i,t}$ as evidence of intraregional spillovers of local universities in $(t-q,t)$ and an influence of $S^U_{i,t-q}$ as evidence of interregional spillovers of universities located outside the region. A lack of significance of α_1 and α_2 would suggest that all production of new knowledge is generated internally to the corporate sector, either with interregional knowledge spillovers originating from firms outside the region if α_4 is significant or without such spillovers if α_4 is not significant.

3. Data, variable definition and the spatial scale of the analysis

This paper follows in a tradition that uses patents to measure the outcome of the inventive process, that is knowledge increments. Patents are preferred to innovation counts because it is conceptually more closely related to invention activities[7]. Data on corporate patents of high-technology firms are from the Austrian Patent Office. The patent data file contains information on the application date that can be considered as being relatively close to the date of invention, the name of the assignee(s), the address of the assignee(s), the name of inventor(s), the location of the inventor(s), one or more International Patent Classification (IPC) codes and some information on the technology field of the patent classification.

There is no simple, consistent practice with respect to the names to which corporate patents are assigned. Some patents go only to the assignee. As a consequence, we used the address of the assignee(s) to trace patent activity back to the region of knowledge generation. This approach may be biased in the case of large companies since patents are filed by the headquarter of a company. An extensive effort was made to identify patent-receiving subsidiaries and to redistribute the patents correctly. In the case of multiple assignees located in different regions, we followed the standard procedure of proportionate assignment[8]. We made use of the MERIT concordance table between IPC classes and the industrial ISIC sectors (Verspagen et al. 1994). This table assigns the technical knowledge in the patent classes to the industrial sector best corresponding to the origin of this knowledge. In some cases where the IPC code corresponds to more than one industrial sector, a fractional count was made. *Appendix A* gives detailed information on the assignment of the patent classes to the industry sectors as used in the paper.

At the sectoral scale, the patent data were aggregated to the two-digit ISIC code level. This is essentially due to data limitations for the explanatory variables in the model, more specifically for the variable on industry R&D investment. Our interest focused on patents in the high-technology sector as an aggregate. The determination of this sector is not unambiguous. We define

[7] See Griliches (1990) for a discussion of the use of patent statistics as economic indicators. It is noteworthy that patents provide only a partial picture of the contributions of university research. But innovation counts are less useful because they measure more aspects of the economic impact of inventive activities rather than the output of the invention process. Innovation counts (generally in terms of improved products on the market) that have been used in most of the US American studies are too far away from the idea of outputs of the inventive process.

[8] Note that our dependent variable is, thus, metric.

the high-technology sector to consist broadly of the following six two-digit industries: Computers and Office Machines (ISIC 30); Electronics and 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). These industries are not equally technology intensive. Some produce more inventions than others, and the propensity to patent these inventions differs between them (see Fischer et al. 1994 for some evidence).

The industries contain most of the three- and four-digit-ISIC categories that are typically classified as high-technology. 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 industries shows some systematic variation over space in its 'pure' high-technology content, our results on the relationship between the increment of economically valuable knowledge and research investment could be affected. But we are confident that we will be able to detect such systematic variation by means of careful specification tests for spatial effects.

We measure industry R&D investment in the high-technology sector using data on R&D expenditures, even though expenditure data might not be a particularly accurate measure of the *real* resources actually used to do R&D (see Alston et al. 1998). The data 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%. 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 data are broken down by a very specific Industrial Classification System of the Chamber of Commerce that can be converted to the International Standard Classification System only at the fairly broad two-digit ISIC-level.

A major effort was pursued to estimate university research expenditure data for the variable U. There are no consolidated research budgets or expense reports available that present data in sufficient detail. We utilised the 1991 survey of the Austrian Federal Ministry for Science and Research to get access to global university research expenditure data. These data include research-related basic and on-going operational costs, but not all relevant funding sources. Thus, the data may understate the resources actually used in support of research. But there is no way to overcome this data problem. We proceeded as follows to link university research expenditures to the high-technology industries. First, the global data were broken down by university department on the basis of some simplifying assumptions and a simple disaggregation procedure (see Fischer et al. 2001). Then – using results from Levin et al.'s (1987) survey[9] and Varga's (1998) study in the spirit of Feldman (1994), Audretsch and Feldman (1994), Feldman and Audretsch (1999) – we assigned academic departments and the associated expenditure figures to the six two-digit high-technology industries to which knowledge spillovers from university research may flow. *Appendix B* shows the match to the two-digit

[9] In Levin et al.'s (1987) survey, R&D managers were asked to indicate on a 7-point Likert scale the relevance of eleven basic and applied fields of science and the importance of external sources of knowledge to technological change in a broad range of manufacturing industries.

industries. Note that only a smaller set of academic departments produce knowledge relevant to the high-technology sector.

Skilled workers endowed with a high level of human capital are a mechanism through which knowledge externalities materialise. The concentration of skilled labour in one place facilitates flows of information and knowledge because timeliness and face-to-face communication are important for generating new knowledge. To capture such agglomeration externalities (see also Feldman and Florida 1994), we included a location quotient for high-technology employment as a proxy for Z.

The lack of evidence for local geographical spillovers in most US studies is partly – and probably primarily – due to a too high level of spatial data aggregation. In order to overcome this deficiency of previous studies, we have chosen a rather fine level of spatial detail, the scale level of a political district rather than that of a province (Bundesland)[10]. But the price we have to pay for this choice is that this rather fine spatial scale – Austria is divided into 99 political districts – does not support to estimate Equation (9) any more. This is a consequence of the very uneven spatial distribution of universities over the regional system of political districts. There are not enough degrees of freedom or independent variations in the university research expenditure data to allow us to distinguish between inter- and intraregional knowledge spillovers.

One way out of this problem – and the way taken here – is to combine the knowledge spillover aggregates that reflect the pools of intraregional and interregional knowledge spillovers. Let us define, thus, $\Phi_{i,t-q} \equiv (U_{i,t-q} + S^U_{i,t-q})$ and $\Omega_{i,t-q} \equiv (R_{i,t-q} + S^R_{i,t-q})$. Then we get:

$$\log K_{i,t} = \beta_0 + \beta_1 \log \Phi_{i,t-q} + \beta_2 \log \Omega_{i,t-q} + \beta_3 \log Z_{i,t} + \xi_i \quad \text{for } i = 1, \ldots, N \tag{10}$$

where β_1, β_2, and β_3 are the parameters of interest; β_0 is a constant and ξ_i a stochastic error term. Φ captures the pool of intra- and interregional university spillovers as an aggregate, and Ω the pool of intra- and interregional knowledge spillovers within the high-technology sector. Specification of the length of the lag relationship has been – and this study makes no exception – largely ad hoc, since past attempts to estimate rather than impose the parameter q have been inconclusive. We follow Verspagen and de Lo (1999) to assume $q = 2$, that is, an average lag of two years for inventions to accompany research expenditures. In our study t refers to the year 1993 and, thus, $t - q$ to 1991.

Finally, it is worth noting that the Cobb-Douglas specification (10) of the regional knowledge production function creates a particular sample selection problem in so far as only observations for which all the variables (dependent and independent) are non-zero can be utilised. Hence, our final data set only includes those political districts for which patents and research expenditures are available. The estimation is carried out with 72 out of 99 observational units for which data are complete. These sample districts represent 100 per-

[10] This spatial scale is the lowest at which relevant data are available. Political districts – though political-administrative spatial units – are relatively homogeneous in so far that they generally include one larger urban centre and its surroundings.

cent 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 sector. The data and specifications used are listed in *Appendix C*.

4. Estimation issues

When models such as the Cobb-Douglas versions of (1), (2) and (8) or Eq. (10) 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 such as Anselin et al. (1997, 2000). We assess these effects by means of a Lagrange Multiplier (LM) test using six different spatial weights (N, N)-matrices $\boldsymbol{W}$ with $N = 72$ 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 knowledge production function model. 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 or in the error structure. The former is referred to as *Spatial Lag Model* and the latter *Spatial Error Model*.

For convenience let be $\boldsymbol{K} = (\log K_{1,t}, \ldots, \log K_{N,t})'$ and $\boldsymbol{\xi} = (\xi_1, \ldots, \xi_N)'$ with $N = 7$. Then the *Spatial Lag Version* of (10) may be expressed in matrix notation as

$$\boldsymbol{K} = \rho \boldsymbol{W} \boldsymbol{K} + \boldsymbol{X} \boldsymbol{\beta} + \boldsymbol{\xi} \tag{11}$$

where $\boldsymbol{K}$ is the $(72, 1)$-vector of observations on the patent variable, $\boldsymbol{WK}$ is the corresponding lag for the $(72, 72)$-weights matrix $\boldsymbol{W}, \boldsymbol{X}$ is a $(72, 4)$-matrix of observations on the explanatory variables $\Phi, \Omega, \boldsymbol{Z}$ and a constant term, with matching regression coefficients in the vector $\boldsymbol{\beta}$. $\boldsymbol{\xi}$ is a $(72, 1)$-vector of normally distributed random error terms, with zero mean and constant homoskedastic variance σ^2. ρ is the spatial autoregressive parameter. $\boldsymbol{WK}$ 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 (10) is to specify a spatial process for the disturbance terms. The resulting error covariance will be non-spherical, thus, while unbiased, ordinary least squares [OLS] 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 in the following matrix form of the *spatial error model for regional knowledge production*:

$$\boldsymbol{K} = \boldsymbol{X\beta} + \xi \tag{12}$$

with

$$\xi = \lambda \boldsymbol{W}\xi + \boldsymbol{\eta} \tag{13}$$

that is a linear regression with error vector $\boldsymbol{\xi}$, where λ is the spatial autoregressive coefficient for the error lag $\boldsymbol{W\xi}$. $\boldsymbol{X}$ is a $(72, 4)$-matrix of observations on the explanatory variables including a constant term as above, and $\boldsymbol{\beta}$ a $(4, 1)$-vector of regression coefficients. The errors ξ are assumed to follow a spatial autoregressive process with autoregressive coefficients, and a white noise error $\boldsymbol{\eta}$.

The similarity between the Spatial Error Model (12)–(13) and the Spatial Lag Model (11) 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 (1988) 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.

5. Empirical results

Table 1 presents the results of the estimation of the cross-sectional regression of the regional knowledge production function for 72 political districts in Austria and the distance friction parameter[11] $\gamma = 2$. All variables are in logarithms.

We estimated the *Spatial Error Model* version of Eq. (10) (see Eqs. (12)–(13)), and for matters of illustration two special cases of (10). Both assume i.i.d. zero mean error terms. The first, termed *Basic Model,* additionally assumes $\beta_3 = 0$, while the second, termed *Extended Model*, does not, but assumes that knowledge externalities of the *Marshall-Arrow-Romer* and *Isard-Jacobs* type play a decisive role. The results of the *Basic Model* are reported in column 1, the results of the *Extended Model* in column 2 and those of the *Spatial Error Model* in column 3. All estimation and specification tests were carried out with SpaceStat Software (see Anselin 1995).

An influence of Ω on patent activities indicates knowledge production internally to the high-technology industries including geographically mediated spillovers between R&D laboratories. We interpret an influence of Φ on patent activities as evidence of the existence of geographically mediated aca-

[11] The distance friction parameter has been optimised for the *Basic Model*. The result achieved ($\gamma = 2$) is in accordance with Sivitanidou and Sivitanides (1995). Note that the modelling results obtained are relatively insensitive to the choice of $\gamma \in [1, \ldots, 4]$.

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***	3.741***	3.315***
	(0.182)	(0.783)	(0.764)
Log Φ	0.128***	0.211***	0.213***
	(0.040)	(0.065)	(0.064)
Log Ω	0.402***	0.100***	0.130***
	(0.054)	(0.037)	(0.037)
Log Z		0.512***	0.438***
		(0.125)	(0.121)
Spatial autoregressive coefficient λ			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% level; ** Significance at the 5% level; *** Significance at the one percent level

demic spillovers. The results provide strong further evidence of the empirical relevance of geographic localisation of knowledge spillovers as was indicated, for example, in Jaffe (1989), Acs et al. (1992), Jaffe et al. (1993), Audretsch and Feldman (1994), and Anselin et al. (1997, 2000) for the American case.

All regression models yield highly significant and positive coefficients for both university research and industry R&D spillovers (at $p < 0.01$). 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* and *Isard-Jacobs* type are twice as important as industry R&D effects. For all models, diagnostic tests were carried out for heteroskedasticity, 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 the six different spatial weights matrices (CONT, IDIS1, IDIS2, D50, D75 and D100). Only the results for the most significant diagnostics are reported in Table 1.

The *Basic Model* (column 1) confirms the strong significance of university research and industry R&D spillovers. 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 heteroskedasticity, but the Lagrange Multiplier test for spatial error dependence strongly indicates misspecification of the model.

When the variable $\boldsymbol{Z}$ is added (see columns 2 and 3), the explanatory power of the regressions is substantially and significantly increased. The model fit increases from 0.60 to 0.70 (measured in terms of adjusted R^2), with a positive and significant effect for the knowledge externalities of the *Marshall-Arrow-Romer* and *Isard-Jacobs* type. Geographically mediated industry R&D and 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 heteroskedasticity, but the Lagrange Multiplier test for spatial error dependence strongly indicates misspecification[12].

The correct interpretation has to 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 [λ], 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 knowledge increment 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. Summary and conclusions

In this paper, we have estimated knowledge spillovers from universities within a knowledge production function framework. The production function approach abandons the details of specific events and concentrates on total output of knowledge generation as a function of industry R&D and university

[12] 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 utilised are correct.

research investment. While this approach is more general than the case study approach, it is also coarser and suffers from a less sound behavioural foundation. Nevertheless, it is currently the only available general way of trying to answer questions about the importance and extent of spatial knowledge spillovers from university research.

The key assumption we made in analysing the link between knowledge spillovers and corporate patent activity was that knowledge externalities are more prevalent in high-technology industries where new – technological and scientific – knowledge plays a crucial role. Knowledge spillovers were captured by means of spatially discounted spillover pools. Our empirical results confirm the presence of geographically mediated knowledge spillovers from university and show that these transcend the geographic scale of the political district. The results also demonstrate that such spillovers follow a clear distance decay pattern, a result that is in accordance with Anselin et al. (1997, 2000) despite differences in research design and context. But these externalities appear to be relatively small in comparison to knowledge externalities of the *Marshall-Arrow-Romer* and *Isard-Jacobs* type. These findings call for policy strategies to facilitate flows of knowledge within Austrian regional systems of innovation.

The findings are also important in that they highlight the relevance of modelling knowledge spillovers in form of spatially discounted external stocks of knowledge. But, some cautionary remarks are in order as well.

- *First*, we have chosen to focus on those districts where patent activity and R&D research in the high-technology industries 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.
- *Second*, we were forced to define the high-technology sector on the basis of two-digit ISIC industries. Many products manufactured by these high-technology industries are medium-tech or even low-tech. This aggregation level evidently masks considerable underlying heterogeneity and may be too crude to capture clearly university research effects. The available industry R&D expenditure data do not match the four- and three-digit ISIC levels. Hence additional progress on the issue will have to await the appearance of better data.
- *Third*, the MAUP problem in spatial analysis teaches us that the results of spatial analytical studies tend to be – more or less – affected by the spatial units of analysis. Thus, the choice of appropriate spatial units is of crucial importance. We have no doubt in mind that political districts qualify as most appropriate units of observation in the Austrian context, not at least because they come rather close to the idea of functional regions. But the choice comes not without some price to be paid: the loss of the ability to clearly distinguish intraregional from interregional spillovers.
- *Fourth*, our knowledge production function framework is comparative-static and hence – as all the previous studies – abstracts from several important dynamic issues. Because changes in knowledge have an impact over many years, there is an intrinsic dynamic relationship between today's research investment and future knowledge generation. There are long, variable and uncertain lags in the interval between the start of a research activity and generating useful knowledge. The problem of the timing of spillovers has – admittedly – not been given adequate attention in our study. Given

the diffuse nature of knowledge spillovers and the likely presence of long and variable lags, the assumption of a two year lag may be too crude to adequately capture knowledge spillovers. Much more work needs to be done to estimate rather than to a priori impose the time shape of the lag between the input and the output of the knowledge production process.

- *Fifth*, in the context of our study some major research questions relate to measurement issues. How much of university research in a region is spillable? What is the appropriate size unit (the university institute, the university department or the research group)? These and several other questions are crucial for measuring knowledge spillovers from universities. We have chosen an approach essentially adapted from Varga (1998) to assign academic departments and the associated expenditure figures to the high-technology sector to which knowledge spillovers from university research may flow. The approach is rather heuristic in nature. No doubt that much more research needs to be done to address the above questions in some more depth with the aim to come up with a somewhat more analytical matching procedure.

Overall, one main conclusion of the study is that the spatial dimension of knowledge spillovers is not something that should be disregarded. Even with a less refined model version we were able to describe and illustrate the theoretical and empirical necessity to test for the presence of spatial effects and – when needed – to revise the knowledge production model to include them explicitly. This type of spatial econometric analysis may lead to an increasing understanding of the spatial extent of knowledge spillovers and, thus, provide important empirical support for the theory of endogenous economic growth.

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Appendix A
Assignment of patent classes to the high technology sectors at the two-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%], B65B, 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,

Appendix A (continued)

ISIC category	Industry sector	IPC patent classes
		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
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 et al. 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 100%, for example, therefore means that all patents in the IPC-class are assigned to the corresponding ISIC-category.

Appendix B
Linking scientific fields/university departments to the two-digit high technology sectors

ISIC category	Industry sector	Associated scientific fields/university departments
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 Levin et al. (1987), Feldman (1994); Audretsch and Feldman (1994) and Varga (1998) in the spirit of Feldman and Audretsch (1999); only the most important scientific fields/university departments 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 Φ)
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
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

Appendix C (continued)

Political District	Patent applications (variable $\boldsymbol{K}$)	Industry R&D (variable $\boldsymbol{R}$)	University research and out-of-district access to university research (variable Φ)
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 data were estimated on the basis of information provided by the Austrian Federal Ministry for Science and Research.