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Fischer, Manfred M.; Varga, Attila

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MANFRED M. FISCHER[*] and ATTILA VARGA[**], Vienna

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1 Introduction

Innovation systems are very knowledge intensive. The knowledge that is used is not necessarily only scientific and technological knowledge. Quite often it is knowledge that may be called organisational. Advances in knowledge may be obtained in a variety of ways: by organised research carried out in universities, by activities in the R&D divisions of corporations, by individual researchers, and by simple experience and observation in the production process. In all cases, however, what is involved is the creation of new knowledge (EDQUIST and REES 2000). This is true irrespective of whether the knowledge advances embody wholly new knowledge or new combinations of already existing pieces of knowledge.

Specific forms of knowledge creation, especially the tacit forms, are localised and territorially specific (see FISCHER 2001). The firms that master knowledge that is not fully codifiable are tied into various kinds of networks with other firms and organisations through localised input-output relations, and especially knowledge spillovers. The term spillover is used in economics to capture the idea that some of

[*] Professor and Head, Department of Economic Geography & Geoinformatics,
Director, Institute for Economic Geography, Urban Development and Evironmental Economics
Vienna University of Economics and Business Administration, A-1090 Vienna, Rossauer Lände 23

[**] Research Scholar, Department of Economic Geography & Geoinformatics, A-1090 Vienna, Rossauer Lände 23

the economic benefits of R&D activities accrue to economic agents other than the party that undertakes the research. Knowledge spillovers have been defined to include any original valuable knowledge generated in the research process that becomes publicly accessible whether it be knowledge fully characterizing an innovation or knowledge of a more intermediate nature (COHEN and LEVINTHAL 1989).

Knowledge spillovers from universities may flow through a number of distinct channels. They may occur when researchers leave university and take a job at a firm or start their own. They also occur between researchers and industry sector researchers – even without formal collaboration projects that bring the two together. In many technology intensive industries the research personnel of firms attend academic conferences, present academic papers and regularly engage in academic discussions with researcher at universities. While there is general agreement in the literature that knowledge from university research spills over there is disagreement as whether there may be boundaries to knowledge spillovers (see KARLSSON and MANDUCHI 2001). Indeed the relationship between knowledge spillovers and space are extremely complex and – given the current state of research – only partially understood. It is the objective of this contribution to shed some light on this research question. The interest is focused on regional corporate knowledge production in the high technology industry sectors where – following ARROW (1962) – knowledge spillovers should be most prevalent.

In the sections that follow we introduce the model for analysing geographic knowledge spillovers first, then describe the data before presenting the empirical results. The contribution concludes with a brief summary and an outlook.

2 *The Knowledge Production Function Framework*

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 is not without pitfalls (see, for example, FISCHER, FRÖHLICH and GASSLER 1994). But patent counts have some advantages over other indicators of knowledge production. In particular, they are applied for at an intermediate state in the process of transforming research input into benefits from knowledge output. Following the standard literature in the field, 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 university research (that is, the knowledge pool of basic research available to the high tech sectors). Academic research will not necessarily results in useful knowledge for every industry. But scientific knowledge from certain academic institutes is expected to be more important for high technology industries. To capture the relevant pool of knowledge, scientific fields were assigned to the high technology industries as an aggregate, using the survey of industrial R&D managers by LEVIN et al. (1987).

Knowledge is measured in terms of patents, and university research and industry R&D in terms of expenditures. The conceptual framework for analysing geographic spillovers from university research on regional knowledge production is derived from the knowledge production function introduced by GRILICHES (1979) that relates the output measure of the knowledge production process (that is, patents in our study) to the above two input measures. We depart from the classical approach by modelling knowledge spillovers in form of a spatially discounted external stock of knowledge and employing spatial econometric tools for model specification and estimation. The model is based on a modified Cobb-Douglas production function and reads in log-linear form as follows (see FISCHER and VARGA 2001 for more details):

$$\log K_i = \alpha_0 + \alpha_1 \log \Omega_i + \alpha_2 \log \Phi_i + \alpha_3 Z_i + \varepsilon_i \tag{1}$$

with

$$\log \Omega_i = \log\left[R_i + A_i^R\right] = \log\left[R_i + \sum_{j \neq i} R_j \, d_{ji}^{-2}\right] \tag{2}$$

and

$$\log \Phi_i = \log\left[U_i + A_i^U\right] = \log\left[U_i + \sum_{j = i} U_j \, d_{ji}^{-2}\right] \tag{3}$$

where i = 1,...,N indexes the spatial unit of observations (N=72, political districts in this study), $\boldsymbol{K}$ is measured in terms of patents as proxy for new corporate knowledge generated by high tech firms, $\boldsymbol{R}$ is industry R&D and $\boldsymbol{U}$ university research [measured in terms of expenditures]. A_i^U is an accessibility measure to university knowledge with a distance decay parameter equal to 2 (see SIVITANIDOU and SIVITANIDES 1995) for each industry R&D district (j ≠ i) in the national innovation system of Austria. d_{ji} is the distance between j and i as perceived by high tech industry located in i to get in touch with knowledge producers at university in j. A_i^R is defined in an analogous manner to capture potential interregional knowledge spillovers between R&D laboratories located in j and i. $\boldsymbol{Z}$ is a variable that measures the concentration of high technology production (measured in terms of high tech employment in the national total) and attempts to capture agglomeration economies. $\boldsymbol{\varepsilon}$ is a vector of stochastic error terms.

It is important to note that university research spillovers are modeled as an external stock of knowledge, represented by variable $\boldsymbol{\Phi}$ [see Equation (1)]. Variable $\boldsymbol{\Phi}$ consists of two components [see Equation 3]. 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 α_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 level of significance of α_2 would suggest that all knowledge production is generated internally to the high tech sector, with or without cooperation between R&D laboratories [variable $\boldsymbol{\Omega}$ in Equation (1)]. This does not preclude the presence of additional externalities, that is, ther presence of agglomeration economies as measured by means of the variable $\boldsymbol{Z}$.

3 The Data

We adopt the political district as the spatial unit of observations in our study. A count of corporate patent applications is used as the dependent variable in our model. The data come from the Austrian Patent Office. Postal code information made it possible to trace patent activity back to the district of knowledge production. In the case of multiple assignees, we followed the standard procedure of proportionate assignment. At the sectoral scale, the patent data were assigned to the two-digit International Standard Industrial Classification (ISIC)-system. The patent data refer to the application year 1993 assuming a lag structure between the time when R&D starts (1991) and the moment it leads to an invention. We consider 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). These six categories contain most of the three- and four-digit ISIC sectors that are typically categorized as high technology sectors. But at the two-digit ISIC sectors 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 specification tests for spatial effects (see ANSELIN 1988a).

We used the MERIT concordance table between patent classes as defined by the International Patent Classification (IPC) and ISIC industrial sectors to match the patent data with the two-digit ISIC codes that form our high technology sector (see VERSPAGEN, MOERGASTEL and SLABBERS 1994). It assigns the technical knowledge in the patent classes to the industrial sector that is corresponding best to the origin of this knowledge. For example, knowledge on a machine for food processing will be assigned to machinery (ISIC 29) and not to the food sector.

The independent variables come from different data sources. The Austrian Central Statistical Office was the source for variable $\boldsymbol{Z}$ that accounts for agglomeration economies and is measured by the share of high technology employment 1991 in the national total. The R&D expenditure figures stem from a

R&D survey for manufacturing firms conducted by the Austrian Chamber of Commerce in 1991. The data received were broken down by the Industrial Classification System of the Chamber. Unfortunately, this scheme can be matched with the International Standard Classification System only at the fairly broad two-digit level and, thus impeded to define the high technology sector on the more appropriate three-digit or four-digit level.

The independent variable ***U*** is measured in terms of university research expenditures in 1991. A breakdown of these figures by scientific fields is needed to link these fields to the high technology sectors (for more details see FISCHER and VARGA 2001). Unfortunately, data with such a breakdown are not available in Austria. But the Federal Ministry for science and research has been able to provide national totals of university research expenditures for broad scientific areas [natural sciences, technical sciences, social sciences, humanities, medicine, agricultural sciences] in 1991 as well as data on the number of professional researchers (university professors, university assistants and contract research assistants) disaggregated by the scientific areas mentioned above and by political districts so that research expenditures of scientific fields/academic disciplines could be estimated and associated with corresponding two-digit ISIC high technology sectors (see FISCHER and VARGA 2001 for the procedure). Postal code information was used to trace university research activities back to the district of knowledge production.

We use a Cobb-Douglas specification for our knowledge production function (see FISCHER and VARGA 2001). The implied log-linear form (see Equations (1)-(3)) creates a practical sample selection problem in so far that only observations for which all the variables are non-zero can be utilized. Thus, our final data set only included those political districts for which there were patents and R&D expenditures available. This results in 72 observational units that cover 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 used are listed in the Appendix.

4 Model Specification and Estimation Issues

The use of a cross-sectional sample may lead to spatial dependence (also termed spatial autocorrelation) and, thus, cause serious problems in specifying and estimating our knowledge production regression model (1) - (3). We assess this by means of a Lagrange Multiplier [LM] test using six different spatial weights matrices 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: *first*, as an additional regressor in the form of a spatially lagged dependent variable $\boldsymbol{W}\,\boldsymbol{K}$, or *second* 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 Knowledge Production* can be expressed in matrix notation as

$$\boldsymbol{K} = \rho\, \boldsymbol{W}\, \boldsymbol{K} + \boldsymbol{X}\, \boldsymbol{\alpha} + \boldsymbol{\xi} \tag{4}$$

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 $\boldsymbol{\Omega}$, $\boldsymbol{\Phi}$ and $\boldsymbol{Z}$ including a constant term [extended model: M = 4], with matching regression coefficients in the vector $\boldsymbol{\alpha}$. $\boldsymbol{\xi}$ is a 72 by 1 vector of normally distributed error terms, with mean 0 and constant homoskedastic variance σ^2. ρ 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 [OLS] will be biased and inconsistent due to the simultaneity bias (ANSELIN 1988a).

The second way to incorporate spatial autocorrelation into the regression model (1) - (3) is to specify a spatial process for the disturbance terms. The resulting error covariance will be non-spherical, thus ordinary least squares 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 (see 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 Knowledge Production*

$$\boldsymbol{K} = \boldsymbol{X}\, \boldsymbol{\alpha} + \boldsymbol{\xi} \tag{5}$$

with

$$\boldsymbol{\xi} = \lambda\, \boldsymbol{W}\, \boldsymbol{\xi} + \boldsymbol{\eta} \tag{6}$$

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

The similarity between the Spatial Error Model (5) – (6) and the Spatial Lag Model (4) for regional 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 [that is the 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 cross-sectional regression of the geographic knowledge production function for the 72 Austrian political districts. All variables are in logarithms. The first column of the table reports the results obtained by estimating the Basic Model (1) – (3), while the second column summarizes the results for the S*patial Error Model*. For the Basic Model (1) – (3) a diagnostic test for heteroskedasticity was carried out, using the White (1980) test. In addition specification tests for spatial dependence and spatial error were performed, utilizing the Lagrange Multiplier tests. These tests for spatial autocorrelation were computed for six different spatial weights matrices [CONT, IDIS1, IDIS2, D50, D75, and D100] as mentioned already in the previous section. Only the results for the most significant diagnostics are reported in Table 1. All estimations and specification tests were carried out with the SpaceStat software developed by ANSELIN (1995).

The starting point of modelling was the Basic Model for Regional Knowledge Production as expressed in the Equations (1) – (3). It confirms the strong significance of university research spillovers, industry R&D and agglomeration effects on the level of patent activity in the high technology sectors in a political district. As already mentioned in Section 2, we interpret the influence of Φ on patent activities at the district level as evidence of the existence of geographically mediated university research spillovers. The regression yields highly significant and positive effects for both university research and industry R&D [at $p<0.01$], confirming similar results obtained in US American studies [see, for example, JAFFE 1989; ANSELIN, VARGA and ACS 1997]. There is a clear dominance of the coefficient of industry R&D over university research, indicating an elasticity that is about two times higher. But agglomeration effects appear to be most important.

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

Model	Basic Model (OLS)	Spatial Error Model (ML)
Constant	3.741*** (0.783)	3.315*** (0.764)
Log Ω	0.211*** (0.065)	0.213*** (0.064)
Log Φ [University Research Spillover]	0.100*** (0.037)	0.130*** (0.037)
Log Z	0.512*** (0.125)	0.438*** (0.121)
Spatial Autoregressive Coefficient λ		0.366* (0.190)
Adjusted R^2	0.672	0.699
Multicollinearity Condition Number	21.341	21.341
White Test for Heteroscedasticity	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	3.444 (D100)	
Lagrange Multiplier Test for Spatial Lag Dependence	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

No evidence of heteroskedasticity was found, but the Lagrange Multiplier test for Spatial Error Dependence shows a strong indication of misspecification. Thus, the correct interpretation should be based on the spatial error model that removes any misspecification in the form of spatial autocorrelation. The significant parameter of the error term [λ], the significant value of the Likelihood Ratio test on spatial error dependence as well as the missing indication for spatial lag dependence and heteroskedasticity (Breusch-Pagan test) are taken as evidence for the correctness of the model. There is little change between the interpretation of the two models which is to be expected. The main effect of the spatial error autocorrelation is on the precision of the estimators, but in this case it is not sufficient to alter any indication of significance.

In sum the maximum likelihood [ML]-estimators in column 2 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 already linked to a distance decay effect. By contrast, the effect of industry R&D seems to be contained within the political district itself. There is no evidence of a significant and positive influence of geographic spillovers between industry R&D laboratories.

6 Conclusions

Our empirical results unequivocally 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 agglomeration effects identified. It is also important to emphasize that the statistical relationship is only suggestive. More detailed estimation of university data will be required to determine if the university research spillover effects materialize 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.

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7 References

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

ANSELIN L. (1988b): Lagrange Multiplier Test Diagnostics for Spatial Dependence and Spatial Heterogeneity: In: Geographical Analysis Vol. 20, pp. 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, pp. 237-289. Marcel Dekker, New York

ANSELIN L. and REY S. (1991): Properties of Tests for Spatial Dependence in Linear Regression Models. In: Geographical Analysis, Vol. 23, pp. 112-131

ANSELIN L., VARGA A. and ACS Z. (1997): Local Geographic Spillovers Between University Research and High Technology Innovations. In: Journal of Urban Economics, Vol. 42, pp. 422-448

ARROW K.J. (1962): The Economic Implications of Learning by Doing. In: Review of Economic Studies, Vol. 29, pp. 155-173

COHEN W.M. and LEWINTHAL D.A. (1989): Innovation and Learning. The Two Faces of R&D. In: Economic Journal, Vol. 99, pp. 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, pp. 29-49. 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

FISCHER M.M. (2001): Innovation, Knowledge Creation and Systems of Innovations. In: The Annals of Regional Science 35 [in press]

FISCHER M.M. and VARGA A (2001) Production of Knowledge and Geographically Mediated Spillovers from Universities. A Spatial Econometric Perspective and Evidence from Austria. Department of Economic Geography & Geoinformatics, Vienna University of Economics and Business Administration

FISCHER M.M., FRÖHLICH J. and GASSLER H. (1994): An Exploration into the Determinants of Patent Activities: Some Empirical Evidence for Austria In: Regional Studies, Vol. 28, pp. 1-12

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

JAFFE A.B. (1989): Real Effects of Academic Research. In: American Economic Review, Vol. 79, pp. 957-970

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]

LEVIN R.C., KLEVORICK A.K., NELSON R.R. and WINTER S.G. (1987): Appropriating the Returns from Industrial Research and Development. In: Brookings Papers on Economic Activity 1987 (3), pp. 783-820

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

SIVITANIDOU R. and SIVITANIDES P. (1995): The Intrametropolitan Distribution of R&D Activities: Theory and Empirical Evidence. In: Journal of Regional Science, Vol. 25, pp. 391-415

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

APPENDIX **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

ctd.

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
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.