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The Role of Space in the Creation of Knowledge in Austria. Final Project Report

Manfred M. Fischer and Attila Varga

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Department of Economic Geography & Geoinformatics [WGI]
Vienna University of Economics and Business Administration

WGI Research Reports

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This series is dedicated to reporting our recent research in spatial science in general and economic geography & geoinformatics in particular. It contains scientific studies focusing on spatial phenomena, utilizing theoretical frameworks, analytical methods and empirical procedures specifically designed for spatial analysis. The aim is to present the research at the Department to an informed readership in universities, research organizations and policy-making institutions throughout the world. The type of materials considered for publication in the series includes reports of research projects and some outstanding MA and Ph.D. theses.

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Project Summary

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 and other research institutions, by activities in the R&D divisions of corporations, by individual researchers, and by simple experience and observations of 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 knowledge advances embody wholly new knowledge or new combinations of already existing knowledge.

Among the most striking implications from the new economic growth theories is that increasing returns to knowledge within spatially abounded regions result in a divergence of growth rates. Perhaps more than most other economic activities, innovation depends on new knowledge. This has led to a new focus on the role that spillovers of knowledge across agents and firms play in generating increasing returns and ultimately economic growth (see, for example, Krugman 1991a, b among others).

The term knowledge spillovers has been coined to include any original valuable knowledge generated in the research process that becomes publicly accessible whether it be knowledge fully characterized as innovation or knowledge of a more intermediate value. There is general agreement that knowledge spills over, but substantial disagreement as whether such spillovers are geographically bounded or not. The relationship between knowledge spillovers and space are extremely complex and only partially understood. This is partly due to the fact that knowledge spillovers are invisible.

The overall objective of the study is to shed some light on this issue by analysing the role of spatial proximity in the creation of technological/scientific knowledge in Austria. The study is empirical in nature, and has an exploratory as well as an explanatory dimension. At the exploratory level the main focus is to utilize some new exploratory spatial analysis techniques such as Moran's I for spatial autocorrelation and the Moran scatterplot to identify spatial patterns of the knowledge production process. Clusters of the output side – measured in terms of patent counts – are compared with spatial patterns of two input measures of knowledge production: industry R&D and academic research. The analysis is based on data aggregated to two-digit ISIC industries and at the level of political districts. A time-space comparison will make it possible to explore whether divergence or convergence processes in knowledge creation have occurred between 1982 and 1998.

At the explanatory level the analysis aims at modelling geographically mediated knowledge spillovers within a knowledge production function framework as derived from Griliches (1979). Interest is focused on university research activities in the high

technology industries. It is assumed that knowledge production in the high technology sector essentially depends on two major sources of knowledge: university research that represents the potential pool of knowledge spillovers and R&D performed by the high technology sector itself. We refine the classical knowledge production function by modelling knowledge spillovers as a spatially discounted external stock of knowledge.

The findings of the explanatory analysis are important in that they highlight the relevance of modelling knowledge spillovers in form of a spatially discounted external stock of knowledge and demonstrate the importance of carefully specifying spatial effects by employing spatial econometric tools. The estimates can be reliably interpreted to indicate the statistically significant and positive 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 research spillovers is directly 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 interregional spillovers between industry R&D laboratories. It is important to emphasise that the statistical relationship between university research and knowledge production at the district level is only suggestive. More detailed examination of university data will be necessary to determine if the university research spillover effects materialise in reality.

1. Introduction

Today, it is widely recognised that technological progress is the primary engine for economic development. Innovation – at the heart of technological progress – is essentially the innovation process that depends upon the accumulation and development of relevant knowledge of a wide variety. Certainly individual firms play a crucial role in the development of specific innovations but the process that nurtures and disseminates technological progress involves a complex web of interactions among a range of firms, other organisations and institutions (Fischer 2001b).

Technological progress, in incorporated form or not, is – according to the new growth theories (see, for example, Romer 1990) – a source of increasing returns, that is of a snowball effect whereby growth generates growth, because its creation, allocation and use engender externalities. The existence of externalities is thus not a technology market imperfection, but the essential condition that enables the accumulation of scientific and technological knowledge and its economic application to reinforce one another reciprocally in a growth spiral (OECD 1995).

Knowledge has some specific features that are worth noting. In particular, knowledge is a non-rivalrous and partially excludable good. Non-rivalry implies that a new piece of knowledge can be utilised 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 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 technological knowledge, and this is an incentive for their R&D investment (OECD 1992). The interest of users of knowledge is thus best served if – once produced – knowledge is widely available and diffused at the lowest possible cost. This implies low appropriability or – in other words – an environment rich in knowledge spillovers.

The term knowledge or research spillover has been defined in economics to include any original valuable knowledge generated in the research process that becomes publicly accessible whether it be knowledge fully characterising on innovation or knowledge of a more intermediate nature. Knowledge spillovers are an example for a positive externality. While there is general agreement in the literature that knowledge from basic research performed at universities spills over there is disagreement as whether there may be boundaries to knowledge spillovers (see Karlsson and Manduchi 2001). Indeed the relationship between knowledge and space are extremely complex and – given the current state of research – only partially understood. This is partly due to the fact that knowledge spillovers are invisible and leave no paper trail by which they may be measured and tracked as Krugman (1991b) has noted.

The overall objective of the study is, thus, to shed some light on this issue by analysing the role of spatial proximity in the creation of technological knowledge in Austria. The analysis of spatial processes is handicapped by a lack of data for what might be considered to be the ideal unit of observation. We adopt the political district as the spatial unit of observation in our study. This is at best a crude proxy of the relevant functional economic region. But the spatial scale of political districts is the finest spatial resolution at which the relevant data are available or can be estimated.

The study is empirical in nature, and has an exploratory as well as an explanatory dimension. At the exploratory level the main focus is to utilise some new exploratory spatial data analysis techniques such as Moran's I for spatial autocorrelation and the Moran scatterplot in order to identify spatial patterns of the knowledge production process. Clusters of the output side – measured in terms of patent accounts – are compared with spatial patterns of two input measures of knowledge production: industry R&D and academic research. The analysis is based on data aggregated to two-digit ISIC industries and at the level of political districts. A time-space comparison will make it possible to explore whether divergence or convergence processes in knowledge creation have occurred between 1982 and 1998.

Patents are a quantitative and rather direct indicator of invention. We are aware that patents as purely technological measure of the output side of knowledge production are not without pitfalls (see Archibugi 1992). The major ones being that not all inventions are patented. Sometimes firms protect their knowledge with alternative methods, notably industrial secrecy. Moreover not all inventions are technically patentable. This is the case for software which has an increasingly important role in current technological advance. These considerations have led to doubts about the 'quality' of patent counts as an indicator of knowledge increments. But patent counts have some advantages over other indicators of knowledge production. In particular, they are applied for at an intermediate stage in the process of transforming research input into benefits from knowledge output.

The results of the exploratory part of the study will be summarised in Section 2 of this report. The section that follows refers to the explanatory level of analysis that aims at modelling geographically mediated knowledge spillovers within a knowledge production function framework derived from Griliches (1979). Following Arrow (1962) interest is focused on knowledge spillovers from university research activities to regional knowledge production in the high technology industries where the direct knowledge generating inputs are the greatest and where knowledge spillovers may be most prevalent. It is assumed that knowledge production in the high technology industry sector essentially depends on two major sources of knowledge: university research that represents the potential pool of knowledge spillovers and R&D performed by the high technology sector itself. Knowledge is measured in terms of patents, and university research and industry R&D in terms of expenditures.

Academic basic research will not necessarily result in useful knowledge for every industry. But scientific knowledge from certain academic institutes [especially in the realm of the transfer sciences] is expected to be more important for high technology industries than for others. To capture the relevant pool of knowledge, academic disciplines/scientific fields are assigned to the two-digit high technology sectors using the survey of industrial R&D managers by Levin et al. (1987).

We refine the classical knowledge production function framework by modelling knowledge spillovers as a spatially discounted external stock of knowledge. We examine the production of patents disaggregated by political districts, and relate this to industry R&D and university research. In doing so we apply spatial econometric modelling tools and interpret an influence of university research on the patents at the level of political districts as indirect evidence of the existence of spatially mediated spillovers. The results will be summarised in Section 3, while Section 4 will briefly evaluate the major findings of the study and point to some directions for future research.

Five Appendices complement the report. *Appendix A* lists the data on patent applications, industry R&D and university research for the political districts that had been used in spatial econometric modelling. *Appendix B* gives the assignment of the International Patent Classification (IPC) codes to the two-digit high technology industry sectors. *Appendix C* shows how the university institutes have been linked to the two-digit ISIC high technology industries via the scientific fields in which these institutes are operating. *Appendix D* provides some simple statistics with respect to the dependent and independent variables of modelling, while the contiguity structures for the political districts are outlined in *Appendix E*.

2. The Role of Space in the Creation of Technological Knowledge in Austria: First Insights from an Exploratory Spatial Data Analysis

This section makes a modest attempt to shed some light on the role of space in the creation of technological knowledge in Austria. The study is exploratory rather than explanatory in nature and is based on descriptive and exploratory techniques such as *Moran's I* test for spatial autocorrelation and the Moran scatterplot. Clusters of the output of the knowledge creation process [measured by patent counts] are compared with spatial concentration patterns of two input measures of regional knowledge production: private R&D and academic research. In addition, we consider employment in manufacturing to capture agglomeration economies. The analyses are based on data aggregated by two digit SIC industries and at the level of Austrian political districts to explore the extent to which knowledge spillovers are mediated by spatial proximity in Austria. A time-space comparison will make it possible to study whether divergence or convergence processes in knowledge creation have occurred between the years of 1982 and 1998.

The reminder of this section is structured as follows. Section 2.1 introduces the exploratory spatial data analysis tools and describes the data to be used in the study. Section 2.2 focuses on the identification of spatial clustering patterns of knowledge production in the last two decades, while Section 2.3 relates spatial distribution of knowledge inputs to spatial patterns of knowledge output. The final section briefly summarises the research findings.

2.1 Methodology and Data

This contribution builds on the proposition that spatial clustering of knowledge production is induced by geographically bounded knowledge externalities: the larger the intensity of knowledge spillovers among the actors of a spatial [national, regional or local] innovation system, the higher the degree of spatial clustering of knowledge production. In order to shed some light into this issue we utilise the normalised Herfindahl index first to measure the degree of spatial concentration of both some input and output measures of knowledge production utilising political districts as the basic spatial units of analysis.

To assess the extent to which the variable of interest is concentrated at the level of spatial units, the Herfindahl index in its normalised version is used in this contribution. This index is defined as $\mathrm{HI} = 1 + \ln \Sigma_i S_i^2 / \ln n$, where S_i stands for the share of the measurement of the variable of interest in basic spatial unit i of the national total and n denotes the number of basic spatial units. A major advantage of this index is that it can provide a basis for straightforward comparisons as it ranges between 0 and 1. The index takes the value of 0 if the variable of interest is evenly distributed across regions and the value of 1 if it is completely concentrated in one basic spatial unit.

Spatial autocorrelation [also referred to as spatial dependence or spatial association] in the data can be a serious problem rendering conventional statistical analysis tools unsafe and requiring specialised spatial analytical tools. This problem refers to situations where the observations are non-independent over space. That is, nearby basic spatial units are associated in some way. Sometimes, this association is due to a poor match between the spatial extent of the phenomenon of interest such as knowledge production in the current context and the administrative units for which data are available. Sometimes, it is due to a spatial spillover effect. The complications are similar to those found in time series analysis, but are exacerbated by the multi-directional, two-dimensional nature of dependence in space rather than the uni-directional nature in time. Avoiding the pitfalls arising from spatially correlated data is crucial to good spatial data analysis (Fischer 1998, 2001b).

Exploratory analysis of area data is concerned with identifying and describing different forms of spatial variation in the data. In the context of this contribution special attention is given to measure spatial association between observations for one variable. The presence of spatial association can be identified in a number of ways, rigorously by using an appropriate spatial autocorrelation statistic, more informally, for example using a scatterplot and plotting each value against the mean of the neighbouring areas. In the rigorous approach to spatial autocorrelation the overall pattern of dependence in the data is summarised into a single indicator, such as *Moran's I* or *Geary's c*. Both require the choice of a spatial weights matrix [also referred to as contiguity matrix] that represents the topology or spatial arrangement of the data and manifests our understanding of spatial association.

In this current study *Moran's* I statistic is used. *Moran's I* is based on cross-products to measure value association:

$$I = (n/S_0)\, \Sigma_i\, \Sigma_j\, w_{ij}\, (x_i - \mu)(x_j - \mu) \,/\, \Sigma_i (x_i - \mu)^2 \qquad (1)$$

where *n* stands for the number of observations, x_i denotes an observation on a variable $\boldsymbol{x}$ at location *i*, w_{ij} is an element of the spatial weights matrix (i=1,…,n; j=1,…,n), μ the mean of the $\boldsymbol{x}$ variable, and S_0 the normalising factor equal to the sum of the elements of the weights matrix:

$$S_0 = \Sigma_i\, \Sigma_j\, w_{ij} \qquad (2)$$

For a row-standardised spatial weights matrix that is the preferred way to implement this test, the normalising factor S_0 equals *n* [since each row sums to 1], and the statistic simplifies the ratio of a spatial cross-product to a variance. The neighbourhood or contiguity structure of a data set is formalised in a spatial weights matrix (w_{ij}) = $\boldsymbol{W}$ of dimension equal to the number of observations (*n*), in which each row and matching column correspond to an observation pair (*i*, *j*). The elements w_{ij} of the weights in the matrix $\boldsymbol{W}$ take on a non-zero value [1 for a binary matrix, or any other positive value for general weights based on the distance view of spatial association] when observations *i* and *j* are considered to be neighbours, and a zero value otherwise. By convention, the diagonal elements of the weights matrix, (w_{ij}), are set to zero. Note that the row-standardised weights matrix is likely to become asymmetric, even though the original matrix may have been symmetric.

Tests for spatial autocorrelation for a single variable in a cross-sectional data set are based in this study on the magnitude of *Moran's I* that combines the value observed at each basic spatial unit with the values at neighbouring locations. Basically, *Moran's I* is a measure of the similarity between association in value and association in space [contiguity]. Spatial autocorrelation is viewed to be present when the statistic for a particular map pattern takes an extreme value, compared to what would be expected under the null hypothesis of no spatial autocorrelation. The interest focuses on instances where large values are surrounded by other large values, or where small values are surrounded by other small values. This is referred to as *positive spatial autocorrelation* that implies a spatial clustering of similar values.

The exact interpretation of what is '*extreme*' depends on the distribution of the test statistic under the null hypothesis, and on the chosen level of the Type I error, that is on the critical value for a given significance level. Two main approaches are used in the study to determine the distribution of a test for spatial autocorrelation under the null hypothesis. The first, and most widely used assumption is that the data follow an uncorrelated *normal* distribution. If this is not the case, the so-called permutation approach is adopted that utilises the data themselves to construct an artificial reference distribution by resampling the data over the basic spatial units [that is by allocating the same set of observations randomly to the different locations]. The degree of '*extremeness*' of the *Moran I* statistic for the observed pattern can then be assessed by comparing it to the frequency distribution of the random permutations. A simple rule of thumb can be based on a so-called pseudo significance level. This is computed as $(T+1)/(M+1)$ where T denotes the number of values in the reference distribution that are equal to a more extreme than the observed statistic, and M is the number of permutations that are carried out [M may be taken to be 99, for example].

Since the $\boldsymbol{x}$-variable is in deviations from its mean, *Moran's I* is formally equivalent to a regression coefficient in a regression of $\boldsymbol{W}\boldsymbol{x}$ on x. The interpretation of I as a regression coefficient provides a way to visualize the linear association between $\boldsymbol{x}$ and $\boldsymbol{W}\boldsymbol{x}$ in form of a bivariate scatterplot of $\boldsymbol{W}\boldsymbol{x}$ against $\boldsymbol{x}$, termed as a *Moran scatterplot* (Anselin 1997). The *Moran scatterplot* can be augmented with a linear regression [as a linear smoother of the scatterplot] that has *Moran's I* as slope, and can be used to indicate the degree of fit, the presence of outliers etc. in the usual manner. The lower left and upper right quadrants represent clustering of similar values. In contrast, the upper left and lower right quadrants contain non-clustering observations. Points in the scatterplot that are extreme with respect to the central tendency reflected by the regression slope may be outliers in the sense that they do not follow the same process of spatial dependence as the other observations. Leverage points are observations that have a large influence on the regression slope. If the regression has a positive slope [that is, positive global spatial association], points further than two standard deviations from the center (0, 0) in the upper left and lower right quadrants are considered in this study as outliers. Observations that are in a two standard deviations distance from the centre in the lower left and upper right quadrants are leverage points.

The interpretation of *Moran's I* as a regression coefficient clearly illustrates the way in which the statistic summarises the overall pattern of linear association, in the sense that a lack of fit would indicate the presence of local pockets of non-stationarity. It also indicates that the global measure of spatial association may be a poor measure of the actual dependence in the process at hand. *Local* measures of spatial association such as the *local Moran* statistic (Anselin 1995a) are suitable to detect potential non-stationarities in a spatial data set, for example, when the spatial clustering is concentrated in one subregion of the study area only. The local Moran for an observation i may be calculated as follows

$$I_i = (x_i-\mu)\ \Sigma_j\, w_{ij}\ (x_j-\mu) \tag{3}$$

where w_{ij} denotes the (i,j)th element of a spatial weights matrix in row-standardised form. Significant local *Moran's* I_i detect non-random local spatial clusters where observation *i* is the centre of the cluster. Significance tests are based on the permutation approach [see above].

Exploratory spatial data analysis in this study focuses explicitly on the spatial aspects of both input and output measures of the knowledge production process. Given the supposedly very micro scale of interactions in knowledge production, the spatial level of data aggregation should be as low as possible. Due to data availability restrictions we were forced to choose political districts as the basic units of analysis in this study. Two input measures of knowledge production are considered: R&D expenditures in manufacturing and university research expenditures. Additionally, manufacturing employment is included to proxy agglomeration effects on knowledge production in an unspecified form. Patent count data are used as indicators of knowledge output despite their widely known drawbacks and problems (Basberg 1987, Pavitt 1988, Griliches 1990, Archibugi 1992, Archibugi and Pianta 1996, Fischer, Fröhlich and Gassler 1994).

Raw data of Austrian patents filed between 1982 and 1998 were provided by the Austrian Patent Office [APO]. The data files contain information on the application date, name of the assignee(s), address of the assignee(s) and the technology field. Since location information on inventor(s) was not consistently provided, the address of the assignee was used for spatial arrangement. It is a common Austrian experience that the location of both the assignee [usually the firm where the inventor has a job] and the inventor are very near, typically in the same political district. Deviation from this pattern was found only for large companies with multiple locations for which patent applications were submitted from the companies' headquarters. For these cases, patents were re-distributed to the addresses of the inventors, in case they located in different political districts. In the case of multiple assignees located in different political districts the common practice in the literature was followed: Patents were distributed across political districts proportional to the number of assignees locating in each political district. International patent classification [IPC] codes for each patent provided the base of industrial classification. The concordance table between IPC and international standard industrial classification [ISIC] codes developed in MERIT (Verspagen, Moergastel and Slabbers1994) was used to classify each patent to a two digit ISIC class.

Data on Austrian R&D expenditures by political districts and manufacturing industries were provided by the Austrian Chamber of Commerce. They originate from a comprehensive survey of firms in Austria held in 1991 (Wirtschaftskammer Österreich

1992). Employment data by manufacturing industries and political districts were provided by the Austrian Statistical Office for 1981 and 1991.

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 two-digit high tech ISIC industries using the survey of industrial R&D managers by Levin et al. (1987) to measure the relevance of a discipline/scientific field to an industry. For example, product innovation activities in drugs (ISIC 24) is linked to research in medicine, biology, chemistry and chemical engineering.

Unfortunately, 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 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

$$R_{DP} = \frac{R_{AN}}{P_{AN}} P_{DP} \tag{4}$$

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

2.2 Time-Space Patterns of Knowledge Production in Austria

During the last two decades knowledge production in Austria measured in terms of patent applications shows an apparent industrial and spatial stability. Tab. 1 shows the sectoral distribution of patent applications in two time periods: 1982-1989 and 1990-1997. Evidently, knowledge production concentrates in mechanical areas of manufacturing, especially in machinery. Emerging high technology fields such as electronics, computers or chemicals and pharmaceuticals are significantly less represented. This mainly corresponds to the sectoral structure of manufacturing production (Gassler 1995). However, no apparent specialization is present at the sectoral level, as indicated by the Herfindahl index [(0.30]. Neither the total number of patents in manufacturing [about 1,800 per year] nor the ranking of manufacturing sectors [as shown by the high correlation of sectoral shares in the two time periods] have changed meaningfully from the 1980s to the 1990s. It is also clear from the table that knowledge production is predominantly concentrated in Vienna, the capital of Austria, as indicated by its share of more than 30 percent of the national manufacturing total.

Tab. 1 Sectoral distribution of Austrian patent applications in the periods of 1982-1989 and 1990-1997

	Time Period		Percentage Change from
	1982-1989	**1990-1997**	**1982-1989 to 1990-1997**
Sectoral Share of Patents in Total Patents in Manufacturing			
Machinery	26.02	24.52	-5.75
Metal Products excl. Machines	18.18	19.97	9.87
Instruments	9.48	10.64	12.27
Transportation Vehicles	9.23	8.47	-8.29
Chemistry and Pharmaceuticals	8.33	7.30	-12.39
Electrical Machinery	6.86	6.54	-4.73
Construction	5.53	5.26	-4.88
Stone, Clay and Glass Products	3.73	3.39	-9.10
Paper, Printing and Publishing	2.53	3.29	30.07
Electronics	2.61	2.78	6.46
Basic Metals	2.62	2.52	-3.73
Textiles and Clothes	1.87	1.38	-26.49
Computers and Office Machines	0.77	1.35	75.95
Food, Beverages, Tobacco	0.83	1.12	34.05
Rubber and Plastics	0.94	1.03	9.87
Oil Refining	0.29	0.25	-11.77
Wood and Furniture	0.18	0.19	5.39
Correlation Coefficient	0.99		
Total Number of Patent Application in Manufacturing	15,019	14,251	-5.11
Normalized Herfindahl Index of Sectoral Concentration	0.30	0.29	
Share of Vienna in the Manufacturing Total [in percent]	32.16	34.05	

Source: Austrian Patent Office

Spatial distribution of knowledge production also shows a clear stability during the time period of the study. As indicated in Fig. 1, patents form three larger concentrations and some smaller ones. The three large areas of knowledge production constitute about two-thirds of the total number of Austrian patents. These include the metropolitan area of Vienna [i.e., the city of Vienna and the political districts building the urban fringe] with more than 30 percent of the national knowledge output; the Salzburg and Linz regions with 21 percent and the Graz region with 8 percent of national knowledge production (see Fig. 1).

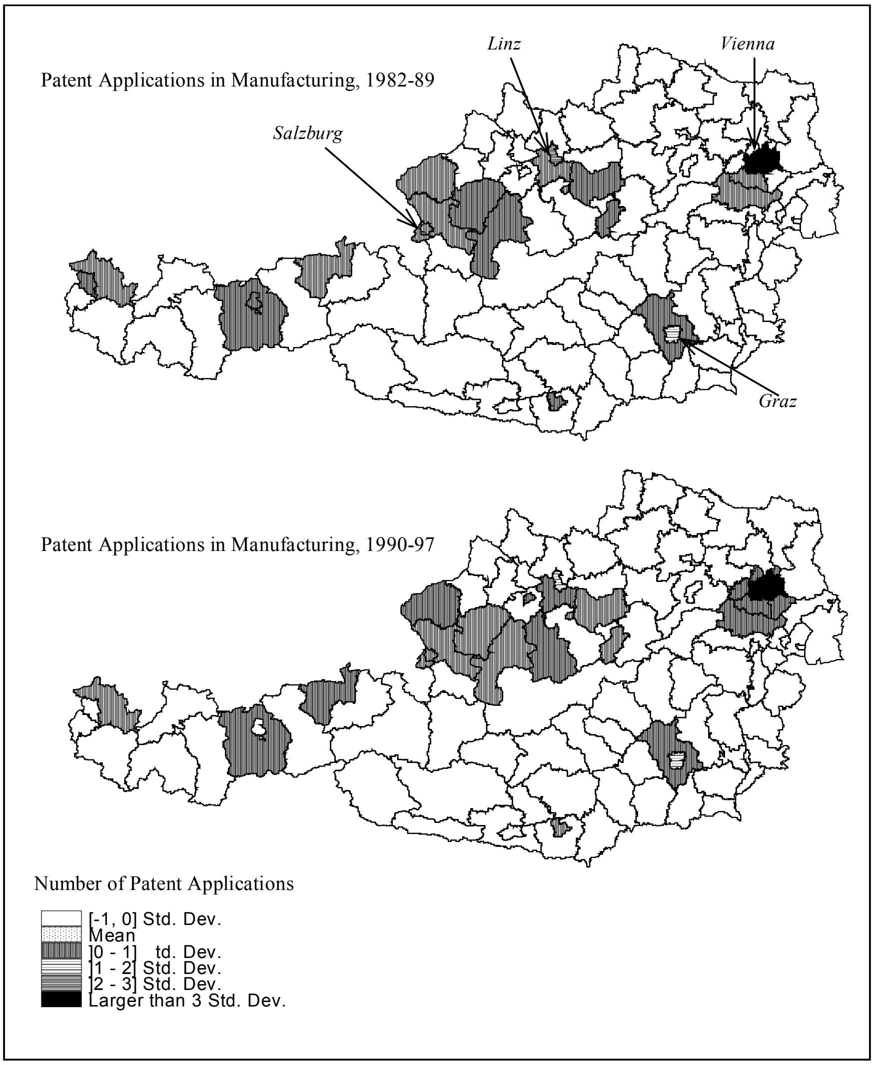


Fig. 1 Spatial distribution of Austrian patent applications in manufacturing in the periods of 1982-1989 and 1990-1997

Fig. 2 provides insights into regional concentration tendencies of Austrian knowledge production for four different manufacturing areas over the period of 1982-1998 measured by means of the normalized Herfindahl Index. There is evidence that electrical industries [including electronics, electrical machinery, computers and office machines] followed by mechanical sectors [such as metal products, machinery, transportation vehicles and instruments] concentrate in a relative small number of political districts, whereas chemistry and drugs [chemistry and pharmaceuticals, rubber and plastics, and oil refining] together with traditional sectors [food, beverages and tobacco, construction, stone, clay and glass products, textiles and clothes, paper, printing and publishing, and wood and furniture] tend to spread more widely over the country.

Interestingly, the level of spatial concentration did not change meaningfully during the eighties, whilst the nineties brought a somewhat notable decrease in geographical concentration especially in traditional and chemical sectors. This change was induced by a transformation in the spatial structure of Austrian patenting activities. Even though the overall level of knowledge creation remained about the same in 1998 [1,637 patents] as it was in 1982 [1,597 patents], the share of total knowledge output in those political districts where above-average level of knowledge creation took place in the beginning of the period had decreased significantly by the end of the 1990s. The average number of patents diminished from 32 to 24 [a decrease of 25 percent] in political districts where knowledge production reached an above-average level in 1982, while regions with less-than-average number of patent applications in the beginning of the time period expanded their patenting activities from the average of 8 to 14 patents by 1998 [an increase of 88 percent]. As a result, the share of those political districts that showed above average activity in knowledge creation in the beginning of the period decreased from 72 percent of the national total to 52 percent by the end of the 1990s.

The extent to which political districts with similar levels of knowledge production locate in each other's neighbourhood is measured by the *Moran's I* statistic for the four manufacturing areas and for the period of 1982-1998 in Fig.3. A general trend of increasing spatial dependence among neighbouring political districts is shown in the figure with no significant variation across industries. However, values of *Moran's I* stay rather low during the entire period of study and become significant only in the beginning of the 1990s. Some sectoral differences are evidenced in this respect. While for traditional sectors clustering became significant [at the 10 percent level] between 1991 and 1996, this took place for the electronic and mechanical areas during the period of 1995-1998 and 1996-1998, respectively. There was no period of significant spatial clustering for chemical sectors. Overall, results in Fig. 3 evidence a low level of spatial dependence among neighbouring political districts in Austrian manufacturing knowledge production.

Fig. 4 exhibits the values of the two compatible measures of spatial clustering of knowledge production: the normalized Herfindahl index of geographical concentration and *Moran's I* statistic of spatial dependence both calculated at the level of Austrian political districts and for manufacturing total over the period of 1982-1998. The fact that patenting activities did not expand significantly during the period of study together

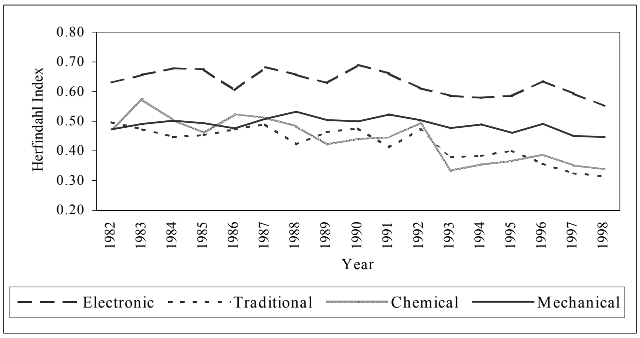


Fig. 2 Geographic concentration of patents for four manufacturing areas, measured by the normalized Herfindahl index [1982-1998]

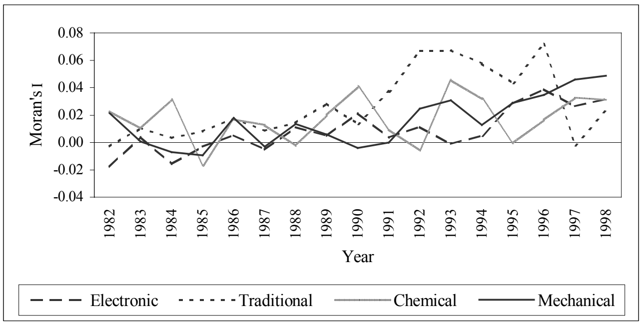


Fig. 3 Spatial association of patents across political districts for four manufacturing areas, measured by the Moran's I statistics [1982-1998]

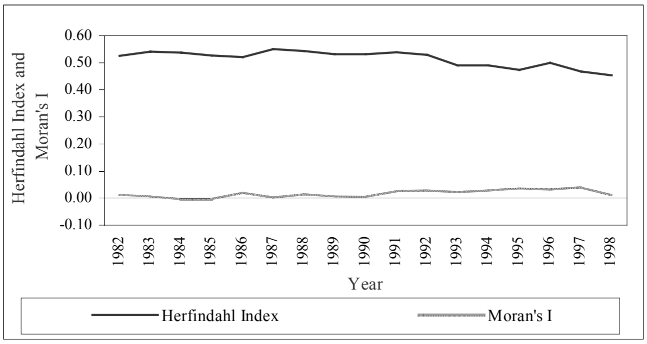


Fig. 4 Geographic concentration and spatial association across political districts of patents in manufacturing in Austria [1982-1998]

with the opposite trends of the two measures in the 1990s suggests that relocation of knowledge production [as indicated by a decrease in the Herfindahl index] took place from core areas of patenting to their neighbouring political districts [as suggested by the positive trend in the *Moran's I*] resulting in increased spatial concentration of knowledge creation. It is important to note here that slightly increasing clustering of Austrian patenting activities in the period of 1982-1998 does not seem to be the outcome of a dynamic, self-reinforcing process induced by knowledge externality-rich local environments resulting in expanding clusters of knowledge production as well as an overall growth in knowledge output. Instead, it is characterized by a spatial shift of knowledge production to neighbouring peripheral areas while the overall level of knowledge output stays largely unchanged.

Moran scatterplot of Austrian patents in 1998 in Fig. 5 characterizes spatial patterns of Austrian knowledge production at the end of the period of study. Observational units are Austrian political districts. The horizontal axis represents standardized values of patent counts while on the vertical axis respective average values of the same variable in neighbouring political districts are measured [i.e., a row-standardized simple contiguity matrix is used for calculations]. The positive slope of the regression line reflects a positive value of *Moran's I* indicating an overall tendency of positive spatial association among neighbouring political districts. This tendency is predominantly supported by spatial clustering of political districts where lower than average level of knowledge creation takes place [as indicated by the high concentration of observations in the lower left quadrant of the scatterplot]. Leverage points in the upper right quadrant [i.e., political districts with above average patenting activity neighboured by similar regions] include Salzburg, Linz and Graz.

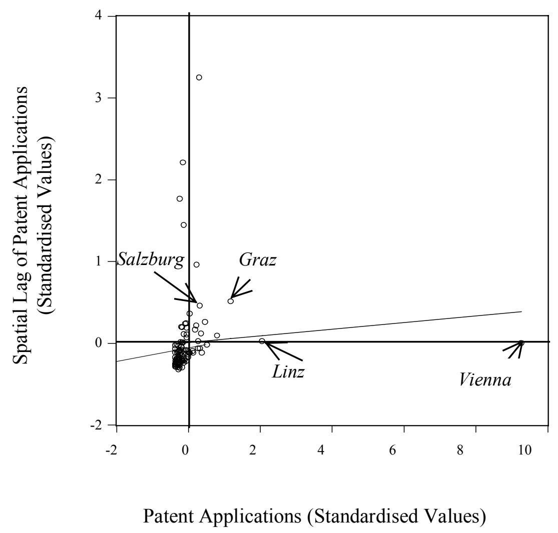


Fig. 5 Moran Scatterplot: Austrian patent applications in manufacturing [1998]

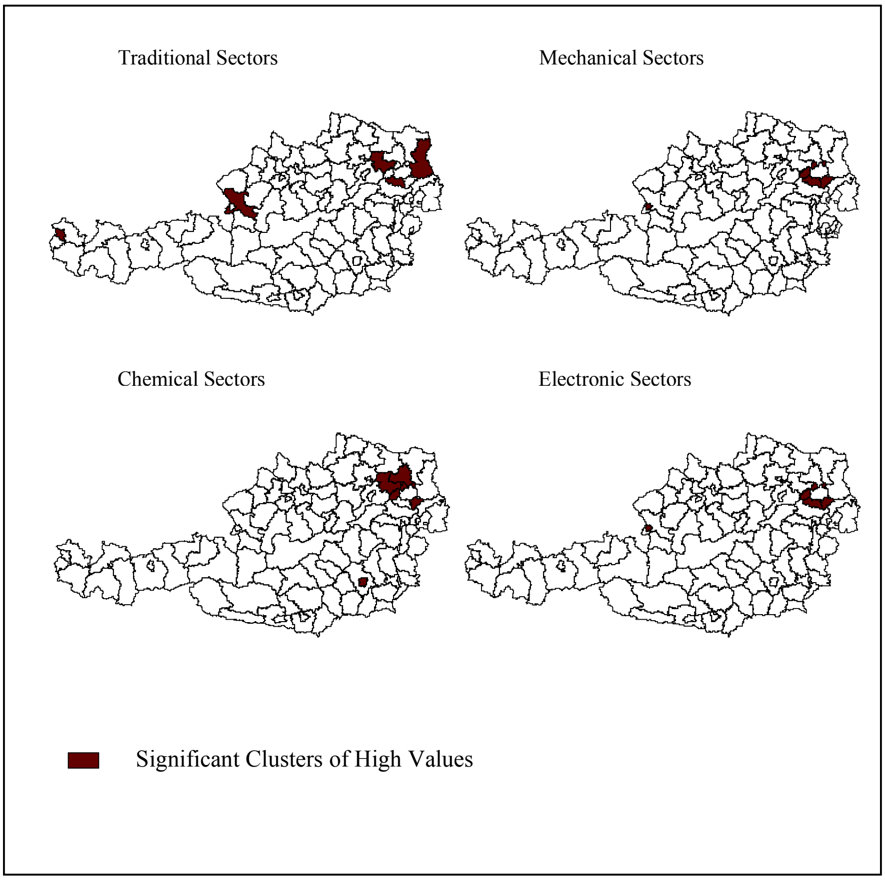


Fig. 6 Clusters of high values of patent counts for four manufacturing areas, measured by significant values of the local Moran statistics [1998]

It is very clear from Fig. 5 that Vienna is a definite outlier in Austrian knowledge production. The standardized value of the number of patents in Vienna is 9 times higher than the respective average Austrian value. On the other hand it is also demonstrated that Vienna is surrounded by political districts with average levels of patenting activities [i.e., the mean value of patents in its neighbourhood equals the country average].

Significant clusters of patenting activity in four manufacturing areas in 1998 are shown in Fig. 6. Significance at $p < 0.05$ is based on 1,000 random permutations. A row-standardized simple contiguity matrix is used for calculations. Dark areas stand for core political districts of spatial clusters. The largest clusters are formed in traditional sectors whereas mechanical and electronic concentrations are relatively small. The Vienna metropolitan area is a significant cluster in all areas of manufacturing. Other clusters are formed around Salzburg [traditional, mechanical and electronic sectors], Graz [chemical sectors] and Dornbirn at the western border of the country [traditional sectors].

2.3 Local Inputs to Innovation – An Assessment of their Relative Significance in Knowledge Production

As emphasized in the innovation systems literature, production of new technological knowledge is not simply the outcome of firms' independent efforts to innovate, but largely influenced by knowledge interactions with different actors in the system including other firms, private and public research institutions. However, knowledge flows are very difficult [if not impossible] to trace empirically. Different methods have been developed in the literature to measure knowledge flows at least partially such as patent citation analysis (Jaffe et al. 1993), analysis of patterns of co-patenting or co-publications (Hicks and Katz 1996) and counts of industry technology alliances (Haagedoorn 1994).

Tab. 2 Sectoral distribution of R&D in manufacturing, university research and manufacturing employment [1991] [ranking follows patent orders in 1990-1997 in Tab. 1]

	R&D Expenditures in Manufacturing	**University Research Expenditures**	**Manufacturing Employment**
Manufacturing Sectors [a]			
Machinery	11.78	11.22	12.64
Metal Products excl. Machines	3.11	9.07	10.09
Instruments	0.73	59.49	3.80
Transportation Vehicles	7.05	21.58	4.62
Chemistry and Pharmaceuticals	15.22	62.41	4.13
Electrical Machinery	7.67	11.81	4.18
Stone, Clay and Glass Products	5.04	4.06	6.06
Paper, Printing and Publishing	2.00	na	7.19
Electronics	29.68	11.81	2.22
Basic Metals	4.28	9.07	5.14
Textiles and Clothes	1.72	na	9.43
Computers and Office Machines	1.98	25.27	0.14
Food, Beverages, Tobacco	2.20	1.55	12.45
Rubber and Plastics	5.86	9.23	4.13
Oil Refining	1.37	9.23	0.37
Wood and Furniture	0.32	0.80	13.40
Manufacturing Total	16.25[b]	6.41[b]	0.72[c]
Normalized Herfindahl Index of Sectoral Concentration	0.31	na	0.15
Correlation with the Sectoral Share of Patents in 1990-1998	0.15	na	0.34

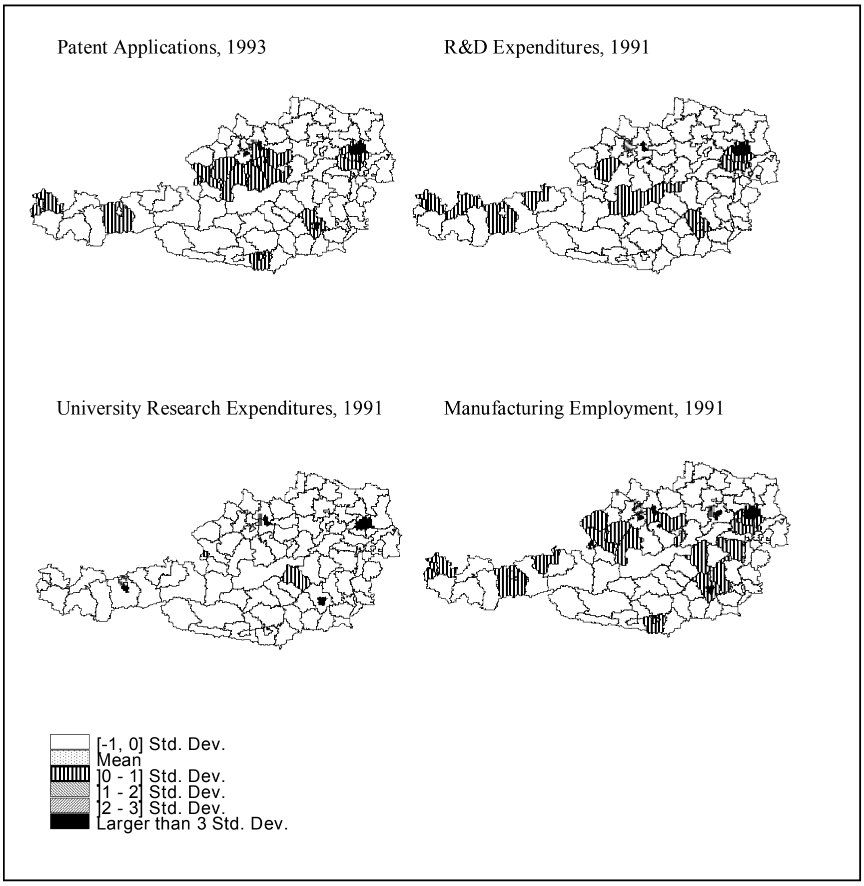
Notes: a denotes column percentage [for R&D expenditures in manufacturing and employment] and percentages of total university R&D expenditures [for university research expenditures]. Given that certain university institutes are allocated to more than one manufacturing sector, sum of percentages is not 100 in the third column.

b is in terms of 10^9 ATS.

c is in terms of 10^6 persons.

A slightly increasing, but still a relatively modest level of geographical clustering of knowledge production has been observed in the previous section. Since no systematically collected data on knowledge interactions are available at the level of Austrian regions' this section applies an indirect approach to assess the significance of local inputs to knowledge production: a positive association in the spatial distribution of patenting and local knowledge inputs is taken as an indication of potentially existing knowledge spillovers in the production of economically useful new technological knowledge. Industrial R&D and university research are considered as potential direct inputs to knowledge production whereas manufacturing employment is included in the analysis as a proxy for unspecified agglomeration effects. Analysis is based on data aggregated at the level of Austrian political districts. In order to account for the time necessary to come up with patentable inventions, following the industrial experience as reported for example in Edwards and Gordon (1984), a two-year time lag is applied between knowledge inputs (1991) and knowledge output (1993).

Tab. 2 provides a general profile of sectoral distribution of the three proxy variables of inputs to knowledge production: R&D in manufacturing and university research expenditures as well as the auxiliary variable of manufacturing employment. The three variables evidently follow different patterns of sectoral specialization. Whereas R&D in manufacturing concentrates in electronics, university research focuses mainly on chemistry and pharmaceuticals, and instruments. On the other hand, about fourty percent of manufacturing employment is in the machinery, food and wood sectors.



Patent Applications, 1993

R&D Expenditures, 1991

University Research Expenditures, 1991

Manufacturing Employment, 1991

Fig. 7 Spatial distribution of patent applications, private R&D expenditures, university research expenditures and manufacturing employment in Austria

However, the overall sectoral concentration is not too strong, especially in manufacturing employment as indicated by the corresponding Herfindahl index. Low values of correlation coefficients with patent counts in manufacturing suggest that sectoral distribution of knowledge production at the country level follows only vaguely the respective patterns of R&D, university research and employment.

Fig. 7 shows that, though by and large the spatial distribution of patent counts follows the geographical patterns of industrial and university R&D as well as manufacturing employment, there are notable differences in pattern matching. A deeper understanding of the geographical patterns of Austrian knowledge production may be gained by calculating correlation coefficients between patent counts and each of the input measures (including the auxiliary variable of employment] at the level of political districts and for four manufacturing areas[1]. In order to account for the supposedly different characteristics of the innovation system of the metropolitan area of Vienna (the definite positive outlier in Austrian knowledge production] as well as the three major cities supporting the overall positive clustering tendency of patent counts [i.e., Salzburg, Linz and Graz].

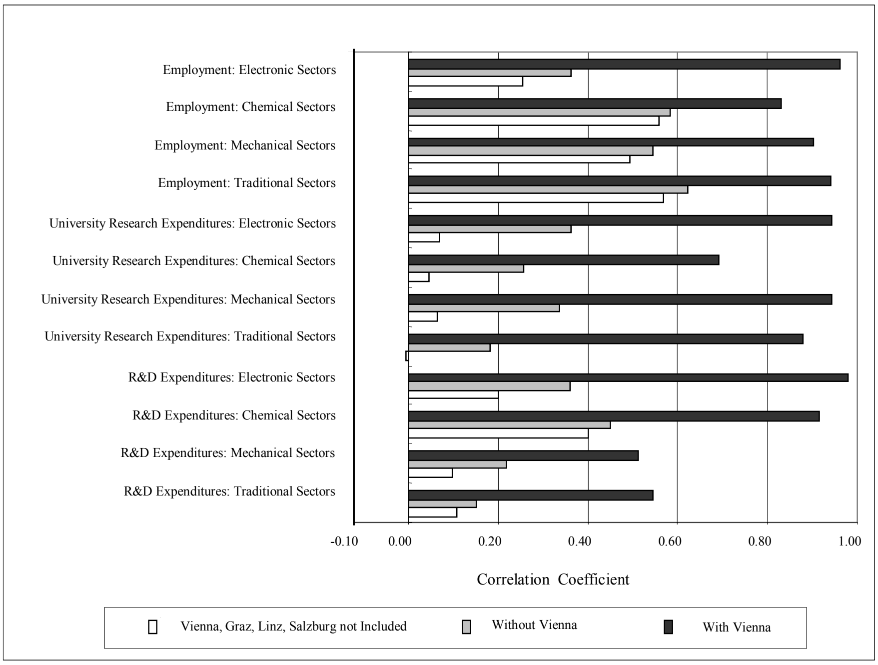


Fig. 8 Correlation between patents in 1993 and selected measures of potential local inputs to innovation in 1991, at the level of Austrian political districts

Fig. 8 shows correlation coefficient values for three different sets of observations: the whole sample, political districts excluding Vienna and political districts without the political districts of Salzburg, Linz, Graz and Vienna. The following three major observations can be derived from Fig. 8. *First*, the four manufacturing areas exhibit dissimilar correlation patterns. Considering only those coefficients calculated for the whole sample, patent counts in electronic sectors are highly correlated with all the three measures of local knowledge inputs, while knowledge production in chemicals is more related to local employment and R&D. On the other hand, in mechanical and traditional sectors the highest correlations are observed with employment and university research. *Second*, information in the figure suggests that the outlier position of Vienna in knowledge production might well be the result of its comparatively strong reliance on local knowledge inputs. After taking Vienna out from the sample, correlation coefficients decrease significantly, especially the R&D measures. The smallest falls are observed in correlations with local employment, with the exception of electronic sectors. *Third*, regarding the degree to which knowledge production in the three major Austrian cities exhibit distinct characteristics relative to the rest of the sample [excluding Vienna], dissimilar patterns are observed for the research variables only, but not for employment.

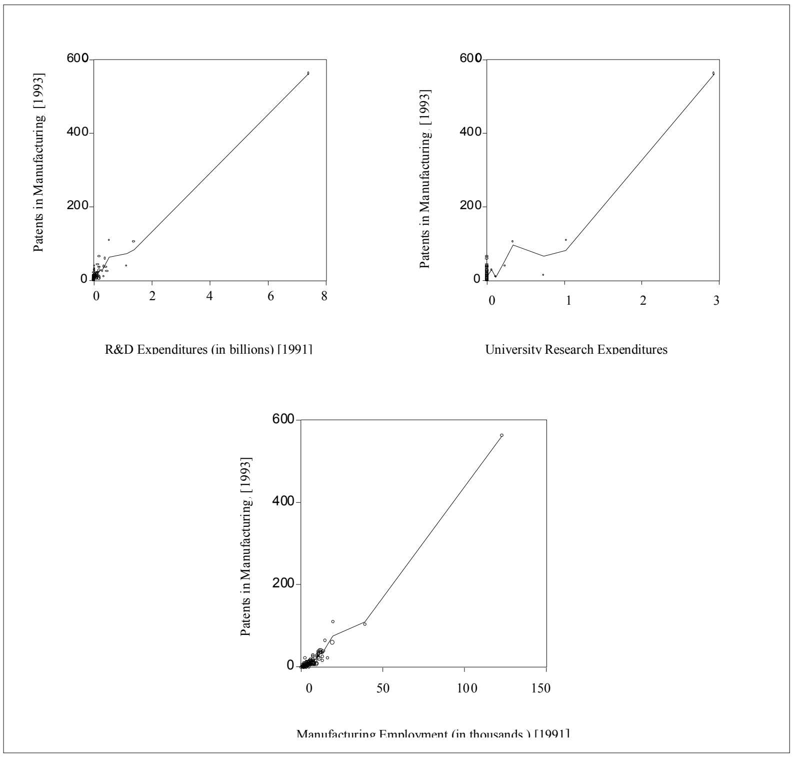


Fig. 9 Scatterplots with curves of nearest neighbour fit [Loess fit] for patents in manufacturing related to R&D in manufacturing, university research and manufacturing employment in Austria

After taking Vienna out from the sample, correlation coefficients decrease significantly, especially the R&D measures. The smallest falls are observed in correlations with local employment, with the exception of electronic sectors. *Third*, regarding the degree to which knowledge production in the three major Austrian cities exhibit distinct characteristics relative to the rest of the sample [excluding Vienna], dissimilar patterns are observed for the research variables only, but not for employment.

It is important to note that if one observes that regional knowledge output increases with a higher speed than any of its local inputs, this might be taken as a sign of regionally mediated knowledge flows. Fig. 9 depicts scatterplot diagrams of patents and R&D in manufacturing, university research and manufacturing employment. Data are arranged in increasing order of the variables on the horizontal axes. Additionally, to have an indication of the direction and size of the change in patents in manufacturing curves of nearest neighbour fit [Loess fit] are estimated as well. For each data point in the sample a locally weighted polynomial regression is estimated. It is a local regression since only the subset of observations is used which lie in a neighbourhood of the point to fit the regression model (Cleveland 1994). In case of increasing returns in knowledge production, Loess fit curves show an exponential growth in patents. The only variable for which increasing returns dominate the entire sample is manufacturing employment. This shows that the higher the concentration of production in an area the higher the probability of knowledge-related linkages among firms to arise which results in a higher than proportional increase in knowledge production. However, this relationship cannot be observed for R&D in manufacturing and university research linkages throughout the whole sample. Some degree of potential research spillover effects might be present in larger cities, and they seem to have a definite role in Vienna [the highest point in each scatterplot]. But Fig. 10 indicates no signs of significant interregional linkages.

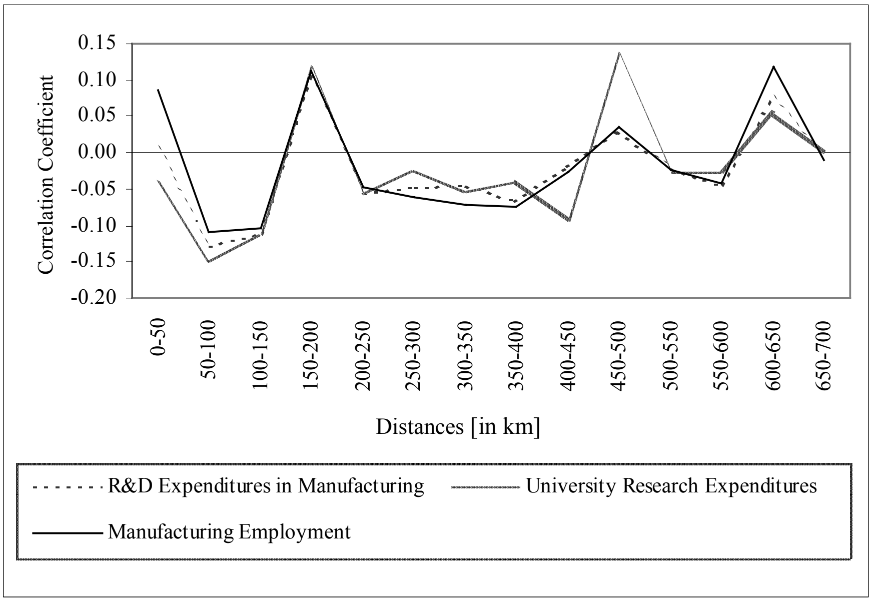


Fig. 10 Cross-regional correlation patterns between patent applications [1993] and knowledge inputs [1991] in increasing distances from the patenting political district

2.4 Summary and Conclusions

In recent years, the role of space in general and of spatial externalities in particular has gained an increasingly prominent position in mainstream economics, partly stimulated by the visibility of Krugman's work on the 'New Economic Geography' (for example, Krugman 1991a). Of course, the importance of space is not new to geographers and regional scientists. Based on descriptive and exploratory techniques [*Moran's I* test for spatial autocorrelation and the Moran scatterplot] this contribution made an initial step to analyse the effect of space in the creation of knowledge. Clusters of the output of the knowledge creation process [measured in terms of patent counts] were compared with spatial concentration patterns of three input measures of local knowledge production: R&D in manufacturing, university research activities and manufacturing employment.

Empirical evidence shows that knowledge production in Austria tends to be largely focused in mechanical areas of manufacturing. It is interesting to note that this pattern did not change very much during the past two decades. Merely a weak trend of growing clusters may be identified. But this does not appear to be the outcome of a dynamic process generated by intensive knowledge flows at the local level, rather than the consequence of a spatial shift in knowledge production. There is no doubt that Vienna with its strong presence of high quality research organisations and R&D in manufacturing dominates the knowledge creation process. Some smaller clustering tendencies were discovered around Salzburg, Linz and Graz.

Geographic stability of knowledge generation characterised by weakly expanding clusters may well be the outcome of relatively less developed linkages among the major actors of the Austrian innovation system as suggested by the limited role of local knowledge flows in the most parts of the country. Cluster generating increasing returns appear to result largely from between-firm knowledge diffusion rather than from knowledge spillover effects. As in the case of any exploratory data analysis the above findings need to be treated with caution and should be viewed only as an initial pre-modelling stage in the endeavour.

3. Production of Knowledge and Geographically Mediated Spillovers from Universities: A Spatial Econometric Perspective

3.1 Introduction: Knowledge and Spillovers

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 2001a). 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.

In fact, several studies have recently identified the extent to which knowledge spillovers take place within the US innovation system. An important finding of Jaffe (1989); Acs, Audretsch and Feldman (1991); Anselin, Varga and Acs (1997) and Varga (1998) was that investment in R&D made by private corporations and universities spills over for economic exploitation by third-party firms. Moreover, Anselin, Varga and Acs (1997) found that such spillovers are most likely to be geographically bounded rather than occurring freely across US regions. 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) and as empirical studies in the US suggest, then knowledge spillovers should be observed in the Austrian innovation system, 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 sector itself and the pool of basic 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.

3.2 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 effects, 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) that describes the relationship between various inputs and the output of the knowledge production process at the micro- or macro-level.

$$\boldsymbol{K} = \alpha_0\, \boldsymbol{R}^{\alpha_1}\, \boldsymbol{U}^{\alpha_2}\, \varepsilon \tag{5}$$

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 α_0 a constant, and α_1 and α_2 as associated parameters. ε 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

$$\log K_i = \alpha_0 + \alpha_1 \log R_i + \alpha_2 \log U_i + \varepsilon_i \tag{6}$$

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 α_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. By contrast, the lack of significance of α_2 would suggest that all knowledge production is generated internally to the high tech sectors, that is, exclusively through the variable **R**.

The above model appears to be unsatisfactory if the spatial range of interaction between industry R&D and university research reaches beyond the district where the 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, A_i^U to university knowledge for each industry R&D district i ($i = 1,...,N$) with respect to all university districts $j \neq i$ ($j = 1,..., N_1 < N$) in the national Austrian innovation system:

$$A_i^U = \sum_{j \neq i} U_j\, d_{ji}^{-ß} \tag{7}$$

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 an exponent assumed to equal to 2 in accordance with Sivitanidou and Sivitanides (1995). Evidently, Equation (7) 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 $\boldsymbol{U}$-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 is introduced

$$A_i^R = \sum_{j \neq i} R_j \, d_{ji}^{-ß} \tag{8}$$

to capture potential interregional knowledge spillovers between R&D laboratories located in districts i and $j \neq i$. R_i is as before, and d_{ji} is a measure of impedance. Again, $ß$ is assumed to equal to 2. Then the knowledge production function model becomes

$$\log K_i = \alpha_0 + \alpha_1 \log \Omega_i + \alpha_2 \log \Phi_i + \varepsilon_i \tag{9}$$

with

$$\log \Omega_i = \log\left[R_i + A_i^R\right] = \log\left[R_i + \sum_{j \neq i} R_j \, d_{ji}^{-ß}\right] \tag{10}$$

and

$$\log \Phi_i = \log\left[U_i + A_i^U\right] = \log\left[U_i + \sum_{j \neq i} U_j \, d_{ji}^{-ß}\right] \tag{11}$$

Model (9) – (11) is the basis for our investigation and 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 (11)]. Variable Φ 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 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 signficance of α_2 would suggest that all knowledge production is generated internally to the high tech sectors, with or without cooperation between R&D laboratories [variable $\boldsymbol{\Omega}$ in Equation (9)]. This does not preclude the presence of additional externalities that is, the presence of agglomeration economies. Following general practice in the literature to capture such externalities, we add the location quotient $\boldsymbol{Z}$ to Patent Equation (5) that measures the concentration of high technology production. This leads to the following E*xtended Model for Regional Knowledge Production*:

$$\log K_i = \alpha_0 + \alpha_1 \log \Omega_i + \alpha_2 \log \Phi_i + \alpha_3 Z_i + \varepsilon_i \tag{12}$$

together with Equations (10)-(11). Z_i denotes the share of high technology employment in the national total; Ω_i, Φ_i, α_0, α_1, α_2, α_3 and ε_i are in the same notation as above.

3.3 Data and Variable Definitions

The analysis of spatial processes is handicapped by a lack of data for what might be considered to be the ideal unit of observation. We adopt the political district as the spatial unit of observation in our study. This is at best a crude proxy of the relevant functional economic region. But the spatial scale of political districts is the finest spatial resolution at which the relevant data are available or may be estimated at least. Measurement problems arise both in the case of output and in the case of inputs of the knowledge production process.

Account of corporate patent applications has been used as the dependent variable in the geographic knowledge production functions [$\boldsymbol{K}$ in Equation (9) and Equation (12)]. 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. 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 assuming a lag structure between the time when a particular R&D project starts and the moment it leads to an invention.

Our interest focuses in 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 (10)] 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 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.

Unfortunately, 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

$$R_{DP} = \frac{R_{AN}}{P_{AN}} P_{DP} \tag{4}$$

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 C*.

In the Extended Knowledge Production Function Model [see Equation (12) together with Equations (10) – (11)] the variable $\boldsymbol{Z}$ was added to account for potential agglomeration economies, $\boldsymbol{Z}$ is proxied by the 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 (9) – (11) and Equations (10) – (12)] 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. This resulted in 72 observational units. The sample 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 A*.

3.4 Estimation Issues

The use of a cross-sectional sample may lead to a spatial dependence [spatial autocorrelation] in the regression equations and, thus, cause serious problems in specifying and estimating the models. We assess this 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

$$\boldsymbol{K} = \rho\,\boldsymbol{W}\,\boldsymbol{K} + \boldsymbol{X}\,\alpha + \xi \tag{13}$$

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 α. ξ is a 72 by 1 vector of normally distributed random 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 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 knowledge production*

$$\boldsymbol{K} = \boldsymbol{X}\,\alpha + \xi \tag{14}$$

with

$$\xi = \lambda\,\boldsymbol{W}\,\xi + \eta \tag{15}$$

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

The similarity between the Spatial Error Model (14) – (15) and the Spatial Lag Model (13) 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.

3.5 Empirical Results

Tab. 3 presents the results of the estimation of the cross-sectional regression of the geographic knowledge production function for 72 political districts in Austria. All variables are in logarithms. In addition to the *Basic Model* [see Equations (9) – (11)], reported in the first column of the table, we also estimated the *Extended Model* [see

Equation (12) with Equations (10) – (11)] that includes a local economic characteristic as an explanatory variable to capture agglomeration economies [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 1995b).

An influence of $\boldsymbol{\Omega}$ 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 $\boldsymbol{\Phi}$ 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. But agglomeration effects 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 Tab. 3. 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 spillovers and industry R&D 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. No statistically significant evidence was found of interregional spillovers between industry R&D laboratories [measured in terms of A_i^R]. There is no evidence of hetereoskedasticity, but the Lagrange Multiplier test for spatial error dependence strongly indicates misspecification of the model.

When the local economic variable is added [see column 2], the model fit increases from $R^2 = 0.60$ to $R^2 = 0.69$, with a positive and significant effect for agglomeration effects. 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[2].

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 [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.

Tab. 3 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 Ω	0.402*** (0.504)	0.211*** (0.065)	0.213*** (0.064)
Log Φ [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 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 percent level, ** significance at the 5 percent level and *** significance at the one percent level

In sum, the maximum likelihood [ML]-estimates in column 3 of Tab. 3 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. 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 interregional spillovers between industry R&D laboratories.

3.6 Summary and 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, Echeverri-Carrol and Brennan 1999). 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 are extremely complex and only partially understood. This is partly due to the fact that knowledge spillovers are invisible and leave no paper trail by which they may be measured and tracked as Krugman (1991a, p. 53) has noted. But Jaffe (1989) found that investment in R&D made by private corporations and universities provides an important knowledge input that influences the patent activity of third-party firms.

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. New technological and scientific knowledge is captured by industry R&D and university research. 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 agglomeration effects identified. 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. One can not really interpret the results structurally in the sense of predicting the resulting change in patents if research spending would be increased exogenously.

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 appropriate spatial units of observation, but at the price that intra- and interregional university spillovers can not be separated 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.

4. Summary and Outlook

In recent years, the role of space in general and of spatial externalities in particular has gained an increasingly prominent position in mainstream economics, partly stimulated by the visibility of Krugman's work on the new economic geography (for example, Krugman 1991a, b). Of course, the importance of space is not new to geographers and regional scientists. Based on novel exploratory techniques as well as spatial econometric modelling tools, this study analysed the effect of space in the creation of knowledge in Austria. Based on a unique data set of patent application counts, R&D and university research expenditures aggregated at the level of Austrian political districts. The study is empirical in nature, and has an exploratory as well as an explanatory dimension. The empirical results of the exploratory analysis are based on utilizing some novel spatial data analysis techniques and may be summarized as follows:

- *First*, knowledge production in Austria tends to be largely focused in mechanical areas of manufacturing rather than in high-tech fields such as electronics or computers. It is interesting to note that this pattern did not change very much during the past two decades.
- *Second*, merely a weak trend of growing clusters may be identified. But this does not appear to be the outcome of a dynamic process generated by intensive knowledge flows at the local level, rather than the consequence of a spatial shift in knowledge production. There is no doubt that Vienna with its strong presence of high quality research institutions and R&D in manufacturing dominates the knowledge creation process. Some smaller clustering tendencies were identified around Salzburg, Linz and Graz.

- *Third*, geographic stability of knowledge generation characterised by weakly expanding clusters may be the outcome of relatively less developed linkages among the major actors of the Austrian innovation system. Cluster generating increasing returns appear to result largely from between – firm knowledge diffusion rather than from knowledge spillover effects.

As is the case of any exploratory data analysis these findings need to be treated with caution and should be viewed as an initial pre-modelling stage. The explanatory level of analysis aimed at modelling mediated knowledge spillovers within a knowledge production framework. The major results obtained may be summarised as follows:

- *First*, there is strong and equivocal evidence of local spatial externalities that is of research spillovers from university and knowledge spillovers between R&D laboratories of high technology firms.
- *Second,* the geographic boundaries of university research spillovers is directly linked to a distance decay effect. By contrast, the effect of industry R&D seems to be contained within the political district itself.
- *Third,* but these university research spillovers appear to be relatively small in comparison to the agglomeration effects identified.
- *Fourth,* it is important to emphasize that the statistical relationship is only suggestive. More detailed examination of university data is necessary to determine of the university research spillover effect materialize in reality.

Our 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 expenditures data available for later points in time, 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 sector 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 technology sectors on the basis of two-digit ISIC industries. Many products manufactured by our high technology firms are medium- or even low-tech. This aggregation level, thus, masks considerable underlying heterogeneity and may be too crude to capture university research effects. *Fourth*, and finally, it is worth noting that the results will be partially affected by the chosen spatial scale of analysis. Political districts qualify as appropriate spatial units of observation, but at the price that intra- and interregional university spillovers cannot be separated within our conceptual framework.

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 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.

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APPENDICES

APPENDIX A: Patent Applications (1993), Industry R&D (1991) and University Research (1991) for the 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

ctd.

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

APPENDIX B: 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, E11B, E11C
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,

ctd.

		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, 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 C: Linking Scientific Fields 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 D: Simple Statistics: Corporate Patent Applications 1993, Industry R&D Expenditures 1991, and Employment 1991 by Sectors of the High Technology Industry

	Mean	Standard Deviation	Maximum
Corporate Patent Applications 1993 in High Technology			
Chemistry and Pharmaceuticals	1.32	3.91	26.00
Rubber and Plastics	0.23	1.20	11.00
Oil Refining	0.03	0.22	2.00
Machinery	4.60	13.58	130.49
Computers and Office Machines	0.18	0.80	7.00
Electrical Machinery	1.36	5.44	52.84
Electronics	0.63	3.43	33.50
Instruments	2.17	7.80	73.60
Transportation Vehicles	1.93	6.13	55.66
R&D Expenditures 1991 in High Technology [in million ATS]			
Chemistry and Pharmaceuticals	79.78	206.32	929.59
Rubber and Plastics	39.68	81.40	255.75
Oil Refining	111.24	156.56	221.94
Machinery	34.82	83.51	487.04
Computers and Office Machines	107.11	130.66	254.50
Electrical Machinery	49.88	117.49	586.68
Electronics	401.88	1355.79	4706.66
Instruments	16.98	30.11	84.50
Transportation Vehicles	76.35	163.58	634.80
University Research Expenditures 1991 Relevant for High Technology [in million ATS]			
Chemistry and Pharmaceuticals	571.57	847.88	2328.00
Rubber and Plastics	84.43	105.51	288.00
Oil Refining	84.43	105.51	288.00
Machinery	102.71	139.17	389.00
Computers and Office Machines	231.43	303.66	886.00
Electrical Machinery	108.14	153.81	429.00
Electronics	108.14	153.81	429.00
Instruments	545.00	803.95	2279.00
Transportation Vehicles	197.71	248.80	738.00
Employment 1991 in High Technology			
Chemistry and Pharmaceuticals	302.00	979.94	8143.00
Rubber and Plastics	301.83	622.48	3779.00
Oil Refining	27.20	163.13	1392.00
Machinery	925.06	1405.03	10302.00
Computers and Office Machines	10.36	46.18	310.00
Electrical Machinery	305.92	836.15	7496.00
Electronics	162.57	1061.54	10501.00
Instruments	277.68	1204.81	11729.00
Transportation Vehicles	338.26	1189.23	10660.00

APPENDIX E: Contiguity Structures for the 99 Political Districts

Weight Matrix	No.	District	Contiguities (sequence numbers)														
D50	1	Eisenstadt (Stadt)	2	3	6	7	8	23	25	26	36	37	42	43	99		
CONT1	1	Eisenstadt (Stadt)	3	26													
CONT2	1	Eisenstadt (Stadt)	2	6	7	25	27	42	43								
CONT3	1	Eisenstadt (Stadt)	8	9	23	31	33	35	36	37	38	40	75	99			
D50	2	Rust (Stadt)	1	3	6	7	23	25	26	42	43						
CONT1	2	Rust (Stadt)	3														
CONT2	2	Rust (Stadt)	1	6	7	25	26	42									
CONT3	2	Rust (Stadt)	8	9	23	27	33	36	37	38	43	75					
D50	3	Eisenstadt-Umgebung*	1	2	6	7	8	23	25	26	36	37	42	43			
CONT1	3	Eisenstadt-Umgebung	1	2	6	7	25	26	42								
CONT2	3	Eisenstadt-Umgebung	8	9	23	27	33	36	37	38	43	75					
CONT3	3	Eisenstadt-Umgebung	4	20	21	31	32	34	35	39	40	70	73	81	85	99	
D50	4	Güssing	5	9	72	73	75										
CONT1	4	Güssing	5	9	73	75											
CONT2	4	Güssing	8	37	42	72	85										
CONT3	4	Güssing	3	6	23	25	33	70	74	78	81	83					
D50	5	Jennersdorf	4	72	73	75	83										
CONT1	5	Jennersdorf	4	72	73												
CONT2	5	Jennersdorf	9	74	75	78	83	85									
CONT3	5	Jennersdorf	8	37	42	69	70	71	77	79	81	84					
D50	6	Mattersburg	1	2	3	7	8	23	25	26	36	37	42				
CONT1	6	Mattersburg	3	8	23	42											
CONT2	6	Mattersburg	1	2	7	9	25	26	33	37	75						
CONT3	6	Mattersburg	4	27	36	38	39	43	70	73	81	85					
D50	7	Neusiedl am See*	1	2	3	6	26	43									
CONT1	7	Neusiedl am See	3	26													
CONT2	7	Neusiedl am See	1	2	6	25	27	42	43								
CONT3	7	Neusiedl am See	8	9	23	31	33	35	36	37	38	40	75	99			
D50	8	Oberpullendorf*	1	3	6	9	23	37									
CONT1	8	Oberpullendorf	6	9	42												
CONT2	8	Oberpullendorf	3	4	23	25	33	37	75								
CONT3	8	Oberpullendorf	1	2	5	7	26	36	38	39	43	70	73	81	85		
D50	9	Oberwart	4	8	73	75											
CONT1	9	Oberwart	4	8	42	75											
CONT2	9	Oberwart	3	5	6	23	25	33	37	73	85						
CONT3	9	Oberwart	1	2	7	26	36	38	39	43	70	72	74	81			
D50	10	Klagenfurt (Stadt)*	11	13	14	16	17	19									
CONT1	10	Klagenfurt (Stadt)	13	14	19												
CONT2	10	Klagenfurt (Stadt)	11	15	16	17	18	76	82								
CONT3	10	Klagenfurt (Stadt)	12	66	67	68	71	77	79	80	84	92					
D50	11	Villach (Stadt)*	10	12	13	14	15	16	19								
CONT1	11	Villach (Stadt)	16	19													
CONT2	11	Villach (Stadt)	10	12	13	14	15	82									
CONT3	11	Villach (Stadt)	17	18	66	67	68	76	80	92							
D50	12	Hermagor*	11	15	16												
CONT1	12	Hermagor	15	16	92												
CONT2	12	Hermagor	11	13	19	66	67	68	82								
CONT3	12	Hermagor	10	14	17	51	64	76	80	89	94						
D50	13	Klagenfurt Land	10	11	14	16	17	19									
CONT1	13	Klagenfurt Land	10	14	16	17	19										
CONT2	13	Klagenfurt Land	11	12	15	18	76	82									
CONT3	13	Klagenfurt Land	66	67	68	71	77	79	80	84	92						
D50	14	Sankt Veit an der Glan*	10	11	13	16	17	19									
CONT1	14	Sankt Veit an der Glan	10	13	17	18	19	76	82								
CONT2	14	Sankt Veit an der Glan	11	15	16	67	71	77	79	80	84						
CONT3	14	Sankt Veit an der Glan	12	24	39	51	53	59	66	68	70	74	78	92			
D50	15	Spittal an der Drau*	11	12	16												
CONT1	15	Spittal an der Drau	12	16	19	66	67	68	82	92							
CONT2	15	Spittal an der Drau	10	11	13	14	51	64	76	80	89	94					
CONT3	15	Spittal an der Drau	17	18	24	39	53	59	61	62	65	70	77	79	84	88	90
D50	16	Villach Land*	10	11	12	13	14	15	19								
CONT1	16	Villach Land	11	12	13	15	19										
CONT2	16	Villach Land	10	14	17	66	67	68	82	92							

ctd.

Weight Matrix	No.	District	Contiguities (sequence numbers)
CONT3	16	Villach Land	18 51 64 76 80 89 94
D50	17	Völkermarkt	10 13 14 18 19
CONT1	17	Völkermarkt	13 14 18
CONT2	17	Völkermarkt	10 16 19 71 76 82 84
CONT3	17	Völkermarkt	11 12 15 67 74 77 78 79 80
D50	18	Wolfsberg*	17 71 76 84
CONT1	18	Wolfsberg	14 17 71 76 84
CONT2	18	Wolfsberg	10 13 19 74 77 78 79 80 82
CONT3	18	Wolfsberg	11 15 16 24 39 51 53 59 66 67 69 70 72 83 85
D50	19	Feldkirchen*	10 11 13 14 16 17
CONT1	19	Feldkirchen	10 11 13 14 15 16 82
CONT2	19	Feldkirchen	12 17 18 66 67 68 76 80 92
CONT3	19	Feldkirchen	24 39 51 53 59 64 70 71 77 79 84 89 94
D50	20	Krems an der Donau (Stadt)*	21 29 30 32 34 38 40 44
CONT1	20	Krems an der Donau (Stadt)	32 38
CONT2	20	Krems an der Donau (Stadt)	21 25 29 30 33 34 39 40 43 44
CONT3	20	Krems an der Donau (Stadt)	3 22 24 26 27 28 31 35 36 37 41 42 50 55 70 80 81 99
D50	21	Sankt Pölten (Stadt)*	20 32 33 34 38 39 40
CONT1	21	Sankt Pölten (Stadt)	38
CONT2	21	Sankt Pölten (Stadt)	20 25 32 33 34 39 40 43
CONT3	21	Sankt Pölten (Stadt)	3 22 24 26 27 29 30 31 35 36 37 42 44 55 70 80 81 99
D50	22	Waidhofen an der Ybbs (Stadt)*	24 39 46 55 59
CONT1	22	Waidhofen an der Ybbs (Stadt)	24 39 59
CONT2	22	Waidhofen an der Ybbs (Stadt)	33 34 38 46 53 54 55 70 80
CONT3	22	Waidhofen an der Ybbs (Stadt)	20 21 25 32 37 40 42 43 44 45 49 50 51 60 62 66 67 74 79 81 82 85
D50	23	Wiener Neustadt (Stadt)*	1 2 3 6 8 25 36 37 42 43 99
CONT1	23	Wiener Neustadt (Stadt)	6 37 42
CONT2	23	Wiener Neustadt (Stadt)	3 8 9 25 33 75 81 85
CONT3	23	Wiener Neustadt (Stadt)	1 2 4 7 26 36 38 39 43 70 72 73 74
D50	24	Amstetten*	22 34 39 46 55 59
CONT1	24	Amstetten	22 34 39 46 54 55 59 80
CONT2	24	Amstetten	32 33 38 44 45 49 50 51 53 60 62 66 67 70 76 79 82
CONT3	24	Amstetten	14 15 18 19 20 21 25 28 29 30 37 40 41 42 43 47 52 57 61 64 65 68 74 77 81 84 85
D50	25	Baden*	1 2 3 6 23 26 31 36 37 42 43 99
CONT1	25	Baden	3 26 33 36 38 42 43
CONT2	25	Baden	1 2 6 7 8 9 20 21 23 27 31 32 34 35 37 39 40 70 81 99
CONT3	25	Baden	4 22 24 29 30 44 55 73 74 79 80 85
D50	26	Bruck an der Leitha	1 2 3 6 7 25 36 43 99
CONT1	26	Bruck an der Leitha	1 3 7 25 27 43
CONT2	26	Bruck an der Leitha	2 6 31 33 35 36 38 40 42 99
CONT3	26	Bruck an der Leitha	8 9 20 21 23 29 32 34 37 39 70 75 81
D50	27	Gänserndorf*	31 35 36 43 99
CONT1	27	Gänserndorf	26 35 43 99
CONT2	27	Gänserndorf	1 3 7 25 29 31 36 38 40
CONT3	27	Gänserndorf	2 6 20 21 30 32 33 34 39 42
D50	28	Gmünd	41 44
CONT1	28	Gmünd	41 44 50
CONT2	28	Gmünd	30 32 34 55 60
CONT3	28	Gmünd	20 24 29 38 39 40 45 49 54 57
D50	29	Hollabrunn	20 30 31 35 40
CONT1	29	Hollabrunn	30 31 32 35 40
CONT2	29	Hollabrunn	20 27 34 38 41 43 44 99
CONT3	29	Hollabrunn	21 24 25 26 28 33 36 39 50 55
D50	30	Horn	20 29 32 41 44
CONT1	30	Horn	29 32 41 44
CONT2	30	Horn	20 28 31 34 35 38 40 50 55
CONT3	30	Horn	21 24 25 27 33 39 43 45 54 60 99
D50	31	Korneuburg*	25 27 29 35 36 40 43 99
CONT1	31	Korneuburg	29 35 40 43 99
CONT2	31	Korneuburg	25 26 27 30 32 36 38

ctd.

Weight Matrix	No.	District	Contiguities (sequence numbers)
CONT3	31	Korneuburg	1 3 7 20 21 33 34 39 41 42 44
D50	32	Krems (Land)	20 21 30 34 38 41 44
CONT1	32	Krems (Land)	20 29 30 34 38 40 44
CONT2	32	Krems (Land)	21 24 25 28 31 33 35 39 41 43 50 55 99
CONT3	32	Krems (Land)	3 22 26 27 36 37 42 45 46 54 59 60 70 80 81
D50	33	Lilienfeld	21 34 38 39
CONT1	33	Lilienfeld	25 37 38 39 42 70 81
CONT2	33	Lilienfeld	3 6 8 9 20 21 22 23 24 26 32 34 36 40 43 74 75 79 85
CONT3	33	Lilienfeld	1 2 4 7 27 29 30 31 35 44 46 51 53 54 55 59 66 67 71 72 73 76 77 78 82 84 99
D50	34	Melk	20 21 24 32 33 38 39
CONT1	34	Melk	24 32 38 39 44 55
CONT2	34	Melk	20 21 22 25 28 29 30 33 40 41 43 45 46 50 54 59 60 70
CONT3	34	Melk	3 26 27 31 35 36 37 42 49 51 53 57 62 66 67 74 76 79 82 85 99
D50	35	Mistelbach	27 29 31 99
CONT1	35	Mistelbach	27 29 31 43
CONT2	35	Mistelbach	25 26 30 32 36 38 40 99
CONT3	35	Mistelbach	1 3 7 20 21 33 34 39 41 42 44
D50	36	Mödling*	1 3 6 23 25 26 27 31 37 38 40 42 43 99
CONT1	36	Mödling	25 43 99
CONT2	36	Mödling	3 26 27 31 33 35 38 40 42
CONT3	36	Mödling	1 2 6 7 8 9 20 21 23 29 32 34 37 39 70 75 81
D50	37	Neunkirchen*	1 3 6 8 23 25 36 42 81
CONT1	37	Neunkirchen	23 33 42 75 81 85
CONT2	37	Neunkirchen	3 4 6 8 9 25 38 39 70 72 73 74
CONT3	37	Neunkirchen	1 2 5 7 20 21 22 24 26 32 34 36 40 43 69 71 77 78 80 83 84
D50	38	Sankt Pölten (Land)*	20 21 32 33 34 36 40 99
CONT1	38	Sankt Pölten (Land)	20 21 25 32 33 34 39 40 43
CONT2	38	Sankt Pölten (Land)	3 22 24 26 27 29 30 31 35 36 37 42 44 55 70 80 81 99
CONT3	38	Sankt Pölten (Land)	1 2 6 7 8 9 23 28 41 45 46 50 51 53 54 59 60 66 74 75 76 79 82 85
D50	39	Scheibbs*	21 22 24 33 34
CONT1	39	Scheibbs	22 24 33 34 38 70 80
CONT2	39	Scheibbs	20 21 25 32 37 40 42 43 44 46 51 53 54 55 59 66 67 74 79 81 82 85
CONT3	39	Scheibbs	3 6 8 9 14 15 18 19 23 26 27 28 29 30 31 35 36 41 49 50 60 61 62 64 65 68 69 71 72 73 75 77 78 84 99
D50	40	Tulln*	20 21 29 31 36 38 43 99
CONT1	40	Tulln	29 31 32 38 43 99
CONT2	40	Tulln	20 21 25 26 27 30 33 34 35 36 39 44
CONT3	40	Tulln	1 3 7 22 24 28 37 41 42 50 55 70 80 81
D50	41	Waidhofen an der Thaya*	28 30 32 44
CONT1	41	Waidhofen an der Thaya	28 30 44
CONT2	41	Waidhofen an der Thaya	29 32 34 50 55
CONT3	41	Waidhofen an der Thaya	20 24 31 35 38 39 40 45 54 60
D50	42	Wiener Neustadt (Land)*	1 2 3 6 23 25 36 37 43 99
CONT1	42	Wiener Neustadt (Land)	3 6 8 9 23 25 33 37 75
	42		
CONT2	42	Wiener Neustadt (Land)	1 2 4 7 26 36 38 39 43 70 73 81 85
CONT3	42	Wiener Neustadt (Land)	5 20 21 22 24 27 31 32 34 35 40 72 74 79 80 99
D50	43	Wien-Umgebung*	1 2 3 7 23 25 26 27 31 36 40 42 99
CONT1	43	Wien-Umgebung	25 26 27 31 35 36 38 40 99
CONT2	43	Wien-Umgebung	1 3 7 20 21 29 32 33 34 39 42
CONT3	43	Wien-Umgebung	2 6 8 9 22 23 24 30 37 44 55 70 75 80 81
D50	44	Zwettl	20 28 30 32 41
CONT1	44	Zwettl	28 30 32 34 41 50 55
CONT2	44	Zwettl	20 24 29 38 39 40 45 54 60
CONT3	44	Zwettl	21 22 25 31 33 35 43 46 49 53 57 59 62 70 80 99
D50	45	Linz (Stadt)*	46 47 49 50 52 53 54 55 57 60 62
CONT1	45	Linz (Stadt)	54 55 60

ctd.

Weight Matrix	No.	District	Contiguities (sequence numbers)
CONT2	45	Linz (Stadt)	24 34 44 49 50 53 57 59 62
CONT3	45	Linz (Stadt)	22 28 30 32 38 39 41 46 47 51 52 58 61 80
D50	46	Steyr (Stadt)*	22 24 45 47 53 54 55 59 62
CONT1	46	Steyr (Stadt)	24 59
CONT2	46	Steyr (Stadt)	22 34 39 53 54 55 80
CONT3	46	Steyr (Stadt)	32 33 38 44 45 49 50 51 60 62 66 67 70 76 79 82
D50	47	Wels (Stadt)*	45 46 49 51 52 53 54 56 61 62
CONT1	47	Wels (Stadt)	62
CONT2	47	Wels (Stadt)	49 51 52 53 54 61
CONT3	47	Wels (Stadt)	24 45 48 55 56 57 58 59 60 64 65 66 80
D50	48	Braunau am Inn*	56 58 65
CONT1	48	Braunau am Inn	56 61 65
CONT2	48	Braunau am Inn	51 52 58 62 63 64
CONT3	48	Braunau am Inn	47 49 53 54 57 66 80
D50	49	Eferding	45 47 52 53 54 56 57 60 62
CONT1	49	Eferding	52 54 57 58 60 62
CONT2	49	Eferding	24 45 47 50 51 53 55 56 59 61
CONT3	49	Eferding	22 28 34 39 44 46 48 64 65 66 80
D50	50	Freistadt	45 54 55 57 60
CONT1	50	Freistadt	28 44 55 60
CONT2	50	Freistadt	24 30 32 34 41 45 49 54 57
CONT3	50	Freistadt	20 22 29 38 39 40 46 52 53 58 59 62 80
D50	51	Gmunden*	47 52 53 56 61 62
CONT1	51	Gmunden	53 61 62 64 65 66 80
CONT2	51	Gmunden	15 24 39 47 48 49 52 54 56 59 63 67 68 70 76 79 82
CONT3	51	Gmunden	12 14 16 18 19 22 33 34 38 45 46 55 57 58 60 74 77 81 85 89 92 94
D50	52	Grieskirchen*	45 47 49 51 54 56 57 58 61 62
CONT1	52	Grieskirchen	49 56 58 61 62
CONT2	52	Grieskirchen	47 48 51 53 54 57 60 65
CONT3	52	Grieskirchen	24 45 50 55 59 63 64 66 80
D50	53	Kirchdorf an der Krems*	45 46 47 49 51 54 61 62 80
CONT1	53	Kirchdorf an der Krems	51 54 59 62 80
CONT2	53	Kirchdorf an der Krems	22 24 39 45 46 47 49 52 55 60 61 64 65 66 67 70 76 79
CONT3	53	Kirchdorf an der Krems	14 15 18 19 33 34 38 44 48 50 56 57 58 63 68 74 77 81 85
D50	54	Linz-Land*	45 46 47 49 50 52 53 55 60 62
CONT1	54	Linz-Land	24 45 49 53 55 59 60 62
CONT2	54	Linz-Land	22 34 39 44 46 47 50 51 52 57 58 61 80
CONT3	54	Linz-Land	28 30 32 33 38 41 48 56 64 65 66 67 70 76 79 82
D50	55	Perg*	22 24 45 46 50 54 60
CONT1	55	Perg	24 34 44 45 50 54 60
CONT2	55	Perg	22 28 30 32 38 39 41 46 49 53 57 59 62 80
CONT3	55	Perg	20 21 25 29 33 40 43 47 51 52 58 61 66 67 70 76 79 82
D50	56	Ried im Innkreis*	47 48 49 51 52 58 61 62
CONT1	56	Ried im Innkreis	48 52 58 61
CONT2	56	Ried im Innkreis	49 51 57 62 65
CONT3	56	Ried im Innkreis	47 53 54 60 63 64 66 80
D50	57	Rohrbach*	45 49 50 52 60
CONT1	57	Rohrbach	49 58 60
CONT2	57	Rohrbach	45 50 52 54 55 56 62
CONT3	57	Rohrbach	24 28 34 44 47 48 51 53 59 61
D50	58	Schärding*	48 52 56
CONT1	58	Schärding	49 52 56 57
CONT2	58	Schärding	48 54 60 61 62
CONT3	58	Schärding	24 45 47 50 51 53 55 59 65
D50	59	Steyr-Land*	22 24 46
CONT1	59	Steyr-Land	22 24 46 53 54 80
CONT2	59	Steyr-Land	34 39 45 49 51 55 60 62 66 67 70 76 79 82
CONT3	59	Steyr-Land	14 15 18 19 32 33 38 44 47 50 52 57 58 61 64 65 68 74 81 84 85
D50	60	Urfahr-Umgebung	45 49 50 54 55 57

ctd.

Weight Matrix	No.	District	Contiguities (sequence numbers)
CONT1	60	Urfahr-Umgebung	45 49 50 54 55 57
CONT2	60	Urfahr-Umgebung	24 28 34 44 52 53 58 59 62
CONT3	60	Urfahr-Umgebung	22 30 32 38 39 41 46 47 51 56 61 80
D50	61	Vöcklabruck*	47 51 52 53 56 62 65
CONT1	61	Vöcklabruck	48 51 52 56 62 65
CONT2	61	Vöcklabruck	47 49 53 54 58 63 64 66 80
CONT3	61	Vöcklabruck	15 24 39 45 55 57 59 60 67 68 70 76 79 82
D50	62	Wels-Land*	45 46 47 49 51 52 53 54 56 61
CONT1	62	Wels-Land	47 49 51 52 53 54 61
CONT2	62	Wels-Land	24 45 48 55 56 57 58 59 60 64 65 66 80
CONT3	62	Wels-Land	15 22 34 39 44 46 50 63 67 68 70 76 79 82
D50	63	Salzburg (Stadt)*	64 65
CONT1	63	Salzburg (Stadt)	65
CONT2	63	Salzburg (Stadt)	48 51 61 64
CONT3	63	Salzburg (Stadt)	52 53 56 62 66 80
D50	64	Hallein*	63 65 66
CONT1	64	Hallein	51 65 66
CONT2	64	Hallein	15 48 53 61 62 63 67 68 80
CONT3	64	Hallein	12 16 19 24 39 47 49 52 54 56 59 70 76 79 82 89 92 94
D50	65	Salzburg-Umgebung*	48 61 63 64
CONT1	65	Salzburg-Umgebung	48 51 61 63 64
CONT2	65	Salzburg-Umgebung	52 53 56 62 66 80
CONT3	65	Salzburg-Umgebung	15 24 39 47 49 54 58 59 67 68 70 76 79 82
D50	66	Sankt Johann im Pongau	64 68
CONT1	66	Sankt Johann im Pongau	15 51 64 67 68 80
CONT2	66	Sankt Johann im Pongau	12 16 19 24 39 53 59 61 62 65 70 76 79 82 89 92 94
CONT3	66	Sankt Johann im Pongau	10 11 13 14 18 22 33 34 38 46 47 48 49 52 54 55 56 63 77 81 84 85 88 90
D50	67	Tamsweg	82
CONT1	67	Tamsweg	15 66 80 82
CONT2	67	Tamsweg	12 14 16 19 24 39 51 53 59 64 68 70 76 79 92
CONT3	67	Tamsweg	10 11 13 17 18 22 33 34 38 46 54 55 61 62 65 74 77 81 85 89 94
D50	68	Zell am See*	66
CONT1	68	Zell am See	15 66 89 92 94
CONT2	68	Zell am See	12 16 19 51 64 67 80 82 88 90
CONT3	68	Zell am See	10 11 13 14 24 39 53 59 61 62 65 70 76 79 86 87
D50	69	Graz (Stadt)*	71 72 74 78 84 85
CONT1	69	Graz (Stadt)	74
CONT2	69	Graz (Stadt)	70 71 72 77 78 79 84 85
CONT3	69	Graz (Stadt)	5 18 33 37 39 73 75 76 80 81 83
D50	70	Bruck an der Mur*	74 77 79 81
CONT1	70	Bruck an der Mur	33 39 74 79 80 81 85
CONT2	70	Bruck an der Mur	22 24 25 34 37 38 42 51 53 59 66 67 69 71 72 73 75 76 78 82 84
CONT3	70	Bruck an der Mur	3 4 5 6 8 9 14 15 18 19 20 21 23 26 32 36 40 43 46 54 55 61 62 64 65 68 83
D50	71	Deutschlandsberg*	18 69 74 78 84
CONT1	71	Deutschlandsberg	18 74 78 84
CONT2	71	Deutschlandsberg	14 17 69 70 72 76 77 79 83 85
CONT3	71	Deutschlandsberg	5 10 13 19 33 37 39 73 75 80 81 82
D50	72	Feldbach*	4 5 69 73 75 78 83 85
CONT1	72	Feldbach	5 73 74 78 83 85
CONT2	72	Feldbach	4 37 69 70 71 75 77 79 81 84
CONT3	72	Feldbach	9 18 23 33 39 42 76 80
D50	73	Fürstenfeld*	4 5 9 72 75 83 85
CONT1	73	Fürstenfeld	4 5 72 75 85
CONT2	73	Fürstenfeld	9 37 42 70 74 78 81 83
CONT3	73	Fürstenfeld	3 6 8 23 25 33 39 69 71 77 79 80 84
D50	74	Graz-Umgebung*	69 70 71 78 79 84 85
CONT1	74	Graz-Umgebung	69 70 71 72 77 78 79 84 85

ctd.

Weight Matrix	**No.**	**District**	**Contiguities (sequence numbers)**
CONT2	74	Graz-Umgebung	5 18 33 37 39 73 75 76 80 81 83
CONT3	74	Graz-Umgebung	4 9 14 17 22 23 24 25 34 38 42 51 53 59 66 67 82
D50	75	Hartberg*	4 5 9 72 73 85
CONT1	75	Hartberg	4 9 37 42 73 85
CONT2	75	Hartberg	3 5 6 8 23 25 33 70 72 74 81
CONT3	75	Hartberg	1 2 7 26 36 38 39 43 69 71 77 78 79 80 83 84
D50	76	Judenburg*	18 77 79 82 84
CONT1	76	Judenburg	14 18 77 79 80 82 84
CONT2	76	Judenburg	10 13 15 17 19 24 39 51 53 59 66 67 70 71 74
CONT3	76	Judenburg	11 12 16 22 33 34 38 46 54 55 61 62 64 65 68 69 72 78 85 92
D50	77	Knittelfeld*	70 76 79 84
CONT1	77	Knittelfeld	74 76 79 84
CONT2	77	Knittelfeld	14 18 69 70 71 72 78 80 82 85
CONT3	77	Knittelfeld	5 10 13 15 17 19 24 33 37 39 51 53 59 66 67 73 75 81
D50	78	Leibnitz*	69 71 72 74 83 84
CONT1	78	Leibnitz	71 72 74 83
CONT2	78	Leibnitz	5 18 69 70 73 77 79 84 85
CONT3	78	Leibnitz	4 14 17 33 37 39 75 76 80 81
D50	79	Leoben*	70 74 76 77
CONT1	79	Leoben	70 74 76 77 80
CONT2	79	Leoben	14 18 24 33 39 51 53 59 66 67 69 71 72 78 81 82 84 85
CONT3	79	Leoben	5 10 13 15 17 19 22 25 34 37 38 42 46 54 55 61 62 64 68 73 75 83
D50	80	Liezen*	53
CONT1	80	Liezen	24 39 51 53 59 66 67 70 76 79 82
CONT2	80	Liezen	14 15 18 19 22 33 34 38 46 54 55 61 62 64 65 68 74 77 84 85
CONT3	80	Liezen	10 11 12 13 16 17 20 21 25 32 37 40 42 43 44 45 47 48 50 52 56 60 63 69 71 72 73 75 78 89 92 94
D50	81	Mürzzuschlag*	37 70
CONT1	81	Mürzzuschlag	33 37 70 85
CONT2	81	Mürzzuschlag	23 25 38 39 42 72 73 74 75 79 80
CONT3	81	Mürzzuschlag	3 4 5 6 8 9 20 21 22 24 26 32 34 36 40 43 51 53 66 67 69 71 76 77 78 82 83 84
D50	82	Murau	67 76
CONT1	82	Murau	14 15 19 67 76 80
CONT2	82	Murau	10 11 12 13 16 17 18 24 39 51 53 59 66 68 70 77 79 84
CONT3	82	Murau	22 33 34 38 46 54 55 61 62 64 65 71 74 81 85 89 94
D50	83	Radkersburg	5 72 73 78
CONT1	83	Radkersburg	72 78
CONT2	83	Radkersburg	5 71 73 74 85
CONT3	83	Radkersburg	4 18 37 69 70 75 77 79 81 84
D50	84	Voitsberg*	18 69 71 74 76 77 78
CONT1	84	Voitsberg	18 71 74 76 77
CONT2	84	Voitsberg	14 17 69 70 72 78 79 80 82 85
CONT3	84	Voitsberg	5 10 13 15 19 24 33 37 39 51 53 59 66 67 73 75 81 83
D50	85	Weiz*	69 72 73 74 75
CONT1	85	Weiz	37 70 72 73 74 75 81
CONT2	85	Weiz	4 5 9 23 33 39 42 69 71 77 78 79 80 83 84
CONT3	85	Weiz	3 6 8 18 22 24 25 34 38 51 53 59 66 67 76 82
D50	86	Innsbruck-Stadt*	88 94
CONT1	86	Innsbruck-Stadt	88
CONT2	86	Innsbruck-Stadt	87 94
CONT3	86	Innsbruck-Stadt	68 89 90 91 93
D50	87	Imst	91 93
CONT1	87	Imst	88 91 93
CONT2	87	Imst	86 94 95 96
CONT3	87	Imst	68 89 90 97 98
D50	88	Innsbruck-Land*	86 94
CONT1	88	Innsbruck-Land	86 87 94
CONT2	88	Innsbruck-Land	68 89 90 91 93
CONT3	88	Innsbruck-Land	15 66 92 95 96

ctd.

Weight Matrix	**No.**	**District**	**Contiguities (sequence numbers)**
D50	89	Kitzbühel*	90
CONT1	89	Kitzbühel	68 90 94
CONT2	89	Kitzbühel	15 66 88 92
CONT3	89	Kitzbühel	12 16 19 51 64 67 80 82 86 87
D50	90	Kufstein	89 94
CONT1	90	Kufstein*	89 94
CONT2	90	Kufstein	68 88
CONT3	90	Kufstein	15 66 86 87 92
D50	91	Landeck	87
CONT1	91	Landeck	87 93 95
CONT2	91	Landeck	88 96 98
CONT3	91	Landeck	86 94 97
D50	92	Lienz*	
CONT1	92	Lienz	12 15 68
CONT2	92	Lienz	16 19 66 67 82 89 94
CONT3	92	Lienz	10 11 13 14 51 64 76 80 88 90
D50	93	Reutte	87
CONT1	93	Reutte	87 91 95 96
CONT2	93	Reutte	88 97 98
CONT3	93	Reutte	86 94
D50	94	Schwaz*	86 88 90
CONT1	94	Schwaz	68 88 89 90
CONT2	94	Schwaz	15 66 86 87 92
CONT3	94	Schwaz	12 16 19 51 64 67 80 82 91 93
D50	95	Bludenz*	96 97 98
CONT1	95	Bludenz	91 93 96 98
CONT2	95	Bludenz	87 97
CONT3	95	Bludenz	88
D50	96	Bregenz	95 97 98
CONT1	96	Bregenz*	93 95 97 98
CONT2	96	Bregenz	87 91
CONT3	96	Bregenz	88
D50	97	Dornbirn*	95 96 98
CONT1	97	Dornbirn	96 98
CONT2	97	Dornbirn	93 95
CONT3	97	Dornbirn	87 91
D50	98	Feldkirch*	95 96 97
CONT1	98	Feldkirch	95 96 97
CONT2	98	Feldkirch	91 93
CONT3	98	Feldkirch	87
D50	99	Wien*	1 23 25 26 27 31 35 36 38 40 42 43
CONT1	99	Wien	27 31 36 40 43
CONT2	99	Wien	25 26 29 32 35 38
CONT3	99	Wien	1 3 7 20 21 30 33 34 39 42 44

Notes: D50 is distance based contiguity for 50 kilometers
CONT1 is first order simple contiguity
CONT2 is second order simple contiguity
CONT3 is third order simple contiguity
* denotes politcal districts included in the explanatory spatial analysis