The Role of Space in the Creation of Knowledge in Austria. An Exploratory Spatial Data Analysis

Fischer, Manfred M.; Fröhlich, Josef; Gassler, Helmut; Varga, Attila

Published: 01/03/2001

WGI Discussion Papers

Department of Economic Geography & Geoinformatics
Abteilung für Wirtschaftsgeographie & Geoinformatik [WGI]

WIRTSCHAFTSUNIVERSITÄT WIEN

The Role of Space in the Creation of Knowledge in Austria. An Exploratory Spatial Data Analysis

Manfred M. Fischer, Josef Fröhlich,
Helmut Gassler and Attila Varga

WGI Discussion Paper No. 76
March 2001

ISBN 3 85037 091 7

WGI Discussion Papers

WGI Discussion Paper No. 76
March 2001

The Role of Space in the Creation of Knowledge in Austria. An Exploratory Spatial Data Analysis

Manfred M. Fischer, Josef Fröhlich,
Helmut Gassler and Attila Varga

The paper is accepted for publication in
Manfred M. Fischer and Josef Fröhlich (Eds.) (2001):
Knowledge, Complexity and Innovation Systems.
Springer, Berlin, Heidelberg, New York

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

WGI Discussion Papers

Aims and Scope
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 interim reports presenting work in progress and papers which have been submitted for publication elsewhere.

Editor: Professor Dr. Manfred M. Fischer
Assistant Editor: Dr. Petra Staufer-Steinnocher

Department of Economic Geography and Geoinformatics [WGI]
Vienna University of Economics and Business Administration
Roßauer Lände 23/1
1090 Vienna, Austria

Phone: +43/1/31336-4808
Fax: +43/1/31336-703
E-mail: wgi-team@wigeo.wu-wien.ac.at
Internet: wigeoweb.wu-wien.ac.at

Printed with support of the
Federal Ministry of Education, Science and Culture, Vienna
Gedruckt mit Unterstützung des
Bundesministerium für Bildung, Wissenschaft und Kultur, Wien

ISBN 3 85037 091 7

WGI Discussion Papers are published on an occasional basis by the Department of Economic Geography & Geoinformatics, Vienna University of Economics and Business Administration, Vienna, Austria.

Abstract

The paper 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 based on descriptive techniques such as *Moran's I* test for spatial autocorrelation and the Moran scatterplot. Clusters of the knowledge 'output' [measured in terms of patent counts] are compared with spatial concentration patterns of two input measures of knowledge production: private R&D and academic research. In addition, employment in manufacturing is utilised to capture agglomeration economies. The analysis is based on data aggregated for two digit SIC industries and at the level of Austrian political districts. It explores the extent to which knowledge spillovers are mediated by spatial proximity in Austria. A time-space comparison makes it possible to study whether divergence or convergence processes in knowledge creation have occurred in the past two decades. As in the case of any exploratory data analysis, the findings need to be treated with caution and should be viewed only as an initial pre-modelling stage in the enterprise. Future research activities will be devoted to further exploring the issue of local university knowledge spillovers within a refined production framework (see Griliches 1979).

1 Introduction

The systems of innovation approach has recently received considerable attention as a promising conceptual framework for advancing our understanding of the innovation process in the economy. A system of innovation may be thought of as a set of actors such as firms, other organisations, and institutions that interact in the generation, diffusion and use of new – and economically useful – knowledge in the production process. Territorially based systems of innovation build on spatial proximity in terms of both spatial distance and contiguity – as either regional [subnational], national or global systems of innovation. The central idea underlying territorially based systems is that the economic performance of territories depends not only on how business corporations perform, but also on how they interact with each other and with the public sector in knowledge creation and dissemination. Knowledge creation is viewed as interactive and cumulative process contingent on the institutional set-up (Fischer 2001a).

The concept of territorially based systems of innovation evolved first in a national context (Freeman 1987), and then in a regional context (see, for example, Cooke et al. 1997, Brazcyk et al. 1998). It is being increasingly recognised that important elements of the process of innovation have become transnational and global, or regional rather than national. The driving forces behind this are two processes that are simultaneously at work: the process of globalisation of factor and commodity markets, and the regionalisation of knowledge creation and learning. Specific forms of technological learning and knowledge creation, especially the tacit forms, are both localised and territorially specific. The firms that master knowledge which is not fully codifiable are tied into various kinds of networks with other firms and organisations through localised input-output relations, as well as knowledge spillovers and their untraded interdependencies (Storper 1997).

Knowledge spillovers occur because knowledge created by a firm or other organisation is not normally contained solely within that organisation, but is also exploited by other firms. The spillover beneficiary may use the new knowledge to copy or imitate the commercial products of the innovator, or may use it as an input to R&D leading to the development of other new products or processes. Three vehicles of such spillovers may be distinguished: first, the scientific sector with its general scientific and technological knowledge pool; second, the firm specific knowledge pool; and, third, the business-business and industry-university relations that make them possible (Fischer 2001a).

In this chapter we make 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 remainder of the paper is structured as follows. Section 2 introduces the exploratory tools used to analyse the spatial data and describes the data on which the study is based. Section 3 focuses on the identification of spatial clustering patterns of knowledge production in the last two decades, while Section 4 relates spatial distribution of knowledge inputs to spatial patterns of knowledge output. The final section summarises the research findings and points to directions for future research.

2 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 have used the normalised Herfindahl index first to measure the degree of spatial concentration of both some input and output measures of knowledge production utilizing 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 $HI = 1 + \ln \Sigma_i S_i^2 / \ln n$, 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 invalid and hence requiring specialised spatial analytical tools. This problem occurs in situations where the observations are non-independent over space, that is where 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 of time dependence. Avoiding the pitfalls arising from spatially correlated data is crucial to good spatial data analysis (Fischer 1998, 2001b).

Exploratory analysis of area data involves identifying and describing different forms of spatial variation in the data. In the context of this contribution, special attention has been given to measuring the spatial association between observations for one variable. The presence of spatial association can be identified in a number of ways: a rigorous method is to use an appropriate spatial autocorrelation statistic, a more informal one to use, for example, a scatterplot and plot each value against the mean of the neighbouring areas. In the former 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 of these 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:

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

where n stands for the number of observations, x_i denotes an observation on a variable 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 x variable, and S_0 the normalising factor equal to the sum of the elements of the weights matrix:

$$S_0 = \Sigma_i\ \Sigma_j w_{ij} \tag{2}$$

For a row-standardised spatial weights matrix – 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}) = 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 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-standardized 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 considered to be present when the statistic for a particular map pattern has an extreme value compared to what would be expected under the null hypothesis of no spatial autocorrelation. We are interested in 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* and 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. This 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 or more extreme than the observed statistic, and M is the number of permutations carried out [M may be taken to be 99, for example].

Since the x-variable is in deviation from its mean, *Moran's I* is formally equivalent to a regression coefficient in a regression of Wx on x. The interpretation of I as a regression coefficient provides a way to visualise the linear association between x and Wx in form of a bivariate scatterplot of Wx against 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. By 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 1995) are suitable for detecting 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:

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

where w_{ij} denotes the (i,j)th element of a spatial weights matrix in row-standardized form. Significant local *Moran's* I_i detect non-random local spatial clusters where observation *i* is the center 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 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 on 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), name of the inventors(s), location of the inventor(s), one or more International Patent Classification (IPC) codes and some information on the technology field of the patent application. Since location information on the inventor(s) was not always provided, the address of the assignee was used for tracing patent activity back to the region of knowledge production. It is common in Austria that the location of both the assignee [usually the firm where the inventor has a job] and the inventor are very near, and often in the same political district. Deviation from this pattern was found only for large multiple-location companies where patent applications were submitted by the companies' headquarters. For these cases, patents were re-distributed to the addresses of the inventors when these were located in different political districts. In the case of multiple assignees located in different political districts, we followed the standard procedure of proportionate assignment. We used the MERIT concordance table (Verspagen, Moergastel and Slabbers 1994) between patent classes (International Patent Classes, IPC) and industrial sectors (ISIC) to match the patent data with the two-digit ISIC codes.

Finally, we needed data on the amount of university research relevant to each two-digit ISIC industry. 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 industry, but scientific knowledge from certain academic institutes [especially those operating in the transfer sciences] is expected to be important for specific industries. To capture the relevant pool of knowledge, scientific fields/academic disciplines have been assigned to relevant industrial fields at the broad level of two-digit ISIC industries using the survey of industrial R&D managers by Levin et al. (1987) to measure the relevance of a discipline 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 disciplines are not available in Austria. But they can be roughly estimated 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. The best that can be done is to break down the university research expenditure data to the level of scientific disciplines disaggregated by political districts using the following disaggregation procedure:

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

where R_{DP} denotes university expenditure in a specific discipline D and in political districts, 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 belonging to discipline D and located in political district P.

3 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 stability both spatially and by industry. Tab. 1 shows the sectoral distribution of patent applications in two time periods: 1982-1989 and 1990-1997.

It can be seen from Tab. 1 that knowledge production concentrates in mechanical areas of manufacturing, especially in machinery. High technology fields such as electronics, computers or chemicals and pharmaceuticals are significantly less represented. This corresponds to the sectoral structure of manufacturing production (Gassler 1993). However, no apparent specialisation 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 shown by its share of more than 30 percent of the national manufacturing total.

Spatial distribution of knowledge production also shows clear stability during the time period of the study. As indicated in Fig. 1, there are three larger concentrations of patents 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).

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

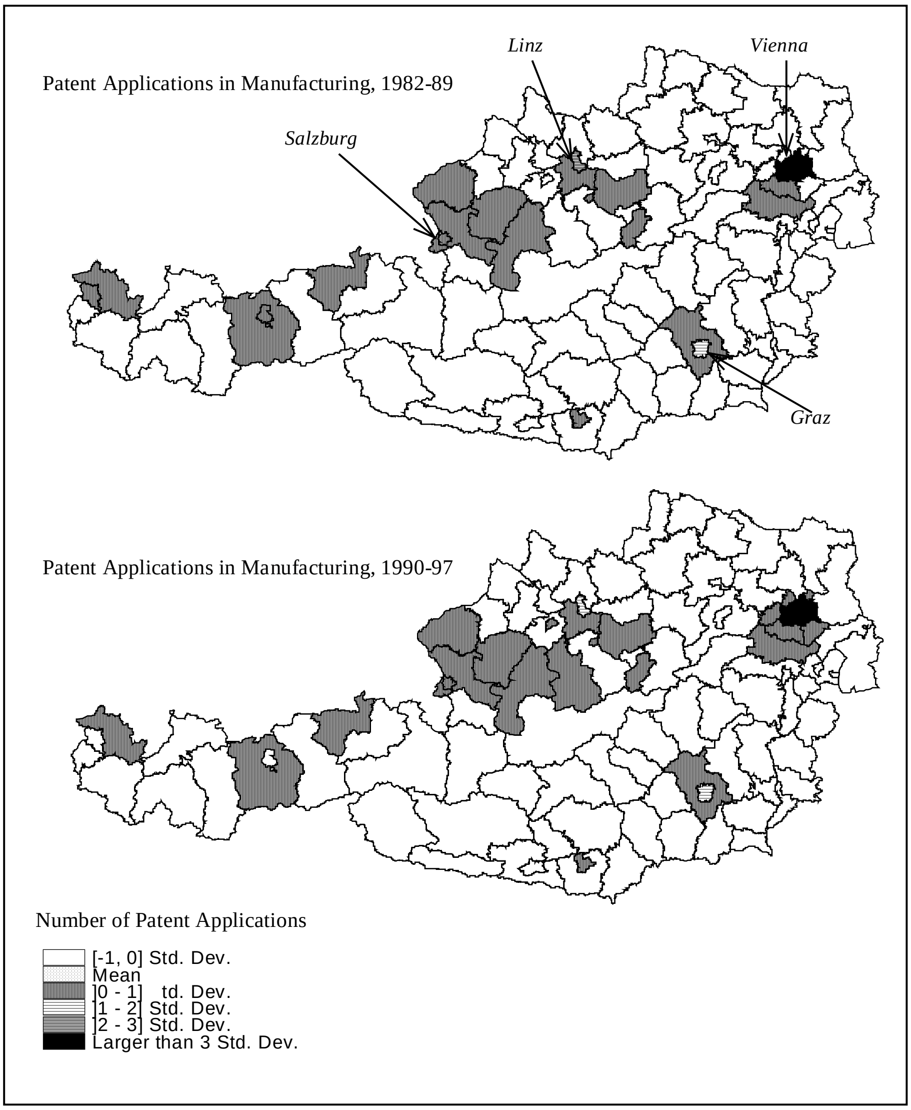
	Time Period 1982-1989	*Time Period 1990-1997*	*Percentage Change from 1982-1989 to 1990-1997*
Sectoral Share of Patents in Total Patents in Manufacturing			
Machinery	26.02	24.52	-5.75
Metal Products excluding Machines	18.18	19.97	9.87
Instruments	9.48	10.64	12.27
Transportation Vehicles	9.23	8.47	-8.29
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	-9.1
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
Normalised Herfindahl Index of Sectoral Concentration	0.30	0.29	
Share of Vienna in Manufacturing Total [as percentage]	32.16	34.05	

Source: Austrian Patent Office

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 normalised 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 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 was about the same in 1998 [1,637 patents] as it had been in 1982 [1,597 patents], the share of total knowledge output in political districts which had had an above-average level of knowledge creation 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 with above-average level of knowledge production in 1982, while regions with below-average patent applications at the beginning of the time period expanded their patenting activities from an average of 8 to 14 patents by 1998 [an increase of 88 percent]. As a result, the share of those political districts that had above average levels of knowledge creation at the beginning of the period decreased from 72 percent of the national total to 52 percent by the end of the 1990s.

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



The extent to which political districts with similar levels of knowledge production locate in each other's neighbourhood was measured by the *Moran's I* statistic for the four manufacturing areas for the period of 1982-1998, and is shown in Fig. 3. A general trend of increasing spatial dependence among neighbouring political districts emerges with no significant variation across industries.

However, values of *Moran's I* remain rather low during the entire period of study and become significant only at the beginning of the 1990s. Some sectoral differences are highlighted 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, the results in Fig. 3 show a low level of spatial dependence among neighbouring political districts in Austrian manufacturing knowledge production.

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

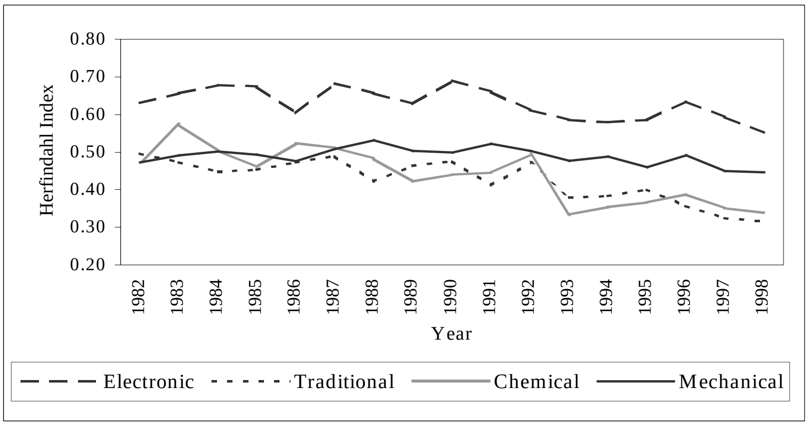


Fig. 3: Spatial association of patents across political districts for four manufacturing areas, measured by Moran's I statistics [1982-1998]

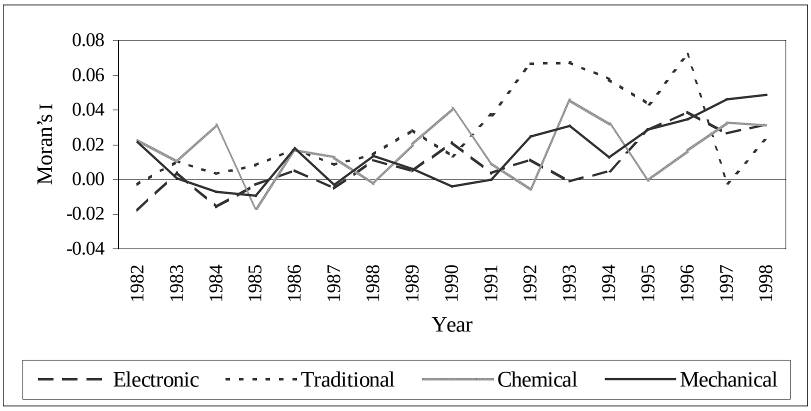
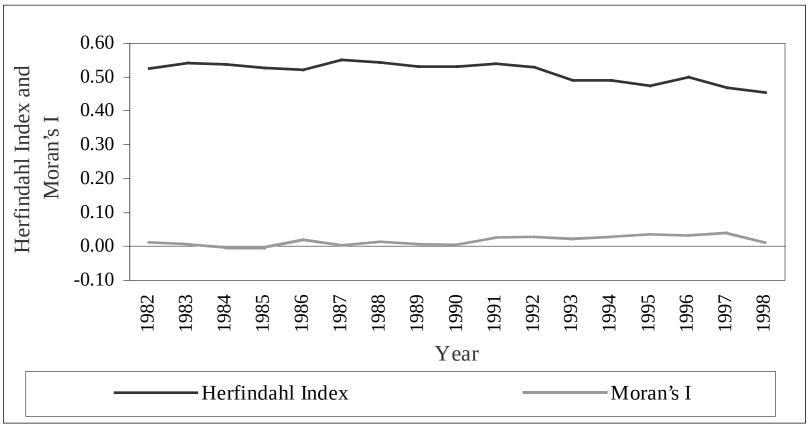


Fig. 4 illustrates the values of the two compatible measures of spatial clustering of knowledge production: the normalised Herfindahl index of geographical concentration and *Moran's I* statistic of spatial dependence, both calculated at the level of Austrian political districts for manufacturing over the period of 1982-1998. The fact that patenting activities did not expand significantly during the period of study together 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 *Moran's I* statistics] resulting in increased spatial concentration of knowledge creation. It is important to note here that the slight increase of clustering in Austrian patenting activities in the period of 1982-1998 does not seem to be the outcome of a dynamic, self-reinforcing process induced by local environments with many knowledge externalities leading to expanding clusters of knowledge production and an overall growth in knowledge output. Instead, it is characterised by a spatial shift of knowledge production to neighbouring peripheral areas, while the overall level of knowledge output stays largely unchanged.

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



The *Moran scatterplot* of Austrian patents in 1998 in Fig. 5 shows spatial patterns of Austrian knowledge production at the end of the study period. The units of observational are Austrian political districts. The horizontal axis represents standardised values of patent counts while on the vertical axis average values of the same variable in neighbouring political districts are given [i.e. a row-standardised 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 neighbouring similar regions] include Salzburg, Linz and Graz.

It is very clear from Fig. 5 that Vienna is an outlier in Austrian knowledge production. The standardised value of the number of patents in Vienna is nine times higher than the respective Austrian average. On the other hand, it is also demonstrated that Vienna is surrounded by political districts with levels of patenting activities around the average [i.e. the mean value of patents in its neighbourhood equals the national 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-standardised simple contiguity matrix has been 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].

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

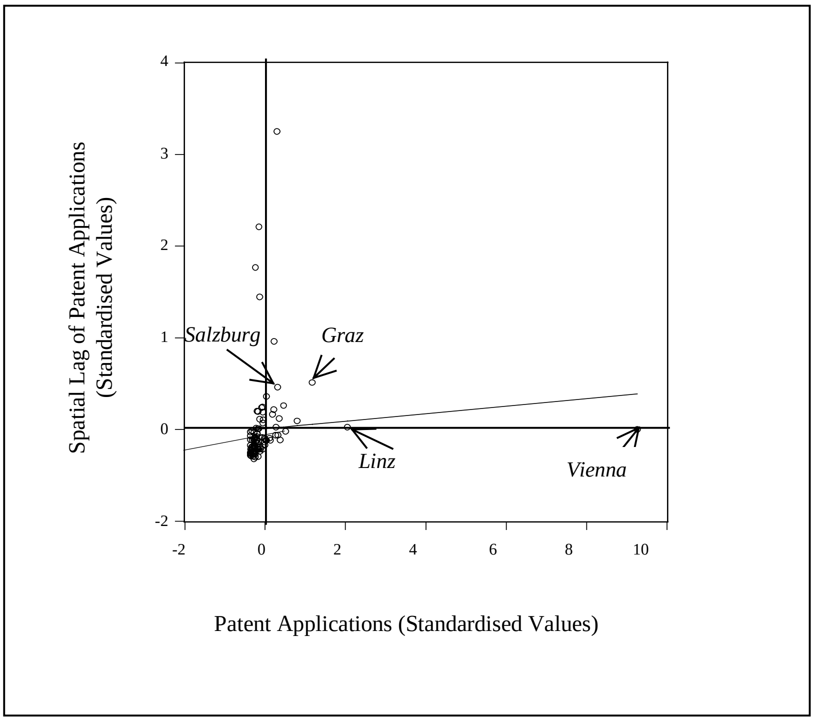
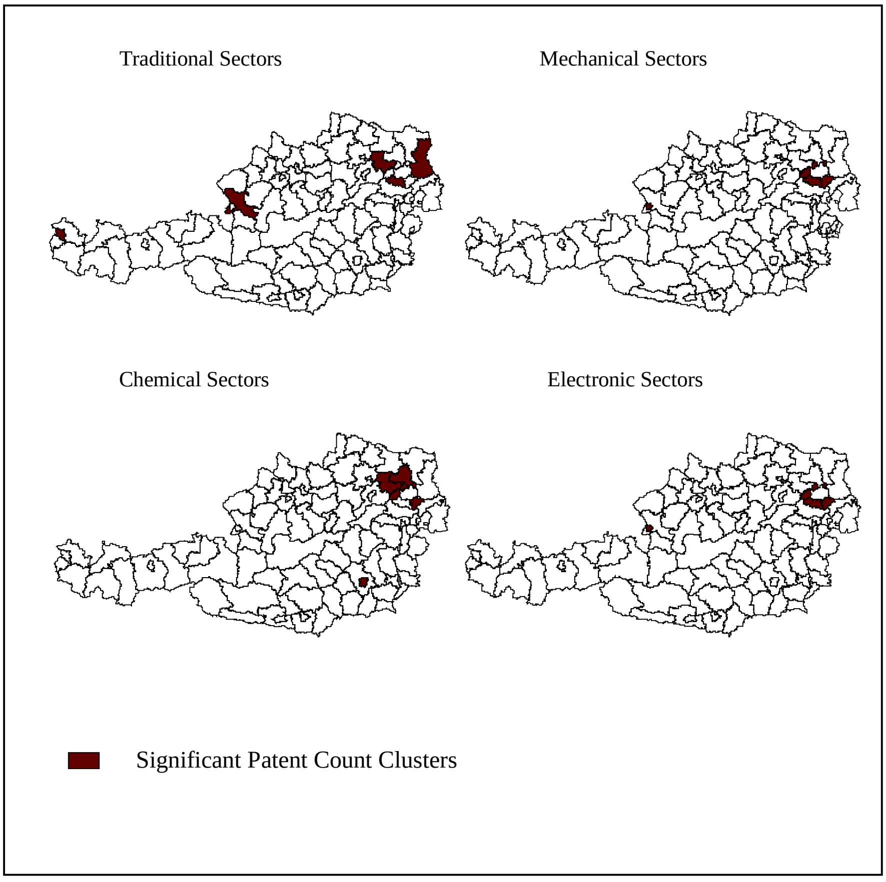


Fig. 6: Clusters of high values of patent counts for four manufacturing areas, measured by significant values of the local Moran statistics [1998]



4 Local Inputs to Innovation – an Assessment of Their Relative Significance in Knowledge Production

As emphasised in the literature on innovation systems, production of new technological knowledge is not simply the outcome of the independent efforts of firms to innovate, but is also influenced by knowledge interactions with various actors in the system including other firms, and private and public research institutions. However, knowledge flows are very difficult [if not impossible] to trace empirically. Different methods have been proposed 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).

In the previous section we observed that there has been a slightly increasing, but still a relatively modest level of geographical clustering of knowledge production in Austria. Since no systematically collected data on knowledge interactions are available at the level of the regions, in this section we have applied 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 to be an indication of knowledge spillovers existing in the production of economically useful new technological knowledge. Industrial R&D and university research are considered as potentially providing 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 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 specialisation. Whereas R&D in manufacturing concentrates in electronics, university research focuses mainly on chemistry and pharmaceuticals, and instruments. On the other hand, about forty percent of manufacturing employment is in the machinery, food and wood sectors. However, the overall sectoral concentration is not very 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 only vaguely follows 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] and the three major cities supporting the overall positive clustering tendency of patent counts [i.e. Salzburg, Linz and Graz].

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]

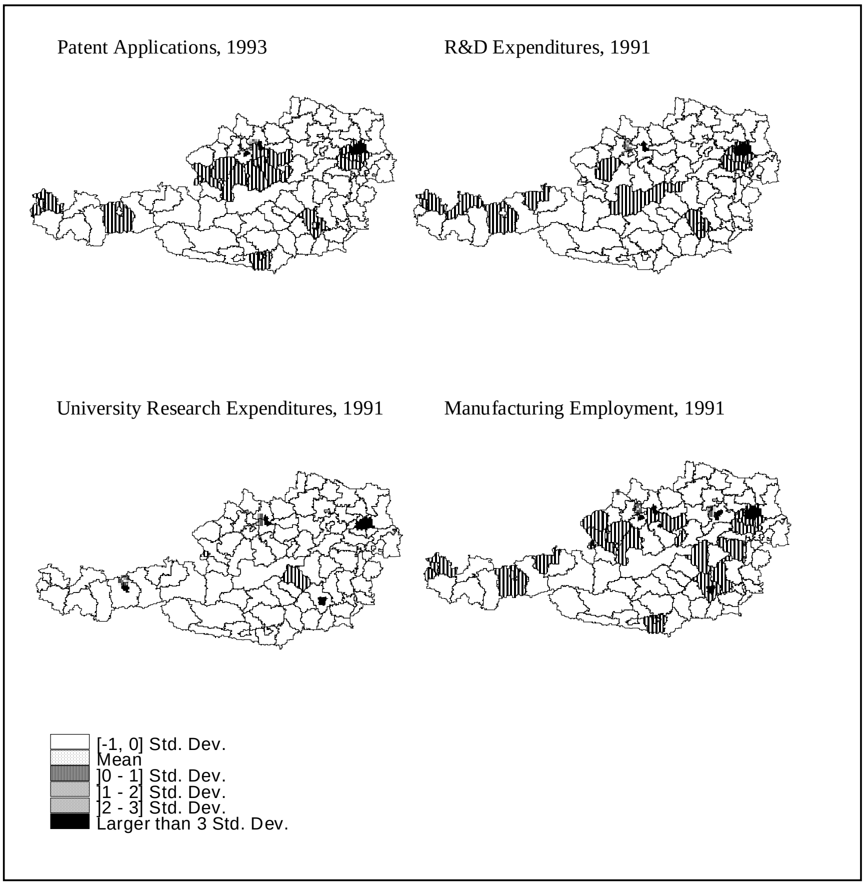
	R&D Expenditure in Manufacturing	*University Research Expenditure*	*Manufacturing Employment*
Manufacturing Sectors [a]			
Machinery	11.78	11.22	12.64
Metal Products excluding Machines	3.11	9.07	10.09
Instruments	0.73	59.49	3.80
Transportation Vehicles	7.05	21.58	4.62
Chemistry and Pharmaceuticals	15.22	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]
Normalised 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.

Fig. 8 shows correlation coefficient values for three different sets of observations: the whole sample, political districts excluding Vienna and political districts excluding Salzburg, Linz, Graz and Vienna. The following three major observations can be derived from this figure. *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*, the data shown 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 excluding Vienna 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 the 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, but not for employment.

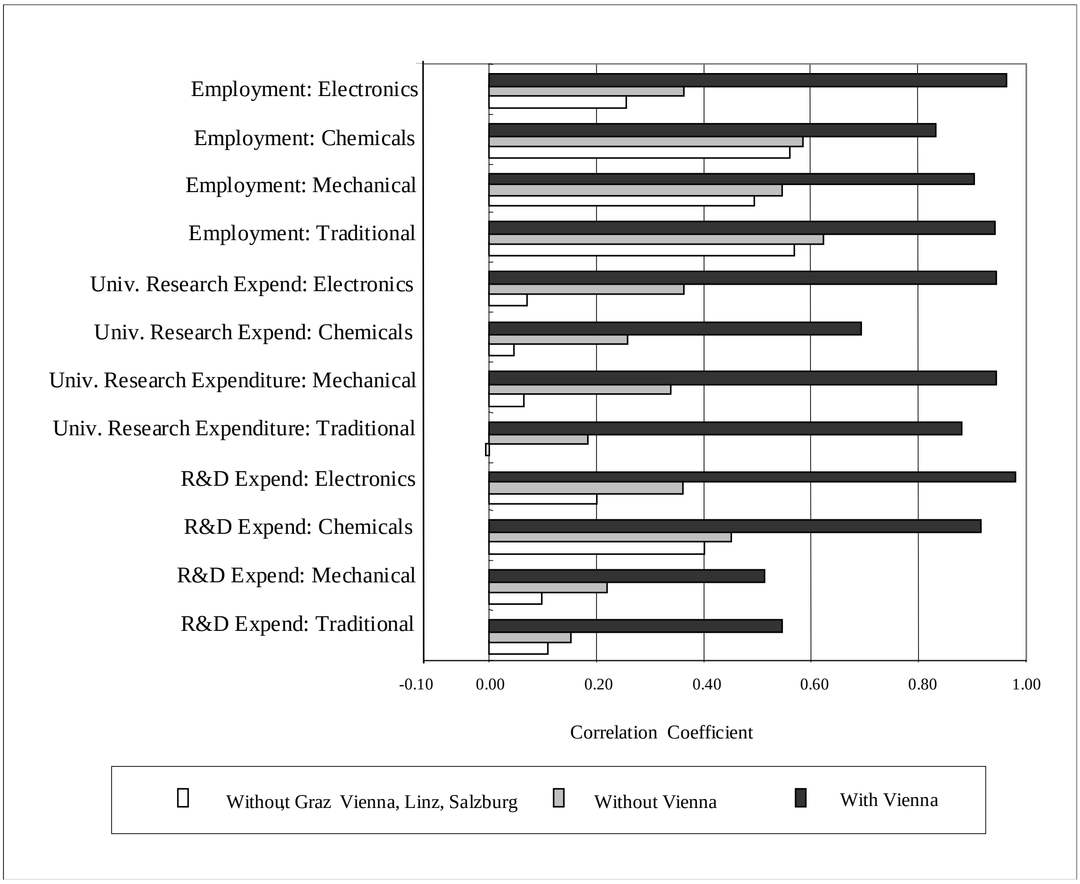
Fig. 7: Spatial distribution of patent applications, private R&D expenditures, university research expenditures and manufacturing employment in Austria



It is important to note that regional knowledge output increases faster than any of its local inputs. This might be taken as a sign of the existence of regionally mediated knowledge flows. In Fig. 9 we can see 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, in order to give an indication of the direction and size of the change in patents in manufacturing, we have also estimated the curves of nearest neighbour fit [Loess fit]. For each data point in the sample, a locally weighted polynomial regression has been estimated.

This is a local regression, since we have used only the subset of observations which lie in the neighbourhood of each 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.

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



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 arising among firms, resulting 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]. However, Fig. 10 indicates no signs of significant interregional linkages.

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

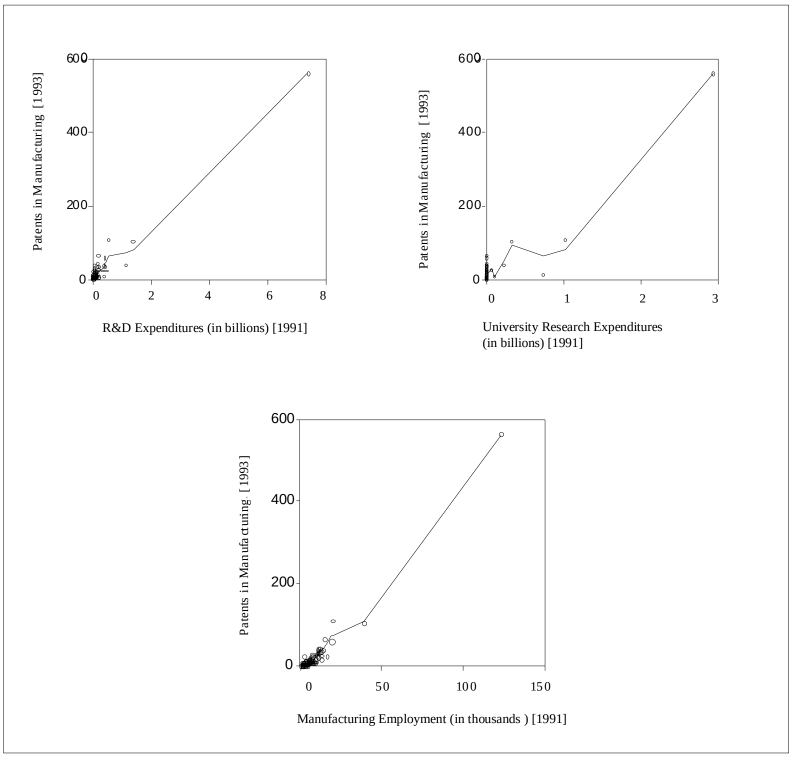
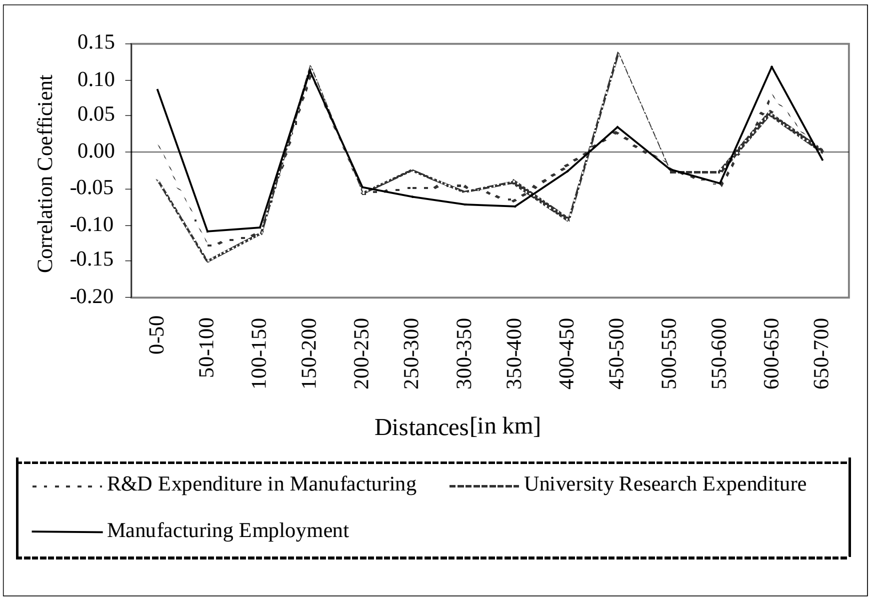


Fig. 10: Cross-regional correlation patterns between patent applications [1993] and knowledge inputs [1991] in increasing distances from the patenting political district



5 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' (Krugman 1991). 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] in this chapter we have made an initial attempt 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] are 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 focus largely in mechanical areas of manufacturing rather than in high-tech fields such as electronics or computers. It is interesting to note that this pattern has changed little during the past two decades. We have been able to identify only a weakly growing trend of clustering. However, this does not appear to be so much the outcome of a dynamic process generated by intensive knowledge flows at the local level, as 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 undeveloped 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. Future research activities will be devoted to shedding further light on the issue of local university knowledge transfer by transforming the analytical Griliches-Jaffe knowledge production approach (see, Griliches 1979; Jaffe 1989) into an operational spatial regression modelling framework that reflects the importance of spatial autocorrelation and spatial heterogeneity in applied empirical work.

Acknowledgements

The authors gratefully acknowledge the grant no. 7994 provided by the Jubiläumsfonds of the Austrian National Bank, and the support received from the Department of Economic Geography & Geoinformatics at the Vienna University of Economics and Business Administration, and the Austrian Research Centers Seibersdorf. They also wish to express their thanks to Christian Rammer, Doris Schartinger, Norbert Böck [Austrian Research Centers Seibersdorf], Werner Hackl [Austrian Chamber of Commerce, Vienna] and Karl Messman [Austrian Central Statistical Office, Vienna] for assisting in various phases of data collection.

Endnotes

[1] Traditional sectors include food, beverages and tobacco [ISIC 15-16], construction [ISIC 45], stone, clay and glass [ISIC 25], textiles and clothing [ISIC 17 and 18], paper, printing and publishing [ISIC 21 - 22] and wood and furniture [ISIC 20 and 36]. The mechanical sectors include basic metals [ISIC 27], instruments [ISIC 33], transportation vehicles [ISIC 34 - 35], machinery [ISIC 29] and metal products [ISIC 28]. The chemical sectors consist of rubber and plastics [ISIC 25], chemistry and pharmaceuticals [ISIC 24] and oil refining [ISIC 23], whereas the electronic sectors include electronics [ISIC 32], electrical machinery [ISIC 31] and computers and office machines [ISIC 30].

References

Anselin, L. (1995): Local Indicators of Spatial Association - LISA. *Geographical Analysis* 27, 93-115

Anselin, L. (1997): The Moran Scatterplot as an ESDA Tool to Assess Local Instability in Spatial Association. In: Fischer M, Scholten, H. Unwin, D. (Eds.): *Spatial Analytical Perspectives on GIS in Environmental and Socio-Economic Sciences*. Taylor and Francis, London, 111-125

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

Archibugi, D. (1992): Patenting as an Indicator of Technological Innovation: A Review. *Science and Public Policy* 19, 357-368

Archibugi, D., Pianta, M. (1996): Measuring Technological Change through Patents and Innovation Surveys. *Technovation* 16, 451-468

Audretsch, M. (1994): Knowledge Spillovers and the Geography of Innovation and Production. Discussion Paper No. 953, Centre for Economic Policy Research, London

Basberg, B. (1987): Patents and the Measurement of Technological Change: A Survey of the Literature. *Research Policy* 16, 131-141

Braczyk, H., Cooke, P., Heidenreich, M. (1998): *Regional Innovation Systems. The Role of Governances in a Globalized World*. UCL Press, London

Bundesministerium für Wissenschaft und Verkehr (1993): Arbeitsberichte der Institutsvorstände gemäß § 95 UOG ’75 über das Studienjahr (1991/92). Vienna

Cleveland, W. (1994): *The Elements of Graphic Data*. Hobart Press, Summit

Cooke, P., Uranga, M., Etxebarria, G. (1997): Regional Innovation Systems: Institutional and Organisational Dimensions. *Research Policy* 26, 475-491

Edwards, K., Gordon, T. (1984): Characterization of Innovations Introduced on the U.S. Market in 1982. The Futures Group, U.S. Small Business Administration, Washington D.C.

Fischer, M. M. (1998): Spatial Analysis: Retrospect and Prospect. In: Longley, P., Goodchild, M. F., Maguire, D. J., Rhind, D. W. (Eds.) *Geographical Information Systems: Principles, Technical Issues, Management Issues and Applications.* Wiley, New York, 283-292

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

Fischer, M. M. (2001b): Spatial Analysis. In: Smelson, N., Baltes, P. (Eds.): *International Encyclopedia of the Social & Behaviourial Sciences*. Pergamon, Amsterdam (forthcoming)

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

Freeman, C. (1987): *Technology and Economic Performance: Lessons from Japan*. Pinter, London

Gassler, H. (1993): Regionale Disparitäten der betrieblichen Inventionsaktivitäten in Österreich. Eine empirische Analyse unter Verwendung von Patentdaten. *Klagenfurter Geographische Schriften* 11, 173-186

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

Griliches, Z. (1990): Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature* 28, 1661-1707

Haagedoorn, J. (1994): Technological Partnering in Strategic Alliances. Paper prepared for the Austrian Conference on R&D Co-Operation, Vienna

Hicks, D., Katz, S. (1996): Systemic Bibliometric Indicators for the Knowledge-Based Economy. Paper presented at the OECD Workshop on New Indicators for the Knowledge-based Economy, Paris

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

Jaffe, A., Trajtenberg, M., Henderson, R. (1993): Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *Quarterly Journal of Economics* 108, 577-598

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

Pavitt, K. (1988): Uses and Abuses of Patent Statistics. In: Raan, A.F.J. van (Ed.): *Handbook of Quantitative Studies of Science and Technology*. North Holland, Amsterdam, 509-535

Storper, M. (1997): *The Regional World. Territorial Development in Global World*. The Guilford Press, New York

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

Varga, A. (2000): Local Academic Knowledge Spillovers and the Concentration of Economic Activity. *Journal of Regional Science* 40, 289-309

Verspagen, B., Moergastel T., Slabbers, M. (1994): MERIT Concordance Table: IPC-ISIC (rev.2). MERIT Research Memorandum 2-94-004, Maastricht

Wirtschaftskammer Österreich (1992): Forschung Entwicklung Österreich, Vienna

Appendix

Tab. A.1: Patent Applications, R&D Expenditure, University Research Expenditure and Employment in Manufacturing for 99 Austrian Political Districts

Political District	Patent Applications (1993)	Industrial R&D Expenditure in 10^3 ATS (1991)	University Research Expenditure in 10^6 ATS (1991)	Employment (1991)
Eisenstadt (Stadt)	6	0	0	596
Rust (Stadt)	0	0	0	41
Eisenstadt-Umgebung	4	32,344	0	1,776
Güssing	0	1,000	0	1,023
Jennersdorf	1	0	0	1,427
Mattersburg	4	10,548	0	3,461
Neusiedl am See	5	14,771	0	1,731
Oberpullendorf	1	4,390	0	2,555
Oberwart	0	3,978	0	5,096
Klagenfurt (Stadt)	27	13,527	36	7,113
Villach (Stadt)	11	25,919	0	5,647
Hermagor	2	160	0	1,045
Klagenfurt Land	22	0	0	2,251
Sankt Veit an der Glan	5	8,160	0	5,162
Spittal an der Drau	5	90,711	0	4,655
Villach Land	8	52,886	0	3,687
Völkermarkt	1	3,200	0	3,236
Wolfsberg	5	18,586	0	4,497
Feldkirchen	2	1,439	0	1,702
Krems (Stadt)	5	52,877	0	4,057
Sankt Pölten (Stadt)	7	33,383	0	8,333
Waidhofen (Stadt)	7	4,595	0	1,606
Wiener Neustadt (Stadt)	5	36,376	0	5,143
Amstetten	36	107,121	0	12,255
Baden	38	348,885	0	13,350
Bruck an der Leitha	2	34,450	0	2,343
Gänserndorf	13	7,225	0	4,711
Gmünd	9	0	0	5,514
Hollabrunn	1	770	0	1,743
Horn	7	1,456	0	2,279
Korneuburg	16	26,586	0	5,579
Krems (Land)	2	0	0	1,823
Lilienfeld	1	3,521	0	3,253
Melk	9	9,790	0	4,714
Mistelbach	8	0	0	3,697
Mödling	32	196,105	0	10,616
Neunkirchen	13	67,802	0	8,637
Sankt Pölten (Land)	14	51,303	0	7,303
Scheibbs	2	3,600	0	2,847
Tulln	4	28,057	0	3,445
Waidhofen an der Thaya	1	11,930	0	3,168
Wiener Neustadt (Land)	7	7,618	0	5,515
Wien-Umgebung	23	305,350	0	10,303
Zwettl	4	0	0	2,233
Linz (Stadt)	101	1,375,777	218	39,068
Steyr (Stadt)	39	1,124,624	0	11,399
Wels (Stadt)	28	35,720	0	9,744
Braunau am Inn	14	158,617	0	12,958
Eferding	5	3,772	0	2,725
Freistadt	1	420	0	2,571

Tab. A.1 continued

Political District	Patent Applications (1993)	Industrial R&D Expenditure in 10^3 ATS (1991)	University Research Expenditure in 10^6 ATS (1991)	Employment (1991)
Gmunden	42	133,864	0	11,832
Grieskirchen	14	51,170	0	5,883
Kirchdorf an der Krems	23	17,706	0	7,065
Linz-Land	21	102,877	0	16,499
Perg	13	23,580	0	4,894
Ried im Innkreis	7	50,189	0	6,108
Rohrbach	4	3,650	0	3,817
Schärding	8	33,760	0	4,239
Steyr-Land	12	9,314	0	3,317
Urfahr-Umgebung	10	0	0	2,658
Vöcklabruck	56	386,655	0	19,110
Wels-Land	9	79,982	0	7,511
Salzburg (Stadt)	37	41,309	137	10,594
Hallein	12	123,539	0	6,642
Salzburg-Umgebung	31	22,640	0	10,490
Sankt Johann im Pongau	14	21,155	0	5,200
Tamsweg	1	0	0	1,044
Zell am See	7	32,316	0	4,575
Graz (Stadt)	105	519,747	1,288	19,544
Bruck an der Mur	7	99,697	0	9,246
Deutschlandsberg	9	114,536	0	5,595
Feldbach	3	6,705	0	4,050
Fürstenfeld	2	12,416	0	2,308
Graz-Umgebung	25	461,144	0	9,425
Hartberg	4	10,400	0	4,929
Judenburg	14	79,326	0	6,633
Knittelfeld	3	19,529	0	3,805
Leibnitz	4	3,017	0	5,377
Leoben	9	48,238	176	6,755
Liezen	7	191,806	0	6,040
Mürzzuschlag	6	26,212	0	6,336
Murau	4	0	0	1,837
Radkersburg	0	383	0	1,249
Voitsberg	13	40,615	0	4,010
Weiz	9	142,596	0	7,566
Innsbruck (Stadt)	15	5,692	907	5,637
Imst	5	14,050	0	2,352
Innsbruck (Land)	35	422,458	0	13,247
Kitzbühel	10	22,031	0	3,233
Kufstein	10	356,486	0	9,382
Landeck	0	0	0	1,776
Lienz	5	9,147	0	4,043
Reutte	5	183,676	0	2,722
Schwaz	18	102,295	0	7,303
Bludenz	5	24,674	0	7,075
Bregenz	65	180,774	0	14,763
Dornbirn	23	191,232	0	13,117
Feldkirch	20	134,127	0	10,918
Vienna	541	7,374,721	3,652	122,960

Sources: Patent applications data come from the Austrian Patent Office; industrial R&D data from the Austrian Chamber of Commerce; university research data from the Austrian Federal Ministry for Science and Research; employment data from the Austrian Central Statistical Office.