DISCUSSION PAPER

Spatial R&D Spillovers and Economic Growth – Evidence from West Germany

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Abstract

The paper bases itself on recent theoretical writings in growth economics that emphasize the effects of both own R&D efforts and of interregional technology spillovers on regions´ productivity. We propose robust estimation techniques to evaluate the R&D spillovers across West German functional regions during the period 1976 – 1996. The findings suggest the existence of knowledge spillovers across functional regional boundaries. Moreover, significant spillovers are mainly found among geographically close regions. This finding confirms the hypothesis that proximity matters.

Zusammenfassung

Das Papier basiert auf jüngeren Beiträgen zur Wachstumstheorie, die den Stellenwert eigener F&E-Anstrengungen und interregionaler Spillover-Effekte für die regionale Produktivitätsentwicklung betonen. F&E-Spillover zwischen funktionalen Regionen in Westdeutschland werden auf der Grundlage robuster Regressionsmethoden für den Zeitraum zwischen 1976 und 1996 untersucht. Die empirischen Ergebnisse deuten darauf hin, dass Wissensspillover die Grenzen funktionaler Regionen überschreiten. Zudem sind signifikante Spillover-Effekte vor allem zwischen räumlich benachbarten Gebieten festzustellen. Dieses Resultat bestätigt die Hypothese, dass räumliche Nähe von wesentlicher Bedeutung ist.

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Keywords: R&D Spillovers, Economic Growth, Germany
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1. INTRODUCTION

During the last decade, models of economic growth have emphasized the importance of investment in intangible assets as a major source of productivity growth. Investment in R&D has been ascribed to yield high social returns. Empirical studies have also confirmed the positive correlation between growth and R&D expenditures at the macroeconomic level. Consequently, an important topic for economist who deal with growth issues is the study of the interaction of R&D activities in one place with those in another place. New economic geographers argue that increasing returns and externalities are not international or even national in scope, but arise through a process of regional economic agglomerations. The agglomerating forces are basically localisation and urbanisation externalities which tend to lead to the local clustering of economic activity. This may lead to a core-periphery pattern of economic development and therefore and increasing ß-divergence between the "rich" core and a less prosperous "periphery". Alternatively, if labour remains relatively immobile between regions, knowledge spillovers are high, and congestion costs are significant, then economic growth will induce spatial dispersal of economic activity and therefore ß-convergence. Case studies of Silicon Valley [Saxenian (1994)], Northern Italy [Storper (1992)] and Baden-Württemberg [Sternberg (1992)] are often cited to stress the importance of geographical proximity for productivity and growth in "core" regions. Are these examples mere exceptions or does there exist a systematic effect of the neighbour regions activity on other regions´ economic performance? Have the externalities (technological spillovers, labour market pooling, and intermediate goods demand and supply linkages) led to a polarization pattern or a spatial dispersal of economic activity? What is the role of geographic proximity in the R&D and growth process? Does proximity support the transmission of knowledge and therefore promote future growth?[1]

The empirical work reported here attempts directly to test some of these policy concerns. We use recently developed methods of spatial data analysis and robust estimation techniques to provide new insights on the spatial pattern of the interaction of 71 regions (*Raumordnungsregionen*) in West Germany over the 1976-1996 period. In the remainder of the study, we first provide an overview of spillover models and studies. Since the basic models of this theory are well-known, we provide in this Section only rudimentary

1 In Eastern Germany, for example, the Treuhandanstalt has rescued "industrial cores" on the theory that new businesses will spring up only where some industry still survives. The core of this policy approach therefore is the assumption that geographic proximity matters. The importance of "industrial cores" has recently been modelled by Englmann and Walz (1995).

details and concentrate instead on the results that are relevant for our purposes. The data, the empirical methodology, the empirical results and its economic interpretation are presented in section 3 and 4. Section 5 concludes.

2. A REVIEW OF SPILLOVER MODELS AND STUDIES

According to endogenous growth models, an important element of theories of innovation is the concept of knowledge and research spillovers. The models generally combine imperfect competition with innovation-based growth and learning-by-doing in innovation. These forces generate intra- and interregional spillovers from R&D and patenting. A recent model by Aghion and Howitt (1998, pp. 365-395) is driven by product differentiation, quality improvements and research spillovers. The underlying theory allows new intermediate products to open up as in Romer´s (1990) horizontal innovations model which are then subject to quality improvements as in Young´s (1998) vertical innovations model. Bottazzi and Peri (1999) consider a model with *N* regions in the spirit of the endogenous growth literature. The setup of their model is as follows. Skilled workers are perfectly mobile both between research and production and across regions. Each region innovates by adding further intermediate goods that increase the productivity and technological level of the region itself. Finally they allow for spillovers in the level of knowledge across regions. In particular, there exists a catch-up process which prevents regions´ per capita income level to grow increasingly apart or a diffusion of knowledge across space which binds regions together. Kelly and Hageman (1999) consider a quality ladder model of growth augmented by Marshallian externalities in innovation. An important feature of their model is that the Marshallian externalities are more important for innovation than for production. Another ingredient of their model is that innovation and production need not occur in the same locations. As a result, R&D activities can have an important effect on growth irrespective of the location. Audretsch (1998) and Krugman (1998) add to these theories that there may be geographical boundaries to R&D spillovers, particularly because of tacit knowledge. While the cost of transmitting information across regions and countries may be increasingly invariant to distance due to the internet revolution, presumably the marginal costs of transmitting tacit knowledge rises with distance because non-codified knowledge is vague and requires face-to-face interaction.[2] As a result, R&D spillovers may be restricted in space and therefore geographical proximity matters.

2 For an in depth analysis of the importance of face-to-face interaction see Gaspar and Glaeser (1996).

The seminal contribution of Romer (1990) can serve as a starting point to formulate a consistent growth model with endogenous technological progress. A key feature of the model is that knowledge is non-rival and therefore everyone engaged in R&D has free access to the entire stock of knowledge. The mechanism which produces this result is the rate of growth of A, the stock of non-rival knowledge. This is modelled as a function of researchers in R&D (L_A). Thus, the stock of A and the level of L_A drive economic growth. This leads to the equation:

(1) $$\dot{A} = \delta A L_A$$

where δ is a constant and $\dot{A} = \partial A/\partial t$. In equation (1) it is assumed that everyone engaged in R&D has free access to the entire stock of knowledge. A more plausible assumption for regional economists is to assume a distance-decay function associated with access to R&D reflecting the existence of tacit knowledge. This idea can easily be incorporated within the following version of equation (1):

(2) $$\dot{A}_R = \delta A L_{A,R} \theta_R$$

and

(3) $$\theta_R = L_{A,R}^{\alpha}$$

where R denotes the region and θ_R denotes knowledge spillovers. The parameter α (α > 0) measures the concentration of R&D employees within a region and therefore represents the opportunities for productive contacts. Equation (2) and (3) yield:

(4) $$\dot{A}_R = \delta A L_{A,R}^{\alpha+1}$$

A characteristic feature of this innovation-driven growth model is that the knowledge production function is characterized by increasing returns to scale because of the existence of spillover effects. The logical consequence of such an explanation is that all R&D personnel would ultimately end up in one region and this region would have the fastest rate of economic growth. In order to prevent all R&D concentrating in a single region, a model in the spirit of that suggested by Jones (1995) can be used. In a highly influential paper, Jones (1995) points out that the OECD countries have experienced various important policy changes that might have been expected to raise growth. Yet there has been no apparent payoff in terms of faster growth. If anything, productivity growth has slowed, at least until recently. Jones (1995) argues that this is evidence of decreasing returns in the production of new knowledge. To accommodate such decreasing returns, he proposes to modify the artificial and unrealistic equation (1) into:

$$(5) \qquad \dot{A} = \delta A L_A^{\lambda} A^{\phi-1} = \delta L_A^{\lambda} A^{\phi}$$

with $\lambda \leq 1$ and $\phi < 1$. This suggests focusing on the following "semi-endogenous" regional production function for new ideas which eliminates the long-run growth effects of policy:

$$(6) \qquad \dot{A}_R = \delta L_{A,R}^{\lambda+\alpha} A^{\phi}$$

In equation (6), the steady state growth rate is exclusively determined by exogenous factors, i.e. the effects of an increase in R&D effort would not last forever. The practical implications of equation (6), however, would not be that different provided that the transition dynamics could nevertheless be long.

Notwithstanding the encouraging development of formal models, the empirical basis of the new growth models is still rather thin. In a highly influential article at the macro level Coe and Helpman (1995) have found that both domestic and foreign R&D contribute significantly to TFP growth. Moreover, foreign R&D has become increasingly important, especially for smaller countries.[3] Econometric studies for the United States and Europe using aggregate and microlevel data have also underlined the importance of geographical proximity. Feldman (1994) and Audretsch and Feldman (1996) have modified the model of knowledge production function to include an explicit specification for the spatial dimension. They document the clustering of innovative activity, especially at the early stage of the life cycle of products. Brandstetter (1996) has estimated the size of intranational spillovers (which exceed international spillovers) using microlevel data. He shows that technological externalities can generate persistent growth differentials. Finally, Bottazzi and Peri (1999) use European regional data to test for the existence of spatial spillovers of R&D.

3 These results are, however, not undisputed. Kao et al. (1999) and Keller (1998) have presented panel cointegration results and Monte-Carlo-based robustness tests which cast doubt on the claim that patterns of international trade are important in driving R&D spillovers.

To summarize, the international evidence tends to confirm the existence of intraregional R&D spillovers. The empirical evidence on the importance of R&D proximity for regional growth in Germany, however, is still very scarce.[4] This begs the question of whether and to what extent knowledge externalities are localized in Germany. Using data for 75 West German *Raumordnungsregionen*, we carry out a regression analysis that links regional per capita GDP growth to the R&D activity of both this region and its neighbouring regions.[5]

3. THE SPECIFICATION OF SPATIAL INTERACTION

In this paper we analyse spatial interaction by means of accessibility measures. The applied potential measure approximates spatial interaction, assuming that accessibility and degree of interaction decline with increasing geographical distance. Potential measures reflect the intensity of spatial interaction in the considered region as well as the possible interaction with neighbouring areas [Bröcker (1984) and (1989)]. Thus, in contrast to explanatory variables that are simply based on observations for given geographical units, potential measures do not neglect spatial externalities between regions since they are continuous over space [Talen and Anselin (1998)].[6]

The potential measure applied to capture the effects of R&D spillovers is based on regional R&D employment RD_i. The negative relation between distance and intensity of spatial interaction of R&D employees is taken into account by spatial weights w_{ij} that are based on a negative exponential function with distance decay parameter β_E. The R&D-potential of region *i* reflects the accessibility of all R&D employees in the centre of the considered region and is given by:

4 The few exceptions include Bode (1999a) and (1999b).

5 We have used data for the *Raumordnungsregionen* because West German state-level data (*Bundesland-Daten*) are likely to be too aggregated to be useful. Another advantage of the *Raumordnungsregionen* is that these spatial units are functional regions which are economically coherent and relatively self-contained.

6 An approach that ignores spatial externalities is only appropriate if the extent of spatial effects and geographical units coincide. But this is more likely to be the exception than the rule because regional data are usually available for administrative units that were arranged without consideration of economic ties and spatial interaction.

$$(7) \qquad RDP_i = \sum_{j=1}^{R} RD_j \cdot w_{ij} = RD_i \cdot w_{ii} + \sum_{\substack{j=1 \\ j \neq i}}^{R} RD_j \cdot w_{ij}$$

$$= \left[rd_i \int_0^{c_i} 2 \cdot \pi \cdot \breve{c} \exp(-\beta_E \cdot \breve{c}) d\breve{c} \right] + \sum_{\substack{j=1 \\ j \neq i}}^{R} RD_j \cdot \exp(-\beta_E \cdot d_{ij})$$

The potential measure consists of the self-potential of region i and the cumulated influence of the other (R-1) regions. The self-potential is given by the first term in brackets. The computation assumes that R&D employment is evenly distributed on the circular area of the region F_i with corresponding radius $c_i = (F_i / \pi)^{1/2}$. The density of R&D employment is $rd_i = RD_i / F_i$. The self-potential measures the accessibility of R&D employees within the respective region. Thus, given the number of R&D employees the spatial interaction declines with increasing regional area respectively growing intraregional distances. The computation of interregional effects assumes that R&D employment is concentrated in the centres of the (R-1) regions. The intensity of interaction declines with increasing distance d_{ij} between the centres of the regions i and j according to the negative exponential function.

The interpretation of the empirical results is based on the "half-life distance" $d_E = (\ln 2) / \beta_E$, i.e. the distance that reduces the spatial interaction by 50% [Bröcker (1984), Stetzer (1982)] and a transformed distance decay parameter γ_E [Bröcker (1989)]:

$$(8) \quad \beta_E = -(\ln(1 - \gamma_E)) / \overline{D}_{MIN} \qquad (0 \leq \gamma_E \leq 1)$$

$\overline{D}_{MIN}$ denotes the average distance between the centres of immediately neighbouring regions. The parameter γ_E measures the percentage decrease of the spatial interaction, i.e. the decline of the weights as distance expands by the unit $\overline{D}_{MIN}$. With increasing γ_E geographical impediments gain in strength, so that the decline of spatial interaction becomes more pronounced with increasing distance from region i. Hence, alternative spatial extents of R&D spillovers can be generated by a variation of the distance decay.

A fundamental problem results from the incorporation of parameters determining the proper distance relationships in equation (7). The choice of a distance function is not clear-cut, often done in an ad hoc manner and/or governed by convention. This creates problems for the estimation and interpretation of the results. In particular, it could potentially lead to the inference of *spurious* relationships, since the validity of estimates is pre-conditioned by the extent to which the assumed spatial structure is correct. More importantly, it could even results in a circular reasoning, in that the spatial interaction structure, which the researcher may wish to discover in the data, is assumed before estimation is actually carried out.[7]

Traditional procedures which have been used to identify appropriate spatial weights include information criteria and tests for spatial autocorrelation.[8] This paper takes a different point of view. We use a robust estimation technique which can determine unrepresentative or outlying observations in the cross-section dataset in order to investigate which spatial weight is consistent with the unknown data generating process. So far, in the empirical growth literature an explanatory variable has been called "robust" in case changes in the list of explanatory variables do not alter its estimated coefficient too much.[9] Subsequently, we will use a different definition of "robustness". In our paper "robustness" is defined with respect to the observations included in the regression. Hence, we start sensitivity analysis by looking at the regions included in the regression. Does the spatial interaction structure affect the estimation results and the number of outliers? Can robust regression methods be used to guide the weight specification for a particular problem? Since outliers are always defined with respect to the specific model being estimated, examination of unusual observations might lead to the formulation of a more appropriate spatial interaction structure in which these observations are no longer outlying. In order to shed further light on these issues we first have to pinpoint the so-called outlying observations.

We will use the least trimmed squares (LTS) estimator of Rousseeuw and Leroy (1987) as a specification device to identify outlying observations and the distance parameters.[10] We restrict our attention to the linear regression model and define an "outlier" as an ob-

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7 For example, Bode (1999a, pp. 20-21) has recently specified the geographic weights in his paper on Germany in an ad hoc manner. The paper is therefore ill-suited to determine the spatial extent of R&D spillovers.

8 The issue of the possible impacts of misspecification of the spatial weights matrix has not yet received great attention in the literature. Among the few exceptions are Stetzer (1982) and Florax and Rey (1995). Their results suggest that specification of spatial dependence is important, especially when sample size is small.

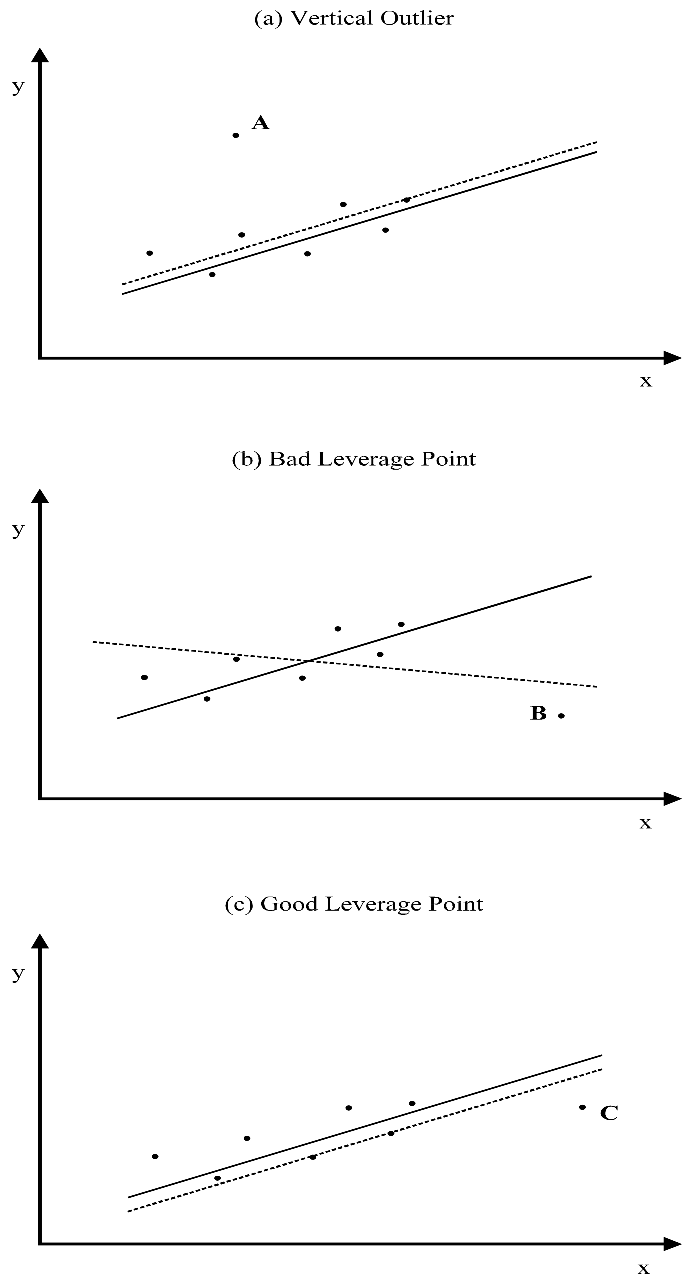
9 Levine and Renelt (1992) have used extreme-bound tests to investigate the robustness of explanatory variables linked with economic growth in cross-section regressions. Their overall conclusion is that very few regressors pass such extreme-bound tests.

10 For a brief survey of robust estimation methods and applications, see Rousseeuw (1997).

servation lying outside the typical relationship between the dependent and explanatory variables revealed by the majority of the data. Take for instance Figure 1(a). In that Figure point A is clearly an outlier; it lies outside the typical relationship between x and y. Especially such outliers in the dependent variable, i.e. in the y-direction, have received quite some attention in the literature. Such vertical outliers often possess large positive or large negative residuals, which are easy to identify when plotting the residuals. Note, however, that if x_i is near the centre of the set of explanatory variables, as is the case in Figure 1(a), it will mainly affect the constant and hardly alter the slope. Alternatively, outliers can occur in the x-direction. As Figure 1(b) shows, even one unusual observation in the x-direction (point B) can actually tilt the OLS regression line. It does not fit the main sequence (in fact, it does slope downwards) because it attempts to fit all the data points and is pulled away by point B. In such a case we call the outlier a bad leverage point, in analogy to the notion of leverage in mechanics. In general we call an observation a leverage point whenever it lies far away from the bulk of the observed x in the sample. Note that this does not take y into account, so a leverage point does not necessarily have to be an outlier. For instance in Figure 1(c), the leverage point C lies exactly on the regression line determined by the majority of the data, and hence is not an outlier. We consider it to be a good leverage point. Therefore, saying that an observation is a leverage point refers only to its potential for strongly affecting the regression coefficients. Obviously, the most worrysome outliers, i.e. bad leverage points often cannot be discovered by looking at the OLS residuals. As in Figure 1(b), if the regression line is tilted by the bad leverage point, deleting the points with the largest OLS residuals implies that some "good" observations would be deleted instead of the bad leverage point. Hence, outliers pose a serious threat to standard least squares analysis.[11]

11 For example, in the recent empirical growth literature, the link between equipment investment and economic growth has been analyzed for a broad cross section of countries. DeLong and Summers (1991, 1992) have initially argued that equipment investment yields high externalities. Auerbach et al. (1994) have, however, demonstrated that this result is very fragile and essentially driven by *one* outlier in the cross-section dataset (Botswana).

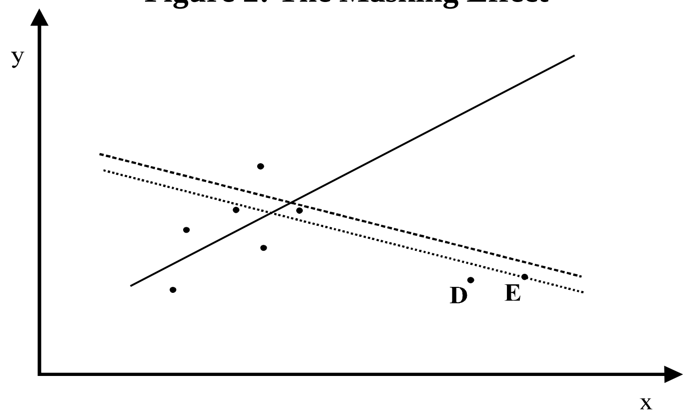
Figure 1: Outlying Observations and Leverage Points



Note: The dashed lines represent the OLS estimates including the unusual observation. The solid lines represent the OLS estimates without the unusual observations.

Basically, there are two solutions to this problem: regression diagnostics and robust estimation. Regression diagnostics are certain statistics mostly computed from the OLS regression estimates with the purpose of pinpointing outliers and leverage points.[12] Often the outliers are then removed from the dataset. When there is only one outlier, then some of these methods work quite well. It is, however, much more difficult to identify outliers when there are several of them. Take for instance Figure 2. Deleting either of the two observation D and E will have little effect on the regression outcome and will therefore not be spotted by single-case diagnostics. The potential effect of one outlying observation is actually masked by the presence of the other. This so-called masking-effect can only be solved when observations are considered to be jointly outliers and/or leverage points.[13]

Figure 2: The Masking Effect



Note: The dotted line represents the OLS estimates including both outlying observations D and E. The dashed line represents the OLS estimates without the first unusual observations D. The solid line represents the OLS estimate without both unusual observations D and E.

In this paper we turn to the second approach, called robust regression. It tries to devise estimators which are not so strongly affected by outliers. When using as a diagnostic tool, robust techniques first fit a regression to the majority of the data and then determine outliers as those points which possess large residuals from that robust solution.

The most well-known estimator is the OLS method. The basic idea behind this estimator is to optimize the fit by minimizing the sum of squared residuals (e_i):

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12 Of course, in simple regression this is not a big problem since one should first look at a scatterplot of the (x_i, y_i) data. But in multiple regression, this is no longer possible, i.e. the real challenge is multiple regression. Chatterjee and Hardi (1988) and Rousseeuw and Leroy (1987) discuss regression diagnostics.

13 Such joint tests, however, pose serious computational problems. For the single-case diagnostic measure we need to compute n diagnostics, one for each observation. In the multiple observations case, for each subset of variables of size m, there are $n!/[m!(n-m)!]$ possible subsets for which diagnostic test statistics can be computed. For n=75 and m=3 this results in 67525 diagnostics.

(9) $$\min_{\hat{\beta}} \sum_{i=1}^{n} e_i^2$$

For OLS we know that one outlier can be sufficient to cause the estimator to take on values for $\hat{\beta}$ arbitrarily far from β. As shown in Figure 1(b), one observation like point *B* is sufficient to throw the OLS line indefinitely far off target. This is independent of the total number of observations *n* available. The OLS breakdown point equals $1/n$ which tends to zero for increasing sample size, which reflects the extreme sensitivity of the OLS method to outliers.[14]

The least trimmed squares (LTS) estimator proposed by Rousseeuw and Leroy (1987) can formally be written as:

(10) $$\min_{\hat{\beta}} \sum_{i=1}^{h} \left(e^2\right)_{i:n}$$

where$(e^2)_{1:n} \leq (e^2)_{2:n} \leq ... \leq (e^2)_{n:n}$ are the ordered squared residuals (note that the residuals are first squared and than ordered). Formula (10) is very similar to OLS, the only difference being that the largest squared residuals are not used in the summation, thereby allowing the fit to stay away from the outliers. The LTS estimator is consistent and asymptotically normal. In order to determine the LTS location estimate one has to consider the n-h+1 subsamples $\{y_{1:n}, ..., y_{h:n}\}, \{y_{2:n}, ..., y_{h+1:n}\}, ..., \{y_{n-h+1:n}, ..., y_{n:n}\}$. With *k* unknown parameters the LTS method attains the highest possible breakdown value, namely {[(n-k)/2]+1}/n which asymptotically equals 50 percent, i.e. it can withstand a lot of bad leverage points occurring anywhere in the data.[15] Equation (10) resembles that of OLS but does not count the largest squared residuals, thereby allowing the LTS fit to stear clear of outliers. The default setting for *h* suggested in the literature is $h \approx n/2$.[16] The LTS regression and scale estimates can then be used to identify outlying observations, defined to be those observations whose residual is greater than 2.5 times the robust scale estimate $[(e_i/\sigma) > 2.5]$.[17] It should be noted that the LTS method does not

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14 The so-called breakdown point is the smallest fraction of contamination that can cause the estimated coefficients arbitrarily far from the coefficients for the majority of the data.

15 Bad leverage points often overwhelm methods like least-absolute-errors regression and the M-estimators which deal effectively with outliers in the dependent variable.

16 For larger *h* the breakpoint value is approximately given by $(n-h)/n$.

17 Various resampling algorithms have been suggested to obtain the LTS regression and scale estimates. The resampling approach is required because the LTS criterion function is not at all smooth; it typically contains many local minima and therefore cannot be minimized by conventional methods. Rousseeuw and Leroy (1987) propose drawing a large number of subsamples, each of size k (the

"throw away" 50 percent of the data. Instead, it finds a majority fit, which can then be used to detect the actual outliers (of which there may be none at all, few, or many). Also the purpose is not to delete the points outside the tolerance band, but to study the residual plot in order to find out more about the data. We therefore recommend to perform LTS as a specification device in the initial stage to obtain results that otherwise would be hidden.

4. EMPIRICAL RESULTS

4.1 The regression model

The identification of the spatial interaction structure is based on a regression analysis that focuses on the relationship between regional productivity growth and R&D activity. The dependent variable is the average annual productivity growth [$\ln(y_{96}/y_{76})/T$] between 1976 and 1996. R&D activity and corresponding spillovers in 1976 are measured by R&D-potentials ($RDP\gamma_E$) computed according to equation (7). In the theoretical approach, higher R&D may lead to higher GDP per capita. Investment in R&D, however, yields results only after a relatively long lag. The implementation of new results into the production process implies further delays. Thus, current R&D should affect future GDP. We have therefore used R&D data for 1976 in the cross-section estimates.[18] In order to avoid misspecifications apart from the R&D-potential additional explanatory variables are included in the cross-sectional regressions. The R&D-potential might also capture more general economies or diseconomies of agglomeration, especially when a high distance decay is employed. In order to differentiate between overall growth effects of agglomeration and the effects of spatial R&D spillovers, potential measures based on population in 1977 are applied to control for corresponding effects. They serve either as an indicator for agglomeration effects (*AG* – potential based high distance decay) or as an indicator for a central location, i.e. accessibility and proximity of large markets (*CL* – potential based small distance decay). Finally, initial regional productivity in 1976

number of regression coefficients, including the constant term) and evaluate the objective function (10). This is repeated often, and the solution with lowest objective function is kept. Both authors show that, if the number of subsamples is large, at least one of them is virtually certain to be uncontaminated by outliers. The LTS regression is based on these "clean" subsamples. In this paper 3000 subsamples have been drawn. Recently, Rousseeuw and van Driessen (1999) have developed a FAST-LTS algorithm.

18 Econometrically, this also allows us to deal with the endogeneity problem. Blomström et al. (1996), for example, have demonstrated in a cross-country dataset that growth Granger-causes physical investment expenditures rather than that investment expenditures Granger-cause growth.

[$\ln(y_{76})$] is considered as an additional explanatory variable in the regressions in order to test for conditional ß-convergence because in a "semi-endogenous" growth setting the conditional convergence through technological diffusion will be reinforced by the familiar Solow-like conditional convergence.

For these reasons we start by estimating the following regression model in order to determine the spatial extent of R&D spillovers:

$$(11) \qquad \ln \frac{1}{T}\left(\frac{y_{96}}{y_{76}}\right)_i = \beta_0 + \beta_1 \ln y_{76,i} + \beta_2 AG_{77,i} + \beta_3 CL_{77,i} + \beta_4 RDP\gamma_{E,76,i} + u_i$$

At the initial stage equation (11) is estimated by LTS for R&D-potentials with varying spatial extent, i.e. for distance decay parameters between 0.1 and 0.99 in order to select an appropriate spatial interaction structure equation. The LTS residuals are then used to identify outlying regions. Finally, the selected model that generates no outliers is estimated by OLS.

4.2 The Data Set

Due to the long-term nature of analysis the study is constrained to the West-German regions.[19] The spatial units of observation base on German planning regions (*Raumordnungsregionen*). These regions comprise several NUTS III-regions that are linked by intensive commuting. In other words, our definition of region centres on the spatial sphere of socio-economic influence of any unit.[20] The modified regional system consists of 71 units of observation. The cross section contains both highly agglomerated areas and rural-peripheral regions.[21] Therefore, the regions considerably differ for example with regard to GDP per capita or R&D density, as shown in Figure 3 and 4.

The dependent variable, average annual productivity growth [$\ln(y_{96}/y_{76})/T$] is measured by gross value added per employee. The corresponding data are not available from official statistics at a small regional scale. Thus, estimates of regional employment and

19 For East-German regions neither the required data are available nor could an analysis provide reasonable conclusions in view of the transformation process.

20 Because of the isolated location until 1989 the agglomeration "Berlin" is not considered.

21 Obviously, there still exists the border or edge problem, pertaining to the problem that inferences are based on a German dataset, whereas the spatial process extends to foreign units not represented in the data.

gross value added based on information from official statistics have to supply the necessary data [Bade (1997a)].[22] The computation of the R&D-potentials ($RDP\gamma_E$) is based on regional data on R&D employment in 1976 from the German employment statistics [Bade (1997b)]. The calculation of the population potentials *AG* and *CL* also comprises regional population data on neighbouring European states.[23] Population data for 1977 were collected from the EUROSTAT REGIO database and the Penn World Table (Mark 5.6).

Table 1: Descriptive Statistics for the Regional Cross Section

Variable	Mean	Standard deviation	Minimum	Maximum
$\ln(y_{96}/y_{76})/T$	0.047	0.003	0.042	0.054
$\ln(y_{76})$	10.56	0.13	10.28	10.87
AG (in 1000)	2699	1219	669	7152
CL (in 1000)	84819	9415	56533	96741
$RDP_{0.1}$ (in 1000)	97.4	14.5	56.4	118.5
$RDP_{0.5}$ (in 1000)	21.9	10.6	4.3	52.9
$RDP_{0.9}$ (in 1000)	2.7	2.8	0.2	13.4

Source: Own calculations, Bade (1997a), (1997b).

Figure 3 and 4 provide a visual impression of the spatial structures of productivity and R&D in West Germany for the beginning and the end of the sample period. A high concentration of R&D-activity characterizes the agglomerations especially in the western and southern parts of West Germany, whereas the R&D-density is comparatively low in the northern agglomerations - for example in Hamburg or Hannover. However, the spatial structure of R&D is first of all marked by the striking disparities between the highly agglomerated areas and the rural peripheral regions. More or less the same centre-periphery-differential can be observed for GDP per capita. With growing degree of agglomeration the GDP per capita tends increase.[24] As a comparison of the data for 1976 and 1996 reveals, the general structure of spatial disparities has not changed very much during the last two decades. In other words, there seems to be only little "eyeball" evidence of convergence towards a single per capita income level across regions (*Raumordnungsregionen*).

22 For a detailed description of estimation method see Bade and Niebuhr (1999).

23 Included are Denmark, Norway, Sweden, former East Germany, former Czechoslovakia, Austria, Switzerland, France, Belgium, the Netherlands, Ireland and the UK.

24 A remarkable exception of this rule is the region Ingolstadt, that attains an extraordinarily high productivity in view of its below average population density. The high productivity is probably due to the automobile industry located in the region Ingolstadt.

Figure 3: R&D Densities 1976 and 1996

(Number of R&D Employees Per Square Kilometre)

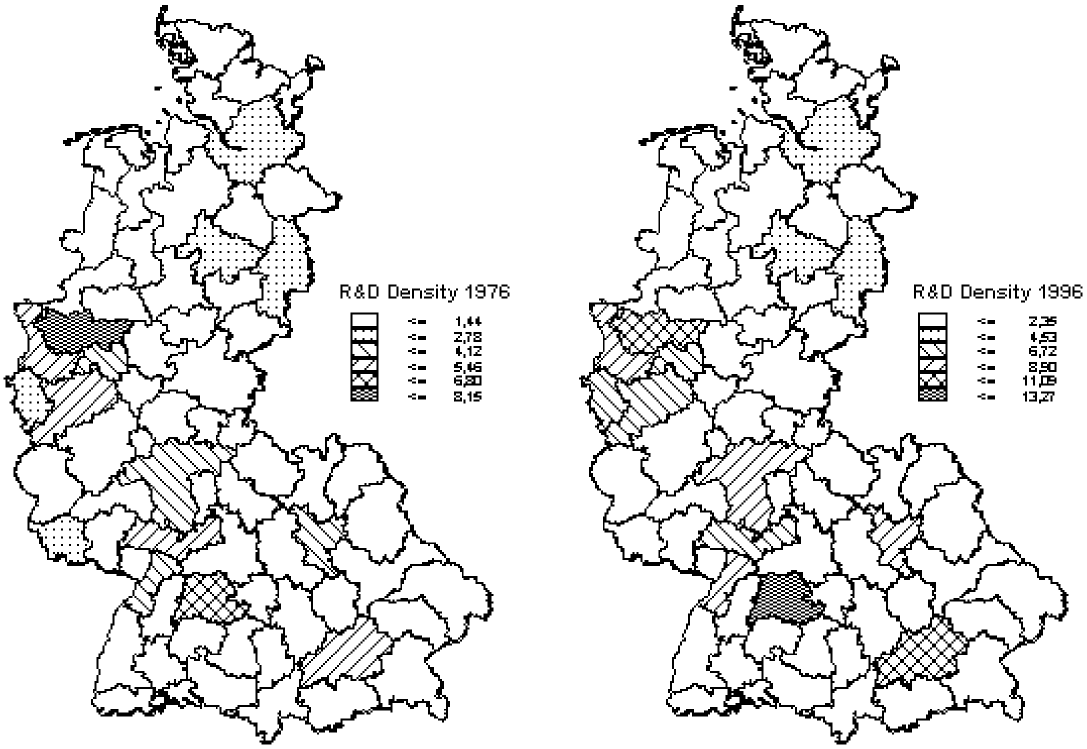
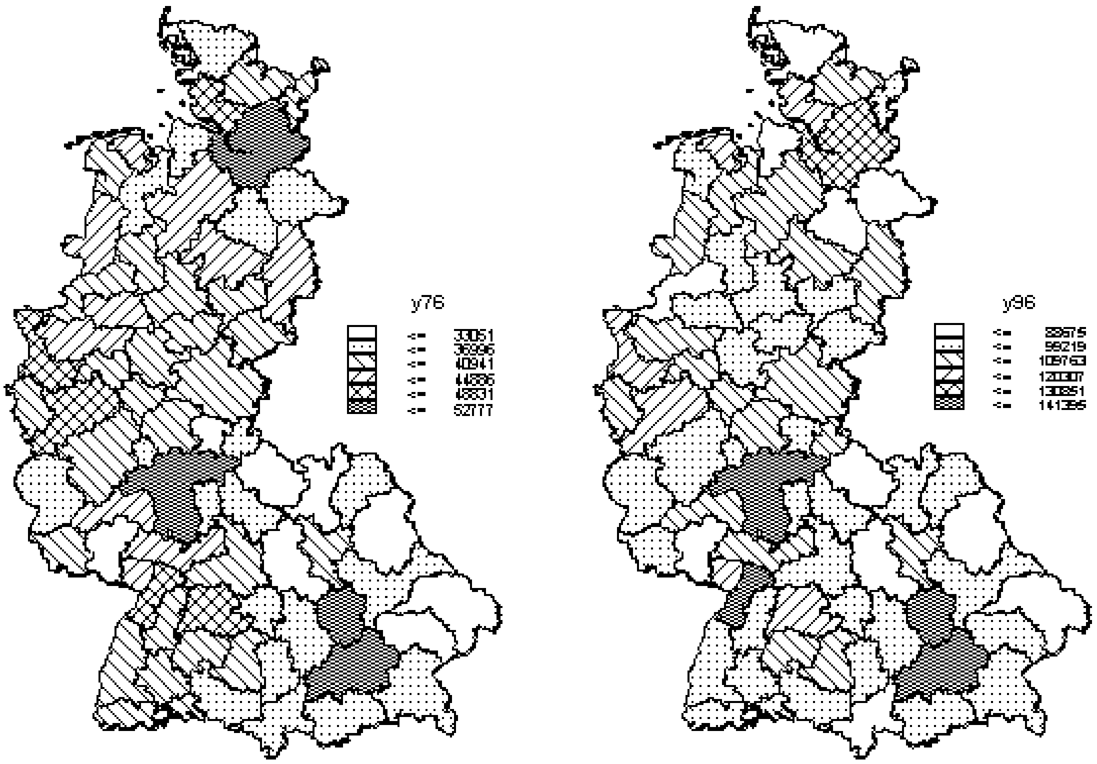


Figure 4: GDP per Capita 1976 and 1996



Source: Own calculations, Bade (1997a), (1997b).

4.3 Estimation Results

The results of the outlier analysis based on LTS estimation of equation (11) are summarized in Table 2. In order to select an appropriate spatial interaction structure the model is estimated for R&D-potentials with varying spatial extent. The LTS residuals are then used to identify outlying regions. The results for R&D-potentials with distance decay parameters between 0.1 and 0.99 are reported in the second column of Table 2. For each R&D-potential all regions whose standardized LTS residuals exceed 2.5 are listed.

Table 2: Identification of Outlier Regions Using the LTS Residuals

R&D-potential	Outlying Regions	AIC	Spatial autocorrelation (range of γ_E)
$RDP_{0.1}$	Ingolstadt, Hamburg, Rhein-Main, Karlsruhe, München	-648.2	0.1 – 0.8
$RDP_{0.2}$	Wilhelmshaven, Main-Rhön, Mittelfranken, Ingolstadt, Hamburg, Ruhr, Düsseldorf, Wuppertal-Hagen, Köln-Bonn, Rhein-Main, Karlsruhe, München	-651.3	0.1 – 0.7
$RDP_{0.3}$	Südpfalz, Main-Rhön, Mittelfranken, Ingolstadt, Hamburg, Ruhr, Düsseldorf, Wuppertal-Hagen, Köln-Bonn, Rhein-Main, Karlsruhe, München	-644.1	0.1 – 0.8
$RDP_{0.4}$	Südpfalz, Main-Rhön, Mittelfranken, Ingolstadt, Hamburg, Ruhr, Düsseldorf, Wuppertal-Hagen, Köln-Bonn, Rhein-Main, Karlsruhe, München	-648.0	0.1 – 0.7
$RDP_{0.5}$	Wilhelmshaven, Südpfalz, Main-Rhön, Mittelfranken, Ingolstadt, Hamburg, Ruhr, Düsseldorf, Wuppertal-Hagen, Rhein-Main, Karlsruhe, München	-652.7	0.2
$RDP_{0.6}$	-	-656.1	-
$RDP_{0.7}$	Wilhelmshaven, Südpfalz, Ingolstadt, Rhein-Main, Karlsruhe, München	-655.7	-
$RDP_{0.8}$	Ingolstadt, Rhein-Main, Karlsruhe	-652.2	-
$RDP_{0.9}$	Südpfalz, Ingolstadt, Rhein-Main, Karlsruhe	-647.6	0.2 – 0.7
$RDP_{0.99}$	Wilhelmshaven, Vogelsberg, Südpfalz, Ingolstadt, Rhein-Main, Karlsruhe	-643.8	0.1 – 0.8

Notes: AIC = Akaike Information Criterion; the last column of the table gives the range of γ_E with significant Moran statistic for the error term at the 1% level. The outlying regions are defined as those with standardized LTS residuals exceeding 2.5.

The results indicate that the proposed method can serve as a guideline for spatial weight specification. The number of outliers is affected by the structure of spatial interaction. In other words, it depends on the assumed geographical extent of R&D spillovers. Only for the regression with the R&D-potential $RDP_{0.6}$ no outlying regions can be detected.

On the contrary, all other spatial structures generate observations that are not consistent with the unknown data generating process. We would therefore suggest to use robust estimation techniques like LTS as a rule-of-thumb to guide the proper degree of spatial dependency. The result of the outlier analysis is confirmed by the additional selection criteria, reported in the third and fourth column of Table 2. The spatial structure selected by the standardized LTS residuals also minimizes the Akaike Information Criterion. Finally, for $RDP_{0.6}$ here is no evidence for spatial autocorrelation in the corresponding residuals. The OLS estimation results of the selected model are presented below (White-corrected *t*-statistics are given in parentheses):

(12)

$$\ln\frac{1}{T}\left(\frac{y_{96}}{y_{76}}\right) = \underset{(3.27)}{0.095} - \underset{(1.93)}{0.005}\ln y_{76} - \underset{(6.03)}{3.9\cdot 10^{-6}}\, AG_{77} + \underset{(3.13)}{1.3\cdot 10^{-7}}\, CL_{77} + \underset{(5.15)}{4.4\cdot 10^{-4}}\, RDP_{0.6,76}$$

The regression yields significant coefficient for all explanatory variables. The negative coefficient of the initial productivity level confirms the findings of previous studies on conditional ß-convergence in West Germany. However, with less than 1% the rate of convergence points to a very slow decline of disparities. The significant and negative coefficient of the population potential with high distance decay AG indicates adverse congestion effects. Since the indicator for agglomeration diseconomies is positively correlated with the initial productivity level, it might capture a significant part of the overall convergence process. The positive coefficient for the central location CL points to growth enhancing effects of the proximity of large markets and regional accessibility.

Finally, the regression yields a positive coefficient for the R&D-potential with a comparatively high distance decay parameter (γ_E = 0.6). Thus, the analysis provides empirical evidence for the hypothesis that R&D spillovers are geographically bounded and constitute a significant source of regional productivity growth. Proximity matters for knowledge spillovers and growth. Furthermore, the distance decay parameter of the R&D-potential supplies precise information about the geographical extent of R&D spillovers. The corresponding half-life distance implies that the intensity of spillovers declines by 50% over a range of 30 kilometres. On average, the spatial effects decrease by 60% between the centres of two neighbouring regions. The agglomerations in West Germany can be assessed as the main origin of R&D spillovers because R&D-activity is to a large extent concentrated in these densely populated areas. Taking into account an average distance of 40 kilometres between the centres of the regions, the half-life distance indicates that a significant proportion of spillovers transcends the borders of agglomerations and contributes to productivity growth in neighbouring regions.

5. DISCUSSION AND CONCLUSION

How do these respective results compare with the findings in the empirical literature? The results confirm the empirical evidence on geographically bounded knowledge spillovers provided by a number of recent studies, as for example Jaffe et al. (1993), Audretsch and Feldman (1996), Bode (1998) and Bottazzi and Peri (1999). A weakness of the aforementioned studies, however, is that they do not investigate the spatial extent of spillovers. Frequently the studies restrict the geographical range of spillovers to the boundaries of the considered regions or the applied methods do not allow quantitative conclusions in this respect.[25] Therefore, most analyses on R&D spillovers do not offer precise informations about the extent of spatial interaction. Rare exceptions are the studies of Anselin et al. (1997) and Varga (1998). They use a model of the knowledge production function extended by spatially lagged variables to investigate knowledge spillovers between US metropolitan statistical areas (MSA). Their findings suggest that spillover effects exceed the MSA boundaries. Anselin et al. (1997) provide evidence on a significant relation between university research and high technology innovations at the MSA level. Moreover, the university knowledge spillovers are characterized by a strong distance decay pattern. They have found that the spillovers of university research on innovation extend over a range of 50 miles. Varga (1998) concludes that, in addition to spillovers originated in the same MSA, technology transfer from neighbouring MSAs within a range of 75 miles has also substantial effects on the generation of new knowledge. In view of the differences with regard to data and method this evidence corresponds surprisingly precise with the results of our analysis. The spatial structure derived above implies that the intensity of spillovers declines by more than 90% over a range of 120 kilometres or 75 miles. In other words, we do find that regional growth is positively correlated with the R&D activity of neighbouring regions although the half-distance turns out to be 30 kilometres, i.e. the spillovers decrease rather quickly with distance. Thus, the paper confirms Feldman´s and Audretsch´s (1999, p. 410) qualitative hypothesis that "new economic knowledge may spill over, but the geographical extent of such knowledge spillovers is bounded."

25 Moreover, the size of the regions used as units of observation (e.g. US states, US metropolitan areas or German planning regions) varies considerably.

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