Regional Geographic Research and Development Spillovers and Economic Growth: Evidence from West Germany

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(Received February 2004: in revised form June 2004)

Funke M. and Niebuhr A. (2005) Regional geographic research and development spillovers and economic growth: evidence from West Germany, Regional Studies 39, 143–153. The paper is based on recent theoretical writings in growth economics that emphasise the effects of both own research and development efforts and of interregional technology spillovers on regions’ productivity. It proposes robust estimation techniques to evaluate the research and development spillovers across West German functional regions between 1976 and 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.

Research and development (R&D) spillovers Economic growth Germany


Retombeés de R et D Croissance économique Allemagne


Forschungs-und Entwicklungsverbreitung Wirtschaftswachstum Deutschland
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 research and development (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 economists who deal with growth issues is the study of the interaction of R&D activities in one place with those in another. 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 localization and urbanization externalities that tend to lead to the local clustering of economic activity. This may lead to a core–periphery pattern of economic development and therefore β-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 β-convergence. Case studies of Silicon Valley, California, USA (Saxenian, 1994), Northern Italy (Storper, 1992) and Baden-Württemberg, Germany (Sternberg, 1999), are often cited to stress the importance of geographical proximity for productivity and growth in core regions. Are these examples mere exceptions or do 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?

The empirical work reported here attempts directly to test some of these policy concerns. The paper uses recently developed methods of spatial data analysis and robust estimation techniques to provide new insights on the spatial pattern of the interaction of 71 planning regions in West Germany between 1976 and 1996. The remainder of the study first provides an overview of spillover models and studies. Since the basic models of this theory are well known, only rudimentary details are provided in this section and the paper concentrates instead on the results relevant for the present purposes. The data, the empirical methodology, the empirical results and their economic interpretation are presented in the third and fourth sections. The fifth section has conclusions.

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) 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 set-up 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 that prevents regions’ per capita income level to grow increasingly apart or a diffusion of knowledge across space which binds regions together. Kelly and Hagemann (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. Krugman (1998) adds 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. As a result, R&D spillovers may be restricted in space and therefore geographical proximity matters.

To establish some formal ideas about the interaction between R&D spillovers and regional economic growth, the paper starts with a simple neoclassical growth model in which human capital has public good-like qualities. The output of human capital formation is understood to be (at least partly) non-rival and non-excludable. Thus, private investments in human capital may augment others’ productivity, allowing the economy to avoid sufficiently diminishing returns at the aggregate level for some set of parameter values. Suppose that value added in region \( i \) is given by the following:

\[
Y_i = H_i^\alpha L_i^{1-\alpha}(H_i^\beta L_i^{-\beta})
\]  
(1)

where \( H_i \) (\( L_i \)) is the region-specific human capital stock (regional raw labour force), \( H(L) \) is the amount of human capital (raw labour) available in all regions, and \( 0 < \alpha < 1 \) and \( \beta > 0 \). The rationale for equation (1) is that the production process generates knowledge externalities. The higher the aggregate level of human capital in the economy, the greater the incidence of knowledge spillovers to raise the marginal productivity of human capital across all regions. Human capital in region \( i \) is paid its private marginal product, thus:

\[
r = \frac{\partial Y_i}{\partial H_i} = \alpha \left( \frac{H_i^{\alpha - 1}}{L_i} \right) \left( \frac{H_i^\beta}{L_i} \right)
\]  
(2)

In equilibrium, of course, \( H_i/L_i = H/L \), so the marginal product of human capital can be rewritten as follows:

\[
r = \alpha \left( \frac{H}{L} \right)^{\alpha - 1} \left( \frac{H^\beta}{L} \right)
\]  
(3)

The aggregate production function in (1) can be written as:

\[
Y = H^{\alpha + \beta} L^{1-\alpha-\beta}
\]  
(4)

Defining \( y \equiv Y/L \) and \( h \equiv H/L \). The production function in intensive form is then given by:

\[
y = h^{\alpha + \beta}
\]  
(5)

Taking the time derivatives of both sides of \( h \) yields:

\[
h = sh^{\alpha + \beta} - nh
\]  
(6)

where \( s \) is the saving rate and \( n \) is the labour force growth rate. Just as in the standard Solow model, the economy will converge to a situation where actual investment per capita is equal to breakeven human capital investment per capita. The steady-state human capital stock \( h^* \) is then given by:

\[
h^* = \left( \frac{s}{n} \right)^{1/(1-\alpha-\beta)}
\]  
(7)

Note that the steady-state per capita human capital stock \( h^* \) is an increasing function of \( \beta \) and therefore the size of regional spillover effects. The emphasis here is essentially to identify the range of these knowledge externalities in space.

Despite the development of formal models, however, the empirical basis of the new growth models is still rather thin. In three highly influential papers at the macro level, Coe and Helpman (1995), Coe et al. (1997) and Bayoumi et al. (1999) have found that both domestic and foreign R&D contribute significantly to total factor productivity growth. Moreover, foreign R&D has become increasingly important, especially for smaller countries. Finally, Bottazzi and Peri (1999) use European regional data to test for the existence of spatial spillovers of R&D. 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. This asks the question whether and to what extent knowledge externalities are localized in Germany. Using data for 71 West German planning regions, a regression analysis is performed that links regional per capita Gross Domestic Product (GDP) growth to the R&D activity of both the region and its neighbouring regions.

**SPECIFICATION OF SPATIAL INTERACTION**

The paper analyses spatial interaction by means of a potential measure. The applied measure approximates spatial interaction, assuming that accessibility and the degree of interaction among people decline with increasing geographical distance. The potential measure reflects the intensity of spatial interaction among individuals within a region as well as the possible interaction with agents in neighbouring areas (Bröcker, 1984, 1989). Thus, in contrast to explanatory variables that are simply based on observations for given geographical units, the potential measure does not neglect spatial externalities between regions since they are continuous over space (Talen and Anselin, 1998).

The R&D potential applied to capture the effects
of R&D spillovers is based on regional R&D employment, \(RD_i\), which covers the regional R&D personnel employed by commercial firms and the public sector. The indicator is, therefore, designed for representing R&D spillovers that result from possible contacts of researchers. In this context, it is assumed that the frequency of contacts and the exchange of knowledge among researchers decline with increasing distance between their workplaces. This negative relation between distance and intensity of spatial interaction of R&D employees is taken into account by spatial weights, \(w_{ij}\), which are based on a negative exponential function with distance decay parameter \(\beta_E\):

\[
w_{ij} = e^{-\beta_E \cdot d_{ij}} \tag{8}
\]

where \(d_{ij}\) is the distance between the centres of regions \(i\) and \(j\). With increasing \(\beta_E\), the frictional effects of distance rise and interaction declines more quickly with increasing distance between researchers. The R&D potential of region \(i\) reflects the accessibility of all R&D employees and is given by:

\[
RDP_i = \sum_{j=1}^{R} RD_j \cdot w_{ij} = RD_i \cdot w_i + \sum_{j \neq i}^{R} RD_j \cdot w_{ij}
\]

\[
= \left[ rd_i \cdot \int_0^{d_i} 2 \cdot \pi \cdot \xi \exp(-\beta_E \cdot \xi) d\xi \right] + \sum_{j \neq i}^{R} RD_j \cdot \exp(-\beta_E \cdot d_{ij}) \tag{9}
\]

where \(RD_j\) is R&D employment in region \(j\), \(rd_i = RD_i/F_i\) is the density of R&D employment in region \(i\). The potential measure consists of the self-potential of region \(i\) \((RD_i \cdot w_i)\) and the cumulated influence of the other \((R-1)\) regions \((\sum_{j \neq i}^{R} RD_j \cdot w_{ij})\). In order to estimate the self-potential, R&D employment in region \(i\), \(RD_i\), is multiplied by the weight, \(w_{ij}\), that is based on the so-called internal distance of the region, \(d_i\). The internal distance is modelled as being proportional to the region’s area, and the area of each region is approximated with a disk. Thus, the computation of the self-potential assumes that R&D employment is evenly distributed on the circular area of the region \(F_i\) with corresponding radius \(\xi = (F_i/\pi)^{1/2}\). 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 internal distances. The computation of interregional effects, i.e. of the interaction among researchers in different regions, assumes that R&D employment is concentrated in the centres of the regions. The intensity of interaction declines with increasing distance, \(d_{ij}\), between 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 \(\gamma_E\) (Bröcker, 1989):

\[
\beta_E = \frac{-\ln(1 - \gamma_E)}{D_{MIN}} \quad 0 \leq \gamma_E \leq 1 \tag{10}
\]

where \(D_{MIN}\) is the average distance between the centres of immediately neighbouring regions and is used as a basic unit of distance. Thus, on average, \(\gamma_E\) measures the percentage decrease of the spatial interaction between immediately neighbouring regions, i.e. the decline of the weights as distance expands by the unit \(D_{MIN}\). With increasing \(\gamma_E\), 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. In the regression analysis, varying R&D potentials are applied that differ with respect to the distance decay parameter that enters in the calculation. The distance decay parameters used in the present analysis range from \(\gamma_E = 0.1\) (low geographical impediments/large spatial extent of spillovers) to \(\gamma_E = 0.99\) (high geographical impediments/small spatial extent of spillovers).

A fundamental problem results from the incorporation of parameters determining the proper distance relationships in equation (9). 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 preconditioned 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. This amounts not to prove, but rather to assume, the existence of knowledge externalities with a specific spatial extent.

Traditionally, specification tests have been used to identify appropriate spatial weights. This paper proposes a new method as an additional criterion. It uses a robust estimation technique that can determine unrepresentative or outlying observations in the cross-section dataset in order to investigate which spatial weights are appropriate for 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. Subsequently, a different definition of ‘robustness’ will be used. Here, ‘robustness’ is defined with respect to the observations included in the regression. Hence, sensitivity analysis is begun 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. To shed further light on these issues, one first has to pinpoint the so-called outlying observations. The least trimmed squares (LTS) estimator of Rousseeuw and Leroy (1987) will be used as a specification device and diagnostic tool to identify outlying observations and the distance parameters. The least trimmed squares (LTS) estimator can formally be written as:

\[
\min_{\beta} \sum_{i=1}^{n} (c^2)_{i,\alpha}
\]

where \((c^2)_1 \leq (c^2)_2 \leq \ldots \leq (c^2)_{h,n}\) are the ordered squared residuals (note that the residuals are first squared and then ordered). Formula (11) is very similar to ordinary least squares, 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. Thus, the \(n - h\) observations with the largest residuals will not affect the estimator. In other words, the LTS estimator searches for a core subset of data that best follows a certain model without taking into account the rest of observations. The LTS estimator is \(\sqrt{n}\)-consistent and asymptotically normal. Besides these important statistical properties, there are also some less practical aspects. The LTS estimator requires that one minimize the sum of squared residuals for every subsample (there are \(\binom{n}{h}\) of them). To obtain the LTS regression and scale estimates, various resampling algorithms have been suggested. 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 \(h\) (the number of regression coefficients, including the constant term) and evaluate the objective function (11). This is repeated often, and the solution with the 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. With \(k\) unknown parameters, the LTS method attains the highest possible breakdown value, i.e. \(\{(n-k)/2\}+1)/n\), which asymptotically equals 50%, i.e. it can withstand many bad leverage points occurring anywhere in the data. The trimming constant \(h\) suggested in the literature is \(h = [n/2]+(k+1)/2\), where \(k\) is the number of explanatory variables. The LTS 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, \([c/\sigma] > 2.5\).

### EMPIRICAL RESULTS

**Data set**

Due to the long-term nature of analysis, the study is constrained to the West German regions. For East German regions, neither the required data are available nor could an analysis provide reasonable conclusions in view of the transformation process. The agglomeration ‘Berlin’ is not considered because of its isolated location until 1990. The spatial units of observation are based on German planning regions (Raumordnungsregionen). These regions comprise several NUTS III regions that are linked by intensive commuting. In other words, the present definition of a region centres on the spatial sphere of socio-economic influence of any unit. Data for the Raumordnungsregionen have been used because West German state-level (Bundesland) data are likely to be too aggregated to be useful. Another advantage of the planning regions is that these spatial units are functional regions that are economically coherent and relatively self-contained. The regional system consists of 71 units of observation. The cross-section contains both highly agglomerated areas and rural–peripheral regions. Therefore, the regions considerably differ, for example, with regard to GDP per capita or R&D density.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\ln(y_{p3}/y_{p3})/T)</td>
<td>0.047</td>
<td>0.003</td>
<td>0.042</td>
<td>0.054</td>
</tr>
<tr>
<td>(W_{-1}\ln(y_{p3}/y_{p3})/T)</td>
<td>0.216</td>
<td>0.075</td>
<td>0.087</td>
<td>0.469</td>
</tr>
<tr>
<td>(\ln(p_{03}))</td>
<td>10.56</td>
<td>0.13</td>
<td>10.28</td>
<td>10.87</td>
</tr>
<tr>
<td>Population in 1977 (000s)</td>
<td>837.5</td>
<td>840.3</td>
<td>110.7</td>
<td>4906.9</td>
</tr>
<tr>
<td>PD77 (000s inhabitants per km²)</td>
<td>0.238</td>
<td>0.20</td>
<td>0.074</td>
<td>1.27</td>
</tr>
<tr>
<td>(W_{-1}\cdot PD_{77})</td>
<td>1.18</td>
<td>0.66</td>
<td>0.20</td>
<td>3.34</td>
</tr>
<tr>
<td>RDP0.5 (000s)</td>
<td>97.4</td>
<td>14.5</td>
<td>56.4</td>
<td>118.5</td>
</tr>
<tr>
<td>RDP0.9 (000s)</td>
<td>23.9</td>
<td>10.6</td>
<td>4.3</td>
<td>52.9</td>
</tr>
<tr>
<td>RDP0.1 (000s)</td>
<td>2.7</td>
<td>2.8</td>
<td>0.2</td>
<td>13.4</td>
</tr>
</tbody>
</table>

Note: For variables, see the text.
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 for the entire period from official statistics at a small regional scale. Data on regional employment in the 1970s covers only employees registered in the social security system (about 80% of total employment). Moreover, consistent time series data on regional gross value added are not available before 1980. Thus, additional estimates of total regional employment and gross value added based on information from official statistics partly supply the necessary data (Bade, 1997a). The computation of the R&D potentials (RDP) is based on regional data on R&D employment in 1976 from the German employment statistics (Bade, 1997b). The calculation of the population density, PD, bases on regional population data in 1977 collected from the Eurostat REGIO database.

Figs 1 and 2 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. Our index of the regional propensity to innovate appears to be far from uniform across Germany. 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 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. 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. 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 Raumordnungsregionen. However, with respect to spatial dependence both variables are not stable during the sample period under consideration. Whereas GDP per capita and the R&D intensity are characterized by a significant positive dependence in 1976 (measured by Moran’s I), no significant spatial association is detected for the variables in 1996. Thus, regional development between 1976 and 1996 was accompanied by a disintegration of the spatial dependence that characterized the variables in the mid 1970s. These specific spatial features will be explored in more detail below.
Regression model

The identification of the geographical scope of R&D spillovers is based on a regression analysis that focuses on the relationship between regional productivity growth and R&D activity. However, before we can reach a definitive conclusion about this link, we must remember that regional economic growth may differ for reasons other than 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) computed according to equation (9). 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.\(^{12}\) 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 agglomerations and the effects of spatial R&D spillovers, the population density in 1977 \([PD_{77}]\) is used to control for corresponding effects. Moreover, a spatial lag of the population density \([W_{PD_{77}}]\) is considered since with respect to agglomeration effects interregional spillovers, i.e. effects from neighbouring regions might be relevant as well. In addition, also included is a spatial lag of the dependent variable \([W_{ln1/T(y_{96}/y_{76})}]\) to capture the overall spatial dependence during the period under consideration.\(^{13}\) To compute this measure, one first needs to define a spatial weights matrix where the spatial connections between all regions are defined. The simplest (and widely used) matrix is the contiguity matrix \(W\), whose characteristic element \(w_{ij}\) takes the value of 1 if regions \(i\) and \(j\) share a common border, and 0 otherwise. This is in contrast to the specification of the R&D potentials calculated using distance-based weights. The regional population \([\ln POP_{77}]\) is included to shed some light on the growth effects resulting from the regional market size. Finally, initial regional productivity in 1976 \([\ln(y_{76})]\) is considered as an additional explanatory variable in the regressions in order to test for conditional \(\beta\)-convergence because the theoretical model presented above implies conditional convergence. For these reasons, one starts by estimating the following baseline regression model:

\[
\ln \frac{1}{T}(y_{96}/y_{76}) = \beta_0 + \beta_1 W_{ln1/T(y_{96}/y_{76})} + \beta_2 \ln y_{76,i} + \beta_3 PD_{77,i} + \beta_4 W_{PD_{77,i}} + \beta_5 POP_{77,i} + \beta_6 RDP_{76,i} + \epsilon_i \tag{12}
\]
At the initial stage, equation (12) is estimated repeatedly by LTS for R&D potentials $RDP_{k,i}$ with varying spatial extent, i.e. for distance decay parameters $\gamma_k$ between 0.10 and 0.99 in order to select an appropriate spatial interaction structure. The LTS residuals are then used to identify outlying regions. Finally, the selected models are estimated by maximum likelihood (ML). The chosen specification should pass several specification diagnostics and generate no outliers or the minimum number of outlying regions. More precisely, the LTS regressions are applied together with additional specification tests (tests for normal and spatially uncorrelated errors) to identify an adequate model specification. Within the ML estimations, the effects of outliers are controlled by regional dummy variables if necessary.

Estimation results

The results of the outlier analysis are summarized in Table 2. To select an appropriate spatial interaction structure, the model is estimated for R&D potentials with varying spatial extent, i.e. for R&D potentials that differ with respect to the distance decay parameter $\gamma_k$. The LTS residuals are then used to identify outlying regions. For each regression model characterized by a specific R&D potential, all regions whose standardized LTS residuals exceed 2.5 are listed in Table 2.

The results indicate that the proposed method might serve as a guideline for spatial weight specification. The number of outliers is affected by the structure of the spatial interaction. In other words, it depends on the assumed geographical extent of the R&D spillovers – the distance decay parameter. The quantity of outliers ranges between 1 for RDP, ($\gamma_k = 0.7$) and 14 for RDP, ($\gamma_k = 0.4$).

The next stage of analysis controls for the impact of outliers by adding a dummy variable for each outlying region. The corresponding ML regression results are summarized in Table 3. Note that only two models are not misspecified: the models including RDP, ($\gamma_k = 0.4$) and RDP, ($\gamma_k = 0.7$), respectively. However, the specification with RDP, ($\gamma_k = 0.4$) represents no plausible specification since the coefficient of the R&D potential is negative, implying adverse growth effects of R&D activity and associated spillovers, and the number of outlying regions is very large. Consequently, the model with RDP, ($\gamma_k = 0.7$) offers the best specification of the equation in terms of comprehensiveness and statistical fit. Also included in Table 3 are goodness-of-fit measures ($R^2$ and Akaike Information Criterion (AIC)). Unfortunately, these measures do not allow...
one to compare directly the explanatory power of the different models since they are seriously affected by the inclusion of regional dummy variables. The dummies increase the measures without adding explanatory power. Therefore, the preferred specification with \( RDP, (\gamma_E = 0.7) \), containing only one dummy for an outlying region, yields a lower \( R^2 \) than models with a higher number of regional dummies. However, based on \( R^2 \) and AIC, one can evaluate the overall explanatory power of the selected model.

The ML estimation results of this selected model are presented below (\( t \)-values are given below the coefficients):

\[
\ln \left( \frac{y_{56}}{y_{56}} \right) = 0.167 + 0.023 \ln 1/T(y_{56}/y_{56}) \\
-0.012 \ln y_{56} + 3.9 \times 10^{-4} PD_{77} \\
-0.003 \ln PD_{77} + 0.002 \ln POP_{77} \\
+ 2.1 \times 10^{-4} RDP_{76}(\gamma_E = 0.7)
\]

(4.8) (4.1) (3.8) (1.1) (4.1) (2.2) (1.9)

The regression yields significant coefficients for all explanatory variables, except for population density. The negative coefficient of the initial productivity level confirms the findings of previous studies on conditional \( \beta \)-convergence in West Germany. However, with roughly 1%, the rate of convergence points to a very slow decline of regional disparities. The positive growth effect implied by the coefficient of the spatially lagged dependent variable points to significant interregional spillovers in addition to the spillover effects associated with the R&D potential. The negative coefficient of the spatial lag of the population density suggests that the neighbourhood of densely populated regions affects the growth rate adversely. This result might be interpreted as congestion effects that exceed the border of the region of origin. This outcome is somewhat surprising because the population density by itself obviously exerts no significant negative effects. A possible explanation might be that negative growth effects resulting from diseconomies of agglomeration are already captured by the initial productivity level.

The population density is positively correlated with the initial productivity level. Furthermore, the positive coefficient for the population variable applied to approximate the size of the regional market points to growth-enhancing effects of the proximity of a large market. Finally, the regression yields a positive coefficient for the R&D potential with a comparatively high distance decay parameter \( (\gamma_E = 0.7) \). Thus, analysis provides empirical evidence for the hypothesis that the regional growth process is characterized – among other things – by a spatial pattern, where each region benefits by a positive performance of its neighbours, but the growth spillovers fade significantly with distance. The corresponding half-life distance implies that the intensity of spillovers declines by 50% over a range of 23 km. On average, the spatial effects decrease by 66% 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 largely concentrated in these densely populated areas. Taking into account an average distance of 40 km between centres of regions, the half-life distance indicates that a significant proportion of spillovers transcend the borders of agglomerations and contributes to productivity growth in neighbouring regions. 15

**DISCUSSION AND CONCLUSION**

How do the results compare with the findings in the respective academic literature? They confirm the empirical evidence on geographically bounded knowledge externalities provided by a number of recent studies (e.g. Bode, 1998; Bottazzi and Peri, 1999). A weakness of the aforementioned studies, however, is that they do not investigate the spatial extent of spillovers. Frequently, they 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. Therefore, most analyses on R&D spillovers do not offer precise information about the extent of spatial interaction. The present results indicate that regional growth is positively correlated with the R&D activity of neighbouring regions, although the half-distance turns out to be 23 km, i.e. the spillovers decrease rather quickly with distance. 16 Thus, the paper confirms the hypothesis that knowledge can spill over, but the geographical extent of such spillovers is bounded.

**Acknowledgements** – The authors are very grateful to the Editor and two anonymous referees for helpful discussions and advice. They thank Franz-Josef Bade (University of Dortmund) for access to his regional database.

**NOTES**

1. The few exceptions include Bode (1999a, b).
2. 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.
3. A density measure has been used because economists have recently suggested an important link between growth and the concentration of people and firms in regions and/or cities. The high concentration of people creates an environment in which ideas move quickly from person to person and from firm to firm. That is, dense locations, such as cities, encourage knowledge spillovers.
For example, Bode (1999a, pp. 20–21) 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.

The issue of the possible impacts of misspecification of the spatial weights matrix has not yet received much attention in the academic literature. Among the few exceptions are Stetzer (1982) and Florax and Rey (1993). Their results suggest that specification of spatial dependence is important, especially when the sample size is small.

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.

For an excellent survey of robust estimation methods and applications, see Rousseeuw and Leroy (1997). Several robust regression techniques have been proposed, such as the least median of squares (LMS) method of Rousseeuw (1984). LTS regression has several advantages over LMS. Its objective function is more smooth, making LTS less jumpy (sensitive to local effects) than LMS. Moreover, its statistical efficiency is better, because the LTS estimator is asymptotically normal (Hössjer, 1994) and LTS has a higher convergence rate than LMS (Rousseeuw, 1984). This makes LTS more suitable than LMS.

Gross value added per employee is used rather than GDP per capita. It has the advantage that it is a useful proxy for productivity and can be considered a direct outcome of the various factors that determine regional competitiveness.

For a detailed description of data generation and data sources, see Bade and Niebuhr (1998) and Bade et al. (2002). The present paper focuses on 1976–96 because of modifications in the regional system. In the early 1970s and in 1996, the classifications of NUTS III regions and of the German planning regions, respectively, changed. For the data for 1976–96, a consistent regional classification can be generated.

For more detailed information on the Eurostat REGIO database, see Eurostat (2001).

For y76, Moran’s I is significant almost over the whole range of distance decay parameters (0.1–0.8). For the R&D density in 1976, significance at the 5% level is restricted to relatively high-distance decay parameters (>0.4). The asymptotic distribution of the test statistic, \(r = [I - E(I)]/\sqrt{\text{VAR}(I)}\), is standard normal. Moran’s I is given by \(I = x'Wx/x'x\), where \(x\) is the variable under consideration and \(W\) is the weight matrix.

Econometrically, this also allows one to deal with the endogeneity problem.

All specifications without the spatial lag of the dependent variable are misspecified. The residuals of the corresponding models are marked by spatial dependence, pointing to a spatial association of productivity growth that is not sufficiently captured by the explanatory variables. To measure spatial autocorrelation in the regression residuals, the Moran test and two Lagrange Multiplier tests are applied. The latter tests also supply information on the kind of spatial dependence – nuisance dependence or substantive spatial dependence.

It has been carefully checked whether the outliers given in Table 2 convey important information that would allow one to identify equation misspecification. It is apparent, however, that the outlying regions are very inhomogeneous and include both peripheral regions (e.g. Wilhelmshaven and Südpfalz) and centres (e.g. Ruhr, München and Karlsruhe).

The bulk of growth regressions has used cross-section data for a large number of units (amongst the most well-known contributions, see Barro and Sala–I–Martin (1992); and Mankiw et al. (1995), where the dependent variable is the average growth rate over a fairly long period (usually 25 or more years). This data requirement implies that one cannot split the sample to check for the structural stability of the results. Alternatively, researchers have relied on panel data and GMM estimation techniques when testing for conditional \(\beta\)-convergence (e.g. Caselli et al., 1996) by splitting the dataset into 5-year sub-periods. The obvious advantage of this procedure is that it allows one to control for unobservable region-specific fixed effects. On the other hand, the method implies that the resulting growth rates are influenced by business cycle impacts. Moreover, when the time series are persistent, the first-differenced GMM estimator can be poorly behaved, since lagged levels of the series provide only weak instruments for subsequent first differences. Revisiting the work of Caselli et al. (1996), Bond et al. (2001) have shown that this problem may be serious in practice.

There is supplementary empirical evidence that demand linkages in Germany are strongly localized and the effects of local demand shocks on wages are geographically rather limited (Brakman et al., 2000).

REFERENCES


