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DISCUSSION PAPER

Convergence and the Effects of Spatial Interaction

(Revised version: March 2001)

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Abstract

Since the beginning of the 1990s, the issue of income convergence has received considerable attention in economic research. Although a vast number of empirical studies has emerged, evidence on the role of spatial interaction is still rather scarce. The present paper is an attempt to provide additional information on the spatial aspect of convergence. Spatial econometric methods are used to investigate regional convergence in West Germany. The results indicate that spatial interaction is an important element of regional growth. However, considering spatial effects does not alter the general conclusion that regional income growth is characterised by a process of convergence.

JEL Classification: C21, C52, O18, R11
Keywords: Regional convergence, Spatial interaction, Spatial econometrics

1. INTRODUCTION

Since the beginning of the 1990s, the issue of regional disparities has received considerable attention in economic research. The renewed interest is partly caused by the development of new growth theory and new economic geography, starting with the work of *Romer* (1986, 1990), *Lucas* (1988) and *Krugman* (1991). Concerning the implications for regional disparities, the new theorectical approaches have an important similarity. The result, convergence or divergence, depends crucially on details of the models (see *Bröcker* 1996). Thus, theory alone can not provide explicit conclusions with regard to the development of regional disparities. The issue, whether regional per capita income tends to converge, remains a task of empirical research. However, although a vast literature on new economic geography and endogenous growth has emerged during the last decade, empirical research focused on the traditional model of exogenous growth developed by *Solow* (1956) and *Swan* (1956). The majority of empirical studies on convergence applies a methodology that bases on the Solow-Swan model, i.e. on the prediction of absolute or conditional convergence. The model implies that economies grow faster the further they are from their steady state value. Thus, assuming the same steady state, poor economies tend to realise a higher growth of per capita income than rich ones. If the steady states differ, the concept of conditional convergence has to be considered (see *Barro* and *Sala-i-Martin* 1995).

Until the mid of the 1990s, most tests for convergence consisted of cross-sectional regressions, with income growth as the dependent variable and the initial level of income as explanatory variable. This approach was applied to various samples of nations and regions. Frequently, additional variables were included on the right hand side in order to control for differences in the steady states (e.g. *Barro* and *Sala-i-Martin* 1995 or *Mankiw*, *Romer* and *Weil* 1992). During the last years, empirical research on convergence has proceeded in a number of directions. One topic in this respect is the panel data estimation of the convergence equation, that allows to take into account unobservable or unmeasurable differences in the steady states (see *Islam* 1995). A second line of research emphasises the behaviour of the entire regional income distribution over time. *Quah* (1993, 1996a) argues that the traditional cross-section regressions provide only a limited understanding of the convergence process because they analyse an average tendency, the behaviour of a representative economy. In contrast, *Quah* (1996a, 1996b) suggests a Markov chain approach to analyse the dynamics of the entire income distribution.

However, all of these approaches view the region as an isolated entity. Empirical research largely neglected the role of spatial interaction, although theoretical mechanisms such as technological spillovers or factor mobility, that are presumably decisive forces in the process of convergence, have a geographical dimension (see *Rey* and *Montouri* 1999). Up to now only a few studies have explicitly considered the spatial perspective of convergence. The corresponding results provide evidence for the importance of spatial effects with respect to the development of regional disparities. One group of these studies combines spatial methods with the Markov chain approach (see *Quah* 1996b, *Fingleton* 1999 and *Rey* 1999). The integration of spatial association into a Markov chain framework allows to examine the role of spatial proximity in the evolution of regional income distributions. The findings of *Quah* (1996b) suggest that spatial effects are more important than national factors for explaining the dynamics of regional convergence in Europe. This result is confirmed by an analysis of *Rey* (1999) for US States. He shows that the upward and downward mobility for States in the regional income distribution is affected by the relative position of adjacent regions in the same distribution.

A second line of research applies measures of spatial association and spatial regression models to analyse regional convergence. *Armstrong* (1995), *López-Bazo* et al (1999) and *Rodríguez-Pose* (1999) investigate regional convergence in the EU simultaneously considering the spatial perspective of growth. They provide evidence on a significant spatial interaction. For both the income level and the growth of per capita income, a positive spatial autocorrelation is detected. The growth pattern in Europe is characterised by clusters, consisting of several adjacent regions, that tend to grow at similar rates. Moreover, the results indicate that the traditional approach, to test absolute convergence by cross-sectional regressions, is misspecified due to omitted spatial effects. *Armstrong* (1995) and *Rodríguez-Pose* (1999) add national dummies or nationally weighted variables to eliminate the spatial autocorrelation in the error term. However, these specifications are rather restrictive, because they exclude spatial effects across national borders. Moreover, by assuming that all regions of a EU member state belong to the same national growth cluster, the possibility of corresponding spatial structures within each member state is ignored.[1] More flexible approaches in this regard are spatial regression models. *Rey* and *Montouri* (1999) apply these methods to analyse US regional income convergence. Their results suggest that a misspecification due to ignored spatial dependence might also occur if intranational convergence is considered.

Summarising the results of previous studies, there is some empirical evidence on the significance of spatial effects in the analysis of regional income convergence. However,

1 The high degree of spatial aggregation in the data used by *Armstrong* (1995) and *Rodríguez-Pose* (1999) might also hide the existence of different growth clusters below the national level. This supposition is confirmed by the results of *López-Bazo* et al (1999). On the basis of more disaggregated regional data, they detect clusters that comprise only parts of the respective EU member state.

the number of studies that explicitly deals with spatial effects is rather small. Therefore, the issue whether the current results on regional convergence are robust with respect to the ignored spatial dimension of growth has yet to be investigated. The present paper is an attempt to provide additional information on the spatial aspect of convergence. Spatial econometric methods are used to investigate regional convergence in West Germany over the period 1976-1996.

The rest of the paper is organised as follows. In section 2 the empirical methodology is presented. The data and empirical results are described in section 3. Section 4 concludes.

2. METHOD

The point of departure for the analysis of regional convergence in West Germany is the traditional cross-sectional regression applied to analyse absolute convergence. In this notion of convergence, the unit of observation is viewed as an isolated entity. However, the present paper focuses on the spatial perspective of growth and convergence. The central issue is whether spatial interaction is important with respect to regional convergence. In other words, does the consideration of the spatial effects alter the results regarding β-convergence? Therefore, spatial dependence or spatial autocorrelation is an essential element of the analysis.

2.1 Spatial autocorrelation

Spatial autocorrelation describes the relation between the similarity of a considered indicator and spatial proximity. *Anselin* (1988) notes that it is generally taken to mean the lack of independence among observations in cross-sectional data sets. Thus, positive spatial autocorrelation implies a clustering in space. Similar values, either high or low, are more spatially clustered than could be caused by chance. Negative autocorrelation points to spatial proximity of contrasting values (*Anselin* and *Bera* 1998). In contrast to the clearly defined autocorrelation in time-series, the dependence is multidirectional in the spatial case.

Measures of spatial autocorrelation take into account the various directions of dependence by a spatial weights matrix W. For a set of R observations, the matrix W is a $R \times R$ matrix whose diagonal elements are set to zero. The matrix specifies the structure and intensity of the spatial effects. Hence, the element w_{ij} represents the intensity of effects between two regions i and j (see *Anselin* and *Bera* 1998). A frequently applied weight specification is a binary spatial weight matrix such that w_{ij} = 1 if the regions *i* and *j* share a border and w_{ij} = 0 otherwise. Instead of using the concept of binary contiguity, in this study the elements of *W* are based on a distance decay function. To generate different structures of spatial interaction, a negative exponential function is employed:

$$(1) \qquad w_{ij}^{*} = \exp(-d_{ij} \cdot \beta_E) \qquad (0 < \beta_E < \infty),$$

with d_{ij} as distance between the centres of the regions *i* and *j* and β_E as distance decay parameter. To facilitate the interpretation and computation of spatial autocorrelation, the spatial weights matrices are row-standardised, i.e. the weights w_{ij}^{*} are divided by the corresponding row sum. The standardised weights w_{ij} measure the regional share in overall spatial effects on a certain observational unit. Particularly expressive with regard to the interpretation of the results is the "half-life distance" $d_E = (\ln 2)/\beta_E$, i.e. the distance that reduces the spatial effects by 50%. Apart from the half-life distance, a transformed parameter γ_E $(0 \le \gamma_E \le 1)$ will be used for interpreting the results (see *Bröcker* 1989, *Stetzer* 1982).[2] It measures the percentage decrease of the spatial effects if distance expands by a given unit. 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.

The results of tests for spatial dependence are influenced by both the choice of the regional unit of analysis and the choice of spatial weights (*Anselin* 1988). In order to check the sensitivity of the results with respect to a variation of *W*, the whole range of γ_E is considered throughout the analysis. In addition, the variation of *W* seems to be appropriate, since there rarely exists definite a priori information about the geographical range of spatial growth dependence.

The spatial association of the income level and the growth of per capita income is analysed by Moran's correlation coefficient. This coefficient distinguishes by both fairly simple computation and interpretation. In contrast to other measures of spatial autocorrelation, the Moran coefficient is zero in the case of no spatial autocorrelation irrespective of analysed variable or regional system (*Hordijk* 1974). The Moran coefficient is given by:

2 The transformed parameter is given by: $\gamma_E = 1 - e^{-\beta_E \cdot D_{MIN}}$, where D_{MIN} denotes the average distance between the centres of immediately neighbouring regions over the whole cross-section, in the present case 40 kilometres.

(2) $$I_t = \frac{R \cdot \sum_{i=1}^{R} \sum_{j=1}^{R} x_{i,t} x_{j,t} w_{ij}}{R_b \sum_{i=1}^{R} x_{i,t}^2},$$

where $x_{i,t}$ is the considered variable in region i in year t (in deviations from the mean), R the number of regions and R_b the sum of all weights. So, in the present case, with standardised weights, R_b equals R.

For measuring spatial autocorrelation in regression residuals, a number of tests has been developed. In order to derive robust inference, several tests are used in the following regression analysis: a Moran test and two Lagrange Multiplier tests (LM_{LAG}, LM_{ERR}). The Moran test provides reliable results for alternative forms of ignored spatial dependence, whereas the LM tests supply precise information about the kind of spatial dependence (see *Anselin* and *Rey* 1991, *Anselin* and *Bera* 1998, *Anselin* and *Florax* 1995). According to the results of these tests, different spatial models can be estimated if necessary, i.e. in case of a misspecification.[3]

2.2 Spatial regression models

A common approach to investigate regional convergence is the traditional cross-sectional regression with income growth $\ln(y_{t+T} / y_t)$ as dependent variable and the initial level of income $\ln(y_t)$ as explanatory variable. Using matrix notation, the unconditional convergence model is given by:

(3) $$\ln\left(\frac{y_{t+T}}{y_t}\right) = \alpha_0 \iota + \alpha_1 \ln(y_t) + u \ ,$$

where ι is a column vector of R ones. The rate of convergence β can be obtained using the relation $\beta = -\ln(1-\alpha_1)/T$. The OLS estimation of equation (3) provides the Best Linear Unbiased Estimator (BLUE) if the error terms are independently and identically distributed with zero mean. Moreover, standard inference procedures assume that the joint probability distribution is a normal distribution:

(4) $$u \sim N(0, \sigma^2 I).$$

In order to analyse conditional convergence, differences in the steady states have to be considered by adding explanatory variables in equation (3) that proxy these differences.

3 See *Anselin* (1988) for a detailed description of test statistics and spatial regression models.

Frequently, the investment rate or human capital variables are included to control for different steady states in conditional convergence models.

Spatial effects are not considered in the standard models applied to analyse conditional or unconditional convergence. However, ignoring spatial effects, when they are in fact present, leads to serious econometric problems. If a spatial association of growth is not sufficiently covered by the explanatory variables, the misspecification is reflected by spatially autocorrelated residuals. Thus, in this case, the assumption of uncorrelated error terms is violated. The definite consequences of the misspecification depend on the form of spatial autocorrelation. *Anselin* and *Rey* (1991) distinguish two different forms: substantive spatial dependence and nuisance dependence. The latter refers to spatial autocorrelation that pertains to the error term and can be caused by measurement problems, such as a poor match between the spatial pattern of the analysed phenomenon and the units of observation. The substantive form of dependence characterises economic phenomena that incorporate spatial interaction. Both forms of spatial dependence can result in model misspecifications if they are ignored. The presence of spatially autocorrelated residuals violates the assumptions of the OLS model and may lead to biased or inefficient estimates, depending on the form of spatial autocorrelation.

Although the omission of spatial interaction can adversely affect the econometric results, empirical evidence on the importance of spatial effects for regional convergence is still rather scarce. *Rey* and *Montouri* (1999) conclude that it is unclear to what extent the current evidence on convergence is robust to ignored spatial effects. Spatial econometrics provide a number of approaches to detect such misspecifications. Specific regression methods can be applied to analyse regional convergence in models that explicitly incorporate spatial effects.

The spatial error model is an appropriate approach if nuisance dependence causes the misspecification of the traditional convergence model. Although an OLS regression of equation (3) still yields unbiased estimates of the convergence rate, inference may be misleading since the precision of the estimates is affected. The spatial process pertaining to the error terms can be expressed as:

(5) $$u = \lambda W u + \varepsilon \qquad \varepsilon \sim N(0, \sigma^2 I),$$

where ε is a vector of independently and identically distributed disturbances, λ is a spatial autoregressive parameter and Wu is the weighted average of the errors in adjacent regions. Taking into account the spatial autocorrelation of the error term, the unconditional convergence model becomes:

(6) $$\ln\left(\frac{y_{t+T}}{y_t}\right) = \alpha_0\iota + \alpha_1 \ln(y_t) + \lambda W u + \varepsilon = \alpha_0\iota + \alpha_1 \ln(y_t) + (I - \lambda W)^{-1}\varepsilon \,.$$

The matrix $(I - \lambda W)$ is invertible if λ lies strictly between (–1, 1) since the weight matrix W is row-standardised (see *Anselin* 1988, *Case* et al 1993).[4] In the model given by equation (6), the effect among neighbouring regions is limited to error term or respectively unmodeled effects. Thus, on average the growth of per capita income is properly explained by the convergence hypothesis (see *Anselin* et al 1998). *Rey* and *Montouri* (1999) point to an interesting implication of the spatial error model when applied to the subject of regional growth. A random shock introduced to a specific region will not only affect the growth rate in the respective region. The effects of the shock will diffuse throughout the entire regional system because of the spatial dependence of the error term. Movements away from a steady state equilibrium induced by a shock are not restricted to the corresponding region, but instead apply to a set of adjacent regions by spatial spillovers.

If the ignored spatial effects are of the substantive form, the OLS regression of equation (3) will result in biased estimates of the convergence rate. All inference based on the traditional regression will be incorrect. To achieve proper estimates, the dependence can be incorporated into the traditional specification through a spatial lag of the dependent variable:

(7) $$\ln\left(\frac{y_{t+T}}{y_t}\right) = \alpha_0\iota + \alpha_1 \ln(y_t) + \rho W \ln\left(\frac{y_{t+T}}{y_t}\right) + u$$

$$= (I - \rho W)^{-1}(\alpha_0\iota + \alpha_1 \ln(y_t)) + (I - \rho W)^{-1} u \,,$$

where ρ is the spatial autoregressive parameter of the spatially lagged dependent variable.[5] The spatial lag model can be interpreted in several ways (see *Rey* and *Montouri* 1999, *Anselin* and *Bera* 1998). From an essentially technical perspective, the model can be viewed as a filter controlling either for a spatial association of growth or for convergence, i.e. the effect of the initial income level. Thus, it allows to investigate whether a spatial dependence of regional growth is a by-product of convergence and a spatial clustering of the initial income. In contrast, if the focus is on the convergence process,

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4 The regularity conditions can more precisely be expressed in terms of the eigenvalues of W. The corresponding inequality is : $-(1/\omega_{max}) < \lambda < 1$, where ω_{max} is the absolute value of the largest negative eigenvalue of W (see *Anselin* 1988, p. 79).

5 As in the spatial error model, the matrix $(I-\rho W)$ is invertible if the spatial autoregressive parameter ρ lies strictly between (–1,1).

the model can indicate whether the negative relationship between growth and initial level remains robust after spatial dependence has been controlled for.

Another interpretation emphasises the spatial interaction in the data generating process. The lag specification implies that the growth rate of a region is affected not only by its own initial income level, but likewise by the income growth and, therefore, the initial income level in adjacent regions. On average regional income growth is not solely explained by the local level of the initial income, but also, indirectly through the effect on income growth, by the income level everywhere in the regional system (*Anselin* et al 1998).

A substantive dependence in the process of regional convergence can as well be incorporated by a spatial lag of the explanatory variable $W \ln(y_t)$. As in the case of the spatially lagged dependent variable, the consequences of a corresponding specification error are serious, biased coefficient estimates and invalid inference procedures (see *Florax* and *Folmer* 1992). The corresponding spatial cross-regressive model is given by:

$$(8) \qquad \ln\left(\frac{y_{t+T}}{y_t}\right) = \alpha_0 \iota + \alpha_1 \ln(y_t) + \tau W \ln(y_t) + u \,.$$

In general, the spatial lag model and the cross-regressive model with a spatially lagged income level tend to explain the same spatial growth effect, i.e. that regional income growth is affected by both the local income level and the initial income in adjacent regions. However, whereas the spatial interaction in the lag approach extends over the entire regional system, of course with declining intensity due to a distance decay, the spatial effects in the cross-regressive model are restricted to regions that are adjacent according to the matrix *W*.

3. EMPIRICAL RESULTS

3.1 Data

Due to the long-term nature of the analysis, the study is constrained to the West German regions.[6] The spatial units of observation base on German planning regions (Raumordnungsregionen). These functional regions comprise several NUTS III-regions that are linked by intensive commuting. Thus, the regional system considers the spatial range of

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

economic activity to some extent. The applied spatial methods require slight modifications of some planning regions in order to provide reasonable centres for all regions that allow the computation of interregional distances. The largest city of the region serves usually as the centre. The agglomeration Berlin is not considered because of the isolated location until 1989. The modified regional system consists of 71 units of observation.

The growth of regional per capita income, measured by gross value added per employee, is analysed for the period between 1976 and 1996. The corresponding data are not available from official statistics at a small regional scale. Thus, estimates of regional employment and gross value added, based on information from official statistics, have to supply the necessary data (*Bade* 1997a, 1997b)[7]. In order to check whether the results are robust, in additional regressions conditional convergence is analysed. A human capital variable is included on the right hand side of the convergence equation to take into account differences in the steady states.[8] The regional disparities with respect to human capital are measured by the share of highly qualified employees (academic degree) in total employment in 1976. The data on regional employment base on the German employment statistics.

3.2 Spatial autocorrelation of per capita income and growth

The analysis of regional per capita income and growth by means of the Moran coefficient provides strong evidence of spatial dependence. The results point to a significant positive correlation of both initial income level and subsequent regional growth (see Table 1). The variables are more spatially clustered than could be caused by chance. This result is rather robust with regard to a variation of the spatial weight matrix. Irrespective of the used distance decay, a significant positive autocorrelation is detected for income growth and the initial income level. A fairly different result emerges for the income level in 1996. The coefficient is not significant and even changes the sign. This suggests that the regional growth process caused a dissolution of high and low income clusters between 1976 and 1996.

Although the Moran coefficient for $\ln(y_{76})$ and $\ln(y_{96}/y_{76})$ increases with growing distance decay parameter γ_E, the findings do not allow to conclude that the intensity of spatial dependence rises with declining spatial distance, since simultaneously the significance of Moran's I_t declines. The coefficient rises but at the same time the standard

7 For a detailed description of the estimation method see *Bade* and *Niebuhr* (1999).

8 It is not possible to consider differences in the investment rate since corresponding regional data are not available.

deviation of the estimates systematically increases. Thus, so far the analysis provides no precise information about the geographical extent of spatial dependence.

Table 1. Spatial autocorrelation of income and income growth 1976-1996

Spatial weight matrix (Negative exponential function)	Moran coefficient I_t (standardised z-value)		
Distance decay parameter γ_E	$\ln(y_{76})$	$\ln(y_{96})$	$\ln(y_{96} / y_{76})$
0.1	0.01 (3.57)**	-0.02 (0.60)	0.02 (5.21)**
0.2	0.04 (3.38)**	-0.02 (0.71)	0.07 (5.52)**
0.3	0.06 (3.17)**	-0.03 (0.74)	0.11 (5.64)**
0.4	0.08 (2.98)**	-0.04 (0.70)	0.15 (5.55)**
0.5	0.10 (2.83)**	-0.04 (0.61)	0.19 (5.28)**
0.6	0.12 (2.71)**	-0.04 (0.51)	0.22 (4.85)**
0.7	0.14 (2.57)*	-0.04 (0.43)	0.24 (4.27)**
0.8	0.16 (2.38)*	-0.04 (0.38)	0.25 (3.59)**
0.9	0.17 (2.09)*	-0.05 (0.40)	0.24 (2.80)**

Notes: ** significant at the 0.01 level,
* significant at the 0.05 level.

The pattern of spatial association, i.e. different income and growth clusters, can be illustrated by a mapping of decomposed results of the Moran test. The positive spatial autocorrelation indicated by the Moran coefficient bases on clusters of regions with similar income levels or growth rates. The decomposition of the coefficient into the contributions of individual regions distinguishes four types of spatial association. Regions contribute to positive spatial autocorrelation in two cases: a region with a high (low) value of the variable is surrounded by regions with similar high (low) values. Negative spatial autocorrelation arises if regions with a high (low) value of the variable are surrounded by areas with low (high) values (*Anselin* 1994). In Fig. 1 to 3 these categories are mapped for income growth and the income levels in 1976 and 1996. The corresponding distance decay γ_E is 0.5.

Fig. 1. Spatial association of ln(y_{76})

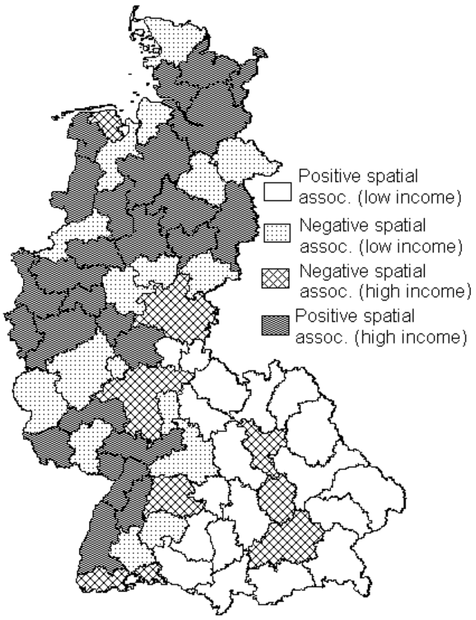


Fig. 2. Spatial association of ln(y_{96})

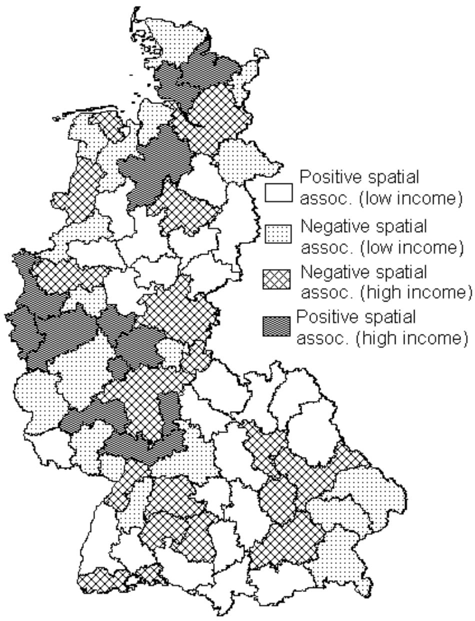
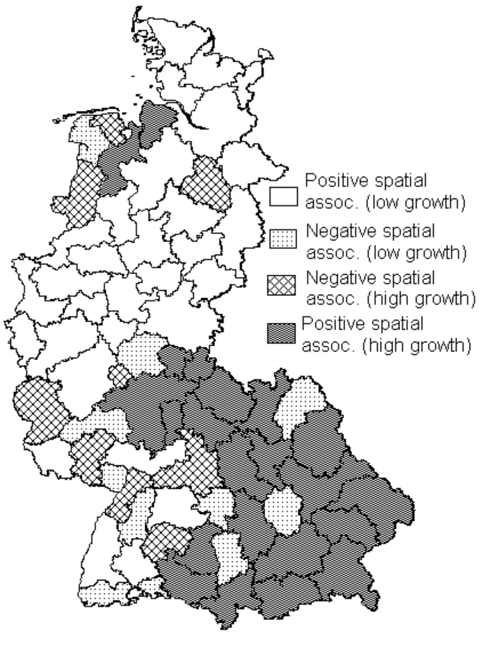


Fig. 3. Spatial association of ln($y_{96\,/}\,y_{76}$)



The regional income distribution in 1976 as well as income growth between 1976 and 1996 in West Germany are characterised by a marked contrast between the northern and the southern part, though with opposite sign (see Fig. 1 and 3). Concerning income growth, the regions can roughly be assigned to two large clusters characterised by similar growth rates: a southern area with most regions realising above average increases and a northern part experiencing only a modest growth.[9] The spatial pattern of the initial income is slightly more dispersed. However, there is a large cluster of low income regions in Bavaria roughly coinciding with the high growth cluster in the south. High income regions cluster primarily in the northern part of West Germany. Though, there is a second group of high income regions in the south-west. As expected, regions characterised by a negative spatial association are primarily located at the margin of different clusters, since in these areas regions with dissimilar growth rates or income border on each other.

Due to the high growth between 1976 and 1996, some regions of the low income cluster in the south moved upward in the regional income distribution. The opposite applies to the wealthier cluster of northern regions. Because of the slow income growth, some of these regions moved downward into lower income categories. These moves within the regional income distribution caused a disintegration of the low and high income clusters that marked the regional disparities in 1976. This raises the question whether the spatial dependence of income growth is merely a by-product of convergence. In other words, the clustering of the initial income level together with a process of absolute convergence might have caused the positive autocorrelation of income growth.

3.3 Estimation results

The estimation results for the traditional convergence equation (3) as well as for the different models that incorporate spatial effects are summarised in Table 2. In the first column the OLS estimates of the non-spatial model are presented. The coefficient of the initial income level is significant and negative, providing support for the hypothesis of absolute β-convergence. However, with a rate of roughly 1% the implied speed of convergence is rather slow compared to the findings of previous studies on regional convergence. A considerable number of studies yields very stable estimates of the convergence rate of about 2% per year for different cross sections of regions (e.g. *Barro* and *Sala-i-Martin* 1995). *Seitz* (1995) and *Schalk* and *Untiedt* (1996) provide similar evidence on regional convergence in West Germany.

Furthermore, the overall fit of the specification with an adjusted R^2 of 0.09 is rather poor. Additionally, all three tests for spatial autocorrelation provide strong evidence of a misspecification due to ignored spatial effects. A comparison of the LM_{LAG} test and the LM_{ERR} test suggests that the omitted spatial dependence is of the substantive form, since

9 Regional employment growth in West Germany is characterised by a similar pattern between 1976 and 1996. See *Niebuhr* (1999) for an extensive description of the corresponding results.

the LM_{LAG} test achieves a higher level of significance. Thus, the consequences with regard to the quality of the model can be expected to be severe because ignoring substantive spatial dependence results in biased estimates and invalid inference. The poor performance of the traditional convergence equation is underlined by the significant Breusch-Pagan test for heteroscedasticity and the presence of two outlying observations, the regions München and Wilhelmshaven.[10]

Table 2. Regression results for regional income growth 1976-1996
- entire cross section -

Explanatory variables	OLS		Maximum Likelihood (ML)	
	(1)	(2)	(3)	(4)
$\ln(y_{76})$	-0.010** (2.41)	-0.006 (1.63)	-0.005 (1.65)	-0.007* (2.12)
$W \ln(y_{76})$ ($\gamma_E = 0.5$)		-0.035** (3.79)		
λ ($\gamma_E = 0.5$)			0.58** (3.09)	
ρ ($\gamma_E = 0.5$)				0.57** (3.11)
R^2_{adj}	0.09	0.24		
AIC	-591.7	-603.2	-596.7	-596.4
HQ	-589.9	-600.5	-594.9	-593.7
Moran´s I_t	3.2** (0.4)[1)] [0.1-0.7][2)]	-		
LM_{ERR}	5.4* (0.5) [0.4-0.6]	-		3.9* (0.3) [0.3]
LM_{LAG}	10.5** (0.5) [0.3-0.8]	-	4.6* (0.4) [0.4]	
Breusch-Pagan	13.9**	10.8**	15.1**	17.0**
Outlying observation	Wilhelmshaven München	Wilhelmshaven Karlsruhe	Wilhelmshaven Südpfalz Nordschwarzwald	Wilhelmshaven Südpfalz Nordschwarzwald Karlsruhe

Notes: ** significant at the 0.01 level,
* significant at the 0.05 level,
1) corresponding distance decay γ_E,
2) range of γ_E with significant spatial autocorrelation of the error term at the 0.05 level.
The OLS *t*-statistics are based upon White's heteroscedasticity-adjusted standard errors.

10 The outlying observations are defined as those with standardised OLS residuals exceeding 2.5.

The estimation results for the models with spatial effects are given in the columns (2) to (4). The selection of the spatial models bases on a variation of the distance decay parameter, respectively weight matrix, of the integrated spatial effects. Information criteria and tests for spatial autocorrelation are used to identify appropriate spatial weights. Thus, the chosen model, i.e. distance decay, provides the best fit simultaneously capturing, if possible, the overall spatial interaction that characterises the regional income growth. The regressions yield significant spatial coefficients with expected signs in all three specifications. As the Akaike Information Criterion (AIC) and the Hannan-Quinn Criterion (HQ) indicate, the integration of spatial effects increases the fit of the model.[11] The tests for spatial dependence suggest that there is no or only little spatial interaction remaining unexplained in the models. In the case of the spatial cross-regressive model (column 2), none of the tests is significant for any weight matrix. The significant spatial dependence of productivity growth detected above is sufficiently captured by the explanatory variables. For the spatial lag and the spatial error model the evidence of spatial dependence in the error term is rather weak. No test is significant at $p=0.01$ and the significance at $p=0.05$ only relates to one weight matrix.

However, a number of problems also marks the spatial approaches. The significance of the initial income level decreases considerably. In the cross-regressive model and the error model (column 3) only the spatial effects remain significant. There is no reasonable interpretation of this results with regard to the neoclassical convergence hypothesis. Additionally, the Breusch Pagan test indicates that taking into account spatial effects does not solve the problem of heteroscedastic error terms. And finally, there are still outlying observations in the spatial models. This suggests that besides ignored spatial interaction outliers might affect the estimation results. Since the estimation of heteroscedastic error models does not lead to a satisfactory outcome, in the following the focus is on outlying observations and leverage points.

In general, the outlying regions do not correspond with the convergence relationship formed by the majority of the observations. But not every outlier will seriously affect the estimate of the convergence rate. Vertical outliers that are characterised by an unusual growth rate, but are not outlying with respect to the initial income, will mainly affect the constant. The effect on the convergence rate tends to be rather small. In contrast, leverage points, i.e. outlying observations with regard to the initial income level,

11 The fit of the alternative models can only be compared by information criteria, since the traditional R^2 measure is not applicable to the spatial regression models that have to be estimated by maximum likelihood.

might have severe consequences for the precision of the regression coefficients if they are also marked by an unusual growth rate (bad leverage points).[12]

In order to identify highly influential observations that might adversely affect the estimate of the convergence rate, Cook's distance is used. [13] This measure takes into account leverage and the size of the residual. Concerning the traditional convergence regression, the results of Cook's distance indicate that six observations (Wilhelmshaven, München, Karlsruhe, Frankfurt, Südpfalz, Nordschwarzwald) should be examined. This group of regions includes all observations that were identified as outliers in one of the regression models described above. The potential effect of these conspicuous observations for the estimated rate of convergence is ambiguous because they have large positive and negative residuals. The marked deviation from the average convergence relationship that characterises these regions might be traced back to quite different explanations. Concerning the regions Wilhelmshaven and Karlsruhe, the results of other studies (e.g. *Schalk* et al 1995) suggest that the unusual values are caused primarily by data problems, i.e. deficiencies of the applied indicator gross value added at market prices.[14] In the case of München, spatial effects seem to matter since the region is an outlier only in the initial OLS regression without spatial interaction. This suggests that the growth of the region München corresponds rather precise with the average spatial interaction estimated in the spatial regression models. The opposite might apply to the regions Südpfalz and Nordschwarzwald. They are identified as outlying observations only in the spatial approaches pointing to an unusual performance with respect to the spatial effects of growth.

To investigate the influence of the potential leverage points, dummy variables for the outlying regions are introduced. This allows to control the effect of the outliers without removing the observations from the data set. In contrast to the deletion of unusual data points, this approach permits to comprise the spatial interaction of the outlying regions in the spatial regression models. The estimation results for the traditional and the spatial convergence models including the dummy variables for the outlying regions are summarised in Table 3. The findings confirm the identification of leverage points based on

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12 *Rousseeuw* (1997) provides a survey on robust estimation methods applied to detect outliers in multiple regressions. For an application of the least trimmed squares estimator see *Funke* and *Niebuhr* (2000).

13 Cook's distance is given by: $D_i = h_i e_i^2 / ks^2 (1-h_i)^2$, where h_i is the *i*-th diagonal element of the hat matrix ($H = X(X'X)^{-1} X'$), s^2 is an unbiased estimate of the residual variance and k is the number of explanatory variables including the constant.

14 In both regions the share of production taxes and subsidies in gross value added at market prices lies significantly above the average level. The same explanation might also apply to the region Südpfalz where the area Germersheim realises a high proportion of production taxes and subsidies. The analysis of *Schalk* et al (1995) indicates that the inclusion of such observations can result in biased estimates.

Cook's distance since in the modified regressions the convergence rate and the R^2_{adj} significantly differ from the previous results. Controlling the effects of the leverage points increases the fit of the convergence equation[15] and the estimated speed of convergence. The Breusch-Pagan test indicates that the outlying observations also caused the heteroscedastic error terms in the initial specifications. However, the non-spatial approach presented in the first column is still misspecified due to ignored spatial interaction.

Table 3. Regression results for regional income growth 1976-1996
- Dummy variables for leverage points -

Explanatory variables	OLS		Maximum Likelihood (ML)	
	(1)	(2)	(3)	(4)
$\ln(y_{76})$	-0.015** (6.73)	-0.013** (5.74)	-0.012** (5.11)	-0.012** (5.42)
$W \ln(y_{76})$ ($\gamma_E = 0.3$)		-0.032** (3.71)		
λ ($\gamma_E = 0.5$)			0.64** (3.90)	
ρ ($\gamma_E = 0.5$)				0.60** (4.28)
R^2_{adj}	0.62	0.67		
AIC	-651.5	-661.2	-658.5	-663.3
HQ	-647.9	-656.7	-654.9	-658.8
Moran´s I_t	4.1** (0.3)[1)] [0.1-0.8][2)]	2.2* (0.5) [0.4-0.6]		
LM_{ERR}	7.4** (0.5) [0.3-0.7]	-		-
LM_{LAG}	21.5** (0.4) [0.2-0.9]	5.0* (0.6) [0.5-0.7]	6.8** (0.4) [0.3-0.5]	
Breusch-Pagan	2.5	1.7	2.0	1.6

Notes: ** significant at the 0.01 level,
* significant at the 0.05 level,
1) corresponding distance decay γ_E,
2) range of γ_E with significant spatial autocorrelation of the error term at the 0.05 level.
The OLS *t*-statistics are based upon White's heteroscedasticity-adjusted standard errors.

The results of the diagnostics point to a spatial dependence of the substantive form since the LM_{LAG} test achieves highest significance. This is confirmed by the estimates of the spatial models. The specifications that incorporate substantial effects, i.e. the spatial

15 Deleting the leverage points in an OLS regression of the traditional model yields an adjusted R^2 of about 0.4.

cross-regressive model (column 2) and the spatial lag model (column 4) realise a better fit than the spatial error model (column 3). Additionally, Moran's I_t and the LM_{ERR} test indicate that there might remain spatial dependence unexplained in the spatial cross-regressive and the spatial error model. A comparison of the three spatial models suggests that the lag approach with a distance decay of 0.5 offers the appropriate specification of spatial interaction.

The coefficient of the initial income level decreases in the spatial lag model when compared with the traditional non-spatial regression. This is to be expected since the coefficient of the spatial lag is significant, and in this case the OLS estimates of the traditional model are biased due to the omission of the lagged dependent variable. The consideration of spatial effects results in a slightly slower rate of convergence compared to the estimate of the traditional approach. However, taking into account the spatial dimension of growth does not alter the general conclusion that regional income growth in West Germany is characterised by a process of convergence. In other words, poor regions tend to realise a higher growth of per capita income than rich ones. But an important aspect of regional growth is that simultaneously regions considerably benefit from high growth in adjacent areas. The significant spatial dependence that characterises the growth of per capita income can not be explained by a clustering of the initial income coupled with a process of absolute convergence. The results suggest that the spatial effects are a substantive element of the regional growth process, not a by-product of convergence.[16]

Finally, by estimating conditional convergence models, the sensitivity of the results with respect to the assumption of a common steady state is checked. The findings of *Funke* and *Strulik* (1999) suggest that regions in West Germany do not share a common steady state. This evidence raises the question whether the model of unconditional convergence suffers from these unconsidered differences which might cause spatial error dependence. If region-specific steady states are spatially autocorrelated, ignoring the differences in the steady states will result in spatially autocorrelated residuals. In this case, the spatial effects detected in the unconditional convergence models might not point to spatial interaction since the autocorrelation is due to the spatial structure of the steady states.

16 There are some differences with respect to the evidence provided by *Rey* and *Montouri* (1999) for US regional income convergence. According to their results, the spatial error model appears to be the appropriate specification for the growth process of US regions, suggesting that the spatial effects are of the nuisance form. This deviation might be caused by the differences between the units of observation. Whereas *Rey* and *Montouri* (1999) investigate US States, i.e. rather large administrative areas, the present analysis is based on smaller functional regions. Thus, the effects of an inadequate regional system, a poor match between the spatial dimension of the analysed phenomenon and the units of observation, might dominate and hide the substantial dependence of income growth.

The results for the conditional convergence models are summarised in Table 4. The share of highly qualified employees in total employment in 1976, HC_{76}, is used to control for differences in the steady states. The regressions yield a positive and significant coefficients for HC_{76} in all specifications, indicating growth enhancing effects of human capital. Moreover, the inclusion of the human capital variable raises the estimated rate of convergence. This change implies that ignoring differences in the steady states results in a downward biased rate of convergence.[17] However, the non-spatial approach (column 1) is still marked by spatially autocorrelated residuals.

Table 4. Regression results for regional income growth 1976-1996 – conditional convergence -

Explanatory variables	OLS		Maximum Likelihood (ML)	
	(1)	(2)	(3)	(4)
$\ln(y_{76})$	-0.020** (4.57)	-0.015** (3.66)	-0.016** (4.21)	-0.016** (4.60)
HC_{76}	0.18** (2.78)	0.13** (2.38)	0.16** (3.59)	0.16** (3.72)
$W\ln(y_{76})$ ($\gamma_E = 0.4$)		-0.033** (4.62)		
λ ($\gamma_E = 0.5$)			0.57** (2.97)	
ρ ($\gamma_E = 0.5$)				0.55** (3.11)
R^2_{adj}	0.33	0.41		
AIC	-611.7	-620.0	-616.3	-617.0
HQ	-608.1	-615.5	-612.7	-612.5
Moran´s I_t	3.1** (0.4)$^{1)}$ [0.1-0.8]$^{2)}$	-		
LM_{ERR}	4.98* (0.5) [0.4-0.7]	-		-
LM_{LAG}	11.1** (0.5) [0.2-0.8]	-	4.6* (0.4) [0.4]	
Breusch-Pagan	8.0*	6.9	9.6*	10.1

Notes: ** significant at the 0.01 level,
* significant at the 0.05 level,
1) corresponding distance decay γ_E,
2) range of γ_E with significant spatial autocorrelation of the error term at the 0.05 level.
The OLS *t*-statistics are based upon White's heteroscedasticity-adjusted standard errors.

17 Furthermore, the number of outlying observations is reduced by applying the concept of conditional convergence. The decreasing number of regions that is controlled by dummy variables probably explains the reduction of the information criteria compared to the results in Table 3.

The estimates of the spatial effects (columns 2 to 4) are more or less unaffected by the inclusion of the human capital variable. The coefficients of the spatial variables remain significant and just slightly change. As in the unconditional models, the rate of convergence declines if spatial effects are considered. Thus, ignoring spatial interaction in the conditional approach as well causes biased estimates of the speed of convergence. In addition, a comparison of the spatial models confirms that the spatial dependence is probably of the substantive form, since the specifications incorporating substantial effects tend to realise a better fit, simultaneously capturing all spatial dependence, than the spatial error model. These results suggest that the spatial dependence of income growth is generated essentially by spatial interaction.

The specifications of the spatial models imply that effects of random shocks will diffuse throughout the regional system. Therefore, convergence to a steady state equilibrium possesses simultaneously a temporal and a spatial dimension. The impact of a region-specific shock extends by a complex pattern of spatial spillovers throughout the regional system (*Rey* and *Montouri* 1999). The coefficient of the spatially lagged dependent variable implies that income growth of a region increases by more than 0.5 percent points if the growth rate in adjacent areas (adjacent according to the matrix *W*) increases by one percent point. However, according to the distance decays of the spatial approaches (γ_E = 0.4 respectively 0.5), the magnitude of the corresponding effects declines rather quickly with increasing distance. The estimates suggest that the intensity of spatial growth effects decreases by 50% over a range of approximately 50 kilometres.

4. CONCLUSIONS

The findings of the present analysis indicate that spatial interaction is an important element of regional growth and convergence. Growth of per capita income in West Germany is marked by a significant spatial dependence, i.e. both regions realising high growth rates and areas characterised by an unfavourable development tend to cluster in space. However, the regional growth process between 1976 and 1996, respectively the corresponding moves within the regional income distribution, caused a disintegration of the low and high income clusters that marked the regional disparities in 1976. The results confirm the evidence provided by a number of recent empirical studies on spatial dependence and growth (e.g. *Armstrong* 1995, *López-Bazo* et al 1999, *Rodríguez-Pose* 1999, *Rey* and *Montouri* 1999). The findings suggest that the non-spatial models applied to analyse β-convergence suffer from a misspecification due to omitted spatial effects. Taking into account spatial effects results in a slightly slower rate of convergence but does not alter the general conclusion that the development of regional income is characterised by a process of convergence.

The spatial dependence that characterises the growth of per capita income is of a substantive form, i.e. it is not an artifact of a convergence process combined with a spatial autocorrelation of the initial income level. The findings indicate that regions can significantly benefit from high income growth in adjacent areas and might as well considerably suffer from an economic decline in neighbouring regions. Spatial spillovers matter for the evolution of regional disparities, and, as *Rey* and *Montouri* (1999) emphasise, more attention has to be paid to the spatial dimension, respectively to the interaction between spatial and temporal dimension of effects induced by random shocks.

With respect to convergence on the European level, the conclusions of the present analysis imply that the usual approach of previous studies to incorporate the spatial dimension of growth by national dummy variables is presumably not sufficient. The existence of different growth clusters at the national level requires a more general incorporation of spatial effects. The exclusion of spatial interaction across national borders and the assumption that all regions of a EU member state belong to one national growth cluster can not serve as an adequate framework to analyse convergence among European regions. Since the proceeding integration process reduces the barriers of spatial interaction between European regions, transnational growth effects and clusters should become increasingly important. Thus, especially with regard to regional growth in an area marked by deepening economic integration, a number of interesting issues remain to be analysed. Are growth clusters still limited by national borders? Has the pattern of spatial interaction changed in the course of the integration process? How does the relationship between spatial dependence and convergence appear on the European level?

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