Regional Convergence in Unified Germany: A Spatial Econometric Perspective

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Abstract. *This paper investigates regional convergence in unified Germany for the period 1992-2000. We adopt a spatial econometric approach on the basis of an extended Solow model. If spatial dependence across regions turns out to be substantial, its ignorance leads to biased and inconsistent estimates of the convergence rate and impacts of control variables; in case of a nuisance dependence biased estimates of standard errors would mislead statistical inference. In the parsimonious spatial setting proposed here, we allow for higher order spatial lags as well as mixed forms of spatial dependencies across regions. On the basis of this framework findings on ß-convergence are presented for unified Germany.*

JEL: R11, R15, C21

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1. Introduction

The issue on whether poor countries and regions tend to catch-up richer economies plays a prominent role in growth theory. The so-called convergence debate has originally arisen from predictions of neo-classical growth theory (Baumol, 1986) but is nowadays lead by contrary propositions of endogenous growth theory. Influential articles on the convergence of countries and US regions stem from Barro and Sala-I-Martin (1991), Mankiw, Romer and Weil (1992), Islam (1995) and Bernhard and Jones (1996a, 1996b). Armstrong (1995) and Fingleton (1999) have studied convergence across European regions. The papers of Seitz (1995), Schalk and Untiedt (1996), Bohl (1998), Funke and Strulik (1999) and Niebuhr (2001) address the issue of regional income convergence to West Germany. Barrell and te Velde (2000) and Funke and Strulik (2000) provide evidence on East-West convergence in unified Germany.

For testing the convergence hypothesis different econometric approaches have been employed which comprise traditional cross-section regressions, panel econometric methods and Markov chains. Although single papers pointed to the spatial dimension of growth processes (e.g. Armstrong, 1995), for a long time no spatial effects have explicitly been taken into account in convergence studies. The crucial question is not *whether* a growth impetus comes to a halt at a regional border but *how strong* its effect will be. Are spatial effects in convergence analysis sufficiently strong that they really matter? What changes are involved if spatial effects will explicitly taken into account in econometric growth analysis? Rey and Montouri (1999) first addressed these questions when investigating US regional income convergence. They showed that ignorance of spatial effects is not justified in general. The consequences of theirs ignorance depend on the kind of spatial dependence which is actually present in the growth process.

This paper adopts a spatial econometric perspective for testing the convergence hypothesis for unified Germany. For West Germany both absolute and conditional income convergence is strongly reported by nearly all growth studies. Regarding unified Germany econometric evidence is missing. Just recently regionally disaggregated data on economic growth for a short decade are available from official statistic sources which enables us to trace the economic development in unified Germany up to now in a spatial econometric setting. Although not explicitly distinguished in neo-classical growth theory, a differentiation between income per capita and labour productivity turns out to be highly relevant for assessing German regional convergence. Econometrically, the existing spatial approaches are extended by choosing a general spatial model as suitable framework for growth analysis. It turns out that the usually employed spatial lag or spatial error model can fall short in catching spatial dependence in convergence models. For model identification we mainly make use of robust LM diagnostics (Bera and Yoon, 1993) which have been shown to be superior compared to traditional criteria (see Anselin and Florax, 1995) applied up to now in spatial convergence analysis.

The paper is organised as follows. In Section 2 the human capital augmented Solow model as the base for convergence analysis is outlined. Section 3 deals with spatial econometric modelling issues. Alternative models and diagnostics for spatial dependence are presented. Section 4 contains a description of the regional data set. Section 5 offers an exploratory analysis on spatial dependence of the variables employed. Results on convergence are discussed in detail in Section 6. Section 7 concludes.

2. Growth Theoretic Basis

In empirical studies of growth human capital has proved to provide a significant contribution in explaining the variation of labour productivity even in a neoclassical modelling framework (see e.g. Mankiw, Romer and Weil, 1992; Seitz, 1995; Islam, 1995; Niebuhr, 2001).. Stressing the importance of human capital as an input factor, Lucas (1988) modelled the production function for human capital different from that for other goods. Here we adopt the view of Mankiw, Romer and Weil (1992, pp. 416) who suppose that both production functions are not fundamentally different (see also Romer, 1996, pp. 126).

The regional production functions in the augmented Solow model are of type Cobb-Douglas:[1]

(2.1) $Y(t) = K(t)^{\text{á}} H(t)^{\text{â}} [A(t) \cdot L(t)]^{1-\text{á}-\text{â}}$.

Y, K, H, A, and L denote the production, physical capital, human capital, level of technology and labour input of a region considered at time t, respectively; $A{\cdot}L$ denotes the regional labour input in efficiency units. The parameters a and $\text{â}\ (0 < \text{á} < 1, 0 < \text{â} < 1)$ are the production elasticities of physical and human capital; 1-a-ß >0 is the elasticity of labour input. On competitive markets the input factors are paid by their marginal products. Labour L and the level of technology A are assumed to grow exogenously at rates n and g. While technology growth g is supposed to be uniform in all regions of the economy, the growth rate of population, n, generally differs from region to region.

To trace the evolution of production, physical and human capital in the economy we define the variables in efficiency units of labour:

$$\hat{y} = Y/(A \cdot L), \hat{k} = K/(A \cdot L) \text{ and } \hat{h} = H/(A \cdot L) .$$

With constant fractions of income invested in physical and human capital, s_k and s_h, a regional economy evolves according to the differential equations[2]

(2.2) $\dot{\hat{k}}(t) = s_k \cdot \hat{y}(t) - (n + g + \text{ä}) \cdot \hat{k}(t)$

and

(2.3) $\dot{\hat{h}}_i(t) = s_h \cdot \hat{y}(t) - (n + g + d) \cdot \hat{h}(t)$,

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[1] It is assumed that (2.1) underlies the production of consumption, physical and human capital. The goods can be transformed costless in either of each utilisation.

[2] A dot above a variable describes its derivation with respect to time: $\dot{x} = dx / dt$.

where *d* denotes the uniform depreciation rate of physical and human capital. If there are decreasing returns to "aggregate" capital ($á + â < 1$), a region converges to its steady-state

$$(2.4)\ \ \hat{k}^* = \left(\frac{s_k^{1-â} s_h^{â}}{n+g+ä}\right)^{1/(1-á-â)}$$

and

$$(2.5)\ \ \hat{h}^* = \left(\frac{s_k^{á} s_h^{1-á}}{n+g+ä}\right)^{1/(1-á-â)}$$

in which the relation

$$(2.6)\ \ y^* = A(0)\cdot e^{g\cdot t}\left(\frac{s_k^{á} s_h^{â}}{(n+g+ä)^{á+â}}\right)^{1/(1-á-â)}$$

with y=Y/L holds for labour productivity. Since the parameters n, g and δ as well as the quantities s_k and s_h can differ from region to region, only conditional convergence applies in general. Unconditional convergence would presuppose a catching-up by poorer regions without a need to control for regional-specific differences.

Barro and Sala-i-Martin (1999, pp. 87) have shown how the evolution of labour productively can be traced for an economy outside the steady-state in the Solow model. In the case of the augmented Solow model the same dynamic equation results (Mankiw, Romer, Weil, 1992, pp. 422; Romer, 1996, pp. 139). By a Taylor series expansion around the steady state, one gets[3],

$$(2.7)\ \ \ln\,\hat{y}(t) = (1-e^{-ë\,t})\cdot \ln\,\hat{y}^* + e^{-ë\,t}\cdot \ln\,\hat{y}(0)\,,$$

where the parameter $ë\,(ë > 0)$ is the rate of convergence. Using equation (2.6) it can be shown that the growth of labour productivity, $\ln[\hat{y}(t)/\hat{y}(0)]$, is a function of the model parameters determining the steady state and of its initial level $\hat{y}(0)$:

$$(2.8)\ \ \ln[\hat{y}(t)/\hat{y}(0)] = (1-e^{-ë\cdot t})\frac{á}{1-á-â}\ln s_k + (1-e^{-ë\cdot t})\frac{á}{1-á-â}\ln s_h$$
$$-(1-e^{-ë\cdot t})\frac{á+â}{1-á-â}\ln\,(n+g+ä) - (1-e^{-ë\cdot t})\ln\,\hat{y}(0)\,.$$

According to the transition equation (2.8) the growth of labour productivity is positively related to the accumulation rates of physical and human capital and negatively related to the

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[3] Only the steady state value $\hat{y}^*$ of the production per efficiency unit labour (eq. 2.6) is different determined.

sum of the exogenous quantities n, g and δ and the initial level of labour productivity. The latter effect implies that a regional economy will grow the faster towards its steady state the farer away it is from it in the starting position. A catching-up seems to be possible for poorer regions, but absolute convergence can only be expected if economic conditions tend to equalise across the regions.

Convergence occurring by a higher growth rate of poorer regions is called ß convergence. In case of ß convergence the dispersion of labour productivity does not necessary diminish, since disturbances can offset the negative effect of growth rate differences (see e.g. Barro and Sala-I-Martin, 1999, pp. 383). An equalisation of dispersion across regions characterises the concept of σ convergence. It ensues ß convergence but the reverse does not necessarily hold.

3. Spatial Econometric Methods

3.1 Modelling Spatial Processes

In order to study the convergence process empirically, the transition equation (2.8) has to be transformed into an appropriate econometric model. Since the cross-sections in this study are labour markets, we adopt a spatial econometric modelling approach. Spatial dependence can be substantive in the sense that it "follows from the existence of a variety of spatial interaction phenomena" or as "a by-product of measurement errors" (Anselin, 1988, p. 11). In the first case it has to be captured by spatial lags of the relevant economic variables, whereas in the latter the disturbances are spatially autocorrelated. Usually, in spatial econometric models only spatial lags in the dependent variable are taken into account, while spatial lagged exogenous variables are not explicitly modelled.[4]

Here we consider the mixed regressive, spatial autoregressive moving average model (spatial ARMAX model) as a general spatial model which allows for both kind of spatial dependence.[5] Given n spatial units in the economy we can state the convergence equation (2.8) in terms of the general spatial model compact in matrix form. Let $\mathbf{y}$ be an nx1 vector of the dependent variable ln[y(t)/y(0)], $\mathbf{X}$ an nx4 observation matrix of the exogenous variables

[4] In analogy to time series analysis a spatial econometric model with lagged exogenous variables could be termed as a spatial distributed lag model (see e.g. Lauridsen, 2002). As in time series analysis one can argue that spatial effects stemming from exogenous variables will be captured by a spatial lagged endogenous variable.

[5] Huang (1984) has been the first who has introduced the spatial ARMA model in econometrics. In addition to the spatial lags, our model includes control variables (X).

1, ln s_k, ln s_h and ln $(n+g+\delta)$, **ß** an nx4 parameter vector reflecting the effects of the exogenous variables on the dependent variable $\ln[y(t)/y(0)]$ and **e** an nx1 disturbance vector. The autoregressive structure is determined by the AR paramters ρ_i and nxn spatial weight matrices $\mathbf{W}_i$, i=1,2,…,p, whereas the moving average structure is defined by the MA parameters θ_j and nxn spatial weight matrices $\mathbf{W}_j$, j=1, 2,…q. Then the ARMAX(p,q) model of the growth equation (2.8) can be presented in the form

(3.1) $\mathbf{y} = \rho_1 \cdot \mathbf{W}_1 \cdot \mathbf{y} + \ldots + \rho_p \cdot \mathbf{W}_p \cdot \mathbf{y} + \mathbf{ß} \cdot \mathbf{X} + \mathbf{e} + \theta_1 \cdot \mathbf{W}_1 \cdot \mathbf{e} + \ldots + \theta_q \cdot \mathbf{W}_q \cdot \mathbf{e}$

with $\mathbf{e} \sim N(\mathbf{0}, \sigma^2 \cdot \mathbf{I})$. From (3.1) one obtains the mixed regressive, spatial autoregressive model [ARX(p) model] by imposing the parameter restrictions $\theta_1=\theta_2=\ldots=\theta_q=0$:

(3.2) $\mathbf{y} = \rho_1 \cdot \mathbf{W}_1 \cdot \mathbf{y} + \ldots + \rho_p \cdot \mathbf{W}_p \cdot \mathbf{y} + \mathbf{ß} \cdot \mathbf{X} + \mathbf{e}$.

By contrast, for the parameter restrictions $\rho_1=\rho_2=\ldots=\rho_p=0$ the mixed regressive, spatial moving average model [MAX(q) model]

(3.3) $\mathbf{y} = \mathbf{ß} \cdot \mathbf{X} + \mathbf{e} + \theta_1 \cdot \mathbf{W}_1 \cdot \mathbf{e} + \ldots + \theta_q \cdot \mathbf{W}_q \cdot \mathbf{e} + \mathbf{ß} \cdot \mathbf{X} + \mathbf{e}$

results.

In our regional growth analysis the spatial weight matrices $\mathbf{W}_1$, $\mathbf{W}_2$, …, $\mathbf{W}_s$, s=p,q are considered to be neighbourhood or contiguity matrices. More exactly $\mathbf{W}_i$ denotes an *i*th order neighbourhood matrix having only non-zero entries for contiguous regions. Let $\mathbf{W}_i^*$ be an nxn neighbourhood matrix which entries $W_{i,k\ell}^*$ take only the values 1 and 0:

(3.4) $W_{i,k\ell}^* = \begin{cases} 1 \text{ if regions } k \text{ and } \ell \text{ are } i\text{th order neighbours} \\ \quad 0 \text{ otherwise} \end{cases}$.

The entries of $\mathbf{W}_i$ result from a row normalization of $\mathbf{W}_i^*$ which is done by dividing the elements of the *k*th row of $\mathbf{W}_i^*$ by the *k*th row sum $\sum_\ell W_{i,k\ell}^*$. Thus the *k*th component of the nx1 spatial lag vector $\mathbf{W}_i \cdot \mathbf{y}$ renders the mean of the variable Y_k in the *i*th order neighbourhood regions of k.[6]

Anselin (1998, p.6) brings into prominence that the general spatial model has rarely considered in empirical studies. Instead, special cases like the ARX(1) model (first order spatial lag model)

(3.5) $\mathbf{y} = \rho_1 \cdot \mathbf{W}_1 \cdot \mathbf{y} + \mathbf{ß} \cdot \mathbf{X} + \mathbf{e}$

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[6] While a first order neighbourhood is defined by two regions having a common border, in an *i*th order neighbourhood of two regions i-1 regions must lie between them.

or the MAX(1) model

(3.6) $\mathbf{y} = \mathbf{ß}\cdot\mathbf{X} + \theta_1\cdot\mathbf{W}_1\cdot\mathbf{e} + \mathbf{e}$.

have obtained attention in applied spatial econometrics (see e.g. Ord, 1975; Haining, 1988; Schulze, 1999; Niebuhr, 2001). The ARX(1) model is conventionally called mixed regressive, autoregressive model or spatial lag model. Instead of the moving average error process in (3.6) in spatial econometrics traditionally a first order autoregressive process,

(3.7) $\mathbf{e} = \theta_1\cdot\mathbf{W}_1\cdot\mathbf{e} + \mathbf{n}$,

is preferred for modelling the spatial error process$^-$ (see- Hordijk, 1979; Anselin, 1988, pp. 34; LeSage, 1998, pp. 50). In this case the spatial error model, i.e. the linear regression model with spatial autoregressive errors, reads

(3.8) $\mathbf{y} = \mathbf{ß}\cdot\mathbf{X} + \theta_1\cdot\mathbf{W}_1\cdot\mathbf{e} + \mathbf{n}$.[7]

Its equivalent form

(3.9) $\mathbf{y} = \mathbf{ß}\cdot\mathbf{X} + (\mathbf{I} - \theta_1\cdot\mathbf{W}_1)^{-1}\cdot\mathbf{n} = \mathbf{ß}\cdot\mathbf{X} + (\mathbf{I} + \theta_1\cdot\mathbf{W}_1 + \text{è}_1^2\cdot\mathbf{W}_1^2 + \text{è}_1^3\cdot\mathbf{W}_1^3 + \ldots)\cdot\mathbf{n}$ [8]

gains attraction since it shows that a random shock hitting a special region will not only effect this region but propagate in space. In order to guarantee diminishing nuisance dependence we impose the parameter restriction $|\theta|<0$. A propagation mechanism results likewise from the spatial lag model since it can be equivalently represented by an infinite spatial moving average error process (Anselin, 1999, p. 7). This opens the possibility to trace spillover effects within a spatial modelling frame.

Usually only first order variants of the general spatial model are used in practice. One reason may be the lack of efficient algorithms in spatial econometric software.[9] Add to this powerful diagnostics tools for model identification are only available since the mid 90ties (see Anselin and Florax, 1995). In view of the former issue and potential multicollinearity the estimation of the general spatial model can be simplified if one is willing to allow for spatial effects in a condensed form. The contiguity matrix $\mathbf{W}^*_{12\ldots s}$ for neighbourhoods up to the *s*th

[7] The spatial error models (3.6) and (3.8) are observationally equivalent. However, one has to be conscious that an identification problem arises if one wishes to combine the spatial lag model (3.5) with the spatial error model (3.8) using the same weight matrix (Anselin and Florax, 1995, p. 24). The identification problem does not occur in the special variant of the spatial ARMAX model.

[8] The last representation follows from the properties of lag polynomials well-known form time-series analysis (see e.g. Franses pp. 32). In contrast to time series analysis, we have to distinguish between the *i*th order weight matrix $\mathbf{W}_i$ and the *i*th power of the weight matrix $\mathbf{W}^i$.

[9] Even at present time the general spatial model can only be applied in SpaceStat (Anselin, 1999) in a restricted form with a uniparametric spatial autoregressive error process.

order (cumulative contiguity) can be easily calculated from the ith (i=1,2,…s) order neigbourhood matrices $\mathbf{W}_1$, $\mathbf{W}_2$, …, $\mathbf{W}_s$:

$$\mathbf{W}^*_{12\ldots s} = \mathbf{W}^*_1 + \mathbf{W}^*_2 + \ldots + \mathbf{W}^*_s, \, s = p, q \, .$$

Using the row-standardized cumulative contiguity matrix $W_{12\ldots s}$ the spatial ARMAX model (3.1) simplifies to

(3.10) $\mathbf{y} = \rho \cdot \mathbf{W}_{12\ldots p} \cdot \mathbf{y} + \mathbf{ß} \cdot \mathbf{X} + \theta \cdot \mathbf{W}_{12\ldots q} \cdot \mathbf{e} + \mathbf{e}$.

In the representation (3.7) ρ and θ are global autoregressive and moving average parameters, which comprise spatial effects from *1*st up to *p*th and *q*th order neighbours, respectively. The spatial lag vector $\mathbf{W}_{12\ldots p} \cdot \mathbf{y}$ here contains e.g. the means of all regions up to a neighbourhood of *p*th order so that the autoregressive parameter measures the total effect of the dependent variable in the broader defined neighbourhood regions on **y**. Of course, the use of the contiguity matrix $\mathbf{W}^*_{12\ldots s}$ can also offer a way for a generalisation of the first order spatial autoregressive error model (3.8). Moreover, the ARMAX representation reflects the structure of the general spatial model if one works with a general spatial weight matrix.[10]

3.2 Tests for Spatial Dependence

In a spatial econometric analysis spatial dependence can be established by examining the residuals $\mathbf{e} = \mathbf{y} - \mathbf{X}\hat{\mathbf{a}}$ obtained from OLS estimation of the multiple linear regression model

(3.11) $\mathbf{y} = \mathbf{X} \cdot \mathbf{ß} + \mathbf{e}$.

It can be conceived as the most restricted form of the general spatial model (3.1) when all spatial effects are ignored ($\rho_1 = \rho_2 = \ldots = \rho_p = 0$ and $\theta_1 = \theta_2 = \ldots = \theta_q = 0$). If spatial effects are present, the residuals will not be white noise but spatially autocorrelated. In this case nuisance effects would imply a loss of efficiency in the OLS estimator of **ß.** . Standard errors of the regression coefficient would be biased and usual t tests misleading. If spatial dependence arises from spatial lags in the dependent variable, the problem is more serious insofar as the OLS estimator of **ß** would become biased and inconsistent (Cliff and Ord, 1973, pp. 87; Anselin, 1988, pp.58).

[10] For the construction of general spatial weight matrices see Anselin (1988, pp. 19).

Tests for spatial dependence in general are rarely applied in empirical economic research. However, Moran's I test plays a predominant role in applied spatial econometric analysis. Let **x** be an nx1 observation vector of a variable X measured in deviations from the mean. Then for a general weight matrix **W** Moran's I takes the form

$$(3.12)\ I = \frac{\mathbf{x}'\cdot\mathbf{W}\cdot\mathbf{x}/S_w}{\mathbf{x}'\cdot\mathbf{x}/n},$$

where n is the number of regions and S_W the sum of weights.[11] The numerator of I is a covariance measure between X and its spatial lag and the denominator corresponds to the variance of X -; its expected value $E(I)=-(n-1)^{-1}$ approaches zero for large n. Since Moran's I is expected to lie in the range between –1 and 1, its interpretation resembles the well-known non-spatial correlation measures. For carrying out a test on spatial autocorrelation one can take advantage of the asymptotically standard normal distribution of Moran's I in standardised form (Cliff and Ord (1973), pp. 29).

In our study the Moran test is used to establish if and up to what neighbourhood order the variables entering the extended neoclassical growth model are spatially autocorrelated. When applied to the residuals (**x**=**e**) the multiple linear regression model (3.11) it is not very helpful for spatial model building, since it cannot discriminate among spatial alternatives (Anselin and Rey, 1991; Anselin and Florax, 1995, pp. 34). As an overall test it could only indicate, whether the errors prove to be spatially autocorrelated at all.

On the assumption that the disturbances are normally distributed a Likelihood Ratio test (LR test) can also applied for discovering spatial effects. Let $\hat{\boldsymbol{\beta}}$ be the OLS estimator (= ML restricted estimator) for **ß** in the regression model without allowing for spatial dependence and $\hat{\boldsymbol{\beta}}_{spat}$ the maximum likelihood (ML) estimator (= ML unrestricted estimator) for the presumed spatial regression model. Then the LR statistic defined as twice the difference of the log likelihood functions (ℓ) of the unrestricted and restricted regressions models,

$$(3.13)\ LR = 2\cdot[\,\ell(\hat{\boldsymbol{\beta}}_{spat}) - \ell(\hat{\boldsymbol{\beta}})\,],$$

is known to be asymptotically distributed as a χ^2 variate with degrees of freedom given by the number of constraints (Anselin, 1988, pp. 67; Darnell, 1994, pp. 222). In the spatial case the

[11] Cliff and Ord, 1973, pp. 8; Anselin, 1988, pp. 101. In case of a row-standardised because of S_w=n the quantities S_w and n cancel out. For the sake of simplicity in this section we suppress any order index for the spatial weight matrix in definitions of diagnostics for spatial dependence.

number of constraints correspond exactly with the number of spatial parameters included in the unrestricted model.

For testing the kind of spatial dependence two Lagrange Multiplier tests by Bera and Yoon (1993) have proved to be promising. In Monte Carlo experiments Anselin and Florax (1995) have shown that the Bera-Yoon Lagrange Multiplier tests has high power in discriminating between spatial lag and error dependence. The basic idea of these tests consists in correcting the Lagrange Multiplier test statistics for spatial error and lag dependence, LM(err) and LM(lag) (see e.g. Anselin and Florax, 1995, pp. 25),

(3.14) $\text{LM(err)} = (\mathbf{e}'\cdot\mathbf{W}\cdot\mathbf{e}/\hat{\sigma}^2)^2 / \text{tr}(\mathbf{W}'\mathbf{W}+\mathbf{W}^2)$

and

(3.154.4) $\text{LM(lag)} = (\mathbf{e}'\cdot\mathbf{W}\cdot\mathbf{y}/\hat{\sigma}^2)^2 / [(\mathbf{WX}\hat{\boldsymbol{\beta}})'\mathbf{MWX}\hat{\boldsymbol{\beta}})/\hat{\sigma}^2 + \text{tr}(\mathbf{W}'\mathbf{W}+\mathbf{W}^2)]$,

with the ML estimator $\hat{\sigma}^2 = \mathbf{e}'\cdot\mathbf{e}/n$ for the error variance σ^2 and $\mathbf{M} = \mathbf{I} - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$ known from regression analysis as a projection matrix. In order to discriminate among the alternatives, the spatial lag dependence is eliminated from LM(err) by extracting a function of $\mathbf{e}'\cdot\mathbf{W}\cdot\mathbf{y}$, whereas a function of $\mathbf{e}'\cdot\mathbf{W}\cdot\mathbf{e}$ is subtracted from LM(lag) in order to control spatial error dependence.[12] This means that the adjusted LM error test, LM_{rob}(err), responds to spatial error dependence but not to spatial lag dependence. In contrary, the adjusted LM lag test, LM_{rob}(lag), is expected to indicate spatial lag dependence but not spatial error dependence. Under the assumption that the errors are normally distributed both test statistics, LM_{rob}(err) and LM_{rob}(lag), obey a χ^2 distribution with one degree of freedom.

4. Data

The study of regional convergence in unified Germany refers to the period 1992-2000. Although official statistics provides data for disaggregated administrative areal units, our notion of a region is economic in nature. Making no allowance for economic relationship in space may involve distortions regarding economic conditions and development (see Eckey, Horn and Klemmer, 1990). For this Eckey (2001) has defined German functional regions by aggregating districts (*Kreise*) on the basis of commuter flows. The functional regions arising in this way are called ‘regional labour markets’. Starting from 440 German districts Eckey

[12] See Bera and Yoon (1993); Anselin and Florax (1995, pp. 25).

(2001) constructed 180 German labour markets of which 133 are mainly located in West Germany and 47 in East Germany.[13]

Since growth theory takes full employment for granted, the convergence relationship can be applied to both income per capita and labour productivity.[14] Both indicators are calculated in real terms, where districtional data on gross domestic product (GDP), employment and polulation have been aggregated and state data on the GDP price index have been disaggregated to match with the regional labour markets concept. All data stem from the "National Accounts of the States" ("*Volkswirtschaftliche Gesamtrechnung der Länder*") compiled by the Statistical State Office Baden-Württemberg.

In the augmented Solow model the sum of population growth, capital depreciation and growth of technological progress enters as an exogenous variable. Mankiw, Romer and Weil (1992, p. pp. 413) and Islam (1995, p. pp.1139) e.g. view the last two components to be constant in their country samples and set them equal to 0.05 in order to "match the available data".[15] Since for unified Germany regional differentiated depreciation rates are not available as well, we have calculated a uniform average depreciation rate of 4.8% for the period of investigation from data on depreciation and invested capital (Statistisches Bundesamt, 1999, 2001).[16] Our choice of the rate of technological progress is based on an empirical study of Grömling (2001) who estimated a value of 0.6% for unified Germany in the period 1992-1999. Investment rates for the overall regional economies as measures of regional savings rates s_k are not available on the disaggregation level required. Regional investment rates are only available for the industrial sector. Because the industrial sector no more represents even the largest sector of the economy, there is a founded danger that distortions may produce uncontrolled effects when working with such restricted indicator. That is why we prefer to measure regional investment intensity by the newly established enterprises in relation to the working population. Districtional data on newly established businesses are available for 1998-2000 on the CD "Statistik regional" are offered by the Federal Statistical Office Germany. In our study the regional data for the investment proxy are computed in form of temporal averages per capita

[13] There are three overlapping regions which consists of a majority of West German districts. Therefore they are labelled as West German regions.

[14] Formally the equality of both concepts is established by normalising the labour participation rate to 1. In applied work a differentiation between the two concepts is necessary.

[15] Mankiw, Romer and Weil (1992), p. 413. In both studies the deprecation rate is set equal to 0.03, whereas for the rate of technological progress a value of 0.02 is chosen.

[16] The depreciation rate appears to be very stable over the period of investigation.

Since investment in human capital is much more difficult to measure than investment in physical capital, we substitute s_h in convergence equation (2.8) by an indicator of the level of human capital.[17] Human capital is in general viewed as labour qualifications acquired in education and training. In West German regional growth studies the proportion of working population with a university degree or a degree at an advanced technical college is used as an indicator for human capital.[18]

Due to data accessibility it is usually referred only to the part of population bounded by law to the social security system. Beside the self-employed persons, especially all officials and civil servants are missing in this statistic. To reduce distortion effects as far as possible we construct a comprehensive human capital indicator which comprises officials and civil servants. The two highest career groups of civil servants are well matched with the degrees of the employees being bound to the social security system. Disaggregated data on the qualifications and careers of the working population have been provided by the German Federal Statistical Office and the German statistical state offices. It is assumed that the 2000 data are representative for the period under investigation.

5. Spatial Autocorrelation of Variables

In order to get an impression on the extent of spatial autocorrelation - encounter Moran's I is applied to all variables that enter the regional growth model. This can be viewed as a preliminary spatial data analysis to our spatially econometric modelling approach. Since Moran's I is just an overall measure of spatial autocorrelation we do not expect to get an insight in the kind of spatial dependence we ultimately have to take into account. However, beyond a general impression of the strength of spatial autocorrelation we additionally expect to obtain some clues on the possible dimension of spatial dependence. For this we use contiguity matrices up to an order of six in calculating Moran's I.

Table 5.1 shows the pattern of spatial autocorrelation for the growth rate of real GDP per capita and total employment (columns 2 and 5) in the period 1992 - 2000 for the 180 German labour markets. In general the spatial autocorrelation diminishes with a higher order of

[17] Formally, if $\ln(s_h)$ is substituted by the log level variable H, equation (2.8) changes insofar as the production elasticity of human capital, ß, now only appears in the numerator of the coefficient of ln(H). See Mankiw, Romer and Weil (1992), p. 418.

[18] See Seitz (1995), p.180; Niebuhr(2001), p. 121.

neighbourhood. Regarding the - growth rates a considerable positive spatial dependence can be stated up to regional neighbourhoods of order three. Although Moran's I is still highly significant for a neighbourhood of order four, its absolute value is markedly reduced. Despite partly significant autocorrelation coefficients spatial dependence is practically negligible for neighbourhoods of fifth and sixth order, because of the low values of the statistic. The pattern of spatial autocorrelation for the logs of real GDP per capita (columns 3 and 4) and GDP per total employment (columns 6 and 7) at the two edges of the sample period is very similar to that of the growth rate.

Table 5.1: Moran's I for regional GDP growth and level variables

Order of contiguity	WGDPC	LGDPC92	LGDPC00	WGDPE	LGDPE92	LGDPE00
1st order	0.668**	0.698**	0.525**	0.655**	0.777**	0.684**
2nd order	0.545**	0.551**	0.394**	0.561**	0.639**	0.518**
3rd order	0.427**	0.454**	0.335**	0.461**	0.525**	0.419**
4th order	0.245**	0.295**	0.248**	0.215**	0.320**	0.296**
5th order	0.047*	0.128**	0.139**	0.013	0.112	0.146**
6th order	-0.076**	-0.0147(*)	-0.023	-0.097**	-0.056*	-0.010

Notes: WGDPC: growth rate of real per capita GDP, WGDPE: growth rate of real GDP per total employment, LGDPC92 (LGDPC00): logarithmic GDP per capita 1992 (2000), LGDPER92 (LGDPE00): logarithmic GDP per total employment 1992 (2000)
** Significance at 1% level; * significance at 5% level; (*) significance at 10% level

From Table 5.2 a somewhat different picture emerges for human capital and investment intensity, whereas the growth rate of population[19] resembles the former one. Human capital and investment intensity seem only be linked within immediately contiguous regions or

Table 5.2: Moran's I for control variables

Order of contiguity	LHUMAN	LNFB	LDTW
1st order	0.228**	0.101*	0.725**
2nd order	-0.015	0.169**	0.589**
3rd order	0.076**	-0.017	0.509**
4th order	0.070**	-0.030	0.273**
5th order	0.010	-0.038(*)	0.066**
6th order	-0.044(*)	-0.058*	-0.084**

Notes: LHUMAN: log human capital (proportion of highly educated people per total employment);
NFB: log newly founded businesses; LDTW: log of $(n+g+\delta)$
** Significance at 1% level; * significance at 5% level; (*) significance at 10% level

[19] Since the parameters g and δ are hold constant across the regions, the behaviour of the variable LDTW is determined by the growth rate of population.

second order neighbourhood regions, respectively. Moreover, in both cases spatial autocorrelation is not strongly marked.

In summary, spatial correlation analysis brought some evidence that growth spillovers seem to be more important than the spillovers arising from human capital and investment strength. All in all it would appear from this that spatial dependence in the data could be well captured by a spatial model.

6. Empirical Evidence on Regional Convergence

6.1 Tests on Regional Income Convergence

At first we investigate the convergence hypothesis of neoclassical growth theory with respect to income per capita. The sample comprises 180 labour markets in West and East Germany. The time period covers not quite a decade from 1992 till 2000.[20] We test for absolute as well as for conditional convergence. Tests of absolute convergence hypothesis rely on models where apart from the intercept only log income per capita in the initial year is taken into account. In a spatial setting regional dependence has to be accounted for by modelling spatial error and/or spatial lag effects.

The estimation of the convergence equation (2.8) without control variables and spatial effects serves as a point of departure. Classical regression analysis leads to estimation results shown in the second column of the upper part of Table 6.1. Out of this a rate of convergence of 6.5% on the average can be inferred[21] The coefficient of initial log income per capita which "explains" the variation of income growth to about 75% is highly significant and takes the expected sign.

Against OLS estimation of the convergence parameter it is objected that random fluctuations of GDP in the starting period result in a "regression towards the mean" (Quah, 1993). As a consequence the "true" value of the convergence parameter will be systematically overestimated in absolute value which means that there is a bias towards convergence. Its

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[20] Although most growth studies refer to long periods, potential structural breaks often require a division of the sample period into sub-periods. Barro and Sala-i-Martin (1995, pp.382) e.g. analyse economic growth for the period 1880-1990 but divide it into 10-, 15- and 20- but also just 5-years sub-periods for studying convergence.

[21] The speed of convergence, λ, is obtained from the convergence parameter â $= -(1- e^{ë \cdot t})$: ë $= -[\ln(1-$â$)]/t$;

Table 6.1: Tests on absolute income convergence

Dependent variable WGDPC	Classical regression model (OLS)	Spatial lag model (1st order)[a]	
		Maximum Likelihood (ML)	Instrument Variables Method (IV)
Variables	Coefficients	Coefficients	Coefficients
Constant	4.0846**	2.9496**	2.74289**
	(0.1673)	(0.2630)	(0.3504)
W_LAG		0.3581**	0.4234**
		(0.0643)	(0.0993)
LGDPC92	-0.4035**	-0.2924**	-0.2722**
	(0.0171)	(0.0262)	(0.0346)
Implied λ	0.0646	0.0432	0.0397
R^2	0.758	0.795	0.796
SSE	0.00702	0.00589	0.0060
AIC	-379.802	-402.269	
BIC	-373.416	-392.690	
JB	6.642*	5.623(*)	
	Diagnostics for spatial dependence		
	$\mathbf{W}_1$	$\mathbf{W}_2$	$\mathbf{W}_3$
Moran	2.863**	1.981*	1.042
LM_{rob}(err)	0.305	0.000	0.0344
LM_{rob}(lag)	15.589**	8.833**	3.802*
LR(err vs clas)=24.467**		LM(err in lag): 0.950 (ML) and 1.023 (IV)	

Notes: a Mixed regressive, 1st order spatial autoregressive model [ARX(1) model]
**: 1% significance level; *: 5% significance level; (*): 10% significance level
R^2: Coefficient of determination (for spatial models: pseudo R^2); SSE: Standard error of regression;
AIC: Akaike information criterion; BIC: Schwartz criterion; JB: Jarque-Bera statistic;
Moran: Moran's I for residuals; W_i, i=1,2,3: *i*th order contiguity matrix (row-standardised);
LM(err), LM_{rob}(err), LM(lag), LM_{rob}(lag): Lagrange Multiplier statistics (see Section 3.2);
LR(err vs clas): Likelihood Ration statistic (see Section 3.2);
LM(err in lag): LM test for spatial error dependence in spatial lag model

size depends on the magnitude of the error variance relative to the variance of the flawless GDP per total employment. The bias does not disappear with an increasing sample size but it will be negligible if the error variance proves to be small in relation to the variance of the "true" regressor.[22] For obtaining a consistent estimator of the convergence parameter λ the method of instrumental variables (IV method) is recommended (see e.g. Johnston and DiNardo, 1997, pp. 155).

[22] The problems of regression towards the mean can be formally treated in an errors in the variables model (see e.g. Johnston and DiNardo, 1997, pp.153). From such a setting it can be shown that for the OLS estimator of the independent variable $\ln \hat{y}(0)$ of the convergence equation (2.8) the relation $p\lim \hat{a}_1 = \hat{a}_1 (s^2_{\ln \tilde{y}(0)} / (s^2_{\ln \tilde{y}(0)} + s^2_v)$ holds where $\ln \tilde{y}(0)$ denotes the flawless independent variable and v the error of the actual used regressor $\ln \hat{y}(0)$.

However, using an adequate instrument for the starting value of income per capita would not solve the problem in presence of spatial effects. In case of a substantive spatial dependence parameter estimation would continue to be inconsistent, whereas in occurrence of spatial error dependence standard errors of the parameter estimates would be biased with the consequence of a misleading inference. It is this issue we focus attention in our work.

From spatial autocorrelation analysis of the model variables we know that spatial dependence is present in the data. However, we have to investigate through which channels spatial dependence manifests itself in the convergence equation. In the lower part of Table 6.1 various diagnostics on spatial dependence are listed. At first the Moran test and robust LM tests are carried out for neighbourhood matrices of first, second and third order, respectively, for the OLS residuals. The high significance of Moran's I for $\mathbf{W}_1$ clearly indicates the existence of spatial effects which could invalidate the results obtained from the classical regression setting. This finding is strongly confirmed by the LR test. The robust LM statistics unambiguously point to a spatial lag model for capturing these effects. Using the information criteria AIC and BIC for model identification the 1st order spatial lag model turns out to be favourable to mixed regressive, higher order spatial autoregressive models.

The ML estimates of the first order spatial lag model (Table 6.1) show a high significance of coefficient of the spatial lag term. The relevance of spatial lag dependence is also brought about on the basis of the information criteria as well as the standard error of regression.[23] From ML estimation a noticeable lower rate of convergence of 4.3% per year in comparison to the corresponding OLS estimate results.

Note that the LM(lag in err) statistic does not point to a relevance of the alternative spatial lag model. However, despite the good model fit the assumption of normal disturbances underlying ML estimation may be doubted. In contrary to OLS residuals the Jarque-Bera statistic for the ML residuals is not significant at the 5% but on the 10% level. In order to check the robustness of inference we additionally estimate the first order spatial lag model by applying the method of instrument variables (IV method). In essence IV estimation of the spatial lag model backs the results of ML estimation. The convergence rate decreases further by about a third percentage point to 4%. Some caution yet remains advisable as heteroscedasticity of OLS errors could be decreased but not fully eliminated in the spatial

[23] In case of ML estimation the R^2 measure is only a pseudo coefficient of determination which is not comparable to the standard R^2 measure of OLS estimation.

setting.[24] Moreover, the role of control variables in the course of the process of income convergence has to be assessed.

Here we start again with the classical regression model in order to test for spatial effects Table 6.2).. Indeed, the existence of spatial dependence is clearly indicated by Moran's I and

Table 6.2: Tests on conditional income convergence

Dependent variable WGDPC	Classical regression model (OLS)	Spatial models	
		Spatial lag model (1st order)^{a} (ML)	ARX(1) with spatial autoregr. errors^{b} (2SLS)
Variables	Coefficients	Coefficients	Coefficients
Constant	3.5604**	3.3093**	3.4133**
	(0.4553)	(0.4392)	(0.4554)
W_ERROR(2)			0.9122
W_LAG(1)		0.2688**	0.2692$^{(*)}$
		(0.0714)	(0.1484)
LGDPC92	-0.4010**	-0.3429**	-0.3707**
	(0.0267)	(0.0307)	(0.0364)
LDTW	-0.0523	0.0525	0.0400
	(0.0819)	(0.0818)	(0.0867)
LHUMAN	0.1186**	0.1041**	0.1343**
	(0.0221)	(0.0219)	(0.0230)
LNFB	0.0248	0.0173	0.0301$^{(*)}$
	(0.0152)	(0.0145)	(0.0170)
Implied λ	0.0641	0.0525	0.0579
R^2	0.803	0.818	0.477
SSE	0.00583	0.00522	0.00580
AIC	-410.367	-420.524	
BIC	-394.402	-401.366	
JB	1.999	5.888$^{(*)}$	
	Diagnostics for spatial dependence		
	$\mathbf{W}_1$	$\mathbf{W}_2$	$\mathbf{W}_3$
Moran	0.162**	0.145**	0.068**
LM_{rob}(err)	2.169	14.751**	7.386**
LM_{rob}(lag)	2.245	0.040	1.042
LR(lag vs. Clas)=12.157**	LM(err in lag)=0.832 ($\mathbf{W}_1$)	LM(err)=11.487** ($\mathbf{W}_2$)	

Notes: a Mixed regressive, 1st order spatial autoregressive model; b Mixed regressive, 1st order spatial autoregressive model with a 2nd order spatial autoregressive error process (using $\mathbf{W}_2$)
**: 1% significance level; *: 5% significance level; (*): 10% significance level
R^2: Coefficient of determination (for spatial models: pseudo R^2); SSE: Standard error of regression;
AIC: Akaike information criterion; BIC: Schwartz criterion; JB: Jarque-Bera statistic;
Moran: Moran's I for residuals; W_i, i=1,2,3: *i*th order contiguity matrix (row-standardised);
LM(err), LM_{rob}(err), LM(lag), LM_{rob}(lag): Lagrange Multiplier statistics (see Section 3.2);
LR(err vs clas): Likelihood Ration statistic (see Section 3.2);
LM(err in lag): LM test for spatial error dependence in spatial lag model

[24] In the spatial setting he spatial Breusch-Pagan (spatial BP) statistic is only weakly significant (10% level), whereas the BP test displays high significance in the classical regression model. Thus, along with allowing for spatial dependence it is succeeded to reduce heteroscedasticity to a large degree.

LM statistics. In contrary, though, to unconditional convergence analysis model identification turns out be much more difficult. Although Moran's I indicates the strongest spatial dependence in case of the first order contiguity matrix, the robust LM statistics fail to reflect this finding. But both the LM(err) as well as the LM(lag) statistics are highly significant.[25] According to the traditional identification criterion because of LM(lag) > LM(err) a spatial lag model could be viewed to be preferable to a spatial error model (Anselin and Rey, 1991). However, a 1^{st} order spatial lag cannot eliminate the 2^{nd} order spatial error dependence stressed before by the robust LM test statistic. Therefore we choose a mixed regressive, 1^{st} order spatial autoregressive model with a 2^{nd} order spatial autoregressive error process to capture the spatial effects. The speed of convergence of 5.8% per year lies well below the implied value from OLS estimation.

The importance of human capital as a driving source for the growth process is exposed by its high significance in all regression models. In contrary, population growth does not matter for growth in unified Germany. Note that the relevance of physical investment for productivity growth is only found in the last spatial setting. OLS estimation in the classical model failed to prove the significance of newly founded investments as a proxy for the investment rate. Although far from being perfect, this proxy seems to be able to resolve at least the problem of uncontrolled effects that occurred in German regional convergence studies when working with purely industrial investment rates.[26] .

6.2 Tests on Regional Convergence of Labour Productivity

While income per capita is usually interpreted to reflect the prosperity of a region, real GDP per total employment mimics the labour productivity. Since in growth theory full employment is presupposed, there is no need to distinguish between the two concepts.[27] However, empirically an increase in regional productivity over time may not go hand in hand with in increase in prosperity. Since one cannot assume convergence to be unaffected by different developments of both quantities, an extension of spatial econometric analysis to labour productivity could shed more light into the convergence process in unified Germany.

The findings on unconditional convergence of labour productivity across German labour market regions are displayed in Table 6.3. From preliminary OLS estimation of the classical

[25] LM(err) and LM(lag) take values of 11.3385 (p=0.00074) and 11.461 (0.00071), respectively.
[26] See Seitz (1995), p. 184; Schalk and Untiedt (1996), p. 575.
[27] In the extended Solow model the employment rate is set to one for sake of simplicity.

regression model a high speed of productivity convergence is uncovered. But the diagnostics for spatial dependence clearly indicate a misspecification of the non-spatial regression model. In the 1st order spatial error model, which follows straightforwardly from model identification, the ML estimator of the coefficient of the spatial error term proves to be highly significant. However, the implied convergence rate of 7.61% does only differ slightly from the OLS estimate.

Table 6.3: Tests on absolute productivity convergence

Dependent variable WGDPE	Classical regression model (OLS)	Spatial error model (1st order)[a]	
		Maximum Likelihood (ML)	General Method of Moments (GMM)
Variables	Coefficients	Coefficients	Coefficients
Constant	4.9736**	4.9616**	4.9595**
	(0.1803)	(0.2204)	0.2240)
W_ERROR		0.2805**	0.3013
		(0.1012)	
LGDPE92	-0.4570**	-0.4561**	-0.4559**
	(0.0170)	(0.0208)	(0.0218)
Implied λ	0.0763	0.0761	0.0761
R^2	0.802	0.802	0.802
SSE	0.00406	0.00377	0.00380
AIC	-478.358	-486.667	
BIC	-471.972	-480.281	
JB	6.219*	5.953(*)	
	Diagnostics for spatial dependence		
	$\mathbf{W}_1$	$\mathbf{W}_2$	$\mathbf{W}_3$
Moran	0.1586**	0.0527	0.0314
LM_{rob}(err)	4.400*	0.655	0.383
LM_{rob}(lag)	0.400	1.715	1.427
	LR(err vs clas) = 8.310**	LM(lag in err) = 0.272	

Notes: a Regression model (3.8) with 1st order spatial autoregressive error process
**: 1% significance level; *: 5% significance level; (*): 10% significance level
R^2: Coefficient of determination (for spatial models: pseudo R^2); SSE: Standard error of regression;
AIC: Akaike information criterion; BIC: Schwartz criterion; JB: Jarque-Bera statistic;
Moran: Moran's I for residuals; W_i, i=1,2,3: *i*th order contiguity matrix (row-standardised);
LM_{rob}(err), LM_{rob}(lag): Robust Lagrange Multiplier statistics (see Section 3.2);
LR(err vs clas): Likelihood Ration statistic (see Section 3.2)

If one questions the normality assumption because of the weak significance of the Bera-Jarque statistic for ML residuals an application of the general method of moments (GMM) for parameter estimation could be taken into consideration.. The Keljian-Prucha GMM estimator

(Keljian and Prucha, 1998) corroborates highly the results of ML estimation.[28] The main difference to the non-spatial setting lies in an explicit accounting for spillovers in form of random shocks. The spatial error model offers a framework for tracing the propagation of a random shock emerging in a region throughout the neighbourhood regions.

Table 6.4: Tests on conditional productivity convergence

Dependent variable WGDPE	Classical regression model (OLS)	Spatial error models (ML)[a]		
		1st order	2nd order	3rd order
Variables	Coefficients	Coefficients	Coefficients	Coefficients
Constant	4.7050**	4.7526**	4.7076**	4.7172**
	(0.3266)	(0.3347)	(0.3324)	(0.3220)
W_ERROR		0.2597*	0.5239**	0.6758**
		(0.1026)	(0.1323)	(0.1389)
LGDPE92	-0.4542**	-0.4591**	-0.4583**	-0.4605**
	(0.0278)	(0.0288)	(0.0292)	(0.0286)
LDTW	-0.0181	-0.0198	-0.0284	-0.0238
	(0.0426)	(0.0431)	(0.0420)	(0.0414)
LHUMAN	0.0708**	0.0729**	0.0787**	0.0845**
	(0.0173)	(0.0174)	(0.0166)	(0.0167)
LNFB	0.0192	0.0173	0.0219(*)	0.0223(*)
	(0.0120)	(0.0117)	(0.0119)	(0.0117)
Implied λ	0.0757	0.0768	0.0766	0.0771
R^2	0.826	0.825	0.825	0.825
SSE	0.00364	0.00335	0.00323	0.00320
AIC	-494.971	-502.240	-507.677	-509.468
BIC	-479.007	-486.275	-491.712	-493.503
JB	1.674	1.803	1.641	1.447

	Diagnostics for spatial dependence		
	$\mathbf{W}_1$	$\mathbf{W}_2$	$\mathbf{W}_3$
Moran	0.1503**	0.1047**	0.0854**
LM_{rob}(err)	9.036**	9.838**	10.580**
LM_{rob}(lag)	1.070	0.668	0.788
	1st order model	2nd order model	3rd order model
LR(err vs. clas)	7.268**	12.705**	14.496**
LM(lag in err)	1.180	0.442	0.035

Notes: a ARX error model (3.8) with cumulative weight matrices $\mathbf{W}_1$, $\mathbf{W}_{1,2}$ and $\mathbf{W}_{1,2,3}$
**: 1% significance level; *: 5% significance level; (*): 10% significance level
R^2: Coefficient of determination (for spatial model: pseudo R^2); SSE: Standard error of regression;
AIC: Akaike information criterion; BIC: Schwartz criterion; JB: Jarque-Bera statistic;
Moran: Moran's I for residuals; W_i, i=1,2,3: *i*th order contiguity matrix (row-standardised);
LM(err), LM_{rob}(err), LM(lag), LM_{rob}(lag): Lagrange Multiplier statistics (see Section 3.2);
LR(err vs clas): Likelihood Ration statistic (see Section 3.2);
LM(lag in err): LM test for spatial lag dependence in spatial error model

[28] Since heteroscedasticity seems still to be present the spatial model could not regarded as being "perfect". Heteroscedasticity cannot be captured- adequate by the exogenous variables used in this study.

Table 6.4 refers to the issue of conditional productivity convergence in unified Germany. The diagnostics for spatial dependence unequivocally point to the spatial error model as an adequate spatial modelling framework. Spatial effects turn out to be strong which implies that the classical regression model is misspecified. But unlike to the case of income convergence the convergence rate differs only slightly in all three spatial error models. Note also that the increase in the speed of convergence is small in comparison to the unconditional model. In any case with a value of about 7.7% the convergence rate of labour productivity exceeds that of income per capita considerably.

The robust LM(err) statistics show significance up the 3rd order neighbourhood matrix. Obviously, the 1st and 2nd order spatial error model do not succeed to catch the spatial effects sufficiently well. According to all goodness of fit criteria the 3rd order spatial error model displays the best performance. The outcomes of the Jarque-Bera test give no reason to question the normality assumption in any case so that ML estimation is best suitable. Heteroscedasticity cannot be unambiguous assessed because the spatial Breusch-Pagan test and the White test indicate contradictory evidence. Regarding the control variables the same inference as in the spatial income per capita model holds which emphasises the importance of human capital and investment intensity for productivity convergence.

Spatial econometric analysis has brought about a considerable difference in the speed of convergence between labour productivity and income per capita. Since income per capita, GDPC, equals the product of labour productivity, GDPE, and the employment rate, EC,

$$GDPC = GDPE \cdot EC,$$

the log income per capita, LGDPC, is given by

$$LGDPC = LGDPE + LEC,$$

where LGDPE and LEC denote the natural logs of labour productivity and the employment rate, respectively. Hence, the variance of log income per capita can be decomposed into the variances of the logs of labour productivity and employment rate and twice the covariance of the latter variables:

$$\text{(6.1)}\quad Var(LGDPC) = Var(LGDPE) + Var(LEC) + 2 \cdot Cov(LGDPE, LEC).$$

Table 6.5 displays the variance decomposition (6.1) for the starting year 1992 and the latest year 2000. Since the variances of income per capita and labour productivity diminish for the

Table 6.5: Variances decomposition of income per capita

Year	Var(LGDPC)	Var(LGDPE)	Var(LEC)	Cov(LGDPE,LEC)
1992	0.133647	0.077930	0.013617	0.021050
2000	0.054505	0.026892	0.009770	0.008922
Variance ratio/ Covariance ratio	0.408	0.345	0.718	0.424

period of investigation σ-convergence holds. Note that the variance ratio for labour productivity is markedly lower than that for income per capita. This outcome can be attributed to two factors. Firstly, the reduction of variance in the employment rate turns out to be small; its variance ratio is about twice as large as the variance ratio for labour productivity. Secondly, a positive covariance between labour productivity and employment rate means that employment benefits not in low but in high productivity regions.[29] Because of the covariance ratio lies above the variance ratio for labour productivity the relationship between the two variables exerts an adverse effect on income convergence.

7. Conclusions

Convergence across regional labour markets in unified Germany has to be judged differently depending on what growth phenomenon exactly becomes the focus of attention. Although spatial econometric analysis corroborates both regional income and productivity convergence for unified Germany, the speed of convergence turns out to be considerably higher in case of the latter quantity. Moreover, human capital and the investment intensity measured by the newly founded business prove to be relevant control variables in the progress of the convergence process. However, only for income per capita the convergence rate in the conditional model differs markedly from that of the absolute convergence case. Since conditional convergence is stronger backed, a well-founded scope for policy measures seems to be given for reducing regional inequalities in the standard of living.

An exploratory data analysis of exogenous variables displays strong spatial effects in form of distinct spatial autocorrelations up to a neighbourhood order of three. The spatial lag or spatial error model employed in recent empirical convergence analysis are not suited to

[29] The correlation between labour productivity and the employment rate takes a value of 0.646 in 1992 and is yet marked in 2000 where its value lies at 0.550.

capture to spatial effects present in the data. For that reason we propose a parsimonious variant of the general spatial lag model with an identification strategy analogue to ARMA model building in time series analysis. Although robust LM tests for spatial lags and errors prove to be valuable criteria for model identification, conventional criteria are supplementary diagnostics.

The spatial setting has brought about a conditional rate of convergence for income per capita between 5 1/4 and 5 ¾%. From this range a half-life time between about 12 and 13 years can be inferred. With regard to the East-West income gap the spatial growth model predicts a reduction of about one third within a decade. This means that East Germany's relative income level of 66,1% in 2000 is expected to increase to a value between 77.2 and 78% in 2010 if the East-West proportions in the control variables will remain stable. Productivity converges with a considerable higher rate of about 7.7 which implies a half-life time of about 9 years. For the growth decade 2000-2010 our variant of the neo-classical model predicts for East German regions an increase of relative labour productivity from 73.5% in 2000 to 87.7% in 2010.

In view of a great many incentive measures and development programmes by German government and EU funds the danger could occur to loosen the efforts in supporting the catching-up process of East Germany's regions. Examples of other EU countries are suitable to become aware that despite of extensive external support a catching-up of poorer regions does by no means natural take place. Although income differences have been diminished across EU member states during the past fifteen years, regional inequalities have increase (Basile, de Nardis and Girardi, 2002). It turns out that it is above all catching-up of richer regions in periphery countries that caused across-country convergence. This example makes clear that the outcomes of our regional convergence study are specific to the growth process in unified Germany which cannot be translated to regional development in other countries.

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