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Dynamic Spatial Modelling of Regional Convergence Processes

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Dynamic Spatial Modelling of Regional Convergence Processes

ABSTRACT

Econometric analysis of convergence processes across countries or regions usually refers to a transition period between an arbitrary chosen starting year and a fictitious steady state. Panel unit root tests and panel cointegration techniques have proved to belong to powerful econometric tools if the conditions are met. When referring to economically defined regions, though, it is rather an exception than the rule that coherent time series are available. For this case we introduce a dynamic spatial modelling approach which is suitable to trace regional adjustment processes in space instead of time. It is shown how the spatial error-correction mechanism (SEC model) can be estimated depending on the spatial stationarity properties of the variables under investigation. The dynamic spatial modelling approach presented in this paper is applied to the issue of conditional income and productivity convergence across labour market regions in unified Germany.

Keywords: Regional convergence, dynamic spatial models, spatial unit roots, spatial error-correction

JEL-Classification: C21, R11, R15

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1. Introduction

When analysing convergence processes of countries, time-series of the core variables of growth theory, namely production, income and employment, are available from publicly accessible data-bases. With some restrictions the same applies to indicators for control variables such as e.g. investment rate, human capital, innovation, policy instruments. In this situation it seems to be advantageous to investigate adjustment processes of economic growth in a combined cross-section and time-series analysis by means of panel unit root tests and panel cointegration techniques. Convergence studies for panels of countries using this kind of econometric analysis were conducted e.g. by Evans and Karras (1996), Evans (1998), Holmes (2000), Kónya (2001). Although panel unit root tests can increase the degrees of freedom considerably they offer by no means a "free lunch". In contrary to cross-sectional analysis the problems of structural stability can prove to be a serious obstacle. In addition the researcher has to cope with the loss of uniqueness which goes along with the application of panel unit root tests.[1] A serious disadvantage of most panel convergence studies is the insufficient modelling of cross-sectional dependence.

In regional convergence studies a panel analysis of adjustment processes is often not feasible. Generally it is only at the state level that quarterly or yearly data on the relevant economic variables are available for a sufficiently long time period.[2] When focussing on functional regions production and income data are generally available only from structural surveys which are carried out in Germany in time spans of at least two years. In our view the definition of functional regions is highly relevant in convergence analysis, since whether a spatial unit is to be regarded as rich or poor crucially depends on the assignment of the surrounds to a relevant regional centre (see e.g. Eckey, Horn and Klemmer, 1990, pp. 1). Apart of the long time interval between the surveys, regional data are usually subjected to changes of nomenclatures which can restrict their comparability to a large extent. As far as convergence between West and new East Germany is concerned, in view of the sample size, analysis cannot even be performed at the state level in the time dimension. The question arises if it is at all

[1] See also Vorbeek (2000, p. 334) who argues that "neither the null nor the alternative hypothesis" in panel unit root tests "is satisfied and it is unclear whether we would wish our test to reject or not".

[2] Convergence studies for West German states on the basis of panel unit root tests are conducted by Bohl (1998) and Funke and Strulik (1999).

possible to render regional adjustment processes transparent when panel analysis is not operational.

The idea of tracing regional adjustment processes between two points in time only from spatial data is an outcome of new developments in spatial econometrics. They started off with a seminal paper of Fingleton (1999) where he introduces the concepts of spatial cointegration and spatial error correction models. He shows that not only time trends but spatial trends, too, can lead to spurious regression with severe consequences concerning statistical inference. Lauridsen (2002) analyses the dynamics of adjustment based on a spatial autoregressively distributed lag model (local model) to a global equilibrium. For model estimation spatial properties of the involved variables have to be identified. This can be done by applying a powerful testing strategy recently proposed by Lauridsen and Kosfeld (2002).

In this paper we aim to trace adjustment processes across functionally defined regions by means of dynamic spatial models. Section two outlines the growth theoretical basis consisting of an extended Solow model in which capital accumulation takes place not only in physical capital but in human capital as well. In section three the global model and local models are developed for the implied growth relationship. It is shown that a spatial error-correction mechanism turns out to be a special representation of the dynamic spatial setting. Moreover, issues regarding model estimation and testing are addressed. Section four contains a description of the regional data set for investigating conditional income and productivity convergence in unified Germany. The empirical findings are discussed in section five. Section six concludes.

2. Growth theoretic basis

In empirical studies of growth, human capital provides a significant contribution to explanations of 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 differently 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:[3]

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

Y, K, H, A, and L denote the level of output, physical capital, human capital, technology and labour input of a region considered at time t, respectively; A·L denotes regional labour input in efficiency units. The parameters α and ß (0<α<1, 0<ß<1) are the production elasticities of physical and human capital; 1-α-ß>0 is the elasticity of labour input. In competitive markets the input factors are paid their marginal products. Labour L and 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 labour efficiency units:

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

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[4]

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

and

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

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

(2.4) $\hat{k}^* = (\frac{s_k^{1-\beta} s_h^{\beta}}{n + g + \delta})^{1/(1-\alpha-\beta)}$

and

(2.5) $\hat{h}^* = (\frac{s_k^{\alpha} s_h^{1-\alpha}}{n + g + \delta})^{1/(1-\alpha-\beta)}$

[3] 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.

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

where labour productivity y=Y/L is given by

$$(2.6)\quad y^* = A(0)\cdot e^{g\cdot t}\left(\frac{s_k^{\alpha} s_h^{\beta}}{(n+g+\delta)^{\alpha+\beta}}\right)^{1/(1-\alpha-\beta)}.$$

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

Mankiw, Romer and Weil (1992, pp.410) consider the log of A(0) to be composed of a constant c which is common to all cross-sectional units and a country-specific shock u:

(2.7) ln A(0) = c + u.

In regional analysis u can be viewed to include different levels of technology, different regional inefficiencies (Schalk, Untiedt and Lüschow, 1995, pp. 26), a different composition of produced goods and other regional-specific characteristics. As a regional-specific shock u ultimately captures all random variation in regional labour productivity y. Using the composition (2.7) the equilibrium relationship (2.6) has the log-linearized form

$$(2.8)\quad \ln y = d - \frac{\alpha+\beta}{1-\alpha-\beta}\ln(n+g+\delta) + \frac{\alpha}{1-\alpha-\beta}\ln s_k + \frac{\beta}{1-\alpha-\beta}\ln s_h + u$$

with y=y* and d = c + g·t.[5] According to (2.8), in the steady state, regional labour productivity is determined by population growth, growth technology, depreciation of capital and physical and human capital accumulation. With regard to the region-specific variables we can establish a negative dependence of labour productivity to population growth and a positive dependence on both kinds of capital accumulation.

[5] For a cross-section regression the time index t is fixed. Hence, the term g·t is a constant which can be added to the common shock c to give the intercept of equilibrium relationship (2.8).

3. Modelling spatial processes

3.1 Spatially integrated processes and stationarity

In order to analyse local adjustment processes we have to introduce the concepts of spatial stationarity and spatial cointegration. We start with the first-order autoregressive process as a spatial data generating process for a variable y which is given in matrix notation by

(3.1) $\mathbf{y} = \rho \cdot \mathbf{W} \cdot \mathbf{y} + \boldsymbol{\varepsilon}$

with $\mathbf{y} = (y_1, y_2, \ldots, y_n)`$. In our cross-sectional analysis the components of **y** refer to the n regions of an economy. The disturbance vector $\boldsymbol{\varepsilon}=(\varepsilon_1, \varepsilon_2, \ldots \varepsilon_n)`$ is assumed to follow a normal distribution with an expectation vector of zero and a scalar covariance matrix:

(3.2) $\varepsilon \sim N(\mathbf{0}, \sigma^2 \mathbf{I})$.

ρ denotes an autoregressive parameter and σ^2 the variance of the disturbances ε_i. **W** defines an nxn contiguity matrix with non-zero entries for spatially contiguous regions.

Let **W*** be an nxn neighbourhood matrix which entries W^*_{ij} take only the values 1 and 0:

$$W^*_{ij} = \begin{cases} 1 \text{ if regions i and j are neighbours} \\ 0 \text{ otherwise} \end{cases}.$$

The entries of **W** result from a row normalisation of **W*** which is achieved by dividing the elements of the *i*th row of **W*** by the *i*th row sum $\sum_j W^*_{ij}$. Thus the *i*th element of the nx1 vector $\mathbf{W} \cdot \mathbf{y}$ is the mean of the variable y_i in the neighbourhood regions of i.

In spatial econometrics one must be cautious when wishing to interpret the autogressive parameter ρ as an autocorrelation coefficient as in time series analysis. Generally, in maximum likelihood estimation, the likelihood function ensures that the autoregressive parameter lies in interval $[1/\omega_{min}, 1/\omega_{max}]$ hence the bounds are the reciprocals of the minimum and maximum eigenvalues ω_{min} and ω_{max} of the weight matrix. For the row-normalised matrix **W** ω_{max}=1 and hence $\rho \leq 1$ is ensured, but not ω_{min}=-1 (Anselin, 1982). However using instrumental variables, there is no guarantee that the estimate will fall within this interval, and this may lead us to uncertain areas of interpretation and inference, for example associated with the existence of spatial unit roots. From simulation studies (e.g. Kelejan and Robinson, 1995) the range of the autoregressive parameter ρ appears to be considerably narrower when spatial analysis is conducted on the basis of an unstandardised weight matrix **W***.

In accordance with Fingleton (1999) we adopt $|\rho|<1$ for the data generating process to be stationary, although the validity of this inequality is not a sufficient condition for it. However, asymptotically stationarity is ensured for $|\rho|<1$. Taking this restriction into account it is straightforward to call y, generated by equation (3.1) with ρ=1, a spatially integrated process of order one [SI (1)]; for $|\rho|<1$ y is called spatially stationary [SI(0)]. An SI(1) variable y said to have a unit root. It has to be spatially differenced once,

$$\Delta\mathbf{y} = \mathbf{y} - \mathbf{W}\mathbf{y} = (\mathbf{I}\text{-}\mathbf{W})\mathbf{y},$$

to become stationary. In general, a spatially integrated process of order d, SI(d), has d unit roots. It becomes stationary after applying the spatial difference operator Δ=**I-W** d times:

$$\Delta^d\mathbf{y} = (\mathbf{I}\text{-}\mathbf{W})^d\mathbf{y}.$$

3.2 Spatial cointegration and spatial dynamics

Let x and y be both SI(1) variables. Then in general any linear combination of x and y is also SI(1). If, however, a linear combination y-βx exists which is stationary, x and y are said to be spatially cointegrated. In this case the cointegrating vector is given by (1 -β). More generally, x and y are both SI(d) variables. For a linear combination y-βx of lower order of spatial integration than d, say SI(d-b) with 0<b≤d, x and y are said to be spatially cointegrated of order (d, b) denoted by SCI(d,b). In the special case of two SI(1) variables cointegration implies d=b=1 (see Fingleton, 1999).

Our growth model consists of the four variables labour productivity y, $x_1 = \ln(n + g + \delta)$, $x_2 = \ln s_k$ and $x_3 = \ln s_h$. In terms of spatial econometrics the equilibrium relationship (2.8) represents a **global model** which can be written here in the form

(3.3) $\mathbf{y} = \beta_0\mathbf{i} + \beta_1\mathbf{x}_1 + \beta_2\mathbf{x}_2 + \beta_3\mathbf{x}_3 + \mathbf{u}$

when using the above defined variables. **y,** $\mathbf{x}_1$, $\mathbf{x}_2$ and $\mathbf{x}_3$ are nx1 vectors which components are regionally determined, **i** is the nx1 unit vector and **u** an nx1 vector of disturbances,

$\mathbf{u} \sim N(\mathbf{0},\mathbf{\Omega})$,

where $\mathbf{\Omega}$ denotes an nxn covariance matrix. The parameters β_0, β_1, β_2 and β_3 measure the effects of the exogenous variables 1, x_1, x_2 and x_3 on labour productivity y. As is well-known from time-series analysis in our multiple variable case the existence of a cointegrating vector (1 $-\beta_0$ $-\beta_1$ $-\beta_2$ $-\beta_3$) does not necessarily require the variables y, x_1, x_2 and x_3 to be of the same order of integration (Charemza and Deadman, 1992, pp. 147).

In case of conditional convergence regional adjustment towards the global equilibrium will arise. In contrary, when convergence is missing local discrepancies will tend to persist. Thus we have to investigate what the kind of spatial dynamics is driving the economy. In time series econometrics adjustment processes are evaluated by means of an error-correction model (ECM). The analogous local model construction to capture regional dynamics is called a spatial error-correction model (SEC model) (Fingleton, 1999; Lauridsen, 2002).

Local developments can be imagined to spread out at first in the neighbourhood regions before diffusing over the whole economy. Indeed, observed spatial correlations seem to confirm a marked spatial dimension of regional adjustment processes (see e.g. Kosfeld, Eckey and Dreger, 2002). They may be probably attributed to rigidity barriers such as substantial costs which prevent economic agents to adjust instantaneously to new information. Not only the spatially lagged values of the dependent variable but also those of the exogenous variables generally have to be taken into account during the transition periods. In the simplest case where only spatial lags of first order are allowed for, a **local model** can be establish in the form

$$(3.4)\ \mathbf{y} = \alpha_0\mathbf{i} + \alpha_1\mathbf{Wy} + \beta_{10}\mathbf{x}_1 + \beta_{11}\mathbf{Wx}_1 + \beta_{20}\mathbf{x}_2 + \beta_{21}\mathbf{Wx}_2 + \beta_{30}\mathbf{x}_3 + \beta_{31}\mathbf{Wx}_3 + \mathbf{\nu}$$

$$= \alpha_0\mathbf{i} + \alpha_1\mathbf{Wy} + \sum_{i=1,2,3}(\beta_{i0}\mathbf{x}_i + \beta_{i1}\mathbf{Wx}_i) + \mathbf{\nu}$$

with $\mathbf{\nu}$ as an nx1 disturbance vector:

$\mathbf{\nu} \sim N(0, \sigma_\nu^2\mathbf{I})$.

A local model of the form (3.4) is termed spatial autoregressively distributed lag model (SADL model) (see Lauridsen, 2002). It can be easily transformed to obtain a link to the global model (3.3):

$$(3.5)\ \mathbf{y} = \kappa_0\cdot\mathbf{i} + \kappa_1\cdot\mathbf{x}_1 + \kappa_2\cdot\mathbf{x}_2 + \kappa_3\cdot\mathbf{x}_3 + \theta_0\cdot\Delta\mathbf{y} + \theta_1\Delta\mathbf{x}_1 + \theta_2\Delta\mathbf{x}_2 + \theta_3\Delta\mathbf{x}_3 + \mathbf{\nu}$$

with

$$\kappa_0 = \frac{\alpha_0}{1-\alpha_1}, \kappa_1 = \frac{ß_{10} + ß_{11}}{1-\alpha_1}, \kappa_2 = \frac{ß_{20} + ß_{21}}{1-\alpha_1}, \kappa_3 = \frac{ß_{30} + ß_{31}}{1-\alpha_1}$$

$$\theta_0 = -\frac{\alpha_1}{1-\alpha_1}, \theta_1 = -\frac{ß_{11}}{1-\alpha_1}, \theta_2 = -\frac{ß_{21}}{1-\alpha_1} \text{ and } \theta_3 = -\frac{ß_{31}}{1-\alpha_1}.$$

An adjustment to the global model (3.3) can only arise if the spatial lag coefficient α_1 lies in the interval (0, 1), since regional discrepancies would persist otherwise. In case of convergence spatial differences in the variables decrease more and more during the adjustment process. This means that ultimately the local model (3.5) degenerates with the global model (3.3).

3.3 Spatial error-correction

Some easy manipulations of (3.4) provide the equivalent representation

(3.6) $\mathbf{\Delta y} = \alpha_0\mathbf{i} + (\alpha_1\text{-}1)\mathbf{Wy} + \sum_{i=1,2,3}(ß_{i0}\mathbf{\Delta x}_i + ß_{i1}\mathbf{Wx}_i) + \boldsymbol{\varepsilon}$,

where $\mathbf{\Delta} = (\mathbf{I}\text{-}\mathbf{W})$. Further manipulations result in

(3.7a) $\mathbf{\Delta y} = \alpha_0\mathbf{i} + (\alpha_1\text{-}1)(\mathbf{Wy} - \sum_{i=1,2,3}\mathbf{Wx}_i) + \sum_{i=1,2,3} ß_{i0}\mathbf{\Delta x}_i + \sum_{i=1,2,3}(ß_{i0} + ß_{i1} + \alpha_1 - 1)\mathbf{Wx}_i + \boldsymbol{\varepsilon}$.

Alternatively, (3.7a) can be rewritten as

(3.7b) $\mathbf{\Delta y} = \alpha_0\mathbf{i} + (\alpha_1\text{-}1)(\mathbf{Wy} - \sum_{i=1,2,3}\kappa_i\mathbf{Wx}_i) + \sum_{i=1,2,3} ß_{i0}\mathbf{\Delta x}_i + \boldsymbol{\varepsilon}$.

A final set of manipulations provide

(3.8) $\mathbf{y} = \kappa_0\cdot\mathbf{i} - \theta_0\cdot\mathbf{\Delta y} + \sum_{i=1,2,3}(\kappa_i\mathbf{x}_i - \theta_i\mathbf{\Delta x}_i) + \kappa_0\cdot\boldsymbol{\varepsilon}$.

The forms (3.6), (3.7) and (3.8) are algebraically equivalent to (3.4), but provide different interpretations. Equation (3.6) is a spatial generalization of the time series Baardsen specification, which we will denote the SBA model. Models (3.7a) and (3.7b) generalize the Error Correction (EC) model and will be denoted as the SEC model. Finally, (3.8) is a generalization of the Bewley transfom which we will call the SBE model. In contrast to the SADL, the SBA and the SEC describe the formation of expected local differences in **y** as depending on local differences in **x** and locally lagged values in **x**. They are distinctive in that the SBA introduces locally lagged levels in **y**, whereas the SEC introduces the locally lagged discrepancy between **y** and **x**. Thus, in the SEC, the term (α_1-1) represents the local adjustment to any discrepancy. The

SBE is especially interesting as it incorporates the global multipliers directly with κ_0 as the constant and κ_1 as the coefficients for **x**.

If the spatially lagged variables **Wy**, $\mathbf{Wx}_1$, $\mathbf{Wx}_2$ and $\mathbf{Wx}_3$ are spatially nonstationary, this property transfers immediately to the error-correction term $(\mathbf{Wy}-\sum_{i=1,2,3}\mathbf{Wx}_i)$ in (3.7a). Here spurious regression prevents a meaningful estimation of the SEC form (3.7a). In contrary, for spatially stationary lagged variables the SEC model (3.7a) provides a straightforward estimation equation of the error-correction mechanism. If the spatially lagged variables turn out to be spatially nonstationary, the SEC form (3.7b) may be the focus of interest. This is the case for the spatially lagged variables **Wy**, $\mathbf{Wx}_1$, $\mathbf{Wx}_2$ and $\mathbf{Wx}_3$ being spatially cointegrated which ensures the existence of a spatially stationary linear combination $(\mathbf{Wy}-\sum_{i=1,2,3}\kappa_i\mathbf{Wx}_i)$.

None of the specifications (3.4)-(3.8) can be estimated using OLS. This is due to the presence of contemporaneous **y** values in the variable **Wy** emerging in some form or another as an explanatory variable, implying correlation between **Wy** and $\boldsymbol{\varepsilon}$. For the case of the SAR, this is proved in details in Anselin (1988a, pp. 57), whereas Fingleton (1999) provides the proof for the SEC model. Their arguments are directly carried over to the SADL, SBA and SBE models. Due to the aforementioned correlation, asymptotically justified methodologies must be applied. The IV estimation is based on the idea of finding a variable **z** which is uncorrelated with $\boldsymbol{\varepsilon}$**,** but correlated with **Wy** (or whatever form in which **y** appears on the right-hand side of (3.4)-(3.8)) and using this as an instrument variable in a one-step least squares estimation. Formally, if we want to estimate the SADL in (3.4), we define $\mathbf{X}_0 = [\mathbf{x}_1\ \mathbf{x}_2\ \mathbf{x}_3]$, $\mathbf{X} = [\mathbf{i}\ \mathbf{Wy}\ \mathbf{X}_0\ \mathbf{WX}_0]$ and $\mathbf{Z} = [\mathbf{i}\ \mathbf{z}\ \mathbf{X}_0\ \mathbf{WX}_0]$, where **i** is an n×1 vector of 1's. Defining $\gamma_{SADL} = (\alpha_0\ \ \alpha_1\ \ \beta'_0\ \ \beta'_1)'$ and inserting the projections of the columns of **X** in the column space of **Z** (i.e. $= \mathbf{P_z X}$, where $\mathbf{P_z} = \mathbf{Z}(\mathbf{Z'Z})^{-1}\mathbf{Z'}$, see Greene, 2002, p. 78), the IV estimator is

$$\hat{\gamma}_{SADL} = (\mathbf{X'P_Z X})^{-1}\mathbf{X'P_Z y}$$

where $\mathbf{P_z} = \mathbf{Z}(\mathbf{Z'Z})^{-1}\mathbf{Z'}$. The covariance matrix is given by

$$\mathbf{V}_{SADL} = \sigma^2(\mathbf{X'P_z X})^{-1}$$

with σ^2 estimated consistently by

$$s^2 = (\mathbf{y}-\mathbf{X}\hat{\gamma}_{SADL})'(\mathbf{y}-\mathbf{X}\hat{\gamma}_{SADL})/n\ .$$

As a choice for $\mathbf{z}$, Anselin (1988a, p. 85) suggests the lagged value of the prediction of $\mathbf{y}$ from an OLS regression on those variables in $\mathbf{X}$ not correlated with $\boldsymbol{\varepsilon}$, i.e. $\mathbf{x}$ and $\mathbf{Wx}$. Denoting the predicted $\mathbf{y}$ by $\hat{\mathbf{y}}$, the instrument variable is defined as $\mathbf{W}\hat{\mathbf{y}}$, and the IV estimator is obtained by setting $\mathbf{Z} = [\mathbf{i}\ \ \mathbf{W}\hat{\mathbf{y}}\ \ \mathbf{X}_0\ \ \mathbf{WX}_0]$.

Using $\hat{\mathbf{y}}$ as an instrument for any occurrence of $\mathbf{y}$ on the right-hand sides, IV estimation of the alternative forms-(3.4)-(3.8) is easily provided. The choices of $\mathbf{X}$, $\mathbf{Z}$, and dependent variable for (3.4), (3.6), (3.7), and (3.8) are summarized in Table 3.1.

Table 3.1: Choices of $\mathbf{X}$, $\mathbf{Z}$ and dependent variable

Model	$\mathbf{X}$	$\mathbf{Z}$	dep. var.
SADL	$[\mathbf{i}\ \ \mathbf{Wy}\ \ \mathbf{X}_0\ \ \mathbf{WX}_0]$	$[\mathbf{i}\ \ \mathbf{W}\hat{\mathbf{y}}\ \ \mathbf{X}_0\ \ \mathbf{WX}_0]$	$\mathbf{y}$
SBA	$[\mathbf{i}\ \ \mathbf{Wy}\ \ \Delta\mathbf{X}_0\ \ \mathbf{WX}_0]$	$[\mathbf{i}\ \ \mathbf{W}\hat{\mathbf{y}}\ \ \Delta\mathbf{X}_0\ \ \mathbf{WX}_0]$	$\Delta\mathbf{y}$
SEC	$[\mathbf{i}\ (\mathbf{Wy}\text{-}\mathbf{Wx})\ \Delta\mathbf{X}_0\ \mathbf{WX}_0]$	$[\mathbf{i}\ (\mathbf{W}\hat{\mathbf{y}}\text{-}\mathbf{Wx})\ \Delta\mathbf{X}_0\ \mathbf{WX}_0]$	$\Delta\mathbf{y}$
SBE	$[\mathbf{i}\ \ \Delta\mathbf{y}\ \ \mathbf{X}_0\ \ \Delta\mathbf{X}_0]$	$[\mathbf{i}\ \ \Delta\dot{\mathbf{y}}\ \ \mathbf{X}_0\ \ \Delta\mathbf{X}_0]$	$\mathbf{y}$

At first sight, an obvious and tempting generalization of the IV approach seems to be inclusion of further spatial lags of $\hat{\mathbf{y}}$, i.e. $\mathbf{W}^2\hat{\mathbf{y}}$, $\mathbf{W}^3\hat{\mathbf{y}}$,... However, as pointed out by Fingleton (2000; 2001), this may lead to a risk of linear dependence among the columns of $\mathbf{Z}$ (see also Kelejian and Robinson, 1993; Kelejian and Prucha, 1998).

As one possible further complication, the error terms for the single regions may be spatially autocorrelated. A recent Cochrane-Orcutt type generalization of the IV method allows one to adjust for this (see Kelejian and Prucha, 1998). For matters of simplicity and focus, we refrain from incorporating this adjustment in the present investigation.

Using the one-to-one correspondence between the parameters of the four models, IV estimators for $\boldsymbol{\gamma}_{\text{SADL}}$ may be derived from any of the four models upon IV estimation of the chosen one, just as the $\mathbf{V}_{\text{SADL}}$ is easily derived using for example the delta method (Greene, 2002). Of course, this is equivalent to a separate IV estimation of all four models, which is easier in practice. In the present study, separate IV estimations were used. This may lead to minor rounding-off errors in reported parameters.

3.4 Testing for spatial unit roots

In order to know how to estimate the equilibrium relationship of the augmented Solow model [eq. (2.8)], we need to know the degree of integration of the involved variables. If the variables are nonstationary but integrated with the same degree, a test of cointegration is straightforward. For different degrees of integration a cointegration is only possible if special conditions are met.

The present study suggests a strategy based on a twofold application of a Lagrange Multiplier test for spatially autocorrelated errors.[6] The LM error statistic (LME) developed in Anselin (1988a, 1988b),

$$(2.3) \quad \text{LME} = (\mathbf{e}'\mathbf{W}\mathbf{e}/\sigma^2)^2 \,/\, \text{tr}(\mathbf{W}^2+\mathbf{W}'\mathbf{W}),$$

is asymptotically χ^2 distributed with one degree of freedom under H_0: $\lambda=0$.

In the case of spurious regression, the error term of the regression

$$(2.4) \quad \mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

will contain a unit root, i.e

$$\boldsymbol{\varepsilon} = \lambda\mathbf{W}\boldsymbol{\varepsilon} + \boldsymbol{\mu}\ ,\ \boldsymbol{\mu}\sim N(\mathbf{0}, \sigma^2\mathbf{I}),$$

with $\lambda=1$. Therefore, a large LME value indicates either spatial nonstationarity or stationary (positive or negative) autocorrelation. This result corresponds to the suggestions of Fingleton (1999) with the Moran I test replacing the LM test. Next, under H_0: nonstationarity, it follows that

$$\boldsymbol{\varepsilon} = \mathbf{W}\,\boldsymbol{\varepsilon} + \boldsymbol{\mu} \Leftrightarrow \boldsymbol{\varepsilon} = \boldsymbol{\Delta}^{-1}\,\boldsymbol{\mu}$$

so that

$$(2.5) \quad \boldsymbol{\Delta}\mathbf{y} = \boldsymbol{\Delta}\mathbf{X}\boldsymbol{\beta} + \boldsymbol{\mu},$$

with $\boldsymbol{\Delta}=\mathbf{I}-\mathbf{W}$ as the spatial difference operator. Equation (2.5) implies that a regression of $\boldsymbol{\Delta}\mathbf{y}$ on $\boldsymbol{\Delta}\mathbf{X}$ provides a white noise error, so that a LM error test statistic for this spatially differenced model (DLME) will be close to zero. On the other hand, if H_0: nonstationarity does not hold,

[6] In a Monte Carlo study Lauridsen and Kosfeld (2002) have shown the finite sample properties of the suggested test strategy to be satisfactory.

then the spatial differencing will bring about a negative (stationary) spatial residual autocorrelation leading to a positive DLME value. Concluding, the test strategy consists of calculating and inspecting the LME and the DLME values, leading to one of three conclusions:[7] Nonstationary, spurious regression (LME positive, DLME zero), stationary spatial autocorrelation (LME and DLME positive), and absence of autocorrelation (LME zero, DLME positive).

It may be further relevant to investigate whether **y** or any of the **x** variables are spatially nonstationary. This may be revealed by using the suggested procedure for a regression of the variable in question (i.e. **z** being one of **y**, $\mathbf{x}_1$, $\mathbf{x}_2$, …) on a constant term. Specifically, the regressions

$$(2.6) \quad \mathbf{z} = \alpha\mathbf{i} + \boldsymbol{\varepsilon}$$

and

$$(2.7) \quad \Delta\mathbf{z} = \alpha\Delta\mathbf{i} + \boldsymbol{\varepsilon}$$

readily provides the LME and DLME test statistics, which lead to one of three conclusions: **z** is spatially nonstationary (LME positive, DLME zero), **z** represents a stationary SAR scheme (LME positive, DLME positive), or **z** is free of any spatial pattern (LME zero, DLME positive).

4. Data

The study of regional convergence in unified Germany refers to the state of development in 2000 i.e. about a decade after the unification. 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 is expected to result in 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’.

[7] The test result is termed to be “positive” if the LM test statistic differs significantly from zero and “zero” otherwise.

Table 4.2. Variables used in the empirical study

Variable	Definition	Mean	S.D.	Min	Max
LGDPER	Log gross domestic product per total employment 2000	10.72	0.16	10.29	11.12
LGDPCR	Log gross domestic product per capita 2000	20.94	4.88	12.07	40.32
EAST	East-West Dummy	0.26	0.44	0	1
LDTW	Log (depreciation rate + rate of technical progress + growth rate of population) (Averages resp. representative values for 90ties)	-2.89	0.12	-3.17	-2.60
LHUMAN	Log proportion of highly educated people per total employment 2000 (Secondary school + technical college + university degree)	2.55	0.28	1.98	3.41
LNBF	Log newly founded business per 1000 inhabitants 2000	1.90	0.17	1.51	2.34
Proximity matrix:					
W*	Neighbourhood matrix for N=180 German labour markets[b]				
	Number of links per labour market	5.22	1.90	1	12
	Density of **W*** = .029				
W	Row standardization of **W***				

Data constructed for N=180 German labour markets from districtional and state data

Source: a : Volkswirtschaftliche Gesamtrechnung der Länder (Statistical State Office Baden-Württemberg); Statistik regional, Statistisches Jahrbuch (Federal Statistical Office Germany); German statistical state offices; Own construction.

b : University of Kassel, Department of Economics (see Eckey, 2001).

Starting from 440 German districts Eckey (2001) constructed 180 German labour markets of which 133 are mainly located in West Germany and 47 in East Germany.[8]

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

Since growth theory takes full employment for granted, the convergence relationship can be applied to both income per capita and labour productivity.[9] Both indicators are calculated in real terms, where district data on gross domestic product (GDP), employment and population have been aggregated and state data on the GDP price index have been disaggregated to match with the regional labour markets concept. The 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. 413) and Islam (1995, p.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".[10] Since for unified Germany regional differentiated depreciation rates are not available either, we have calculated a uniform average depreciation rate of 4.8% from data on depreciation and invested capital which proves to be very stable in the nineties (Statistisches Bundesamt, 1999, 2001). The choice of the rate of technological progress is based on an empirical study of Grömling (2001) who estimated a value of 0.6% for the 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 longer represents even the largest sector of the economy, there is a danger that distortions may produce uncontrolled effects when working with such a restricted indicator. That is why we prefer to measure regional investment intensity by the newly established enterprises per capita. Regional data on newly established businesses are available for 2000 on the CD "Statistik regional" which is offered by the Federal Statistical Office Germany.

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

[9] 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.

[10] 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.

human capital.[11] 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 (see Seitz, 1995; Niebuhr, 2001).

Due to data accessibility it is usual to only refer to that part of population bounded by law to the social security system. Besides the self employed, the most notable other omissions are all officials and civil servants. 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 in 2000 have been provided by the German Federal Statistical Office and the German statistical state offices.

5. Empirical evidence on German regional convergence

We investigate the conditional convergence hypothesis with respect to income per capita and labour productivity within the dynamic spatial setting provided by the spatial autoregressively distributed lag model (SADL model). With human capital one potential growth relevant factor neglected in the neoclassical Solow model is additionally taken into account. However, there may be a lot of other factors e.g. technical efficiency, industrial organisation, conditions of competition, research and development, policy measures which have to be controlled for when studying the convergence process. Since they are assumed to differ especially between East and West Germany due to the formerly different economic systems, we introduce an East-West dummy in order to control for growth relevant factors not explicitly modelled. In this way dynamic spatial convergence analysis across German labour markets can be conducted in a tractable manner.

As a point of departure the baseline OLS estimation of the global model 3.3 together with LM error tests for spatial stationarity is displayed Table 5.1. Both the income and productivity relationship are capable of meaningful economical interpretation. In both models human capital

[11] 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,

proves to be highly significant. Although the coefficient of investment intensity has the theoreticcally expected sign in either model it only shows significance in the income model.

Table 5.1: Baseline OLS model estimation and LM tests for stationarity

	Income model: LGDPCR		Productivity model: LGDPER	
Variable	Coefficient	Stand. err.	Coefficient	Stand. err.
Intercept	10.018**	0.445	10.613**	0.291
EAST	-0.346**	0.037	-0.290**	0.024
LDTW	0.317*	0.144	0.110	0.094
LHUMAN	0.254**	0.039	0.168**	0.025
LNFB	0.138*	0.068	0.041	0.044
R^2	0.728		0.764	
SSE	0.01525		0.00652	
F	117.17 (p<0.0001)		141.72 (p<0.0001)	

	LM error tests for stationarity			
Variable	LME	p	DLME	p
LGDPCR	148.468	<0.0001	29.240	<0.0001
LGDPER	202.064	<0.0001	26.107	<0.0001
LDTW	430.996	<0.0001	7.946	0.0048
LHUMAN	433.277	<0.0001	13.290	0.0003
LNFB	433.344	<0.0001	26.508	<0.0001
Residuals (1st model)	19.093	<0.0001	40.602	<0.0001
Residuals (2nd model)	19.480	<0.0001	41.017	<0.0001

Notes: LGDPER: Log gross domestic product per total employment;
LGDPCR: Log gross domestic product per capita; EAST: East-West Dummy;
LDTW: Log (depreciation rate + rate of technical progress + growth rate of population);
LHUMA: Log proportion of highly educated people per total employment
LNBF :Log newly founded business per 1000 inhabitants
**: 1% significance level; 5%: significance level; p: actual significance level
R^2: coefficient of determination; SSE: standard error of regression; F: F statistic
EAST: East-West dummy (East German regions 1, West German regions 0)
LME:LM error statistic for original model [(2.4) or (2.6)];
DLME: LM error statistic for spatially differenced model [(2.5) or (2.7)]

This result may be due to imperfections of newly founded businesses as an investment indicator. Differences in population growth across German labour market regions seem to exert an effect on income per capita but not on labour productivity. Evidently the high significance of

Romer and Weil (1992), p. 418.

the East dummy supports the supposition that non-explicitly modelled control variables are relevant to explaining differences between East and West German regions.

The results of the LM error tests confirm that we are not concerned with the problem of spurious regression when estimation the global model (3.3). Like the LME statistic the DLME statistic is also highly significant for all variables. This means that the null of a spatial unit root is rejected for all manifest variables. Consistently with this the errors of both models turn out to be spatially stationary, too.

Table 5.2: IV Estimation of the SADL Model

	Income model: LGDPCR		Productivity model: LGDPER	
Variable	Coefficient	Stand. err.	Coefficient	Stand. err.
Constant	3.007	3.136	9.849	26.511
W_Y	0.722*	0.281	0.094	2.416
LDTW	0.242	0.157	0.039	0.114
LHUMAN	0.303**	0.041	0.158**	0.028
LNFB	0.161*	0.075	0.034	0.121
EAST	-0.369**	0.061	-0.264**	0.042
W_LDTW	-0.192	0.334	0.182	0.772
W_LHUMAN	-0.302**	0.096	0.037	0.456
W_LNFB	-0.208(*)	0.123	0.001	0.154
W_EAST	0.272*	0.127	0.021	0.602
Wald	1373121**		3443117**	

Notes: **: 1% significance level; 5%: significance level; p: actual significance level
W_Y: spatial lag of LGDPCR resp. LGDPER, W_X: spatial lag of variable X
EAST: East-West dummy (East German regions 1, West German regions 0)

Results from the IV estimation of the SADL income and productivity models are shown in Table 5.2. The high coefficient of the spatial lag of the dependent variable (W_Y) in the income model does not differ significantly from one which could indicate spatial nonstationarity in the Fingleton sense (Fingleton, 1999). From the simulation study in Lauridsen (2002), however, we learned that this estimate may be overstated. Human capital and investment intensity in a region exert a positive influence on regional income per capita, whereas their spatial lags act in the opposite direction. Essential the same holds for control variables comprised in the EAST dummy with a change in sign. This means that in homogenous regional environs the overwhelming part of influences of regional and lagged exogenous variables are captured by the endogenous spatial lag variable. Only in heterogeneous regional neighbourhoods does explicitly allowing for regional endowments change the picture.

The situation turns out to be somewhat different in the productivity model. Here we are not faced with the case of near nonstationarity. As in the income model population growth plays only a subordinated role. Moreover, spatial lags of the exogenous variables are not suitable for explaining productivity.[12] On the one hand, regional productivity levels can be understood by different endowments of human capital. On the other hand, adverse realisations of aforementioned factors in East German regions prove to be still crucial for establishing productivity differences. The insignificance of investment intensity may be due to the imperfect indicator problem.

Table 5.3: IV Estimation of SBA model

	Income model: ΔLGDPCR		Productivity model: ΔLGDPER	
Variable	Coefficient	Stand. err.	Coefficient	Stand. err.
Constant	3.007	3.136	9.849	26.511
W_Y	-0.278	0.281	-0.906	2.416
ΔLDTW	0.242	0.157	0.039	0.114
ΔLHUMAN	0.303**	0.041	0.158**	0.028
ΔLNFB	0.161*	0.075	0.034	0.121
ΔEAST	-0.369**	0.061	-0.264**	0.042
W_LDTW	0.050	0.308	0.220	0.729
W_LHUMAN	0.001	0.086	0.196	0.457
W_LNFB	-0.047	0.108	0.035	0.251
W_EAST	-0.097	0.105	-0.243	0.607
Wald	178.991**		97.502**	

Notes: **: 1% significance level; 5%: significance level; p: actual significance level
W_Y: spatial lag of LGDPCR resp. LGDPER, W_X: spatial lag of variable X,
ΔX: spatial difference of variable X
East-West dummy (East German regions 1, West German regions 0)

Tables 5.3 and 5.4 summarise the IV estimated SBA and SEC models, which provide insight in the local dynamics. It is seen from both tables that local differences in income and productivity

[12] This can be inferred although we known that the coefficients and t values are probably slightly downward biased (Lauridsen, 2002).

are caused by local differences in the explanatory variables but not by their spatial lags. These results reflect accurately the findings for the SADL models (table 5.2) where we have worked exclusively with level variables.

In both models the same reaction coefficient occurs for the expression which includes an endogenous spatial lag. While it returns simply the spatial lag of the dependent variable in the SBA model, in the SEC model it embodies an error-correction mechanism. For both dependent variables, ΔLGDPCR and ΔLGDPER, the adjustment coefficient takes a negative sign which generally indicates the "working" of the error-correction mechanism. Since an effective error-correction mechanism drives economies towards a global equilibrium, it is straightforwardly

Table 5.4: IV Estimation of SEC model

	Income model: ΔLGDPCR		Productivity model: ΔLGDPER	
Variable	Coefficient	Stand. err.	Coefficient	Stand. err.
Constant	3.007	3.136	9.849	26.511
W_LAGYX	-0.278	0.281	-0.906	2.416
ΔLDTW	0.242	0.157	0.039	0.114
ΔLHUMAN	0.303^{**}	0.041	0.158^{**}	0.028
ΔLNFB	0.161^{*}	0.075	0.034	0.121
ΔEAST	-0.369^{**}	0.061	-0.264^{**}	0.042
W_LDTW	-0.227	0.296	-0.686	1.720
W_LHUMAN	-0.277	0.241	-0.710	1.962
W_LNFB	-0.324	0.255	-0.871	2.175
W_EAST	-0.375	0.370	-1.149	3.022
Wald	178.991^{**}		97.502^{**}	

Notes: **: 1% significance level; 5%: significance level; p: actual significance level
W_Y: spatial lag of LGDPCR resp. LGDPER, W_X: spatial lag of variable X,
ΔX: spatial difference of variable X
EAST: East-West dummy (East German regions 1, West German regions 0)

linked with the concept of conditional convergence. Although the adjustment coefficients point to economic forces driving the regional economies towards their steady states, it has not been possible to prove their significance. The reason for this may be found in the sharp slowdown of the speed of convergence as of the second half of the 90s. After a strong catching-up process at the beginning of the 90s both the income and productivity gap between West and East Germany has only slightly closed since the mid 90s. This background stresses that our dynamic spatial modelling approach records a “snapshot” of the current functioning of the convergence process. At the end of the 20s century only weak local adjustment processes across German labour markets regions towards a global equilibrium can be established.[13]

6. Conclusions

In this paper a dynamic spatial modelling approach for analysing regional convergence processes is introduced. Instead of tracing adjustment processes in a time sequence, local adjustment to a global equilibrium is investigated. For this we have made use of recently developed concepts of spatial unit roots, spatial cointegration and spatial error-correction. It is shown that alternative dynamic representations of the general spatial distributed lag model (SADL model) provide deeper insights in the spatial dynamics of the economic system underlying regional convergence analysis. Moreover, we highlight how the spatial error-correction model (SEC model) can be estimated in accordance with the properties of the spatial variables.

In an application we address the issue of income and productivity convergence in the unified Germany. Due to expected distortions arising from administrative areal units we refer to labour market regions defined economically on the basis of commuter flows. From a new test strategy for identifying the data generating process of spatial variables spatial stationarity of all model variables is established. Thus, a simple form of the SEC model can be estimated without being liable to encounter the problem of spurious regression. About a decade after German unification only weak evidence for conditional convergence is obtained from IV estimation of the SEC models. The lack of significance may be due to a slowdown in closing the income and productivity gap in the second half of the nineties. Overall deeper insight into the spatial dimension of regional convergence is obtained by the dynamic spatial modelling approach.

[13] The estimation results for the SBE models are suppressed here in view of space limitations. In essence they provide no additional insights on spatial dynamics beyond the findings from IV estimation of SADL models.

References

Anselin, L. (1982), A note on small sample properties of estimators in a first-order spatial autocorrelative model, Environment and Planning A14, 1023-1030.

Anselin, L. (1988a), Spatial econometrics: methods and models, Kluwer, Dordrecht.

Anselin, L. (1988b), Lagrange multiplier test diagnostics for spatial dependence and spatial heterogeneity, Geographical Analysis 20, 1-17.

Bohl, M.T. (1998), Konvergenz westdeutscher Regionen? Neue empirische Ergebnisse auf der Basis von Panle-Einheitswurzeltests, Konjunkturpolitik 44, 82-99.

Charemza, W. and Deadman, D. (1992), New directions of econometrics, Edward Elgar, Cheltenham, UK.

Eckey, H-F. (2001), Der wirtschaftliche Entwicklungsstand in den Regionen des Vereinigten Deutschlands, Discussion Papers in Economics No. 20/01, University of Kassel, Dept. of Economics.

Eckey, H.-F., Horn, K. und Klemmer, P. (1990), Abgrenzung von regionalen Diagnoseeinheiten für die Zwecke der regionalen Wirtschaftspolitik, Bochum.

Evans, P. (1998), Using panel data to evaluate growth theories, International Economic Review 39, 295-306.

Evans, P. and Karras, G. (1996), Convergence revisited, Journal of Monetary Economics 37, 249-265.

Fingleton, B. (1999), Spurious spatial regression: some Monte Carlo results with spatial unit Root and Spatial Cointegration, Journal of Regional Science 39, 1-19.

Fingleton, B. (2000), Spatial econometrics, economic geography, dynamics and equilibrium: a ‘third way’?, Environment and Planning A, 32, 1481-1498.

Fingleton, B. (2001), Equilibrium and economic growth: spatial econometric models and simulations. Journal of Regional Science, 41, 117-147.

Funke, M. and Strulik, H. (1999), Regional growth in West Germany: convergence or divergence?, Economic Modelling 16, 489-502.

Greene, W.H. (2002), Econometric analysis, 5th ed., Prentice-Hall, London.

Grömling, M. (2001), Produktivitätstrends der 90er Jahre, Statistische Überzeichnung dämpft New Economy Hoffnungen, IW-trends, 21-37.

Holmes, M.J. (2000), Convergence in international output: evidence from panel data unit root tests, Research Paper No. 00-6, Department of Economics, Loughborough University.

Islam, N. (1995), Growth empirics: a panel data approach, Quarterly Journal of Economics 110, 1127-1170.

Kelejian, H.H. and I. Prucha (1998), A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances, Journal of Real Estate Finance and Economics 17, 99-121.

Kelejian, H.H. and Robinson, D.P. (1993), A suggested method of estimation for spatial interdependent models with autocorrelated errors, and an application to a county expenditure model, Papers in Regional Science 72, 297-312.

Kelejian, H.H. and Robinson, D.P. (1995), Spatial correlation: a suggested alternative to the autoregressive model, in: Anselin, L. and Florax, R.J.G.M. (eds.), New directions in spatial econometrics, Springer, Berlin, New York, 75 – 95.

Kónya, L. (2001), Panel data unit root tests with an application, Discussion Paper, School of Applied Economics, Victoria University, Melbourne, Australia.

Kosfeld, R., Eckey, H.-F. and Dreger, Ch. (2002), Regional convergence in the unified Germany: a spatial econometric perspective, Economic Discussion Papers No. 39/02, University of Kassel, Dept. of Economics.

Lauridsen, J. (2002), Spatial autoregressively distributed lag models: equivalent forms, estimation, and an illustrative commuting model. Discussion Paper, Department of Statistics and Demogarphy, University of Southern Denmark, conditionally accepted: Journal of Regional Science.

Lauridsen, J. and R. Kosfeld, R. (2002), A test strategy for spurious regression, spatial nonstationarity, and spatial cointegration, Economic Discussions Paper No. 8/2002, Faculty of Social Sciences, University of Southern Denmark.

Lucas, R.E. (1988), On the mechanics of economic development, Journal of Monetary Economics 22, 3-42.

Mankiw, N.G., Romer, D. and Weil, D.N. (1992), A contribution to the empirics of economic Growth, Quarterly Journal of Economics 107, 407 – 437.

Niebuhr, A. (2001), Convergence and the effects of spatial interaction, Jahrbuch für Regionalwissenschaft 21, 113-133.

Romer, D. (1996), Advanced macroeconomics, New York.

Schalk, H.J. Untiedt, G. and Lüschow, J. (1995), Technische Effizienz, Wachstum und Konvergenz in den Arbeitsmarktregionen der Bundesrepublik Deutschland (West), Jahrbücher für Nationalökonomie und Statistik 214, S. 25–49.

Seitz, H. (1995), Konvergenz: Theoretische Aspekte und empirische Befunde für Westdeutschland, Konjunkturpolitik 41, 25-49.

Statistisches Bundesamt (Hrsg.) (1999), Statistisches Jahrbuch 1999 für die Bundesrepublik Deutschland, Stuttgart.

Statistisches Bundesamt (Hrsg.) (2001), Statistisches Jahrbuch 2001 für die Bundesrepublik Deutschland, Stuttgart.

Vorbeek, M. (2000), A guide to modern econometrics, Wiley, Chichester, New York.