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ABSTRACT

We estimate the speed of income convergence for a sample of 196 European NUTS 2 regions over the period 1985-1999. So far there is no direct estimator available for dynamic panels with strong spatial dependencies. We propose a two-step procedure, which involves first spatial filtering of the variables to remove the spatial correlation, and application of standard GMM estimators for dynamic panels in a second step. Our results show that ignorance of the spatial correlation leads to potentially misleading results. Applying a system GMM estimator on the filtered variables, we obtain a speed of convergence of 6.9 per cent and a capital elasticity of 0.43.

JEL-classification: C23, O00, R11
Keywords: growth, convergence, spatial dependence, spatial filtering, dynamic panels, GMM

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1. Introduction

The issue of whether European regions show convergence in income levels has been a major concern in the EU during the last decades and thus has geared a considerable amount of research work in the field. From a methodological point of view, a number of related econometric concepts were applied and developed. Nevertheless, critical arguments can be brought forward even against the most recently applied econometric frameworks, namely dynamic panel data models and spatial models as such. The aim of this paper is to reconcile the critical points raised in the current debate and to propose a new method of estimating convergence which combines spatial and panel data econometrics.

Convergence studies were originally based on cross-sections and estimated using OLS. Following the seminal paper by Barro (1991), such analyses were carried out for a large set of countries (e.g Barro and Sala-i-Martin 1991, Levine and Renelt 1992) as well as regions (see Neven and Gouyette 1995, Armstrong 1995, Fagerberg and Verspagen 1996, Tondl 1999, Martin 1999, Vanhoudt et al. 2000, Martin 2000 for regional convergence in the EU, Herz and Röger 1995, Hofer and Wörgötter 1997, Paci and Pigliaru 1995, de la Fuente 1996 etc. for regional convergence in EU member states). These studies concluded that convergence between EU regions took place, however, at a fairly slow pace, reaching 2-3 per cent in the 1960s and 1970s and slowing down to 1.7 per cent after 1975.

The framework of cross-section studies for the estimation of conditional convergence was soon critisized for econometric reasons: The initial level of technology, which should be included in a conditional convergence specification, is not observed. Since it is also correlated with another regressor (initial income), all cross-section studies suffer from an omitted variable bias. Islam (1995) proposed to set up convergence analyses in a panel data framework where it is possible to control for individual–specific, time invariant characteristics of countries (like the initial level of technology) using fixed effects. Panel data convergence studies using the least squares dummy variable (LSDV) procedure (for countries Knight et al 1993, Islam 1995, for regions de la Fuente 1996, Cuadrado-Roura et al. 1999, Tondl 1999) found extremely fast convergence rates of up to 20 per cent. More recent studies account for the fact dynamic panel data models – as panel convergence models inevitably are - require a different estimation technique than the LSDV estimator. From the different procedures suggested in the literature for dynamic panel data models (see e.g. Baltagi 1996), most studies (Caselli et al. 1996, Henderson 2000, Dowrick and Rogers 2001, Tondl 2001, Panizza 2002) employ the GMM estimator in first differences suggested by Arellano and Bond (1991); most of them find equally high convergence rates as studies using the LSDV estimator. The most recent convergence studies (Yudong and Weeks 2000, Deininger and Olinto 2000, Bond et al. 2001) pick up new results from dynamic panel data econometrics, which suggest the use of system GMM estimators as proposed by Arellano and Bover (1995) and Blundell and Bond (1998) to overcome the problem of weak instruments, which is likely to be encountered in convergence studies using the first differences estimator. These studies find more modest rates of convergence, ranging from 2 to 4 per cent per annum. Comparing these studies, it is evident that no single estimator for dynamic panels appears to be superior in all circumstances.

The second substantial criticism of the original OLS cross-section convergence studies was raised by regional economists, who argued that regions could not be treated as isolated economies (see e.g. Fingleton 1999, Rey and Montouri 1999, but the point was also made by Quah 1996). Rather it had to be assumed that the growth of fairly small territories which are close to each other is linked. Therefore, convergence analyses would have to account for spatial dependence of regional growth. Leaving this aspect aside would lead to a serious model misspecification. The spatial econometric literature (Anselin 1988, Anselin and Florax 1995, Anselin and Bera 1998, Kelejian and Prucha 1998) offers econometric models which account for spatial autocorrelation of the endogenous variable and in the error term. Thus in these models regional growth is also specified as dependent of other regions growth by including a spatial lag (substantial spatial dependence). Alternatively, or in addition, systematic spatial dependence may be reflected in the error term (nuisance dependence). Spatial dependence is the outcome of a number of linkages between regions such as trade (demand linkages), interacting labour markets, technology spillovers, etc. Note, however, that spatial econometric analysis so far is constrained to cross-sections and static panels. There is yet no estimation procedure for dynamic spatial panels as required for convergence regressions.

Using the Moran´s I statistic as a test for spatial dependence (Anselin 1988, Anselin and Florax 1995) several studies found that growth of European regions exhibits spatial correlation (Fingleton and McCombie 1998, Vayá et al 2000, Ertur et al. 2002, Badinger and Tondl 2002). There are a few studies which have used the spatial econometric framework for investigating regional convergence in a cross-section analysis. Rey and Montouri (1999) investigated convergence of US states over the period 1929-1994 and find that their growth rates exhibit spatial correlation. Estimating convergence with a spatial error model, results in a slightly lower rate of convergence of 1.4 per cent for 1946-94 against 1.7 per cent obtained with the OLS estimation. For Europe Vayá et al. (2000) estimate regional convergence of 108 EU regions for the period 1975-1992 in a spatial model, where growth is dependent on the own initial income position as well as the neighbour regions´ growth and their initial income. The study suggests that the neighbour's growth is an important determinant of regional growth in the EU. A one per cent increase in growth in the neighbour region translates into a 0.63 per cent increase in growth of the region considered. Surprisingly, the rate of convergence does seem to be unaffected by the inclusion of spatial dependence in their study. It amounts to about 2 per cent, both with the simple cross-section model estimated with OLS as well as with the spatial model estimated using ML. The same spatial model with spatially lagged growth is also estimated by Carrington (2002) for 110 EU regions for the more recent period 1989-98, where she finds that convergence is reduced in the spatial specification dropping from 3.6 per cent to 1.8 per cent. On the member state level, a thorough spatial convergence analysis for German regions is provided by Niebuhr (2001). Her study shows that also within Germany regional growth is clustered. If considering this fact in a spatial lag model, the convergence speed drops from one per cent to 0.6 per cent. A different conjecture is made by Baumol et al. (2002). Looking at growth of 135 EU regions in the period 1985-95, they find that in the spatial model estimated by ML the convergence coefficient rises to 1.2 per cent compared with 0.85 per cent of the basic model estimated with OLS. Accounting for the fact that regional incomes – and not only regional growth – show a high spatial correlation in the EU, they then estimate a model with two spatial regimes where the convergence speed differs between northern and southern regions. The results indicate a convergence rate of the South of 2.9 per cent while the North does not show any convergence. From the above studies it follows that regional growth in Europe is evidently characterized by spatial dependence which must be taken into account in a correctly specified convergence model. The effect is a change in the speed of convergence compared with the standard cross-section OLS model. The extent of this change is not clear a priori since it depends on the strength of spatial dependence, which varies across samples and over time.

Given the two recent developments in convergence analysis, the dynamic panel data model on the one hand, the spatial model on the other hand, the straightforward wish appears to combine both viewpoints in a spatial dynamic panel data model in order to meet the underlying arguments of both approaches. However, so far no suitable estimator addressing both issues simultaneously is available. To overcome this deficit, we propose to employ a two step procedure in order to estimate a dynamic spatial panel data convergence model for EU regions. First, a filtering technique as proposed in Getis and Griffith (2002) is applied to remove the spatial correlation from the data. Then standard GMM estimators are used to make inference on convergence. We shall show that the estimated speed of convergence changes significantly with respect to the estimation method. Ignoring the presence of spatial dependence may lead to seriously misleading results. As in recent studies, we also find that the GMM estimator in first differences performs relatively poor, suggesting the use of the system estimator. In our preferred specification, the speed of convergence amounts to some 7 percent.

The rest of the paper is organized as follows. Section 2 presents the empirical convergence model. Section 3 discusses the estimation issues and describes the spatial filtering technique and the estimation procedure for dynamic panels. Section 4 presents the results of our convergence estimation and section 5 concludes.

2. The empirical model

Following Mankiw et al. (1992) we assume a Cobb-Douglas production function with labour-augmenting technological progress and constant returns to scale

$$Y = K^{\alpha}(AL)^{1-\alpha} \tag{2.1}$$

where Y = output, K = capital, L = labour, and α and $(1-\alpha)$ denote output elasticities.[1] Factor accumulation is described by the following equation:

$$\dot{K} = sY - \kappa K \tag{2.1a}$$

where s is the investment-ratio and κ the depreciation rate of the stock of physical capital. Finally, technological progress (A) and labour (L) grow at the exogenously given rates g and n. Solving for the steady-state output per capita ($y^* = Y/L$), we have in log-form:

$$\ln y^* = \ln A_0 + gt + \frac{\alpha}{1-\alpha}\ln s + \frac{\alpha}{1-\alpha}\ln(n+g+\kappa) \tag{2.2}$$

The standard convergence specification is then obtained by a Taylor series approximation around the steady state, which yields ultimately

$$\begin{aligned}\ln y_t &= (1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}\ln s - (1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}\ln(n+g+\kappa) - (1-e^{-\lambda\tau})\ln y_{t-\tau} \\ &+ (1-e^{-\lambda\tau})A_0 + g(t-e^{-\lambda\tau}(t-\tau))\end{aligned} \tag{2.3}$$

where τ refers to the time period, to which equation (2.3) applies and λ is the convergence rate. This cross-section specification was extended to the panel case by Islam (1995), which has several advantages. Most importantly, it allows to control for differences in the initial level of technology (A_0), which is reflected in the country (here: region) specific fixed effects. Also, the assumptions that n and s are constant over the period τ are more realistic, when applied to shorter periods. Finally, using a panel approach yields a much larger number of observations.

Using the conventional notation of the panel data literature, equation (2.3) can be rewritten as

$$\ln y_{it} = \gamma \ln y_{i,t-1} + \beta_1 \ln s_{it} + \beta_2 \ln(n+g+\kappa)_{it} + \mu_i + \eta_t + \upsilon_{it}$$

(2.4)

with $\gamma = e^{-\lambda\tau}$, $\beta_1 = \beta = (1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}$, $\beta_2 = -\beta$

$\mu_i = (1-e^{-\lambda\tau})\ln(A_0)$ = region-specific effect (time invariant)

$\eta_t = g(t_2 - e^{-\lambda\tau}t_1)$ = time specific effect (region invariant)

υ_{it} = error term usually assumed $IID(0,\sigma^2)$, τ = 5 years,

[1] In their extended model, Mankiw et al. also included human capital as production factor. We had to omit

$i = 1,\ldots,N, \qquad t = 1,\ldots,T$

Imposing the restriction on β_2 in (2.4) gives us our final empirical model:

$$\ln y_{it} = \gamma \ln y_{i,t-1} + \beta \ln x_{it} + \mu_i + \eta_t + \upsilon_{it}, \qquad (2.5)$$

where the regressor variable is denoted by $x_{it} = s_{it} / (n+g+\kappa)_{it}$.

3. Estimation Issues

Two important characteristics distinguish the parameter estimation problem in this paper from standard panel data approaches (as for instance surveyed in Hsiao 1986 and Baltagi 1995). First, due to the potential spatial effects there is much reason to believe that the assumption of uncorrelated errors is invalid and that we face a substantial amount of spatial dependence. A typical model for this phenomenon would express a part of the region specific effects (or to an equal effect the errors) as a so-called spatially autoregressive (SAR) process $\upsilon = \rho W \upsilon + \varepsilon$, with $\varepsilon \sim IID(0,\sigma^2)$ and $\upsilon=(\upsilon_1,\ldots, \upsilon_N)$ where W is a N x N given weighting matrix (with N denoting the number of regions) describing the general structure of the regional dependence and ρ is a scalar parameter related to its intensity, which usually has to be estimated. In this setting standard panel estimation procedures (such as the least square dummy variable estimator – LSDV – that uses mean centred variables) yield unbiased but inefficient parameter estimates and biased estimates of the standard errors.

The second problem is the dynamic nature of our model given in (2.5). It is well known, that in this case standard panel estimators yield biased coefficients for short panels (Nickel 1981). In the treatment of each of these problems the generalized method of moments (GMM) estimation technique gained popularity (see Kelejian and Prucha 1999 for the spatial cross-section, Arellano and Bond 1991 for the dynamic panel variant). A unified GMM approach, however, that addresses both issues under fairly general assumptions, considering the restricting necessary assumptions and the resulting highly complex moment conditions, seems out of sight. To overcome these problems, we propose a two-step procedure, which involves

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human capital as no data are available for our sample for the whole period of investigation.

- filtering of the data to remove spatial effects and subsequently
- the application of a standard estimator for dynamic panels.

The first step provides a transformation of the data so that it fulfils the assumptions (spatial independence) required in the second stage, which in turn will yield consistent parameter estimates of a "spaceless" version of model (2.5). Note that such a procedure is justified by having ruled out any interspatio-temporal correlations (i.e. Cov$(\upsilon_{it},\upsilon_{js}) = 0$ for $i \neq j$ and $t \neq s$).

3.1 Spatial Filtering

The aim of the spatial filtering techniques is to rid the data of regional interdependencies as imposed by – say – a SAR, thus allowing an analyst in the second step to use conventional statistical techniques that are based on the assumption of spatially uncorrelated errors (such as OLS or, as is more relevant here, dynamic panel GMM). Recently, two well established spatial filtering methods have been reviewed and compared by Getis and Griffith (2002), one based on the local spatial autocorrelation statistic G_i by Getis and Ord (1992), the other on an eigenfunction decomposition related to the global spatial autocorrelation statistic, the Moran's *I*. In the following we briefly describe and eventually employ the first technique, which is equally effective but more intuitive and computationally simpler.

The G_i statistic, which is the defining element of the filtering device, was originally developed as a diagnostic to reveal local spatial dependencies that are not properly captured by global measures as the Moran's *I*. It is defined as a distance-weighted and normalized average of observations $(x_1,\ldots,x_N)$ from a relevant variable:

$$G_i(\delta) = \textstyle\sum_j w_{ij}(\delta)\, x_j \,/\, \sum_j x_j, \qquad i \neq j. \tag{3.1}$$

Here, $w_{ij}(\delta)$ denotes the elements of the spatial weight matrix W, which is conventionally row-standardized and usually depends upon a distance parameter δ (observations which are geographically further distant are downweighted). Consequently, the G_i statistic varies with this parameter too and a proper choice of δ is required for practical applications. Moreover, from (3.2) the difference to Moran's *I*, which can be written as similarly defined from centred variables

$$I(\delta) = \textstyle\sum_i\sum_j w_{ij}(\delta)\,(x_i - \bar{x})(x_j - \bar{x}) \,/\, \sum_j (x_j - \bar{x})^2 \qquad i \neq j. \tag{3.2}$$

as a global characteristic becomes evident. Both statistics can be standardized to corresponding approximately Normal(0,1) distributed z-scores z_{Gi} and z_I, which can be directly compared with the well-known critical values (e.g. 1.96 for 95% significance). [2]

Since the expected value of (3.2) (over all random permutations of the remaining $N\text{-}1$ observations) $E[G_i(\delta)] = \sum_j w_{ij}(\delta) / (N-1)$ represents the realization at location i when no autocorrelation occurs, its ratio to the observed value will indicate the local magnitude of spatial dependence. It is then natural to filter the observations by

$$\tilde{x}_i = x_i \, [\textstyle\sum_j w_{ij}(\delta) / (N-1)] \, / \, G_i(\delta), \qquad (3.3)$$

such that $(x_i - \tilde{x}_i)$ represents the purely spatial and $\tilde{x}_i$ the filtered or "spaceless" component of the observation. Getis and Griffith (2002) demonstrate that if δ is chosen properly the z_I corresponding to the filtered values $\tilde{x}_i$ will be insignificant. Thus by applying this filter to all variables in a regression model (dependent and explanatory variables) we can assume to effectively remove the undesired spatial dependencies, which can eventually be checked by calculating the z_I corresponding to the residuals of this regression.

The remaining practical problems are the choices of the structure of W and the locality parameter δ the regional weighting scheme. As most researchers in a similar context, e.g. Niebuhr (2001), we model the distance decay by a negative exponential function, i.e.

$$w_{ij}(\delta) = \exp(-\delta\, d_{ij}), \quad 0 < \delta < \infty, \qquad (3.4)$$

with d_{ij} denoting the geographical distance between the centres of the regions i and j. It turns out that while the choice of the structure does not have decisive impact on the outcomes, the choice of δ is more delicate. Getis (1995) discusses several methods to determine δ, amongst them the value that corresponds to the maximum absolute sum over all locations i of the z-scores of the G_i related to a specific variable, i.e.

$$\tilde{\delta} = \text{Arg max}_{\delta} \textstyle\sum_i |z_{Gi}(\delta)|. \qquad (3.5)$$

This also proved to be the most appropriate criterion for our problem. Note, that rather than comparing different δ, the scaling of which is rather meaningless, we will compare

[2] The exact distribution of Moran's I - depending upon a variety of assumptions - may possess a rather complicated form and we thus refrain from using it here; for a detailed elaboration of the issue refer to Tiefelsdorf (2000).

localities by the so-called half-life distance $d_{1/2} = d_{min} + \ln(2)/\delta$, which is the (approximate) distance after which the spatial effects are reduced to 50% (d_{min} denotes the average distance between centres of neighbouring regions).

Although so far only applied in a cross-section setting, the extension of the spatial filtering technique to a panel data model is straightforward. For every separate point of time t all relevant variables are filtered according to a predetermined $W(\tilde{\delta}_i)$, i.e. we will allow variation with respect to locality over variables and time but not structure of the spatial weighting scheme.

3.2 Estimation in dynamic panels

As shown by Nickell (1981), the LSDV estimator yields biased estimates in the case of dynamic panels. Although this bias tends to zero as T approaches infinity, it cannot be ignored in small samples. Using Monte Carlo studies, Judson et al. (1996) find that the bias can be as large as 20 per cent even for fairly long panels with T=30.

The most commonly used estimator for dynamic panels with fixed effects in the literature is the GMM estimator by Arellano and Bond (1991). Thereby, the fixed effects are first eliminated using first differences. Then an instrumental variable estimation of the differenced equation is performed. As instruments for the lagged difference of the endogenous variable – or other variables which are correlated with the differenced error term – all lagged levels of the variable in question are used, starting with lag two and potentially going back to the beginning of the sample. Consistency of the GMM estimator requires a lack of second order serial correlation in the residuals of the differenced specification. The overall validity of instruments can be checked by a Sargan test of over-identifying restrictions (see Arellano and Bond, 1991). In growth analyses, the GMM estimator was first applied in the influential paper of Caselli et al. (1996).

Applying the procedure to (2.5) we have

$$\Delta \ln y_{it} = \gamma \Delta \ln y_{i,t-1} + \beta \Delta \ln x_{it} + \Delta \mu_i + \Delta \eta_t + \Delta \upsilon_{it} \qquad \text{for } t = 3, ...T, \text{ and } i = 1, ..., N \qquad (3.6)$$

where y_{it-2} and all previous lags are used as instruments for Δy_{it-1} assuming that $E[\upsilon_{it}\upsilon_{is}] = 0$ for $i=1,...N$ and $s \neq t$ and exploiting the moment conditions that

$E\lfloor y_{i,t-s}\Delta\upsilon_{it}\rfloor = 0$ for $t = 3,...,T$ and $s \geq 2$. Of course, differencing cancels out the fixed effect ($\Delta\mu_i$ = 0).

The GMM estimator in first differences has been critisized recently in the literature, as Blundell and Bond (1998) argue that in the case of persistent data and a γ close to one, the lagged levels are likely to be poor instruments for first differences. As shown by Bond et al. (2001) an indication for weak instruments might be that the coefficient obtained with the GMM estimator in first differences is close to the coefficient from the within estimator, which tends to show a downward bias in the dynamic panel (Nickel 1981). An upper bound for the coefficient of the lagged endogenous variable is provided by the simple pooled OLS-estimator of a panel data model, which is seriously biased upwards in the presence of fixed effects. A reasonable parameter estimate should thus lie within this range. Blundell and Bond (1998) suggest a system GMM estimator, where a system of equations is estimated in first differences and in levels. The (T-2) differences equations, given by (3.6) are supplemented by the following (T-1) levels equations

$\ln y_{it} = \gamma \ln y_{it-1} + \beta \ln x_{it} + \mu_i + \eta_t + \upsilon_{it}$ for t = 2, ... , T , and i = 1, ..., N,

(3.7)

where lagged first differences are used as instruments[3] for the additional equations, based on the assumption that $E(\mu_i \Delta y_{i2}) = 0$ for i = 1,...,N, which (together with the standard assumptions for (3.6)) yields the additional moment conditions $E(u_{it}\Delta y_{i,t-1}) = 0$ for i = 1,...,N and t = 3, 4, ..., T, $u_{it} = \mu_i + \upsilon_{it}$.[4] Again, the validity of instruments can be checked by the Sargan test and the validity of additional instruments by the Difference Sargan test.

Using Monte Carlo studies, Blundell and Bond (1998) showed for the AR(1) model that the finite sample bias of the difference GMM estimator can be reduced dramatically with the system GMM estimator. Similar results were obtained for a model with additional right-hand side variables by Blundell et al. (2000). In an application to growth empirics, Bond et al. (2001) re-estimated the model by Caselli et al. (1996), who

[3] Note that there are no instruments for the first observation y_{i2} available.

[4] Note that this requires the first moment of y_{it} to be stationary. Including time dummies in the estimation is equivalent to transforming the series into deviations from time means. Thus any pattern in the time means is consistent with a constant mean of the transformed series of each country (Bond et al. 2000).

obtained a convergence rate of 12.9 per cent using the Arellano-Bond estimator. Bond et al. (2001) expect that this high rate is due to the downward bias of the coefficient of lagged income, appearing with the GMM estimator in first differences in the case of weak instruments, as the coefficient is below the value of the LSDV estimator. Using the system GMM estimator, they arrive at a speed of convergence of 2.4 per cent, which is surprisingly close to the results of many cross-section studies. These studies clearly show that it will be important to check the sensitivity of the results with respect to this potential weak instruments problem.

4. Results of estimation

Before presenting the results of the estimation we discuss the spatial properties of the data. Since the regions in our sample are no closed economies and thus maintain a number of interactions with each other, we expect strong spatial correlation in our data. Table 1 shows the results of a Moran's *I* test on our dependent variable (*y*) and the regressor (*x*) in equation (2.5), performed on each of the 6 cross-sections with 194 regions (1975, 1980, 1985, 1990, 1995, 1999), which comprise our total panel data sample. As expected the results show very strong spatial correlation; the standard normally distributed Moran's *I* values range from 25 to 26 with income (*y*) and 13 to 21 with the regressor (*x*). Thus, we go on to filter our variables as outlined in section 3.1 (see equation (3.3)) to obtain $\tilde{x}_i$ and $\tilde{y}_i$; overall, the results show that the filtering procedure removes successfully the spatial correlation from the variables. The significant joint test for $\tilde{y}_i$ is due to the cumulation of negative values and should not be overstressed, given that the cross-section tests indicate no spatial correlation. After all, the huge Moran's I values of the original variables are reduced dramatically. Table 1 also indicates the resulting half life distance ($d_{1/2}$), after which interactions have decreased by 50 per cent. Note that $d_{1/2}$ is implied by the value of δ, which is allowed to vary over variables and time and chosen according to criterion (3.5). These results show that the half life distance for both variables is approximately 130 kilometres (95 per cent within 600 kilometres). Given the average size of Nuts 2 regions the conclusion is that most of the economic interactions take place within the neighbouring regions. That (technology) spillovers are geographically rather limited because of the importance of face-to face contacts was suggested by Audretsch and Feldman (1996) and Krugman (1991). Empirically, Paci and Pigliaru (2001) found that productivity growth of an EU region is highly correlated with those of its neighbouring regions when estimating spatial lag models. Paci and Usai (2000) detect R&D spillovers between Italian adjacent regions. Funke and Niebuhr (2000) investigate R&D spillovers with spatial interaction models for West German regions and find a significant contribution of R&D spillovers to productivity growth which decay fairly fast with distance. Bottazzi and Peri (1999) regard EU regions and similarly find that local clustering, i.e. spillovers, is important for R&D results, while R&D spillovers quickly fade with distance.

Table 1 – Test for spatial correlation of the variables in (2.5)

	x		$\tilde{x}_i$	y		$\tilde{y}_i$
z_I (75)				25.71***	$d_{1/2} = 135$	-1.09
z_I (80)	21.68***	$d_{1/2} = 127$	1.24	26.30***	$d_{1/2} = 133$	-1.14
z_I (85)	15.99***	$d_{1/2} = 122$	-1.27	24.85***	$d_{1/2} = 133$	-1.81*
z_I (90)	15.99***	$d_{1/2} = 118$	-0.81	23.59***	$d_{1/2} = 136$	-1.47
z_I (95)	13.32***	$d_{1/2} = 119$	-2.01**	26.34***	$d_{1/2} = 133$	-1.58
z_I (99)	13.66***	$d_{1/2} = 117$	1.74*	26.17***	$d_{1/2} = 133$	-1.27
z_I (joint)	16.13***		-0.22	25.50***		-1.39***

***, **, * indicate significance at the 1, 5 and 10 per cent level. – z_I-values are standardised Moran's I values (see equation (3.2)), which are assumed to be standard normally distributed under the null of no serial correlation (standardization based on expectation and variance as given in Tiefelsdorf (2000), joint statistic is based on average of individual values and is distributed with a mean of zero and a standard deviation of $1/\sqrt{5}$ (x), respectively $1/\sqrt{6}$ (y). – $d_{1/2}$ is expressed in kilometres and refers to both the original and the filtered variables.

Tables 2 and 3 present the results of our estimation for equation (2.5) using different estimators for both the original data and the spaceless models with the filtered variables. Our sample comprises 194 cross-section units; the data refer to 5 year intervals over the time period 1975 to 1999.[5] A detailed description of the data used in the estimation of (2.5) is given in the Appendix.

[5] As we have no data on the year 2000, the last time period covers only four years. This implies an average τ of 4.75, which we use to recover the structural parameters of our model.

Table 2 – Results of estimation of model (2.5) (unfiltered variables)

dependent variable: y_{it}	OLS[1)]	LSDV[2)]	GMM-FD[3)]	GMM-SYS[4)]
constant[5)]	0.002*** (14.69)	5.048	5.614	-0.691
$y_{i,t-1}$	1.007*** (138.13)	0.474*** (13.07)	0.353*** (4.44)	1.092*** (20.24)
x_{it}	0.035*** (3.05)	0.151*** (9.42)	0.213*** (6.44)	0.321*** (10.37)
implied structural coefficients				
λ	-	0.157	0.219	-
α	-	0.223	0.248	-
Instruments diagnostics				
Sargan[6)]			7.76 (4)	27.89*** (8)
Diff-Sargan[6)]				20.13*** (4)
Moran's I tests of residuals[7)]				
z_I (e_{85})	5.26***	12.95***	13.44***	5.67***
z_I (e_{90})	11.55***	4.52***	5.36***	9.73***
z_I (e_{95})	6.74***	11.98***	16.50***	14.05***
z_I (e_{99})	21.93***	16.30***	15.27***	19.39***
z_I (joint)	11.37***	11.44***	12.65***	12.21***
R^2	0.965	0.983	0.960	0.944
obs.	776	776	776	970

Numbers in parentheses are t-values, respectively degrees of freedom of the test statistics. – ***, **, * indicate significance at the 1, 5 and 10 per cent level. – All models estimated including time-specific effects. – 1) OLS-estimation of pooled data (common intercept) – 2) Least squares dummy variable estimation, based on mean centred data. – 3) two-step GMM estimator, based on first differences (Arellano and Bond 1991); the third and fourth lags ($y_{i,t-3}$, $y_{i,t-4}$) were used as instruments for Δy_{it} (similar as in the case of the levels equations in the system estimator, there are no instruments for the first observation; the third lag was chosen because the use of lag two resulted in a significant Sargan test). – 4) two-step GMM system estimator, based on first differences and levels equations (Blundell and Bond, 1998), the first lagged difference ($\Delta y_{i,t-1}$) was used as instruments for y_{it} (starting with lag two leads to no improvement in the Sargan test).– The variable x is treated as exogenous; no improvement in the Sargan-test is attainable, if x is instrumented, too. – t-statistics refer to two –step estimates; significance levels do not change, if two step or one step robust estimates are used. – 5) constant (in OLS), respectively average of fixed effects μ_i . – 6) Sargan validity of instruments test: under H_0 of valid instruments distributed χ^2 with p-k degrees of freedom, where p is the number of columns in the instrument matrix and k is the number of variables; Differences-Sargan test of the validity of the additional instruments in the levels equations of the system, calculated as difference between Sargan (system) and Sargan (first differences). – 7) Moran's I; see Table 2; half life distances of endogenous variable were used. – R^2 calculated as squared correlation between y_{it} and $\hat{y}_{it}$. – GMM estimators were calculated using the DPD98 Software for GAUSS (Arellano and Bond 1998).

Let us first look at the results, if spatial dependence is not taken into account (table 2). The coefficient of lagged income varies considerably according to the estimation procedure. The OLS coefficient is slightly larger than one indicating an absence of convergence. It goes down to 0.47 with the LSDV (within groups) estimator and still further to 0.35 with the difference GMM estimator. The coefficient varies in the expected way. The OLS coefficient is expected to suffer from an upward bias in the presence of fixed effects (Hsiao 1986), the within groups estimator from a serious downward bias in a dynamic panel (Nickell 1981, Judson et al. 1999). The coefficient of the difference GMM estimator may even be more downward biased than the LSDV in the case of weak instruments (Bond et al. 2001). A plausible parameter estimate should lie between the LSDV and the OLS estimate (Bond et al. 2001, Blundell and Bond 1995), a result which has been obtained by using the system GMM estimator (Yudong and Weeks 2000, Bond et al. 2001). However, note that in our case we obtain the surprising result that the coefficient exceeds that of the OLS estimation, which may be due to a misspecification of the model in the presence of spatial effects and invalid instruments (see below). The coefficient of net investment is implausibly low with the OLS estimator and increases with the LSDV and the dynamic panel estimators. The implied capital elasticity ranges from 0.22 to 0.24.

Looking at the Sargan tests and the Difference Sargan test, we have to note that the instruments employed with the system GMM estimator are invalid. The test would rather suggest that the difference GMM estimation operates with correct instruments although there remain some doubts on their quality, because the coefficient is even below the LSDV estimate. If the difference GMM was our "preferred" specification, we would conclude from this estimation that the convergence speed is 21.9 per cent and capital elasticity 0.25.

This convergence coefficient from the first differences GMM estimate is even higher than the results reported by other panel data convergence studies. With the difference GMM estimator, Caselli et al. (1996) obtain a convergence rate of 12.9 per cent, Tondl (2001) of 21 per cent, Panizza (2002) of 14.4 per cent. (Also with LSDV our results resemble those of other studies, for example, de la Fuente (1996) finds a convergence rate of about 10 per cent, Deininger and Olinto (2000) of 16.3 per cent, Yudong and Weeks (2000) of 19.3 per cent.) If we did not care about spatial dependence, that would probably be the (unfortunate) end of our estimation exercise. However, if we look at the Moran´s *I* statistic of the residuals which indicates serious spatial correlation, it is evident that the above results are potentially misleading due to a model misspecification and that we have to take spatial dependencies into account.

Table 3 – Results of estimation of model (2.5) (based on spatially filtered variables)

dependent variable: $\tilde{y}_{it}$	OLS[1)]	LSDV[2)]	GMM-FD[3)]	GMM-SYS[4)]
constant	0.718*** (5.78)	6.692	5.614	2.712
$\tilde{y}_{i,t-1}$	0.932*** (71.75)	0.305*** (7.80)	0.416*** (3.56)	0.720*** (13.73)
$\tilde{x}_{i,t}$	0.121*** (8.92)	0.156*** (8.47)	0.228*** (5.93)	0.214*** (8.92)
implied structural coefficients				
λ	0.015	0.250	0.184	0.069
α	0.640	0.183	0.281	0.433
Instruments diagnostics				
Sargan[5)]			3.85 (4)	11.32 (8)
Diff-Sargan[5)]				7.48 (4)
Moran's I tests of residuals[6)]				
z_I (e85)	-3.21***	-1.19	-1.54	-2.16**
z_I (e90)	-1.37	-1.22	-1.04	-1.38
z_I (e95)	0.55	1.93*	3.40***	3.25***
z_I (e99)	2.31**	1.74	1.29	0.39
z_I (joint)	-0.43	0.32	0.53	0.03
R^2	0.932	0.941	0.917	0.928
obs.	776	776	776	970

Notes: see Table 2 and Table 1 (for Moran's I). R^2 calculated as squared correlation between y and $[\hat{\tilde{y}} + (y - \tilde{y})]$.

Therefore we re-estimate model (2.5) with the spatially filtered variables $\tilde{y}$ and $\tilde{x}$. The results are reported in table 3. If we compare the size of the coefficients of lagged income, the consideration of spatial dependence obviously has a significant impact on convergence. The coefficients of lagged income change considerably. With OLS it is now below one, the other estimates follow the expected pattern where the LSDV coefficient is heavily downward biased. Both the coefficients of the difference GMM and of the system GMM now lie within the bound given by the OLS and LSDV coefficient. The Sargan test statistics suggest that both estimators use valid instruments and that the additional instruments of the system GMM are correct. The difference GMM estimates are close to the LSDV results which is considered to indicate a weak instruments problem. We therefore give preference to the results from the system GMM specification which indicates a rate of convergence of 6.9 per cent and a capital elasticity of 0.43. Our results are similar to the coefficients found with these estimators in the convergence studies of Yudong and Weeks (2000) and Bond et al. (2001), both with respect to the size of the coefficients and their relative magnitude. In line with these authors, our findings cast further doubt on the high convergence rates obtained in previous panel data studies.

The effectiveness of the spatial filtering procedure becomes evident from the Moran´s *I* statistics of the new residuals. Spatial correlation has practically disappeared, although there still seems to be a small rest of spatial correlation for the observation 1995. From this analysis we can point to two important findings. First, we see that correct treatment of spatial dependence is essential in regional convergence analyses and that this can be effectively done with a spatial filter. Using this filter, one can continue to use a dynamic panel data framework. Second, we have seen how sensitive the results from panel data analysis can be with respect to the chosen estimator. According to our results we have to reject the extremely high rates of convergence reported by previous panel data studies. Our estimated convergence rate of 6.9 per cent gives a more plausible case. This convergence speed corresponds to a half-life time of 10 years, after which regions would reach their individual steady state income, which is determined by region specific factors.

5. Conclusions

In this paper, we estimated the speed of convergence for a broad set of EU NUTS 2 level regions over the period 1985-1999. The objective of this study was to address a major econometric problem in regional convergence analysis: How to account for spatial effects in a dynamic panel data model? This estimation problem departs from two important issues. First, regions are no closed economies but show intensive economic interactions with each other. Therefore, one has to expect spatial dependence in the observations. Second, making inference on convergence in a panel data model means that one has to chose a consistent estimator for a dynamic panel data model. Since there exists no dynamic panel data estimator which accounts for spatial dependence we propose a two-step procedure, which involves filtering of the data to remove spatial effects (step 1) and the application of a standard GMM estimators for dynamic panels (step 2).

Our analysis shows that EU regional data at the NUTS 2 level exhibits a large degree of spatial correlation. Our variables, regional income and investment are highly dependent on that of other regions as shown by the Moran´s *I* statistic. Our first regression analysis that does not account for this fact yields regression residuals with a high degree of spatial correlation. This indicates that a common model that neglects spatial factors is misspecified and yields misleading results.

We show that the estimation of our convergence model with the spatially filtered observations removes successfully spatial correlation and that it changes our results on convergence substantially. We now found evidence for convergence with all relevant estimators as opposed to the model with the unfiltered data. The parameter estimates with different panel data estimators now lie within a range and in relationship as proposed by panel data econometrics.

As several recent studies in the empirical growth literature, we found that the system GMM estimator performs best. With this estimator we obtain a convergence speed of about 7 per cent and an output elasticity of capital of 0.4. This indicates a more modest and more plausible convergence process than proposed by previous panel data convergence analyses for EU regions.

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Appendix

Data

$\ln y_{it}$ = *GVA*/*POP* gross value added per capita in million ECU at time *t* (1990 prices, 1990 exchange rate) (t = 1, ..., 6).

s_{it} = investment-ratio = INV_{it}/GVA_{it}, average of the (five year) period (t = 2, ..., 6).

n_{it} = growth of population over the (5 year) period *t* to *t*-1, calculated as differences in natural logs (t = 2, ..., 6).

g_{it} = growth of technological progress, κ_{it} = depreciation rate of capital stock; $(g + \kappa)$ is assumed to be equal to 25 per cent for all regions over the 5 year period *t* to *t*-1 (t = 2, ..., 6).

INV_{it} = investment expenditures (including public investment) in million ECU (1990 prices, 1990 exchange rate)

GVA_{it} = gross value added in million ECU (1990 prices, 1990 exchange rate)

POP_{it} = population in 1000 persons.

i = 1, . . . , 194 European regions (all NUTS2 regions of the EU-15 countries as available in the Cambridge Econometrics dataset, part of the regions had to be eliminated due to missing data or because they turned out as obvious ouliers****), *t* = 1, . . . , 6 (1975, 1980, 1985, 1990, 1995, 1999). All data were taken from the Cambridge Econometrics Dataset (2001). Distances between capitals of the NUTS2 districts were kindly provided by Eurostat.

original data set: 212 regions (Cambridge econometrics)
**** of the originally 212 regions we had to exclude the following 18 regions:

BE34	Luxembourg
DE4	Brandenburg
DE8	Mecklenburg-Vorpomm.
DED1	Chemnitz
DED2	Dresden
DED3	Leipzig
DEE1	Dessau
DEE2	Halle
DEE3	Magdeburg
DEG	Thuringen
ES63	Ceuta y Melilla
FR91	Guadeloupe
FR92	Martinique
FR93	Guyane
FR94	Reunion
PT15	Algarve
PT2	Acores
PT3	Madeira

INCLUDED REGIONS (194)

AT11	Burgenland	GR11	Anat.Mak.
AT12	Niederosterreich	GR12	Kent. Makedonia.
AT13	Wien	GR13	Dytiki Makedonia
AT21	Karnten	GR14	Thessalia
AT22	Steiermark	GR21	Ipeiros
AT31	Oberosterreich	GR22	Ionia Nisia
AT32	Salzburg	GR23	Dytiki Ellada
AT33	Tirol	GR24	Sterea Ellada
AT34	Vorarlberg	GR25	Peloponnisos
BE1	Bruxelles-Brussel	GR3	Attiki
BE21	Antwerpen	GR41	Voreio Aigaio
BE22	Limburg	GR42	Notio Aigaio
BE23	Oost-Vlaanderen	GR43	Kriti
BE24	Vlaams Brabant	IE01	Border
BE25	West-Vlaanderen	IE02	Southern and Eastern
BE31	Brabant Wallon	IT11	Piemonte
BE32	Hainaut	IT12	Valle d'Aosta
BE33	Liege	IT13	Liguria
BE35	Namur	IT2	Lombardia
DE11	Stuttgart	IT31	Trentino-Alto Adige
DE12	Karlsruhe	IT32	Veneto
DE13	Freiburg	IT33	Fr.-Venezia Giulia
DE14	Tubingen	IT4	Emilia-Romagna
DE21	Oberbayern	IT51	Toscana
DE22	Niederbayern	IT52	Umbria
DE23	Oberpfalz	IT53	Marche
DE24	Oberfranken	IT6	Lazio
DE25	Mittelfranken	IT71	Abruzzi
DE26	Unterfranken	IT72	Molise
DE27	Schwaben	IT8	Campania
DE3	Berlin	IT91	Puglia
DE5	Bremen	IT92	Basilicata
DE6	Hamburg	IT93	Calabria
DE71	Darmstadt	ITA	Sicilia
DE72	Giessen	ITB	Sardegna
DE73	Kassel	NL11	Groningen
DE91	Braunschweig	NL12	Friesland
DE92	Hannover	NL13	Drenthe
DE93	Luneburg	NL21	Overijssel
DE94	Weser-Ems	NL22	Gelderland
DEA1	Dusseldorf	NL23	Flevoland
DEA2	Koln	NL31	Utrecht
DEA3	Munster	NL32	Noord-Holland
DEA4	Detmold	NL33	Zuid-Holland
DEA5	Arnsberg	NL34	Zeeland
DEB1	Koblenz	NL41	Noord-Brabant
DEB2	Trier	NL42	Limburg
DEB3	Rheinhessen-Pfalz	PT11	Norte
DEC	Saarland	PT12	Centro
DEF	Schleswig-Holstein	PT13	Lisboa e V.do Tejo
DK01	Hovedstadsreg.	PT14	Alentejo

DK02	O. for Storebaelt	PT15	Algarve
DK03	V. for Storebaelt	SE01	Stockholm
ES11	Galicia	SE02	Ostra Mellansverige
ES12	Asturias	SE04	Sydsverige
ES13	Cantabria	SE06	Norra Mellansverige
ES21	Pais Vasco	SE07	Mellersta Norrland
ES22	Navarra	SE08	Ovre Norrland
ES23	Rioja	SE09	Smaland med oarna
ES24	Aragon	SE0A	Vastsverige
ES3	Madrid	UKC1	Tees Valley and Durham
ES41	Castilla-Leon	UKC2	Northumb. et al.
ES42	Castilla-la Mancha	UKD1	Cumbria
ES43	Extremadura	UKD2	Cheshire
ES51	Cataluna	UKD3	Greater Manchester
ES52	Com. Valenciana	UKD4	Lancashire
ES53	Baleares	UKD5	Merseyside
ES61	Andalucia	UKE1	East Riding
ES62	Murcia	UKE2	North Yorkshire
FI13	Ita-Suomi	UKE3	South Yorkshire
FI14	Vali-Suomi	UKE4	West Yorkshire
FI15	Pohjois-Suomi	UKF1	Derbyshire
FI16	Uusimaa	UKF2	Leics.
FI17	Etela-Suomi	UKF3	Lincolnshire
FI2	Aland	UKG1	Hereford et al.
FR1	Ile de France	UKG2	Shrops.
FR21	Champagne-Ard.	UKG3	West Midlands (county)
FR22	Picardie	UKH1	East Anglia
FR23	Haute-Normandie	UKH2	Bedfordshire
FR24	Centre	UKH3	Essex
FR25	Basse-Normandie	UKI1	Inner London
FR26	Bourgogne	UKI2	Outer London
FR3	Nord-Pas de Calais	UKJ1	Berkshire et al.
FR41	Lorraine	UKJ2	Surrey
FR42	Alsace	UKJ3	Hants.
FR43	Franche-Comte	UKJ4	Kent
FR51	Pays de la Loire	UKK1	Avon et al.
FR52	Bretagne	UKK2	Dorset
FR53	Poitou-Charentes	UKK3	Cornwall
FR61	Aquitaine	UKK4	Devon
FR62	Midi-Pyrenees	UKL1	West Wales
FR63	Limousin	UKL2	East Wales
FR71	Rhone-Alpes	UKM1	North East Scot.
FR72	Auvergne	UKM2	Eastern Scotland
FR81	Languedoc-Rouss.	UKM3	South West Scot.
FR82	Prov-Alpes-Cote d'Azur	UKM4	Highlands and Islands
FR83	Corse	UKN	Northern Ireland