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Pan-European Regional Income Growth and Club-Convergence
Insights from a Spatial Econometric Perspective

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Abstract. Club-convergence analysis provides a more realistic and detailed picture about regional income growth than traditional convergence analysis. This paper presents a spatial econometric framework for club-convergence testing that relates the concept of club-convergence to the notion of spatial heterogeneity. The study provides evidence for the club-convergence hypothesis in cross-regional growth dynamics from a pan-European perspective. The conclusions are threefold. First, we reject the standard Barro-style regression model which underlies most empirical work on regional income convergence, in favour of a two regime [club] alternative in which different regional economies obey different linear regressions when grouped by means of Getis and Ord's (1992) local clustering technique. Second, the results point to a heterogeneous pattern in the pan-European convergence process. Heterogeneity appears in both the convergence rate and the steady-state level. But, third, the study also reveals that spatial error dependence introduces an important bias in our perception of the club-convergence and shows that neglection of this bias would give rise to misleading conclusions.

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1 Introduction

At the beginning of the twenty-first century, the convergence debate has become one of the foremost topics in economic research. While much of the research has initially centred on cross-country patterns and trends, the issue of *regional* income convergence has received increasing attention in recent years[1]. This interest has been enhanced by both the deepening and widening of the integration process in Europe, in particular by the expectations of catch-up of the new EU-member states in the eastern periphery of Europe. The expectations largely rest – explicitly or implicitly – on the acceptance of the *unconditional convergence hypothesis* which suggests that per capita incomes of regional economies converge to one another in the long-run independently of initial conditions.

The traditional neoclassical model of growth (see Solow 1956) provides a simple rationale for this hypothesis. Because production functions display constant returns to scale, and because there are diminishing returns to capital, economies with a relatively small capital stock have higher marginal productivity and will catch up with more developed regions. This led to the notion of convergence which can be understood in two different ways. The first is in terms of level of income. If regions are similar in terms of preferences and technology, then their steady-state income levels will be the same, and over time they will tend to reach that level of per capita income. The second way is convergence in terms of the growth rate. Since in the Solow model the steady-state growth rate is determined by the exogenous rate of technological process, then – provided that technology has the characteristics of a public good – all regions will eventually attain the same steady-state growth rate (Islam 1995).

The failure of conventional neoclassical growth theory to explain sustained growth has been addressed in recent years by the advent of new variants of the standard neoclassical model which seek to endogenise the accumulation of factors. These endogenous growth models incorporate various processes – such as localised collective learning and the accumulation of knowledge – which prevent social returns to investment (broadly defined) from diminishing. This opens up the possibility that economic integration can contribute to a higher long-run growth rate, by stimulating the

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1 For a review of the empirical literature on regional income convergence see Magrini (2004). The vast majority of regional or international growth studies fail to consider and model spatial dependence and heterogeneity in the convergence process.

accumulation of those forms of capital to which returns are not diminishing (Martin 2001). It also allows the possibility for national and regional economies to converge to different long-run equilibria, depending on initial conditions. If regional economies differ in their basic growth parameters such as saving rates, human capital development and technological innovativeness, or if interregional spillovers of knowledge are weak, they may not converge to a common steady-state position as postulated in the unconditional convergence hypothesis, but there might be convergence among similar groups (clubs) of regional economies (*club-convergence*)[2], but little or no convergence between such groups (Martin 2001).

The focus in this paper is on the *club-convergence hypothesis* which suggests that per capita incomes of regional economies that are identical in their structural characteristics converge to one another in the long-run provided that their initial conditions are similar as well. Empirical evidence for this hypothesis is – quite in contrast to the vast literature on the unconditional convergence hypothesis – rather scarce. One notable exception is the study by Durlauf and Johnson (1995) that finds evidence for multiple regimes in cross-country growth dynamics in a world-wide context.

Our study aims at two central objectives. The *first* is to extend the Barro-style methodology for convergence analysis to a spatial econometric framework for club-convergence testing. The *second* is to apply this framework in a cross-regional growth context in Europe. We consider the behaviour of output differences, measured in terms of per capita gross regional product [GRP] across 256 NUTS-2 regions in 25 European countries[3]. The data cover the period 1995 to 2000, when economic recovery in Central and East Europe [CEE] gathered pace. The sample period is admittedly short by any standard[4], but Barro-style growth regressions are valid for shorter time periods as well,

[2] Multiplicity of steady-state equilibria is consistent with the neoclassical paradigm (Azariadis and Drazen 1990). If heterogeneity is permitted across regions, the dynamical system of the Solow growth model could be characterised by multiple steady-state equilibria, and club-convergence becomes a viable testable hypothesis despite diminishing marginal productivity of capital (Galor 1996).

[3] The countries chosen are the EU-25 countries (except Cyprus and Malta) and the two accession countries Bulgaria and Romania.

[4] There is a lack of reliable gross regional product figures in CEE countries. This comes partly from the change in accounting conventions now used in the CEE economies. More important, even if reliable estimates of the change in the volume of output produced did exist, these would be hardly possible to interpret meaningfully because of the fundamental change of production, from a centrally planned to a market system. As a consequence, figures for GRP are difficult to compare between EU-15 and CEE regions until the mid 1990s (European Commission 1999).

as pointed out by Islam (1995), Durlauf and Quah (1999)[5]. Nevertheless, the results of this short-run analysis should be interpreted with care.

The paper is divided into two parts. The first, Section 2, outlines the empirical framework. Subsection 2.1 starts with the standard Barro-style methodology for unconditional convergence testing. Subsection 2.2 extends this methodology to club-convergence testing. The extension relates the concept of club-convergence to the notion of spatial heterogeneity and suggests an approach that distinguishes three major steps in the analysis. The first involves the identification of spatial regimes in the data in the sense that groups [clubs] of regions identified by initial income obey distinct growth regressions. The second relates to checking whether convergence holds within the clubs or not. Use is made, here, of specification techniques which take a single regime model as the null hypothesis. Spatial dependence may invalidate the inferential basis of the test methodology and a third step may be necessary, namely testing for spatial dependence and – if necessary – appropriate respecification of the test equation. Subsection 2.3 shows that club-convergence hypothesis testing is becoming considerable more complex then.

The second part of the paper, Section 3, provides empirical evidence for a pan-European view of club-convergence. Subsection 3.1 describes the data we analyse and the empirical procedure we use to identify spatial regimes in the data. Subsection 3.2 then presents the results of club-convergence hypothesis testing. Our conclusions are threefold. *First*, we reject the linear growth regression model commonly used to study cross-regional growth behaviour in favour of a two regime [club] alternative in which different regional economies obey different linear regressions when grouped by means of Getis and Ord's (1992) local clustering technique. *Second*, the results point to a heterogenous pattern in the pan-European convergence process. Heterogeneity appears in both the convergence rate and the steady-state level. But, *third*, the study reveals that spatial error dependence introduces an important bias in our perception of the club-convergence. Neglection of this bias would give rise to misleading conclusions.

[5] Islam (1995), and Durlauf and Quah (1999) argue, that such regressions are also valid for shorter time spans since they are based on an approximation around the steady-state and supposed to capture the dynamics towards the steady-state.

2 The Framework for Convergence Testing

2.1 The Conventional Approach to Convergence Analysis

The empirical growth literature has produced various convergence definitions. In this study we follow Bernard and Durlauf (1996) to define convergence as a process by which each region moves from a disequilibrium position to an equilibrium or steady-state position. Let y_{jt} denote the log-normal per capita output[6] of region j at time t and $\mathfrak{F}_t$ all information available at t, then regions j and j' are said to converge between dates t and $t+\tau$ if the log-normal per capita output disparity at t is expected to decrease in value[7]. Formally expressed: If $y_{jt} > y_{j't}$ then

$$E\left[y_{jt+\tau} - y_{j't+\tau} \,|\, \mathfrak{F}_t \right] < y_{jt} - y_{j't}, \qquad (1)$$

where $E[\,.\,]$ denotes the expectation operator. This definition considers the behaviour of the output difference between two regional economies j and j' over a fixed time interval (t, $t+\tau$) and equates convergence with the tendency of the difference to narrow. Convergence between members of a set of n regions may be defined by requiring that any pair shows convergence. We say there is *unconditional* convergence if the conditional expectation is taken with respect to the linear space generated by current and lagged regional output differences rather than in a general $\mathfrak{F}_t$ sense.

Since the notion of convergence pertains to the steady-states of the regional economies, a test for convergence would require the assumption that the regions included in the sample are in their steady-states. But evaluating whether regions are in their steady-states or not is fraught with difficulties (Islam 1995). One way around this problem is to analyse the correlation between initial levels of regional income and subsequent growth rates. This leads to the so-called Barro-style regression[8] that – so widely used to test the hypothesis of unconditional convergence – may be written as follows:

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6 We express the definition in terms of the logarithm of per capita output between economies, as the empirical literature has generally focused on logs rather than levels.

7 This definition implies that σ-convergence is not guaranteed if $y_{jt} - y_{j't}$ does not converge to a limiting stochastic process. For example, if $y_{jt} - y_{j't}$ equals one in even periods and minus one in odd periods, the two economies will fail to converge in the sense of σ-convergence, although the sample mean of the differences is equal to zero.

8 In some formulations of cross-section tests Equation (2) is modified to include a set of control variables. Here, a negative β means that convergence holds conditional on some set of exogenous factors such as national dummies, regional industrial structure, and various terms intended to capture possible endogenous growth effects such as

$$g_{j\tau} = \alpha + \beta y_{jt} + \varepsilon_{jt} \qquad j=1, ..., n \qquad (2)$$

where $g_{j\tau} \equiv \frac{1}{\tau} \log(y_{jt+\tau} / y_{jt})$ is region's j annualised growth rate of per capita gross regional product [GRP], y_{jt} economy's j GRP per capita at time t, τ the length of the time period, α and β unknown parameters[9] to be estimated and ε_{jt} a disturbance term with $E\left[\varepsilon_{jt} \mid \mathfrak{F}_t\right] = 0$. There is *unconditional β-convergence* when β is negative and statistically significant [treating $\beta \geq 0$ as the no-convergence null-hypothesis] as this implies that the average growth rate of per capita GRP between t and $(t+\tau)$ is negatively correlated with the initial level of per capita GRP.

It is convenient to work with an equivalent matrix expression for Equation (2) which is

$$\boldsymbol{g} = \boldsymbol{\mathcal{Y}} \gamma + \varepsilon \qquad (3)$$

with

$$\varepsilon \sim N(0, \sigma^2 \boldsymbol{I}_n) \qquad (4)$$

where $\boldsymbol{g}$ is a (n, 1)-vector of observations on the average growth rate of per capita GRP over the given time period $(t, t+\tau)$ as the dependent variable. $\boldsymbol{\mathcal{Y}}$ is a (n, k=2) design matrix containing a unit vector and one exogenous variable [the initial level of log-normal per capita GRP], and γ =[α, β]' the associated parameter vector where $[\alpha, \beta]'$ is the transpose of $[\alpha, \beta]$. For the data-generating process it is assumed that the elements of ε are identically and independently distributed (*i.i.d.*) with zero mean and variance σ^2. Thus, the error variance-covariance matrix is $E[\varepsilon\, \varepsilon']= \sigma^2 \boldsymbol{I}_n$, where the scalar σ^2 is unknown and $\boldsymbol{I}_n$ a nth-order identity matrix. Assuming non-singularity of the $\boldsymbol{\mathcal{Y}}$ matrix, ordinary least-squares [OLS] estimation can be used to determine the sign and significance of the parameter β, for the case of unconditional β-convergence.

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regional educational levels and proxies for regional R&D. Galor (1996) has shown that the assessment of the conditional and the club-convergence hypothesis is nearly isomorphic from a neoclassical perspective.

9 Since the pioneering paper of Baumol (1986) β has become a popular criterion for evaluating whether or not convergence holds. A negative correlation is taken as evidence of convergence as it implies that – on average – regions with lower per capita initial incomes are growing faster than those with higher initial per capita incomes.

In equating convergence[10] with the neoclassical model of growth (see, for example, Barro and Sala-i-Martin 1992, Sala-i-Martin 1996), α can be interpreted as an equilibrium rate of GRP growth, while the estimate of β makes it possible to compute the convergence rate, β^*, which measures the speed at which the steady-state is approached:

$$\beta^* = -\tfrac{1}{\tau} \ln\left(1 - \tau\,\beta\right) \tag{5}$$

with

$$\text{s.e. } (\beta^*) = \frac{\text{s.e.}(\ \beta)}{\exp(-\beta^* \tau)}. \tag{6}$$

Estimating Equation (3) jointly with Equation (5) constitutes what Quah (1996) terms the *canonical* β-convergence analysis[11]. Given the convergence rate estimate β^*, it is easy to calculate approximate convergence times (Fingelton 1999), such as the half-distance to the steady-state that may be computed as $\ln(2)/\beta^*$ with the approximate 95 percent confidence interval defined as $\ln(2)/(\beta^* \pm 2\,\text{s.e.}(\beta^*))$.

2.2 Testing for Club-Convergence

The formal cross-section equation outlined in Equation (3) has been used to study club-convergence too, but not that frequently[12]. In their contribution to this line of research within a cross-country context, Durlauf and Johnson (1995) observe that convergence in

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[10] Test Equation (3) can be derived as a log-linear approximation from the transition path of the neoclassical model of growth for closed economies (Solow 1956), by taking a Taylor series approximation around a deterministic steady-state. Many studies share this neoclassical underpinning. The assumption of diminishing returns that drives the neoclassical convergence process and the assumption of a closed economy are particularly questionable for regional economies. But there are solid empirical reasons why it makes sense to fit growth regression models in which there is a significant convergence process even if the reasons for this convergence may be debated.

[11] Instead of estimating Equation (3) and using Equation (5) to compute the speed, β^*, one can also estimate the non-linear least squares relation directly.

[12] Convergence clubs had been studied in Baumol (1986); Chatterji (1992); Armstrong (1995); Dewhurst and Mutis-Gaitan (1995); Durlauf and Johnson (1995); Chatterji and Dewhurst (1996); Fagerberg and Verspagen (1996); Baumont, Ertur and LeGallo (2003), and LeGallo and Dall'erba (2005). But only the latter two studies have considered and modelled the spatial dimension of the growth and convergence process to avoid misspecification.

the whole sample (*global convergence*) does not hold or proves to be weak because countries belonging to different regimes are brought together. The proper thing, in their view, is to identify country groups, where members share the same equilibrium, and then to check whether convergence holds within these groups (*local convergence*).

Despite the conceptual distinction, it is not easy to distinguish club-convergence from conditional convergence empirically. This finds reflection in the problems associated with the choice of the criteria to be used to group the economies in testing for club-convergence. Evidently, steady-state determinants cannot be used for this purpose, since a difference in their levels causes equilibria to differ even under conditional convergence (Islam 2003). Durlauf and Johnson (1995) use initial levels of income and literacy levels to group the countries and find the rates of convergence within the groups (clubs) to be higher than that of the whole sample. The authors perform two sets of analysis. In the first, the countries are clustered on the basis of arbitrarily chosen cut off levels of initial income and literacy. Apprehending selection bias in such grouping, the authors present a second analysis in which the grouping is endogenised using the regression-tree procedure[13]. The results received from these two methods of grouping[14], however, prove to be qualitatively similar.

We follow Durlauf and Johnson (1995) to view club-convergence testing as consisting essentially of two steps. The *first* is to determine whether the data exhibit multiple regimes in the sense that groups [clubs] of regions identified by initial income obey distinct growth regressions, and then to check whether convergence holds or not within these clubs. While Durlauf and Johnson (1995) relate the concept of club-convergence to the notion of heterogeneity we relate it to the notion of spatial heterogeneity[15]. This is justified by the fact that the process of economic growth and convergence is inherently endowed with a spatial dimension. Equilibria of convergence clubs seem to be characterised by latent variables which are correlated among cross-sectional

[13] See Breiman et al. (1984) for a description of the procedure and its properties.

[14] Fagerberg and Verspagen (1996) have attempted to identify groups of similarly behaving European regions using, in principle, the second method and taking unemployment as control variable. The regression-tree procedure partitions the cross-section of 70 regions from six EU member countries (W-Germany, France, Italy, UK, Netherlands and Belgium) into three distinct groups of regions determined by unemployment levels (high, intermediate, low). But the study – this holds also true for Durlauf and Johnson (1995) – fails to consider and model the spatial dimension of the growth and convergence process although it is evident from López-Bazo et al. (1999), Fingleton (1999) and others that this may be necessary to avoid misspecification.

[15] Heterogeneity in a spatial context means, broadly speaking, that the parameters describing the data vary from location to location.

observations located nearby in geographic space. Then the problem of determining regimes in the data leads to one of identifying spatial regimes. For solving this problem exploratory spatial data analysis [ESDA]-tools such as Getis and Ord's (1992) local clustering technique may be used.

The *second* step refers to testing whether convergence holds or not within the clubs of regions that correspond to the spatial regimes. This can be done through the use of specification techniques which take the single regime model as the null hypothesis. We consider two estimating equations. First, we estimate growth equation (3) by ordinary least squares. This estimate represents the unconstrained version of the growth model. Then we estimate a constrained version of the model by imposing cross-coefficient restrictions in line with the existence of multiple regimes.

Let us assume a core-periphery pattern of growth, in accordance with theoretical models from New Economic Geography (see, for example, Fujita and Thisse 2002). The index A may denote the club of core regions and the index B that of peripheral regions. Then the constrained version of the growth model, that is the two-club specification of model (3) where each club of regions is represented by a different cross-sectional equation, can be formally expressed as

$$\begin{bmatrix} \boldsymbol{g}_A \\ \boldsymbol{g}_B \end{bmatrix} = \begin{bmatrix} \mathcal{Y}_A & 0 \\ 0 & \mathcal{Y}_B \end{bmatrix} \begin{bmatrix} \gamma_A \\ \gamma_B \end{bmatrix} + \begin{bmatrix} \varepsilon_A \\ \varepsilon_B \end{bmatrix} \qquad (7)$$

where $\boldsymbol{g}_A$ and $\boldsymbol{g}_B$ are the dependent variables; $\mathcal{Y}_A$ and $\mathcal{Y}_B$ denote the explanatory variables; γ_A and γ_B the associated coefficients; and ε_A and ε_B the errors in the respective clubs of regions A and B. Let n_A and n_B denote the number of observations in club A and club B, respectively. Then $n=n_A+n_B$.

For convenience, we express the simple block structure of the two club-convergence model (7) more succinctly in one equation

$$\boldsymbol{g} = \boldsymbol{Y}\,\boldsymbol{\gamma} + \boldsymbol{\varepsilon} \qquad (8)$$

where the boldface variables $\boldsymbol{g}$, $\boldsymbol{Y}$, $\boldsymbol{\gamma}$ and $\boldsymbol{\varepsilon}$ refer to the combined variable, coefficient and error matrices, respectively. Since the full set of elements of the error variance matrix $E[\boldsymbol{\varepsilon}\,\boldsymbol{\varepsilon}']$ is generally unknown and cannot be estimated from the data due to a lack of degrees of freedom, it is necessary to impose a simplifying structure. The most straightforward assumption is a model with a constant error variance over the whole set of observations:

$$E[\boldsymbol{\varepsilon}\,\boldsymbol{\varepsilon}'] = \sigma^2 \boldsymbol{I}_n \tag{9}$$

where σ^2 is the constant error variance. This specification leads to the *two club-convergence model* that conforms to the assumptions of the β-convergence test methodology outlined in the previous section. Estimation can be done by means of OLS.

The constancy of parameters across clubs is a testable hypothesis, for example, by means of a Chow (1960) test. This is a test on the null hypothesis H_0: $\gamma_A=\gamma_B$ which can be implemented for all coefficients jointly, as well as for each coefficient separately [that is, $\alpha_A = \alpha_B$, $\beta_A = \beta_B$]. The Chow test is distributed as a *F* variate with (2, *n*–4) degrees of freedom:

$$C = \frac{\frac{1}{2}\,(\hat{\boldsymbol{\varepsilon}}'_R\,\hat{\boldsymbol{\varepsilon}}_R - \hat{\boldsymbol{\varepsilon}}'_U\,\hat{\boldsymbol{\varepsilon}}_U)}{\frac{1}{n-4}\,\hat{\boldsymbol{\varepsilon}}'_U\,\hat{\boldsymbol{\varepsilon}}_U} \sim F_{2,n-4} \tag{10}$$

where $\hat{\boldsymbol{\varepsilon}}_R$ and $\hat{\boldsymbol{\varepsilon}}_U$ are the restricted and unrestricted OLS residuals, respectively. When spatial error dependence is present in the cross-sectional equations, however, the Chow test is no longer applicable[16].

2.3 Club-Convergence Testing in the Presence of Spatial Dependence

Spatial dependence can invalidate the inferential basis of the test methodology since the assumption of observational independence no longer holds. It is convenient to distinguish two types of spatial dependence: substantive and nuisance spatial dependence (Anselin and Rey 1991). The relevance of *substantive* spatial dependence partly derives from the importance attributed to externalities in the contemporary growth literature, notably from knowledge externalities across regional boundaries, with knowledge acknowledged as an important driving force of economic growth. *Nuisance*

[16] The Chow test has been extended to spatial models (see Anselin 1990). In both, the spatial lag and the spatial error models, the test is based on an asymptotic Wald statistic, distributed as chi-square with *k*=2 degrees of freedom.

spatial dependence, in contrast, can arise from a variety of measurement problems, such as boundary mismatching between the administrative boundaries used to organise the data series and the actual boundaries of the economic process believed to generate regional convergence or divergence. Nuisance spatial dependence may also arise when there are omitted variables that are spatially autocorrelated, given that the omitted variables are relevant and the dependent variable is itself spatially autocorrelated.

Spatial dependence can invalidate the inferential basis of the test methodology[17]. Spatial autocorrelation in the error terms violates one of the basic assumptions of ordinary least squares estimation in linear regression analysis, namely, the assumption of uncorrelated errors. When the spatial dependence is ignored, the OLS-estimates will be inefficient, the *t*- and *F*-statistics for tests of significance will be biased, and the R^2 goodness-of-fit measure will be misleading. In other words, the statistical interpretation of the club-convergence model will be wrong. But the OLS-estimates themselves remain unbiased[18]. In contrast ignoring spatial dependence in the form of substantive spatial dependence will yield biased estimates.

The Case of Substantive Spatial Dependence. An indirect way to control for the effects of interregional interactions in the two club-convergence model is through the inclusion of a spatially lagged dependent variable. If $\boldsymbol{W}$ is a (n, n)-matrix of spatial weights that specify the interconnections between different regions in the system, Equation (8) is respecified as

$$\boldsymbol{g} = \boldsymbol{Y}\,\boldsymbol{\gamma} + \rho \boldsymbol{W}\,\boldsymbol{g} + \boldsymbol{\varepsilon} \qquad \text{with } |\rho| < 1 \tag{11}$$

where $\boldsymbol{g}$, $\boldsymbol{Y}$, $\boldsymbol{\gamma}$ and $\boldsymbol{\varepsilon}$ are defined as before[19]. Equation (11) contains a spatially lagged dependent variable $\boldsymbol{Wg}$ and is, thus, referred to as the *spatial* (*autoregressive*) *lag model of club-convergence*, assuming the error process is white noise. ρ is the spatial autoregressive parameter. A significant spatial lag term indicates substantive spatial dependence, that is, it measures the extent of spatial externalities.

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17 The literature on club-convergence has been very slow to account for spatial dependence, with notable exceptions of the studies by Baumont, Ertur and LeGallo (2003), and LeGallo and Dall'erba (2005).

18 For a more technical discussion of the effect of spatial autocorrelation see Anselin (1988a).

19 The vector of error terms $\boldsymbol{\varepsilon}$ is assumed to be normally distributed and independently of $\boldsymbol{Y}$ and $\boldsymbol{Wg}$, under the assumption that all spatial dependence effects are captured by the lagged variable.

In this study, $\boldsymbol{W}$ is a row-standardised binary spatial weight matrix[20]. While there is a number of ways to specify $\boldsymbol{W}$ (see, for example, Cliff and Ord 1973, Upton and Fingleton 1985, Anselin and Bera 1998), we specify the spatial weights on the basis of a distance criterion such that regions *i* and *j* are defined as neighbours (that is w_{ij}=1) when the great circle distance between them [more precisely: their economic centres] is less than a critical value[21], say δ. By construction, the elements of the main diagonal of $\boldsymbol{W} = (w_{ij}(\delta))$ are set to zero to preclude an observation from directly predicting itself. Row-standardisation of the matrix scales each element in the spatial weight matrix so that the rows sum to unity, producing a spatial lag variable $\boldsymbol{Wg}$ that reflects the average of growth rates from neighbouring observations.

This two club spatial lag model is a model which poses certain problems for estimation (see Cliff and Ord 1981, Upton and Fingleton 1985). But it can be estimated using maximum likelihood procedures[22] (see Anselin 1988a) assuming that there is a homogenous relationship between $\boldsymbol{g}$ and $\boldsymbol{Y}$ across the spatial sample of observations. Under the assumption of a normal distribution for the error terms, the corresponding likelihood function may be derived. A crucial role is played hereby by the Jacobian term, that is, the determinant of the spatial filter ($\boldsymbol{I}_n - \rho\ \boldsymbol{W}$). The estimates for the γ and σ^2 coefficients can be expressed in function of the spatial autoregressive parameter ρ, and the maximum of the resulting non-linear concentrated likelihood function can be found by means of a straightforward search (see Anselin and Bera 1998 for technical details).

The Case of Spatial Error Dependence. Another form of spatial dependence, nuisance or error spatial dependence, occurs when the disturbances in the cross-section growth regression are not independently distributed across space. As a result OLS estimates

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20 Row-standardisation guarantees estimates for the spatial autoregressive coefficient, ρ, that yield a stable spatial model (see Anselin and Bera 1998).

21 The identification of the critical distance δ in this study is based on sensitivity analyses along with theoretical considerations.

22 Another approach towards estimating the two club spatial lag model is based on the instrumental variable (IV) principle. This is equivalent to the two stage least squares estimation in systems of simultaneous equations. The correlation between the spatial lag $\boldsymbol{Wg}$ and the error term $\boldsymbol{\varepsilon}$ is controlled for by replacing the spatial lag variable with an appropriate instrument, that is, a variable which is highly correlated with $\boldsymbol{Wg}$, but uncorrelated with $\boldsymbol{\varepsilon}$. The choice of the appropriate instrument is a major problem in the practical implementation of this approach. Since there are insufficient variables available to construct a good instrument in the context of the current study, we will not use this approach here.

will be inefficient. We follow the standard assumption that the error term in Equation (8) follows a first order spatial autoregressive process:

$$\boldsymbol{\varepsilon} = \lambda \boldsymbol{W} \boldsymbol{\varepsilon} + \boldsymbol{\mu} \qquad \text{with } |\lambda| < 1. \tag{12}$$

Then the reduced form of the *two club-convergence model with spatial error dependence* is given as

$$\boldsymbol{g} = \boldsymbol{Y} \boldsymbol{\gamma} + (1 - \lambda \boldsymbol{W})^{-1} \boldsymbol{\mu}, \tag{13}$$

where $\boldsymbol{W}$ is defined as above[23]. The error term $\boldsymbol{\mu}$ is assumed to be well-behaved, that is, $\boldsymbol{\mu}$ is a (n, 1)-vector of *i.i.d.* errors with $E[\boldsymbol{\mu}] = 0$ and $E[\boldsymbol{\mu}^2] = \sigma^2$. In order to stress the difference with substantive spatial dependence, the autoregressive parameter in the error dependence club-convergence model is expressed by the symbol λ rather than ρ. The coefficient λ is considered to be a *nuisance* parameter, usually of little interest in itself, but necessary to correct for the spatial dependence. The row and column sums of $(\boldsymbol{I}_n - \lambda \boldsymbol{W})^{-1}$ are bounded uniformly in absolute value by some finite constant so that $(\boldsymbol{I}_n - \lambda \boldsymbol{W})$ is non-singular.

It is easy to show that the variance matrix of the error term $\boldsymbol{\varepsilon}$ is no longer the homoskedastic and uncorrelated $\sigma^2 \boldsymbol{I}_n$, but instead becomes[24]

$$E[\boldsymbol{\varepsilon}\, \boldsymbol{\varepsilon}'] = \sigma^2 \left[(\boldsymbol{I}_n - \lambda \boldsymbol{W})' \, (\boldsymbol{I}_n - \lambda \boldsymbol{W}) \right]^{-1}. \tag{14}$$

As is well-known, use of ordinary least squares in the presence of non-spherical errors would yield unbiased estimates for club-convergence (and intercept) parameters, but a biased estimate of the parameters' variance. Thus, inferences based on the OLS-estimates would be misleading. Instead inferences about the convergence process should be based on maximum likelihood estimation[25]. A normal distribution is assumed

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23 From Equation (13) it is evident that a random shock that affects growth in a region diffuses to all the others as described in Rey and Montouri (1999). Note that the spatial process behind the two club-convergence model could be originated by some kind of spillover mechanism.

24 Note that Equation (12) can also be expressed as $\boldsymbol{\varepsilon} = (\boldsymbol{I}_n - \lambda \boldsymbol{W})^{-1} \boldsymbol{\mu}$.

25 Kelejian and Prucha (1999) suggest an alternative estimation approach leading to a generalised moment estimator that is computationally simpler, irrespective of the sample size.

for the error term ε and the corresponding likelihood function is derived. As in the spatial lag specification, a crucial role is played by the Jacobian term, that is, the determinant of the spatial filter $(\boldsymbol{I}_n - \lambda \boldsymbol{W})$. The estimates for the γ and σ^2 coefficients can be analytically expressed in function of the spatial autoregressive parameter λ, and the maximum of the resulting non-linear concentrated likelihood function can be found by means of a straightforward search (see Anselin and Bera 1998).

The ***standard approach to detect the presence of spatial dependence*** in the club specific β-convergence model (8) is to apply diagnostic tests. This is complicated by the high degree of formal similarity between a spatial error and spatial lag specification of the club-convergence hypothesis. It is straightforward to see that further manipulations of Equation (13) lead to an alternative structural form known as *common factor* or *spatial Durbin* model (Anselin 1990). This specification includes both a spatially lagged dependent variable as well as spatially lagged explanatory variables[26]:

$$\boldsymbol{g} = \lambda \boldsymbol{W} \boldsymbol{g} + \boldsymbol{Y} \gamma - \lambda \boldsymbol{W} \boldsymbol{Y} \gamma + \mu. \tag{15}$$

Model (15) has a spatial lag structure, but with the spatial autoregressive parameter λ from Equation (12), and a well-behaved error term μ. The formal equivalence between this model and the spatial error model described by (13) is only satisfied if a set of non-linear constraints on the coefficients is satisfied. Specifically, the negative of the product of λ (the coefficient of $\boldsymbol{W} \boldsymbol{g}$) with each γ(coefficient of ***Y***) should equal $-\lambda\gamma$ (see Anselin 1988a for more details). This is termed the *common factor hypothesis* in spatial econometrics[27].

The implications are twofold. *First*, it is very difficult to distinguish substantive spatial dependence from nuisance spatial dependence in a diagnostic test, since the latter implies a special form of the former. *Second*, once a spatial error specification of the club-convergence hypothesis has been chosen, the common factor constraints need to be satisfied, or else this specification will be invalid.

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[26] In practice, the spatially lagged constant is not included in ***WY*** since there is an identification problem for a row-standardised ***W***.

[27] The common factor hypothesis can be tested, for example, by means of a likelihood ratio test: $\chi^2_{(1)} = -2(L_r - L_{ur})$ where $L_r (L_{ur})$ is the value of the log likelihood function for the restricted (unrestricted) estimator.

Testing for Possible Presence of Spatial Dependence in the Club-Convergence Analysis. In view of the above discussion it is clear that we need two types of diagnostic tests for spatial dependence: Tests for substantive spatial dependence and tests for spatial error dependence. The latter have received most attention in the literature. The best known approach is an application of Moran's I to the residuals of the two club β-convergence model (see Cliff and Ord 1972, 1973). In matrix notation the statistic takes the form

$$I = \frac{\hat{\boldsymbol{\varepsilon}}' \boldsymbol{W} \hat{\boldsymbol{\varepsilon}}}{\hat{\boldsymbol{\varepsilon}}' \hat{\boldsymbol{\varepsilon}}} \tag{16}$$

where $\boldsymbol{W}$ is the spatial weights matrix as defined above, and $\hat{\boldsymbol{\varepsilon}}$ the (n, 1)-vector of OLS residuals of the specification $\boldsymbol{g} = \boldsymbol{Y}\, \boldsymbol{\gamma} + \boldsymbol{\varepsilon}$. Statistical inference can be based on the assumption of asymptotic normality, or alternatively, when the distribution is unknown, on a theoretical randomisation or empirical permutation approach (Cliff and Ord 1981). Anselin and Rey (1991) have shown that this test statistic is very sensitive to the presence of other forms of specification error, such as non-normality and heteroskedasticity. The test is, moreover, not able to properly discriminate between spatial error dependence and substantive spatial dependence[28].

An alternative, more focused ***test for spatial error dependence*** is based on the Lagrange multiplier principle, suggested by Burridge (1980). It is similar in expression to Moran's I and is also computed from the OLS residuals. But a normalisation factor in terms of matrix traces is needed to achieve an asymptotic chi-square distribution [with one degree of freedom] under the null hypothesis of no spatial dependence [H_0: λ=0]. The test statistic is given by

$$\text{LM}\left(\text{error}\right) = \frac{\left(\hat{\boldsymbol{\varepsilon}}' \boldsymbol{W} \hat{\boldsymbol{\varepsilon}} \frac{1}{\hat{\sigma}^2}\right)^2}{tr\left(\boldsymbol{W}' \boldsymbol{W} + \boldsymbol{W}^2\right)} \tag{17}$$

[28] Focused tests for spatial dependence have been developed in a ML framework, and generally take the Lagrange multiplier form rather than the asymptotically equivalent Wald or Likelihood Ratio form, because of ease of computation. The Wald and Likelihood Ratio tests are computationally more demanding because they require ML estimation under the alternative; for technical details see Anselin and Bera (1998).

where $\hat{\boldsymbol{\varepsilon}}$ is defined as above, *tr* stands for the trace operator[29] and $\hat{\sigma}^2$ is a maximum likelihood estimator for the error variance, $\hat{\sigma}^2 = \frac{1}{n}(\hat{\boldsymbol{\varepsilon}}'\,\hat{\boldsymbol{\varepsilon}})$.

A ***test for substantive spatial dependence***, that is for an erroneously omitted spatially lagged dependent variable, can also be based on the Lagrange multiplier principle as suggested by Anselin (1988b). As in the case of LM(error) the test requires the results of an OLS-regression, but its form is slightly more complex. Formally, the test reads as

$$\text{LM}\left(\text{lag}\right) = \frac{(\hat{\boldsymbol{\varepsilon}}'\,\boldsymbol{W}\,\boldsymbol{g}\,\frac{1}{\hat{\sigma}^2})^2}{\hat{\boldsymbol{J}}} \tag{18}$$

with

$$\hat{\boldsymbol{J}} = \frac{1}{\hat{\sigma}^2}\left[\,\left(\boldsymbol{W}\;\;\boldsymbol{Y}\,\hat{\boldsymbol{\gamma}}\right)'\,\boldsymbol{M}\left(\boldsymbol{W}\,\boldsymbol{Y}\,\hat{\boldsymbol{\gamma}}\right) + tr\left(\boldsymbol{W}'\,\boldsymbol{W} + \boldsymbol{W}^2\right)\hat{\sigma}^2\,\right] \tag{19}$$

where $\boldsymbol{W}\,\boldsymbol{g}$ is the spatial lag, $\boldsymbol{W}\,\boldsymbol{Y}\,\hat{\boldsymbol{\gamma}}$ is a spatial lag for the predicted values ($\boldsymbol{Y}\,\hat{\boldsymbol{\gamma}}$) and $\boldsymbol{M}$ is a familiar projection matrix, $\boldsymbol{M} = \boldsymbol{I}_n - \boldsymbol{Y}\,(\boldsymbol{Y}'\boldsymbol{Y})^{-1}\boldsymbol{Y}'$. The other notation is as before. The LM(lag) test is also chi-square distributed with one degree of freedom under the null hypothesis of no spatial dependence $\left[\text{H}_0 : \rho = 0\right]$.

Anselin and Florax (1995) have shown that ***robust Lagrange multiplier tests*** may have more power in discriminating between substantive and nuisance spatial dependence. The robust tests are similar to those given in Equations (17) and (18)-(19), extended with a correction factor to account for local misspecification. The robust test for the presence of a spatial autoregressive error process when the specification contains a spatially lagged dependent variable reads as

$$\text{LM}^*\left(\text{error}\right) = \frac{\left[\hat{\boldsymbol{\varepsilon}}'\,\boldsymbol{W}\,\hat{\boldsymbol{\varepsilon}}\,\frac{1}{\hat{\sigma}^2} - tr\left(\boldsymbol{W}'\,\boldsymbol{W} + \boldsymbol{W}^2\right)\hat{\boldsymbol{J}}^{-1}\,\hat{\boldsymbol{\varepsilon}}'\,\boldsymbol{W}\,\boldsymbol{g}\,\frac{1}{\hat{\sigma}^2}\right]^2}{tr\left(\boldsymbol{W}'\,\boldsymbol{W} + \boldsymbol{W}^2\right)\left[1 - tr\left(\boldsymbol{W}'\,\boldsymbol{W} + \boldsymbol{W}^2\right)\hat{\boldsymbol{J}}\right]^{-1}}, \tag{20}$$

while the robust test for an erroneously omitted spatially lagged dependent variable in the presence of a spatial error process is given by

[29] The sum of the main diagonal elements of the matrix in question.

$$\mathrm{LM}^*(\mathrm{lag}) = \frac{\left(\hat{\boldsymbol{\varepsilon}}'\boldsymbol{W}\,\boldsymbol{g}\,\frac{1}{\hat{\sigma}^2} - \hat{\boldsymbol{\varepsilon}}'\,\boldsymbol{W}\,\hat{\boldsymbol{\varepsilon}}\,\frac{1}{\hat{\sigma}^2}\right)^2}{\hat{\boldsymbol{J}} - tr\left(\boldsymbol{W}'\,\boldsymbol{W} + \boldsymbol{W}^2\right)}. \tag{21}$$

Note that the distinction between a spatial error and a spatial lag specification of the club-convergence hypothesis is often difficult in practice. Even though the interpretation of the two specifications is fundamentally different, they are closely related in formal terms as seen above. We use the *canonical classical* (forward step) *strategy* outlined in Florax, Folmer and Rey (2003) to effectively distinguish between the alternative specifications of the club-convergence hypothesis and to respecify the club-convergence model in the presence of spatial dependence. The strategy consists of the estimation of the standard club-convergence model without a spatially lagged variable and with a well-behaved error term as a first step. Subsequently, the model is checked for spatial dependence. The tests applied in this framework are the (robust) Lagrange multiplier tests for spatial residual autocorrelation and spatial lag dependence.

3 Revealing Empirics

3.1 Sample Data and Spatial Regimes

The data used in this study are based on the European System of Accounts and – as in most other convergence studies – stem from the EUROSTAT REGIO database. We use the log-normal per capita GRP[30] over the period 1995 to 2000 expressed in ECUs, the former European Currency Unit, replaced by the Euro in 1999 to measure the output differences. The time period is short due to a lack of reliable figures for the regions in the new member states and the accession countries of the EU. This comes partly from the change in accounting conventions now used in CEE economies. But more

[30] Some authors (for example, Armstrong 1995, López-Bazo et al. 1999) use per capita GRP expressed in purchasing power standards (PPS). But as Ertur, LeGallo and LeSage (2004) point out, the construction of regional accounts in PPS that are comparable across space and time is very complicated and can raise serious problems. *First*, the conversion should be based on regional purchasing power parity, but – due to data non-availability – this adjustment is computed on the basis of national price levels. *Second*, per capita GRP expressed in PPS can change in one regional economy relative to another not only because of a difference in the rate of GRP growth in real terms but also because of relative price level changes. This complicates the analysis of growth changes over time because a relative increase in per capita GRP arising from a reduction in the relative price level might have a different implication than one resulting from a relative growth in real GRP (Ertur, LeGallo and LeSage 2004).

important, even if estimates of the change in the volume of output did exist, these would be impossible to interpret meaningfully because of the fundamental change of production, from a centrally planned to a market system. As a consequence, figures for GRP are difficult to compare between the CEE and the EU-15 regions until the mid of 1990s (European Commission 1999). Our sample includes 256 NUTS-2 regions[31] in 25 countries:

- *the EU-15 member states*[32]: Austria [9 regions], Belgium [11 regions], Denmark [1 region], Finland [6 regions], France [22 regions], Germany [40 regions], Greece [13 regions], Ireland [2 regions], Italy [20 regions], Luxembourg [1 region], the Netherlands [12 regions], Portugal [5 regions], Spain [16 regions], Sweden [8 regions], and the UK [37 regions];

- *eight new member states*: Czech Republic [8 regions], Estonia [1 region], Hungary [7 regions], Latvia [1 region], Lithuania [1 region], Poland [16 regions], the Slovak Republic [4 regions] and Slovenia [1 region]; and

- *the two accession countries*: Bulgaria [6 regions] and Romania [8 regions].

NUTS-2 regions[33] although considerably varying in size are generally considered to be the most appropriate spatial units for modelling and analysis (Fingleton 2001). In most cases the NUTS-2 region is sufficiently small to capture subnational variations. But we are aware that NUTS-2 regions are formal rather than functional regions and their delineation does not represent the boundaries of growth and convergence processes very well[34]. The choice of the NUTS-2 level might also give rise to a form of the modifiable

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[31] A full list of the regions along with the data used appear in the Appendix.

[32] We exclude the French overseas Departments (French Guyane in South America and the small islands Guadaloupe, Martinique and Réunion), the Portuguese regions of Azores and Madeira, the Canary Islands and Ceuta y Mellila in Spain.

[33] NUTS is the acronym for "Nomenclature of Territorial Units for Statistics" which is a hierarchical system of regions used by the statistical office of the European Community for the production of regional statistics. At the top of the hierarchy are the NUTS-0 regions (countries), below which are NUTS-1 regions (regions within countries) and then NUTS-2 regions (subdivisions of NUTS-1 regions).

[34] The European Commission uses NUTS-2 and NUTS-3 regions as targets for the convergence process, and has defined NUTS-2 as the spatial level at which the persistence or disappearance of unacceptable inequality should be measured (Boldrin and Canova 2001). Since 1989, NUTS-2 is the spatial level at which eligibility for Objective 1 Structural Funds is determined (European Commission 1999). Cheshire and Carbonaro (1995) argue that functional urban areas would be more appropriate, but the problem with these spatial units is that they are dynamic rather than static so that their definition is not fixed in time.

areal unit problem[35] well known in geography (see, for example, Arbia 1989). This may induce nuisance spatial dependence.

The introduction of heterogeneity into growth models provides a channel through which income distribution affects economic growth. A large number of theoretical studies have documented the importance of initial conditions with respect to the distribution of income for the evolution of economies, and their steady-state behaviour may cluster around different steady-state equilibria (Galor 1996). In this study, club formation is driven by spatial differences in per capita GRP at the beginning of the sample period. We use Getis and Ord's (1992) $G^*(\delta)$-statistic as a spatial heterogeneity descriptor to identify spatial regimes in the data in accordance with LeGallo and Dall'erba (2005). Formally, the statistic is defined as

$$G_{it}^*(\delta) = \frac{\sum_{j=1}^{n} w_{ij}^*(\delta)\, y_{jt}}{\sum_{j=1}^{n} y_{jt}} \qquad (22)$$

where y_{jt} denotes the log-normal per capita GRP in region j at time t=1995, $w_{ij}^*(\delta)$ is the (i, j)-th element of a row-standardised binary spatial weight matrix $\boldsymbol{W}^*$ where $w_{ij}^*=1$ if the distance from region i to region j, say d_{ij}, is smaller than the critical distance band δ, and $w_{ij}^*=0$ otherwise[36]. The statistic is based on the expected association between weighted points within a distance δ of region i. The statistic's value then becomes a measure of spatial clustering [or non-clustering] for all regions j within δ of region i. When the statistic is computed for each δ and for all i, one has a description of the clustering characteristics of the study area (Ord and Getis 1995).

$G^*(\delta)$ is well suited to identify spatial regimes. But rather than using the statistic as defined by Equation (22) we use the statistic in its standardised form

35 The modifiable areal unit problem [MAUP] consists of two related parts: the scale problem and the zoning problem. The scale problem refers to the challenge to choose an appropriate spatial scale for the analysis while the zoning problem is concerned with the spatial configuration of the sample units. Study results may differ depending on the boundaries of the spatial units under study. If the regions of a country, for example, were configured differently, the results based on data for those regions would be different (Getis 2004).

36 Note that the statistic is based on a specification of the spatial weight matrix that is distinct from that in subsection 2.3, a specification where the main diagonal elements are set equal to one. This allows the statistic to include the information at region i. The statistic is asymptotically normally distributed as δ increases. Under the null hypothesis that there is no association between i and j within δ of i, the expectation is zero, the variance is one, thus values of this statistic may be interpreted as the standard normal variate.

$$z[G_{it}^{*}(\delta)] = \frac{G_{it}^{*}(\delta) - E[G_{it}^{*}(\delta)]}{\sqrt{\text{var}[G_{it}^{*}(\delta)]}} \qquad (23)$$

where positive values indicate spatial clustering of high values, and negative values clustering of low values. In this study $\delta = 350$ km has been a priori chosen, on the basis of sensitivity analyses combined with theoretical considerations. Based on this information we determine two spatial regimes [clubs] as follows: If $z[G_{it}^{*}(\delta)]$ is positive, region *i* is allocated to club *A*; and if $z[G_{it}^{*}(\delta)]$ is negative, region *i* becomes a member of club *B*[37].

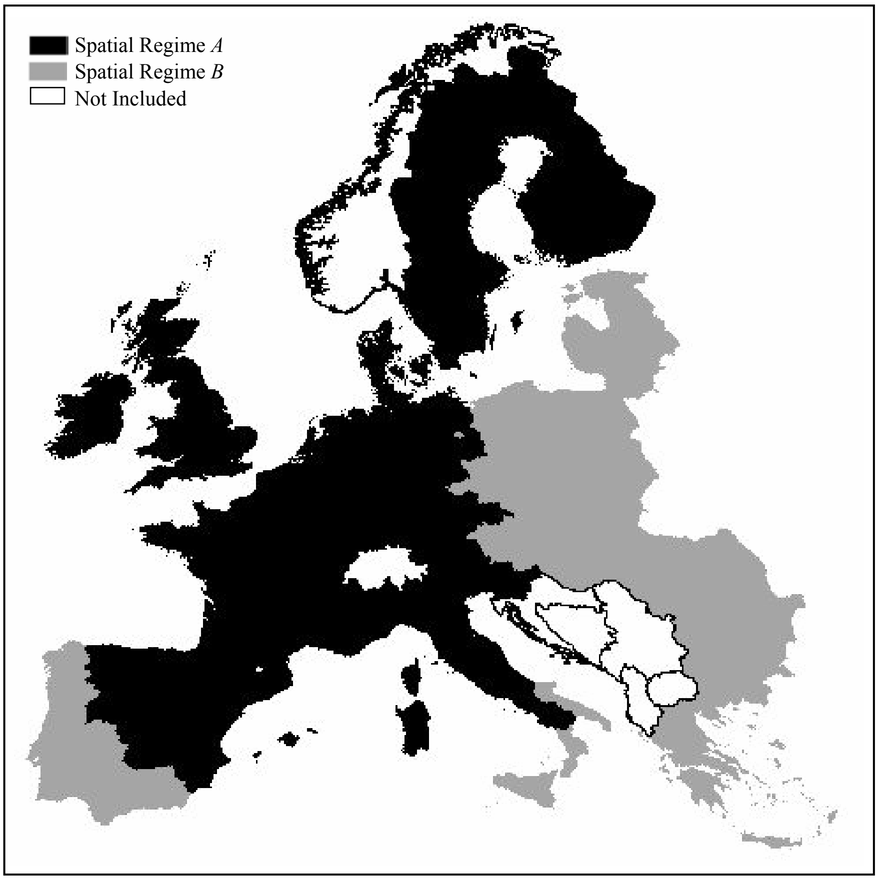

Figure 1: Two spatial regimes in the initial per capita GRP identified by means of the Getis-Ord statistic $G^{*}(\delta)$ [with t=1995, δ=350 km]

[37] Club *A* (club *B*) represents a strong pattern which suggests that around region *i* regions with high (low) per capita GRP tend to be clustered more often than would be due to random choice.

Regions with low income tend to cluster in space as well as economies with high income. Figure 1 indicates that there is substantial geographic homogeneity within each group and that each group may be viewed as a spatial regime. The split into two clubs seems to be quite reasonable. The clubs of regions appear to reflect very different production opportunities. These differences in turn may suggest – from a neoclassical perspective – that the more developed regions in groups *A* have higher output-labour ratios than implied by their capital-labour ratios alone. *Club A* consists of 173 regions and includes all the EU-15 regions except those in Greece and Portugal, some Spanish regions, some Southern Italian regions, regions located in Eastern Austria, as well as Dresden and Berlin; plus two regions located in CEE [Slovenia and the most Western region in the Czech Republic]. *Club B* [83 regions] is made up of all the remaining NUTS-2 regions[38].

3.2 Estimation Results

Given the above two clubs of regions, we estimate the constrained version of the growth model, that is, the two club-convergence model (8) with independent and homoskedastic errors, as suggested by the canonical classical strategy to distinguish between the alternative specifications of the club-convergence hypothesis (see subsection 2.3). The first column of Table 1 presents the parameter estimates and corresponding probability levels[39]. The model yields highly significant and negative coefficients for the starting income levels ($\hat{\beta}_A = -0.054$ with s.d.=0.007 and $\hat{\beta}_B = -0.021$ with s.d.=0.004). The null hypothesis on the joint equality of coefficients across the two clubs is rejected by the Chow-Wald test[40]. The same indication is provided by the tests on the individual coefficients. This strongly supports the view of two-club convergence in Europe.

[38] The Appendix details the regions in the two clubs.

[39] All estimation and specification tests in this study were carried out with SpaceStat (Anselin 1999).

[40] A value of 12.225 for a chi-square distribution with two degrees of freedom.

Table 1: Two Club-Convergence Testing in a Cross-Regional [256 regions] Context in Europe, 1995-2000

	The *iid* Specification with Constant Error Variance [OLS]	The Spatially Autocorrelated Error Specification [ML]
Parameter Estimates (p-values in brackets)		
Constant		
Club *A*	0.580 (0.000)	0.205 (0.001)
Club *B*	0.251 (0.000)	0.297 (0.000)
Beta		
Club *A*	-0.054 (0.000)	-0.016 (0.004)
Club *B*	-0.021 (0.000)	-0.026 (0.000)
Lambda		0.908 (0.000)
The Time to Convergence		
Annual Convergence Rate (in percent)		
Club *A*	4.8	1.6
Club *B*	2.0	2.4
Half-Distance to the Steady-State (in years, 95% bounds in brackets)		
Club *A*	14.5 (11.7-19.1)	44.6 (26.6-136.1)
Club *B*	34.4 (25.4-53.2)	28.7 (22.2-40.5)
Performance Measures		
R^2	0.307	0.353
Log Likelihood	525.802	634.179
Sigma sq.	0.00098	0.00037
Diagnostic Tests (p-values in brackets)		
Heteroskedasticity		
Koenker-Bassett	0.717 (0.397)	–
Breusch-Pagan	–	24.127 (0.000)
Spatial Error Dependence		
Moran's *I*	22.592 (0.000)	–
LM(error)	425.835 (0.000)	–
Robust LM(error)	45.588 (0.000)	–
Likelihood Ratio	–	216.754 (0.000)
Spatial Lag Dependence		
LM(lag)	404.463 (0.000)	6.159 (0.013)
Robust LM(lag)	24.226 (0.000)	–
Common Factor Hypothesis Test		
Wald Test	–	2.088 (0.352)
Likelihood Ratio Test	–	1.936 (0.380)
Chow-Wald Tests on Coefficient Stability		
Joint	12.225 (0.000)	1.927 (0.382)
Constant	17.277 (0.000)	1.758 (0.185)
Beta	15.322 (0.000)	1.889 (0.169)

Notes: The *iid specification* of the two club-convergence model is defined by Equations (8)-(9), and the *spatially autocorrelated error specification* by Equation (13), given the two clubs of regions identified by means of the Getis-Ord statistic $G^*(\delta)$. *Beta* is the convergence coefficient, *Lambda* the parameter of the autoregressive error process. Fitting the models results into the *time to convergence* [see Equations (5)-(6)]. R^2 is the ratio of the variance of the predicted values over the variance of the observed values for the dependent variable in the case of the spatial error specification; Sigma sq. is the error variance. *Heteroskedasticity* is tested using the Koenker-Bassett (1982) test and the Breusch-Pagan (1979) test, respectively. *Spatial error dependence* is tested using Moran's *I* [see Equation (16)], LM(error) [see Equation (17)], and robust LM(error) [see Equation (20)]; *spatial lag dependence* is tested using LM(lag) [see Equations (18)-(19)] and robust LM(lag) [see Equation (21) with Equation (19)]. The *Likelihood Ratio test on the spatial error dependence* corresponds to twice the difference between the log likelihood in the spatial error model specification (13) and the log likelihood in the specification given by Equations (8)-(9); it is distributed as chi-square variate with one degree of freedom. The *Wald* and the *Likelihood Ratio tests* on the set of non-linear constraints implied by the common factor model [see Equation (15)] follow a chi-square distribution asymptotically, with two degrees of freedom. The *Chow-Wald tests* [see Equation (10)] on the coefficient stability are based on asymptotic Wald statistics, distributed as chi-square with two degrees of freedom (joint test) and one degree of freedom (individual coefficient tests); in the case of the spatially autocorrelated error specification the Wald statistics are spatially adjusted (Anselin 1990).

The bottom part of the first column gives the diagnostics[41]. The Koenker-Bassett test points to homoskedasticity. All the diagnostics for spatial dependence reject the null hypothesis of absence of spatial dependence at the one percent level of significance. This indicates that the two club-convergence model is misspecified due to omitted spatial dependence[42]. The Lagrange multiplier tests and their robust versions point to a spatial error specification rather than a spatial lag one[43]. This result appears to be quite usual in studies that have tested for spatial dependence, though in the context of (un)conditional convergence and in a different modelling framework (see Fingleton 1999, Rey and Montouri 1999, López-Bazo, Vayá and Artís 2004, and others).

The ML-estimates of the spatial error specification, given by Equation (13), are reported in the second column of the table[44]. Relative to the OLS-estimates of the two club-convergence model with well-behaved error terms, the spatial error specification achieves a higher log likelihood which is to be expected, given the indications of the various diagnostics for spatial error dependence in the initial model and the high significance of Lambda ($\hat{\lambda} = -0.908$ with p=0.000). The estimated coefficients indicate that the intercept and the initial income variable are highly significant with appropriate signs on the coefficient estimates. The β-parameter estimates are negative: $\hat{\beta}_A = -0.016$ with s.d.=0.005 and $\hat{\beta}_B = -0.026$ with s.d.=0.005, and, thus, consistent with an inference of two club-convergence.

Estimation of the rate of convergence is slightly above the traditional figure of two percent per annum in the case of *Club B* and slightly below in the case of *Club A*. It is estimated to be 2.4 percent for regional economies in *Club B*. If we think of its

41 Note that many of the specification tests are based on normality of errors. But this is rejected by the Jarque-Bera (1987) test. Because of the large sample, the test is very powerful, detecting significant deviations from normality which have, however, little practical significance in practice.

42 This conclusion confirms that spatial dependence in growth rates is not just caused by the spatial pattern in the distribution of initial GRP per capita.

43 The LM(error) test value is equal to 425.835 which is highly significant when referred to the chi-square distribution with one degree of freedom, and exceeds the LM(lag) test value of 404.463. The same indication is given by the robust versions of the LM tests: LM*(error)=45.588 exceeds LM*(lag)=24.226.

44 The spatial view of the Breusch-Pagan test reveals heterogeneity. To accommodate error heterogeneity we estimated a clubwise error specification using a generalised methods of moments approach (Kelejian and Prucha 1999). It is beyond the scope of this paper to go into details, but it is worth mentioning that jointly modelling error heteroskedasticity and spatial dependence does change neither the estimates of the convergence parameters nor the estimates of the constants. The β-parameter estimates are $\hat{\beta}_A = -0.016$ (0.001) and $\hat{\beta}_B = -0.026$ (0.000). The α-parameter estimates are $\hat{\alpha}_A = 0.206$ (0.000) and $\hat{\alpha}_B = 0.296$ (0.000). $\hat{\lambda} = 0.904$ (0.000) and Sigma sq. is 0.00021.

economic meaning, however, we note that a speed of 2.4 percent per year for regional economies in Central and Eastern Europe is quite slow. It implies, for example, that the regions take 28.7 years (95 percent bounds of 22.2–40.5 years) for half of the distance between the initial level of income and the club-specific steady-state level to vanish. In the case of *Club A* the convergence model estimates an annual convergence rate of 1.6 percent. The associated half time is 44.6 years with approximate 95 percent bounds: 26.6–136.1 years. The slow speed of 2.4 percent and 1.6 percent per year in *Club B* and *Club A*, respectively, suggests that technology does not instantaneously flow across regions, and countries in Europe. The theoretical reason for such a slow speed of technical adaptation may be the existence of barriers to spillovers of knowledge[45].

Since the constant term associated with *Club A* is smaller than that for *Club B*, regions of type *A* will converge to a lower level of per capita GRP in the long-run. This result is interesting because it suggests that regional economies that are predicted to be richer in a few decades from now on are not the same regions that are wealthy today. These results point to a heterogeneous pattern in the convergence process involving European regions. Thus, heterogeneity exists not only in the convergence rate, but also in the steady-state level. The LM(lag) test on the null hypothesis of the absence of an additional autoregressive spatial lag variable, as well as the Likelihood Ratio test and the Wald test on the common factor hypothesis[46] cannot be rejected at the ten percent level of significance, indicating that the spatial error model specification is appropriate.

There are several implications of the spatial error specification of the club-convergence hypothesis. The *first* is evident when comparing the implied rates of convergence from the original two-club-convergence model with those from the spatial error model specification. The effect of explicitly taking the spatial error dependence into account is to drastically lower the estimated rate of convergence in the case of *Club A* and to slightly increase the estimated rate in the case of *Club B*. Hereby, the estimate of the convergence rate of the initially poorer regions [*Club B*] turns out to be higher than the one of the club of initially wealthier regions [*Club A*]. The *second* implication concerns a comparison of the estimates for the club-specific constant terms [the equilibrium rates] from the initial club-convergence model (see the first column in Table 1) against the

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45 For prima-facie empirical evidence of barriers to knowledge spillovers between high-technology firms in Europe see Fischer, Scherngell and Jansenberger (2004).

46 The Likelihood Ratio test statistic is 1.936 (p=0.380), and the Wald statistic 2.088 (p=0.352). Neither are strongly significant, indicating no inherent inconsistency in the spatial error specification.

estimates from the spatial error model specification (see the second column). The effect of explicitly taking the spatial error dependence into account is to lower the equilibrium rate for the regions in *Club A* and to increase that for the regions in *Club B* so that the CEE regions will converge to a higher equilibrium level of per capita GRP than most of the EU-15 regions.

The *third* implication follows from the properties of the spatial error model as a data generating process. From Equation (13) it is evident that a random shock introduced into a specific region will not only affect the growth rate in that region but – through the inverse of the spatial filter $(1-\lambda \boldsymbol{W})$ – also the growth rates of other regions in the club to which the region belongs. The *fourth* implication refers to the tests on coefficient homogeneity across the two clubs. While the original two club-convergence model rejects the null hypothesis on the joint equality of coefficients, the spatial error specification cannot do it. Its value is 1.936 (p=0.380) for a chi-square distribution with two degrees of freedom. The same indication is provided by the tests on the individual coefficients. In light of the results obtained from the Chow-Wald tests the conclusions from the spatial error model specification have to be tempered somewhat from a spatial econometric perspective.

4 Summary and Conclusions

The process of regional convergence in Europe is complex and cannot be adequately captured by the growth regression convergence models that have thus far tended to dominate research and debate in this field. This paper contributes to the convergence debate by suggesting a general setup for club-convergence testing that allows modelling spatial dependence and heterogeneity of the convergence process. The approach takes the Barro-style equation as a point of departure and relates the concept of club-convergence to the notion of spatial heterogeneity. In essence, it consists of three major steps. The *first* involves identifying spatial regimes in the data, in the sense that groups [clubs] of regions identified by the spatial distribution of initial per capita GRP obey distinct [club-specific] growth regressions. The *second* refers to checking whether convergence holds or not within the clubs of regions that correspond to the spatial regimes. If the null hypothesis of a single regime model is rejected, the *third* and final step of the approach applies. This step involves testing for spatial dependence in the club-specific convergence model since spatial dependence invalidates the inferential basis of the approach and requires to respecify the test equation appropriately. To effectively distinguish between spatial error and spatial lag specifications of the club-convergence hypothesis we suggest to follow the canonical classical (forward step) strategy outlined in Florax, Folmer and Rey (2003). The tests to apply in this context are the (robust) Lagrange multiplier tests for spatial residual autocorrelation and spatial lag dependence.

We have considered the behaviour of output differences, measured in terms of per capita GRP, across 256 NUTS-2 regions in 25 European countries to apply the approach and to see whether the cross-regional growth process in Europe shows club-convergence or not. Our results are threefold. *First*, we reject the standard [that is, the single regime] Barro-style regression model which underlies most empirical work on regional income convergence, in favour of a two regime [club] alternative in which different regional economies obey different linear regressions when grouped by means of Getis and Ord's (1992) local clustering technique. *Second*, the results point to a heterogeneous pattern in the pan-European convergence process. Heterogeneity appears in both the convergence rate and the steady-state level. But, *third*, the study reveals that spatial error dependence introduces an important bias in our perception of club-convergence and illustrates that neglection of this bias would give rise to misleading conclusions.

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Appendix: The Regions and the Data Used in the Study

Country	NUTS-2 Region	Club Membership	GRP 1995 per capita in ECU	GRP 2000 per capita in EURO
Austria	Burgenland	B	14,471.4	16,362.3
	Niederösterreich	B	18,010.3	21,616.2
	Wien	B	31,565.1	35,067.6
	Kärnten	A	19,129.5	21,440.0
	Steiermark	B	18,649.8	21,417.8
	Oberösterreich	B	20,965.3	24,445.6
	Salzburg	A	25,927.4	29,220.7
	Tirol	A	22,548.7	25,202.9
	Vorarlberg	A	23,251.8	26,347.1
Belgium	Région Bruxelles-Capitale	A	42,263.1	48,920.2
	Antwerpen	A	24,487.9	28,109.5
	Limburg (B)	A	17,865.4	20,364.3
	Oost-Vlaanderen	A	18,142.9	21,056.1
	Vlaams Brabant	A	20,496.4	25,217.2
	West-Vlaanderen	A	19,187.1	22,174.8
	Brabant Wallon	A	18,572.5	22,639.7
	Hainaut	A	14,067.6	15,915.0
	Liège	A	16,452.4	18,372.2
	Luxembourg (B)	A	15,542.1	17,145.3
	Namur	A	14,727.3	16,841.9
Bulgaria	Severozapadan	B	1,006.2	1,573.6
	Severoiztochen	B	1,012.2	1,479.4
	Severozapad	B	1,045.4	1,512.4
	Yugozapaden	B	1,616.1	2,207.0
	Yuzhen Tsentralen	B	1,089.9	1,389.7
	Yugoiztochen	B	1,009.7	1,691.5
Czech Republic	Praha	B	7,073.7	11,689.7
	Stredni Cechy	B	2,997.0	4,536.4
	Jihozapad	A	3,658.7	5,059.8
	Severozapad	B	3,609.3	4,423.9
	Severovychod	B	3,353.5	4,645.5
	Jihovychod	B	3,433.2	4,726.2
	Stredni Morava	B	3,277.5	4,344.8
	Moravskoslezsko	B	3,638.9	4,505.0
Denmark	Denmark	A	26,387.1	32,575.7
Estonia	Estonia	B	1,884.2	4,063.7
Finland	Itä-Suomi	A	15,014.5	18,167.6
	Väli-Suomi	A	16,373.4	20,574.0
	Pohjois-Suomi	A	17,676.8	22,297.4
	Uusimaa	A	25,724.6	34,898.4
	Etelä-Suomi	A	18,103.1	23,394.6
	Åland	A	23,817.6	33,926.6
France	Île de France	A	30,888.4	36,616.1
	Champagne-Ardenne	A	18,337.4	21,873.0

	Picardie	A	16,890.3	19,039.6
	Haute-Normandie	A	18,757.1	22,022.8
	Centre	A	18,535.2	20,996.5
	Basse-Normandie	A	17,090.6	19,734.6
	Bourgogne	A	18,185.2	21,442.4
	Nord-Pas-de-Calais	A	15,886.5	18,652.1
	Lorraine	A	17,275.9	19,312.2
	Alsace	A	20,977.8	23,790.8
	Franche-Comté	A	17,759.7	20,265.4
	Pays de la Loire	A	17,587.8	20,826.3
	Bretagne	A	16,769.7	19,933.1
	Poitou-Charentes	A	16,579.1	19,179.5
	Aquitaine	A	17,776.3	20,899.1
	Midi-Pyrénées	A	17,605.5	20,477.6
	Limousin	A	16,205.5	18,959.9
	Rhône-Alpes	A	20,168.8	23,852.0
	Auvergne	A	16,600.3	20,006.1
	Languedoc-Roussillon	A	15,376.0	17,968.9
	Provence-Alpes-Côte d'Azur	A	18,365.3	21,001.4
	Corse	A	14,493.3	17,588.5
Germany	Stuttgart	A	27,944.7	31,135.3
	Karlsruhe	A	26,541.4	29,112.6
	Freiburg	A	22,498.8	24,408.3
	Tübingen	A	23,735.1	25,553.9
	Oberbayern	A	31,173.9	35,827.8
	Niederbayern	A	21,775.6	22,573.7
	Oberpfalz	A	22,260.5	25,029.8
	Oberfranken	A	22,901.9	24,044.5
	Mittelfranken	A	26,412.3	29,318.3
	Unterfranken	A	22,255.0	24,068.5
	Schwaben	A	23,701.7	24,963.4
	Berlin	B	23,278.2	22,197.6
	Brandenburg	A	15,063.8	16,117.9
	Bremen	A	30,308.7	33,165.9
	Hamburg	A	38,803.0	42,127.7
	Darmstadt	A	31,967.6	34,525.7
	Gießen	A	20,703.2	22,058.0
	Kassel	A	22,163.8	23,517.7
	Mecklenburg-Vorpommern	A	14,895.2	16,101.6
	Braunschweig	A	21,656.4	24,617.2
	Hannover	A	23,894.8	25,124.4
	Lüneburg	A	18,406.3	18,220.3
	Weser-Ems	A	20,468.5	20,909.6
	Düsseldorf	A	26,003.6	28,126.1
	Köln	A	25,922.2	26,800.1
	Münster	A	20,025.4	20,362.5
	Detmold	A	23,233.0	24,483.8
	Arnsberg	A	21,728.2	23,143.3
	Koblenz	A	20,073.0	20,777.9
	Trier	A	19,256.3	19,817.4
	Rheinhessen-Pfalz	A	22,798.0	24,366.1
	Saarland	A	21,869.4	22,475.9
	Chemnitz	A	14,053.4	15,303.1
	Dresden	B	15,372.8	16,627.9

	Leipzig	A	17,014.7	17,415.1
	Dessau	A	13,457.5	14,892.2
	Halle	A	14,823.6	16,245.8
	Magdeburg	A	13,877.9	16,043.1
	Schleswig-Holstein	A	21,999.8	22,323.0
	Thüringen	A	14,136.0	16,148.1
Greece	Anatoliki Makedonia, Thraki	B	7,249.6	9,407.6
	Kentriki Makedonia	B	8,398.2	11,701.3
	Dytiki Makedonia	B	8,215.2	11,550.7
	Thessalia	B	7,444.3	10,574.1
	Ipeiros	B	5,611.0	8,112.1
	Ionia Nisia	B	7,326.6	10,193.0
	Dytiki Ellada	B	6,873.3	8,799.1
	Sterea Ellada	B	10,790.6	13,158.8
	Peloponnisos	B	6,751.8	9,933.8
	Attiki	B	9,876.4	13,287.0
	Voreio Aigaio	B	7,677.0	11,297.1
	Notio Aigaio	B	9,642.3	13,742.3
	Kriti	B	8,497.5	11,389.6
Hungary	Közép-Magyarország	B	2,990.3	4,975.5
	Közép-Dunántúl	B	4,769.4	7,540.8
	Nyugat-Dunántúl	B	3,402.1	5,641.5
	Dél-Dunántúl	B	2,697.3	3,706.2
	Észak-Magyarország	B	2,404.5	3,198.6
	Észak-Alföld	B	2,355.7	3,142.2
	Dél-Alföld	B	2,748.3	3,559.9
Ireland	Border, Midland and Western	A	10,679.7	19,710.9
	Southern and Eastern	A	15,366.9	29,733.5
Italy	Piemonte	A	17,221.0	23,634.5
	Valle d'Aosta	A	19,790.3	24,340.9
	Liguria	A	15,127.6	21,360.3
	Lombardia	A	19,490.3	26,588.9
	Trentino-Alto Adige	A	19,439.7	26,941.0
	Veneto	A	17,258.8	23,526.1
	Friuli-Venezia Giulia	A	16,839.8	22,559.6
	Emilia-Romagna	A	18,771.9	25,522.6
	Toscana	A	15,949.3	22,441.9
	Umbria	A	14,388.1	19,883.2
	Marche	A	14,603.1	20,173.3
	Lazio	A	16,579.7	22,312.2
	Abruzzo	A	12,499.7	16,543.4
	Molise	A	10,962.9	15,573.9
	Campania	A	9,252.9	12,907.7
	Puglia	B	9,446.9	13,270.3
	Basilicata	A	9,975.3	14,510.6
	Calabria	B	8,671.0	12,285.5
	Sicilia	B	9,327.9	12,935.1
	Sardegna	A	10,756.9	14,926.1
Latvia	Latvia	B	1,359.4	3,276.7

Lithuania	Lithuania	B	1,268.4	3,484.9
Luxembourg	Luxembourg	A	33,481.1	47,199.5
The Netherlands	Groningen	A	24,380.6	28,263.6
	Friesland	A	17,123.1	20,794.3
	Drenthe	A	17,212.5	19,986.2
	Overijssel	A	17,631.0	21,471.8
	Gelderland	A	18,009.3	21,969.3
	Flevoland	A	15,647.8	18,170.2
	Utrecht	A	24,502.0	31,900.2
	Noord-Holland	A	23,639.4	29,608.6
	Zuid-Holland	A	21,395.6	26,310.2
	Zeeland	A	19,867.7	22,172.6
	Noord-Brabant	A	20,004.7	25,018.1
	Limburg (NL)	A	17,968.4	22,198.0
Poland	Dolnoslaskie	B	2,617.8	4,571.8
	Kujawsko-Pomorskie	B	2,507.5	3,965.1
	Lubelskie	B	1,940.9	3,030.3
	Lubuskie	B	2,475.4	3,967.0
	Lódzkie	B	2,298.5	3,922.7
	Malopolskie	B	2,229.0	3,948.4
	Mazowieckie	B	3,135.4	6,704.2
	Opolskie	B	2,484.9	3,778.9
	Podkarpackie	B	1,950.1	3,145.5
	Podlaskie	B	1,908.9	3,286.7
	Pomorskie	B	2,526.9	4,446.9
	Slaskie	B	3,098.5	4,867.4
	Swietokrzyskie	B	2,000.1	3,460.0
	Warminsko-Mazurskie	B	2,007.9	3,295.9
	Wielkopolskie	B	2,479.0	4,715.3
	Zachodniopomorskie	B	2,591.0	4,363.3
Portugal	Norte	B	6,966.9	9,259.9
	Centro (P)	B	6,737.6	8,959.1
	Lisboa e Vale do Tejo	B	10,719.4	15,023.7
	Alentejo	B	6,993.3	9,006.2
	Algarve	B	8,474.4	10,908.1
Romania	Nord-Est	B	956.1	1,250.9
	Sud-Est	B	1,176.2	1,592.1
	Sud	B	1,139.5	1,472.0
	Sud-Vest	B	1,146.5	1,512.8
	Vest	B	1,298.9	1,846.0
	Nord-Vest	B	1,122.5	1,664.4
	Centru	B	1,286.0	1,910.6
	Bucuresti	B	1,631.8	3,698.9
Slovenia	Slovenia	A	7,214.8	9,815.0
Slovak Republic	Bratislavský kraj	B	5,443.2	8,426.4
	Západné Slovensko	B	2,562.6	3,669.0
	Stredné Slovensko	B	2,354.1	3,329.2

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	Východné Slovensko	B	2,166.1	3,050.8
Spain	Galicia	B	9,210.2	12,010.6
	Principado de Asturias	A	10,043.4	13,155.9
	Cantabria	A	10,595.3	14,900.5
	País Vasco	A	13,599.2	18,836.2
	Comunidad Foral de Navarra	A	14,447.6	19,546.0
	La Rioja	A	13,082.2	16,929.8
	Aragón	A	12,355.1	16,316.0
	Comunidad de Madrid	A	14,997.4	20,411.8
	Castilla y León	A	10,858.2	14,089.0
	Castilla-la Mancha	A	9,349.4	12,391.0
	Extremadura	B	7,189.3	9,838.3
	Cataluña	A	13,922.5	18,468.3
	Comunidad Valenciana	A	10,814.5	14,705.2
	Islas Baleares	A	14,151.8	18,249.0
	Andalucia	B	8,454.5	11,353.4
	Región de Murcia	A	9,506.6	12,749.8
Sweden	Stockholm	A	26,281.1	40,454.1
	Östra Mellansverige	A	19,592.8	25,164.8
	Sydsverige	A	19,572.0	27,095.6
	Norra Mellansverige	A	20,855.4	25,038.4
	Mellersta Norrland	A	22,031.1	26,716.1
	Övre Norrland	A	21,423.1	25,309.2
	Småland med öarna	A	20,476.9	26,724.7
	Västsverige	A	20,572.4	27,871.3
UK	Tees Valley & Durham	A	12,161.9	19,779.5
	Northumberland & Tyne & Wear	A	12,344.7	20,429.0
	Cumbria	A	14,999.7	23,681.9
	Cheshire	A	17,136.5	29,756.7
	Greater Manchester	A	13,367.7	23,048.0
	Lancashire	A	12,821.5	21,095.1
	Merseyside	A	10,506.5	18,263.3
	East Riding & North Lincolnshire	A	14,123.8	24,609.3
	North Yorkshire	A	13,874.6	24,503.4
	South Yorkshire	A	10,822.6	19,447.9
	West Yorkshire	A	13,669.7	23,807.5
	Derbyshire & Nottinghamshire	A	13,177.3	23,382.0
	Leicestershire, Rutland & Northamptonshire	A	15,275.5	26,690.4
	Lincolnshire	A	12,591.2	22,059.3
	Herefordshire, Worcestershire & Warwick	A	14,226.3	25,289.8
	Shropshire & Staffordshire	A	12,461.1	22,393.8
	West Midlands	A	14,274.4	24,151.0
	East Anglia	A	15,833.4	28,414.8
	Bedfordshire & Hertfordshire	A	15,212.5	27,831.5
	Essex	A	13,231.9	24,358.2
	Inner London	A	35,279.9	62,788.2
	Outer London	A	12,599.4	22,754.4
	Berkshire, Buckinghamshire & Oxfordshire	A	18,411.4	33,957.4
	Surrey, East & West Sussex	A	14,476.3	27,403.8
	Hampshire & Isle of Wight	A	14,682.6	28,432.7

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Kent	A	14,054.3	24,380.7
Gloucestershire, Wiltshire & N. Somerset	A	15,848.5	27,311.1
Dorset & Somerset	A	12,936.5	22,612.6
Cornwall & Isles of Scilly	A	9,443.8	16,898.0
Devon	A	12,174.0	20,595.4
West Wales & The Valleys	A	10,720.4	18,397.2
East Wales	A	15,450.8	25,433.2
North Eastern Scotland	A	19,820.5	31,983.1
Eastern Scotland	A	15,574.4	26,084.2
South Western Scotland	A	14,167.8	24,097.6
Highlands and Islands	A	11,872.0	19,606.6
Northern Ireland	A	12,066.0	20,223.9