THE EUROPEAN REGIONAL GROWTH PROCESS REVISITED: INCREASING RETURNS AND SPATIAL DYNAMIC SETTING

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Abstract

Most of the recent contributions based on spatial econometrics which measure convergence among regions rely on a cross-sectional estimation of the Solow's (1956) model. However, this type of approach presents two main drawbacks. The first one is the lack of consideration for increasing returns to scale, which are at the origin of endogenous growth and new economic geography models. The second one is that it does not consider explicitly the role of space on the development process. In that purpose, we find more appropriate to use Fingleton's (2001) model which links manufacturing labor productivity growth to manufacturing output growth and technology gap. We extend this specification to the case of 244 European regions over 1991-2003. In addition, we develop a spatial method to endogenously detect and include the presence of spatial heterogeneity in our sample. The conclusions give new insights for policy-makers interested in convergence and regional policies developed to promote it.

Keywords: Regional Convergence, European enlargement, Regional Growth, Spatial Econometric Models

JEL Classification: C21, C23, R11, R12.

1. Introduction

Since Solow's 1956 famous article, economic growth and its empirics have been one of the most debated issues in economics. Accordingly, regional scientists have spent much effort in finding out the sources and the characteristics of the regional growth process. While there is no consolidated agreement on which factor should be considered as a significant source of economic growth (with the sole exception of investment in private and human capital), literature has convincingly shown that space does matter in shaping regional growth (see for instance Abreu *et al.* 2005).

In the European context, most of the literature focusing on regional growth in a spatial framework has been using a spatial econometric setting applied to the Solow growth model (see, for instance, Ertur *et al*., 2006; Dall'erba, 2005; Bivand and Brunstad, 2003; Lopez-Bazo *et al*.,1999). We also stress that spatial econometrics is the only available tool allowing to model spatial interactions for a sample as big as the European regions. Indeed, input/output tables still do not exist at the EU regional level. With regard to the utilization of the β-convergence model, which is directly linked to Solow's theory, Friedman (1992) and Quah (1993) have shown that estimation results may be plagued by Galton's fallacy of regression toward the mean. Furthermore, they face several methodological problems such as heterogeneity, endogeneity, and measurement problems (Durlauf and Quah, 1999; Temple, 1999).

Because of the drawbacks of the neoclassical approach, we pay attention in this paper to the role of space on regional growth and we use Fingleton's approach (2001) which considers the presence of increasing returns in the Verdoorn's Law context. In particular, the Verdoon's Law (Verdoorn, 1949) or its empirical implementation firstly proposed by Kaldor (1957) and successively extended by Kaldor (1970) and Dixon and Thirlwall (1975), states that a pattern of cumulative causation growth raises from a linear relationship between labour productivity growth and output growth in the manufacturing sector. The model is thus characterized by the presence of multiple steady states, or, said in other terms, each region potentially converges to a different constant output growth rate (McCombie and Thirlwall, 1994). Furthermore, the advantage of focusing on regional disparities in productivity levels (instead of per capita levels differences) is first to allow for changes in the living standards of an economy since they are dependent in the long run upon labor productivity increases (Melachroinos and Spence, 1999). In addition, productivity dynamics has often been analyzed at the national level (Baumol, 1986; Dollar and Wolff, 1988; Doyle and O'Leary, 1999) but much less at the regional level. Finally, regional policies implemented in backward regions (transportation infrastructures, firms subsidies, human capital improvement) act directly on the production function of firms and thus may favor the productivity levels in the poor regions but not necessarily their per capita income levels (Lopez-Bazo *et al.*, 1999).

In this paper we make use of Fingleton's (2001) model to study the regional growth process of the enlarged Europe. Although there is extensive literature on the economics of East European transition and on the economic geography of European Enlargement at national level (see, *inter alia*, Baldwin, 1997; Sachs, 1997), few studies have pointed out the relevance of the regional dimension of those processes. A notable exception[1] is the recent paper by Boldrin and Canova (2003) in which the authors make

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[1] Other analyses can be found in Bachtler and Downes (1999), Blomstrom and Kokko (1997), Petrakos (1996).

an attempt at estimating the impact of the Eastern Enlargement on the actual and optimal allocation of Structural Funds among European regions[2]

From a methodological viewpoint, our approach differentiates itself from Fingleton's (2001) in that we consider the presence of spatial heterogeneity in our sample and perform the relevant tests to reveal the correct form of spatial autocorrelation.

The paper is organized as follow. In Section 2 we present the European enlargement process and its consequences on regional disparities. We also draw the characteristics of the model we use. The dataset and the weight matrix are described in Section 3. Cross sectional estimates and the methodology we develop to endogenously define spatial heterogeneity are presented in Section 4. The last section discusses the results and adds some concluding remarks.

2. Regional Growth and the EU Enlargement

The enlargement of the European Union (EU) to Central and Eastern countries as well as to Cyprus and Malta is broadly recognized as a source of political concern because of the widening of economic disparities. In fact, according to the Second and Third Reports on Economic and Social Cohesion (European Commission, 2003, 2004), the enlargement has resulted in a 30% increase in the European area, a 25% increase in the total population, but only in a 5% shift of the total GDP.

The process of accession of new countries is likely to have resulted in deep changes in the geography of European development by shifting from the historical

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[2] For an analysis of the impact of the enlargement process on regional economies, see also Traistaru and Wolff (2002).

North/South dualism to the North-West/East disparities in terms of *per capita* GDP (Ertur and Koch, 2005).

As convincingly argued by several authors (see Rey and Janikas, 2005, and Abreu *et al.,* 2005, for literature reviews), spatial interaction can be regarded as a significant determinant of the processes of growth and convergence in the European context. This effect is exploited both in terms of spatial autocorrelation and heterogeneity. Positive (negative) spatial autocorrelation is defined as the coincidence of value similarities (dissimilarities) in neighbour locations (Anselin, 1988). In other words, this effect is meant to capture the source of dependence of a variable over space. Spatial dependence can also be thought as a measure of spatial spillovers among areal units. On the other hand, spatial heterogeneity measures the stability of variables across space and the presence of spatial regimes in the considered sample.

In the spirit of a number of papers claiming for the central role played by space in the determination of the process of economic growth in the EU (see, for instance, Le Gallo *et al.*, 2003), a change in the geography of development is likely to affect growth and its transmission mechanisms over space. The magnitude and the sign of the impact of the enlargement on regional growth are not known *a priori*. As pointed out in the economic literature, the growth process induced by the enlargement is likely to be driven by foreign direct investment flows from West to East (Altomonte and Resmini, 2002; Markusen and Venables, 1999) as well as by the increase in international trade flows (Resmini and Traistaru, 2003).

However, in this paper we are interested in investigating the link between the spatial structure of development and its impact on the economic growth of the EU regions over the last decade. A natural framework for such analysis is given by the New Economic Geography (NEG) models as proposed by Krugman (1991). At the heart of this approach lies the Verdoorn's Law as developed by Kaldor (1957 and 1970), which aims at explaining the link between productivity and output growth rates and explicitly test for the presence of increasing returns[3]. A former contribution based on this approach can be found in Fingleton (2001) where the dynamic Verdoorn's Law is written as :

$$p = m_0 + m_1 q + u \ . \tag{1}$$

where p is the growth rate of labour productivity, q is the growth rate of the output and u is an error term. The usual interpretation of parameters in (1) is that a value of m_1 around 0.5 implies the existence of increasing returns to scale[4]. By assuming a Cobb-Douglas production function of the form:

$$Q = A_0 e^{\lambda t} K^{\alpha} E^{\beta} \tag{2}$$

where A_0 is the initial level of technological development, λ is the growth rate of technology, Q is the output, K is the capital stock, E is the employment and α and β are their respective elasticities. Fingleton (2001) shows that, under constant capital/output ratio, equation (1) can be reformulated into:

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[3] Kaldor and Thirlwall (1973) put Verdoorn's Law at the centre of the well-known model of cumulative causation growth which should be considered as the base for successive models *à la* Krugman.

[4] For a review of the different approaches to the estimation of the Verdoorn's Law see Leon-Ledesma (2000).

$$p = \frac{\lambda}{\beta} + \frac{\alpha + \beta - 1}{\beta} q + u \tag{3}$$

where, if $b_1 = \frac{\alpha + \beta - 1}{\beta} > 0$, then $\alpha + \beta > 1$ which means that the economy displays increasing returns to scale. Notice that in (3) the capital stock has been dropped on the basis of the stylized fact that the growth of capital stock equals the output growth q (McCombie and Thirlwall, 1994).

At this point, a difference between this approach and the class of neoclassical growth models should be made clear. In models *à la* Solow, assuming production technology uniform across space, the *per capita* GDPs of regions tend naturally to the same steady state λ. Differences in steady states are explained in terms of difference in depreciation rate of capital, saving rate, employment growth patterns and technological progress.

The approach we decided to follow assumes that the growth rate of technical progress evolves according to spatial interactions due to regional spillover effects, technology diffusion and the level of human capital within the regions, that is:

$$\lambda = \lambda^* + \phi p + \varpi W p \tag{4}$$

where W is a spatial weight matrix, λ^* is the steady state level of λ (that is when, in the long run, $p = 0$), and ϕ, ϖ are model parameters. Thus, we explicitly consider the role of space by allowing the model to take into account the spillover effect included in the third term on the right-hand side of equation (4).

At this point the aforementioned difference should be clear: while in the model obtained by the simple estimation of (2) the growth rate of technology is completely exogenous, in our approach we assume it to be dependent on the labour productivity growth and on its spatial structure. In addition, the fact that we link productivity to technological progress allows us to introduce a proxy of public policy spending in different regions. In fact, government and EU interventions in a given region are related to the productivity gap of that region with respect to a benchmark one.

After some algebra, Fingleton (2001) proposes a different specification for the Verdoorn's Law, that is:

$$p = \varpi Wp + b_0 + b_1 q + b_2 G + b_3 u + b_4 l + \varepsilon \tag{5}$$

where G is the technological gap, in terms of labour productivity, between each region of the sample and the leading region. Notice that the coefficient ϖ is meant to reflect the presence of interregional spillovers, i.e. that productivity growth occurring in surrounding regions does affect the growth of productivity (viz., technological progress) in the region. In (5) two explanatory variables have been added: a measure of urbanization (u) and a measure of peripherality (l). The urbanization is measured in terms of population density and is meant to proxy the density of economic activity in the spirit of Ciccone and Hall (1996). Those authors found that, by estimating two models – one considering geographical externalities and the other the diversity of services to industry – for U.S. county, a great part of the variability of the productivity across states is explained by the variance in the density of economic activity. In (5) we assume that economic activity density can be approximated by population density. We thus expect the coefficient b_3 to be positive and significant.

Finally, l measures the geographical distance of a given region from Luxembourg, which is thought to be the central location of Europe. While the core-periphery pattern has often been documented in the case of European Union 12 or 15, we want to test whether this pattern is still relevant for the EU enlarged to 25 members.

The first a-spatial model we estimate takes the following form:

$$p = b_0 + b_1 q + b_2 G + b_3 d + b_4 l + \varepsilon \text{ with } \varepsilon \sim N(0, \sigma_\varepsilon^2 I) \qquad (6)$$

where q is the growth rate of manufacturing output (in log), p is the growth rate of hourly manufacturing productivity (in log), d represents the regional population density and the other variables are the same as above.

In essence, equation (6) describes a specification in which manufacturing productivity growth is positively related to output growth. This specification calls for a brief discussion. According to the endogenous growth theory, it is assumed that productivity growth is positively associated with the technological progress in core and more urbanized regions (as expressed by G and d). It is also a positive function of the diffusion of technology from more advanced to less developed regions.

3. Data and spatial weight matrix

The data on manufacturing productivity, manufacturing output, initial productivity level gap (which is used as a proxy for the initial technology gap) and density come from the most recent version of the Cambridge Econometrics database (2004). They cover the 1991-2003 period. In 1991, Groningen was the region with the highest level of hourly productivity. Regional productivity ratios are in between 0.26% for Latvia to 40.5% for Drenthe (Netherlands). Data are in 1995 euro prices. Data in euro (as opposed to data in purchasing power parity) allows us to consider differences in the capacity to produce goods. The peripherality measure is the distance from Luxembourg. However, contrarily to Fingleton (2001) approach, we do not use the pure geographical distance, but the transportation time by road from Luxembourg to the most populated city of each region. We believe that it is a better way to define peripherality. Information on the most populated town comes from www.citypopulation.de/Europe.html. Data on travel time come from the web site of Michelin (www.viamichelin.com). We adopt the travel time instead of the distance by road because the existence of islands in our sample forces us to include the time spent to load and unload trucks on boats. This information would not have been taken into account if we had considered the pure geographical distance or distance by road only. The difference between both definitions of peripherality is pretty big because of islands and the characteristics of the transportation network. Indeed, new transportation infrastructures improve accessibility among core regions relatively faster than among peripheral regions, because this is where the transport demand is the highest (Vickerman *et al.*, 1999). In addition, with hub-and-spoke interconnections dominating the European highway system, accessibility to the hub from a spoke location may be greater than accessibility from any spoke location to another one (Puga and Venables, 1997).

Our sample is composed of 244 regions at NUTS II level. NUTS (Nomenclature of Territorial Units for Statistics) is the spatial classification established by Eurostat on the basis of national administrative units. It is used by the Commission as regional statistical concept. In addition to the regions of the EU15 members, we include those of Poland (16 regions), of the Czech Republic (8 regions) and of Hungary (7 regions), Estonia (1 region), Lithuania (1 region), Latvia (1 region), Slovenia (1 region), Slovakia (4 regions), Cyprus (1 region), Malta (1 region)[5]. To our knowledge, the present study is the first one to assess growth at the regional level for the whole EU25.

The existence of islands does not allow us to consider simple contiguity matrices; otherwise the weight matrix would include rows and columns with only zeros for these islands. Since unconnected observations are eliminated from the results of the global statistics, this would change the sample size and the interpretation of the statistical inference. As a result, the matrices are based on the great circle distribution of geographical distance. Each matrix is row standardized so that it is relative and not absolute distance which matters. They can be written as follows:

$$\begin{cases} w_{ij}^{*}(k) = 0 \text{ if } i = j, \forall k \\ w_{ij}^{*}(k) = 1/d_{ij}^{2} \text{ if } d_{ij} \leq D(k) \\ w_{ij}^{*}(k) = 0 \text{ if } d_{ij} > D(k) \end{cases} \quad \text{and} \quad w_{ij} = w_{ij}^{*} / \sum_{j} w_{ij}^{*} \quad \text{for } k = 1,\ldots 3 \qquad (7)$$

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[5] We are aware that our empirical results could be affected by the choice of the spatial aggregation which influences the magnitude of various measures of association. This problem is refereed as modifiable area unit problem (Openshaw and Taylor, 1979), also called problem of ecological fallacy (Anselin and Cho, 2000). However, the choice of this disaggregation level is driven by the preference of the European Commission while assessing convergence in its official reports.

where w^*_{ij} is an element of the unstandardized weight matrix; w_{ij} is an element of the standardized weight matrix **W**; d_{ij} is the great circle distance between centroids of region *i* and *j*; $D(1) = Q1$, $D(2) = Me$ and $D(3) = Q3$, $Q1$, Me and $Q3$ are respectively the lower quartile, the median and the upper quartile of the great circle distance distribution. $D(k)$ is the cutoff parameter for $k = 1,...3$ above which interactions are assumed negligible. We use the inverse of the squared distance, in order to reflect a gravity function[6].

4. Cross-section Estimations

In the present section, we will proceed stepwise. Firstly, the OLS version of the model without spatial effects is considered. Then, we will move forward to considering the issues deriving from spatial autocorrelation. The new methodology developed for the identification of the clusters is presented in Subsection 4.2. Finally, we will consider spatial heterogeneity into the model both in the form of spatial regimes and groupwise heteroskedasticity. .

4-1 Spatial autocorrelation

We start with the OLS estimation of model (6). Estimation results displayed in column 1 of table 1 show that all the variables have the expected sign. All the variables are significant. The coefficient of manufacturing output growth is 0.842, which does corroborate the presence of increasing returns to scale. Density and peripherality are

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[6] The robustness of the results is also tested by using other weight matrices based on the *k*-nearest neighbors, with *k*=5, 10, 15, 20 neighbors. Results are available from the authors.

significant and have the expected signs, but their extent is very little. Looking at the diagnostic tests, the Jarque-Bera test rejects the assumption of normality of the residuals (p-value = 0.000). This is due to the presence of spatial effects which will be identified below. We note also that the White test clearly does reject homoskedasticity (p-value = 0.000) as well as the Koenker-Bassett test (p-value = 0.000).

We use Anselin (1988) and Anselin *et al.* (1996) tests to detect the presence of spatial effects. In order to identify the form of the spatial dependence (spatial error model or spatial lag), the Lagrange Multiplier tests (resp. LMERR and LMLAG) and their robust version are performed. The decision is subject to Anselin and Florax (1995) rule: if LMLAG (resp. LMERR) is more significant than LMERR (resp. LMLAG) and R-LMLAG (resp. R-LMERR) is significant whereas R-LMERR (resp. R-LMLAG) is not, then the most appropriate model is the spatial lag model (resp. the spatial error model).

Table 1: Estimation results of models (6) by OLS and (7) by ML with weight matrix W(D1)

	1	2	3	4	5
	OLS-White	ML-ERR	Tests	OLS estimation	ML-ERR estimation
Constant	**0.221 (0.000)**	**0.220 (0.001)**	Moran's *I*	5.867 (0.000)	-
Manufacturing output growth	**0.842 (0.000)**	**0.823 (0.000)**	LMERR	25.656 (0.000)	-
Gap	**0.061 (0.076)**	**0.075 (0.083)**	R-LMERR	16.308 (0.000)	-
Density	**$4.73.10^{-5}$ (0.002)**	**$5.70.10^{-5}$ (0.000)**	LMLAG	9.399 (0.002)	-
Peripherality	**$-7.35.10^{-5}$ (0.015)**	**$-9.18.10^{-5}$ (0.053)**	R-LMLAG	0.051 (0.820)	-
Lambda	**-**	**0.530 (0.000)**	K-B for heteroskedasticity	30.233 (0.000)	
Squ.-corr.	-	0.639	White test	40.294 (0.000)	
LIK	63.481	73.609	JB-test for normality of errors	436.877 (0.000)	-
AIC	-116.964	-137.218	BP test	-	102.178 (0.000)
SC	-99.477	-119.732	Spatial BP test	-	102.192 (0.000)
			LR test on spatial error dependence	-	20.254 (0.000)
			LR test on common factor hypothesis	-	2.242 (0.691)
			Wald test on common factor hypothesis	-	2.187 (0.701)
			LM test on spatial lag dependence	-	0.142 (0.705)

Notes: *p*-values are in brackets. *OLS-White* indicates the use of heteroskedasticity consistent covariance matrix estimator. *ML* indicates maximum likelihood estimation. *GMM* indicates iterated generalized moments estimation (Kelejian and Prucha 1999). *Sq. Corr.* is the squared correlation between predicted values and actual values. *LIK* is value of the maximum likelihood function. *AIC* is the Akaike information criterion. *SC* is the Schwarz information criterion.

Since R-LMERR is significant while R-LMLAG is not, we adopt a spatial error model which can be written as follows:

$$p = b_0 + b_1 q + b_2 G + b_3 d + b_4 l + \varepsilon \quad \text{with } \varepsilon = \lambda W \varepsilon + e \text{ and } e \sim N(0, \sigma_e^2 I) \tag{7}$$

The results of the decision rule above lead us to adopt a form of spatial autocorrelation which is different from the one in Fingleton (2001). This may come from several reasons: the sample and time period we cover are different form the oe sin Fingleton (2001) and he simply imposed a spatial lag specification without using the decision rule mentioned above.

The second column of table 2 shows the estimation results of model (7) by ML (those results are confirmed by GMM-two steps). In this case again, all the coefficients are significant. The presence of significant increasing returns to scale is confirmed in this specification too. The coefficient of the spatial error term is 0.530 and is highly significant, indicating that the presence of positive spatial autocorrelation. The two tests against heteroskedasticity (the unadjusted and spatially adjusted Breusch-Pagan statistics) are significant (p-value = 0.000) indicating the presence of remaining heteroskedasticity. This issue is taken into account in the following section. The LR-test on the spatial autoregressive coefficient $\hat{\lambda}$ is highly significant (p-value = 0.000) and the Wald-test and LR-test on common factor hypothesis are not significant, indicating that the spatial error model is indeed the appropriate specification.

4-2 Determination of regional clusters

The significant results of the B-P tests against heteroskedasticity in table 1 may come either from the presence of structural instability, groupwise heteroskedasticity or both. In order to define the regimes or convergence clubs (also called clusters) that are at the basis of heterogeneity in our sample, we propose first a short review of former contributions defining and treating spatial heterogeneity. Then we describe our methodology and apply it to the case under study.

Various methodologies have been developed in the literature to consider and detect convergence clubs. The reader interested in these issues can, for instance, refer to the contributions of Durlauf and Johnson (1995), Berthelemy and Varoudakis (1996), Desdoigts (1999), Feve and Le Pen (2000), Bloom *et al*. (2003), Hobijn and Franses (2000), Liu and Stengos (1999). In the case of the European regions, the methodologies that have been used are not unanimous either. Neven and Gouyette (1995) choose to define convergence clubs arbitrarily. Corrado *et al*. (2005) use a methodology that allows for endogenous selection of regional clusters using a multivariate test for stationarity, where the number and composition of clusters are determined by the application of pairwise tests of regional differences in per capita output over time. Canova (2004) proposes a technique based on the predictive density of the data and conditional on the parameters of the model to jointly test for the number of convergence clubs and to estimate the parameters of each of them.

The reason for which we do not follow any of the previous methodologies relies on their lack of consideration for spatial effects described in section 2. Indeed, because of the important geographical component of the data upon which our analysis is based, we want the methodology we use for the detection of spatial heterogeneity (convergence clubs) to take spatial dependence into account. This is because former empirical evidences (see references on section 1) clearly indicate the presence of spatial dependence in the growth dynamics of European regions.

The methodology that has been used so far to include spatial autocorrelation in the detection of spatial heterogeneity among EU regions relies on the tools of exploratory spatial data analysis (Le Gallo *et al.*, 2003; Dall'erba, 2005). However, this approach is limited in the sense that it cannot determine more than two clubs. For our sample, the usual North-South polarisation pattern that is relevant for the EU15 would be replaced by a North-West – East pattern because the new member states are included in the sample (see Ertur and Koch, 2005). This is mostly due to the significant decrease in the European mean per-capita income (upon which most spatial analysis tools rely) because of the adhesion of the new entrants. Their per capita GDP is so low that the former poor countries of EU15 (Spain, Portugal, Greece) have now a per capita GDP above the EU25 average.

The methodology we use here combines a spatial approach with an endogenous club detection based on Berthelemy and Varoudakis (1996). In order to avoid the *a priori* exogenous choice of the number of clubs as in Durlauf and Johnson (1995), Berthelemy and Varoudakis (1996) perform successive F-tests on coefficients stability (Chow tests) on the entire sample by moving the sample break's point forward by one observation each time. However, when the first club has been detected, they should repeat their process on the remaining sample to verify whether it is also composed of two sub-groups. In our opinion, the degree of homogeneity between the first and the third group remains to be analyzed. This is what we propose in our methodology of which successive steps are described as follows:

1) We sort the entire sample in increasing order according to the growth rate of manufacturing output, *q,* and change the rows and columns of the *W* matrix accordingly.

2) We estimate model (7) with spatial regimes (structural instability treated with dummy variables per regime in model 7) defined as follows: regime 1 is made of the 5 regions with the smallest *q* (in order to have a sufficient degree of freedom), regime 2 is made of the other regions.

3) Perform the F-test on stability (with the spatial Chow-Wald test, Anselin, 1995) as well as the test on individual stability of the coefficients. We add one more region in regime 1 if the tests reveal stability between regimes (at 10% significance level).

4) As soon as the Chow-Wald test and the test on individual stability reveal instability, the regime 1 regions are eliminated from the sample and steps 2 to 4 are repeated on the remaining sample. A new weight matrix is built in order to match the size of the remaining sample.

5) If multiple regimes are found (say regimes 1, 2 and 3), we need to test how the coefficients of regime 3 are similar to those of regime 1.

The reason of performing both the Chow test of overall stability in addition to the individual stability tests is because the Chow test rejects homogeneity far too often when the sample size is not large relative to the number of parameters in the model under study (Candelon and Lütkepohl, 2001). For instance, the Chow-Wald test of overall stability is already significant (p-value = 0.000) when regime 1 is made of 6 regions only. With such a small number of regions, none of the tests on the stability of individual coefficient is significant.

Table 2 below reports the results of the Chow-Wald test of overall stability and the tests on individual stability for different break points. We are aware that the process we describe here must be taken with caution because the recursive properties of this test are unknown at finite distance.

Table 2- P-values of the spatial Chow-Wald test and individual stability tests for different breakpoints

	Overall stability	Individual stability test				
		Constant	Growth manufacturing ouptut	Technology gap	Density	Peripherality
Regime 1: 46 regions Regime 2: 198 regions	(0.000)	(0.000)	(0.000)	(0.410)	(0.000)	(0.138)
Regime 1: 47 regions **Regime 2: 197 regions**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.361)**	**(0.000)**	**(0.105)**
Regime 1: 48 regions Regime 2: 198 regions	(0.000)	(0.000)	(0.000)	(0.349)	(0.000)	(0.089)
Regime 2: 159 regions Regime 3: 38 regions	(0.000)	(0.194)	(0.046)	(0.995)	(0.706)	(0.037)
Regime 2: 160 regions **Regime 3: 37 regions**	**(0.000)**	**(0.129)**	**(0.034)**	**(0.725)**	**(0.072)**	**(0.031)**
Regime 2: 161 regions Regime 3: 36 regions	(0.000)	(0.007)	(0.007)	(0.540)	(0.065)	(0.023)
Regime 3: 28 regions Regime 4: 9 regions	(0.000)	(0.000)	(0.000)	(0.148)	(0.397)	(0.115)
Regime 3: 29 regions **Regime 4: 8 regions**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.116)**	**(0.001)**	**(0.037)**
Regime 3: 30 regions Regime 4: 9 regions	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: results are obtained by ML estimation. They all are confirmed by GMM estimation.

The results of the Chow-Wald tests above indicate the presence of 4 regimes in our sample: regime 1 is made of 44 regions, regime 2 has 160 regions, regime 3 has 29 regions, regime 4 has 8 regions. However, as indicated in point 5 above, one needs to test how the coefficients of each regime are different from one another. The results of these tests are displayed in table 3 below. All the spatial Chow-Wald results indicate that the regimes defined above are statistically different one from another.

Table 3- Spatial Chow-Wald test results for the regimes defined above.

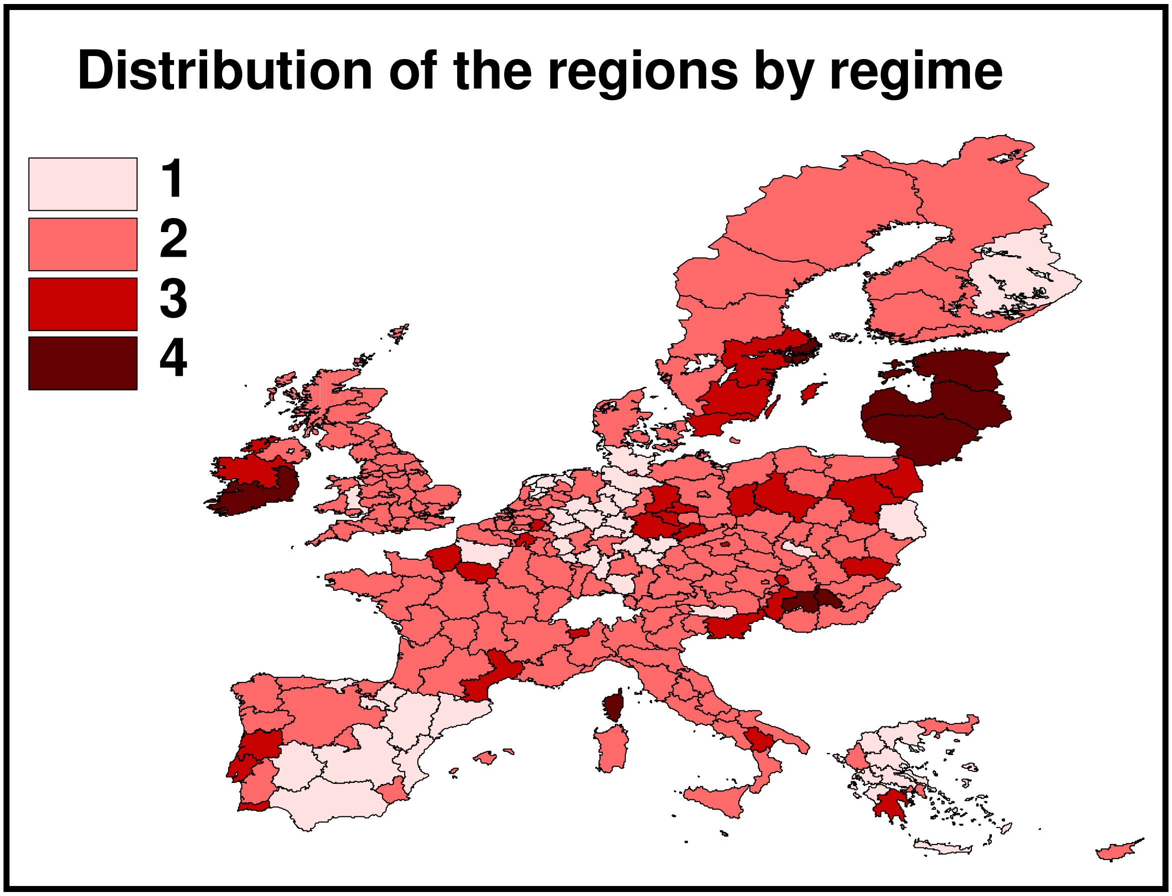
	Overall stability	Individual stability test				
		Constant	Growth manufacturing ouptut	Technology gap	Density	Peripherality
Regime 1 vs. Regime 3:	(0.002)	(0.097)	(0.877)	(0.050)	(0.355)	(0.020)
Regime 1 vs. Regime 4	(0.000)	(0.190)	(0.000)	(0.431)	(0.096)	(0.003)
Regime 2 vs. Regime 4	(0.000)	(0.021)	(0.000)	(0.453)	(0.000)	(0.003)

Note: p-value into brackets.

The 4 regimes defined above are represented in figure 1 below. The regions with the lowest growth rate of manufacturing output are in light color. Those are some Spanish and Greek regions, former East Germany and some other Eastern peripheral regions. The most productive regions (regime 3 and 4) are spread over the territory. We note that they often include the capital city of the country. Three new member countries belong to this category: Latvia, Lithuania, Estonia, as well as two Hungarian regions.

It is obvious from the map below that the regions that belong to one particular regime are not always contiguous. This indicates that some regions may have similar dynamics even if they are not geographically clustered. In the methodology used above, space is controlled for in the determination of the clubs, but it is not the only factor at the origin of the clubs.

Figure 1- Distribution of the regions by regime



4-3 Convergence with regional clusters

Now that we have clearly defined the clubs that are present in our sample, we turn to a cross-section estimation of model (7) to which we add spatial heterogeneity. Indeed, the significance of the BP and spatial BP tests in table 1 clearly indicates the presence of spatial heterogeneity. This may take the form of spatial regime, groupwise heteroskedasticity or both. Let us start with the estimation of the presence of spatial regimes. The model we estimate can be written as follows:

$$p = b_{0i} + b_{1i}q + b_{2i}G + b_{3i}d + b_{4i}l + \varepsilon \text{ with } \varepsilon = \lambda W\varepsilon + e \text{ and } e_t \sim N(0,\sigma_e^2 I) \qquad (8)$$

with subscript *i*= 1 to 4, according to the regime the region belongs to. We stress that the cut-off of the *W* we have used so far allows every region would be connected to another region of the same group. The results of this estimation are displayed below.

Table 4- Estimation results with spatial regimes (ML estimation)

	Regime 1	Regime 2	Regime 3	Regime 4	Stability tests	
Constant	-0.070 (0.402)	**0.426** **(0.000)**	**1.012** **(0.000)**	-0.469 (0.117)	Constant	58.123 (0.000)
Manufacturing output growth	**0.245** **(0.003)**	**0.441** **(0.000)**	-0.025 (0.815)	**0.948** **(0.000)**	Manuf. output growth	41.969 (0.000)
Gap	**0.108** **(0.100)**	-0.024 (0.432)	-0.023 (0.772)	0.151 (0.175)	Gap	5.184 (0.158)
Density	**$3.99.10^{-4}$** **(0.000)**	**$2.49.10^{-5}$** **(0.010)**	$4.34.10^{-5}$ (0.356)	**0.001** **(0.001)**	Density	22.722 (0.000)
Peripherality	**$-1.66.10^{-4}$** **(0.001)**	$-1.91.10^{-5}$ (0.598)	$5.50.10^{-5}$ (0.502)	**$6.61.10^{-4}$** **(0.002)**	Peripherality	17.962 (0.000)
Lambda	**0.348** **(0.003)**				Chow-Wald test	378.394 (0.000)
Squ.-corr.		0.844			B-P test	137.571 (0.000)
LIK		186.493			Spatial B-P	230.000 (0.000)
AIC		-332.986			LR-test on spatial error dependence	18.032 (0.000)
SC		-263.043			LM-test on spatial lag dependence	22.227 (0.000)

Note: all the results above are confirmed by GMM estimation

Significant coefficients are in bold. Immediately, it can be noticed that the coefficient for spatial error autocorrelation is still significant. Furthermore, regimes 1, 2 and 4 display the significant presence of increasing returns to scale. Those are greater in group 4 than group 2 and 1. It may explain why group 4 is made of the most productive regions: an increase in production results in a greater increase in productivity than in the other regions. The impact of peripherality and density measures is very small. We note that the sign of peripherality changes with the regime (negative for regime 1 and positive for regime 4). The Chow-Wald test and the individual stability tests indicate the relevance of using those for groups. However, the B-P and spatial B-P tests indicate that all the heterogeneity has not been taken into account. This is why we test also for the presence of groupwise heteroskedasticity.

4-4 Convergence with regional clusters and groupwise heteroskedasticity

This model can be written as follows:

$p = b_{0i} + b_{1i} q + b_{2i} G + b_{3i} d + b_{4i} l + \varepsilon$ with $\varepsilon = \lambda W \varepsilon + e$ and

$$u \sim N\left(0, \begin{bmatrix} \sigma_{e,1}^2 I_{47} & 0 & 0 & 0 \\ 0 & \sigma_{e,1}^2 I_{160} & 0 & 0 \\ 0 & 0 & \sigma_{e,1}^2 I_{29} & 0 \\ 0 & 0 & 0 & \sigma_{e,1}^2 I_8 \end{bmatrix} \right) \qquad (9)$$

with subscript *i*= 1 to 4, according to the regime the region belongs to

Table 5- Estimation results with spatial regimes and groupwise heteroskedasticity (GMM estimation)

	Regime 1	Regime 2	Regime 3	Regime 4	Stability tests	
Constant	0.103 (0.300)	**0.403 (0.000)**	**0.826 (0.000)**	-0.347 (0.417)	Constant	53.622 (0.000)
Manufacturing output growth	**0.195 (0.038)**	**0.461 (0.000)**	0.031 (0.582)	**0.835 (0.000)**	Manuf. output growth	35.079 (0.000)
Gap	0.072 (0.316)	-0.015 (0.538)	-0.021 (0.588)	0.194 (0.294)	Gap	2.624 (0.453)
Density	$6.66.10^{-5}$ (0.672)	**$2.18.10^{-5}$ (0.017)**	**$5.24.10^{-5}$ (0.061)**	$7.79.10^{-4}$ (0.246)	Density	2.400 (0.493)
Peripherality	**$1.57.10^{-4}$ (0.003)**	$-1.71.10^{-5}$ (0.515)	$4.43.10^{-5}$ (0.220)	**$5.09.10^{-4}$ (0.088)**	Peripherality	12.569 (0.005)
Lambda	**0.028 (0.000)**				Chow-Wald test	455.352 (0.000)
$\sigma^2_{e,1}$	0.020 (0.000)					
$\sigma^2_{e,2}$	0.011 (0.000)					
$\sigma^2_{e,3}$	0.004 (0.000)					
$\sigma^2_{e,4}$	0.045 (0.000)					
Squ.-corr.	0.859					

Results of table 5 confirm those of the previous table: increasing returns are significantly present in group 1, 2 and 4. This last one displays the greatest extent of increasing returns compared to other groups. Density and peripherality are significant for half of the groups. Peripherality is now positive for both groups 1 and 4. The spatial autocorrelation coefficient is still positive and significant, but its extent is much smaller than in previous specifications. GMM estimations do not display the LR test on groupwise heteroskedasticity, but all the coefficients of the variances are significant.

5. Discussion and Conclusions

This paper has shed some light on two important issues while estimating the European regional growth process. First we decided to adopt a Verdroon's law specification that includes the spatial dimension of the process and takes explicitly into account the presence of increasing returns. This has been missing in most of the previous empirical contributions since the neoclassical framework (beta-convergence) is still by far the most popular model used. Second, while the presence of heterogeneity in the European convergence process has been documented many times in the case of EU12 or EU15, there is no doubt the recent enlargement has brought even more disparity. In order to detect convergence clubs, we use an endogenous methodology to which spatial effects are added. This is the first time this methodology is proposed and applied. It allows us to reject previous methodologies that are considering only one aspect (space or endogenous detection), but not both.

Our results, based on a cross-sectional estimation, indicate that increasing returns are significant in determining the level of growth at the regional level. This is a clear evidence that the neo-classical approach is not always relevant. It appears that three new member countries, Estonia, Lithuania, Latvia, as well as two Hungarian regions belong to the club of the regions where increasing returns are estimated to be the highest in the European territory. This last finding has some interesting implications for the development of those countries. Indeed, it means that investing there guarantees much higher returns than in any other place in Europe. In addition, because of the significant presence of spatial effects, it future public investments could contribute to their neighbors also. Two other explanatory variables (density and peripherality) have proven to be significant in half of the groups, but their extent is very little. The technological gap is almost never significant.

The groups we detected using the spatial endogeneous methodology are significant in all our estimations. This methodology improves traditional methodologies based on exploratory spatial data analysis, which cannot split a sample in more than 2 groups, and traditional endogenous detection which does not consider spatial autocorrelation. We hope this methodology opens the way to many more empirical works willing to consider both aspects in the detection of data heterogeneity. Finally, our analysis relies so far on the manufacturing sector only, because we decided to stay as close as possible to the original Verdoon's law. It would be interesting to measure externalities and the extent of increasing returns in the services sector since this is the main source of activity and employment in most Western European countries.

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