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## **What about regions in regional science? An exercise of convergence using different geographic scales of European Union<sup>1</sup>**

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### **Abstract**

*The choice of the spatial scale of analysis is a problematic issue in applied research, particularly in the literature of regional economic growth. Nevertheless, it is evident that regional scientists have been slow at demonstrating the empirical implications of changes in spatial scale of analysis which is usually known by Modifiable Areal Unit Problem (MAUP). The aim of this paper is to examine the alterations in the empirical results caused by the use of different spatial scales in the analysis of the convergence process of European Union (EU15) regions by systematically applying a method to examine this phenomenon at a single scale across multiple scales, namely, NUTS1, NUTS2 and NUTS3, between 2000 and 2008. The results suggest that convergence pattern of EU regions depends on the spatial scale of analysis and that convergence occurs within countries at finer scales (NUTS3 level) rather than between EU countries. Furthermore, these findings hold when we correct our econometric specifications for spatial dependence.*

**Keywords:** *Spatial scales; Convergence; Economic growth; European Union; NUTS.*

**JEL:** *C21, R11*

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<sup>1</sup> This paper borrows – at least partially – for other purpose the title of the well know paper from Hägerstrand (1970), ‘What about people in regional science?’ which argued that Regional Science is about people and not just about locations.

# 1. Introduction

The idea of this paper is to investigate the distortions in the empirical results caused by the use of different spatial scales.<sup>2</sup> The paper analyses the convergence process of European Union (EU) regions by systematically repeating a method originally developed to examine this phenomenon at a single scale across multiple scales.<sup>3</sup> The focus of this paper is to investigate the measurement issue that might cause variability in EU economic growth estimates between 2000 and 2008 due to the use of different spatial scales, likely due to the Modifiable Areal Unit Problem (MAUP)<sup>4</sup>. This empirical exercise is carried out using three geographic stratifications of the EU commonly employed in the empirical literature, the so-called Nomenclature of Territorial Units for Statistics typology (NUTS1, NUTS2 and NUTS3). On the MAUP, Openshaw and Taylor (1981: 62) noted that “*there are no longer grounds for believing that methods exist which are not affected, unless there is proof. It cannot be assumed as a matter of faith*”. Although this paper recognises that micro level analyses (e.g., at firm, individual or household level) may enhance the understanding of spatial/regional processes, it is also true that regional analyses still rely primarily on aggregated data. This is partially because, by definition, some variables (such as gross domestic product- GDP, inflation, investment, road infrastructure and amenities, among others) are aggregated at geographic levels.

Recently, Resende (2011, 2013) analysed Brazilian economic growth on different spatial scales, ranging from municipalities to state regions and provided some potential explanations for the variability in the results as the regional scale level changed. The author shed light, for instance, on the fact that each spatial scale can play a role in terms of the assignment of functions to different levels of government, which can differently influence economic growth at different spatial scales. Furthermore, such differences may arise because interregional mobility

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<sup>2</sup> In this paper, the term “scale” is defined as nested sets of spatial units of different spatial resolutions (e.g., NUTS 3 nested within NUTS 2, nested in turn within NUTS 1).

<sup>3</sup> Yamamoto (2008) applied this approach to examine regional per capita income disparities in the USA on multiple spatial scales between 1955 and 2003 using methods such as inequality indices, kernel density estimation and spatial autocorrelation statistics. Resende (2011, 2013) also used the same approach to study economic growth determinants and convergence process in the Brazilian context.

<sup>4</sup> MAUP has two components. As discussed in Openshaw and Taylor (1981), the scale of study is related to the selection of an appropriate number of zones; however, it is possible to produce alternative zoning systems by regrouping zones at a given scale. This paper will only explore the scale effect of MAUP.

varies across geographic scale levels or the use of the same initial and final periods for all spatial scales that might be translated into different impacts across scale levels (Resende, 2011). Although the understanding of why economic growth differs from one scale to another is important for regional economic growth research in the EU, this issue is beyond the scope of this paper and will be left for future studies<sup>5</sup>. This current paper will only highlight how the rate of convergence and the magnitude of the coefficients of some explanatory variables in the EU vary according to the level of spatial aggregation used in the data.

Behrens and Thisse (2007) point out that from an empirical point of view the concept of region is often intrinsically linked to the availability of data<sup>6</sup>. For this reason, the authors argue that the question of the spatial scale of analysis becomes a problematic issue in applied research. It is worth noting that most studies on convergence process of European Union regions (Barro and Sala-I-Martin, 1991; Armstrong, 1995; Fingleton, 1999; López-Bazo et al., 2004; LeGallo and Dall'erba, 2006; Ertur et al., 2006; Frenken and Hoekman, 2006; Lesage and Fischer, 2008; Fischer, 2011; Elhorst et al., 2010; Sardadvar, 2012) do not employ a rigorous analysis of spatial scale choice and do not make any comparison between spatial scales. One exception is Cheshire and Carbonaro (1996) that tried to deal with MAUP on growth equations for the EU by obtaining functional regions that would be 'geographically meaningful' to capture the economic sphere of influence of a group of NUTS3 regions.<sup>7</sup>

Furthermore, Behrens and Thisse (2007) observe that some new techniques should alleviate the MAUP. They argue that the use of geographical information systems (GIS) and the increasing availability of micro-spatial data

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<sup>5</sup> Resende et al. (2012) shed some light on the reasons for such differences.

<sup>6</sup> Behrens and Thisse (2007) discuss that the concept of region is problematic in theory. In this respect, they argue that *"it is well known how poorly representative the so-called "representative consumer" may be (Kirman, 1992). Likewise, the word "industry" is still in search of a well-defined theoretical meaning (Triffin, 1940). Grouping locations within the same spatial entity, called a region, gives rise to similar difficulties. It is, therefore, probably hopeless to give a clear and precise answer to our first question (What is a region?), which is essentially an empirical one. When we talk about a region, we must be happy with the same theoretical vagueness that we encounter when using the concept of industry. Note that both involve some "intermediate" level of aggregation between the macro and the micro"* (Behrens and Thisse, 2007: 459).

<sup>7</sup> For more detail as to the aggregation method used, see Cheshire and Hay (1989). Another exception is the work developed by Dall'erba and Hewings (2003). These authors using NUTS2 and country data for the EU show that there is convergence of the poorest European Union countries (Ireland, Spain, Portugal and Greece) characterized by a catching-up of their income on the EU average at the country level; however it is also observed increasing regional disparities within each country between 1960 and 2001.

allow scholars to deal with MAUP in the way suggested by Duraton and Overman (2005). However, as noted earlier most empirical research on convergence and economic growth processes are intrinsically dependent of geographic aggregate data. Besides, as highlighted by Briant et al. (2010: 1) “*authors do not work with the same economic specifications to evaluate one particular phenomenon, which is a further source of discrepancy between studies*”. For this reason, the same econometric specifications are employed at all spatial scales used in this paper. Finally, Arbia and Petrarca (2011) present a general framework to investigate the effects of MAUP on spatial econometric models showing how the presence of spatial effects affects the results. Arbia and Petrarca (2011) concentrate on the loss in efficiency of the parameters’ estimators due to aggregation.




The rest of the paper is organised as follows. Section 2 presents the spatial scales and the dataset used in the paper. Section 3 discusses the econometric specifications of the study. In section 4, the results are reported and discussed. The final section presents the concluding remarks.

## **2. Spatial Scales and Dataset**

The regional data used in this paper is from Eurostat, which covers main aspects of economic and social life in the EU. The EU regions are classified according to three levels of spatial aggregation, using the so-called NUTS1, NUTS2 and NUTS3. The group of countries used in this paper is composed of 15 EU countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden and the United Kingdom. The data is available for 74 spatial units of NUTS1, 213 NUTS2 and 1,087 NUTS3. Figure 1 illustrates these three geographic scales.

Figure 1

Spatial scales of European Union 15: NUTS1, NUTS2, NUTS3

NUTS 1	NUTS 2	NUTS 3
		
Number of spatial units = 74	Number of spatial units = 213	Number of spatial units = 1,087

Source: EUROSTAT. © EuroGeographics for the administrative boundaries

Eurostat provides the Gross Domestic Product (GDP) of 2000 and 2008 (in Euros) at NUTS1, NUTS2 and NUTS3 levels and the number of employed persons for the same period. Thus, it is possible to calculate the average annual GDP per worker growth between 2000 and 2008, which is the dependent variable. The explanatory variables are: the (log of) GDP per worker in levels of 2000<sup>8</sup> and the country dummies<sup>9</sup>, as explained in Section 3.

Finally, the spatial weight (W) matrix is used to test for spatial autocorrelation in the error term of the regressions. Pure geographical neighbouring weights are considered. The W matrix used in the paper is based on the 5, 10, 20 and 40-nearest neighbours calculated from the great circle distance between region centroids. As pointed out by LeGallo and Ertur (2003) these matrices are preferred to the simple contiguity matrix, as used for example by López-Bazo et al. (1999), for various reasons. One important reason is because they connect a number of islands to continental Europe, thus avoiding rows and columns in W with only zero values.<sup>10</sup>

<sup>8</sup> The Italian NUTS regions did not have data for GDP in 2008. Thus, the growth rate was calculated based on the period 2000-2007. Netherlands did not have data for GDP in 2000 and the growth rate was calculated based on the period 2001-2008 and the lagged GDP per worker was also used the GDP per worker in 2001. The employment (in persons) is the EUROSTAT series coded [nama\_r\_e3empl95] and Gross domestic product (GDP) at current market prices is the series coded [nama\_r\_e3gdp].

<sup>9</sup> We excluded one (United Kingdom dummy) of the country dummy variables from the regressions to avoid multicollinearity

<sup>10</sup> The analyses carried out in this paper are conditional upon the choice of the spatial weight matrix.

### 3. Econometric Specifications

Traditionally, in empirical studies, the  $\beta$ -convergence hypothesis is tested by a simple linear regression model (for example, Barro and Sala-i-Martin, 1991, 1992) where the per worker GDP growth rate is estimated compared to the initial per worker GDP of the region. Equation (1) is the basic equation of this test.

$$g = \alpha + \beta \ln(y_0) + \varepsilon \quad (1)$$

$g = (1/T) * \ln(y_{T,i}/y_{0,i})$ , where  $y_{T,i}$  and  $y_{0,i}$  are, respectively, the final period and the initial period of GDP per worker,  $T$  is the time period in years, and  $\varepsilon_i$  error term. A negative correlation between the growth rate and the initial GDP per worker ( $\beta < 0$ ) indicates that there is absolute  $\beta$ -convergence.

It is possible to modify Equation (1) to include other regional characteristics important in the economic growth dynamic (avoiding the omission of relevant variables). Thus, the absolute  $\beta$ -convergence gives way to the conditional  $\beta$ -convergence which can be expressed by Equation (2).

$$g = \alpha + \beta \ln(y_0) + \delta X + \varepsilon \quad (2)$$

where  $X$  represents a vector of member state dummy variables. As explained by Armstrong (1995), these dummies are important variables with enormous explanatory power in an EU context because they can be considered as proxies for differences among countries in steady state levels of GDP per worker and growth rates of GDP per worker. Conditional  $\beta$ -convergence is indicated by a negative coefficient  $\beta$ , after controlling the regional differences captured by the dummies variables. It is worth noting that conditional  $\beta$ -convergence means that the economies tend to different steady states, where the regional disparities will persist (Islam, 2003).

In section 4, the empirical strategy is to estimate Eq. (1) and (2) using Ordinary Least Squares (OLS) estimator to analyse the convergence rate, the coefficients of controlling variables as well as to test for the existence of spatially auto-correlated errors at all scale levels under study. Then, the analysis uses spatial econometrics techniques when necessary.

There are alternative spatial econometric models to control for spatial autocorrelation. Corrado and Fingleton (2012) describe a general single equation

spatial econometric model specification – the spatially autoregressive model with autoregressive disturbances (SARAR) model – as follow:

$$g = \alpha + \rho W_1 g + X\beta + W_2 X\rho_x + \varepsilon \quad , \quad (3)$$

$$\varepsilon = \lambda W_3 \varepsilon + u \quad , \quad (4)$$

$$u \sim iid(0, \sigma^2) \quad . \quad (5)$$

In Eq. (3)  $g$  is an  $N \times 1$  column vector with observations for the dependent variable,  $X$  is an  $N \times K$  matrix of observations on exogenous variables (for the sake of simplicity  $X$  includes the  $\ln(y_0)$  term), and  $\varepsilon$  and  $u$  are vectors of error terms. The spatial matrices  $W_1$  and  $W_2$  allow, respectively, endogenous and exogenous spatial lags and the spatial matrix  $W_3$  represents a spatial error process. Thus,  $\rho$  and  $\lambda$  are the spatial autoregressive parameters; and  $\beta$  and  $\rho_x$  are  $K \times 1$  vectors of coefficients. Note that, for the error process, there is a scalar  $\lambda$  and an  $N \times 1$  vector of innovations  $u$  drawn from an *iid* distribution with variance  $\sigma^2$ .

The SARAR model nests the most common spatial econometric models usually employed in the empirical literature. For instance, as discussed in LeSage and Fischer (2008), imposing that  $\lambda = 0$  leads to the Spatial Durbin Model (SDM), imposing that  $\lambda = 0$  and  $\rho_x = 0$  leads to the Spatial Autoregressive (SAR) model and assuming that  $\rho = 0$  and  $\rho_x = 0$  leads to the Spatial Error Model (SEM). Finally, imposing the restriction that  $\rho = 0$ ,  $\rho_x = 0$  and  $\lambda = 0$  leads to the standard non-spatial least squares (OLS) regression model. It is important to note that if  $\rho$  and  $\rho_x$  are significantly different from zero, their omissions in a regression provides biased estimates of  $\beta$  coefficients. These omissions will cause the residuals to be spatially correlated. Moreover, the regression may have spatially correlated residuals because of measurement error or misspecification of the functional form; in this case, using OLS in the presence of non-spherical errors yields unbiased estimates for the estimated parameters ( $\beta$ ) but a biased estimate of the parameters' variance.

As shown above, the spatial process in the error terms may be translated into alternative spatial econometric specifications. In the next section, we focus on the SDM to illustrate the results. LeSage and Fischer (2008) argue that SDM



specification is a natural choice over competing alternatives and it provides a substantive justification for the spatial externalities by the inclusion of spatial lags of both the dependent and explanatory variables. Of course, exploring alternative spatial econometric specifications at different spatial scales can provide more insights on the spatial externalities across space.

## 4. Results and Discussion

In Section 4.1, the estimation of Equations (1) and (2) as well as diagnostics for spatial dependence are discussed with regard to the three geographic scales. Next, spatial econometric specifications are used to correct for potential spatial dependence when necessary.

### 4.1. OLS model results and discussion

Table 4.1 presents the results estimated through OLS and diagnostics tests for spatial dependence for all geographic scales (NUTS1, NUTS2 and NUTS3 levels). Column 1 shows the result for the test of absolute  $\beta$ -convergence (Equation 1) considering NUTS1 regions between 2000 and 2008. Next, as suggested by Armstrong (1995), we add a set of member state dummy variables (Equation 2) and the results are in column 2. Similarly, columns 3 and 4 show the results for NUTS 2 and column 5 and 6 for NUTS 3.<sup>11</sup> First, it is important to note that OLS estimates without country dummies show a negative sign of the coefficient on initial GDP per worker, indicating absolute convergence in all geographic scales. The magnitude of convergence is similar in NUTS 1 and NUTS 2. The results for NUTS 3, that has smaller regions, indicate convergence of a greater magnitude. This higher rate of convergence suggests that NUTS3 units are more open economies (Barro et al., 1995)<sup>12</sup> than more aggregated regions such as NUTS1 and NUTS2. The assumption of a more open economy is not difficult to justify in the NUTS3 level, considering that the intensity of flows of capital, trade and people across these units is higher than across NUTS1 or NUTS2 borders.

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<sup>11</sup> We use alternative spatial weight matrices ( $k = 5, 20$  and  $40$  nearest neighbors) for all diagnostics for spatial dependence shown in Table 1 and the qualitative results are similar.

<sup>12</sup> Barro et al.'s (1995) neoclassical model of open economy with perfect capital mobility predicts that economies will jump instantaneously to a steady state of income per capita. This fact can be understood as a higher rate of convergence.

To assess formally the presence of spatial dependence in the OLS regressions we use the Spatial Lagrange Multiplier (LM) tests to compare OLS models against the alternative SEM and SAR spatial models under the null hypothesis of no spatial dependence<sup>13</sup>. The LM<sub>ERR</sub> test and its robust version (LMR<sub>ERR</sub>), and the LM<sub>LAG</sub> test and its robust version (LMR<sub>LAG</sub>) are reported at the bottom of Table 1. The LM test results for OLS regressions (without country dummies) have a statistically significant value for all three scales, indicating the presence of spatial dependence in the residuals.

**Table 4.1 – Cross Section OLS – NUTS 1, NUTS 2 and NUTS 3**

Spatial Scale =	NUTS 1		NUTS 2		NUTS 3	
	(1) Without Country Dummies	(2) With Country Dummies	(3) Without Country Dummies	(4) With Country Dummies	(5) Without Country Dummies	(6) With Country Dummies
lnGDP <sub>t-1</sub>	-0.016060*** (-2.858)	0.003560 (0.476)	-0.016866*** (-4.334)	0.003836 (0.710)	-0.020211*** (-8.299)	-0.014849*** (-4.132)
Intercept	0.090606*** (4.121)	0.006961 (0.238)	0.093134*** (6.144)	0.005308 (0.250)	0.103315*** (10.967)	0.078382*** (5.605)
Observations	74	74	213	213	1087	1087
R-squared	0.08943	0.6671	0.07738	0.5766	0.05882	0.2514
LM <sub>ERR</sub>	49.1147(0.0000)	0.5494(0.4586)	186.8563(0.0000)	0.0768(0.7817)	134.8008(0.0000)	7.262(0.007043)
LMR <sub>ERR</sub>	0.5902(0.4424)	0.3793(0.538)	0.0421(0.8375)	0.2104(0.6465)	0.761(0.383)	1.0396(0.3079)
LM <sub>LAG</sub>	50.6951(0.0000)	0.2222(0.6374)	212.6496(0.0000)	0.00(0.996)	150.5849(0.0000)	6.3204(0.01194)
LMR <sub>LAG</sub>	2.1705(0.1407)	0.0521(0.8195)	25.8354(0.0000)	0.1336(0.7147)	16.545(0.0001)	0.0979(0.7543)
Spatial Weight Matrix	W(k)=10	W(k)=10	W(k)=10	W(k)=10	W(k)=10	W(k)=10

Note: t statistics in parentheses; \*\*\*significant at 1%; \*\*significant at 5%; \*significant at 10%.  
P-values in the parentheses for the diagnostics for spatial dependence

Interestingly, the convergence results change with the inclusion of country dummies. The results for NUTS 1 and 2 do not support the hypothesis of convergence any longer. On the contrary, results for NUTS 3 controlling for country specific characteristics still suggest convergence. This might be an indication that convergence occurs within countries (as NUTS 3 are smaller regions that are more interconnected with neighbouring regions in the same country) and not across countries (as NUTS 1 and 2 are larger regions that are more interconnected with other countries).<sup>14</sup> For the regressions in Table 1 with country dummies, only for the case of NUTS 3 (column 6) the LM tests suggest

<sup>13</sup> See Anselin and Hudak (1992), Anselin et al. (1996) and Elhorst (2010) for a detailed discussion on these tests. The Lagrange Multiplier tests compare the OLS model against the alternative SEM and SAR models under the null of no spatial dependence. In relation to the spatial error model as the alternative, the LMERR and its robust version (LMRERR) are reported, whereas for the spatial lag model the LMLAG and its robust version (LMRLAG) are reported.

<sup>14</sup> This evidence is line with the structural problems faced by Europe since the emergence of the 2008 financial crises.

the use of spatial models. This suggests that country dummies are intrinsically linked to the spatial dependence in Europe at NUTS 1 and 2, spatial spillovers occur within and not across countries.

## **4.2. Spatial Durbin model results and discussion**

In order to provide more insights about different economic dynamics in different geographical scales, this section provides the results for the SDM model mentioned in section 3. Lesage and Fisher (2008) and Lesage and Pace (2009) provide a detailed discussion about the motivations and advantages of the SDM specification for growth models from statistical point of view. Moreover, this model can be supported by theoretical spatial growth models such as those developed by López-Bazo et al. (2004), Ertur and Koch (2007) and Sardadvar (2012).

This section shows spatial correction only for the NUTS3 level as Table 4.1 suggests there is no need for spatial models at the NUTS1 and NUTS2 levels (with country dummies) according to diagnostic tests. Tables 4.2.1 and 4.2.2 report estimation results for the Spatial Durbin Models using alternative  $W$  matrices. The tables show the results of the b-convergence for the NUTS3 level without and with country dummies, respectively.

The results for absolute convergence (Table 4.2.1) show that the convergence coefficient is negative but not statistically significant. In other words, the results do not support the idea that poorer NUTS3 regions grow faster than richer ones when country specific factors are not considered.<sup>15</sup> Nevertheless, the autocorrelation coefficient ( $\rho$ ) suggests positive spillover stemming from the growth rates of neighboring regions, the growth rates of neighbors induces growth at NUTS 3 level.

As in the case of non-spatial regressions, the inclusion of country dummies to control for country specific characteristics produces different results. The “spatial” conditional b-convergence evidence cannot be rejected and the autocorrelation coefficient ( $\rho$ ) now suggests that the growth rates of neighboring

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<sup>15</sup> Comparing with the non-spatial estimation in Table 4.1 (column 5), the results suggest that the initial per worked GDP is correlated with the spatial structure, this is because once the spatial structure is considered for Europe, the absolute convergence effect disappears. In other words, the absolute convergence in the non-spatial estimation is likely to be capturing the convergence effect occurring in the neighborhood of the regions.

NUTS 3 regions affect a given region negatively<sup>16</sup>. As noted by Lall and Shalizi (2003: 678) “*although much of the theoretical discussion on spatial externalities focuses on positive externalities from knowledge diffusion, labor market pooling, and policy adoption, there are several reasons why we observe negative spatial externalities*”. One reason for the existence of negative externalities is given by the authors and can be extended to the EU context: “[i]f growth in a particular region is higher than that of its neighbors, the region is likely to attract mobile capital and skilled labor from neighboring regions, thereby having a detrimental effect on growth performance in neighboring regions (Lall and Shalizi (2003, 679). Moreover, the spatial lag of GDP per worker at the start of the sampling period ( $W \cdot \ln GDP_{t-1}$ ) is not statistically significant in Table 4.2.2.

In sum, the results for Tables 4.2.1 and 4.2.2 provide support to the idea that convergence occurs within countries rather than between countries. In the absence of country dummies (i.e., specific country characteristics are not considered), there is no indication of convergence at NUTS3 level (Table 4.2.1). On the other hand, after the inclusion of country dummies (Table 4.2.2) the convergence coefficient is negative and statistically significant, suggesting that poorer regions grow faster within each EU15 member state. The inclusion of country dummies alters the regression results, providing another indication that the spatial structure might be correlated with country specific factors. In the appendix, we included the SDM results at NUTS1 and NUTS2 levels. The main finding is that there is no b-convergence at NUTS1 and NUTS2 levels even if we try to correct for spatial dependence (see Tables A.1 to A.4 in the Appendix). These results reinforce the findings using the OLS method shown in section 4.1.

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<sup>16</sup> It is important to highlight that the autocorrelation coefficient ( $\rho$ ) (in Table 4.2.2) wanes as the number of neighboring regions increases, suggesting that spatial externalities working through the economic growth rates are bounded in space (inside each country as the estimations include country-specific dummies). Indeed, when a wider spatial structure is considered ( $k=40$ ) the autocorrelation parameter ( $\rho$ ) becomes statistically insignificant.

**Table 4.2.1 - SDM Cross-Section (Without Country Dummies) – NUTS 3**

	SDM (1)	SDM (2)	SDM (3)	SDM (4)
$\ln GDP_{t-1}$	-0.0068438 (-1.3605)	-0.0051585 (-1.1255)	-0.0044677 (-1.0707)	-0.0035499 (-0.9497)
$W * \ln GDP_{t-1}$	-0.0120680** (-2.1951)	-0.0089344* (-1.7299)	-0.0066570 (-1.3584)	-0.0042869 (-0.9128)
$\rho$ (SAR)	0.20131 (4.4013)	0.44182*** (8.8484)	0.58604*** (10.499)	0.7284*** (12.805)
Intercept	0.0932129*** (8.2444)	0.0685711*** (5.9215)	0.0536704** (4.3791)	0.0375851*** (2.9728)
Observations	1087	1087	1087	1087
Log likelihood (LIK)	2715.009	2745.227	2761.615	2780.505
LR test	21.022 (0.0000)	75.443 (0.0000)	106.59 (0.0000)	134.84 (0.0000)
AIK	-5420	-5480.5	-5513.2	-5551
Spatial Weight Matrix	W(k)=5	W(k)=10	W(k)=20	W(k)=40

Note: t statistics in parentheses; \*\*\*significant at 1%; \*\*significant at 5%; \*significant at 10%.  
P-values in the parentheses for the diagnostics for spatial dependence

**Table 4.2.2 - SDM Cross-Section (With Country Dummies) – NUTS 3**

	SDM (1)	SDM (2)	SDM (3)	SDM (4)
$\ln GDP_{t-1}$	-0.013456*** (-2.8013)	-0.0125972*** (-2.6886)	-0.0133785*** (-3.0570)	-0.0116872*** (-2.7681)
$W * \ln GDP_{t-1}$	-0.0074162 (-1.1507)	-0.00910826 (-1.2869)	-0.00951595 (-1.2524)	-0.01473259 (-1.6040)
$\rho$ (SAR)	-0.39479*** (-7.1159)	-0.23687*** (-2.9925)	-0.24148** (-2.1069)	-0.015185 (-0.10491)
Intercept	0.11009*** (5.9364)	0.11009695*** (5.0729)	0.11485962*** (4.4991)	0.12399750*** (3.7623)
Observations	1087	1087	1087	1087
Log likelihood (LIK)	2855.859	2836.534	2834.27	2833.915
LR test	48.311 (0.00000)	9.0693 (0.0025994)	4.8631 (0.027437)	0.010391 (0.91881)
AIK	-5645.7	-5607.1	-5602.5	-5601.8
Spatial Weight Matrix	W(k)=5	W(k)=10	W(k)=20	W(k)=40

Note: t statistics in parentheses; \*\*\*significant at 1%; \*\*significant at 5%; \*significant at 10%.  
P-values in the parentheses for the diagnostics for spatial dependence

## 5. Concluding Remarks

The choice of the spatial scale of analysis is a problematic issue in applied research and this paper demonstrates the implications of aggregation problems on empirical regional economic growth studies. The paper examines the changes in the empirical results caused by the use of different spatial scales in the analysis of convergence process of European Union (EU) regions. The convergence pattern changes with geographic scale and the paper advocates that it is still necessary to incorporate in this important line of research a deeper investigation of the implications caused by changes in spatial scale of analysis which is usually known by Modifiable Areal Unit Problem (MAUP).

In sum, the results for NUTS 1 and 2 do not support the hypothesis of b-convergence when country dummies are included in the OLS regressions. On the other hand, results for NUTS 3 controlling for country specific characteristics suggest b-convergence. This might be an indication that convergence occurs within countries at finer scales (NUTS3 level) rather than between countries. Thus, the partial conclusion based on the results for NUTS2 that there is no conditional b-convergence in the EU is misleading as in the EU conditional b-convergence is occurring at finer scales (NUTS3) within countries.

The models are also estimated controlling for spatial dependence using the Spatial Durbin Model. The main findings are: (i) there is indication that spatial models are preferred at NUTS 3 level and the existence of b-convergence appear only after the inclusion of country dummies, suggesting that poorer regions grown faster within each EU15 member state between 2000 and 2008; and (ii) there is no indication of spatial dependence in the estimations for NUTS 1 e 2 and no b-convergence (absolute and conditional) are observed after correcting for spatial dependence. Finally, it is important to note that the results presented here are specific to the study period.

The aim of the paper is to illustrate the serious implications of MAUP for regional applied research. Studies used to design regional policies should consider results based on various spatial scales to provide better information for policy makers. Decisions made based on studies that use only one geographic scale might provide misleading information; the policy prescription might not be correct for the specific geographic scale affect by a given policy and might have

the opposite results. Additionally, the analyses provided in the paper can be improved by including additional explanatory variables if relevant data were available. Also, spatial heterogeneity should be assessed. These issues will be left for future research as they are beyond the scope of this paper.

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## Appendix

**Table A.1 - SDM Cross-Section (Without Country Dummies) – NUTS 1**

	SDM (1)	SDM (2)	SDM (3)	SDM (4)
$\ln GDP_{t-1}$	0.0066300 (1.0283)	-0.0019606 (-0.3002)	0.0025030 (0.3580)	-0.0046950 (-0.8251)
$W* \ln GDP_{t-1}$	-0.0175156** (-2.1185)	-0.0135738 (-1.1693)	-0.0576136*** (-2.8888)	-0.2739875*** (-5.4937)
$\rho$ (SAR)	0.67471*** (7.0952)	0.75687*** (7.334)	0.82087*** (8.4087)	-3.4327*** (-2.9365)
Intercept	0.0524406** (2.2569)	0.0690245** (2.0347)	0.2256152*** (3.5808)	1.2299822*** (5.7578)
Observations	74	74	74	74
Log likelihood (LIK)	240.2385	236.1978	231.8938	235.5297
R-squared				
LR test	29.174 (0.0000)	24.964 (0.0000)	10.711 (0.0010)	8.5634 (0.0034)
LR COMFAC	4.7713 (0.02894)	3.1074 (0.07794)	11.3418 (0.00075)	19.8791 (0.00000)
AIK	-470.48	-462.4	-453.79	-461.06
Spatial Weight Matrix	W=5	W(k)=10	W(k)=20	W(k)=40

Note: t statistics in parentheses; \*\*\*significant at 1%; \*\*significant at 5%; \*significant at 10%.

P-values in the parentheses for the diagnostics for spatial dependence

**Table A.2 - SDM Cross-Section (With Country Dummies) – NUTS 1**

	SDM (1)	SDM (2)	SDM (3)	SDM (4)
$\ln GDP_{t-1}$	0.011544 (1.6296)	0.01721551*** (2.8571)	-0.00008912 (-0.0117)	0.0042668 (0.5190)
$W* \ln GDP_{t-1}$	-0.01022682 (-0.6723)	0.04096685 (1.0906)	-0.09775513 (-1.1978)	0.2761643 (1.3777)
$\rho$ (SAR)	-0.22039 (-1.0188)	-2.135*** (-6.1117)	-2.6515*** (-3.9116)	-6.5184*** (-4.8186)
Intercept	0.02246851 (0.3549)	-0.15551020 (-1.019)	0.42622100 (1.2631)	-0.9278407 (-1.1406)
Observations	74	74	74	74
Log likelihood (LIK)	272.9241			281.7779
LR test	0.92798 (0.33539)	17.355 (0.000031)	10.847 (0.00098968)	281.7779 (0.0013451)
LR COMFAC	9.3709 (0.8066)	20.1082 (0.1678)	28.4034 (0.01918)	15.6432 (0.3356)
AIK	-481.85	-501.95	510.36	-499.56
Spatial Weight Matrix	W=5	W(k)=10	W(k)=20	W(k)=40

Note: t statistics in parentheses; \*\*\*significant at 1%; \*\*significant at 5%; \*significant at 10%.

P-values in the parentheses for the diagnostics for spatial dependence

**Table A.3 - SDM Cross-Section (Without Country Dummies) – NUTS 2**

	SDM (1)	SDM (2)	SDM (3)	SDM (4)
lnGDPt-1	0.0134281 (2.4080)	0.0119799 (2.3241)	0.0097372 (1.9134)	0.0047598 (0.9722)
W* lnGDPt-1	-0.0241727*** (-3.8550)	-0.0193412** (-3.2242)	-0.0214680** (-2.9305)	-0.0329378** (-3.1489)
$\rho$ (SAR)	0.60946*** (9.3336)	0.72696*** (10.819)	0.80873*** (11.972)	0.92669*** (23.249)
Intercept	0.0528484*** (3.4086)	0.0366000 (2.4361)	0.0520221* (2.7098)	0.1145932*** (3.8409)
Observations	213	213	213	213
Log likelihood (LIK)	654.5386	662.5685	659.0688	648.7495
LR test	67.726 (0.0000)	79.683 (0.0000)	75.766 (0.0000)	62.801 (0.0000)
LR COMFAC	15.0416 (0.0001052)	6.5183 (0.01068)	7.5028 (0.00616)	14.1757 (0.0001665)
AIK	-1299.1	-1315.1	-1308.1	-1287.5
Spatial Weight Matrix	W=5	W(k)=10	W(k)=20	W(k)=40

Note: t statistics in parentheses; \*\*\*significant at 1%; \*\*significant at 5%; \*significant at 10%.  
P-values in the parentheses for the diagnostics for spatial dependence.

**Table A.4 - SDM Cross-Section (With Country Dummies) – NUTS 2**

	SDM (1)	SDM (2)	SDM (3)	SDM (4)
lnGDPt-1	0.00693504 (1.2469)	0.00746365 (1.3574)	0.0091670* (1.7288)	0.0099331* (1.8370)
W* lnGDPt-1	-0.00302616 (-0.3147)	-0.00631257 (-0.4629)	-0.0275804 (-1.1055)	0.0570827 (0.7724)
$\rho$ (SAR)	-0.22491* (-1.8255)	-0.12103 (-0.69627)	-0.68063** (-2.1759)	-2.1821*** (-3.4269)
Intercept	0.01012050 (0.2815)	0.01945645 (0.3745)	0.1086676 (1.1081)	-0.2008057 (-0.6755)
Observations	213	213	213	213
Log likelihood (LIK)	705.8547	704.652	708.545	710.9256
LR test	3.09 (0.078777)	0.41237 (0.52077)	4.1267 (0.042212)	7.9745 (0.0047442)
LR COMFAC	11.575 (0.7109)	10.7563 (0.7697)	15.8569 (0.3916)	18.1558 (0.2546)
AIK	-1345.7	-1343.3	-1351.1	-1355.9
Spatial Weight Matrix	W=5	W(k)=10	W(k)=20	W(k)=40

Note: t statistics in parentheses; \*\*\*significant at 1%; \*\*significant at 5%; \*significant at 10%.  
P-values in the parentheses for the diagnostics for spatial dependence