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What about regions in regional science? A convergence exercise using different geographic scales of European Union

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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 as the 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.

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1. Introduction[1]

This paper investigates the distortions in empirical results caused by the use of different spatial scales.[2] It analyses the convergence process of European Union (EU) regions by systematically repeating a method used to examine this phenomenon at a single scale across multiple scales.[3] The focus 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)[4]. This exercise is carried out using three geographic stratifications of the EU, the so-called Nomenclature of Territorial Units for Statistics (NUTS1, NUTS2 and NUTS3). Although this paper recognises that micro level analyses (at firm, individual or household level) may enhance the understanding of spatial processes, regional analyses still rely primarily on aggregated data, partially because by definition, some variables (i.e. gross domestic product, inflation, road infrastructure and amenities) are aggregated at geographic levels.

Recently, Resende (2011, 2013) analysed Brazilian economic growth on different spatial scales, from municipalities to state regions. The author shed light 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 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[5]. This paper will only highlight how the rate of convergence and the magnitude of the coefficients of some explanatory variables in the EU vary with the level of spatial aggregation used in the data because of the MAUP. The problems of observing different results at different aggregation levels is also referred to in the literature as aggregation bias (e.g. Wu and Cutter, 2011).

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[1]This paper borrows, partially, for other purpose the title of the well know paper from Hägerstrand (1970) 'What about people in regional science?' that argued Regional Science is about people and not just about locations.

[2] In this paper, the term "scale" is defined as nested sets of spatial units of different spatial resolutions (e.g., NUTS 3 nested within NUT 2, nested in turn within NUTS 1).

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

[4] 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.

[5] Resende et al. (2012) shed some light on the reasons for such differences.

Behrens and Thisse (2007) point out that from an empirical point of view the concept of region is intrinsically linked to the availability of data[6]. For this reason, the authors argue that the question of the spatial scale of analysis becomes a problematic issue in applied research. Importantly, most studies on convergence of European Union regions do not employ a rigorous analysis of spatial scale choice and do not make any comparison between spatial scales. The major characteristics and spatial scale of analysis of a sample of studies on convergence in the EU are summarised in Table A.1 (Appendix A). 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.[7]

Furthermore, they observe that some new techniques should alleviate the MAUP. The use of geographical information systems (GIS) and the increasing availability of micro-spatial data 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)"*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 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 discussed and the final section presents the concluding remarks.

2. Spatial Scales and Dataset

The regional data used in this paper is from Eurostat and the EU regions are classified according to three levels of spatial aggregation: NUTS1, NUTS2 and NUTS3. The group of countries used

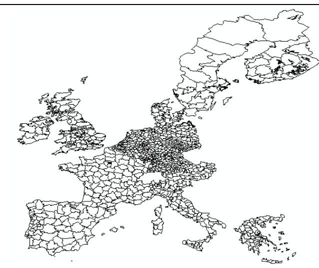
[6] Behrens and Thisse (2007) discuss that the concept of region is problematic in theory and argue that "*it is well known how poorly representative the so-called "representative consumer" may be (Kirman, 1992). Likewise, the word "industry" is still in search of a well-defined theoretical meaning (Triffin, 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*".

[7] For more detail as to the aggregation method used, see Cheshire and Hay (1989). Another exception is the work of Dall'erba and Hewings (2003) that uses NUTS2 and country data for the EU and 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.

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, allowing the calculation of the average annual GDP per worker growth. The explanatory variables are: the (log of) GDP per worker in 2000[8] and the country dummies, as explained in Section 3. Finally, the spatial weight (W) matrix, based on the 5, 10, 20 and 40-nearest neighbours calculated from the great circle distance between region centroids, is used to test for spatial autocorrelation in the error term of the regressions. As pointed out by LeGallo and Ertur (2003) one important reason for the use of these matrices is because they connect a number of islands to continental Europe, thus avoiding rows and columns in W with only zero values.[9]

3. Econometric Specifications

Traditionally, in empirical studies, the β-convergence hypothesis is tested by a linear regression model (Barro and Sala-i-Martin, 1991, 1992) where the per worker GDP growth rate is estimated against the initial per worker GDP of the region as in Equation (1):

$$g = \alpha + \beta \ln(y_0) + \varepsilon \tag{1}$$

[8] The Italian NUTS regions did not have data for GDP in 2008 and the growth rate was based on the period 2000-2007. Netherland did not have data for GDP in 2000 and the growth rate was based on the period 2001-2008 and the lagged GDP per worker in 2001 was used. The employment (in persons) is the EUROSTAT series coded [nama_r_e3empl95] and GDP at current market prices is the series coded [nama_r_e3gdp].

[9] The analyses carried out in this paper are conditional upon the choice of the spatial weight matrix.

$g = (1/T)*ln(y_{T,i}/y_{0,i})$, 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 ε_i error term. A negative correlation between the growth rate and the initial GDP per worker ($\beta<0$) suggests absolute β-convergence.

Augmenting Equation (1) to include other regional characteristics important in the economic growth dynamic (avoiding the omission of relevant variables) gives way to the conditional β-convergence which can be expressed by Equation (2).

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

where X represents 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. Importantly, conditional β-convergence means that the economies tend to different steady states, where the regional disparities will persist (Islam, 2003). In section 4, the strategy is to estimate Eq. (1) and (2) using Ordinary Least Squares (OLS) estimator 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:

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

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

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

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 ε 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, ρ and λ are the spatial autoregressive parameters; and β and ρ_x are $K \times 1$ vectors of coefficients. Note that, for the error process, there is a scalar λ and an $N \times 1$ vector of innovations u drawn from an *iid* distribution with variance σ^2.

The SARAR model nests the most common spatial econometric models employed in the empirical literature. LeSage and Fischer (2008) show that imposing different restrictions lead to different models: $\lambda = 0$ leads to the Spatial Durbin Model (SDM), $\lambda = 0$ and $\rho_x = 0$ leads to the Spatial Autoregressive (SAR) model and $\rho = 0$ and $\rho_x = 0$ leads to the Spatial Error Model

(SEM). If ρ and ρ_x are significantly different from zero, their omissions in a regression provides biased estimates of β and 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 yields unbiased estimates for the estimated parameters (β) 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, however, LeSage and Fischer (2008) argue that the SDM specification is a natural choice over competing alternatives because of two circumstances that are likely to arise in applied regional spatial growth regressions: the spatial dependence in the disturbances of an ordinary least squares (OLS) regression; and endogeneity in the form of an omitted explanatory variable (that follows a spatial autoregressive process) that exhibits non-zero covariance with the variables in the model. These plausible circumstances provide justification for the inclusion of spatial lags of both the dependent and explanatory variables.

4. Results and Discussion

In Section 4.1, the estimation of Equations (1) and (2) as well as diagnostics for spatial dependence are discussed. Next, spatial econometrics is used to correct for potential spatial dependence.

4.1. OLS model results and discussion

Table 4.1 presents the OLS estimates for spatial dependence in all geographic scales (NUTS1, NUTS2 and NUTS3). Column 1 shows the result of absolute β-convergence (Equation 1) for 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. The OLS estimates without country dummies suggest 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 and suggest that NUTS3 units are more open economies[10] than more aggregated regions. 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.

To assess formally the presence of spatial dependence we report the Spatial Lagrange Multiplier (LM) tests at the bottom of Table 1 to compare OLS models against the alternative

[10] 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.

SEM and SAR spatial models under the null hypothesis of no spatial dependence[11]. The LM test results for OLS regressions (without country dummies) indicate the presence of spatial dependence in the residuals in all three scales.

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
$lnGDP_{t-1}$	-0.016060***	0.003560	-0.016866***	0.003836	-0.020211***	-0.014849***
	(-2.858)	(0.476)	(-4.334)	(0.710)	(-8.299)	(-4.132)
Intercept	0.090606***	0.006961	0.093134***	0.005308	0.103315***	0.078382***
	(4.121)	(0.238)	(6.144)	(0.250)	(10.967)	(5.605)
Observations	74	74	213	213	1087	1087
R-squared	0.08943	0.6671	0.07738	0.5766	0.05882	0.2514
LM_{ERR}	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_{ERR}	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_{LAG}	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_{LAG}	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).[12] For the regressions with country dummies, only for the case of NUTS 3 (column 6) the LM tests suggest 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[13].

[11] See Anselin and Hudak (1992), Anselin et al. (1996) and Elhorst (2010) for a detailed discussion on these tests. 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. 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.

[12] This evidence is in line with the structural problems faced by Europe since the emergence of the 2008 financial crises.

[13] Another approach for convergence can be used by determining whether the cross-sectional dispersion of GDP per worker diminishes over time, i.e., the so-called σ (sigma)-convergence hypothesis. Table B.1 (in the Appendix B) shows that the σ-convergence suggest that GDP per worker are converging at NUTS1 level, however within each NUTS1 region, the GDP per worker at NUTS3 level is diverging between 2000 and 2008. As highlighted by Sala-i-Martin (1996), σ-convergence relates to whether or not the GDP per worker distribution across regions diminishes over time and β-convergence relates to the mobility of different individual regions within the given distribution of European GDP per worker. Recently, Rey and Dev (2006) and Egger and Pfaffermayr (2006) investigated σ-convergence in the presence of spatial effects and Table B1 indicates that the phenomenon of σ-convergence should also be examined across different geographic scales.

4.2. Spatial Durbin model results and discussion

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.

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	-0.0051585	-0.0044677	-0.0035499
	(-1.3605)	(-1.1255)	(-1.0707)	(-0.9497)
$W^* \ln GDP_{t-1}$	-0.0120680**	-0.0089344*	-0.0066570	-0.0042869
	(-2.1951)	(-1.7299)	(-1.3584)	(-0.9128)
ρ (SAR)	0.20131	0.44182***	0.58604***	0.7284***
	(4.4013)	(8.8484)	(10.499)	(12.805)
Intercept	0.0932129***	0.0685711***	0.0536704**	0.0375851***
	(8.2444)	(5.9215)	(4.3791)	(2.9728)
Observations	1087	1087	1087	1087
Log likelihood (LIK)	2715.009	2745.227	2761.615	2780.505
LR test	21.022	75.443	106.59	134.84
	(0.0000)	(0.0000)	(0.0000)	(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

The results in Table 4.2.1 show that the absolute convergence coefficient is negative but not 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.[14] Nevertheless, the autocorrelation coefficient (ρ) 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-

[14] 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.

convergence evidence cannot be rejected and the autocorrelation coefficient (ρ) now suggests that the growth rates of neighboring NUTS 3 regions affect a given region negatively[15]. One reason for the existence of negative externalities is given by Lall and Shalizi (2003, 679) 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*. Moreover, the spatial lag of GDP per worker at the start of the sampling period ($W^*\ln GDP_{t-1}$) is not statistically significant in Table 4.2.2.

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***	-0.0125972***	-0.0133785***	-0.0116872***
	(-2.8013)	(-2.6886)	(-3.0570)	(-2.7681)
$W^*\ln GDP_{t-1}$	-0.0074162	-0.00910826	-0.00951595	-0.01473259
	(-1.1507)	(-1.2869)	(-1.2524)	(-1.6040)
ρ (SAR)	-0.39479***	-0.23687***	-0.24148**	-0.015185
	(-7.1159)	(-2.9925)	(-2.1069)	(-0.10491)
Intercept	0.11009***	0.11009695***	0.11485962***	0.12399750***
	(5.9364)	(5.0729)	(4.4991)	(3.7623)
Observations	1087	1087	1087	1087
Log likelihood (LIK)	2855.859	2836.534	2834.27	2833.915
LR test	48.311	9.0693	4.8631	0.010391
	(0.00000)	(0.0025994)	(0.027437)	(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

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). 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 C, 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 when

[15] It is important to note that the autocorrelation coefficient (ρ) (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 (ρ) becomes statistically insignificant.

we correct for spatial dependence (see Tables C.1 and C.2 in the Appendix C). These results reinforce the suggestions drawn from the OLS method shown in section 4.1 that convergence is more likely to occur within countries[16].

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 European Union (EU) economic growth studies. 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 in occurring at finer scales (NUTS3) within countries.

The LM tests are used to assess the existence of spatial dependence in the OLS estimations. When necessary, Spatial Durbin Model regressions are used to control for spatial dependence and 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 have grown faster within each EU15 member state; and (ii) there is no indication of spatial dependence in the estimations for NUTS 1 e 2 and no b-convergence (absolute and conditional).

The aim of the paper is to illustrate the serious implications of MAUP for regional applied research. Studies designing 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.

[16] The LM tests in Table 4.1 suggest the need to control for spatial dependence at NUTS 1 and 2 only in the regressions without country fixed effect, the inclusion of country dummies changes the results and indicate that spatial dependence is related to country specific characteristics. The regressions that include spatial correction (Tables C1 and C2) are presented and do not indicate convergence.

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Appendix A

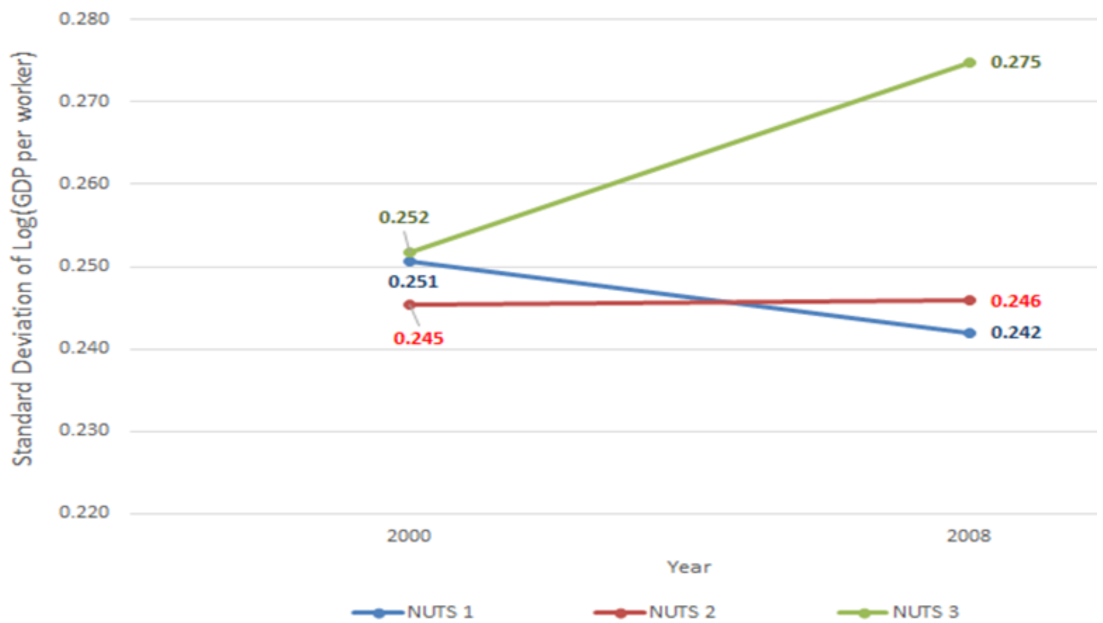
Table A.1 - Sample of studies on convergence in the European Union

Paper	Scale level	Period	Convergence type	Spatial effects
Barro and Sala-i-Martin (1991)	73 EU NUTS 1,2*	1950-1985	Conditional β-convergence	No
Armstrong (1995)	85 EU NUTS 1,2*	1950-1990	Conditional β-convergence	No
Fingleton (1999)	178 EU NUTS 2	1975-1995	(weak) Conditional β-convergence	Yes
Vayá and Moreno (2002)	108 EU NUTS 1,2*	1975-1992	Absolute β-convergence	Yes
López-Bazo et al. (2004)	108 EU NUTS 1,2*	1975-1992	Conditional β-convergence	Yes
Ertur et al. (2006)	138 EU NUTS 1,2*	1980-1995	Conditional β-convergence for southern regions; no convergence for northern regions	Yes
Frenken and Hoekman (2006)	1088 EU NUTS 3	1995-2002	Conditional β-convergence	No
Piras and Arbia (2007)	125 EU NUTS 2	1977-2002	Conditional β-convergence	Yes
Ramajo et al. (2008)	163 EU NUTS 1,2*	1981-1996	Conditional β-convergence (club convergence)	Yes
Dall'erba and Le Gallo (2008)	145 EU NUTS 1,2*	1989-1999	Conditional β-convergence	Yes
Elhorst et al. (2010)	193 EU NUTS-2	1977-2002	Conditional β-convergence	Yes
Sardadvar (2012)	255 EU NUTS-2	1995-2004	Conditional β-convergence	Yes

Note: Own elaboration. *The "NUTS 1,2" level means that the dataset includes a combination of NUTS1 and NUTS2 regions in order to define a single spatial scale of analysis.

Appendix B

Table B.1 – σ (sigma) - convergence at different spatial scales in the EU (NUTS1, NUTS 2 and NUTS 3)



Note: Own elaboration.

Appendix C

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

	SDM (1)	SDM (2)	SDM (3)	SDM (4)
$\ln GDP_{t-1}$	0.0066300	-0.0019606	0.0025030	-0.0046950
	(1.0283)	(-0.3002)	(0.3580)	(-0.8251)
W* $\ln GDP_{t-1}$	-0.0175156**	-0.0135738	-0.0576136***	-0.2739875***
	(-2.1185)	(-1.1693)	(-2.8888)	(-5.4937)
ρ (SAR)	0.67471***	0.75687***	0.82087***	-3.4327***
	(7.0952)	(7.334)	(8.4087)	(-2.9365)
Intercept	0.0524406**	0.0690245**	0.2256152***	1.2299822***
	(2.2569)	(2.0347)	(3.5808)	(5.7578)
Observations	74	74	74	74
Log likelihood (LIK)	240.2385	236.1978	231.8938	235.5297
R-squared				
LR test	29.174	24.964	10.711	8.5634
	(0.0000)	(0.0000)	(0.0010)	(0.0034)
LR COMFAC	4.7713	3.1074	11.3418	19.8791
	(0.02894)	(0.07794)	(0.00075)	(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 C.2 - SDM Cross-Section (Without Country Dummies) – NUTS 2

	SDM (1)	SDM (2)	SDM (3)	SDM (4)
lnGDPt-1	0.0134281	0.0119799	0.0097372	0.0047598
	(2.4080)	(2.3241)	(1.9134)	(0.9722)
W* lnGDPt-1	-0.0241727***	-0.0193412**	-0.0214680**	-0.0329378**
	(-3.8550)	(-3.2242)	(-2.9305)	(-3.1489)
ρ (SAR)	0.60946***	0.72696***	0.80873***	0.92669***
	(9.3336)	(10.819)	(11.972)	(23.249)
Intercept	0.0528484***	0.0366000	0.0520221*	0.1145932***
	(3.4086)	(2.4361)	(2.7098)	(3.8409)
Observations	213	213	213	213
Log likelihood (LIK)	654.5386	662.5685	659.0688	648.7495
LR test	67.726	79.683	75.766	62.801
	(0,0000)	(0.0000)	(0.0000)	(0.0000)
LR COMFAC	15.0416	6.5183	7.5028	14.1757
	(0.0001052)	(0.01068)	(0.00616)	(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.