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SECTORAL PRODUCTIVITY, CONVERGENCE AND SPACE BETWEEN EUROPEAN REGIONS

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Abstract: *The aim of our analysis is the evaluation of the total and sectoral convergence of labour productivity between 896 NUTS-3 regions of EU-12 over the period 1980-2010. We adopt a β- and σ-convergence approach along with a methodology based on Getis' spatial filters that allows decomposing the variables into their spatial and a-spatial components ensuring their spatial independence. This guarantees reliable regression results and unbiased variance estimation. The estimates highlight a process σ- and β-convergence of regional economies in which spatial interrelations among regions play an important role.*

JEL classification: C14, O52, R11, R15

Key words: Spatial econometrics, convergence, sectoral labour productivity

1. INTRODUCTION

In the EU Treaty, adopted in 1986, we can read: "*In order to promote its overall harmonious development, the Community shall develop and pursue its actions leading to the strengthening of its economic and social cohesion. In particular, the Community shall aim at reducing disparities between the levels of development of the various regions and the backwardness of the least favoured regions or islands, including rural areas*" (Art. 158). Economic and social cohesion, therefore, is recognized as one of the three main pillars of European integration, alongside economic and monetary union and the single market.

Since the beginning of the Cohesion Policy, its main objective has been the economic convergence of European regions. This explains, at least partially, why, over the past two decades, we observed a revival of interest in the topic of economic growth, which has been marked by new approaches (endogenous growth theory) and by a great emphasis on empirical analysis. In these studies, two major focuses emerged. The first was the evaluation of the impact of factors such as human capital, economic policies and infrastructure in explaining differences in economic growth. The second regards the issue of convergence, that is, a real and significant trend to the alignment of economic conditions between rich and poor European economies in the long term.

Accordingly, most of the studies carried on by scholars and the EU Commission focus on regional disparities utilising the GDP per capita. Nevertheless, in our study, we utilise the Gross Valued Added (GVA) per worker, i.e. productivity, instead of GDP per capita. This choice depends on some reasons. The first lies on the fact that productivity is the engine of the sustainable development of a country (see Krugman, 1992); the second motivation consists in the possibility to disaggregate productivity at sectoral level, making makes possible to assess the contribution of each sector to the convergence of total productivity.

Few authors adopted a disaggregated approach at the sectoral level for evaluating European convergence process. We remember Paci (1997), Paci and Pigliaru (1999a, 1999b) and Le Gallo and Dall'erba (2008) for the EU regions; Cuadrado-Roura et al. (1999) and Dall'erba (2005) for the Spanish regions; Paci and Pigliaru (1997) and Di Giacinto and Nuzzo (2006) for the Italian ones; Vagionis and Spence (1994) and Carluer and Gaulier (2005) for the Greek and French regions, respectively. These authors agree that the changes in the structure of the regional economies are the main determinants of the process of aggregate productivity convergence. In this context, convergence at the sectoral level plays only a marginal role.

In measuring the convergence process, we analyse both σ and β-convergence for total productivity and for five selected sectors: agriculture, manufactory, constructions, market services and non-market services.

The choice to use both σ and β-convergence is related to the belief that there is no convergence measure capable of capturing all relevant aspects of a convergence process. Consequently, we include two measures able to catch both the evolution of the dispersion and the catching-up process of productivity. In addition, we filter the variables according with Getis' (1995) technique in order to avoid problems related to spatial dependence in the estimates. Spatial autocorrelation and heterogeneity, indeed, influence the bias of the sample variance as an indicator of σ-convergence (Rey and Dev, 2006) and spatially autocorrelation in the residuals of OLS-growth regression yields to a bias of regression coefficients or an invalidation of significance tests (Anselin, 1988; Fingleton, 1999 and Cliff and Ord, 1973).

The paper is organized as follows: in section 2 we present the convergence estimation techniques, the problems related with spatial dependence and the spatial filtering technique, in section 3 we estimate empirically σ and β-convergence according to the methods proposed in previous section. Finally we present some conclusions.

2. CONVERGENCE ESTIMATION AND SPATIAL FILTERING APPROACH

To estimate the convergence process on labour productivity, we refer to a cross-country growth regression model, also defined β-convergence model (Barro and Sala-i-Martin, 1992) and to σ-convergence model (Sala-i-Martin, 1996).

According to the concept of β-convergence, economies with lower values of initial productivity grow faster than the ones with higher values (less developed would catch-up more advanced). This implies a negative correlation between growth rates of productivity and the initial levels of this variable. The standard cross-section regressions model is defined as:

$$\frac{y_{i,T} - y_{i,T-t}}{t} = \beta y_{i,T-t} + x_i^{'}\gamma + \varepsilon_{iT} \tag{1}$$

where $i = 1, \ldots, n$ represents the number of regions (896) and $t = 1, \ldots, T$ the time. β is the well-known β-convergence parameter (that should be negative and significant), $x_i^{'}$ the vector of time invariant explanatory variables (e.g. regional dummies) and ε_{iT} the i.i.d. normally distributed error term.

Three cases are usually considered in the literature: first, the hypothesis of *absolute* β-convergence relies on the idea that if all economies are structurally identical and have access to the same technology, they are characterised by the same steady state, and differ only by their initial conditions. Second, convergence *clubs* refers to groups of economies that have similar structural characteristics and tend to reach a common steady state. Third, *conditional* convergence foresees that each economy approaches its own (unique and globally stable) steady state.

As shown by Mankiw (1985) and Quah (1996), a weakness of β-convergence model is to consider the economies as “isolated islands”, neglecting their mutual interdependence. In the European context this assumption is very strong and leads to various problems related to the presence of spatial autocorrelation in the residuals. The problems, summarized by Fingleton and López-Bazo (2006) and López-Bazo et al. (2004), are related mainly to unreliable results. In the case of β-convergence, a large literature on estimating spatial effects together with growth regression has taken place. The most common methodologies used are the spatial lag and spatial error models (Anselin, 1988; Anselin and Bera, 1998), but, to the extent that the spatially correlated errors mask an omitted variable problem, the consequences can be an incorrectly specified regression model. To avoid this, according with Getis and Griffith (2002), when spatial filtration (explained in detail below) is considered in combination with OLS technique, although georeferenced data are used, residuals are demonstrated to be not spatially autocorrelated.

The concept of σ-convergence focuses on how the level of cross-sectional dispersion, measured as the sample variance, changes over time. Formally the logarithm of productivity for an economy i in period t is denoted by y_{it}, and the sample variance for period t can be defined as:

$$s_t^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(y_{it} + \bar{y}_{it}\right)^2 \tag{2}$$

where $\bar{y}_{it}$ is the sample average over period t. As we will see below, we can set the condition $\sigma_t^2 = s_t^2$ if there are no spatial effects (θ = 1). There is σ-convergence over the study period between the n economies if the sample variance declines over time, while increasing values indicate divergence in the cross-sectional distribution. Sigma-convergence can therefore be considered as a form of inequality reduction.

β-convergence is a necessary but not a sufficient condition for σ-convergence (Sala-i-Martin, 1996). Therefore absence of σ-convergence can co-exist with β-convergence.

In order to formally verify the existence of σ-convergence, we adopt the approach of Eggert and Pfaffermayer (2009) that propose a simple Wald test for conditional and unconditional σ-convergence. They start with the estimation of the β-convergence OLS regression as in equation (1) where they define $\pi_T=1+t\beta$ and $\bar{\pi}_T^2 = 1 - \frac{\sigma_{uT}^2}{\sigma_{y,T-t}^2}$. Thus, they formally test

$$H_0 = \pi_T^2 = \bar{\pi}_T^2 \text{ vs. } H_1 = \pi_T^2 < \bar{\pi}_T^2$$

that is equivalent to

$$H_0 = \sigma_{yT}^2 = \sigma_{yT-t}^2 \text{ vs. } H_1 = \sigma_{yT}^2 < \sigma_{yT-t}^2$$

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The Wald statistics test for conditional convergence becomes:

$$\hat{W}_2 = \frac{n\left(\hat{\sigma}^2_{y,T-t}\hat{\Delta}_T\right)^2}{2\hat{\sigma}^4_{y,T-t}\left(2n\hat{\pi}^2_T\hat{\sigma}^2_{\pi_T} + \left(\hat{\pi}^2_T - 1\right)^2\right) + 2\hat{\sigma}^4_{uT}} \tag{3}$$

where $\hat{\Delta}_T = \hat{\pi}^2_T - 1 - \frac{\sigma^2_{uT}}{\sigma^2_{y,T-t}}$.

With unconditional convergence, under the assumption $n\hat{\sigma}^2_{\pi_T} = \frac{\sigma^2_{uT}}{\sigma^2_{y,T-t}}$, we have:

$$\hat{W}_0 = \frac{n\left(\hat{\sigma}^2_{y,T-t}\hat{\Delta}_T\right)^2}{2\hat{\sigma}^2_{y,T-t}\left(2\hat{\sigma}^2_{uT}\hat{\pi}^2_T + \hat{\sigma}^2_{y,T-t}\left(\hat{\pi}^2_T - 1\right)^2\right) + 2\hat{\sigma}^2_{uT}} \tag{4}$$

The test statistic is distributed as $\chi^2(1)$. The estimate $\hat{\pi}_T$ is based on the corresponding OLS regression (1): $\hat{\pi}_T = 1 + t\hat{\beta}$, while $\hat{\sigma}^2_{\pi T}$ on its estimated variance: $\hat{\sigma}^2_{\pi t} = t^2\hat{\sigma}^2_{\beta}$. Furthermore we have $\hat{y}_{iT} = y_{i,T-t} + \left(y_{i,T} - y_{i,T-t}\right)/t$ and $\mu_1 = \varepsilon_{i1} - y_{i,T}$. Finally, we have to define: $\hat{\sigma}^2_{y,T-t} = \frac{1}{N}\sum_{i=1}^{N}\left(y_{i,T-t} - x_i^{'}\hat{\gamma}_{T-t} - \hat{\pi}_{T-t}\mu_1\right)^2$ and $\hat{\sigma}^2_{uT} = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{y}_{i,T} - \left(1 + t\hat{\beta}\right)y_{i,T-t} - x_i^{'}\hat{\gamma}_T\right)^2$.

The analysis of the σ-convergence, with few exceptions[1], has been carried out by scholars treating the variables as spatially independent. Nevertheless, as demonstrated by Rey and Dev (2006), this does not hold when regional data are used. Indeed, variance is unbiased only if mean and variance homogeneity hold (i.e. no spatial heterogeneity) and if all covariances are zero (i.e. no spatial autocorrelation).

Formally, in order to investigate the bias in the sample variance due to the presence of spatial effects, we assume that the observations on regional labour productivity are a collection of observations such as: $y \sim N(\mu,\sigma^2\Omega)$ where Ω is a general n-by-n matrix and σ^2 is the global dispersion parameter. The sample variance is then decomposed as follows, omitting the time subscript:

$$s^2 = \sigma^2\theta \text{ with } \theta = \frac{1}{n-1}\left(\sum_{i=1}^{n}\left(\mu_i^2 + \omega_i\right) - \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n}\left(\mu_i\mu_j + \omega_{i,j}\right)\right) \tag{5}$$

[1] According to our knowledge, in addition to Rey and Dev (2006), only Le Gallo and Dall'erba (2008) faced the issue of spatial filtered σ-convergence.

where s^2 is the sample variance, σ^2 captures the influence of a-spatial dispersion on s^2; θ reflects the combined effects of any spatial heterogeneity and dependence on s^2; μ_i is the i^{th} element of μ and ω_{ij} is element (i, j) of matrix Ω.

As noted by Rey and Dev (2006), this decomposition can be performed using a spatial filtering process, as suggested by Getis (1995) or Tiefelsdorf and Griffith (2007), or by fully specifying the structure of θ and then directly estimating all the parameters. Instead of choosing the second alternative as in Rey and Dev (2006) and in Le Gallo and Dall'erba (2008), we chose the first one and in particular the spatial filtering approach suggested by Getis (1995). The reason of this choice lies in the extremely flexibility of this technique since it is able to transform the spatial dependent and independent variables into independent removing the spatial dependence component embedded in them. This allows to use a set of different statistical tools that require this precondition for achieving reliable results. These tools, in case of analysis of the regional economic development, are essentially stochastic kernel (Fischer and Stupner, 2008) and the mentioned variance (σ-convergence) and regression analysis (essentially β-convergence).

According to Getis' spatial filtering technique, the original variable, X, can be decomposed into two parts: a filtered non-spatial component, say X^*, and a spatial residual, L_X.

The estimation of the spatial and non-spatial component of each variable follows the steps reported below.

The first crucial point regards the definition of the area of influence of each variable. This implies to find a reasonable distance[2] for which spatial autocorrelation should be sufficiently strong. To solve this issue, we firstly define the global autocorrelation measure G defined by Getis and Ord (1992):

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij} x_i x_j}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j} \tag{6}$$

where W_{ij} is a n-by-n spatial weight matrix in which the element w_{ij} is equal to 1 if the region i is a neighbour of region j and 0 otherwise,[3] and x_i and x_j are, respectively, the value of observation i and j. The strategy consists in an iterative process in which we add a new degree

[2] There are many definitions of distance. Among the others, we have Euclidean distance, distance measured as the time to reach a destination, etc. In our study we considered the nearest neighbors.
[3] By convention the diagonal of W_{ij} is set equal to zero, i.e. a region is not a neighbor of itself.

of neighbourhood to matrix W_{ij} until the marginal difference between the statistic G computed with the new matrix W_{ij} and the one computed with the previous becomes negligible.[4]

Once the distance spatially weight matrix is created, we have to compute the local statistic G_i for each variable:

$$G_i = \frac{\sum_{j=1}^{n} W_{ij} x_j}{\sum_{j=1}^{n} x_j} \qquad \text{for } j \neq i \tag{7}$$

where the numerator is the sum of all neighbours x_j but it does not include x_i and the denominator is the sum of all x_j excluding x_i.

Then, the variable can be filtered according with:

$$x_i^* = \frac{x_i \left[\frac{1}{n-1} W_{ij} \right]}{G_i} \tag{8}$$

In equation (8) the observed values of G_i are compared with their expected values, $(n-1)^{-1} W_{ij}$ where $E[G_i]$ represents the realization X^* of the variable X at region i when no autocorrelation occurs.

Three cases are possible:

- if there is no autocorrelation between i and its neighbours, then the observed and expected values, x, and x^*, will be the same;
- if G_i is high relative to its expectation, the difference $x_i - x_i^*$ will be positive, indicating spatial autocorrelation among observations of X with high values;
- if G_i is low relative to its expectation, the difference $x_i - x_i^*$ will be negative, specifying spatial autocorrelation among observations of X with low values.

Thus:

$L_x = X - X^*$ represents a spatial variable associated, but not correlated, with the variable X.

According to Le Gallo and Dall'erba (2008), G_i statistics allows us also to determine the spatial regimes to which regions belong. These regimes can be interpreted as spatial

[4] Getis (1995) proposes to define the spatial weight matrix according to the results of the local statistic G_i but this is a very computationally intensive methodology because we work with a large number of regions.

convergence clubs and are defined as follows: if the statistic for region *i* is positive, then this region belongs to the group of "high labour productivity" regions, or "core" and if the statistic for region *i* is negative, then this region is part of the group of "low productivity" regions, or "periphery" [5].

3. REGIONAL PRODUCTIVITY, CONVERGENCE AND SPACE

In this paragraph we follow the procedure described above to estimate filtered and unfiltered σ and β-productivity convergence of 896 NUTS-3 regions of EU-12[6] from 1980 to 2010.

We define a nearest neighbour spatial weight matrix with a number of neighbours equal to 6 regions. This approach guarantees that there are no regions without neighbours and the results obtained are robust with respect to other definitions of contiguity.

According to figure 1 in which we observe the first thirty marginal values of $G_i(d)$, we consider the sixth neighbour as a cut-off.

The spatial regimes identified by G_i for total productivity are characterized by a strong spatial pattern (figure 2). In south-east Germany, west France, Italy, Spain, Portugal, Greece and Great Britain we observe a cluster of regions with spatial autocorrelation among low observations of X, i.e. the "periphery" with low productivity regions while the rest of regions exhibit a spatial autocorrelation among high observations of X, which corresponds to the "core" with high productivity regions.[7] The case of Great Britain, which belongs almost entirely to low productivity club, can find an explication in the lack of investment in equipment, infrastructure, technology and skills reported by the British Department of Trade and Industry (1997).

The σ-convergence for total labour productivity, computed both with "standard" and spatial filtering technique is in figure 3. The standard σ-convergence pattern (solid line) computed with equation (1) shows a tendency to convergence until 1993, a stabilization in the nineties and then a clear divergence after the 2003. When the variable is spatially filtered (dotted line),

[5] The same convergence clubs can be archived as follows: if the difference x_i - x_i* for region *i* is positive, then this region belongs to the group of "high labour productivity" regions, or "core" while if the difference for region *i* is negative, this region falls in the group of "low productivity" regions, or "periphery".

[6] We exclude ex-DDR because of the absence of data from 1980 to 1991. The data on labour productivity come from the Cambridge Econometrics (2012) database.

[7] The core area corresponds to the "Blue Banana", often identified as the area that traditionally has shown the greatest development potential in Europe (RECLUS, 1989; Delamaide, 1994).

we observe that the variance is lower and smoothed for the whole period. The graphical path shows a decreasing until 1991, a stabilization until the 2007 and then a divergence.

The motivation of the different path of σ-convergence between spatially filtered and unfiltered variable lies in the existence or co-existence of spatial heterogeneity and dependence, which would need a much deeper analysis on the territorial pattern of the variable.

In figure 4 we reported the spatial distribution of the quintiles of the total labour productivity in 1980, of the spatial component (L), and of the spatial filtered component (g^*). The total labour productivity in 1980 and its spatial component (L) show a clear spatial pattern, while in the spatial filtered component homogeneous clusters are not observable: removing the residual spatial component, the spatial distribution of the variables result completely random. This is also confirmed by *Moran's I tests*: while in the first and second case we can reject the null hypothesis of no spatial autocorrelation, in the last one we have to accept the null.[8]

Figure 5 shows the evolution of filtered and unfiltered σ-convergence by sector. In all the cases a strong decreasing of variability has been observed in the first half of the eighties, followed by a stabilization and then by a divergence in the last five years. The sectoral patterns are very different: the higher variability is observed in agriculture and manufactory and the lower for the remaining sectors: market and non-market services and constructions. Looking at the differences between the spatially filtered and a-spatial σ-convergence, we observe that agriculture and manufactory, until the early nineties, are characterized by a strong spatial effect that affect total variance decreasing its value. This evidence disappears over the time showing a diminution of the spatial effects.

Spatial effects are present in the early eighties for market and non-market services but, after these first years, the spatial filtered σ-convergence is below the a-spatial probably because of a process of concentration in space. At this regard, it is interesting to observe that this phenomenon seems to be present also for constructions but the variance is very small and then the differences upon the volatility of filtered and unfiltered variables are negligible. Finally, in the last three years considered divergence of constructions is stronger than in the other sectors.

[8] The Moran's I test for the total labour productivity in 1980 is 0.6561 (p-value < 0.000), for its spatial component (L) is 0.9632 (p-value < 0.000) and for the spatial filtered labour productivity (g*) is -0.1439 (p-value = 1).

The first approximation of the dynamics of the σ-convergence has been derived using graphical tools, but, as well as for the β-convergence, we needs a formal test to detect convergence or divergence.

In table 1 we test β- and σ-convergence according to different territorial partitions for both total and sectoral productivity. We considered the five cases: the whole sample (EU-12) without dummies, with country dummies and with spatial regime dummies; finally we take into account singularly each spatial regime, the "core" and the "periphery". Table 2 replicates table 1 but with spatially filtered variables.

The first important result to be mentioned is that β-convergence occurs for both total productivity and for all sectors. When filtered variables are considered, the country dummies become statistically not significant. This occurs because, in the case of spatially filtered variables, the spatial component embedded in each variable, and strictly connected with the country or convergence club to which the variable belongs, is removed. When variables are unfiltered, country dummies become significant because they act like a "spatial filter" characterising the regions not necessarily according to specific economic characteristics, but according with the country or regime to which they belong. The interesting point, however, is the lack of significance of dummies for the spatial regimes. This finding, valid only for the unfiltered variables and for all the sectors, is rather surprising because the identified spatial regimes are interpretable (and often interpreted) like convergence clubs (Le Gallo and Dall'erba, 2008). Furthermore, no appreciable differences between the convergence rates of the two spatial regimes are observed. The comparison of table 1 with table 2 shows that the convergence rates are lower in the case of unfiltered variables. The adjusted R-squared are higher in table 2 and both Moran's I test and robust version of Lagrange Multiplier test, not reported but available upon request, show strong spatial autocorrelation in the residuals of the a-spatial regressions (table 1) and no correlation in the residuals of the regressions with filtered variables (table 2). This confirms the superiority of the estimates performed with spatially filtered variables with respect to the standard ones.

Considering the tests for σ-convergence we observe that in all cases the Wald tests check that σ-convergence values for 2010 are statistically different than those of 1980. Regarding the comparison between table 1 and 2, we cannot observe important differences between filtered and unfiltered estimations.

CONCLUSIONS

In our study we estimate classical and spatially filtered β and σ-convergence of total and sectoral productivity of European regional economies. Under a methodological point of view, the decomposition of the variables into their spatial and a-spatial components, along with ensuring independence among the observations, allows estimating the β and σ-convergence without the problems related to spatial dependence and heterogeneity. Hence, the use of a technique able to deal with the spatial component embedded in each variable adds the possibility to link the growth process to the spatial dynamics, deepening the comprehension of the latter and their impact on the evolution of productivity.

In the case of σ-convergence the conventional approach shows higher variance than the spatial approach both for total productivity and market, non-market and constructions sectors.

For agriculture and manufactory, spatial effects have a role in the initial years making that the levels of unfiltered variance was lower than the filtered and then the two measures tend to be comparable.

The variance estimated with the two methodologies differ for each sector and each year, but it does not lead to contradictory conclusions. Both approaches agree in displaying an initial σ-convergence of aggregate total labour productivity, a stabilization period and then a divergence from 2006 onwards.

The analysis of the β-convergence allows observing that country and regime dummies account for spatial dependence only if spatial dependence is not removed from the variables, otherwise they are not significant. This result, accounting also for the values of the estimated convergence speeds of the spatially filtered variables by club, lets us to think that core and peripheral regions do not converge to their own steady-state. It looks like that the convergence process is also a function of the complex interrelation between regions, and that it cannot be accounted simply defining a country border of club effect. Under the methodological aspect, the spatial filtering technique, which allows obtaining more reliable results, needs a further analysis of economic meaning of the spatial connections among regions, looking in particular at the role of spatial heterogeneity and dependence. This is left to further investigation in the future. Convergence speed varies by sector: looking at the regressions of spatially filtered variables, where spatial autocorrelation in the residuals is absent, we see that the sectors with higher convergence are constructions, market and non-market services, followed by manufactory and agriculture.

The phenomena described above, find at least two explanations in literature. According with Cuadrado-Roura et al. (1999) and Le Gallo and Dall'erba (2008), the process of aggregate productivity convergence might be due to a change in the structure of the regional economies due to the reallocation of employment from agriculture to industry and services rather than to a convergence process at the sectoral level. This result is confirmed by Gutierrez (1999) who finds that off-farm migration has a positive effect on the speed of convergence. The analysis of Paci (1997) considers a different point of view. He observes that, especially in southern regions, the reduction in the number of employees in agriculture does not correspond to an increase of employees in industry and services. This explains some evidence, that is, i) the increase of the unemployment rate and the decrease in labour participation, ii) the increasing productivity of services and manufactory sectors in lagging regions with the consequent decreasing of total variance, and iii) the β-convergence process taking place within sectors and for the overall productivity.

Our results are more in line with the findings of Paci (1997) and denote a process of alignment of productivity levels of the regional economies at the cost of diminishing employment opportunities in the poorer regions and in low productive sectors (European Commission, 2007).[9] In addition, European Commission (2007) observes that, from 2000, not only agriculture, but also manufactory sector lost employment in favour of services. "This, however, was not sufficient to offset job losses in the other sectors, partly reflecting the relatively small size of the service sector in these [lagging] regions but more importantly the scale of productivity increases in a context of relatively high output growth" (European Commission, 2007: 35). To these evidences we have to add that both the market and non-market services are characterised by spatial heterogeneity, that is a concentration of higher productivity services in some areas that often correspond to main cities (DG Regio, 2007). This opens (at least) another problem, namely the interregional migration that leaves poorer

[9] In European Commission (2007: 34) we can read: "The depressing effects of low productivity in the different sectors combined with the unfavourable structure of the economy, however, is not the only reason for GDP per head in the lagging regions being below that elsewhere in the EU. Low employment is also a major contributory factor. In the regions with GDP per head below 50% of the EU average, the lower proportion of the population in employment as compared with other regions reduced GDP per head in 2003 by almost 22% given the level of productivity."

regions without high-skilled employees that move to regions which guarantee higher employment probabilities and expected wages.

To conclude, this analysis demonstrates that the regional growth process is multifaceted and needs to be considered from different points of view and with various tools. We note that β- and σ-convergence patterns tend to coincide but, despite the strong convergence of all sectors, the inequality levels are growing in the last years. In addition to this, the issue of unemployment together with the shift of employment to less productive sectors in less developed areas, as highlighted by the European Commission, and the excessive polarization is a real problem that risks undermining not only the growth potential of lagging regions, but also the entire Community construction. Indeed, it seems that integration between the European economies is leading to similar productivity structure at the price of less opportunities for the populations of poorer regions. At this regard, more must to be done by European Union and national government in order to make effectiveness the still actual Article 158 of the EU Treaty.

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REFERENCES

1. Anselin L. (1988). *Spatial Econometrics. Methods and Models*. Dordrecht, Boston, London: Kluwer Academic Publisher.
2. Anselin L. (2009). Spatial regressions. In P. Fotheringham & P. Rogerson (eds.), *La SAGE Handbook of Spatial Statistics*. 255-275.
3. Anselin L. & Bera, A.K. (1998). Spatial dependence in linear regression models with an introduction to spatial econometrics. In A. Ullah & D.E.A. Giles (eds.), *Handbook of Applied Economic Statistics*. New York et al.: Dekker, 237-289.
4. Barro, R.T. & Sala-i-Martin, X. (1992). Convergence, *Journal of Political Economy*, 100(2) 223-251.
5. British Department of Trade and Industry (1997). Competitiveness UK: A benchmark for business Cambridge Econometrics (2008) European Regional Databank.

6. Carluer, F. & Gaulier, G., (2005). The impact of convergence in the industrial mix on regional comparative growth: Empirical evidence from the French case. *Annals of Regional Science*, 39: 85-104.
7. Cliff A.D. & Ord J.K. (1973). *Spatial Autocorrelation*, London: Pion.
8. Cuadrado-Roura J.R., Garcia-Greciano B. & Raymond J.L., (1999). Regional convergence in productivity and productive structure: The Spanish case. *International Regional Science Review*, 22: 35-53.
9. Dall'erba, S. (2005). Productivity convergence and spatial dependence among Spanish regions. *Journal of Geographical Systems*, 7: 207-227.
10. Delamaide, D. (1994). *The new superregions of Europe*. Dutton, New York.
11. DG Regio (2007). *Changing regions - Structural changes in the EU Regions*, Preparatory studies for the fourth cohesion report, Luxembourg.
12. Di Giacinto, V., Nuzzo, G. (2006). Explaining labour productivity differentials across Italian regions: The role of socioeconomic structure and factor endowments. *Papers in Regional Science*, 85: 299-320.
13. Egger, P., Pfaffermayr, M. (2009). On testing conditional sigma-convergence. *Oxford Bullettin of Economics and Statistics*, 71(4): 453-473.
14. European Commission (2007). Growing regions, growing Europe, Fourth report on economic and social cohesion, Commission of the European Communities, Luxembourg.
15. Fingleton, B. (1999). Economic Geography with Spatial Econometrics. A 'Third Way' to Analyse Economic Development and 'Equilibrium' with Application to the EU Regions. *Working Paper ECO*, 99/21, Department of Economics, European University Institute, San Domenico.
16. Fingleton, D., López-Bazo, E. (2006). Empirical growth models with spatial effects. *Papers in Regional Science*, 85, 177-198.
17. Fischer, M. & Stumpner, S. (2008). Income distribution dynamics and cross-region convergence in Europe. *Journal of Geographical Systems*, 10: 109-139.
18. Getis, A. (1995). Spatial Filtering in Regression Framework: Experiments on Regional Inequality, Governmen Expediture and Urban Crime. In L. Anselin & R.J. Florax, *New Directions in Spatial Econometrics*. 172-188, Berlin, Springer.

19. Getis, A. & Griffith, D.A. (2002). Comparative spatial filtering in regression analysis. *Geographical Analysis*, 34(2): 130-140.
20. Getis, A. & Ord, J.K. (1992). The analysis of spatial association by use of distance statistics, *Geographical Analysis*, 24: 189-206.
21. Gutierrez, L. (2000). Convergence in US and EU agriculture. *European Review of Agricultural Economics*, 27(2): 187-206.
22. Krugman, P. (1992). *The age of diminished expectations: US economic policy in the 1980s*. MIT Press.
23. Le Gallo, G. & Dall'erba, S. (2008). Spatial and sectoral productivity convergence between European regions: 1975-2000. *Papers in Regional Science*, 87(4): 505-524.
24. López-Bazo, E., Vayà E., Mora A.J. & Suriñch J. (2004). Regional Externalities and Growth: Evidence from European Regions. *Journal of Regional Science*, 44, 43-73.
25. Mankiw, G.N. (1985). The growth of nations. *Brookings Papers on Economic Activity*, 1, 276-326.
26. Paci, R. (1997). More similar and less equal: economic growth in the European regions. *Weltwirtschaftliches Archiv*, 133, 609-634.
27. Paci, R., Pigliaru, F. (1997). Structural change and convergence: An Italian regional perspective. *Structural Change and Economic Dynamics*, 8: 297-318.
28. Paci, R., Pigliaru F. (1999a). European regional growth: Do sectors matter?. In J. Adams, F. Pigliaru (eds.), *Economic growth and change. National and regional patterns of convergence and divergence*. Edward Elgar, Cheltenham.
29. Paci, R. & Pigliaru, F. (1999b). Is dualism still a source of convergence in Europe?. *Applied Economics*, 31: 1423-1436.
30. RECLUS (1989). Les villes europeénnes: Rapport pour la DATAR. RECLUS, Montpellier.
31. Rey, S.J. & Dev, B. (2006). σ-convergence in the presence of spatial effects. *Papers in Regional Science*, 85: 217-234.
32. Quah, D. (1996), Regional convergence clusters in Europe, *European Economic Review*, 40, 3-5, 951-958.
33. Sala-i-Martin, X. (1996). Regional cohesion: Evidence and theories of regional growth and convergence. *European Economic Review*, 40, 1325-1352.

34. Tiefelsdorf, M. & Griffith, D.A. (2007). Semi-parametric filtering of spatial autocorrelation: The eigenvalue approach. *Environment and Planning A*, 39: 1193-1221.
35. Vagionis, N. & Spence, N. (1994). Total factor regional productivity in Greece. *Environment and Planning C*, 12: 383-40

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Figure 1 - Marginal G_i*(d)* for total labour productivity

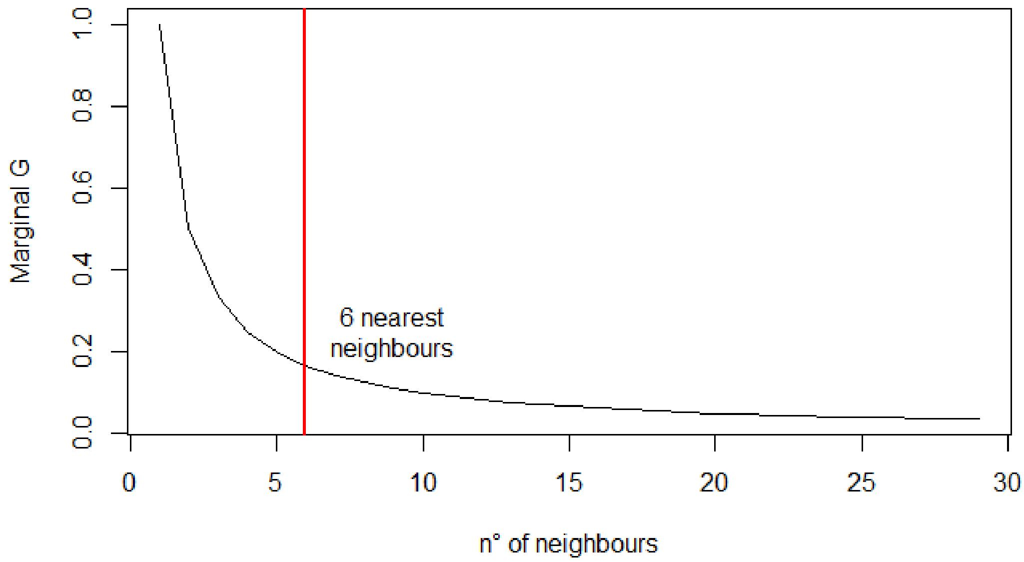

Figure 2 - Spatial regimes according with $G_i(d)$ for total labour productivity

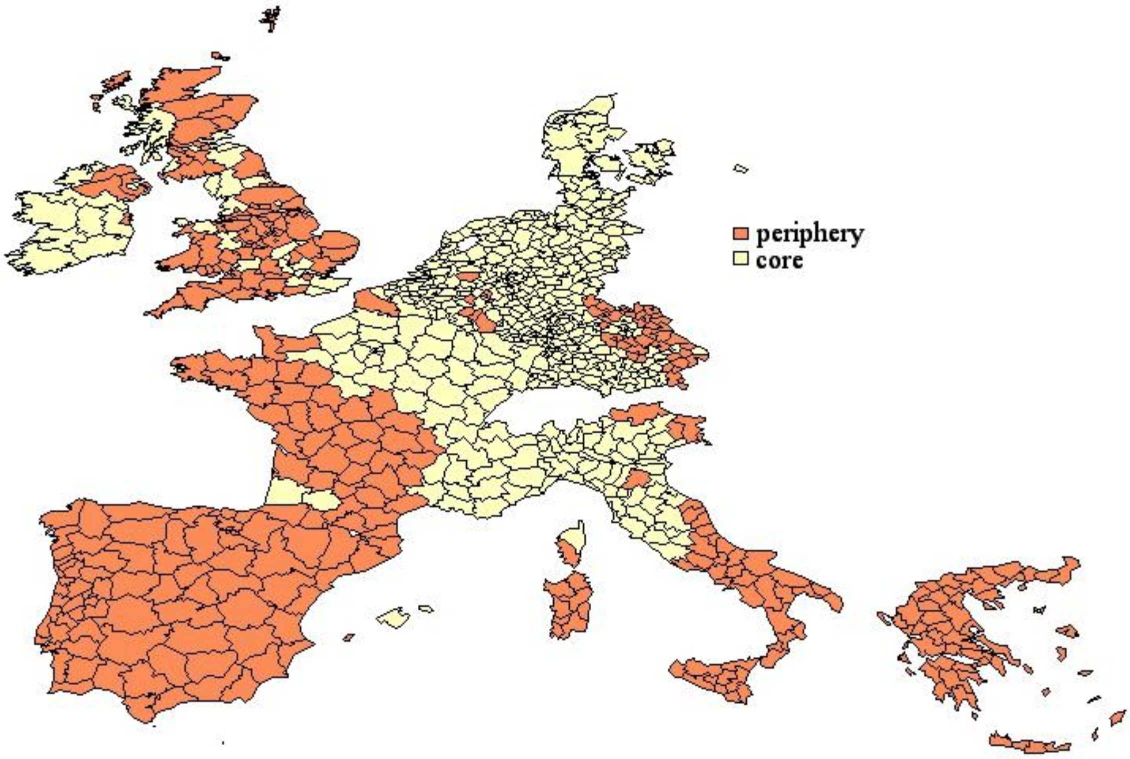

Figure 3 - σ-convergence of total labour productivity

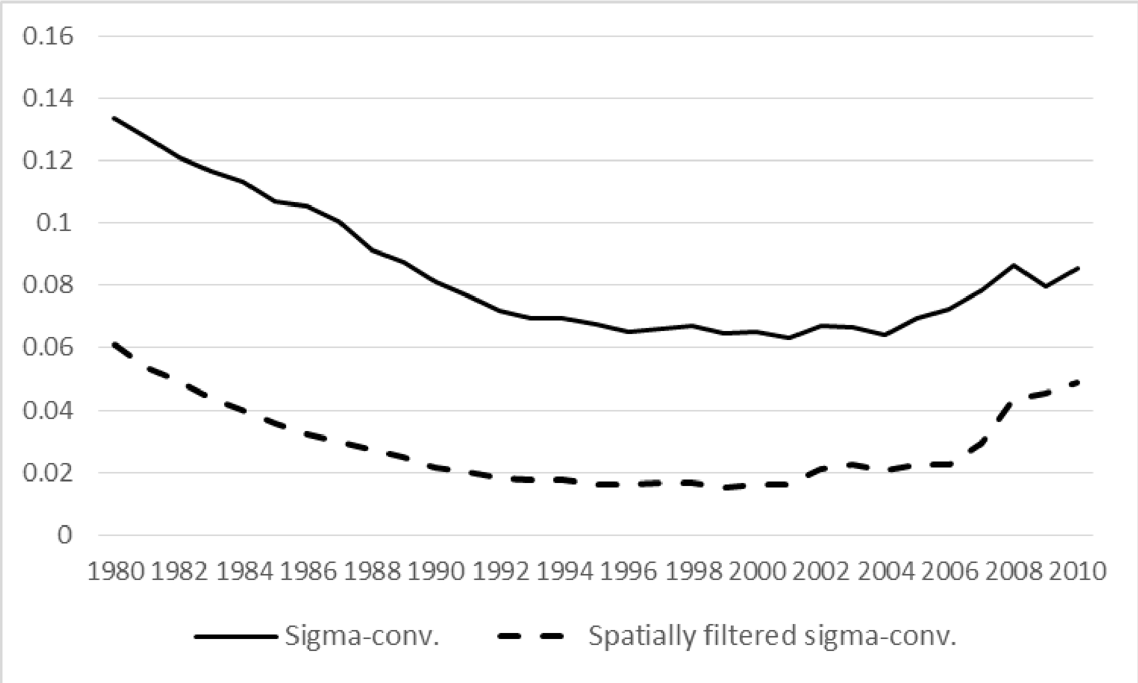

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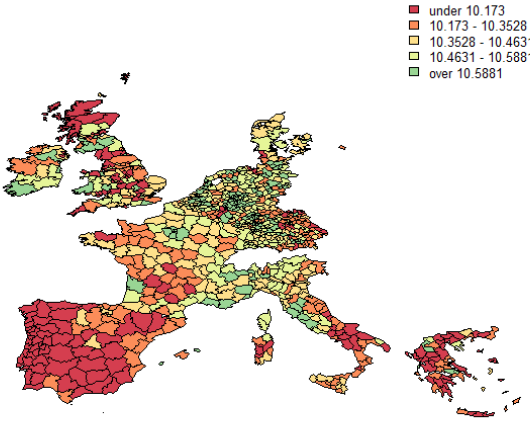
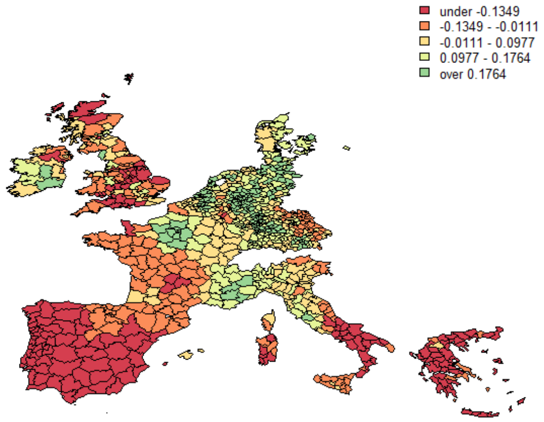
Figure 4 - a) Total, spatial and spatially filtered (non-spatial component) of labour productivity in 1980

a) Original variable



b) Spatial component (*L*)



c) Non-spatial component (*g*)*

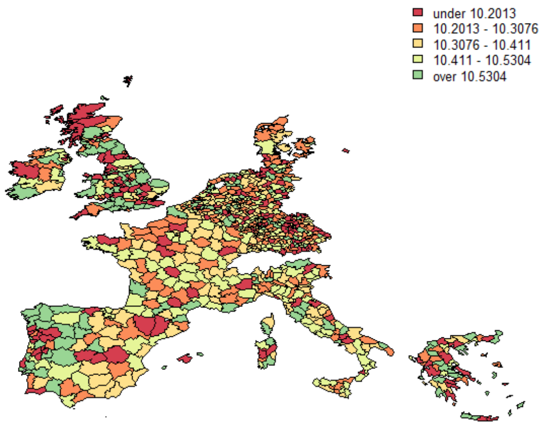


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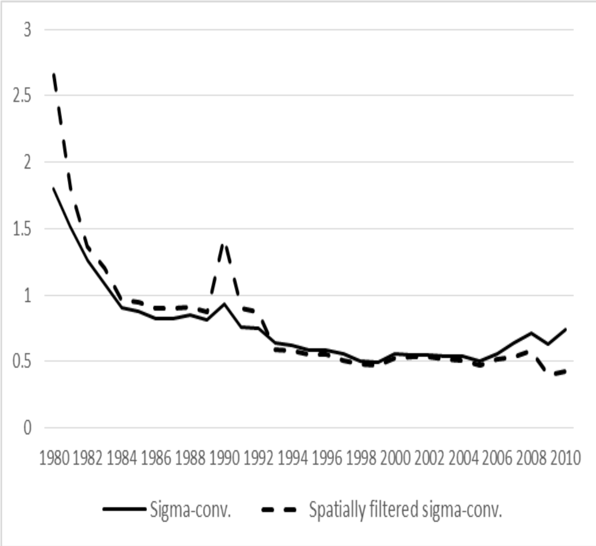
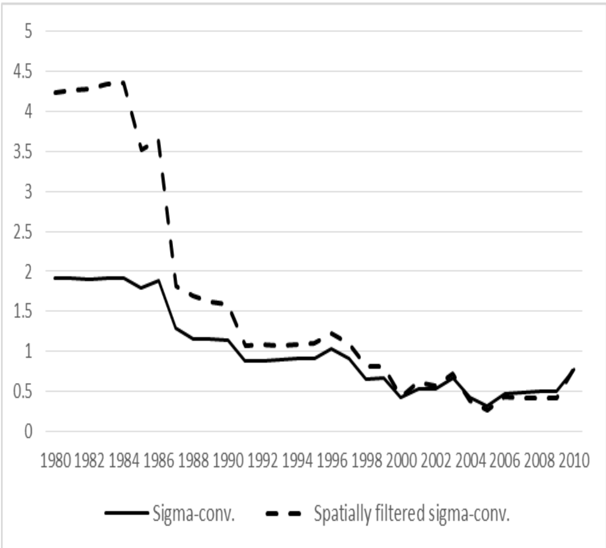
Figure 5 - σ-convergence of productivity by sector

a) Agriculture b) Manufactory





c) Market services d) Non-market services

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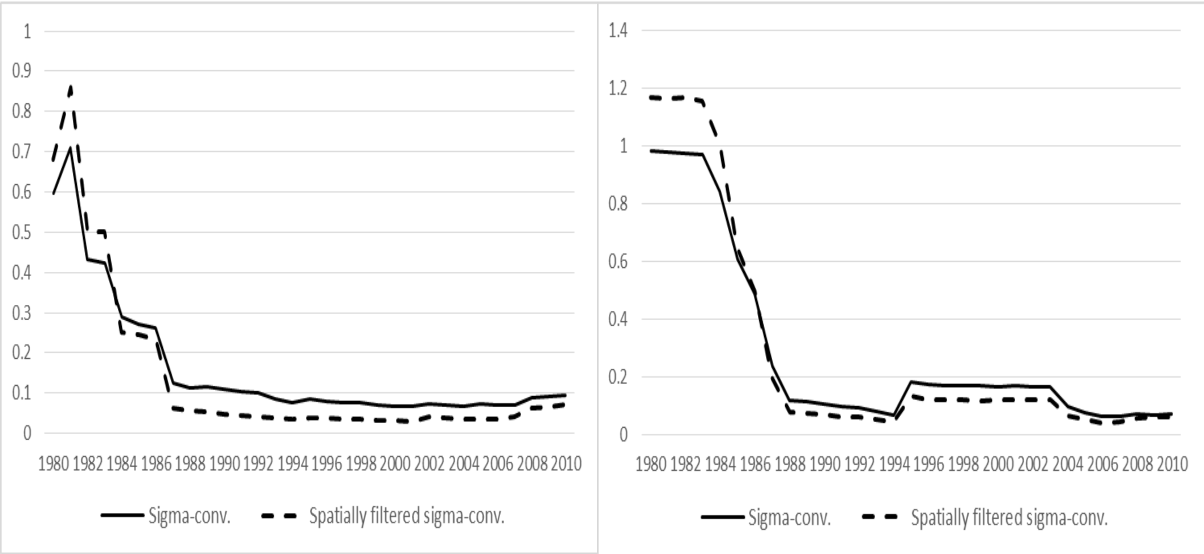

e) Constructions

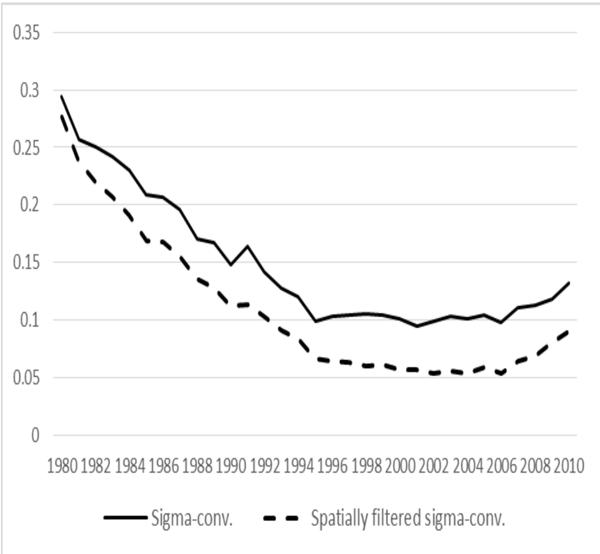

Table 1 – β- and σ-convergence test

	β-convergence			σ-convergence		
Regions	β	Signif. dummies	Adj. R^2	Wald test	P-value	$\sigma^2_T > \sigma^2_{T-t}$
Total labour productivity						
NUTS 3 EU-12	-0.019 (0.008)	-	0.420	149.84	0.000	NO
NUTS 3 EU-12 + country dummy	-0.029 (0.001)	YES	0.607	29.56	0.000	NO
NUTS 3 EU-12 + sp. regime dummy	-0.022 (0.001)	YES	0.451	105.49	0.000	NO
NUTS 3 EU-12 core	-0.029 (0.001)	-	0.460	15.65	0.000	NO
NUTS 3 EU-12 periphery	-0.019 (0.022)	-	0.459	61.32	0.000	NO
Labour productivity in agriculture						
NUTS 3 EU-12	-0.027 (0.001)	-	0.635	53.71	0.000	NO
NUTS 3 EU-12 + country dummy	-0.029 (0.000)	YES	0.800	34.84	0.000	NO
NUTS 3 EU-12 + sp. regime dummy	-0.028 (0.001)	YES	0.696	39.13	0.000	NO
NUTS 3 EU-12 core	-0.028 (0.001)	-	0.760	23.46	0.000	NO
NUTS 3 EU-12 periphery	-0.028 (0.001)	-	0.637	15.82	0.000	NO

Labour productivity in manufactory						
NUTS 3 EU-12	-0.025 (0.001)	-	0.617	76.49	0.302	NO
NUTS 3 EU-12 + country dummy	-0.028 (0.001)	YES	0.670	42.56	0.000	NO
NUTS 3 EU-12 + sp. regime dummy	-0.025 (0.001)	YES	0.620	69.73	0.000	NO
NUTS 3 EU-12 core	-0.029 (0.001)	-	0.447	20.30	0.000	NO
NUTS 3 EU-12 periphery	-0.025 (0.001)	-	0.631	30.32	0.000	NO
Labour productivity in market services						
NUTS 3 EU-12	-0.030 (0.000)	-	0.847	20.31	0.000	NO
NUTS 3 EU-12 + country dummy	-0.033 (0.000)	YES	0.898	3.97	0.046	NO
NUTS 3 EU-12 + sp. regime dummy	-0.031 (0.000)	YES	0.860	14.72	0.000	NO
NUTS 3 EU-12 core	-0.029 (0.001)	-	0.692	16.84	0.000	NO
NUTS 3 EU-12 periphery	-0.031 (0.000)	-	0.901	5.06	0.024	NO
Labour productivity in non -market services						
NUTS 3 EU-12	-0.031 (0.000)	-	0.929	13.94	0.000	NO
NUTS 3 EU-12 + country	-0.032	YES	0.945	8.21	0.004	NO

dummy	(0.000)					
NUTS 3 EU-12 + sp. regime dummy	-0.031 (0.000)	YES	0.933	12.39	0.000	NO
NUTS 3 EU-12 core	-0.032 (0.000)	-	0.902	5.79	0.016	NO
NUTS 3 EU-12 periphery	-0.031 (0.000)	-	0.950	5.96	0.015	NO
Labour productivity in constructions						
NUTS 3 EU-12	0.030 (0.001)	-	0.655	19.07	0.000	NO
NUTS 3 EU-12 + country dummy	-0.034 (0.001)	YES	0.780	2.68	0.101	NO
NUTS 3 EU-12 + sp. regime dummy	-0.031 (0.001)	YES	0.655	17.80	0.000	NO
NUTS 3 EU-12 core	-0.033 (0.001)	-	0.710	2.91	0.088	NO
NUTS 3 EU-12 periphery	-0.029 (0.001)	-	0.615	12.81	0.000	NO

Notes: Moran's I test and robust LM test for residual spatial autocorr.are always significant. Std. errors in brackets

Table 2 - Spatially filtered β- and σ-convergence test

	β-convergence			σ-convergence		
Regions	β	Signif. dummies	Adj. R^2	Wald test	P-value	$\sigma^2_T > \sigma^2_{T-t}$
Total labour productivity						
NUTS 3 EU-12	-0.031	-	0.525	13.40	0.000	NO

	(0.001)					
NUTS 3 EU-12 + country dummy	-0.032 (0.001)	NO	0.528	11.21	0.000	NO
NUTS 3 EU-12 + sp. regime dummy	-0.031 (0.001)	NO	0.524	14.08	0.000	NO
NUTS 3 EU-12 core	-0.032 (0.002)	-	0.421	6.79	0.009	NO
NUTS 3 EU-12 periphery	-0.031 (0.001)	-	0.594	6.47	0.011	NO
Labour productivity in agriculture						
NUTS 3 EU-12	-0.029 (0.000)	-	0.842	31.13	0.000	NO
NUTS 3 EU-12 + country dummy	-0.029 (0.000)	NO	0.800	30.76	0.000	NO
NUTS 3 EU-12 + sp. regime dummy	-0.029 (0.000)	NO	0.842	31.27	0.000	NO
NUTS 3 EU-12 core	-0.028 (0.000)	-	0.901	22.63	0.000	NO
NUTS 3 EU-12 periphery	-0.030 (0.001)	-	0.791	9.76	0.002	NO
Labour productivity in manufactory						
NUTS 3 EU-12	-0.030 (0.000)	-	0.824	19.41	0.000	NO
NUTS 3 EU-12 + country dummy	-0.030 (0.000)	NO	0.822	19.65	0.000	NO
NUTS 3 EU-12 + sp. regime	-0.030	NO	0.	19.55	0.000	NO

dummy	(0.000)		824			
NUTS 3 EU-12 core	-0.029 (0.001)	-	0.549	17.88	0.000	NO
NUTS 3 EU-12 periphery	-0.030 (0.001)	-	0.834	7.81	0.005	NO
Labour productivity in market services						
NUTS 3 EU-12	-0.033 (0.000)	-	0.904	3.51	0.055	NO
NUTS 3 EU-12 + country dummy	-0.033 (0.000)	NO	0.904	3.52	0.061	NO
NUTS 3 EU-12 + sp. regime dummy	-0.033 (0.000)	NO	0. 904	3.74	0.053	NO
NUTS 3 EU-12 core	-0.033 (0.001)	-	0.612	3.35	0.067	NO
NUTS 3 EU-12 periphery	-0.033 (0.000)	-	0.949	1.46	0.23	NO
Labour productivity in non -market services						
NUTS 3 EU-12	-0.031 (0.000)	-	0.968	7.87	0.005	NO
NUTS 3 EU-12 + country dummy	-0.032 (0.000)	NO	0.947	7.81	0.005	NO
NUTS 3 EU-12 + sp. regime dummy	-0.032 (0.000)	NO	0.947	7.89	0. 005	NO
NUTS 3 EU-12 core	-0.032 (0.000)	-	0.896	5.30	0.021	NO
NUTS 3 EU-12 periphery	-0.032	-	0.968	3.08	0.079	NO

	(0.000)					
Labour productivity in constructions						
NUTS 3 EU-12	-0.034 (0.001)	-	0.757	3.02	0.082	NO
NUTS 3 EU-12 + country dummy	-0.034 (0.001)	NO	0.762	2.78	0.095	NO
NUTS 3 EU-12 + sp. regime dummy	-0.034 (0.001)	NO	0.757	3.04	0.081	NO
NUTS 3 EU-12 core	-0.033 (0.001)	-	0.760	3.02	0.082	NO
NUTS 3 EU-12 periphery	-0.034 (0.001)	-	0.753	0.72	0.396	NO

Notes: Moran's I test and robust LM test for residual spatial autocorr. are not significant. Std. errors in brackets