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Sectoral productivity convergence between European regions: does space matter?

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# Sectoral productivity convergence between European regions: does space matter?

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Abstract: The aim of our analysis is the evaluation of the total and sectoral convergence of labour productivity between 182 regions of EU12 in the period 1991-2006. The selected sectors are agriculture, manufactory, market and non-market services. We adopt a  $\beta$ - and  $\sigma$ -convergence approach along with a methodology based on Getis' spatial filters that allows decomposing variables into their spatial and a-spatial components ensuring their spatial independence. This last point is fundamental to avoid i) omitted variables and/or problems of bias and/or inconsistency of coefficients in growth regressions, ii) bias in the computation of variance. The cited econometric approach also permits to identify spatial regimes of regions with high and low productivity, respectively 'core' and 'periphery'.

Our results show significant  $\sigma$ -convergence in aggregate labour productivity, market and non-market services in the first years and a slightly divergence in the second period. Sigma-divergence is present only in manufactory sector when spatial factors are not considered, while in agriculture a strong convergence is perceivable. The analysis highlights that if we do not take into account spatial effects,  $\sigma$ -convergence is overestimated.

In the second part of the paper, we evaluate  $\beta$ -convergence for total labour productivity and for each sector. We considered five cases: the whole sample (EU12) without dummies, with country dummies and with spatial regime dummies, the 'core' and the 'periphery'; finally we take into account singularly each spatial regime. The same estimation performed with and without spatially filtered variables leads to different results. While  $\beta$ -convergence process takes place in all cases and with all techniques, countries dummies are statistically significant only when spatial effects are not considered. In case of spatially filtered variables, the dummies, whose aim is to take into account the specificity of an agglomeration of regions, lose their significance, both theoretical and statistical, because the spatial factors embedded in each variable, and strictly connected with the country or convergence club to which they

belong, are removed. The interesting point, however, is the lack of significance of dummies

for spatial regimes. This finding, common both to filtered and unfiltered variables and to all

sectors, is a little surprising because the identified spatial regimes are interpretable (and often

interpreted) like convergence clubs.

In conclusion, this paper shows that economic structure has to be considered together with

spatial structure. These two factors affect themselves reciprocally and, for a full and reliable

explanation of regional economic dynamics both must be formally included in the analysis.

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, as a consequence, becomes one of the three pillars of European integration,

alongside economic and monetary union and the single market.

Since the inception of the policy and the first programming period (1989-1993), this objective

has often been translated as the promotion of convergence between EU regions in term of

GDP per capita. Partially, this choice explains why over the past two decades we have seen 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 analysis 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 one was on the issue of convergence, that is, a real and

significant trend to cohesion between rich and poor countries or regions in the long term.

According to the criteria of the Commission, most of studied carried on by scholars and by

the EU Commission reports focus on regional disparities utilising the GDP per capita.

In our study we have preferred to utilize the Gross Valued Added (GVA) per worker, i.e.

productivity, instead of GDP per capita. This choice depends on some reasons. The first lies

2

on Krugman's words (1992, p. 9): 'Productivity isn't everything, but in the long run it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker.' Another important reason consists in its possible disaggregation at sectoral level. Therefore, the convergence hypothesis can be tested also for branches allowing to evaluate their dynamics in relation to total productivity.

A disaggregated approach at the sectoral level for evaluating convergence of EU regions has not been commonly performed. Here we can remember 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) respectively for the Greek and French regions. Their results indicate that the process of aggregate productivity convergence is often not due to a convergence process at the sectoral level, but rather to a change in the structure of the regional economies taking the form of a reallocation of employment from agriculture to higher productivity sectors.

In measuring convergence process we have to consider that there are several definitions of convergence and although coherent, they correspond to different concepts of convergence: there is no convergence measure capable of capturing all relevant aspects of a convergence process. In addition to these issues, there is a set of problems related to the spatial dependence.

To overcome the limitations related to the different concepts of convergence we consider both  $\sigma$ - and  $\beta$ -convergence for total productivity for four selected sectors: agriculture, manufactory, market services and non-market services. Finally, to take into account spatial dependence we filter the variables according with Getis (1995) technique.

The paper is organized as follows: in section 2 we present the convergence estimation techniques, the problems related with spatial dependence and the opportunities of the spatial filtering technique, in section 3 we estimate empirically  $\sigma$ - and  $\beta$ -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  $\beta$ -convergence model (Barro and Sala-i-Martin, 1992) and to  $\sigma$ -convergence model (Sala-i-Martin, 1996).

According to  $\beta$ -convergence, regions with lower values of initial productivity grow faster than the ones with higher values (less developed regions would catch-up more advanced regions).

It implies a negative correlation between growth rates of productivity and the initial levels of this variable.

Three cases are usually considered in the literature: first, the hypothesis of *absolute*  $\beta$ -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 economies that are similar in structural characteristics and tend to converge within groups. The equilibrium reached by each region will depend on the range within which its initial conditions belong or other (spatial or a-spatial) attributes. Third, *conditional* convergence foresees that each region approaches its own (unique and globally stable) steady state.

As shown by Mankiw (1985) and Quah (1996), a weakness of  $\beta$ -convergence model is to consider countries and regions as 'isolated islands', not taking into account that the economies, mainly in EU, are mutually interdependent.

To overcome this problem, in case of  $\beta$ -convergence, a large literature on estimating spatial effects together with growth regression have taken place over the last ten years. Loosely speaking spatial dependence between regions yields OLS-growth regression to a bias of regression coefficients or an invalidation of significance tests (Anselin, 1988; Fingleton, 1999 and Cliff and Ord, 1973). The issue can be solved using spatial lag or spatial error models (Anselin, 1988; Anselin and Bera, 1998), but, to the extent that the spatially correlated errors mask an omitted variable, 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 assumed not to be spatially autocorrelated.

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

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

where n is the total number of regions and  $\overline{y}_{it}$  is the sample average for period t. There is  $\sigma$ -convergence over the study period between the n regions if the sample variance, (1), 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- and σ-convergence are not necessarily linked. Indeed, β-convergence is a necessary but not a sufficient condition for σ-convergence (Sala-i-Martin, 1996). Therefore absence of σconvergence can co-exist with  $\beta$ -convergence.

In the analysis of  $\sigma$ -convergence, with few exceptions<sup>1</sup>, scholars did not take into account the spatial dimension treating the variables as independent. Nevertheless, as demonstrated by Rey and Dev (2006), this does not hold when we deal with regional data. 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 productivities are a collection of observations such as:  $y \sim N(\mu, \sigma^2 \Omega)$  where  $\Omega$  is a general  $(n \times n)$  matrix and  $\sigma^2$  is the global dispersion parameter. The sample variance is then decomposed as follows, omitting the time subscript:

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

where n is the number of regions;  $s^2$  is the sample variance,  $\sigma^2$  captures the influence of aspatial dispersion on  $s^2$ ;  $\theta$  reflects the combined effects of any spatial heterogeneity and dependence on  $s^2$ ;  $\mu_i$  is the  $i^{th}$  element of  $\mu$  and  $\omega_{ii}$  is element (i, j) of matrix  $\Omega$ .

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  $\theta$  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 process suggested by Getis (1995). The reason the choice regards the extremely flexibility of this technique because it is able to transform the autocorrelated 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 regional economic development, are essentially stochastic kernel (Fischer and Stupner, 2008) and the mentioned variance (σ-convergence) and regression analysis (essentially  $\beta$ -convergence).

According to Getis spatial filtering technique, the original variable, X is composed by two parts: a filtered non-spatial component, say  $X^*$ , and a spatial residual,  $L_X$ .

According to our knowledge only Rey and Dev (2006) and Le Gallo and Dall'erba (2008) faced the issue of spatial filtered  $\sigma$ -convergence.

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<sup>2</sup> d for which spatial autocorrelation should be sufficiently strong. To solve this issue, following Getis (1995), it is necessary firstly to define the spatial autocorrelation statistic of Getis and Ord (1992),  $G_i(d)$ :

$$G_i(d) = \frac{\sum_{j=1}^{n} W_{ij}(d) x_j}{\sum_{j=1}^{n} x_j} \quad \text{for } j \neq i$$
(3)

with  $W_{ij}(d) = 1$  if the distance from region i to region j (i = j), say  $d_j$ , is smaller than the critical distance band d, and  $W_{ij}(d) = 0$  otherwise. The numerator of (3) is the sum of all  $X_j$  within d of i but not including  $x_i$ . The denominator is the sum of all  $X_j$  not including  $X_i$ .

The strategy consists in following an iterative process in which we add a new degree of neighbourhood to matrix  $W_{ij}(d)$  until when the marginal difference between  $G_i(d)$  computed with the new matrix  $W_{ij}(d)$  and the one computed with the previous become very small.

Once the distance d and the statistics  $G_i(d)$  are defined, the variable can be filtered according with:

$$x_i^* = \frac{x_i \left[ \frac{1}{n-1} W_i \right]}{G_i(d)} \tag{4}$$

In equation (4) the observed values of  $G_i(d)$  are compared with their expected values,  $(n-1)^{-1}W_i$ .  $E[G_i(d)]$  represents the realization,  $X^*$ , of the variable X at region i when no autocorrelation occurs.

Three cases are possible:

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

Thus:

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<sup>&</sup>lt;sup>2</sup> There are many definitions of distance. Among the others we have Euclidean distance, distance measured in time to reach a destination, etc. In our study we considered the number of nearest neighbors.

 $L_x = X - X^*$  represents a spatial variable associated, but not correlated, with the variable X. According to Le Gallo and Dall'erba (2008),  $G_i(d)$  statistics allows us also to determine the spatial regimes to which regions belong. These regimes can be interpreted as spatial 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 belongs to the group of 'low productivity' regions, or 'periphery'.

# 3. Regional productivity, convergence and space

In this paragraph we follow the procedure described above to estimate  $\sigma$ - and  $\beta$ -productivity convergence of 182 NUTS-2 regions of EU12<sup>3</sup>, with the aim to evaluate and compare the cases with and without spatial effects.

In the first step we have to choose the cut-off distance for applying spatial filtration technique according with the marginal values of equation (3). Dealing with regions, we choose the distance d according to the number of nearest neighbour regions instead, for example, of Euclidean distance. This is due to the simplicity in computation, and to the heterogeneity of NUTS-2 regions in term of dimension and number of neighbour regions. An Italian or Spanish region, for example, if we fix a common Euclidean distance, has less neighbour regions than a Nederland region.

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  $G_i(d)$  for total productivity are characterized by a strong spatial patterns (figure 2). In East Germany, Italy, Spain, Portugal, Ireland, Greece and Great Britain we observe a cluster of regions with spatial autocorrelation among low observations of X, the 'periphery' with low productivity regions while the rest of regions exhibit a spatial autocorrelation among high observations of X, the 'core' with high productivity regions. The case of Great Britain which belongs almost entirely to low productivity club can find an explication: British Department of Trade and Industry (1997), reported that a low productivity comes from a lack of investment in equipment, infrastructure, technology and skills.

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

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<sup>&</sup>lt;sup>3</sup> The data on labour productivity come from the Cambridge Econometrics (2008) database.

'core' while if the difference for region i is negative, this region falls in the group of 'low productivity' regions, or 'periphery'.

Because we utilize the Gross Value Added per employee we have to take into account that the definition of spatial regimes, or 'clubs', is referred to the total labour productivity in 1991, the starting year. We did not identify spatial regimes for each sector branch and/or for every year because on the one hand we need a uniform space weights matrix, and on the other the total labour productivity should be able to properly identify the main characteristics of each region. The  $\sigma$ -convergence for total labour productivity, computed both with 'standard' and with spatial technique is in figure 3. The standard  $\sigma$ -convergence pattern (solid line) computed with (1) shows a tendency to convergence until 1999 and a clear divergence after that date. When spatial factors are taken into account (dotted line), until 1995 the trend remained stable, while, after that year, divergence appears, except between 1995 and 1997. Nevertheless, when spatial factors are taken in to account, the variance decreases drastically<sup>4</sup>.

Generally, removing the spatial noise embedded in each variable, the effect is to homogenize the distribution (the dotted line shift down and is more smooth than the solid).

In figure 4 we reported the spatial distribution of quintiles of total labour productivity in 1991, of spatial component (L), and of spatial filtered component  $(g^*)$ . In map 4 a) and 4 b) the total labour productivity in 1991 and its spatial component (L) show a clear spatial pattern, while in map 4 c) homogeneous clusters are not observable: removing the residual spatial component the spatial distribution of the variables results completely (at least visually) 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<sup>5</sup>.

Figure 5 shows the evolution of filtered and unfiltered  $\sigma$ -convergence by sector. Generally, a parallel shift down of the variance of spatially filtered variable is observable in all cases. In case of manufactory we observe a clear tendency to divergence while in agriculture, market and non-market services the convergence takes place until 1999, and then a slightly divergence is perceivable. In case of spatial  $\sigma$ -convergence, when dealing with manufactory and services the variance tends to remain much more stable in time and the initial and final conditions are very similar. Recalling figure 3, sectorial convergence of agriculture, market and non-market services was able to ensure  $\sigma$ -convergence of aggregate labour productivity in spite of divergence of manufactory until 1999. In the following years, the increasing

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<sup>&</sup>lt;sup>4</sup> We archived similar results using spatial lag technique.

<sup>&</sup>lt;sup>5</sup>The p-value for Moran's I test is 0.000 for total labour productivity in 1991, 0.000 for its spatial component (L) and 0.998 for the spatial filtered labour productivity in 1991 (g\*).

variability of market and non-market services, summed up to manufactory sector, determined a slightly  $\sigma$ -divergence in total productivity per worker.

A first approximation of  $\sigma$ -convergence dynamic can be derived using graphical tools, but, like  $\beta$ -convergence, it needs a formal test to detect convergence or divergence. To reach this aim, a set of statistical test were proposed by many authors during the last fifteen years.

In our case we chose the approach of Eggert and Pfaffermayer (2009) because they propose a simple Wald test for conditional and unconditional convergence. The first step consists in computing the classical OLS regression to test  $\beta$ -convergence:

$$\frac{y_{ij,T} - y_{ij,T-t}}{t} = \beta y_{ij,T-t} + x_{ij} \gamma_T + \zeta_{jT} + \varepsilon_{ijT}$$
(5)

Where i=1,...,N represents the number of regions (182), j=1,...,M the convergence clubs or chosen spatial regimes, and t=1,...,T the time.  $\beta$  is the well-known  $\beta$ -convergence parameter (that should be negative and significant),  $x'_{ij}$  time invariant explanatory variables (e.g. regional determinants of growth such as R&D or education),  $\zeta_{jT}$  the fix time invariant group effect and  $\varepsilon_{ijT}$  the i.i.d. normally distributed error term.

If we define  $\pi_T = I + t\beta$ , then the Wald statistics test  $H_0 = \pi_T^2 = \overline{\pi}_T^2$  with  $\overline{\pi}_T^2 = 1 - \frac{\sigma_{uT}^2}{\sigma_{y,T-t}^2}$  for

$$\hat{W}_{1} = \frac{NM \left(\hat{\sigma}_{y,T}^{2} \left(\hat{\pi}_{T}^{2} - 1\right) + \hat{\sigma}_{uT}^{2}\right)^{2}}{4NM \left(\hat{\sigma}_{y,T-t}^{2} - \hat{\sigma}_{y,T-t}^{2} \hat{\sigma}_{uT}^{2}\right) \hat{\sigma}_{\pi_{T}}^{2} + 4\hat{\sigma}_{uT}^{2}}$$
(6)

while with unconditional convergence is:

conditional convergence becomes:

$$\hat{W_0} = \frac{NM \left(\hat{\sigma}_{y,T}^2 \left(\hat{\pi}_T^2 - 1\right) + \hat{\sigma}_{uT}^2\right)^2}{4\hat{\sigma}_{y,T-t}^2 \hat{\sigma}_{uT}^2} \tag{7}$$

With  $\sigma_u^2 = t^2 \sigma_{\varepsilon}^2$ .

The test statistic is distributed as  $\chi^2(1)$ . In small samples, Morrison (1976) recommends replacing NM by NM-2.5 to achieve a better approximation of the  $\chi^2$  distribution.

The estimate  $\hat{\pi}_T$  is based on the corresponding ordinary least squares (OLS) regression (5):  $\hat{\pi}_T = 1 + t\hat{\beta}$ , while  $\hat{\sigma}_{\pi T}^2$  on its estimated variance:  $\hat{\sigma}_{\pi t}^2 = t^2 \hat{\sigma}_{\beta}^2$ .

Furthermore 
$$\hat{y}_{ijT} = y_{ij,T-t} + (y_{ij,T} - y_{ij,T-t})/t$$
, and

$$\hat{\sigma}_{y,T-t}^{2} = \frac{1}{NM} \sum_{i=1}^{N} \sum_{j=1}^{M} \left( y_{ij,T-t} - x_{ij} \hat{\gamma}_{T-t} - \hat{\pi}_{T} \mu_{j1} - \hat{\zeta}_{j,T-t} \right)^{2}$$

$$\hat{\sigma}_{uT}^{2} = \frac{1}{NM} \sum_{i=1}^{N} \sum_{j=1}^{M} (\hat{y}_{ij,T} - (1 + t\hat{\beta}) y_{ij,T-t} - x_{ij} \hat{\gamma}_{T} - \hat{\zeta}_{jT})^{2}$$

In table 1 we estimate  $\beta$ - and  $\sigma$ -convergence according to different territorial partitions for total productivity and for each sector. We considered the five cases: the whole sample (EU12) 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 is identical to table 1 but we used the spatially filtered variables.

In almost all sectors β-convergence occurs. The only exception is (unfiltered) manufactory where there is β-convergence only in case of country dummies and for 'core'. When filtered variables are considered, the country dummies, with exclusion of agricultural productivity, become statistically not significant. In case of spatially filtered variables the dummies, whose aim is to consider the specificity of an agglomeration of regions (e.g., a country or a convergence club), lose their significance, both theoretical and statistical, because the spatial factors embedded in each variable, and strictly connected with the country or convergence club to which they belong, are removed. Clearly, when variables are unfiltered, country dummies become significant because they act like an 'spatial filter' grouping the regions not necessarily according to specific economic characteristics, but to the country or regime to which they belong. The interesting point, however, is the lack of significance of dummies for spatial regimes. This finding, common both to filtered and unfiltered variables and to all sectors, is a little surprising because the identified spatial regimes are interpretable (and often interpreted) like convergence clubs (Le Gallo and Dall'erba, 2008). The comparison of table 1 with table 2, shows the convergence rates are lower in case of filtered variables. Looking at the adjusted R-squared of the various regressions, it is not possible to determine the better technique. Nevertheless, both Moran's I test and robust version of Lagrange Multiplier test show no spatial autocorrelation in the residuals for all cases of table 2.

This achievement leads to choose the filtered model because no spatial autocorrelation in the residuals allows to avoid issues related to omitted variables (Anselin, 2009; Getis and Griffith, 2002).

Considering the tests for  $\sigma$ -convergence we observe that in almost all cases Wald test checks that  $\sigma$ -convergence values for 2006 are statistically different than those of 1991. These findings, to confirm the visual analysis performed above, need to be compared with the variance at time T-t and at time T. When the variance at initial stage is greater (smaller) than variance at last stage and the statistical test rejects  $H_0$ , then divergence (convergence) takes place. According to these criteria the manufactory sector diverge in  $\sigma$ -convergence while all the others converge. Regarding the comparison between table 1 and 2, we cannot observe important differences between filtered and unfiltered estimations. The only point is when we include country dummies with filtered variables. In this case the Wald test is not significant (table 2), but, due to absence of significance of dummies in  $\beta$ -convergence regression, this result must be considered with care.

### **Conclusions**

In our study we estimate classical and spatially filtered  $\beta$ - and  $\sigma$ -convergence to take into account the productive structure of the regional economies. The decomposition of the variables into their spatial and a-spatial components, along with ensuring independence among the observations, allows to estimate the  $\beta$ - and  $\sigma$ -convergence without the problems related to spatial dependence.

In the case of  $\sigma$ -convergence the conventional approach shows higher variance than the spatial approach both for total productivity and all sectors. Nevertheless the relative magnitude of the difference between the two methodologies varies for each sector and each year, but it does not lead to contradictory conclusions. All approaches agree in displaying a  $\sigma$ -convergence of aggregate total labour productivity, market and non-market services sectors until 1999 and a little divergence later. In agricultural sector, both standard and spatially filtering approaches show  $\sigma$ -convergence along the whole period, while manufactory diverges using conventional approach and a remains stable with spatially filtered variable.

In our work we partially agree with the results of Cuadrado Roura *et al.* (1999) and Le Gallo and Dall'erba (2008) who claim that the process of aggregate productivity convergence is often not due to a convergence process at the sectoral level, but rather to a change in the structure of the regional economies taking the form of a reallocation of employment from agriculture to other productivity sectors, more pronounced in the poor regions than in the rich ones. At this regard Gutierrez (2000) finds strong and robust evidence of convergence of

labour productivity in agriculture between all US states and 11 EU countries during 1970-1992. Moreover the off-farm migration has a positive effect on the speed of convergence, especially in the EU. A high convergence process of agricultural productivity is also due to the subsidies of Common Agricultural Policy (Pecci, 2009); furthermore, Sassi and Pecci (2008) highlight that 'the maturity stage of development of agriculture implies its low capacity to affect the economic performance'.

The different results achieved for manufactory using filtered variables is imputable to the role of spatial factors: when they are embedded in the variable, the variability increases because some regions tend to be advantaged (or disadvantaged) by both their spatial location and by their strong (or low) specialization. The spatial filtration allows to look at the values of the variables without the influence of surrounding regions. The  $\sigma$ -divergence of manufactory sector in case of unfiltered variable, as a consequence, is due by agglomeration and/or concentration phenomena instead of a 'real' difference of the sectoral productivity.

Some further investigation, however, should be developed to isolate the spatial and a-spatial  $\sigma$ -convergence for each country and to understand they roles.

The analysis of  $\beta$ -convergence allows to observe that core regions and peripheral regions converge to their own steady-state in all cases when considered separately, but these spatial regimes seem to be rather artificial because the dummies in OLS are not significant. In addition, convergence speeds and the nature of spatial effects vary by sector. Looking at the spatially filtered variables, we see that the sectors with higher convergence are manufactory and non-market services, followed by agriculture and market services.

As a conclusion, we note that  $\beta$ - and  $\sigma$ -convergence patterns do not coincide, showing that both types of analysis are necessary to have a full picture of convergence patterns in EU. Indeed,  $\beta$ -convergence is a necessary but not a sufficient condition for  $\sigma$ -convergence, which explains the result of absence of  $\sigma$ -convergence in conjunction with significant  $\beta$ -convergence. In addition spatial factors plays an important role in determining the type and the 'shape' of convergence processes. A deep exploration of these effects should be further investigated in future research. Similarly, the possible role of the production structure, interregional trade, human capital, infrastructures and technological diffusion on the mechanisms of convergence should be considered in the next researches.

The economic structure has to be considered together with spatial structure; these two factors affect themselves reciprocally and, for a full and reliable explanation of regional economic dynamics both must be formally included in the analysis.

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

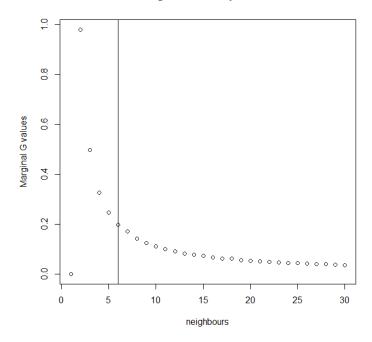


Figure 2 - Spatial regimes according with  $G_i(d)$  for total labour productivity

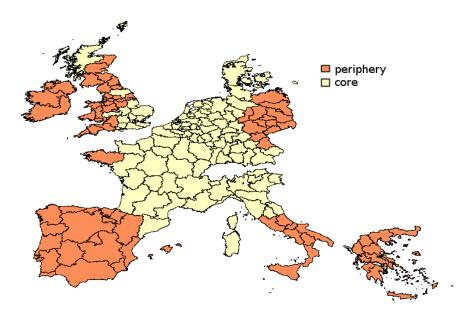


Figure 3 - σ-convergence of total labour productivity

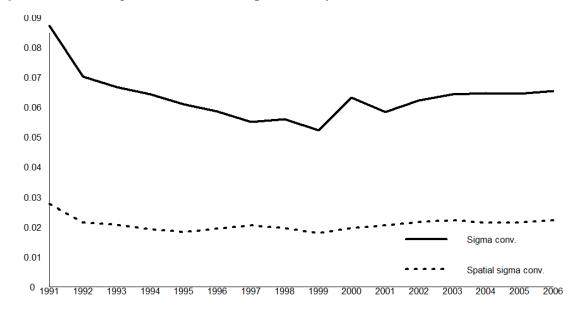


Figure 4 - a) Total labour productivity in 1991, b) Spatial component of total labour productivity in 1991 (L), c) Spatial filtered total labour productivity in 1991 (g\*)

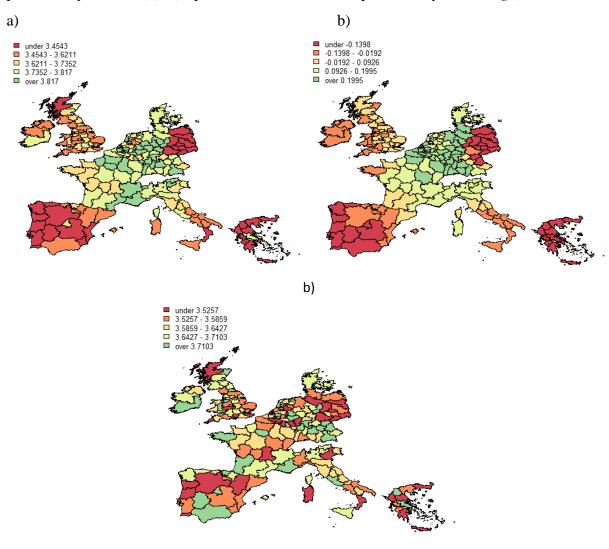
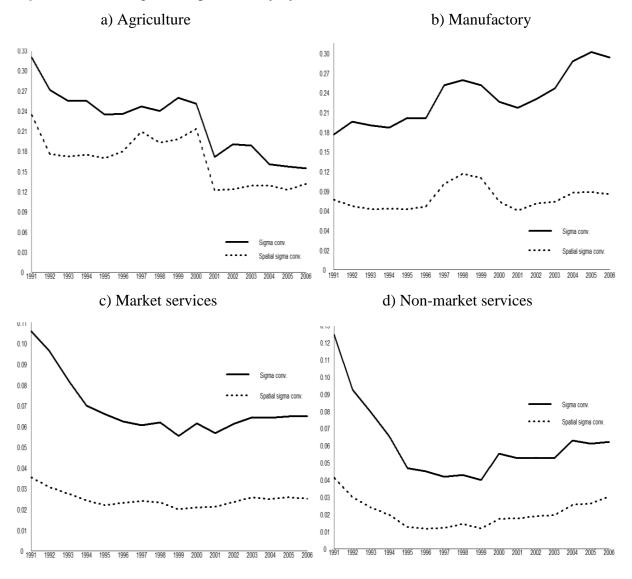


Figure 5 - σ-convergence of productivity by sector



*Table 1* -  $\beta$ - and  $\sigma$ -convergence test

	β-convergence			σ-convergence		
	Tota	l labour productivity				
Spatial regime or country	β	Signif. dummies	Adj. R <sup>2</sup>	Wald test	P-value	$\sigma^2_{T} > \sigma^2_{T-t}$
UE-12	-0.020 (0.002)	-	0.254	127.39	0.000	NO
EU-12 with country dummy	-0.039 (0.002)	YES	0.686	1201.74	0.000	NO
EU-12 with spatial regime dummy	-0.022 (0.003)	NO	0.255	9.07	0.002	NO
Core	-0.011 (0.005)	-	0.052	102.70	0.000	NO
Periphery	-0.025 (0.005)	-	0.232	15.02	0.000	NO
	Labour p	roductivity in agricul	ture	1		
Spatial regime or country	β	Signif. dummies	Adj. R <sup>2</sup>	Wald test	P-value	$\sigma^2_{T} > \sigma^2_{T-t}$
UE-12	-0.034 (0.003)	-	0.372	110.08	0.000	NO
EU-12 with country dummy	-0.038 (0.003)	YES	0.491	884.88	0.000	NO
EU-12 with spatial regime dummy	-0.032 (0.004)	NO	0.373	50.04	0.000	NO
Core	-0.028 (0.004)	-	0.287	102.70	0.000	NO
Periphery	0.036 (0.006)	-	0.315	15.02	0.000	NO
	Labour pr	oductivity in manufa	ctory			
Spatial regime or country	β	Signif. dummies	Adj. R <sup>2</sup>	Wald test	P-value	$\sigma_{T}^{2} > \sigma_{T-t}^{2}$
UE-12	-0.003 (0.004)	-	-0.002	161.37	0.000	YES
EU-12 with country dummy	-0.032 (0.004)	YES	0.578	374.86	0.000	YES
EU-12 with spatial regime dummy	-0.006 (0.004)	NO	0.006	0.72	0.395	YES
Core	-0.022 (0.006)	-	0.109	102.69	0.000	YES
Periphery	-0.002 (0.006)	-	-0.010	15.01	0.000	YES
	Labour pro	ductivity in market se	ervices			
Spatial regime or country	β	Signif. dummies	Adj. R <sup>2</sup>	Wald test	P-value	$\sigma^2_T > \sigma^2_{T-t}$
UE-12	-0.030 (0.003)	-	0.391	208.98	0.000	NO
EU-12 with country dummy	-0.034 (0.002)	YES	0.781	842.48	0.000	NO
EU-12 with spatial regime dummy	-0.041 (0.003)	YES	0.499	31.31	0.000	NO
Core	-0.031 (0.003)	-	0.447	102.70	0.000	NO
Periphery	-0.047 (0.004)	-	0.534	15.12	0.000	NO
	Labour produ	ctivity in non -marke	t services			
Spatial regime or country	β	Signif. dummies	Adj. R <sup>2</sup>	Wald test	P-value	$\sigma_{T}^{2} > \sigma_{T-t}^{2}$
UE-12	-0.036 (0.003)	-	0.501	320.83	0.000	NO
EU-12 with country dummy	-0.054 (0.002)	YES	0.777	1487.63	0.000	NO
EU-12 with spatial regime dummy	-0.038 (0.002)	NO	0.505	28.62	0.000	NO
Core	-0.043 (0.004)	-	0.522	102.70	0.000	NO
Periphery	-0.036 (0.004)	-	0.472	98.92	0.000	NO

*Notes:* standard errors are in brackets. In all cases both Moran's I test and robust version of Lagrange Multiplier test for residual spatial autocorrelation are statistically significant.

*Table 2* - Spatially filtered β- and  $\sigma$ -convergence test

	β-convergence			σ-convergence		
	Total	l labour productivity		1		
Spatial regime or country	β	Signif. dummies	Adj. R <sup>2</sup>	Wald test	P-value	$\sigma^2_{T} > \sigma^2_{T-t}$
UE-12	-0.027 (0.003)	-	0.313	5182.74	0.000	NO
EU-12 with country dummy	-0.029 (0.003)	NO	0.349	18.29	0.000	NO
EU-12 with spatial regime dummy	-0.026 (0.003)	NO	0.313	0.24	0.637	NO
Core	-0.002 (0.003)	-	-0.006	3129.0	0.000	NO
Periphery	-0.035 (0.004)	-	0.444	3576.41	0.000	NO
	Labour p	roductivity in agriculi	ture	1		
Spatial regime or country	β	Signif. dummies	Adj. R <sup>2</sup>	Wald test	P-value	$\sigma^2_{T} > \sigma^2_{T-1}$
UE-12	-0.037 (0.004)	-	0.373	1118.35	0.000	NO
EU-12 with country dummy	-0.037 (0.004)	YES	0.393	334.87	0.000	NO
EU-12 with spatial regime dummy	-0.037 (0.004)	NO	0.369	7.37	0.006	NO
Core	-0.034 (0.004)	-	0.405	1.65	0.198	NO
Periphery	-0.023 (0.006)	-	0.144	379.21	0.000	NO
	Labour pr	oductivity in manufac	etory			
Spatial regime or country	β	Signif. dummies	Adj. R <sup>2</sup>	Wald test	P-value	$\sigma^2_{T} > \sigma^2_{T-1}$
UE-12	-0.039 (0.004)	-	0.335	534.52	0.000	YES
EU-12 with country dummy	-0.042 (0.004)	NO	0.578	35.09	0.000	YES
EU-12 with spatial regime dummy	-0.040 (0.004)	NO	0.332	0.37	0.541	YES
Core	-0.052 (0.005)	-	0.522	3045.17	0.000	YES
Periphery	-0.036 (0.006)	-	0.284	0.001	0.967	YES
	Labour prod	ductivity in market se	rvices	1		
Spatial regime or country	β	Signif. dummies	Adj. R <sup>2</sup>	Wald test	P-value	$\sigma^2_T > \sigma^2_{T-1}$
UE-12	-0.030 (0.003)	-	0.350	5615.33	0.000	NO
EU-12 with country dummy	-0.032 (0.003)	NO	0.353	21.72	0.000	NO
EU-12 with spatial regime dummy	-0.030 (0.003)	NO	0.349	0.31	0.579	NO
Core	-0.011 (0.004)	-	0.065	70.78	0.000	NO
Periphery	-0.037 (0.004)	-	0.483	4057.14	0.000	NO
	Labour produ	ctivity in non-market	services			
Spatial regime or country	β	Signif. dummies	Adj. R <sup>2</sup>	Wald test	P-value	$\sigma^2_T > \sigma^2_{T-1}$
UE-12	-0.043 (0.003)	-	0.412	2095.01	0.000	NO
EU-12 with country dummy	-0.041 (0.004)	NO	0.427	25.03	0.000	NO
EU-12 with spatial regime dummy	-0.043 (0.004)	NO	0.409	0.38	0.535	NO
Core	-0.046 (0.004)	-	0.535	7357.55	0.000	NO
Periphery	-0.041 (0.006)	-	0.362	281.77	0.000	NO

*Notes:* standard errors are in brackets. In all cases both Moran's I test and robust version of Lagrange Multiplier test for residual spatial autocorrelation are not statistically significant.