SPATIAL AND SECTORAL PRODUCTIVITY CONVERGENCE BETWEEN EUROPEAN REGIONS, 1975-2000

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Abstract

This paper analyzes the evolution of labor productivity disparities among 145 European regions over 1975-2000 according to the concepts of σ- and β-convergence and emphasizes the importance of including spatial effects and a disaggregated analysis at the sectoral level. We detect a significant σ-convergence only in aggregate labor productivity and in the services sectors among peripheral regions. We also show that omitting spatial effects leads to biased measures of σ-convergence. We then estimate a pooled β-convergence model including spatial autocorrelation and sectoral differentiation. The results indicate that disparities in productivity levels between core and peripheral regions persist and that the nature of spatial effects vary by sector.

Keywords: Europe, convergence, labor productivity, spatial effects, spatial econometrics

JEL classification: R11, R12, R15, C21

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1. INTRODUCTION

Most reports of the European Commission focus on regional disparities according to the criteria of per capita GDP. However, as Melachroinos and Spence (1999) note, there are at least two reasons to examine more closely regional disparities based on productivity levels. First, improvements in living standards of any economy are dependent in the long run upon labor productivity increases. Second, productivity convergence process between OECD economies (Baumol, 1986; Dollar and Wolff, 1988) or between EU members (Doyle and O'Leary, 1999) is under way; as a consequence, it is necessary to pay more attention to this issue at the regional level as well. Moreover, a disaggregated approach at the sectoral level of the convergence hypothesis has not been commonly performed. Indeed, it may alter the conclusions usually drawn in the literature about the evidence of convergence and the identification of the forces driving to it (Cuadrado-Roura *et al*., 1999; Lopez-Bazo *et al*., 1999). The key results of studies having used this approach are, first, that there is a greater degree of convergence at the aggregate level than at the sectoral levels (Dollar and Wolff, 1993; Bernard and Jones, 1996a; Doyle and O'Leary, 1999); and second, that convergence is different from one sector to another. For example, Bernard and Jones (1996a, 1996b) find no convergence for the manufacturing sector while strong convergence exists for the service sector.

There are even fewer studies dealing with sectoral convergence at the regional level in Europe: Paci and Pigliaru (1999a, b) focus on the EU regions, whereas Cuadrado-Roura *et al.* (1999) and Dall'erba (2005) analyze the Spanish regions, Paci and Pigliaru (1997) the Italian ones, Viagonis and Spence (1994) the Greek ones. Their results indicate most of the time that the process of aggregate productivity convergence is 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 that has been more pronounced in the poor regions than in the rich ones.

In this paper, we disaggregate labor productivity for 145 European regions into 5 sectors in order to highlight whether the process of convergence typically found is also valid for each sector. It allows avoiding the mix of converging and nonconverging sectors in the aggregate. In addition, we pay a special attention to the role played by geographical location and potential interregional linkages of each region. Indeed, we do not accept the idea of considering regions as isolated entities; in that purpose we use the formal tools of spatial statistics and econometrics[1]. They allow us to include two well-known spatial effects: spatial autocorrelation and spatial heterogeneity.

[1] See, among others, Rey and Montouri (1999), Fingleton (1999, 2001), Lall and Shalizi (2003), Lopez-Bazo *et al.* (2005) and Le Gallo and Dall'erba (2006) for empirical studies using these tools. See also Rey and Janikas (2005) and Abreu *et al.* (2005) for literature reviews.

The paper is organized as follows. Section 2 presents the convergence concepts used in this paper and shows why including spatial effects must be taken into account in this analysis. Section 3 describes the data, the weights matrix and an exploratory spatial data analysis is performed on the sample in order to detect spatial regimes. In sections 4 and 5, we perform several tests of labor productivity convergence according to the concepts of σ- and β-convergence to which we add the relevant spatial effects. While the first one measures convergence through a reduction of the variance of regional labor productivity over time, the second one assumes that regions with lower initial level of labor productivity have a higher growth rate than the other regions. Section 5 concludes.

2. σ- AND β-CONVERGENCE IN SECTORAL PRODUCTIVITIES

The convergence debate has given rise to a very large amount of empirical work, mostly based on aggregate convergence (Barro and Sala-I-Martin, 1995; Mankiw, 1995; Durlauf and Quah, 1999). Less work has been performed using a disaggregated approach to the convergence issue (Dollar and Wolff, 1993; Bernard and Jones, 1996a, 1996b; Doyle and O'Leary, 1999; Esteban, 2000). However, convergence appears to be very different from one sector to another and, when it occurs at the aggregate level, it seems to be mostly driven by convergence in the service sectors (Bernard and Jones, 1996a, 1996b). For empirical research, several measures of convergence have been proposed. In this paper, most attention is paid to the two commonly used concepts of σ- and β-convergence (Sala-I-Martin, 1996)[2].

The concept of σ-convergence continues to attract attention (Fan and Casetti, 1994; Carlino and Mills, 1996b, Bernard and Jones, 1996a-c; Cuadrado-Roura *et al*., 1999). This concept focuses on how the level of cross-sectional dispersion, measured as the sample variance, changes over time. Formally, denote by y_{it} the logarithm of productivity for region *i* in period *t*, then the sample variance for period *t* can be defined as:

$$s_t^2 = \frac{1}{n-1}\sum_{i=1}^{n}(y_{it} - \overline{y}_t)^2 \qquad (1)$$

where *n* is the total number of regions and $\overline{y}_t$ is the sample average for period *t*. There is σ-convergence over the study period between the *n* regions if (1) declines over time, while increasing values indicate divergence in the cross-sectional distribution. The concept of σ-convergence can therefore be associated to a form of inequality reduction.

[2] Other methods have been suggested to evaluate convergence: panel data techniques (Islam, 1995), time-series techniques (Carlino and Mills, 1996; Bernard and Jones, 1996b; Choi, 2004) or Markov chain analysis (Magrini, 1999; Fingleton, 1999).

Since the articles of Barro and Sala-I-Martin (1991, 1992), numerous studies have examined β–convergence between different countries and regions[3]. This concept is linked to the neoclassical growth model, which predicts that the growth rate of a region is positively related to the distance that separates it from its steady-state. Empirical evidence for β–convergence has usually been investigated by regressing growth rates of GDP on initial levels. Note that β- and σ-convergence concepts are not necessarily linked. Indeed, β-convergence is a necessary but not a sufficient condition for σ-convergence (Friedman, 1992). Therefore absence of σ-convergence can co-exist with β-convergence.

Two 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 characterized by the same steady state, and differ only by their initial conditions. Formally, this hypothesis is usually tested on the following cross-sectional model, estimated by OLS:

$$g = \alpha S + \beta y_0 + \varepsilon \qquad \varepsilon \sim N(0, \sigma_\varepsilon^2 I) \tag{2}$$

where g is the $(n\times 1)$ vector of average growth rates of per capita GDP between date 0 and T; S is the $(n\times 1)$ sum vector; y_0 is the vector of log per capita GDP levels at date 0. There is absolute β–convergence when the estimate of β is significantly negative. Second, the concept of *conditional* β-convergence is used when the assumption of similar steady-states is relaxed. In this case, a matrix of variables, maintaining constant the steady state of each economy is added to (2). Note that if economies have very different steady states, this concept is compatible with a persistent high degree of inequality among economies.

Both β-convergence concepts have been heavily criticized on theoretical and methodological grounds. For example, Friedman (1992) and Quah (1993b) show that β-convergence tests may be plagued by Galton's fallacy of regression toward the mean. Furthermore, they face several methodological problems such as heterogeneity, endogeneity, and measurement problems (Durlauf and Quah, 1999; Temple, 1999). We focus in this section on the problems linked to the omission of the spatial dimension of regional data. Indeed, in cross-country studies, economies are most of the time treated as "isolated islands" (Mankiw, 1995; Quah, 1996), but this approach is not acceptable for regional settings. More precisely, regional data are often characterized by spatial autocorrelation and spatial heterogeneity. These concepts have been described in numerous recent studies (see, for instance, Anselin, 1988 and 2001; Rey and Montouri, 1999; Le Gallo *et al.*, 2003, 2005). We start by assessing spatial heterogeneity. While several techniques have been used to detect its

[3] See Durlauf and Quah (1999) for a review of this extensive literature.

presence (*a priori* criteria, regression trees, etc.), we use the techniques of exploratory spatial data analysis, which rely on geographic criteria. They are described in the following section.

3. DATA, SPATIAL WEIGHTS MATRIX AND SPATIAL REGIMES

The data on labor productivity come from the Cambridge Econometrics (2001) database. They correspond to the Gross Value Added (GVA) divided by the number of workers. Labor productivity is further disaggregated into 5 different sectors: Agriculture, Energy and Manufacturing, Construction, Market Services, Non-Market Services. We consider 145 European regions at the NUTS 2 level[4] over 1975-2000 which are the following: Belgium (11 regions), Denmark (1 region), Germany (30 regions, Berlin and the nine former East German regions are excluded due to historical reasons), Greece (13 regions), Spain (16 regions, as we exclude the remote islands: Las Palmas, Santa Cruz de Tenerife Canary Islands and Ceuta y Mellila), France (22 regions), Ireland (2 regions), Italy (20 regions), Netherlands (12 regions), Portugal (5 regions, the Azores and Madeira are excluded because of their geographical distance), Luxembourg (1 region), United Kingdom (12 regions, we use regions at the NUTS I level, because NUTS II regions are not used as governmental units, they are merely statistical inventions of the EU Commission and the UK government).

Over our study period, the European regions are characterized by high differences in sectoral specialization and labor productivity. Table 1 below provides these figures for each sector under study and for three years, 1975, 1990 and 2000. We also display the European regional average and the average of the regions that belong to the cohesion countries (Portugal, Spain, Greece and Ireland: 36 regions) as opposed to the regions of the other countries (109 regions). The reason of this distinction relies in the fact that these countries were the poorest members of the EU15 since their adhesion in the 80's, when the share of agriculture in their economy was much higher than in the other members.

[Table 1 about here]

The agricultural sector shows the largest dispersion in labor shares in 1975 and 1990, but not in 2000 anymore. The share of agriculture in the labor force has decreased in cohesion regions, but in 2000 it is still close to three times greater than in the core regions. This divide has been highlighted by Paci and Pigliaru (1997) as well. We also note that the decrease in the share of agriculture has been greater among core regions than cohesion regions. Concerning the other sectors, the share of energy and manufacturing has decreased all over Europe; the one of construction has increased in the cohesion regions, on the opposite

[4] NUTS means: Nomenclature of Territorial Units for Statistics. The European Commission divides its territory according to the classification established by Eurostat. It is based on national administrative units.

of the one in the core regions. This may be due to the cohesion efforts that have been taking place within these countries. Indeed, since the early 90's, the EU Commission has financed heavy investments in the poor members as compensation from being less well placed to benefit from the integration process, necessary before the introduction of the common currency. The share of the market and non market services has always been greater in the core regions, but it has been increasing so much in the cohesion regions that market services are currently the first sector in terms of labor share, whereas it used to be agriculture.

The levels of labor productivity appear on the right hand side of Table 1. They are calculated relatively to the overall EU productivity in order to account for sectoral differences. In any sector, the cohesion regions display productivity levels that are smaller than the EU average, but the greatest difference relies in the agricultural sector. The productivity level gap between core and cohesion regions decreases slightly in the energy and manufacturing sector as well as in the construction sector, whereas it increases in all the others. Finally, we note that the productivity levels in the market and non market services sectors have not evolved much in the core regions, while they have highly increased in the agricultural sector. This may be explained by this sector getting more capital intensive, thus leading to a migration of a large part of the labor force from the primary to the tertiary sector.

Spatial analysis relies on the definition of a spatial weights matrix, which exogenously defines the way regions are spatially connected to each other. We have chosen to use two different types of matrices. First, we follow Bodson and Peeters (1975), Aten (1996, 1997) or Los and Timmer (2002)**,** who find more attractive to base these weights on the channels of communication between regions, such as roads and railways. We have therefore constructed a weights matrix based on travel time by road from the most populated town of a region to the one of another region[5]. These data come from the web site of Michelin[6]. We adopt travel time instead of distance by road because of the existence of islands, which forces us to include the time spent to load and unload trucks on boats. This information would not have appeared if we had considered distance by road only. The second type of weights matrices is based on pure geographical distances, as suggested by Anselin and Bera (1998) or Anselin (1996), as exogeneity of geographical distance is unambiguous.

The particular specification of the weights matrix depends on the European geography, which does not allow us to consider simple contiguity matrices, otherwise the weights matrix would include rows and columns with only zeros for the islands. Since unconnected observations are eliminated from the results of spatial autocorrelation statistics, this would change the sample size and the interpretation of statistical inference. More precisely, we use

[5] Information on the most populated town come from www.citypopulation.de/Europe.html
[6] www.viamichelin.com

the great circle distance between regional centroids. Distance and time-based weight matrices are defined as:

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

where w_{ij}^* is an element of the unstandardized weight matrix; w_{ij} is an element of the standardized weight matrix; d_{ij} is the great circle distance (or time) between centroids of region *i* and *j*; $D(1) = Q1$, $D(2) = Me$ and $D(3) = Q3$, $Q1$, Me and $Q3$ are respectively the lower quartile, the median and the upper quartile of the great circle distance (or time) distribution. $D(k)$ is the cutoff parameter for $k = 1,...3$ above which interactions are assumed negligible. We use the inverse of the squared distance (time), in order to reflect a gravity function. Each matrix is row standardized so that it is the relative and not absolute distance (time) which matters.

As several studies have shown (Dall'erba, 2005; Ertur *et al.*, 2005; Le Gallo and Dall'erba, 2006), there is plenty of evidence of the presence of two spatial regimes among European regions. We therefore use the spatial weight matrices defined previously to detect formally spatial heterogeneity in the distribution of aggregate labor productivity. In that purpose, we use the G-I* statistics developed by Ord and Getis (1995)[7] on the aggregate labor productivity levels in 1975. These statistics are computed for each region and they allow detecting the presence of local spatial autocorrelation: a positive value of this statistic for region *i* indicates a spatial cluster of high values, whereas a negative value indicates a spatial clustering of low values around region *i*. Based on these statistics, we determine our spatial regimes using the following rule: if the statistic for region *i* is positive, then this region belongs to the group of "high labor productivity" regions and if the statistic for region *i* is negative, then this region belongs to the group of "low productivity" regions. The advantage of this technique over Moran scatterplots is that is allows us to keep in the sample the regions that present "atypical" autocorrelation linkages (High-Low or Low-High)[8].

For all weight matrices described above, we detect two spatial regimes at the initial period, which highlights some form of spatial heterogeneity:

- 91 regions belong to the spatial regime "Core":

[7] All computations in this paper have been carried out using SpaceStat 1.91 (Anselin, 1999) and the spatial econometrics toolbox in Matlab (LeSage, 1999).

[8] See Le Gallo and Dall'erba (2006) for more details on the detection of convergence clubs using these statistics.

Belgium, Germany, Denmark, France, Italy (but Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna), Luxembourg, the Netherlands.

- 54 regions belong to the spatial regime "Periphery":

Spain, Greece, Ireland, Southern Italy (Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna), Portugal, the United-Kingdom. It may appear surprising to see the UK in the peripheral regime, but there is a clear gap between its productivity level and the one of the other leading EU members. According to the British Department of Trade and Industry (1997), it comes from a lack of investment in equipment, infrastructure, technology and skills.

4. SPATIAL σ–CONVERGENCE

We first start our analysis with the study of σ-convergence between European regions using equation (1) with n = 145. The evolutions of the sample variances for aggregate labor productivity and the five sectoral labor productivities are depicted in figure 1.

[Figure 1 about here]

While aggregate labor productivity seems to have converged over the period, the situation is very different between sectors. The agricultural sector shows a clear pattern of divergence with a high level of disparities, the energy & manufacturing and construction sectors remain globally stable while the market services and the non-market services sectors have slightly converged. This may be explained by the fact that σ-convergence in aggregate labor productivity depends on sectoral productivities as well as on the productive structure. Therefore, since productivity is usually higher in energy & manufacturing or services than in agriculture, a reallocation of labor from low to high productivity sectors occurring faster in the initially poorer regions may explain a convergence process in total productivity that does not necessarily occur at the level of each individual productive sector. Cuadrado-Roura *et al.* (1999) and Dall'erba (2005) reach a similar conclusion in the case of the Spanish regions, as well as Paci and Pigliaru (1999a, b) in the case of the European regions.

Since the detection of convergence or divergence must be confirmed by a formal test, we apply the test suggested by Carree and Klomp (1997). They show that the statistics for the test of sigma-convergence (i.e. the difference between the final and the initial variance is significantly different from zero) can be defined for sector j as following:

$$T_j = \sqrt{n} \cdot \frac{s_{j1}^2 / s_{jT}^2 - 1}{2\sqrt{1-(1-\hat{\beta}_j)^2}} \tag{4}$$

where n = 145; s_{j1}^2 denotes the sample variance for sector j in 1975; s_{jT}^2 denotes the sample variance for sector j in 2000 and $\hat{\beta}_j$ is the OLS estimator of the following regression for sector j:

$$y_{ijT} = \alpha_j + (1 - \beta_j) y_{ij1} + \varepsilon_{ij} \tag{5}$$

where $\beta_j > 0$ indicates convergence ($y_{ijT} < y_{ij1}$); y_{ij1} is the logarithm of productivity in region i and sector j in 1975; y_{ijT} is the logarithm of productivity in region i and sector j in 2000 and ε_{ij} is an error term with the usual properties. Under the null hypothesis of no σ-convergence, T_j has a standard normal distribution. These statistics for aggregate labor productivity and productivities in the five sectors are displayed in the first column of table 2.

[Table 2 about here]

The results confirm the visual impression obtained previously: over the whole period, only the market services and non-market services sectors converge significantly while the three others sectors don't. Note however that some temporal heterogeneity in the previous patterns can be highlighted. Indeed, figure 1 indicates a clear break around 1990 for most sectors: the sample variance for the sectors of agriculture, energy & manufacturing and construction were stable until 1990 and began to rise afterwards.

In order to investigate the possibility of behavior differences between the core and peripheral regimes, the preceding analysis has been replicated for the two subsets defined in section 3. The results of the test statistics are displayed in the second and third columns of table 2. Significant differences appear across sectors and across spatial regimes. Indeed, for the core regions, there is either absence of σ-convergence (agriculture, energy & manufacturing, construction and non-market services) or non-significant σ-convergence. On the contrary, in the periphery, only energy & manufacturing does not display any pattern of σ-divergence while there is non-significant σ-convergence in agriculture.

While the previous analysis tends to conclude that σ-convergence differs by sector and regime, this concept suffers from several limitations. In addition to Quah's critics (1993a, 1993b) on the lack of information on the dynamics of the whole distribution and on the movement of individual economies within the distribution, Rey and Dev (2004) show that the measure used, the sample variance (2), substantially overestimates global dispersion when spatial effects are present in the data. Indeed, it 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). Several works on the European regions indicate that these assumptions are not true (Fingleton, 1999; Arbia and Paelinck, 2004; Ertur *et al*., 2005); the evolution of the sample variance measured so far will in fact reflects both the effects of changes in the variance but also in the level and form of spatial effects.

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 labor productivities are a collection of observations such as: $y \sim N(\mu, \sigma^2\Omega)$ where Ω is a general $(n \times n)$ matrix. The sample variance is then decomposed as follows, omitting the time subscript:

$$s^2 = \sigma^2\theta$$

with $$\theta = \frac{1}{n-1}\left(\sum_{i=1}^{n}(\mu_i^2 + \omega_{i,i}) - \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n}(\mu_i\mu_j + \omega_{i,j})\right) \tag{6}$$

where n = 145; s^2 is the sample variance defined in (2); 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 (2004), this decomposition can be performed by using a spatial filtering process, as suggested by Getis (1995) or Tiefelsdorf and Griffith (2002), or by fully specifying the structure of θ and then estimating directly all the parameters. We choose this second alternative and compare three different approaches to represent the evolution of s^2 and σ^2: a) the conventional sample variance, when spatial effects are not considered, i.e. $s^2 = \sigma^2$; b) the sample variance where spatial autocorrelation takes the form of a spatial lag model and c) the same but spatial autocorrelation takes the form of a spatial error model . In the last two cases, the estimation of the global variance parameter σ^2 is based on the estimate of the error variance of a spatial error model and is estimated by Maximum Likelihood (ML). The figures 3a-3f below display the estimates of s^2 and σ^2 of the aggregate and sectoral labor productivities according to the three approaches depicted above. The figures are presented using the *D*(*1*) weight matrix based on distance[9]. Note that the estimation of σ^2 based on models with spatial dependence alone or spatial dependence together with spatial heterogeneity in the form of mean heterogeneity (with two regimes previously defined in section 3) are very similar and are not displayed here due to the lack of space[10].

[Figures 3a-3f about here]

First, we note that there is practically no difference between the estimate of σ^2 based on a spatial lag and the one based on a spatial error. Second, the doubled-scaled figures show

[9] The results show similar patterns when weights matrix *D*(*1*) based on travel time by road is used. These results are available from the authors upon request.

[10] Complete results are available from the authors upon request.

the obvious difference existing between the sample variance (on the right) and the global dispersion parameter (on the left), the former being systematically much higher than the latter. It does not necessarily mean that basing an analysis of σ-convergence without considering spatial autocorrelation leads to unreliable conclusions since, as our case indicates, the general trends are similar with or without spatial effects. However, the relative magnitude of the difference between the conventional approach and the two others is not constant over the period. Indeed, the calculation of θ reveals an increase in the influence of spatial effects on the sample variance at the beginning of the 90's for all the variables, further indicating the existence of temporal heterogeneity in our study period. Finally, all the approaches display the presence of σ-convergence in the aggregate labor productivity and in the market and non-market services sectors, but not in the other sectors.

Since the concept of σ-convergence is one of the many ways to look at regional dynamics, it is completed in the next section by an analysis of the β-convergence process to which we add the relevant spatial effects.

5. SPATIAL β–CONVERGENCE

In this section, we turn to the estimation of β-convergence between the regions of our sample. The spatial dimension of data is tested for and introduced by means of spatial autocorrelation and spatial heterogeneity. We start by the estimation of β-convergence in aggregate labor productivity and then compare the results to those obtained for each sector. Differences between sectors are also formally tested.

51. Estimation results for aggregate labor productivity

We use a "specific to general" specification search approach, similar to that suggested by Florax *et al*. (2003). Starting with the OLS estimation of the absolute β-convergence model (model 2) with White's (1980) correction for heteroskedasticity of an unknown form, the estimation results, displayed in columns 1 and 3 of table 3, show that $\hat{\beta}$ has the expected sign (-0.009) and is significant (p-value = 0.000), corresponding to a convergence speed of 0.97% and a half-life of 76 years. Looking at the diagnostic tests, the Jarque-Bera test rejects the assumption of normality of the residuals (p-value = 0.000). We also note that the White test clearly does not reject homoskedasticity (p-value = 0.505) as well as the Koenker-Basset test versus the aggregate labor productivity at the initial period (p-value = 0.359).

[Table 3 about here]

Various tests aimed at detecting the presence of spatial autocorrelation in the estimation of the appropriate β-convergence model have been described in Anselin (1988) and Anselin *et al.* (1996) and are applied here. We start with the OLS estimation of the absolute β-convergence model. In order to identify the form of spatial dependence (spatial error or spatial lag), the Lagrange Multiplier tests (resp. LMERR and LMLAG) and their robust version are performed. The decision rule suggested by Anselin and Florax (1995) is then used to decide the most appropriate specification as follows: if LMLAG (resp. LMERR) is more significant than LMERR (resp. LMLAG) and R-LMLAG (resp. R-LMERR) is significant whereas R-LMERR (resp. R-LMLAG) is not, then the most appropriate model is the spatial autoregressive model (resp. the spatial error model). Following this decision rule, the results displayed in table 3 show that LMERR is more significant than LMLAG, but both R-LMERR and R-LMLAG are significant. Since R-LMERR is more significant, we adopt the spatial error model as the best specification.

The estimation results obtained by Maximum Likelihood (ML) are displayed in columns 2 and 4 of table 3[11]. A positive and significant spatial autocorrelation of the error terms is found ($\hat{\lambda}$ = 0.507 and $\hat{\lambda}$ = 0.623 with weight matrix $D(1)$ based on distance and time respectively). The level of convergence ($\hat{\beta}$ = -0.013 and $\hat{\beta}$ = -0.014) has increased compared to the OLS-estimation and is still significant. The convergence speed is 1.51% (1.76% with the time-based matrix) and the half-life is 54 years (48 years)[12]. The LIK, AIC and SC measures indicate that this model specification is better than the OLS-specification. The LR-test on the spatial autoregressive coefficient $\hat{\lambda}$ is highly significant in both cases.

Next, we perform the same type of analysis for each sector in order to have a more complete idea of the β–convergence phenomenon among European regions.

52. Estimation results for sectoral labor productivity

Pooled models estimated by OLS

Formally, let us take as a starting point the following pooled model where one β-convergence equation is estimated for each sector using OLS:

$$g_j = \alpha_j S + \beta_j y_{0,j} + \varepsilon_j \qquad \varepsilon_j \sim N(0,\sigma^2) \qquad j = 1,...5 \tag{7}$$

[11] All the results are similar when the estimation is based on the Generalized Methods of Moment estimation method.

[12] The convergence speed is the speed necessary for the economies to reach their steady state over the studied time period, which may be defined as: $b = -\ln(1+T\beta)/T$. The half-life is the time necessary for the economies to fill half of the variation which separates them from their steady state, and is defined by: $\tau = -\ln(2)/\ln(1+\beta)$.

where j is the sectoral index, $j = 1,...5$; g_j is the (n×1) vector of average growth rates of productivity of sector j; S is the (n×1) sum vector; $y_{0,j}$ is the vector of log productivity levels at the initial date (1975) for sector j; α_j and β_j are the 10 unknown parameters to be estimated. There is absolute β–convergence for sector j when the estimate of β_j is significantly negative. Moreover, as one equation is specified by sector, this specification allows testing the hypothesis of constant coefficients between sectors, i.e. the *sectoral* stability of the convergence process, using standard Chow tests:

$$\begin{cases} \alpha_j = \alpha & \forall j = 1,...5 \\ \beta_j = \beta & \forall j = 1,...5 \end{cases} \tag{8}$$

The estimation results are displayed in columns 1 to 5 of table 4. All coefficients are significant for all 5 sectors, with varying convergence speeds going from 1% for market services to 2.15% for construction. This confirms the hypothesis of sectoral convergence between the European regions. Looking at specification diagnostics, it appears that estimating one β-convergence model by sector is subject to caution. Indeed, as displayed at the bottom of table 4, it is not possible to reject the hypothesis of sectoral homogeneity of both the constant and the beta coefficient across the five equations since none of the associated sectoral homogeneity tests is significant (resp. p-value = 0.119 and 0.152). The global test of sectoral homogeneity however yields to the rejection of the null hypothesis.

[Table 4 about here]

Nevertheless, these last tests should be considered with caution. Indeed, as indicated by the results of table 4, all spatial autocorrelation Lagrange multiplier tests reject their respective null hypothesis for both weights matrices. Since LMERR and R-LMERR are more significant than respectively LMLAG and R-LMLAG, the pooled model with spatial error autocorrelation terms is the most appropriate specification. Therefore, the results from the simple pooled model estimated by OLS may not be reliable since the presence of spatial autocorrelation has not been taken into account yet.

Before integrating spatial autocorrelation however, we investigate the possibility of structural instability among coefficients. Indeed, in equation (7), the coefficients are assumed to be constant in space for each sector. However, as stated in section 2, there may be some evidence for spatial convergence clubs that should be tested formally. In that purpose, a specification allowing for spatial regimes (Core and Periphery) in each equation should also be considered:

$$g_j = \alpha_{C,j} D_C + \alpha_{P,j} D_P + \beta_{C,j} D_C y_{0,j} + \beta_{P,j} D_P y_{0,j} + \varepsilon_j \qquad \varepsilon_j \sim N(0,\sigma^2) \qquad j = 1,...5 \tag{9}$$

where the subscribe C stands for the core regime and the subscribe P stands for the peripheral regime; D_C and D_P are dummy variables corresponding respectively to the core and periphery regimes previously defined; $\alpha_{C,j}$, $\alpha_{P,j}$, $\beta_{C,t}$, $\beta_{p,j}$ with $j=1,...5$, are 20 unknown parameters to be estimated. This specification, estimated by OLS, allows the convergence process to be different across regimes for each sector. Again, the hypothesis of sectoral stability of the coefficients can be tested based on this specification using F statistics. In this case, the assumptions to be tested are the following:

$$\begin{cases} \alpha_{C,j} = \alpha_C & \forall j = 1,...5 \\ \alpha_{P,j} = \alpha_P & \forall j = 1,...5 \\ \beta_{C,j} = \beta_C & \forall j = 1,...5 \\ \beta_{P,j} = \beta_P & \forall j = 1,...5 \end{cases} \qquad (10)$$

Moreover, since the coefficients are differentiated by regime in each equation, a second test has to be performed, i.e. the test of *spatial* stability of the convergence process for each sector. In other words, we test the following assumptions:

$$\begin{cases} \alpha_{C,j} = \alpha_{p,j} & \forall j = 1,...5 \\ \beta_{C,j} = \beta_{p,j} & \forall j = 1,...5 \end{cases} \qquad (11)$$

These tests can also be performed using standard F statistics. The OLS estimation results of equation (9) are displayed in columns 6 to 10 of table 4. Several results are worth mentioning. First, all constants are significant at 5% (except for non-market services in the core regime where it is significant at 10%) and almost all beta coefficients are significant and negative. The only exception is the coefficient for non-market services in the core regime. Concerning the specification diagnostics, two kinds of stability tests can be performed in this model. First, the F tests on the sectoral stability of the coefficients across equations are displayed in the bottom right column (OLS) of table 4. Only the constant in the peripheral regime cannot be considered as significantly different across sectors (p-value = 0.108). Second, the F tests on the spatial stability of the coefficients in each equation are displayed in column 1 of table 5. It appears that for all sectors, the constant and the beta coefficients are significantly different across regimes (this is true only at 10% for energy and manufacturing). However, as in the pooled model without spatial regimes, all these results must be taken with caution since the presence of spatial autocorrelation, highlighted by the results of the Lagrange Multiplier tests, has not been included yet.

[Table 5 about here]

Pooled models with spatial autocorrelation estimated by ML

Since the previous results showed the presence of significant spatial autocorrelation, we estimated a pooled model with spatial regimes (as in equation 9) and spatial error autocorrelation. Note that in this case, the same spatial autoregressive process affects all the errors, which means that spatial autocorrelation is identical in core and in peripheral regions and that all the regions are interacting through the spatial weights matrix.

The results of the tests of sectoral stability are displayed at the bottom right of table 4 (ML estimation). Since ML estimation is used, these tests cannot be performed using F statistics; rather we computed likelihood ratio tests. For both weights matrices, the results show that while the constant and the beta coefficients are significantly different from one sector to another in the core regime, this is not the case in the peripheral regime. The spatial stability tests, also performed with likelihood ratio statistics, are displayed in columns 2 and 3 of table 5 and indicate the presence of spatial regimes for agriculture, construction and non-market services. On the contrary, no distinction between the core regime and the peripheral regime is necessary for energy and manufacturing and market services.

The final model we estimate is therefore a pooled model with spatial error autocorrelation for all the sectors and spatial regimes for the agriculture, construction and market services sectors only. The estimation results are displayed in table 6. Columns 1 to 5 display the results with the weights matrix based on distance and columns 6 to 10 show the results with the weights matrix based on time. A very high convergence rate is detected in the agriculture and construction sectors between core regions, while convergence remains rather slow between peripheral regions. Convergence between all the European regions in the energy and manufacturing and market services sectors is rather slow too. Fast convergence can be observed between peripheral regions in the non market services sector while no such convergence exists between core regions. The results show also a greater convergence among core regions than peripheral regions in the agriculture and construction sectors. These last findings indicate that there is a phenomenon of persistent differences between the productivity levels of the core and peripheral regions in conjunction with the presence of convergence within each regime.

All sectors display a higher pace of convergence than the aggregate labor productivity, a conclusion which is at odds to that obtained on a sample of OECD countries by Bernard and Jones (1996a). Spatial error autocorrelation is strongly significant and positive. It can be noted that omitted variables may be at the origin of the presence of spatial autocorrelation: since the dataset we are using does not allow controlling for the determinants of the steady state per capita GDP, spatial autocorrelation may act as a proxy to all the omitted variables. Spatial autocorrelation in this case implies the presence of positive growth spillovers between

European regions for each sector (Fingleton, 1999; Le Gallo *et al*., 2003). From an economic point of view, the existence of spatial regimes indicates that the convergence process differs between spatial regimes. Regions belonging to different regimes converge towards different steady-states, which is consistent with the persistence of inequalities between regimes.

[Table 6 about here]

6. CONCLUSION

While most studies on regional inequalities rely on per capita GDP measures and use the famous concepts of σ- and β-convergence, we have shown that indicators considering the productive structure of the economies are also relevant. Furthermore, we have adopted a spatial approach to convergence, by incorporating both spatial dependence and spatial differentiation between European regions. For the first time in the EU case, the modeling of spatial dependence relies on weight matrices defined on transportation time by road. The results they display are globally similar to those based on common weight matrices defined on pure geographical distance.

In the case of σ-convergence, the relative magnitude of the difference between the conventional approach and the spatial ones varies for each sector and each year, but does not lead to contradictory conclusions. All the approaches are in agreement in displaying a constant σ- convergence of the aggregate labor productivity over the period, whereas only the market and non-market services sectors show the same trend among the sectors. Some further investigation indicates that this pattern is true for peripheral regions only while sectors in core regions either display σ-divergence or non-significant σ-divergence.

Continuing the analysis using the concept of β–convergence, to which we add the appropriate spatial effects, it appears that all regions converge to the same steady-state in the aggregate labor productivity, energy & manufacturing and market services sectors whereas core regions and peripheral ones converge to their own steady-state in the agriculture, construction and non-market services sectors. This is consistent with the persistence of differences in productivity levels between these two groups. In addition, convergence speeds and the nature of spatial effects vary by sector. While the core regions do not converge in the non-market services sector, their convergence speed is quite high in the agriculture (9.38%) and construction sectors (19.89%). Inversely, non-market services are the sector within which peripheral regions converge most (6.07%) and the agricultural sector the least (2.52%).

As a conclusion, we note that β- and σ-convergence patterns do not coincide, showing that both types of analysis are necessary to have a full picture of convergence patterns in Europe. Indeed, β-convergence is a necessary but not a sufficient condition for σ-convergence, which explains the result of absence of σ-convergence in conjunction with significant β-convergence. Some temporal heterogeneity pattern has been detected in section

3 and should be further investigated in future research. Similarly, the possible role of the structure of production, migratory flows, human capital, infrastructures and technological diffusion on the mechanisms of convergence should be considered at the next stage of the research.

This paper calls for a grass root approach to the phenomenon of regional inequalities in Europe. Indeed, if the economic structure, the localization and potential linkages of each region are not formally included in the estimation of regional dynamics, then any policy will focus only on the "top-of-the-iceberg" of possible measures to correct regional imbalances.

References:

Abreu, M., H.L.F. de Groot and R.J.G.M. Florax, 2005, Space and Growth: A Survey of Empirical Evidence and Methods, *Région et Développement*, forthcoming.

Anselin, L., 1988, *Spatial Econometrics: Methods and Models*, Dordrecht, Kluwer Academic Publishers.

Anselin, L., 1996, The Moran Scatterplot as an ESDA Tool to Assess Local Instability in Spatial Association, in Fisher M., Scholten H.J., Unwin D., *Spatial Analytical Perspectives on GIS in Environmental and Socio-economic Sciences*, London, Taylor and Francis.

Anselin, L., 1999, *SpaceStat, a Software Package for the Analysis of Spatial Data*, Version 1.90, BioMedware, Ann Arbor.

Anselin, L., 2001, Spatial Econometrics, in Baltagi B., *Companion to Econometrics*, Oxford, Basil Blackwell.

Anselin, L. and A. Bera, 1998, *Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics*, in Ullah A., Giles D.E.A., Handbook of Applied Economic statistics, Berlin, Springer-Verlag.

Anselin, L. and R.G.J.M. Florax, 1995, Small Sample Properties of Tests for Spatial Dependence in Regression Models, in: Anselin L. and R.G.J.M. Florax, *New Directions in Spatial Econometrics*, Berlin, Springer.

Anselin, L., Bera, A., Florax, R.G.J.M. and M. Yoon, 1996, Simple Diagnostic Tests for Spatial Dependence, *Regional Science and Urban Economics* 26, 77-104.

Arbia, G. and J.H.P. Paelinck, 2004, Spatial Econometric Modeling of Regional Convergence in Continuous Time, *International Regional Science Review* 26, 342-362.

Aten, B., 1996, Evidence of Spatial Autocorrelation in International Price, *Review of Income and Wealth* 42, 149-163.

Aten, B., 1997, Does Space Matter? International Comparisons of the Prices of Tradables and Nontradables, *International Regional Science Review* 20, 35-52.

Barro, R.J. and X. Sala-I-Martin, 1991, Convergence Across States and Regions, *Brookings Papers on Economic Activity* 1, 107-182.

Barro, R.J. and X. Sala-I-Martin, 1992, Convergence, *Journal of Political Economy* 100, 223-251.

Baumol, W.J., 1986, Productivity Growth, Convergence, and Welfare: What the Long-run Data Show, *American Economic Review* 76, 1072-1085.

Bernard, A.B. and C.I. Jones, 1996a, Comparing Apples to Oranges: Productivity Convergence and Measurement Across Industries and Countries, *American Economic Review* 86, 1216-1238.

Bernard, A.B. and C.I. Jones, 1996b, Productivity Across Industries and Countries: Time Series Theory and Evidence, *Review of Economics and Statistics* 78, 135-146.

Bernard, A.B. and C.I. Jones, 1996c, Productivity and Convergence Across US States and Industries, *Empirical Economics* 21, 113-135.

Bodson, P. and D. Peeters, 1975, Estimations of the Coefficients in a Linear Regression in the Presence of Spatial Autocorrelation: An application to a Belgian Labour-demand Function, *Environment and Planning A* 7, 455-72.
Cambridge Econometrics (2001) *European Regional Databank.*
Carlino, G. and L. Mills, 1996a, Testing Neoclassical Convergence in Regional Incomes and Earnings, *Regional Science and Urban Economics* 26, 565-590.
Carlino, G. and L. Mills, 1996b, Are US Regional Incomes Converging? Reply, *Journal of Monetary Economics* 38, 599-601.
Carree, M. and L. Klomp, 1997, Testing the Convergence Hypothesis: a Comment, *Review of Economics and Statistics* 79, 683-686.
Choi, C.-Y., 2004, A Re-Examination of Output Convergence in the U.S. States: Toward which Level(s) are they Converging?, *Journal of Regional Science* 44, 713-741.
Cliff, A.D. and J.K. Ord, 1981, *Spatial Processes: Models and Applications*, Pion, London.
Cuadrado-Roura, J., Garcia-Greciano, B. and J.L. Raymond, 1999, Regional Convergence in Productivity and Productive Structure: the Spanish Case, *International Regional Science Review* 22, 35-53.
Dall'erba, S., 2005, Productivity Convergence and Spatial Dependence Among Spanish Regions, *Journal of Geographical Systems*, forthcoming.
Department Of Trade And Industry, 1997, *Competitiveness UK: A Benchmark for Business*.
Dollar, D. and E.N. Wolff, 1988, Convergence of Industry Labour Productivity among Advanced Economies, 1963-1982, *The Review of Economics and Statistics* LXX, 549-558.
Dollar, D. and E.N. Wolff, 1993, *Competitiveness, Convergence and International Specialization*, Cambridge MA, MIT Press.
Doyle, E. and E. O'Leary, 1999, The Role of Structural Change in Labour Productivity Convergence among European Union Countries: 1970 to 1990, *Journal of Economic Studies* 26, 106-120.
Durlauf, S.N. and D. Quah, 1999, The New Empirics of Economic Growth, in: Taylor, J. and M. Woodford, *Handbook of Macroeconomics*, North-Holland, Elsevier Science.
Esteban, J., 2000, Regional Convergence in Europe and the Industry Mix: A Shift-Share Analysis, *Regional Science and Urban Economics* 30, 352-364.
Ertur, C., Le Gallo J. and C. Baumont, 2005, The European Regional Convergence Process, 1980-1995: Do Spatial Dependence and Spatial Heterogeneity Matter? *International Regional Science Review*, forthcoming.
Fan, C.C. and E. Casetti, 1994, The Spatial and Temporal Dynamics of US Regional Income Inequality, 1950-1989, *Annals of Regional Science* 28, 177-196.
Fingleton, B., 1999, Estimates of Time to Economic Convergence: an Analysis of Regions of the European Union, *International Regional Science Review* 22, 5-34.
Fingleton, B., 2001, Equilibrium and Economic Growth: Spatial Econometric Models and simulations, *Journal of Regional Science* 41, 117-147.
Florax, R.J.G.M., Folmer, H. and S.J. Rey, 2003, Specification Searches in Spatial Econometrics: The Relevance of Hendry's Methodology, *Regional Science and Urban Economics* 33, 557-579
Friedman, M., 1992, Do Old Fallacies Ever Die?, *Journal of Economic Literature* 30, 2129-2132.
Getis, A., 1995, Spatial Filtering in a Regression Framework: Examples Using Data on Urban Crime, Regional Inequality, and Government Expenditures, in: Anselin, L. and R.G.J.M. Florax., *New Directions in Spatial Econometrics*, Berlin, Springer-Verlag.
Islam, N., 1995, Growth Empirics: A Panel Data Approach, *Quarterly Journal of Economics* 110, 1127-1170.
Lall, S.V. and Z. Shalizi, 2003, Location and Growth in the Brazilian Northeast, *Journal of Regional Science*, 43, 663-681.
Le Gallo, J. and S. Dall'erba, 2006, Evaluating the Temporal and Spatial Heterogeneity of the European Convergence Process, 1980-1999, *Journal of Regional Science*, forthcoming.

Le Gallo, J., Ertur, C. and C. Baumont, 2003, A Spatial Econometric Analysis of Convergence across European regions, 1980-1995, in: Fingleton, B., *European Regional Growth*, Berlin, Springer.
Le Gallo, J., Baumont, C., Dall'erba, S. and C. Ertur, 2005, On the property of diffusion in the spatial error model, *Applied Economics Letters*, forthcoming.
LeSage, J.P., 1999, The Theory and Practice of Spatial Econometrics, mimeo, University of Toledo.
Lopez-Bazo, E., Vayà, E., Mora, A.J. and J. Suriñach, 1999, Regional Economic dynamics and Convergence in the European Union, *Annals of Regional Science* 33, 343-370.
Lopez-Bazo, E., Vaya, E. and M. Artis, 2004, Regional Externalities and Growth: Evidence from European Regions, *Journal of Regional Science* 44, 43-73.
Los, B. and M. Timmer, 2002, Productivity Dynamics in Italian Regions: on Innovation, Investment and Knowledge Assimilation, Paper presented at the 49th North American Meetings of the Regional Science Association International, San Juan, Puerto Rico, November 14-16.
Magrini, S., 1999, The Evolution of Income Disparities Among the Regions of the European Union, *Regional Science and Urban Economics* 29, 257-281.
Mankiw, N.G., 1995, The Growth of Nations, *Brooking Papers on Economic Activity* 1, 275-310.
Melachroinos, K.A. and N. Spence, 1999, Capital and Labour Productivity Convergence of Manufacturing Industry in the Regions of Greece, in: Fischer, M.M. and P. Nijkamp, *Spatial Dynamics of European Integration*, Advances in Spatial Sciences, Berlin, Springer-Verlag.
Ord, J.K. and A. Getis, 1995, Local Spatial Autocorrelation Statistics: Distributional Issues and an Application, *Geographical Analysis* 27, 286-305.
Paci, R. and F. Pigliaru, 1997, Structural Change and Convergence: an Italian Regional Perspective, *Structural Change and Economic Dynamics* 8, 297-318.
Paci, R. and F. Pigliaru, 1999a, European Regional Growth: Do Sectors Matters? in: Adams, J. and F. Pigliaru, *Economic Growth and Change. National and Regional Patterns of Convergence and Divergence*, Cheltenham, Edward Elgar.
Paci, R. and F. Pigliaru, 1999b, Is dualism still a source of convergence in Europe?, *Applied Economics* 31, 1423-1436.
Quah, D., 1993a, Empirical Cross-Section Dynamics in Economic Growth, *European Economic Review* 37, 426-434.
Quah, D., 1993b, Galton's Fallacy and Tests of the Convergence Hypothesis, *Scandinavian Journal of Economics* 94, 427-443.
Quah, D., 1996, Regional Convergence Clusters across Europe, *European Economic Review* 40, 951-958.
Rey, S.J. and B. Dev, 2004, σ-Convergence in the Presence of Spatial Effects, Paper presented at the 43rd Annual Meeting of the Western Regional Science Association**,** Maui, Hawaii, Feb. 26-28.
Rey, S.J. and M.J. Janikas, 2005, Regional Convergence, Inequality, and Space, *Journal of Economic Geography* 5, 155-176.
Rey, S.J. and B.D. Montouri, 1999, US Regional Income Convergence: A Spatial Econometric Perspective, *Regional Studies* 33, 143-156.
Sala-I-Martin, X., 1996, The Classical Approach to Convergence Analysis, *Economic Journal* 106, 1019-1036.
Temple, J., 1999, The New Growth Evidence, *Journal of Economic Literature* 37, 112- 156.
Tiefelsdorf, M. and D.A. Griffith, 2002, Semi-parametric Filtering of Spatial Autocorrelation: the Eigenvalue Approach, Paper presented at the Regional Science Association International Meetings, San Juan, Puerto Rico, November 14-16.
Viagionis, N. and N. Spence, 1994, Total Factor Regional Productivity in Greece, *Environment and Planning C* 12, 383-407.
White, H., 1980, A Heteroskedastic-consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity, *Econometrica* 48, 817-838.

TABLE 1: Labor shares and productivity levels across EU regions

	Labor shares – Percentage values			Labor productivity level – Index, Europe total = 100		
	1975	*1990*	*2000*	*1975*	*1990*	*2000*
			Agriculture			
Min.	0	0	0	11	17	6
Max.	66	48	36	505	373	1647
EU average	16	10	7	132	124	150
Cohesion regions	33	22	15	75	72	73
Core regions	11	6	4	150	141	175
			Energy & Manufacturing			
Min.	3	6	5	7	20	16
Max.	47	42	42	483	522	552
EU average	28	23	20	99	98	99
Cohesion regions	23	20	18	61	66	64
Core regions	29	24	20	111	109	110
			Construction			
Min.	2	4	1	18	29	11
Max.	18	14	15	488	184	270
EU average	9	8	7	100	96	106
Cohesion regions	8	9	10	70	70	75
Core regions	9	7	6	110	105	116
			Market Services			
Min.	9	22	20	16	23	25
Max.	54	59	66	183	168	187
EU average	30	38	44	100	97	94
Cohesion regions	26	34	40	68	63	60
Core regions	32	39	45	110	107	105
			Non Market Services			
Min.	3	7	6	25	39	38
Max.	38	38	38	168	163	427
EU average	17	21	22	98	98	99
Cohesion regions	10	16	17	76	77	73
Core regions	20	23	24	104	104	107

TABLE 2: Tests for σ-convergence

	All regions	**Core**	**Periphery**
Aggregate labor productivity	4.102 [b]	0.677	3.071 [b]
Agriculture	-	-	0.299
Energy & Manufacturing	0.344	-	-
Construction	0.699	-	1.975 [a]
Market Services	2.580 [b]	0.758	2.902 [b]
Non-Market Services	2.805 [b]	-	8.328 [b]

Notes**:** superscripts *a* and *b* mean significant convergence at the 5% and 1% significant levels. "-" means that the standard deviation in 2000 is greater that the standard deviation in 1975.

TABLE 3: Estimation results of the β-convergence model in aggregate labor productivity

Weight matrix	*D(1) based on distance*		*D(1) based on time*	
	1	2	3	4
	OLS-White	*ML*	*OLS-White*	*ML*
$\hat{\alpha}$	0.110 (0.000)	0.146 (0.000)	0.110 (0.000)	0.162 (0.000)
$\hat{\beta}$	-0.009 (0.000)	-0.013 (0.000)	-0.009 (0.000)	-0.014 (0.000)
$\hat{\lambda}$	-	0.507 (0.000)	-	0.623 (0.010)
$\hat{\sigma}_{\varepsilon}^{2}$	$3.45.10^{-5}$ (0.006)	$3.10.10^{-5}$ (0.006)	$3.45.10^{-5}$ (0.006)	$2.96.10^{-5}$ (0.005)
Convergence Speed	1.02%	1.51%	1.02%	1.76%
Half-life	76.41	54.79	76.41	48.35
R^2 adj.	0.3346	-	0.3346	-
Sq. Corr.	-	0.340	-	0.339
LIK	540.088	544.298	540.088	546.917
AIC	-1076.18	-1084.60	-1076.18	-1089.83
SC	-1070.22	-1078.64	-1070.22	-1083.88
Moran's *I*	3.382 (0.000)	-	4.314 (0.000)	-
LMERR	8.382 (0.003)	-	13.836 (0.000)	-
R-LMERR	25.715 (0.000)	-	25.287 (0.000)	-
LMLAG	0.141 (0.707)	-	0.375 (0.241)	-
R-LMLAG	17.474 (0.000)	-	14.826 (0.000)	-
Jarque-Bera	96.587 (0.000)	-	96.587 (0.000)	-
White test	1.366 (0.505)	-	1.366 (0.505)	-
KB-test for heteroskedasticity	1.479 (0.224)	-	1.479 (0.224)	-
LR test on spatial error dependence	-	8.420 (0.003)	-	13.657 (0.000)

Notes: *p*-values are in brackets. *OLS-White* indicates the use of heteroskedasticity consistent covariance matrix estimator (White, 1980). *ML* indicates maximum likelihood estimation. *Sq. Corr.* is the squared correlation between predicted values and actual values. *LIK* is value of the maximum likelihood function. *AIC* is the Akaike information criterion. *SC* is the Schwarz information criterion. *MORAN* is Moran's *I* test for spatial autocorrelation adapted to regression residuals (Cliff and Ord, 1981). *LMERR* stands for the Lagrange Multiplier test for residual spatial autocorrelation and *R-LMERR* for its robust version. *LMLAG* stands for the Lagrange Multiplier test for spatially lagged endogenous variable and *R-LMLAG* for its robust version (Anselin *et al.*, 1996). *KB* is the Koenker-Bassett of heteroskedasticity robust to non-normality. *LR* is the likelihood ratio test for groupwise heteroskedasticity.

TABLE 4: Estimation results for the pooled model with sectoral regimes; OLS-White estimation

	Simple pooled model (9)						Pooled model with spatial regimes (11)				
	1	2	3	4	5		6	7	8	9	10
	Agr.	**En.**	**Con.**	**MS**	**NMS**		**Agr.**	**En.**	**Con.**	**MS**	**NMS**
$\hat{\alpha}$	0.188 (0.000)	0.152 (0.000)	0.179 (0.000)	0.103 (0.000)	0.164 (0.000)	$\hat{\alpha}_C$	0.379 (0.000)	0.247 (0.000)	0.414 (0.000)	0.342 (0.000)	0.087 (0.082)
						$\hat{\alpha}_P$	0.149 (0.000)	0.137 (0.000)	0.190 (0.000)	0.131 (0.000)	0.261 (0.000)
$\hat{\beta}$	-0.016 (0.000)	-0.012 (0.000)	-0.017 (0.000)	-0.009 (0.000)	0.016 (0.000)	$\hat{\beta}_C$	-0.036 (0.000)	-0.021 (0.000)	-0.039 (0.000)	-0.031 (0.000)	0.008 (0.105)
						$\hat{\beta}_P$	-0.013 (0.003)	-0.011 (0.001)	-0.018 (0.000)	-0.012 (0.000)	0.026 (0.000)
$\hat{\sigma}^2_{\varepsilon}$	$2.29.10^{-4}$ (0.015)						$3.10.10^{-5}$ (0.006)				
Convergence Speed	2.06%	1.46%	2.15%	1.00%	2.03%	*Core*	9.44%	3.09%	16.68%	6.10%	-
						Periph.	1.52%	1.28%	2.47%	1.42%	4.23%
Half-life	42.69	56.22	41.33	78.00	43.25	*Core*	18.79	31.82	17.25	21.79	-
						Periph.	54.46	63.04	37.22	57.53	26.21
R^2 adj	0.5036						0.5824				
LIK	2014.10						2081.90				
AIC	-4008.19						-4123.80				
SC	-3962.33						-4032.07				

Spatial autocorrelation tests

	***D*(1) distance**	***D*(1) time**	***D*(1) distance**	***D*(1) time**
Moran's *I*	15.022 (0.000)	14.951 (0.000)	11.420 (0.000)	10.839 (0.000)
LMERR	188.944 (0.000)	182.866 (0.000)	92.417 (0.000)	88.622 (0.000)
R-LMERR	203.439 (0.000)	189.032 (0.000)	55.379 (0.000)	57.736 (0.000)
LMLAG	70.203 (0.000)	64.366 (0.000)	44.513 (0.000)	40.518 (0.000)
R-LMLAG	84.698 (0.000)	70.532 (0.000)	7.475 (0.006)	9.632 (0.006

Sectoral stability of the coefficients tests

Estimation	*OLS*		*OLS*	*ML*	*ML*
Test	*F test*		*F test*	*LR test with D*(1) *distance*	*LR test with D*(1) *time*
$\hat{\alpha}$	1.844 (0.119)	$\hat{\alpha}_C$	7.604 (0.000)	40.583 (0.000)	33.209 (0.000)
		$\hat{\alpha}_P$	1.903 (0.108)	5.540 (0.236)	6.044 (0.196)
$\hat{\alpha}$	1.685 (0.152)	$\hat{\beta}_C$	7.216 (0.000)	29.437 (0.000)	32.933 (0.000)
		$\hat{\beta}_P$	2.551 (0.038)	6.383 (0.172)	6.104 (0.191)
Global	31.433 (0.000)	Global	2.622 (0.000)	65.956 (0.000)	66.395 (0.000)

***Notes*:** See notes of table 3., Agr.: Agriculture, En.: Energy and Manufacturing, Con.: Construction, MS: Market Services, NMS: Non-Market Services; *ML* indicates maximum likelihood estimation

TABLE 5: Tests on the spatial stability of coefficients

		Model (11)	Model (11) with D(1) based on distance	Model (11) with D(1) based on time
		1	2	3
Estimation		*OLS*	*ML*	*ML*
Test		*F test*	*Likelihood ratio test*	*Likelihood ratio test*
Agriculture	$\hat{\alpha}$	38.073 (0.000)	14.587 (0.000)	17.973 (0.000)
	$\hat{\beta}$	32.263 (0.000)	12.382 (0.000)	15.840 (0.000)
Energy & Manufacturing	$\hat{\alpha}$	3.420 (0.065)	1.517 (0.218)	3.080 (0.079)
	$\hat{\beta}$	3.195 (0.074)	1.599 (0.206)	3.276 (0.070)
Construction	$\hat{\alpha}$	11.332 (0.001)	5.096 (0.024)	9.234 (0.002)
	$\hat{\beta}$	10.027 (0.001)	4.026 (0.044)	7.858 (0.005)
Market services	$\hat{\alpha}$	4.728 (0.030)	0.651 (0.420)	0.987 (0.320)
	$\hat{\beta}$	4.348 (0.037)	0.514 (0.473)	0.850 (0.357)
Non Market services	$\hat{\alpha}$	6.906 (0.009)	8.870 (0.003)	8.561 (0.003)
	$\hat{\beta}$	7.299 (0.007)	9.232 (0.002)	8.857 (0.003)

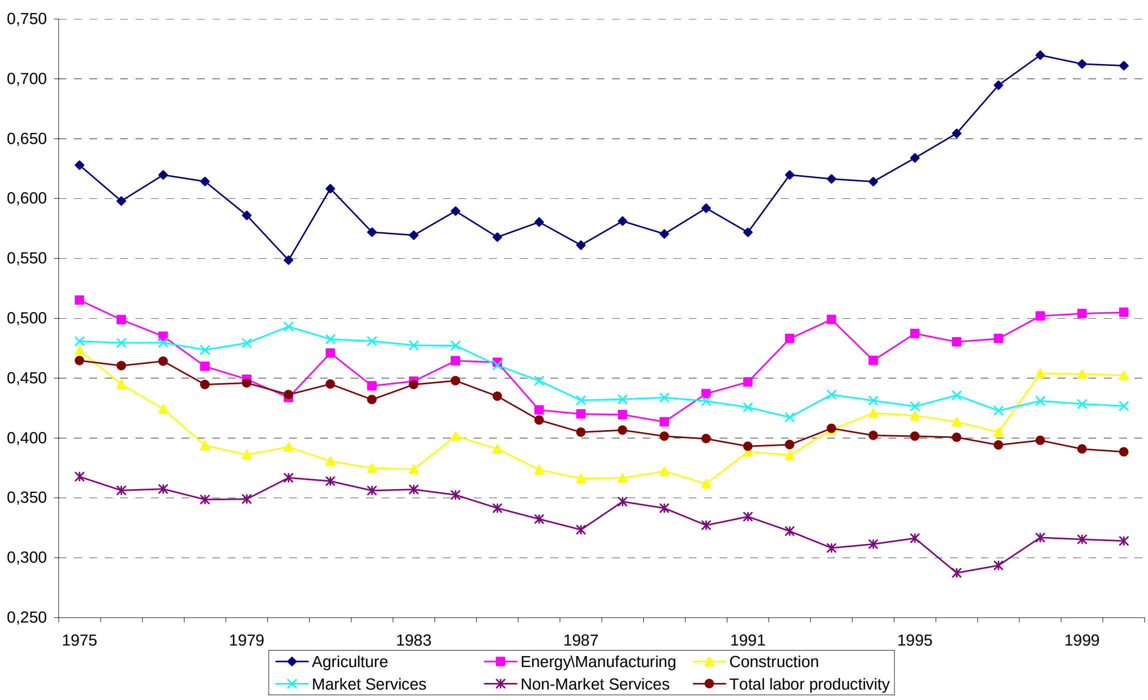
***Notes*:** *p*-values are in brackets. *ML* indicates maximum likelihood estimation.

TABLE 6: Estimation results for the pooled model with the relevant spatial effects for each sector; ML estimation of spatial error model

	D(1) based on distance					D(1) based on time				
	1	2	3	4	5	6	7	8	9	10
	Agr.	**En.**	**Con.**	**MS**	**NMS**	**Agr.**	**En.**	**Con.**	**MS**	**NMS**
$\hat{\alpha}_C$	0.377 (0.000)	0.232 (0.000)	0.418 (0.000)	0.183 (0.000)	0.083 (0.233)	0.386 (0.000)	0.234 (0.000)	0.422 (0.000)	0.187 (0.000)	0.089 (0.132)
$\hat{\alpha}_P$	0.206 (0.000)		0.276 (0.000)		0.314 (0.000)	0.199 (0.000)		0.229 (0.000)		0.311 (0.000)
$\hat{\beta}_C$	-0.036 (0.000)	-0.020 (0.000)	-0.040 (0.000)	-0.016 (0.000)	0.008 (0.261)	-0.037 (0.000)	-0.021 (0.000)	-0.040 (0.000)	-0.017 (0.000)	0.008 (0.152)
$\hat{\beta}_P$	-0.019 (0.000)		-0.027 (0.000)		0.031 (0.000)	-0.018 (0.000)		-0.022 (0.000)		0.031 (0.000)
$\hat{\lambda}$	0.616 (0.000)					0.624 (0.000)				
	Convergence Speed					*Convergence Speed*				
Core	9.38%	2.85%	19.89%	2.13%	-	10.89%	2.90%	19.80%	2.19%	-
Periph.	2.52%		4.56%		6.07%	2.36%		3.30%		5.91%
	Half_life					*Half_life*				
Core	18.82	33.62	17.10	41.58	-	18.20	33.25	16.91	40.69	-
Periph.	36.73		25.14		21.85	38.50		30.52		22.10
$\hat{\sigma}^2_\varepsilon$	0.0002 (0.000)					0.0002 (0.000)				
LIK	2373.4388					2368.9604				
AIC	-4714.8776					-4632.5421				
SC	-4641.4989					-4632.5421				

Notes: *p*-values are in brackets. See notes of tables 3 and 4.

Figure 1: σ-convergence over 1975-2000



Figures 3a-3f: σ-convergence and spatial effects in labor productivity