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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 both spatial effects and a disaggregated analysis at a sectoral level. We detect σ-convergence in aggregate labor productivity and in the service sectors but not in the other sectors. This result can be explained by a transfer of resources from the agricultural sector to the more productive sectors that has been more marked in the poor regions. Empirical results also indicate that the common indicator of σ-convergence lead to a bias when spatial effects are not included in the analysis. We then estimate β-convergence models including the relevant spatial effects for each sector. The results show that inequality in productivity levels between core and peripheral regions persist and highlight how convergence speeds and the nature of spatial effects vary from one sector to another.

Keywords: convergence, spatial econometrics, labor productivity, sectoral approach

JEL Classification: C14, O52, R11, R15

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 fewer studies dealing with sectoral convergence at the regional level in Europe: Paci and Pigliaru (1999) focus on the EU regions, whereas Cuadrado-Roura *et al.* (1999) and Dall'erba (2004) analyse 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 due to 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 in 5 sectors in order to highlight whether the process of convergence typically found is also valid for similar technologies. It also allows to avoid mixing of converging and nonconverging subsectors 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. The first one refers to the coincidence of attribute similarity and locational similarity (Anselin, 1988, 2001). In our case, spatial autocorrelation means that high productivity regions tend to be geographically clustered as well as low productivity regions. The second spatial effect means that economic behaviors are not stable over space. It can be linked to the concept of convergence clubs, characterized by the possibility of multiple, locally stable, steady state equilibria (Durlauf and Johnson, 1995).

The paper is organized as follows. Section 2 describes the data and the weights matrix. In sections 3 and 4, we perform several tests of labor productivity convergence according to the famous 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. We conclude in the last section.

2. - DATA AND SPATIAL WEIGHTS MATRIX

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. We disaggregate labor productivity into 5 different sectors: Agriculture, Energy and Manufacturing, Construction, Market Services, Non-Market Services. We consider 145 European regions at the NUTS 2 level[2] 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).

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[1] See, among others, Rey and Montouri (1999), Fingleton (1999, 2001) or previous works of the authors, such as Le Gallo *et al.* (2003), Dall'erba and Le Gallo (2003), for empirical studies using these tools.

[2] 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.

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 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, which means that the intersectoral migration of labor has been stronger in the core regions. Concerning the other sectors, the share of energy and manufacturing has decreased all over Europe, the one of the construction sector has increased in the cohesion regions, on the opposite 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 in order to favor the integration process, necessary before the introduction of the common currency. For the market and non market services sectors, the share is still higher 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 the migration of a large part of the labor force from the primary to the tertiary sector.

With regards to the spatial weights matrix, upon which all the following analyses rely, 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[3]. These data come from the web site of Michelin[4]. We adopt the travel time instead of the 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 the 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 the great circle distance between regional centroids. Distance and time-based weight matrices are defined as:

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

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 $k = 1,\ldots 3$ above which interactions are assumed

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

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.

3. - SPATIAL σ–CONVERGENCE AND CHANGES IN PRODUCTIVE STRUCTURES

The concept of σ-convergence continues to attract attention (Fan and Casetti, 1994; Carlino and Mills, 1996, 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_{ijt} the logarithm of productivity for region *i* in industry *j* and period *t*, then the sample variance for industry *j* and period *t* for our set of 145 regions is defined as:

$$s_{jt}^2 = \frac{1}{n-1}\sum_{i=1}^{145}(y_{ijt} - \overline{y}_{it})^2 \tag{2}$$

where n = 145. There is σ-convergence in sector *j* if (2) declines over time while increasing values indicate divergence in the cross-sectional distribution.

The evolutions of the sample variances for aggregate labor productivity and the sectoral 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, the energy & manufacturing and construction sectors remain globally stable while the market services and the non-market services sectors have slightly converged. These findings must be confirmed by a formal test. In that purpose, we apply the test suggested by Carree and Klomp (1997) who show that the statistic 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 as following for industry *j*:

$$T_j = \sqrt{n}\cdot\frac{s_{j1}^2 / s_{jT}^2 - 1}{2\sqrt{1-(1-\hat{\beta}_j)^2}} \tag{3}$$

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

$$y_{ijT} = \alpha_j + (1 - \beta_j) y_{ij1} + \varepsilon_{ij} \tag{4}$$

where 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 second column of table 2.

[Table 2 about here]

The results confirm the visual impression obtained previously: on the full period under consideration, only the market services and non-market services sectors converge significantly while the three others sectors don't. As a consequence, the significant σ-convergence obtained at the aggregate level is a consequence from convergence in the service sectors. 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. Therefore, we have divided the whole period in two sub-periods and computed the σ-convergence statistic for each sector in each sub-period. The results are reported in the third and fourth columns of table 2. They clearly indicate a different pattern for the two sub-periods: while all sectors, except agriculture, significantly converge during 1975-1990, none of them does during 1990-2000.

The analysis of σ-convergence shows that the convergence pattern is different between sectors. However, 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. It is unbiased only if mean and variance homogeneity hold (i.e. no spatial heterogeneity) and if all the covariances are zero (i.e. no spatial autocorrelation). Since these assumptions are unlikely for regional datasets, the sample variance, as an estimate of the global dispersion, will in fact reflect both the effects of changes in the variance but also 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 $$\theta = \frac{1}{n-1}\left(\sum_{i=1}^{n} (\mu_i^2 + \omega_{i,i}) - \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{n} (\mu_i \mu_j + \varpi_{i,j}) \right) \quad (5)$$

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. 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 included, i.e. $s^2 = \sigma^2$; b) the sample variance where spatial effects take the form of a spatial lag model and c) idem but spatial effects take 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 the models estimated by Maximum Likelihood (ML). The figures 2-7 below display the estimates of s^2 and σ^2 of the aggregate and the sectoral labor productivities according to the three approaches depicted above. The figures are presented using the *D(1)* weight matrix based on distance[5].

[Figures 2-7 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 the obvious difference existing between the sample variance and the global dispersion parameter, the former being systematically much higher than the latter. It does not

[5] However, the results show similar patterns when we use the weight matrix *D(1)* based on travel time by road. These results are available from the authors upon request.

necessarily mean that basing an analysis of σ-convergence without including the presence of these effects can lead to unreliable results since, in our case, 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. We also 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 two regimes are very similar[6]. Finally, all the approaches show σ-convergence in the aggregate labor productivity over the period, whereas only the market and non-market services sectors show the same trend among the sectors. The reason may come from changes in the sectoral structure of the regions.

In order to examine this hypothesis, we introduce the inequality index in productive structure, based on employment, suggested by Cuadrado-Roura *et al*. (1999):

$$ID = \frac{1}{145}\sum_{j=1}^{5}\sum_{i=1}^{145}\left(P_{ijt} - P_{jt}\right)^2 \tag{6}$$

where P_{ijt} denote the weight of sector j in total employment for region i at time t; and P_{jt} is the corresponding sectoral weight at the European level. The value of this index would be zero if the productive structures were the same across all the regions. This index can be broken down into the sum of inequalities in productive structure for each sector j as follows:

$$ID_j = \frac{1}{145}\sum_{i=1}^{145}\left(P_{ijt} - P_{jt}\right)^2 \tag{7}$$

These indices for each sector as well as the global index for the aggregate labor productivity are represented in the figure below.

[Figure 8 about here]

First, the results show that, in terms of employment, the productive structure of the European regions has become more uniform over time. Second, they highlight that the reason

[6] The results are not displayed because of a lack of space. Complete results are available from the authors upon request.

for the greater homogeneity in productive structures is mainly due to an harmonization of productive structures among regions. It is not due to an increase of the weight of agriculture in employment in the rich regions. On the contrary, it comes from a transfer of resources from agriculture towards sectors with a higher average productivity that has been more marked in the poor regions than in the rich ones.

4. - SPATIAL β–CONVERGENCE

Since the articles of Barro and Sala-I-Martin (1991, 1992), numerous studies have examined β–convergence between different countries and regions[7]. 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. 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. Second, the concept of *conditional* β–convergence is used when the assumption of similar steady-states is relaxed. 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). In order to include the spatial dimension of the data, the lack of which is also a drawback of numerous empirical studies, we start by detecting the presence of spatial regimes in the distribution of initial labor productivity.

4.1. Detection of spatial regimes

Using the spatial weight matrices described in section 2, the first step of our analysis is to detect the existence of spatial heterogeneity in the distribution of the aggregate labor

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

productivity. In that purpose, we use the G-I* statistics developed by Ord and Getis (1995)[8] 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. 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":

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 for the UK to be 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.

4.2. Estimation results

β–convergence model of aggregate labor productivity

Starting with the OLS estimation of the absolute β-convergence model with White's (1980) correction for heteroskedasticity of an unknown form, the estimation results displayed in columns 1 and 4 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[9]. Looking at the diagnostic tests, the Jarque-Bera test rejects the assumption of normality of the residuals (*p*-value = 0.000). We note also that the White test clearly does not

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[8] We do not use the Moran's scatterplot because it would imply dropping out 22 "atypical" regions from our sample. All computations in this section are carried out using the SpaceStat 1.91 software (Anselin, 1999).

[9] The convergence speed is the speed necessary to an economy to reach it steady-state. It may be defined as: $b = -\ln(1+T\beta)/T$. The half-life is the time necessary for an economy to fill half of the variation, which separates it from its steady state, and is defined by: $\tau = -\ln(2)/\ln(1+\beta)$.

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 effects in the estimation of the appropriate β-convergence model have been described in Anselin (1988) and Anselin *et al.* (1996) and are applied here. Therefore, we shortly describe the various steps we followed to find the most appropriate model specification for each of our variables. In all cases, we start with the OLS estimation of the absolute β-convergence model. In order to identify the form of the spatial dependence (spatial error model 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 LMERR is more significant than the LMLAG, but both R-LMERR and R-LMLAG are significant. Since the R-LMERR is more significant, we adopt the spatial error model as the best specification. It can be written as follows:

$$g_T = \alpha S + \beta y_0 + \varepsilon \text{ with } \varepsilon = \lambda W \varepsilon + u \qquad \text{and } u \sim N(0, \sigma_u^2 I) \tag{8}$$

where g_T is the $(n\times1)$ vector of average growth rates of per capita GDP between date 0 and T; S is the $(n\times1)$ sum vector; y_0 is the vector of log per capita GDP levels at date 0. λ is a coefficient indicating the extent of spatial correlation between the residuals. The estimation results by ML are displayed in columns 2 and 5 of table 3[10]. A positive and significant spatial autocorrelation of the errors is found ($\hat{\lambda}$ = 0.565 with *D(1)* based on distance). The level of convergence ($\hat{\beta}$ = -0.013) has increased compared to the OLS-estimation and is still significant. The convergence speed is 1.49% and the half-life is 51.7 years. The LIK, AIC and SC measures indicate that this model specification is better than the OLS-specification. As displayed in column 2, the estimates are followed by a number of specification diagnostics to test the assumption on which the maximum likelihood estimation in the spatial error model

[10] All the results are confirmed with estimation based on GMM.

is based. The two tests for groupwise heteroskedasticity (the unadjusted and spatially adjusted Breusch-Pagan statistics) are significant (p-value = 0.002) indicating that there is some remaining heteroskedasticity in the form of differing variances between the core and the peripheral regime. The LR-test on the spatial autoregressive coefficient $\hat{\lambda}$ is highly significant (p-value = 0.000). The Wald-test on common factor hypothesis and the LM-test on spatial lag dependence are strongly significant with *D(1)* based on distance, less so with the time-based weights matrix, indicating that there is some inherent inconsistency in the spatial error specification. However, it may come from the remaining heteroskedasticity that the BP and spatial BP tests indicate.

Therefore, we decide to test for the presence of groupwise heteroskedasticity, taking the form of the spatial regimes previously defined, in the model specification. This model can be written as follows:

$$g_T = \alpha S + \beta y_0 + \varepsilon \text{ with } \varepsilon = \lambda W \varepsilon + u \text{ and } u \sim N\left(0, \begin{bmatrix} \sigma^2_{\varepsilon,C} I_{91} & 0 \\ 0 & \sigma^2_{\varepsilon,P} I_{54} \end{bmatrix}\right) \tag{9}$$

where $\hat{\sigma}^2_\varepsilon$ represents the variance within each regime. The estimation results by ML estimation are displayed in columns 3 and 6 of table 3. They show the presence of significant convergence ($\hat{\beta}$ = -0.014). A positive and significant spatial autocorrelation of the errors is found ($\hat{\lambda}$ = 0.641) and the convergence speed has increased (1.57%). Moreover, the LR-test on groupwise heteroskedasticity is significant (p-value = 0.000). Therefore, this model is the appropriate specification including the relevant spatial effects in aggregate labor productivity.

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

β–convergence model of labor productivity in the agricultural sector

For agriculture, the results lead to a spatial error model with structural instability[11]. The two weights matrix specifications lead to the same conclusions on the appropriate model definition. It can be written as follows:

$$g_T = \alpha_C D_C + \beta_C D_C y_0 + \alpha_P D_P + \beta_P D_P y_0 + \varepsilon$$

with $\varepsilon = \lambda W \varepsilon + u$ and $u \sim N(0, \sigma^2_u I)$ (10)

[11] Due to space constraints, we directly give the form and the results of the most appropriate model specification. More details on the methodology can be found in Dall'erba and Le Gallo (2003) or Ertur *et al.* (2004).

where D_C and D_P are dummy variables corresponding respectively to the core and periphery regimes previously defined; α_C, α_P, β_C, β_P are the unknown parameters to be estimated. The results of this estimation are displayed in table 4, respectively for *D(1)* based on distance and based on time.

[Table 4 about here]

The results obtained with ML[12] show that the convergence process is significant but differ between core and peripheral regions, with the one in the core regions being stronger whatever the weight matrix. Note that the same spatial autoregressive process affects all the errors, which means that spatial autocorrelation is identical in core and in peripheral regions and all the regions are still interacting spatially through the spatial weights matrix *W*. The Chow-Wald test for overall structural instability rejects the null hypothesis of equality of coefficients. Similarly, the individual coefficient stability tests cannot reject the corresponding null hypotheses. The Breusch-Pagan test *versus* the core-periphery dummy variable does not reject homoskedasticity. The Wald-test on common factor hypothesis is not significant, indicating no inherent inconsistency in the spatial error specification, which is confirmed by the LM-test on spatial lag dependence not being significant. Note also that the LR-test on the spatial autoregressive coefficient $\hat{\lambda}$ is significant.

β–convergence model of labor productivity in the energy & manufacturing sector

Contrary to the two previous variables, the appropriate model specification in this sector is a spatial lag model, with spatial heterogeneity taking the form of structural instability and groupwise heteroskedasticity. This model can be written as follows:

$$g_T = \rho W g_T + \alpha_C D_C + \beta_C D_C y_0 + \alpha_P D_P + \beta_P D_P y_0 + \varepsilon \text{ and } u \sim N\left(0, \begin{bmatrix} \sigma^2_{\varepsilon,C} I_{91} & 0 \\ 0 & \sigma^2_{\varepsilon,P} I_{54} \end{bmatrix}\right) \quad (11)$$

where ρ is a coefficient indicating the extent of spatial correlation between a region and its neighbors. The estimation results are displayed in table 5.

[Table 5 about here]

[12] The results by GMM are similar to those presented here.

Spatial dependence between regions is positive and significant (p-value = 0.000) for both spatial weight matrices. As in the agricultural sector, the results indicate that the convergence process differ between regimes. However, in this sector, only the peripheral regime converges significantly (p-value = 0.005) whereas the core regime does not. Regions that belong to different regimes converge towards different steady-states, which is consistent with the persistence of inequalities between regimes. All the results are robust to GMM estimation and several weights matrices based on nearest neighbors.

β–convergence model of labor productivity in the construction sector

In the construction sector, the appropriate model is a spatial error model with structural instability and groupwise heteroskedasticity which can be written as follows:

$$g_T = \alpha_C D_C + \beta_C D_C y_0 + \alpha_P D_P + \beta_P D_P y_0 + \varepsilon$$

$$\text{with} \quad \varepsilon = \lambda W \varepsilon + u \ \text{ and } \ u \sim N\left(0, \begin{bmatrix} \sigma^2_{\varepsilon,C} I_{91} & 0 \\ 0 & \sigma^2_{\varepsilon,P} I_{54} \end{bmatrix}\right) \tag{12}$$

with the same notation as above. The results, displayed in table 6, show once again that only the regions belonging to the peripheral regime converge, at a faster speed than in the two previous sectors. The estimation of $\hat{\lambda}$ is not significant with weight matrix based on time, but it is when we use GMM estimation.

[Table 6 about here]

β–convergence model of labor productivity in the market services sector

For the market services sector, the correct model specification is model (10). Results in table 7 indicate that each regime converges significantly to its own steady-state. For the weight matrix based on distance, specification diagnostics may raise doubts about the presence of spatial regimes (the individual coefficient stability tests are not significant), and the form of the spatial dependence (LM-test on spatial lag dependence is significant). However, these problems disappear when using other weight matrices, also based on distance.

[Table 7 about here]

β–convergence model of labor productivity in the non-market services sector

The best model specification for this sector is also model (10). Estimation results in table 8 show that each regime converges significantly to its own steady-state, but the convergence speed in the peripheral regime is much greater than the one in the core regime (4.87% versus 0.73%). Even if it means that the low productivity regions within the periphery tend to catch-up to the high productivity regions in this regime, the difference between the productivity levels of the peripheral and core regions will not necessarily decrease over time.

[Table 8 about here]

5. - 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 and have adopted a spatial approach to convergence. For the first time in the EU case, the modelling 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 is obvious for each sector and each year, but do 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 it comes from a transfer of resources from agriculture towards sectors with a higher average productivity that has been more marked in the poor regions than in the rich ones.

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 for the aggregate labor productivity whereas core regions and peripheral ones converge to their own for each sector. 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 energy & manufacturing and the construction sectors, their slowest convergence speed is for the non-market services sector (0.73%) and the highest for the agricultural one. Inversely, non-market services are the sector within which peripheral regions converge most (4.87%) and the energy & manufacturing sector the least (1.39%). Finally, the energy & manufacturing sector is the only one displaying spatial effects taking the form of a spatial lag model. This may come from the fact that agriculture is linked to an immobile factor, the land, and services rely to some extent on physical interactions between producers and customers. On the other hand, externalities in the manufacturing sector depend on technology diffusion, trade and transportation infrastructures. In conclusion, this paper calls for regional policies criteria based on other criteria than simple per capita GDP relative measures. Moreover, if the localization and potential linkages of each region are not formally included in the estimation of the convergence process, then regional policies will focus only on the "top-of-the-iceberg" of possible measures to correct regional inequalities.

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Table 1: Labor shares and productivity levels across the 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: Test for σ-convergence

	1975-2000	**1975-1990**	**1990-2000**
Aggregate labor productivity	4.102 [b]	3.657 [b]	1.181
Agriculture	Negative	1.076	Negative
Energy & Manufacturing	0.344	2.942 [b]	Negative
Construction	0.699	5.004 [b]	Negative
Market Services	2.580 [b]	2.569 [a]	0.419
Non-Market Services	2.805 [b]	2.500 [a]	0.828

Notes: superscripts *a* and *b* mean significant convergence at the 5% and 1% significant levels. "Negative" means that $\hat{\beta}_j$ is negative so that T_j could not be computed.

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

	D(1) based on distance			*D(1) based on time*		
	1	2	3	4	5	6
	OLS-White	*ML-ERR*		*OLS-White*	*ML-ERR*	
$\hat{\alpha}_r$	0.110 (0.000)	0.153 (0.000)	0.160 (0.000)	0.110 (0.000)	0.127 (0.000)	0.134 (0.000)
$\hat{\beta}_r$	-0.009 (0.000)	-0.013 (0.000)	-0.014 (0.000)	-0.009 (0.000)	-0.010 (0.000)	-0.011 (0.000)
$\hat{\lambda}$	-	0.565 (0.000)	0.641 (0.000)	-	0.399 (0.010)	0.514 (0.000)
$\hat{\sigma}_{\varepsilon}^2$ core			$1.99.10^{-5}$ (0.000)			$4.79.10^{-5}$ (0.000)
$\hat{\sigma}_{\varepsilon}^2$ periphery			$4.83.10^{-5}$ (0.000)			$2.39.10^{-5}$ (0.000)
Convergence Speed	0.97%	1.49%	1.57%	0.97%	1.18%	1.26%
Half-life	76.40	51.70	49.37	76.40	64.05	60.29
Sq. Corr.	-	0.340	0.339	-	0.339	0.339
LIK	540.075	547.651	555.099	540.075	543.182	547.222
AIC	-1076.15	-1091.30	-1106.20	-1076.15	-1082.36	-1090.44
SC	-1070.20	-1085.35	-1100.24	-1070.20	-1076.41	-1084.49
Moran's *I*	3.387 (0.000)			2.361 (0.018)		
LMERR	8.411 (0.003)			3.567 (0.058)		
R-LMERR	25.743 (0.000)			8.242 (0.004)		
LMLAG	0.144 (0.704)			1.640 (0.200))		
R-LMLAG	17.477 (0.000)			6.314 (0.011)		
Jarque-Bera	95.960 (0.000)			95.960 (0.000)		
White test	1.366 (0.505)			1.366 (0.505)		
KB-test for heteroskedasticity	0.840 (0.359)			0.840 (0.359)		
BP test	-	9.549 (0.002)	-	-	3.949 (0.046)	-
Spatial BP test	-	9.549 (0.002)	-	-	3.949 (0.046)	-
LR test on spatial error dependence	-	15.152 (0.000)	-	-	6.215 (0.012)	-
Wald test on common factor hypothesis	-	11.958 (0.000)	-		2.001 (0.157)	
LM test on spatial lag dependence	-	23.095 (0.002)	-	-	3.881 (0.048)	-
LR – group. het.			14.896 (0.000)			8.079 (0.017)

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). *BP* is the Breusch-Pagan test for groupwise heteroskedasticity and spatial BP-test is its spatially adjusted version. *LR* is the likelihood ratio test for groupwise heteroskedasticity.

Table 4: ML estimation results of the β-convergence model in labor productivity in agriculture

	D(1) **based on distance**		***D(1)*** **based on time**			***D(1)*** **based on distance**	***D(1)*** **based on time**
	Core	*Periph.*	*Core*	*Periph.*		*Specification diagnostics*	
$\hat{\alpha}_r$	0.384 (0.000)	0.201 (0.000)	0.375 (0.000)	0.170 (0.000)	Chow-Wald	13.551 (0.001)	22.375 (0.000)
$\hat{\beta}_r$	-0.037 (0.000)	-0.018 (0.000)	-0.035 (0.000)	-0.015 (0.001)	Ind. stab. test on $\hat{\alpha}_r$	6.902 (0.008)	10.484 (0.001)
$\hat{\lambda}$	0.544 (0.000)		0.332 (0.042)		Ind. stab. on $\hat{\beta}_r$	5.364 (0.020)	8.467 (0.003)
Convergence Speed	5.54%	2.22%	5.29%	1.74%	BP-test for heteroskedasticity	3.455 (0.063)	2.302 (0.129)
Half-life	18.51	36.67	19.07	45.17	Wald-test common factor hypothesis	1.901 (0.387)	2.334 (0.311)
Sq. Corr.	0.304		0.309		LR-test on spatial error dependence	19.687 (0.000)	5.869 (0.015)
LIK	359.775		352.866				
AIC	-711.549		-697.732		LM-test on spatial lag dependence	0.179 (0.672)	1.554 (0.212)
SC	-699.643		-685.825				

Notes: see notes for table 3. The individual coefficient stability tests are based on a spatially adjusted asymptotic Wald statistics, distributed as χ^2 with 1 degree of freedom. The Chow – Wald test of overall stability is also based on a spatially adjusted asymptotic Wald statistic, distributed as χ^2 with 2 degrees of freedom (Anselin, 1988).

Table 5: ML estimation results of the β-convergence model in labor productivity in energy & manufacturing

	D(1) **based on distance**		***D(1)*** **based on time**			***D(1)*** **based on distance**	***D(1)*** **based on time**
	Core	*Periph.*	*Core*	*Periph.*		*Specification diagnostics*	
$\hat{\alpha}_r$	-0.001 (0.920)	0.135 (0.002)	0.001 (0.894)	0.199 (0.000)	Chow-Wald	9.890 (0.007)	22.510 (0.000)
$\hat{\beta}_r$	0.001 (0.240)	-0.012 (0.005)	0.001 (0.411)	-0.019 (0.000)	Ind. stab. test on $\hat{\alpha}_r$	9.072 (0.002)	22.210 (0.000)
$\hat{\rho}$	0.538 (0.000)		0.596 (0.000)		Ind. stab. on $\hat{\beta}_r$	8.694 (0.003)	21.785 (0.000)
$\hat{\sigma}^2_\varepsilon$	$3.20.10^{-4}$ (0.000)	$1.33.10^{-4}$ (0.000)	$2.97.10^{-4}$ (0.000)	$1.36.10^{-4}$ (0.000)	LR – group. het.	12.830 (0.000)	10.502 (0.001)
Convergence speed	-	1.39%	-	2.32%			
Half-life	-	54.99	-	35.35			
Sq. Corr.	0.181		0.207				
LIK	414.323		417.125				
AIC	-818.646		-824.250				
SC	-803.763		-809.366				

Notes**:** see notes for table 4**.**

Table 6: ML estimation results of the β-convergence model in labor productivity in construction

	***D(1)* based on distance**		***D(1)* based on time**			***D(1)* based on distance**	***D(1)* based on time**
	Core	*Periph.*	*Core*	*Periph.*		*Specification diagnostics*	
$\hat{\alpha}_r$	0.014 (0.186)	0.245 (0.000)	0.011 (0.301)	0.193 (0.000)	Chow-Wald	38.512 (0.000)	27.131 (0.000)
$\hat{\beta}_r$	$0.13.10^{-2}$ (0.898)	-0.024 (0.000)	$0.37.10^{-2}$ (0.733)	-0.018 (0.000)	Ind. stab. test on $\hat{\alpha}_r$	36.021 (0.000)	24.793 (0.000)
$\hat{\lambda}$	0.431 (0.001)		0.196 (0.272)		Ind. stab. on $\hat{\beta}_r$	37.600 (0.000)	25.845 (0.000)
$\hat{\sigma}^2_\varepsilon$	$1.98.10^{-4}$ (0.000)	$1.19.10^{-4}$ (0.000)	$2.13.10^{-4}$ (0.000)	$1.26.10^{-4}$ (0.000)	LR – group. het.	7.086 (0.028)	5.547 (0.062)
Convergence speed	-	3.04%	-	2.23%			
Half-life	-	28.38	-	36.58			
Sq. Corr.	0.221		0.309				
LIK	435.536		352.866				
AIC	-863.071		-697.732				
SC	-851.164		-685.825				

***Notes*: see notes for table 4.**

Table 7: ML estimation results of the β-convergence model in labor productivity in market services

	D(1) based on distance		*D(1)* based on time			*D(1)* based on distance	*D(1)* based on time
	Core	Periph.	Core	Periph.		Specification diagnostics	
$\hat{\alpha}_r$	0.263 (0.000)	0.249 (0.000)	0.293 (0.000)	0.168 (0.000)	Chow-Wald	16.465 (0.000)	20.871 (0.000)
$\hat{\beta}_r$	-0.023 (0.000)	-0.024 (0.000)	-0.026 (0.000)	-0.016 (0.000)	Ind. stab. test on $\hat{\alpha}_r$	0.092 (0.761)	5.752 (0.016)
$\hat{\lambda}$	0.787 (0.000)		0.583 (0.000)		Ind. stab. on $\hat{\beta}_r$	0.012 (0.910)	4.702 (0.030)
Convergence speed	2.95%	3.04%	3.47%	1.82%	BP-test for heteroskedasticity	21.930 (0.000)	12.311 (0.000)
Half-life	29.08	28.44	25.68	43.53	Wald-test common factor hypothesis	12.383 (0.002)	7.610 (0.022)
Sq. Corr.	0.299		0.381		LR-test on spatial error dependence	61.368 (0.000)	19.402 (0.000)
LIK	541.916		520.932				
AIC	-1075.83		-1033.86		LM-test on spatial lag dependence	8.903 (0.002)	2.119 (0.145)
SC	-1063.92		-1021.96				

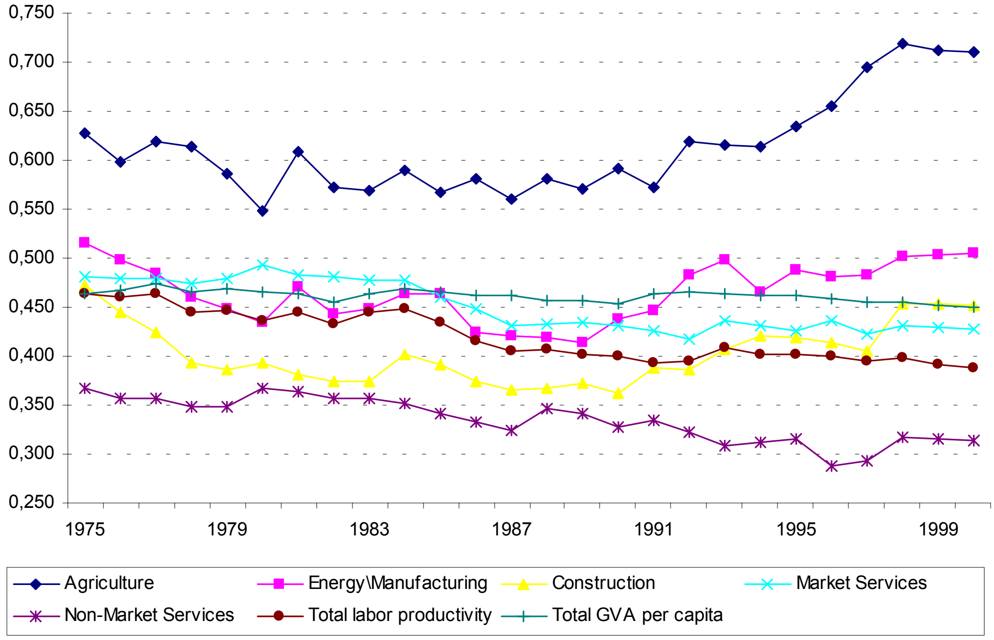
***Notes*: see notes for table 4.**

Table 8: ML estimation results of the β-convergence model in labor productivity in non-market services

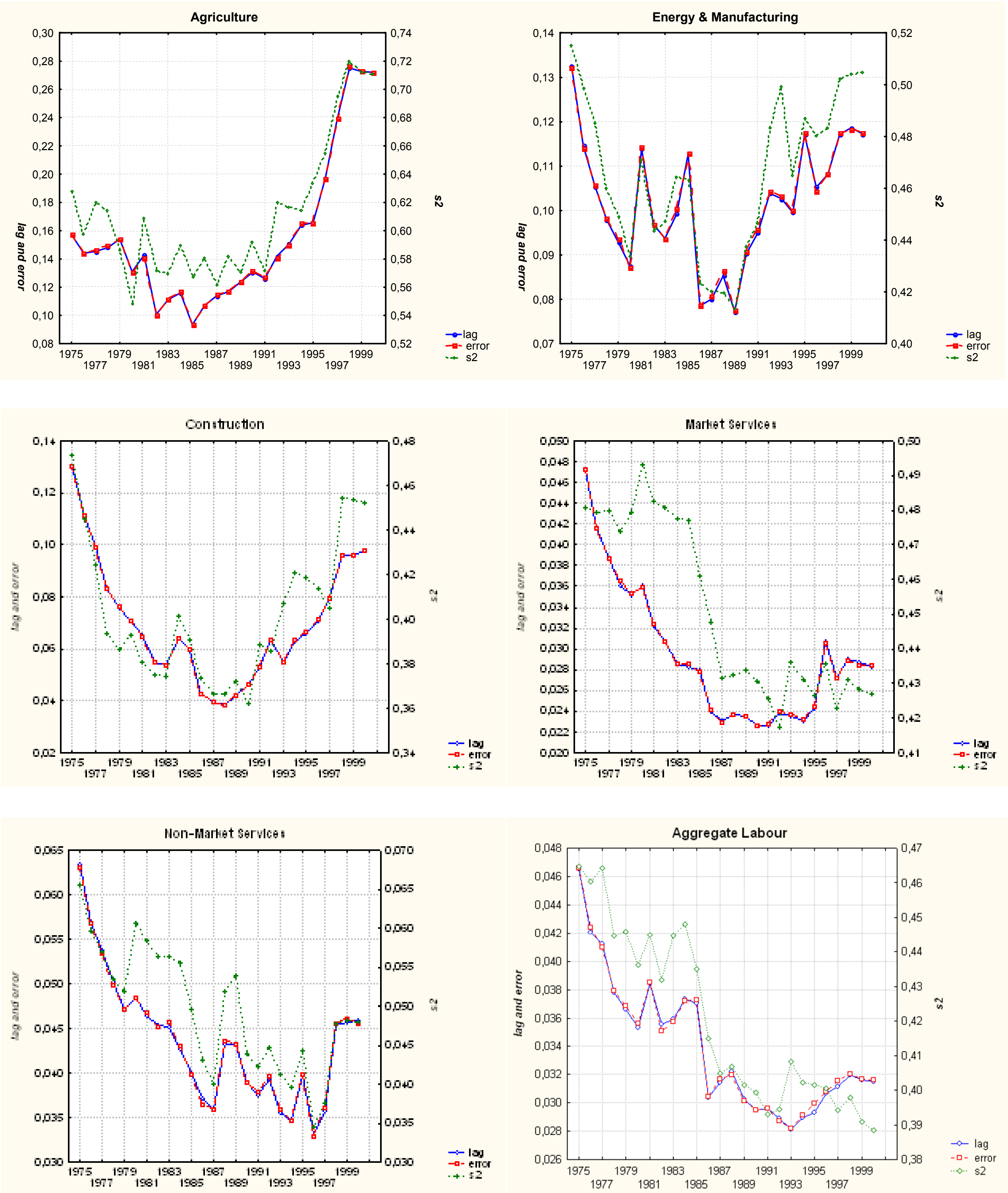
	D(1) **based on distance**		***D(1)*** **based on time**			***D(1)*** **based on distance**	***D(1)*** **based on time**
	Core	*Periph.*	*Core*	*Periph.*		*Specification diagnostics*	
$\hat{\alpha}_r$	0.075 (0.000)	0.337 (0.000)	0.081 (0.015)	0.301 (0.000)	Chow-Wald	41.655 (0.000)	34.155 (0.000)
$\hat{\beta}_r$	-0.007 (0.033)	-0.034 (0.000)	-0.007 (0.024)	-0.030 (0.000)	Ind. stab. test on $\hat{\alpha}_r$	36.882 (0.000)	27.577 (0.000)
$\hat{\lambda}$	0.707 (0.000)		0.627 (0.000)		Ind. stab. on $\hat{\beta}_r$	39.023 (0.000)	29.439 (0.000)
Convergence speed	0.73%	4.87%	0.79%	4.13%	BP-test for heteroskedasticity	2.699 (0.100)	1.700 (0.192)
Half-life	99.59	20.15	92.15	22.57	Wald-test common factor hypothesis	2.896 (0.235)	2.409 (0.299)
Sq. Corr.	0.426		0.428		LR-test on spatial error dependence	54.525 (0.000)	27.826 (0.000)
LIK	521.394		508.044				
AIC	-1034.79		-1008.09		LM-test on spatial lag dependence	4.994 (0.025)	0.061 (0.804)
SC	-1022.88		-996.182				

Notes***:*** *see notes for table 4****.***

Figure 1: σ-convergence over 1975-2000



Figures 2-7: σ-convergence and spatial effects in labor productivity



Figures 8: Inequality indices