PRODUCTIVITY CONVERGENCE AND SPATIAL DEPENDENCE AMONG SPANISH REGIONS

by

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Abstract:
This paper estimates the evolution of labor productivity disparities among 48 Spanish regions over 1980-1996 according to the concepts of β- and σ-convergence and emphasizes the importance of including both spatial effects and a disaggregate analysis at a sectoral level. Various recent contributions have tested the origin of productivity differentials among regions in Europe (Esteban, 2000; Maudos *et al.*, 2000; Cuadrado-Roura *et al.*, 1999, among others). However, despite the literature focusing on the essential role of spatial dependence, the impact of neighboring locations' productivity has not been widely investigated. The results display that spatial effects vary from one sector to another and β- convergence in labor productivity is greater at the aggregate level than at the level of agriculture and industry, but not of services. When σ-convergence is examined in order to measure the narrowing of inequalities, it reveals that convergence occurs in aggregate labor productivity but not in productivities by sector. The reason comes from a transfer of resources from agriculture towards more productive sectors that has been more pronounced in the poor regions than in the rich ones.

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Section 1- Introduction

Since 1986, when Spain decided to become a member of the European Community, this country has seen its per capita Gross Domestic Product converging to the European average, but disparities in per capita incomes among autonomous communities have strongly increased within the country (Neven and Gouyette, 1995; Quah, 1996; Martin, 1998; Dall'erba and Hewings, 2003). While the convergence hypothesis has received considerable attention in the recent literature, convergence is often measured on the Gross Regional Product and according to its most famous concepts, the β- and the σ-convergence (Barro and Sala-I-Martin, 1991, 1992). In spite of the large amount of work in this area, a disaggregated analysis at the sectoral level of the convergence hypothesis has not been commonly used. It may alter the conclusions usually drawn in the literature about the evidence of convergence and about the identification of the forces driving to it (Cuadrado-Roura *et al*., 1999; Lopez-Bazo *et al*., 1999; Cuadrado-Roura, 2001). Moreover, the majority of empirical tests of regional income convergence are based on the same assumptions as the ones underlying for international income convergence: regions are considered as isolated entities, as if their geographical location and potential interregional linkages did not matter. Only recently, the role of spatial effects has been considered in empirical works using the formal tools of spatial statistics and econometrics. For the European regions, papers in this area include, among others, Fingleton

(1999, 2001, 2003a and b), Bivand and Brunstad (2003) or Le Gallo *et al.* (2003), Dall'erba and Le Gallo (2003).

This paper proposes to remedy this gap by supplying an empirical analysis of labor productivity disparities among 48 Spanish regions over 1980-1996 according to the concepts of β- and σ-convergence including both spatial effects and a disaggregate analysis at a sectoral level. We use spatial units that are smaller than the autonomous communities usually used to test for convergence within Spain. Therefore, our results may differ from other studies. This paper is organized as follows: section 2 provides some insights into the β-convergence model and spatial effects upon which the empirical estimations described in the following sections relies. Section 3 presents the data and the weight matrices. In section 4, spatial effects are included in the estimation of the appropriate β-convergence model of per capita GDP, aggregate labor productivity and labor productivity in three sectors (agriculture, industry and services). Since β-convergence does not necessarily imply a narrowing of regional inequalities (Quah, 1993), section 5 proposes to estimate σ-convergence for the same variables. An index of inequality in productive structure is also introduced in order to measure the extent to which employment structure has become more homogeneous across regions.

Section 2- β-convergence Models and Spatial Effects

Since the publication of the well-known works of Barro and Sala-i-Martin (1991, 1995), numerous studies have examined β–convergence between different countries and regions[1]. 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-

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

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 (1993) 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 this paper, we want to point out the fact that very few empirical studies do take into account the spatial dimension of data. The different spatial effects that will be included in our analysis are spatial heterogeneity and spatial autocorrelation.

Spatial heterogeneity means that economic behaviors are not stable over space. In a regression model, spatial heterogeneity can be reflected by varying coefficients, i.e. structural instability, or by varying error variances across observations, i.e. groupwise heteroskedasticity. These variations follow for example specific geographical patterns such as East and West, or North and South.

Spatial heterogeneity can be linked to the concept of convergence clubs, characterized by the possibility of multiple, locally stable, steady state equilibria (Durlauf and Johnson, 1995). A convergence club is a group of economies whose initial conditions are near enough to converge toward the same long-term equilibrium. When convergence clubs exist, one convergence equation should be estimated per club. To determine those clubs, some authors select *a priori* criteria, like the belonging to a geographic zone (Baumol, 1986) or some GDP per capita cut-offs (Durlauf and Johnson, 1995). Others prefer to use endogenous methods, as for example, polynomial functions (Chatterji, 1992) or regression trees (Durlauf and Johnson, 1995). In our context, we choose to detect convergence clubs using exploratory spatial data analysis which relies on geographic criteria (Baumont *et al*., 2003).

The second spatial effect we will include in our analysis is spatial autocorrelation. It refers to the coincidence of attribute similarity and locational similarity (Anselin, 1988). In our case, spatial autocorrelation means that rich regions tend to be geographically clustered as well as poor regions. Spatial concentration of economic activities in European regions has already been highlighted by Lopez-Bazo *et al.* (1999), Le Gallo and Ertur (2003) and Dall'erba (2003) using the formal tools of spatial analysis. Some studies have also taken into account spatial interdependence between regions in the estimation of the appropriate β–convergence model (see, among others, Armstrong, 1995; Moreno and Trehan, 1997, Fingleton, 1999 and 2001; Rey and Montouri, 1999; Baumont *et al*., 2003; Le Gallo *et al*., 2003). This is also the purpose of this paper, but on the opposite of the previous studies, we consider disaggregate β–convergence at a sectoral level.

Integrating spatial autocorrelation into β–convergence models is useful for three reasons. First, from an econometric point of view, the underlying hypothesis in OLS estimations is based on the independence of the error, which may be very restrictive and should be tested since, if it is rejected, the statistical inference based on it is not reliable. Second, it allows capturing geographic spillover effects between regions using different spatial econometric models: the spatial lag model, the spatial error model or the spatial cross-regressive model (Rey and Montouri, 1999; Le Gallo *et al.*, 2003). Third, spatial autocorrelation allows accounting for variations in the dependent variable arising from latent or unobservable variables. Indeed, in the case of β–convergence models, the appropriate choice of these explanatory variables may be problematic because it is not possible to be sure conceptually that all the variables differentiating steady states are included[2]. Furthermore, data on some of these explanatory variables may not be easily accessible and/or reliable. Spatial autocorrelation may therefore act as a proxy to all these omitted variables and catch their effects.

At the regional scale, spatial effects and particularly spatial autocorrelation cannot be neglected in the analysis of convergence processes: several factors, such as trade and commuting between regions, technology and knowledge diffusion, and more generally regional spillovers, may lead to spatially interdependent regions. Neglecting these effects would mean treating regions as if they were "isolated islands" (Mankiw, 1995; Quah, 1996). Before going further in the spatial econometric estimation of regional sectoral convergence in Spain, section 3 will introduce data and the spatial weight matrix since all the following analysis relies on the definition of space through the weight matrix.

Section 3- Data and Spatial Weight Matrices

The data on per capita GDP and regional productivity per worker come from the most recent version of the NewCronos Regio database by Eurostat. This is the official database

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[2] More than 90 of such variables have been included in cross-country regressions using international datasets (Durlauf and Quah, 1999).

used by the European Commission for its evaluation of regional convergence. GDP per capita is measured in PPP (Purchasing Power Parity) in order to take into account the regional ability to purchase goods and thus achieve different levels of well-being, whereas productivity (in terms of GVA, Gross Value Added, per worker) is measured in ECU in order to consider differences in the capacity to produce goods. We first use the aggregate productivity per worker (in log) and then we disaggregate it into three sectors (agriculture, industry and services) for each region over the 1980-1996 period. The database does not provide more recent data at the NUTS III level. Our sample is composed of 48 Spanish regions at NUTS III level[3] which are represented in figure 1 below. Table 1 displays the code and the name of these regions. This is the finest disaggregation possible in our case because no data exist for smaller regions over the country. We exclude the regions of Canary Islands and Ceuta y Mellila due to their remoteness. Most of the studies on regional convergence within Spain work on the sample of NUTS II regions (see, among others, Cuadrado-Roura *et al*., 1999; Maudos *et al*., 2000; De la Fuente, 2002; Donaghy and Dall'erba, 2003). Therefore, due to the modifiable areal unit problem (MAUP) explained below, our results may differ from theirs.

<<insert figure 1 and table 1 here>>

We are aware that our empirical results could be affected by the choice of the spatial aggregation which influences the magnitude of various measures of association. In the literature, this problem is referred to as MAUP well known to geographers (see Openshaw and Taylor, 1979), also called problem of ecological fallacy (Anselin and Cho, 2000).

[3] NUTS: Nomenclature of Territorial Units for Statistics. The Commission uses as regional statistical concept the spatial classification established by Eurostat on the basis of national administrative units. Europe can therefore be shared either in 77 NUTS I level regions, or 211 NUTS II, 1031 NUTS III, 1074 NUTS IV or 98433 NUTS V regions.

Messner and Anselin (2001) add that scale is important as well. If the scale and spatial extent of units of observations for the data do not match up the scale and spatial extent of the studied process, then it may result in a statistical problem wherein spatially correlated and/or heteroskedastic error structures occur (Casellas and Galley, 1999). For instance, the area of Badajoz (in the South-West) is 11 times greater than the one of Guipúzcoa (in the North), but both are official NUTS III regions. Moreover, variables such as productivity per worker or per capita income in open formal NUTS II or III regions may reflect characteristics of neighboring regions. Boldrin and Canova (2001) show the problem linked to measuring a variable on a territorial unit artificially defined in which people are free to move. They give the example of the city of Hamburg which is a NUTS II level region with high per capita income, but half the population of the whole Hamburg metropolitan area lives in the nearby NUTS II level regions of Schleswig-Holstein and Lower Saxony, commuting to Hamburg for work. As a result, the value added in Hamburg is overstated by 20% relative to its effective population, while those of Schleswig-Holstein (value added equals 102% of EU average) and Lower Saxony (104%) are understated. This is similar for Ile de France (160%) and Bassin Parisien (92.7%), Communidad de Madrid (101%) and its two neighboring Castillas, Castilla-y-Leon and Castilla-La-Mancha (resp. 66 and 76%).

We now present the spatial weight matrices, upon which the determination of spatial effects relies. Two different types of matrices will be considered here. The first type relies on travel time by road from the most populated town of a region to the one of another region[4]. These data come from the web site of Michelin[5]. We adopt the travel time instead of the distance by road because the existence of islands (Balearic Islands) forces us to include the time spent to load and unload trucks on boats. This information would not have appeared if

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

we would have considered the distance by road only. The second type of matrices is based on pure geographical distances. The two different types of matrices we choose reflect different points of view with, on the one hand, the one of economists, such as 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; and on the other hand the point of view of statisticians, such as Anselin and Bera (1998) or Anselin (1996), who choose to base them on pure geographical distance, as exogeneity of geographical distance is unambiguous.

With regard to weight matrices based on pure geographical distance, the existence of the Balearic Islands does not allow considering simple contiguity matrices; otherwise the weight matrix would include rows and columns with only zeros for these islands. Since unconnected observations are eliminated from the results of the global statistics, this would change the sample size and the interpretation of the statistical inference. More precisely, we use the travel time by road (resp. great circle distance) between most populated towns (resp. regional centroids). The matrices we use are based on the number of k nearest neighbors, with k=2,3,4,5 neighbors. Each matrix is row standardized so that it is relative and not absolute distance which matters. Finally, the robustness of the results is tested by using other weight matrices based on the great circle distribution of travel time (resp. geographical distance).

Section 4- β-convergence Estimations

4-1 Detection of spatial regimes

Using the spatial weight matrices previously described, the first step of our analysis is to detect the existence of spatial heterogeneity in the distribution of the first variable, the regional per capita GDP. In that purpose, we use the G-I* statistics developed by Ord and

Getis (1995)[6] on the per capita GDP in 1980[7]. Because of the great increase in regional disparities within Spain, which makes the composition of spatial regimes inconsistent over time, we choose to base the regime definition according to the value of regional per capita GDPs at the initial period. 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, which can be interpreted as spatial convergence clubs, using the following rule: if the statistic for region *i* is positive, then this region belongs to the group of "rich" regions and if the statistic for region *i* is negative, then this region belongs to the group of "poor" regions.

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

- 23 regions belong to the spatial regime "North-East" where the G-I* statistics is positive: Asturias, Cantabria, Alava, Guipuzcoa, Viscaya, Navarra, La Rioja, Huesca, Teruel, Zaragoza, Burgos, Leon, Soria, Albacete, Barcelona, Gerona, Lerida, Tarragona, Alicante, Castellon de la Plana, Valencia, Baleares, Murcia.

- 25 regions belong to the spatial regime "South-West" where the G-I* statistics is negative: La Coruna, Lugo, Orense, Pontevedra, Madrid, Avila, Palencia, Salamanca, Segovia, Valladolid, Zamora, Ciudad Real, Cuenca, Guadalajara, Toledo, Badajoz, Caceres, Almeria, Cadiz, Cordoba, Granada, Huelva, Jaen, Malaga, Sevilla.

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6 All computations in this section are carried out using the SpaceStat 1.91 software (Anselin, 1999).

7 We do not use the Moran's scatterplot because it would imply dropping out 10 "atypical" regions from our sample.

4-2 Estimation results

β–convergence model of per capita GDP

In the case of the per capita GDP β-convergence model, the weight matrix based on travel time that maximizes the value of Moran's *I* test statistics adapted to regression residuals is k=5[8] (Cliff and Ord, 1981). This matrix allows connecting a region with the five most accessible regions by road. In order to complete the comparison between weight matrices, we also display the results with a weight matrix based on the five nearest neighbors. In this later case, the distance is based on pure geographical distance. The difference between both weight matrices is narrow, but increases with the number of neighbors. The greater is the number of neighbors, the greater is the chance that a highway exists from the origin region to the nth region. The extent of accessibility by road does not necessarily correspond to the geographical proximity.

Starting with the OLS estimation of the absolute β-convergence model, estimation results displayed in column 1 of table 2 show that $\hat{\beta}$ has the expected sign (-0.004) but is not significant (p-value = 0.265). Looking at the diagnostic tests, the Jarque-Bera test does not reject the assumption of normality of the residuals (p-value = 0.805). We note also that the White test clearly does not reject homoskedasticity (p-value = 0.703) as well as the Breusch-Pagan test versus the per capita GDP at the initial period (p-value= 0.857).

<<Insert table 2 here>>

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[8] Complete results are available upon request from the author.

Various tests aiming 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 (table 2, column 1).

The spatial error model can be written as follows:

$$g_T = \alpha S + \beta y_0 + \varepsilon \text{ with } \varepsilon = \lambda W \varepsilon + u \qquad \text{and } u \sim N(0, \sigma_u^2 I) \qquad (1)$$

where g_T is the (n×1) vector of average growth rates of per capita GDP between date 0 and T; S is the (n×1) 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 and Generalized Method of Moments (GMM, iterated) estimation are displayed in column 2 of table 1. A positive and significant spatial autocorrelation of the errors is found ($\hat{\lambda}$=0.527 by ML-estimation). The level of convergence ($\hat{\beta}$=-0.010) has increased compared to the OLS-estimation and now is significant. The convergence speed is 1.09% and the half-life is 68.78 years[9]. The LIK, AIC and SC measures indicate that this model specification achieves a better likelihood 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 is based. The two tests against heteroskedasticity (the unadjusted and spatially adjusted Breusch-Pagan statistics) are not significant (p-value = 0.852) indicating absence of remaining heteroskedasticity. The LR-test on the spatial autoregressive coefficient $\hat{\lambda}$ is highly significant (p-value = 0.016). The Wald-test on common factor hypothesis is not strongly significant, indicating no inherent consistency in the spatial error specification. As noted by Anselin (1999), if these statistics had been highly significant, the implication would be that the spatial error model is inappropriate. However, the LM-test on spatial lag dependence is significant, which tends to indicate that the spatial error model is not necessarily the appropriate specification.

Before testing formally the relevance of the spatial lag model, we assess whether this remaining dependence is not due to the presence of remaining spatial heteroskedasticity. We therefore assess whether there is significant presence of a) structural instability across the different regimes previously described, b) groupwise heteroskedasticity and finally c) a combination of both. Neither of these effects is significant[10], we then turn to the estimation of the spatial lag model, which can be formalized as follows:

$$g_T = \rho W g_T + \alpha S + \beta y_0 + u \text{ with } u_t \sim N(0, \sigma_u^2 I) \tag{2}$$

[9] The convergence speed 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: $\tau = -\ln(2)/\ln(1+\beta)$.

[10] Complete results available from the author upon request.

with the same notations as above. The results are not displayed here due to space limitation[11], but maximum likelihood estimation as well as two stages least square estimation indicate that the lag in (2) is not significant and the LR-test on spatial lag dependence is not significant neither. Moreover, the model with the spatial error term achieves a better fit. The appropriate model of absolute β-convergence is therefore the spatial error model[12].

When the same type of estimation is performed using the weight matrix *k*=5 based on the nearest neighbors, the results lead to a spatial error model too. The results, displayed in columns 3 and 4 of table 2, show that the spatial dependence is greater in the case of this weight matrix since the value of Moran's *I* is greater (3.850 versus 2.337) and is more significant. With the same idea, $\hat{\lambda}$ in the spatial error model (column 4) has increased compared to the results with the matrix based on accessibility (0.718 versus 0.527 for the ML estimation). The convergence speed is greater too (1.81% versus 1.09%). All the results displayed in table 2 indicate, firstly, that there is significant convergence in per capita income among Spanish regions and, secondly, the significant presence of spatial autocorrelation between regions. In other words, estimating the convergence process without including the presence of these significant spatial effects would lead to unreliable results.

***β*–convergence model in aggregate labor productivity**

When the same type of analysis is performed on the aggregate labor productivity, estimation results lead to a spatial error model for both matrices. Convergence is significant and greater than income convergence ($\hat{\beta}$ = -0.027, see columns 1 and 2 of table 3). However, spatial autocorrelation is smaller than the one for income convergence ($\hat{\lambda}$ is significant only for the GMM estimation and equals 0.277 versus 0.474 in the previous case for *k*=5 most

[11] Complete results available from the author upon request.
[12] This is confirmed when the estimation is performed with other weight matrices, either based on the nearest/most accessible neighbors or on the great circle distribution.

accessible regions). The unadjusted and spatially adjusted Breusch-Pagan statistics are not significant (p-value = 0.343) indicating absence of remaining heteroskedasticity. The LR-test on the spatial autoregressive coefficient $\hat{\lambda}$ is significant (p-value = 0.045) with k=5 nearest regions only, but the LM-test on spatial lag dependence is not significant for any of the weight matrices.

<<insert table 3 here>>

β–convergence model in labor productivity in agriculture

In order to have a more precise idea of the β–convergence phenomenon among Spanish regions, the convergence process is tested for three sectors. Convergence in labor productivity in agriculture is significant and slightly greater than income convergence too ($\hat{\beta}$= -0.017, see columns 3 and 4 of table 3). Spatial autocorrelation takes the form of a spatial error model. Again, $\hat{\lambda}$ is significant only for the GMM estimation and is smaller than the one displayed for income spatial autocorrelation. The unadjusted and spatially adjusted Breusch-Pagan statistics indicate an absence of remaining heteroskedasticity. The LR-test on the spatial autoregressive coefficient $\hat{\lambda}$ is not significant (p-value = 0.109) but is more significant than the LM-test on spatial lag dependence (p-value= 0.381). Moreover, the Wald-tests on common factor hypothesis is not significant.

β–convergence model in labor productivity in industry

Labor productivity in industry is the only variable for which the appropriate β–convergence model is a spatial lag model (see model 2). It reflects the fact that spatial autocorrelation in the convergence model is more important for this variable than for the other variables. Convergence is highly significant (p-value= 0.007) and greater than for labor productivity in agriculture ($\hat{\beta}$ = -0.022 versus –0.017, see columns 1 and 2 of table 4). The lag, $\hat{\lambda}$, is significant only for the ML estimation. It equals 0.406 and 0.372 respectively for *k*=5 most accessible regions and nearest regions. The unadjusted and spatially adjusted Breusch-Pagan statistics indicate that there is an absence of remaining heteroskedasticity. There is no Wald-test on common factor hypothesis for a spatial lag model. The LR-test on spatial lag dependence is not significant (p-value = 0.102) but is more significant than the LM-test on spatial error autocorrelation (p-value= 0.269).

<<insert table 4 here>>

β–convergence model in labor productivity in services

Labor productivity in services presents the highest extent of convergence among our studied variables ($\hat{\beta}$ = -0.041 and is significant, see columns 3 and 4 of table 4). This variable has a convergence speed of 6.8% and a half-life of 16.35 years only. The appropriate convergence model is a spatial error model, of which the coefficient of spatial autocorrelation, $\hat{\lambda}$, is significant and high ($\hat{\lambda}$ = 0.800) for both ML- and GMM-estimations. There is no remaining heteroskedasticity according to the unadjusted and spatially adjusted Breusch-Pagan statistics. The LR-test on spatial error autocorrelation is highly significant (p-value= 0.000) whereas the LM-test on spatial lag dependence is not (p-value= 0.073) for both weight matrices. The Wald-test on common factor hypothesis is not strongly significant, except the Wald- test with the weight matrix *k*=5 most accessible regions (p-value= 0.003). However, when the spatial lag model is tested on this variable, estimation results indicate that the spatial error model is the appropriate specification.

The results displayed in tables 2 to 4 show that a disaggregated analysis at the sectoral level of the convergence hypothesis is necessary in order to alter the conclusions drawn about the evidence of convergence in per capita income and aggregate labor productivity. While testing for β–convergence and spatial effects for each of the three sectors of the economy, the results display that convergence speeds are not similar for all sectors and that spatial effects, always in the form of spatial autocorrelation, vary from one sector to another. Indeed, the appropriate model specification is a spatial lag model for labor productivity in industry, whereas it is a spatial error model for all the other variables. None of the previous models has shown significant evidence of spatial heterogeneity. It may come from the fact that the spatial regimes detected at the initial period for each variable are not consistent over time.

Section 5- σ-convergence and Index of Inequality

5-1 σ-convergence

As explained in section 2, β–convergence hypothesis has been widely criticized. Quah (1993) argues that a negative relationship between growth and initial level of a variable does not necessarily imply a narrowing of inequalities. The reduction in disparities across regions can be referred as σ-convergence (Barro and Sala-I-Martin, 1991, 1992) and measured by a decrease in the variance of the logarithm of the studied variable.

<<insert figure 2 here>>

The process of σ-convergence of GDP per capita is displayed in figure 2 above. The variance of per capita GDP across regions increases until 1986, the accession date of Spain to the European Union, and decreases after 1989. This last tendency seems to indicate that income differences between regions narrowed slightly. However, a deeper analysis is necessary to highlight what factors account for the evolution of per capita GDP across regions. The first step decomposes the per capita GDP of a region *i* as the product of aggregate productivity per worker and the share of employment in total population. In a logarithmic form, it is written as follows:

$$\log\left(\frac{gdp}{pop}\right)_i = \log\left(\frac{gdp}{w}\right)_i + \log\left(\frac{w}{pop}\right)_i \tag{3}$$

<<insert figure 3 here>>

Figure 3 above displays the variance of the logarithm of labor productivity and employment per population. We observe first a divergence in regional employment per capita until 1984. After 1985, we find that σ-convergence in labor productivity is sharp and continues until the end of the period, whereas σ-convergence in employment per capita is small and stops in 1993. As noted by Cuadrado-Roura *et al*. (1999), σ-convergence in labor productivity may be driven by the fact that the less developed economies imitate the technological and organizational processes at a lower cost than the one paid by the more advanced economies for research and development. However, there are other forces that can lead to labor productivity convergence: the value of aggregate labor productivity depends on sectoral productivities as well as on the productive structure. Therefore, since productivity in usually higher in industry or services than in agriculture, a transfer of productive resources from agriculture to the other sectors may explain a convergence process in total productivity that does not necessarily occur at the level of each individual productive sector.

<<insert figures 4, 5 and 6 here>>

The σ-convergence results for agriculture are set out in figure 4. There is no σ-convergence for this variable until 1991, but rather a slight tendency towards divergence. The process ceases to operate afterwards. This result is an evidence that β-convergence found in section 4 is compatible with the absence of σ-convergence. Following Cuadrado-Roura *et al*. (1999), we suggest that increasing differences in agricultural productivity may be due to random factors, like weather conditions, as well as to the individual specificity of each region as regards the type of agricultural production. Moreover, some types of production lend themselves to increased productivity through the introduction of farming improvements whereas some others do not.

With regards the industry sector, there is a sharp tendency to divergence until 1984 then the level of disparities in 1985 comes back to the one in 1983 and a fairly small σ-convergence process that takes place afterward (see figure 5). A similar behavior is observed on figure 6 for the services sector, where the level of disparities from 1985 to 1994 is higher than prior and after that period. After 1994, the level of disparities comes back to the one prior 1985, therefore there is no evidence of σ-convergence throughout the period.

5-2 Convergence in productive structure

Since the previous analysis does not reveal that regional productivity disparities by sector have decreased over time, the question arises of how the aggregate labor productivity displays a clear evidence of σ-convergence over the studied period. Following Cuadrado-Roura *et al*. (1999), the reasons include, among others, the two following factors. The first one relies on the varying weight of the productive sectors in the regions and its interplay with their average productivity levels. For instance, if the weight of the services sector is greater in the rich regions than in the poor ones, and if productivity growth is lower in services than in the other sectors, equal growth of the sectoral productivities in the different regions is compatible with a greater increase in aggregate productivity in the poor regions. In fact, the mean growth rate of productivity in the services sector in Spain was 5.3% versus a mean growth rate in total productivity of 6.2% throughout our studied period. In addition, the mean share of employment in the services sector in the five poorest regions (Badajoz, Orense, Granada, Córdoba, Jaén) was 13.7% over the period, whereas it was 20.2% in the five richest regions (Tarragona, Álava, Gerona, Baleares, Lérida).

The second reason comes from a transfer of resources from the agricultural sector, where productivity is low, to the other productive sectors, where productivity is higher, taking place to a greater degree in the poor regions than in the rich ones. In this respect, the share of agriculture in total employment in the five poorest regions has decreased by 54.8% over the period while it has decreased by 48.9% in the richest ones.

This last argument suggests that convergence in sectoral structure across regions may have been an important source of productivity convergence. To examine the extent to which employment structure has become more similar across regions, we introduce an index of inequality in productive structure based on the one of Cuadrado-Roura *et al*. (1999) and defined as follows:

$$I = \sum_{i=1}^{48}\left[\left(WA_{it} - WA_{t}\right)^2 + \left(WI_{it} - WI_{t}\right)^2 + \left(WS_{it} - WS_{t}\right)^2\right] \tag{4}$$

where $WA_{it}, WI_{it}, WS_{it}$ denote, respectively, the weight of agriculture, industry and services in total employment in region *i* at time *t*; and WA_{t}, WI_{t}, WS_{t} are the corresponding sectoral weights at the national level. The value of this index would be zero if the productive structures were the same across all the regions.

<<insert figures 7 and 8 here>>

This index is represented in figure 7 above and shows that, in terms of employment, the productive structure of the Spanish regions has become more uniform over time. This index can be divided into the sum of inequalities in productive structure by sector as follows:

$$IDA = \sum_{i=1}^{48} \left(WA_{it} - WA_{t} \right)^2 \tag{5}$$

$$IDI = \sum_{i=1}^{48} \left(WI_{it} - WI_{t} \right)^2 \tag{6}$$

$$IDS = \sum_{i=1}^{48} \left(WS_{it} - WS_{t} \right)^2 \tag{7}$$

These indices are represented in figure 8. It shows that the reason for the greater homogeneity in productive structures comes from an harmonization of agricultural 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 other productive sectors with a higher average productivity that has been more marked in the poor regions than in the rich ones. This behavior helps to explain the co-existence of significant σ-convergence in aggregate productivity and the absence of it in regional productivity by sector.

Section 6- Conclusion

This paper has presented an estimation of two concepts of convergence, namely β-and σ-convergence, on 48 Spanish regions over 1980-1996. Estimation results display a clear evidence of β-convergence in income among NUTS III regions. Moreover, various tests aiming at detecting the presence of spatial effects lead to a spatial error model as the most appropriate model specification. Neglecting these effects would have led to unreliable results. The same type of analysis is then performed on the aggregate labor productivity and on labor productivity in three sectors: agriculture, industry and services. Estimation results display evidence of significant β-convergence for each of these variables. However, the results highlight the importance of comparing similar technologies since convergence speeds and spatial effects are not homogeneous across sectors. Moreover, none of the previous estimations requires the presence of spatial heterogeneity. Since the evidence of β-convergence does not necessarily imply a narrowing of regional inequalities (Quah, 1993), σ-convergence is measured on each of the previous variables. The analysis reveals that convergence occurs in aggregate labor productivity but not in productivities by sector. The reason comes from a convergence in productive structure among regions. This is due to a transfer of resources from agriculture towards more productive sectors that has been more marked in the poor regions than in the rich ones.

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Table 1- Regions' and codes' name

Code and name of the Spanish regions			
es111 La Coruña	es242 Teruel	es421 Albacete	es522 Castellón de la Plana
es112 Lugo	es243 Zaragoza	es422 Ciudad Real	es523 Valencia
es113 Orense	es3 Comunidad de Madrid	es423 Cuenca	es53 Baleares
es114 Pontevedra	es411 Avila	es424 Guadalajara	es611 Almería
es12 Principado de Asturias	es412 Burgos	es425 Toledo	es612 Cadiz
es13 Cantabria	es413 León	es431 Badajoz	es613 Córdoba
es211 Álava	es414 Palencia	es432 Cáceres	es614 Granada
es212 Guipúzcoa	es415 Salamanca	es511 Barcelona	es615 Huelva
es213 Vizcaya	es416 Segovia	es512 Gerona	es616 Jaén
es22 Comunidad Foral de Navarra	es417 Soria	es513 Lérida	es617 Málaga
es23 La Rioja	es418 Valladolid	es514 Tarragona	es618 Sevilla
es241 Huesca	es419 Zamora	es521 Alicante	es62 Murcia

Table 2: Estimation results of the per capita GDP β-convergence model with weight matrix K=5

	per capita GDP β-convergence model					
	K=5 most accessible regions			K=5 nearest regions		
	1	2		3	4	
	OLS-White	ML-ERR		OLS-White	ML-ERR	
		ML	GMM (iterated)		ML	GMM (iterated)
$\hat{\alpha}_r$	0.098 (0.002)	0.148 (0.000)	0.142 (0.000)	0.098 (0.002)	0.197 (0.000)	0.191 (0.000)
$\hat{\beta}_r$	-0.004 (0.265)	-0.010 (0.018)	-0.009 (0.024)	-0.004 (0.265)	-0.016 (0.001)	-0.015 (0.002)
$\hat{\lambda}$	-	0.527 (0.006)	0.474 (0.000)	-	0.718 (0.000)	0.689 (0.000)
Convergence speed	-	1.09%	1.01%	-	1.81%	1.73%
Half-life	-	68.78	73.70	-	43.67	45.52
Sq. Corr.	-	0.027	0.027	-	0.0269	0.027
LIK	183.665	186.563		183.665	192.465	
AIC	-363.330	-369.127		-363.330	-380.930	
SC	-359.587	-365.384		-359.587	-377.187	
Moran's I	2.337 (0.019)	-		3.850 (0.000)	-	
LMERR	2.610 (0.106)	-		9.080 (0.002)	-	
R-LMERR	5.260 (0.022)	-		12.868 (0.000)	-	
LMLAG	1.652 (0.199)	-		6.666 (0.009)	-	
R-LMLAG	4.301 (0.038)	-		10.455 (0.001)	-	
Jarque-Berra	0.432 (0.805)	-		0.432 (0.805)	-	
White test	0.704 (0.703)	-		0.704 (0.703)	-	
BP-test for heteroskedasticity	0.032 (0.857)	-		0.032 (0.857)	-	
BP test	-	0.035 (0.852)	-	-	0.263 (0.608)	-
Spatial BP test	-	0.035 (0.852)	-	-	0.263 (0.608)	-
LR test on spatial error dependence	-	5.797 (0.016)	-	-	17.599 (0.000)	-
Wald test on common factor hypothesis	-	3.311 (0.069)	-	-	5.788 (0.016)	-
LM test on spatial lag dependence	-	4.970 (0.026)	-	-	2.852 (0.091)	-

Notes: _p_-values are in brackets. _OLS-White_ indicates the use of heteroskedasticity consistent covariance matrix estimator. _ML_ indicates maximum likelihood estimation. _GMM_ indicates iterated generalized moments estimation (Kelejian and Prucha 1999). _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.

Table 3: Estimation results of the β-convergence models in aggregate labor productivity and labor productivity in agriculture with weight matrix *K*=5

	β-convergence model in aggregate labor productivity				β-convergence model in labor productivity in agriculture GVA			
	K=5 most accessible regions		*K*=5 nearest regions		*K*=5 most accessible regions		*K*=5 nearest regions	
	1		2		3		4	
	ML-ERR		ML-ERR		ML-ERR		ML-ERR	
	ML	GMM (iterated)	ML	GMM (iterated)	ML	GMM (iterated)	ML	GMM (iterated)
$\hat{\alpha}_r$	0.501 (0.000)	0.499 (0.000)	0.498 (0.000)	0.499 (0.000)	0.340 (0.001)	0.345 (0.001)	0.344 (0.001)	0.341 (0.001)
$\hat{\beta}_r$	-0.027 (0.000)	-0.027 (0.000)	-0.027 (0.000)	-0.027 (0.000)	-0.017 (0.013)	-0.017 (0.012)	-0.017 (0.014)	-0.017 (0.014)
$\hat{\lambda}$	0.299 (0.209)	0.277 (0.000)	0.329 (0.093)	0.334 (0.000)	0.174 (0.497)	0.270 (0.000)	0.139 (0.537)	0.099 (0.000)
Convergence speed	3.52%	3.50%	3.49%	3.49%	1.96%	2.00%	1.99%	1.96%
Half-life	25.41	25.53	25.54	25.52	40.93	40.18	40.28	40.83
Sq. Corr.	0.536	0.536	0.536	0.536	0.110	0.110	0.110	0.110
LIK	191.307	-	191.812	-	119.21	-	119.09	-
AIC	-378.614	-	-379.625	-	-234.428	-	-234.18	-
SC	-374.872	-	-375.883	-	-230.68	-	-230.44	-
BP test	0.898 (0.343)	-	1.201 (0.273)	-	0.001 (0.970)	-	0.000 (0.989)	-
Spatial BP test	0.898 (0.343)	-	1.201 (0.273)	-	0.001 (0.970)	-	0.000 (0.989)	-
LR test on spatial error dependence	3.004 (0.083)	-	4.015 (0.045)	-	2.563 (0.109)	-	2.319 (0.127)	-
Wald test on common factor hypothesis	3.879 (0.049)	-	2.118 (0.145)	-	1.209 (0.271)	-	0.669 (0.413)	-
LM test on spatial lag dependence	3.194 (0.074)	-	0.978 (0.322)	-	0.765 (0.381)	-	0.375 (0.540)	-

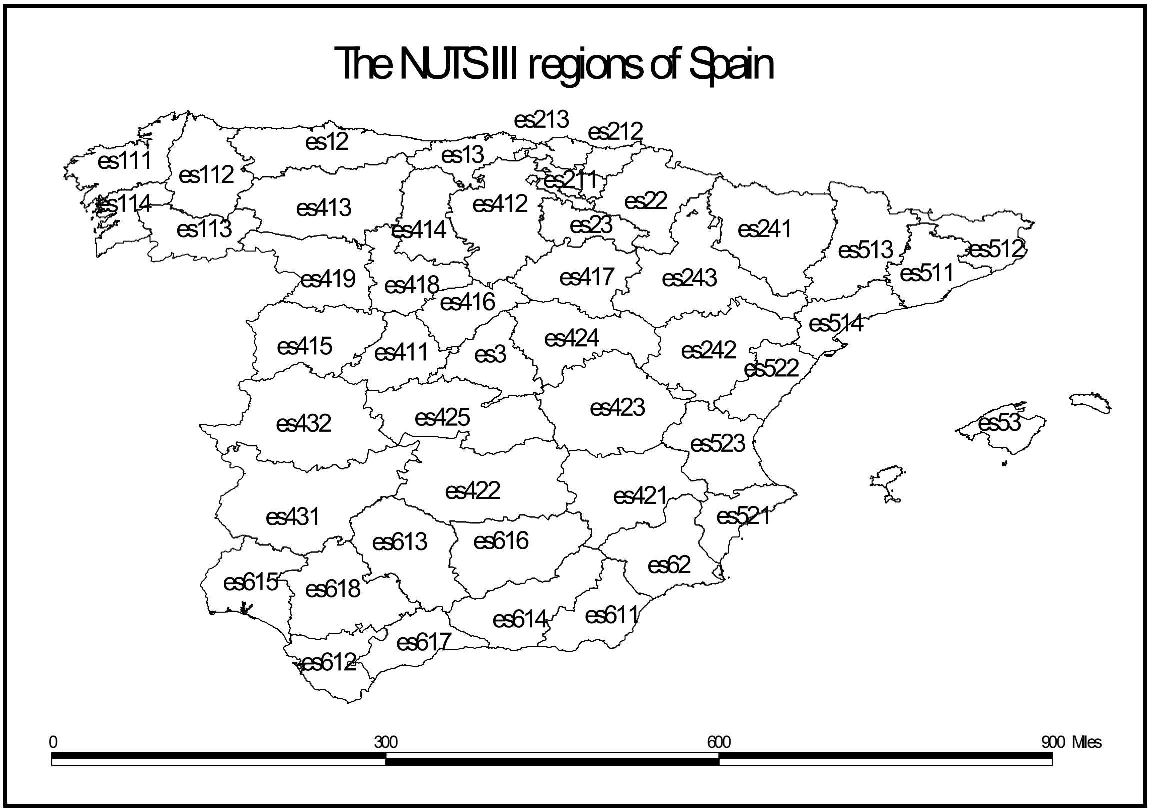
Notes: see notes table 2

Table 4: Estimation results of the β-convergence models in labor productivity in industry and in services with weight matrix K=5

	β-convergence model in labor productivity in industry GVA				β-convergence model in labor productivity in services GVA			
	K=5 most accessible regions		K=5 nearest regions		K=5 most accessible regions		K=5 nearest regions	
	1		2		3		4	
	ML-LAG		ML-LAG		ML-ERR		ML-ERR	
	ML	IV (2SLS)	ML	IV (2SLS)	ML	GMM (iterated)	ML	GMM (iterated)
$\hat{\alpha}_r$	0.403 (0.003)	0.410 (0.004)	0.317 (0.021)	-0.746 (0.749)	0.739 (0.000)	0.740 (0.000)	0.758 (0.000)	0.760 (0.000)
$\hat{\beta}_r$	-0.022 (0.007)	-0.024 (0.006)	-0.017 (0.039)	0.031 (0.771)	-0.041 (0.000)	-0.041 (0.000)	-0.042 (0.000)	-0.043 (0.000)
$\hat{\lambda}$	0.406 (0.048)	0.921 (0.108)	0.372 (0.042)	5.319 (0.621)	0.800 (0.000)	0.808 (0.000)	0.672 (0.000)	0.680 (0.000)
Convergence speed	2.79%	3.13%	2.01%	-	6.82%	6.84%	7.18%	7.22%
Half-life	30.46	27.75	39.99	-	16.35	16.32	15.89	15.84
Sq. Corr.	0.170	0.164	0.177	0.123	0.182	0.182	0.182	0.182
LIK	151.145	-	151.025	-	194.740	-	193.933	-
AIC	-296.290	-	-296.049	-	-385.481	-	-383.866	-
SC	-290.676	-	-290.435	-	-381.738	-	-380.124	-
BP test	0.151 (0.697)	-	0.057 (0.810)	-	2.979 (0.084)	-	2.349 (0.125)	-
Spatial BP test	0.151 (0.697)	-	0.057 (0.810)	-	2.980 (0.084)	-	2.349 (0.125)	-
LM (for industry) / LR (for services)test on spatial error dependence	1.220 (0.269)	-	0.054 (0.814)	-	21.137 (0.000)	-	19.522 (0.000)	-
Wald test on common factor hypothesis	-	-	-	-	8.601 (0.003)	-	2.609 (0.106)	-
LR (for industry) / LM (for services) test on spatial lag dependence	2.666 (0.102)	1.893 (0.168)	2.425 (0.119)	0.005 (0.941)	3.206 (0.073)	-	1.493 (0.221)	-

Notes: see notes table 2. IV stands for Instrumental Variables.

Figure 1- The regions of Spain



Note: See table 1 for the regions' code and name. This figure has been realized using Arcview GIS 3.2 (Esri).

Figure 2: σ-convergence in per capita GDP

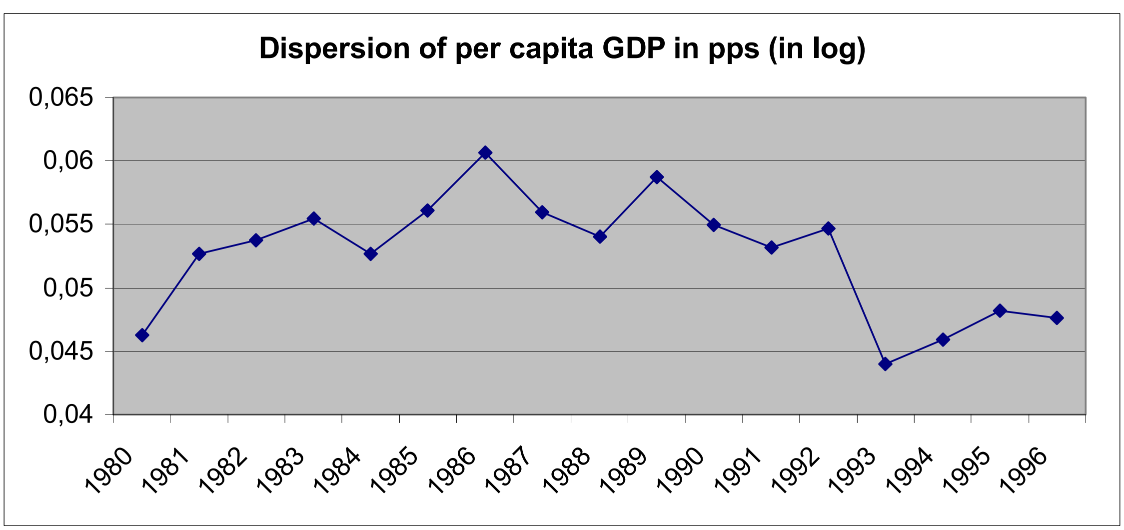


Figure 3: σ-convergence in per capita employment and in labor productivity

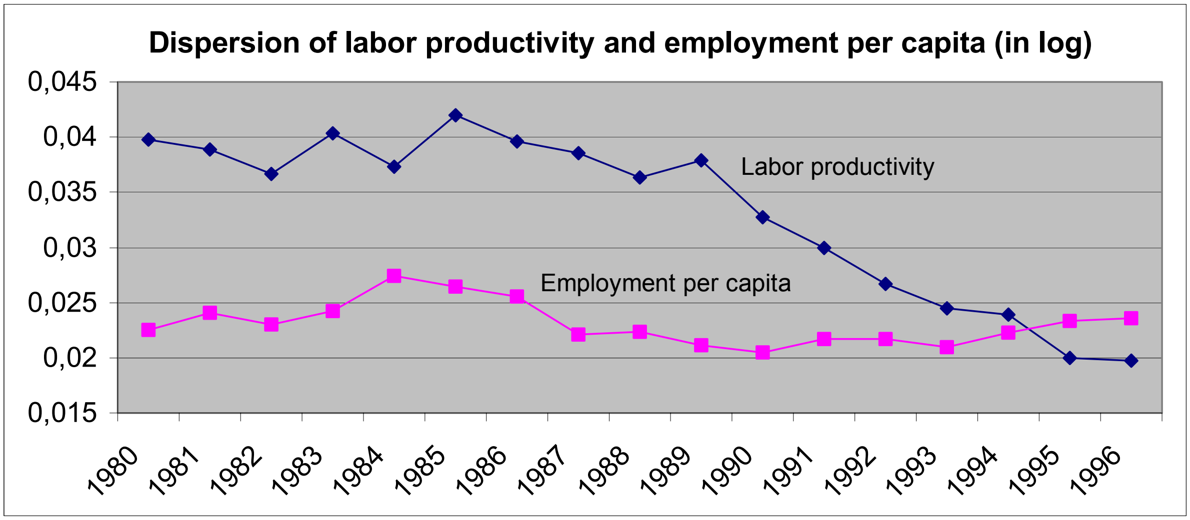


Figure 4: σ-convergence in labor productivity in agriculture

Figure 5: σ-convergence in labor productivity in industry

Figure 6: σ-convergence in labor productivity in services

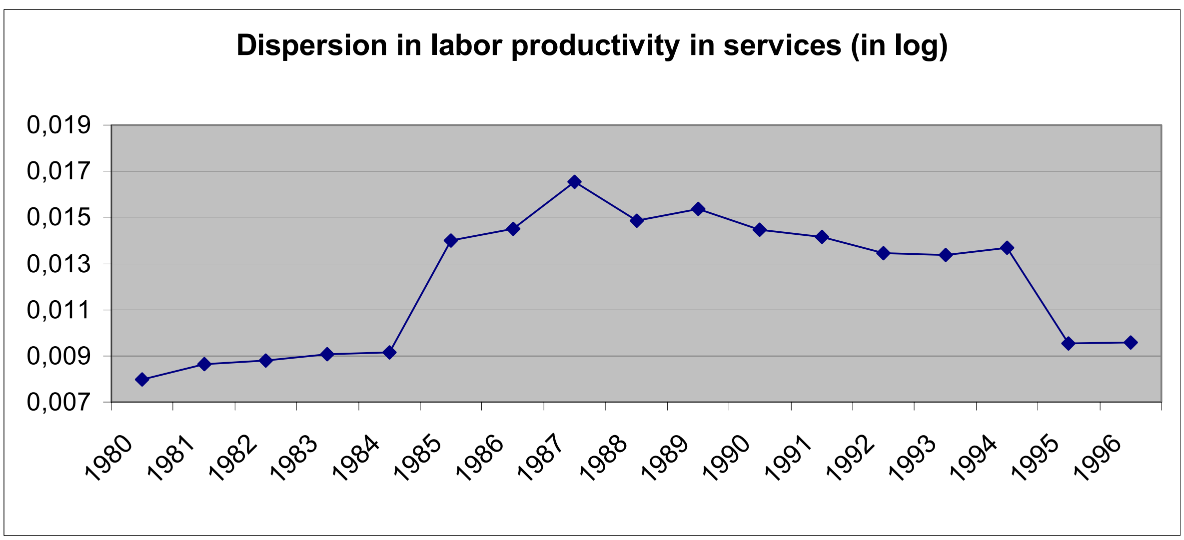


Figure 7: Total index of inequality in productive structure

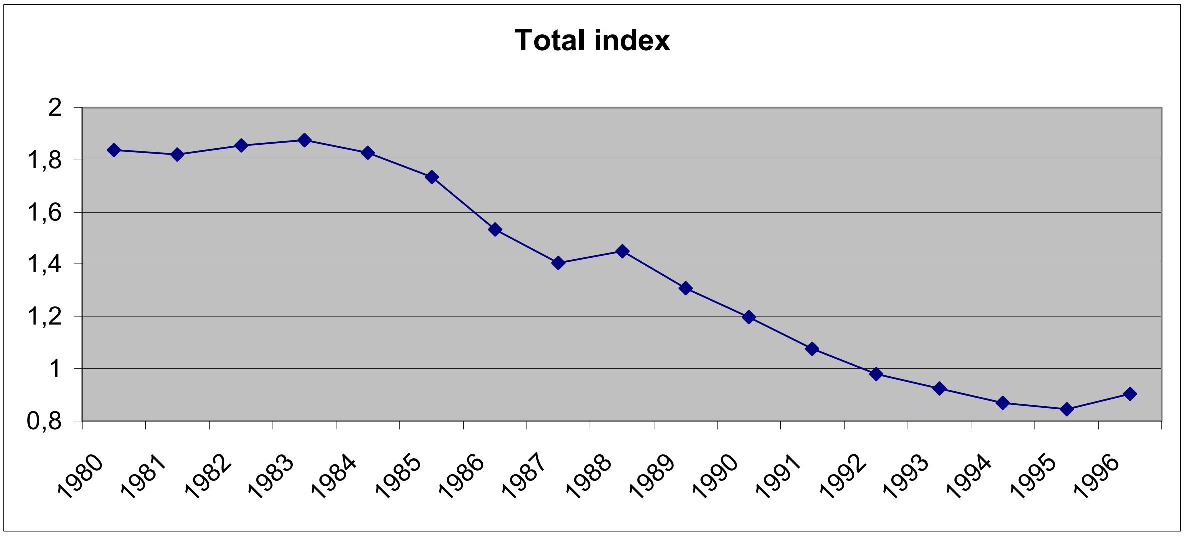


Figure 8: Index of inequality in productive structure by sector