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ORIGINAL PAPER

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Productivity convergence and spatial dependence among Spanish regions

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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. The results of β-convergence emphasize the importance of including the impact of neighboring locations' productivity and a disaggregate analysis at a sectoral level. In order to measure the narrowing of inequalities, we examine σ-convergence and reveal that convergence occurs in aggregate labor productivity but not in productivities per 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.

Keywords Region · Convergence · Productivity · Spatial econometrics

JEL Classification O47 · O52 · R11 · R15

1 Introduction

Since 1986, when Spain decided to become a member of the European Community, the country has seen its per capita Gross Domestic Product

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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 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 done 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 the identification of the forces driving it (Cuadrado-Roura et al. 1999; Lopez-Bazo et al. 1999; Cuadrado-Roura 2001). Moreover, we adopt an approach based on both per capita GDP and per worker gross value added (as a measure of labor productivity) because regional policies implemented in backward regions (transportation infrastructures, firms subsidies, human capital improvement) act directly on the production function of firms and thus may favor the productivity levels in the poor regions but not necessarily their per capita income levels (Lopez-Bazo et al. 1999). Finally, we give a pre-eminent role to the geographical location and potential interregional linkages of each region by adopting a spatial econometric approach. For the European regions, papers in this area include, among others, Fingleton (1999, 2001, 2003a, b), Bivand and Brunstad (2003) or Le Gallo et al. (2003), Dall'erba and Le Gallo (2003), Arbia and Paelinck (2003a, b).

This paper proposes 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: Sect. 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 Sect. 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), Sect. 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.

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. The reader may refer to Durlauf and Quah (1999) for a review of this extensive literature.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 which 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 which 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 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 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, as in belonging to a geographic zone (Baumol 1986) or some GDP per capita cut-offs (Durlauf and Johnson 1995). Others prefer to use endogenous methods, 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 as well as poor nations tend to be geographically clustered. 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 (2005) 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, 2001; Rey and Montouri 1999; Baumont et al. 2003; Le Gallo et al. 2003). This is also the purpose of this paper, but opposite to 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 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. For instance, more than 90 of such variables have been included in cross-country regressions using international datasets (Durlauf and Quah 1999). Furthermore, data on some of these explanatory variables may not be easily accessible and/or reliable due to the small size of the spatial units under study. 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 to the spatial econometric estimation of regional sectoral convergence in Spain, Sect. 3 will introduce data and the spatial weight matrix since all the following analyses rely on the definition of space through the weight matrix.

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 used by the European Commission for its evaluation of regional convergence. GDP per capita is measured in purchasing power parity (PPP) 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 which are represented in Fig. 1 below. Nomen-

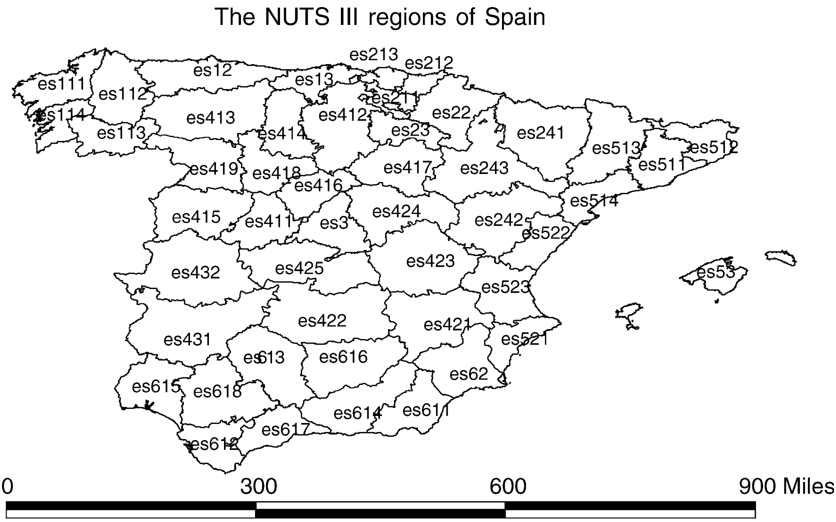

Fig. 1 The regions of Spain *Note*: See Table 1 for the regions' code and name. This figure has been realized using Arcview GIS 3.2 (Esri)

clature of territorial units for statistics (NUTS) is the spatial classification established by Eurostat on the basis of national administrative units which is used by the Commission as regional statistical concept. The European territory 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.

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.

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). Messner and Anselin (2004) 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 charac-

Table 1 Regions' and codes' name

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

teristics 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 another region. Information on the most populated town comes from http://www.citypopulation.de/Europe.html. Data on travel time comes from the Michelin website http://www.viamichelin.com. We adopt the travel time instead of the distance by road because presence of islands (Balearic Islands) forces us to include the time spent to load and unload truck cargo onto boats. This information would not have been presented if we would have considered the distance by road alone. The second type of matrices are based on pure geographical distances. The two different types of matrices we chose reflect different points of view, firstly, the one of economists such as Bodson and Peeters (1975), Aten (1996, 1997) and Los and Timmer (2002), who find it more attractive to base these weights on the channels of communication between regions, such as roads and railways; and secondly, the point of view of statisticians such as Anselin and Bera (1998), and Anselin (1996), who chose 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 the consideration of simple contiguity matrices, since the weight matrix would include rows and columns with only zeros included for these islands. Since unconnected observations are eliminated from the results of global statistics, this would change the sample size and the interpretation of the statistical inference. More precisely, we use the travel time by road (great circle distance respectively) between most populated towns (regional centroids respectively). The matrices we use are based on the number nearest neighbors of k, with $k=2,3,4,5$ neighbors. Each matrix is row standardized so that it is the 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 (geographical distance respectively).

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. For this purpose, we use the G-I* statistics developed by Ord and Getis (1995) on the per capita GDP of 1980. We do not use the Moran's scatterplot because it would imply dropping out ten "atypical" regions from our sample. Because of the great increase in regional disparities within Spain, which makes the composition of spatial regimes inconsistent over time, we chose to base the regime definition on the value of regional per capita GDPs at the initial period. These statistics are computed for each region and they allow the detection 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. All computations are carried out using the SpaceStat 1.91 software (Anselin 1999).

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

- twenty-three regions belong to the spatial regime "North-East" where the G-I* statistics are 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.
- twenty-five regions belong to the spatial regime "South-West" where the G-I* statistics are 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.

4.2 Estimation results

4.2.1 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 $k=5$[1] (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 latter 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 the number of neighbors, the greater is the chance that a highway exists from the origin region to the n^{th} 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).

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 briefly 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 (LMERR and LMLAG respectively) and their

[1] Complete results are available upon request from the author

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:

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

where g_T is the $(n \times 1)$ vector of average growth rates of per capita GDP between date 0 and T; S is the $(n \times 1)$ sum vector; y_0 is the vector of log per capita GDP levels at date 0. 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[2]. 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

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

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 OLS-White	2 ML-ERR		3 OLS-White	4 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)	–

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 both. Neither of these effects is significant[3], so we then turn to the estimation of the spatial lag model, which can be formalized as follows:

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

with the same notations as above. The results are not displayed here due to space limitation, but maximum likelihood estimation as well as two stages least square estimation indicate that the lag in Eq. (2) is not significant and the LR-test on spatial lag dependence is not significant either. 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. 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.

When the same type of estimation is performed using the weight matrix $k=5$ based on the nearest neighbors, the results also lead to a spatial error model. 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.

4.2.2 *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 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.

4.2.3 *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

[3] Complete results available from the author upon request

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.

4.2.4 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). However, in a spatial lag model the marginal effect of $\partial y/\partial x$ is not equal to the estimated beta but to $\hat{\beta}/(I - \rho W)$, therefore each region converges to its own steady-state and convergence speeds vary according to the region. The lag, $\hat{\lambda}$, is significant only for the ML estimation. It equals 0.406 and 0.372 respectively for $k = 5$ for the 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).

4.2.5 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, 3, 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

Table 3 Estimation results of the -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			
	$K = 5$ most accessible regions 1 ML-ERR		$K = 5$ nearest regions 2 ML-ERR		$K = 5$ most accessible regions 3 ML-ERR		$K = 5$ nearest regions 4 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

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.

5 σ-Convergence and index of inequality

5.1 σ-Convergence

As explained in Sect. 2, the 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.

The process of σ-convergence of GDP per capita is displayed in Fig. 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:

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

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. σ-convergence in labor productivity depends on both convergence in the sectoral productivities as well as on the evolution of the productive structure of the regional economies. We examine the evolution of sectoral productivities first.

The σ-convergence results for agriculture are set out in Fig. 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 Sect. 4 is compatible with the absence of σ-convergence. According to Cuadrado-Roura et al. (1999), increasing differences in agricultural productivity may be due to random factors, like

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

	β-convergence model in labor productivity in industry				β-convergence model in labor productivity in services			
	$K = 5$ most accessible regions 1 ML-LAG		$K = 5$ nearest regions 2 ML-LAG		$K = 5$ most accessible regions 3 ML-ERR		$K = 5$ nearest regions 4 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

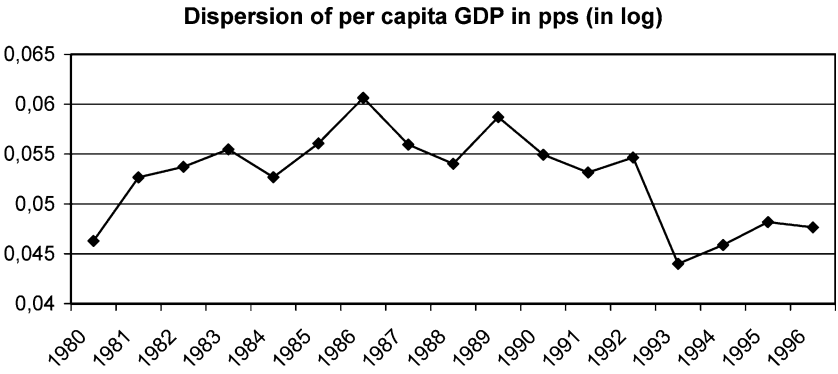

Fig. 2 σ-Convergence in per capita GDP

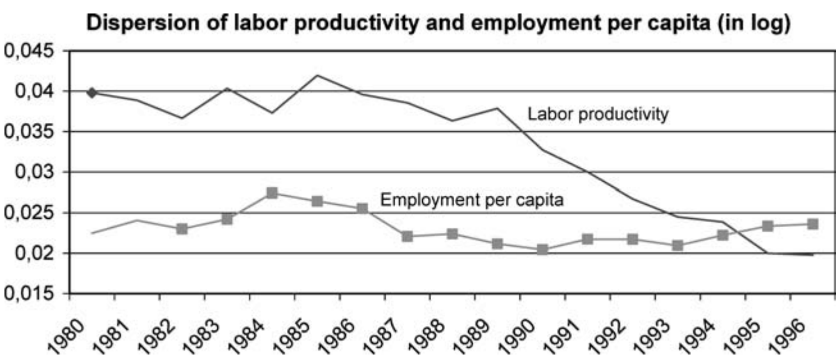

Fig. 3 σ-Convergence in per capita employment and in labor productivity

weather conditions, as well as to the individual specificity of each region with regard to the type of agricultural production and farming improvements.

With respect to the industry sector, there is a sharp tendency to divergence until 1984, after which the level of disparities in 1985 reverts to the one in 1983 and a fairly small σ-convergence process takes place afterwards (see Fig. 5). A similar behavior is observed in Fig. 6 for the services sector, where the level of disparities from 1985 to 1994 is higher than that before and after that period. After 1994, the level of disparities reverts to the one prior to 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. As noted above, σ-convergence in labor productivity depends on sectoral productivities as well as on the productive structure. Therefore, since productivity is 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. Cuadrado-

Fig. 4 σ-Convergence in labor productivity in agriculture

Fig. 5 σ-Convergence in labor productivity in industry

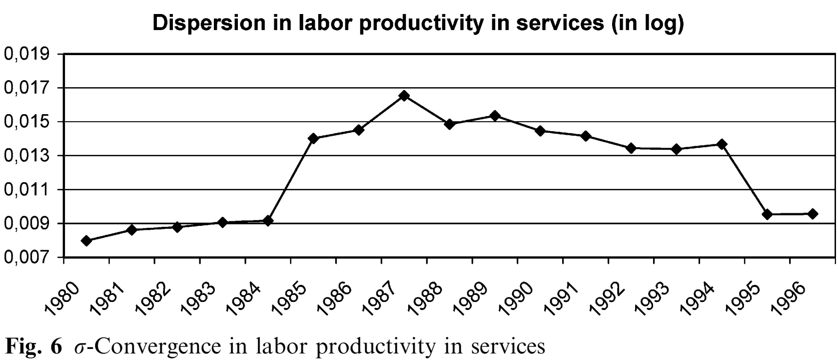

Fig. 6 σ-Convergence in labor productivity in services

Roura et al. (1999) and de la Fuente and Freire (2000) argue that convergence in sectoral structure across Spanish 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) as follows:

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

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.

This index is represented in Fig. 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:

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

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

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

These indices are represented in Fig. 8. It shows that the reason for the greater homogeneity in productive structures comes mainly from harmonization of agricultural structures among regions. It is not due to an increase in 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. In this respect, the share of agriculture in total employment in the five poorest regions (Badajoz, Orense, Granada, Córdoba, Jaén) has decreased by 54.8% over the period while it has decreased by 48.9% in the richest ones (Tarragona, Álava, Gerona, Baleares, Lérida). 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.

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

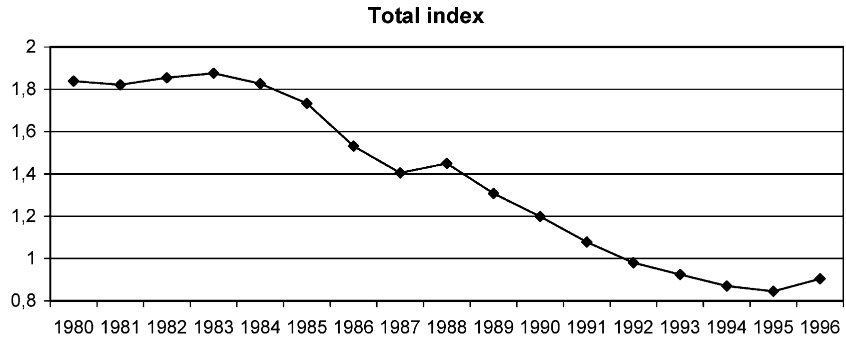

Fig. 7 Total index of inequality in productive structure

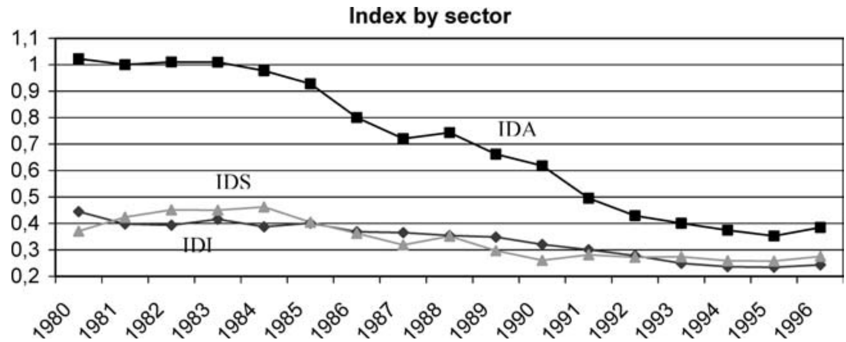

Fig. 8 Index of inequality in productive structure by sector

are not homogeneous across sectors[4]. 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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[4] The hypothesis of spatial and sectoral interdependence has not been tested here and is left for future research. We would like to thank an anonymous referee for raising this point. Approaches to deal with that issue would, for example, rely on pooling sectors and using sectoral regimes or using the spatial SUR approach developed in Anselin (1988)

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