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# The influence of educational attainment on convergence in Spanish and Portuguese regions

**Elías Melchor-Ferrer**

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Articles

# The influence of educational attainment on convergence in Spanish and Portuguese regions

*Elías Melchor-Ferrer**

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## ABSTRACT:

This article empirically analyses regional convergence between Spanish and Portuguese NUTS-3 regions during the period 2000-2015, considering the spatial dependence between these units and the role of educational attainment in this process. After some considerations regarding the model to be estimated, exploratory spatial data analysis (ESDA) is applied to detect two regional clusters grouped by regional product per inhabitant: high-income regions (located in the north-eastern third of the Iberian Peninsula) and low-income regions. For both clusters, various models of educational attainment are examined. These models reveal the presence of regional convergence, and enable us to detect the spatial spillovers that drive this process, which differ between the two clusters. In particular, we observe the influence of tertiary education on the reinforcement of income convergence within the high-income cluster, while for the low-income cluster this role is largely played by secondary education, but in the opposite direction.

**KEYWORDS:** regional convergence; educational attainment level; spatial spillovers; Iberian regions; Spatial Durbin Model.

**JEL CLASSIFICATION:** Q18; R11; R12.

## Influencia del nivel educativo en la convergencia de las regiones españolas y portuguesas

## RESUMEN:

En este artículo se analiza la convergencia regional entre las regiones españolas y portuguesas NUTS-3 durante el periodo 2000-2015, prestando especial atención a la dependencia espacial existente entre dichas unidades, así como al papel del nivel educativo en dicho proceso. Después de unas consideraciones relativas al modelo a estimar, el análisis exploratorio de datos espaciales permite detectar la existencia de dos clústeres regionales en Producto Regional por habitante: regiones de renta alta (situadas en el tercio nororiental de la península ibérica) y las regiones de renta baja. Tras explorar diferentes modelizaciones que integran el nivel educativo para ambos clústeres, los resultados obtenidos nos permiten afirmar la existencia de convergencia regional, así como estimar los desbordamientos espaciales que derivan de ese proceso, también diferentes para ambos clústeres. En concreto, se observa el efecto positivo que la educación terciaria tiene en el refuerzo de la convergencia en renta para el clúster de renta alta, mientras que para el de renta baja dicho papel lo desempeña en buena medida la educación secundaria, pero en sentido contrario.

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* Department of International and Spanish Economics. Faculty of Economics. University of Granada. Campus de Cartuja, s/n. Granada (Spain) E-18071.
**Corresponding author:** emelchor@ugr.es

**Palabras clave:** convergencia regional, nivel de logro educativo, desbordamientos espaciales, regiones ibéricas, Modelo Espacial de Durbin.
**Clasificación JEL:** Q18, R11, R12.

## 1. Introduction

Traditionally, analyses of regional convergence have focused on single-country territorial areas, due to the impact of borders and differences in institutional frameworks on the distribution of economic activity (Barro & Sala-i-Martin, 1990). However, increasing EU integration has led to the analysis of supranational areas becoming common (Borsi & Metiu, 2015; Geppert & Stephan, 2008; Lopez-Bazo, 2017), generally with national units, but more and more with regional units. In this regard, per capita incomes across European regions are neither equal nor constant, thus giving rise to regional convergence clusters across Europe (Quah, 1996). Since geographical and national factors underlie many dynamics of inequality, research in this field usually focuses on countries with common features, for example, those in Western Europe, Central and Eastern Europe or the Mediterranean region.

Econometric applications tend to assume that the development of human capital is an exogenous[1] determinant of income convergence dynamics in European regions. In other words, the sufficiency or otherwise of the stock of human capital in these economies affects their ability to imitate technical progress (Kutan & Yigit, 2007). To the extent that improvements in educational level are a catalyst of innovation and technology, they accelerate progress towards full convergence. For this reason, human capital investment in less developed areas contributes to reducing regional inequality (Fleisher, Li, & Zhao, 2010). However, as has been shown for Eastern European regions (Crespo Cuaresma, Havettová, & Lábaj, 2013), the lag between making an initial investment and reaping its benefits differs among countries and regions.

The question of regional convergence within Spain and Portugal (which jointly form the Iberian regions) has been widely considered in recent years, from multiple perspectives: by territorial unit (NUTS 2 or NUTS 3), by time period, including or excluding the spatial component, according to the dependent and independent variables analysed and, within these, the inclusion or otherwise of human capital. Most such studies have been performed on an individualised, country-by-country basis (Badia-Miró, Guilera, & Lains, 2012; Ligthart, 2002; Tortosa-Ausina, Pérez, Mas, & Goerlich, 2005), although, in some cases, a global perspective has been applied (Melchor-Ferrer, 2018; Viegas & Antunes, 2013). In this context, studies have highlighted the existence of two differential patterns of behaviour in the Iberian regions (Marelli, 2007; Viegas & Antunes, 2013): i) convergence among Spanish regions has ceased, while it has continued in Portugal; ii) Spanish regions, in general, have grown more strongly than those in Portugal. Like most such studies, we include a comparative analysis to reveal similarities and differences and, ultimately, to determine the suitability of addressing convergence in the Iberian regions jointly. Conversely, the spatial polarisation of economic activities in the Iberian regions may reflect the existence of different spatial regimes, in a pattern that transcends national boundaries.

Among the previous studies that include the level of educational attainment as an independent variable (see Table 1), the vast majority take into account spatial feedback effects and examine a time period that finishes before 2008, hence excluding the impact of the major economic changes that have taken place in recent years. Our literature review also shows that no previous studies in this field have focused on Iberian regions in particular. The contribution of the present study, therefore, is to extend the findings of previous empirical research. The growing integration between the Spanish and Portuguese economies, the free movement of labour and the significant rise in levels of educational attainment (in the latter respect, especially around Lisbon, Porto and Coimbra) all highlight the need to analyse the differential impact of educational attainment on regional income and convergence among the Iberian regions. In

[1] However, Crespo Cuaresma et al. (2018) propose a model that is capable of accounting for simultaneity in the relationship between human capital and output growth.

addition, as the literature suggests there may be differentiated behavioural patterns between these regions, they are analysed in order to identify spatial clusters.

**TABLE 1.**
**Key findings of empirical studies of human capital and regional growth in Spain and Portugal at the NUTS 3 level**

| | Authors | Information and analysis | | | Major findings |
|---|---|---|---|---|---|
| | | Data | Spatial | Panel data | |
| Spain | Buendía & Sánchez de la Vega (2015) | 1985-2007 | Yes | Yes | Empirical results show significant and positive spillovers in labour productivity. Slight impact of human capital (tertiary studies) on labour productivity. |
| | Gómez-Antonio & Fingleton (2012) | 1985-2001 | Yes | Yes | There is evidence in support of the wage equation involving market potential, human capital and public capital. The elasticity associated with human capital is statistically significant but small. |
| | Mella & Chasco (2006) | 1985-2001 | Yes | No | Human capital is strongly significant and positively related to urban per capita GDP growth. This influence is greater than for capital growth. |
| | Ramos, Suriñach & Artis (2010) | 1980-2007 | Yes | Yes | Analysis revealed a positive impact of human capital (secondary studies) on regional growth, and the existence of negative geographical spillovers associated with tertiary studies. |
| Portugal | Cardoso & Pentecost (2011) | 1991-2008 | No | Yes | Secondary and tertiary education has played a positive role in regional growth and convergence because the skills needed to adopt the new technologies are provided by higher levels of education. |
| | Guerreiro (2013)[2] | 1991-2002 | Yes | Yes | A strong significant association was observed between the coefficient for the labour force and the uptake of higher education, demonstrating the importance of this variable as a determinant of wage growth and convergence. |
| | Martinho (2011) | 1996-2002 | Yes | No | The level of educational attainment influences productivity convergence, and raises the value and statistical significance of convergence coefficients. |

In the first section of this paper we address methodological issues related to the theoretical framework applied, mainly concerning the general convergence model and the estimation methods that will be applied. In the second section, we define the study variables, the data sources and the model specification.

[2] This author synthetizes several works published regard the income convergence between Portuguese NUTS 3 regions.

With this information, in the third section we perform an exploratory spatial data analysis (ESDA) of gross regional product per capita (GRPpc) in the Iberian regions to determine whether this variable is randomly distributed within the space and to identify the regional clusters. In section four, we discuss the model obtained and remark on the influence of tertiary education on regional growth for the high-income cluster, while for the low-income cluster this role is largely played by secondary education, but in the opposite direction.

## 2. Methodology

Spatial factors are increasingly significant in analyses of economic growth, as revealed by abundant empirical evidence, especially in terms of capital – physical, human and technological (Ertur & Koch, 2007; Ezcurra & Rios, 2015; Fingleton & López-Bazo, 2006; Kubis & Schneider, 2012; Naveed & Ahmad, 2016). The latter studies show that geographic location has a marked impact on regional growth performance. Spatial econometrics is a subfield of econometrics dealing with spatial interaction effects among geographical units (Elhorst, 2014). Key contributions to this field have been made by Anselin (1988; 1995), LeSage (2008) and Arbia (2006), among others. To address this question, some regional economists have suggested incorporating spatial heterogeneity and dependence within regional growth specifications (Fingleton & López-Bazo, 2006; Rey & Montouri, 1999).

The traditional determinants of regional growth are subtly altered when the spatial effect is taken into consideration, and so these effects should be included in the specifications for empirical analyses of growth. The spatial econometric approach has been used in various studies in conjunction with convergence models, whether unconditional (Rey & Montouri, 1999) or conditional (Fingleton & López-Bazo, 2006; López-Bazo, Vayá, Mora, & Surinach, 1999). In both cases, the results obtained provide strong evidence for the existence of spatial externalities, reflecting the need to account for spillover shocks among regions.

In the present study, the model used for analysis is defined taking into account that we wish to estimate both direct and indirect effects on growth rates in the Iberian regions, using a conditional beta-convergence model, incorporating three indices of human capital to analyse their impact on regional growth. Traditional views on convergence (Barro & Sala-i-Martin, 1992) suggest that regions with lower income per capita present faster growth than those with higher initial values (absolute convergence). However, the structural characteristics of regions may give rise to the existence of various steady states, which is a typical feature of conditional convergence models. These models may be estimated by incorporating different explanatory variables (in addition to the previous value of GRPpc) to act as proxies of the steady state. Therefore, the starting point for defining our model is that of a traditional conditional convergence equation, adapted to incorporate the spatial component in the dependent and explanatory variables, and in the disturbance term.

The starting point to select the spatial econometric model that best fits the subject matter is the General Nesting Spatial (GNS) model for panel data, using the following equation (Elhorst, 2014):

$$\left(\frac{1}{T}\right) ln\left(\frac{y_t}{y_{t-T}}\right) = \alpha_t + \mu + W\left(\frac{1}{T}\right) ln\left(\frac{y_t}{y_{t-T}}\right)\delta + ln(x_{t-T})\beta + Wln(x_{t-T})\theta + u_t \tag{1}$$

$$u_t = \lambda W u_t + \varepsilon_t$$

where:

$\left(\frac{1}{T}\right) ln\left(\frac{y_t}{y_{t-T}}\right)$ is the cumulative annual growth rate of the GRPpc for each region (in vector form), measured over $T$-year periods;

$W$ is the spatial weight matrix;

$W\left(\frac{1}{T}\right)ln\left(\frac{y_t}{y_{t-T}}\right)$ is the spatial autoregressive component of the GRPpc;

$ln(x_{t-T})$ is the matrix of exogenous explanatory variables $T$ years ago;

$Wln(x_{t-T})$ is the interaction effect of explanatory variables $T$ years before;

$\alpha_t, \mu,$ and $u_t$ are, respectively, the vector of time period fixed or random effects, the spatial fixed or random effects, and the disturbance term of the different units; and

$\lambda$, $Wu_t$ and $\varepsilon_t$ are vectors, respectively, the spatial autocorrelation coefficient, the interaction effects among the disturbance terms of the different units, and the disturbance terms.

The GNS model can be simplified in alternative specifications depending on the value of the parameters $\delta$, $\theta$ and $\lambda$ in order to estimate the spatial error model (SEM), the spatial Durbin model (SDM) or the spatial autoregressive model (SAR), among others. These models include one or more spatial lags in the dependent variable (SAR and SDM), the explanatory variables (SDM) and the error term (SEM).

The SDM model provides a general starting point for estimating the spatial regression model, since this model subsumes the others mentioned and captures both the direct effect of neighbours' expected outcome on own outcomes and the indirect effect on other regions (LeSage, 2008). LeSage and Fischer (2008) provided a framework for interpreting the resulting estimates which has been generally accepted as the standard approach for spatial models. It is based on analysing three types of impact on economic growth rates arising from changes in explanatory variables: i) the direct effect, summarising the impact of changes of an explanatory variable in region *i* on the dependent variable, both within region *i* and within its neighbours; ii) the indirect effect on the dependent variable for region *i* of changes in independent variables within neighbouring regions; iii) the average total effect, a scalar summary measure that includes both direct and indirect effects. To make statistical inferences about these effects, it is necessary to calculate dispersion measures, using Markov Chain Monte Carlo simulation.

The explanatory power of each component of regional growth is determined via maximum likelihood (ML) estimation of the panel data model, considering four options: no fixed effects, spatial fixed effects, time-period fixed effects and both spatial and time-period fixed effects. In general, the fixed effects model is the most appropriate, because the impact of neighbouring units can only be measured when these units form part of the sample. However, the assumption of zero correlation between the random effects and the explanatory variables can only be tested after Hausman's specification test has been performed. If fixed effects are detected, the next step is to consider the geographic location, because this factor can reveal differences in patterns of behaviour between regions other than improvements in GRPpc. Evidence of such differences would suggest the existence of spatial externalities, and we would then have to incorporate the spatial dimension into the estimation in order to assess its strength (Fingleton & López-Bazo, 2006).

Detecting and analysing the type of spatial dependence model developed, and determining which model is most appropriate, is crucially important to the correct specification and application of an estimation method. To achieve robustness against model misspecifications such as non-constant error variances in a regression model and non-normality, Anselin (1988) proposed incorporating heteroscedasticity in the model estimation using a ML estimator, assuming that the disturbance terms are distributed independently and identically for all spatial and time-period units. However, when spatial specific effects are assumed to be fixed, the log-likelihood function provides a unique numerical solution for the spatial parameter, and must be transformed to take into account the endogeneity of the lagged dependent variable by using a Jacobian iteration method[3]. For this reason, we estimated the model by the concentrated ML estimation procedure proposed by Elhorst[4].

[3] See Elhorst (2014) in chapter 3 for details.

[4] Matlab routines for this procedure, called "sar_panel_FE", are available online at https://spatial-panels.com/software/ This file includes a normalization procedure where each element of W is divided by its largest characteristic root (Kelejian & Prucha, 2010).

The presence of endogeneity is a common occurrence in almost any empirical regression, and may result from measurement errors for explanatory variables or from omitting variables correlated with explanatory variables included (Elhorst, 2010a). Failing to account for these objections increases the risk of obtaining biased estimation results. The remedy proposed by Elhorst (2003) is to introduce a variable intercept $\mu_j$ representing the effect of the omitted variables that are peculiar to each spatial unit considered. As the parameters are fixed but different across spatial units, each spatial unit is treated separately. Nevertheless, as noted in LeSage and Pace (2009) we can identify the presence of omitted variables given two circumstances (Lacombe & LeSage, 2015): omitted variables that are correlated with the explanatory variables included, and spatial dependence in the disturbances within the model. In the resulting SDM model, $\beta$ is replaced by $\beta + \gamma = \emptyset$, as $\beta = \theta/(-\delta)$. It is then possible to identify $\gamma$, and when $\gamma \neq 0$ we can assert the presence of omitted variables. A simple (analogous) way to test this would be to use the reported t-statistics for the indirect effects that are available for ML estimates, since where there is no omitted variables bias, the indirect (spillover) impacts are not significantly different from zero.

## 3. Data sources and model specification

### 3.1. Study variables and data sources

The GRPpc data were obtained from the Regional Economic Accounts (ESA-2010) published by Eurostat. This database presents data for gross regional product (at current market prices). The deflator index for the corresponding NUTS-2 region was then applied in order to express GRP in constant 2000 euros. The model specification includes 82 different units, corresponding to the NUTS-3 Iberian regions (except Ceuta and Melilla, two Spanish enclaves in North Africa), and eleven observations for each group: 2000-2010 for the explanatory variables and 2005-2015 for the independent variable, taking into account that the cumulative growth rate is measured over a five-year period. In total there were 902 observations, 627 for the Spanish regions and 275 for the Portuguese ones. In all cases, a large number of observations were analysed, thus ensuring ample degrees of freedom.

To analyse the impact of human capital on regional growth, with respect to levels of educational attainment, we focused on the population aged 15 years and older. The education data analysed correspond to the highest level achieved by each member of this population. Specifically, we examined three aggregate statistics based on the International Standard Classification of Education: i) primary education (levels 1 and 2); ii) secondary education (levels 3 and 4); iii) tertiary education (levels 5-8). The data are expressed as the share of each population group of the total for these categories.

The Eurostat Database does not provide data at the NUTS-3 level and so we took the national statistics consistent with this classification. For the Spanish regions, we consulted the database developed by Bancaja Foundation and the Valencian Institute of Economic Research (2014) for the period 1977-2013. For the Portuguese regions, the Francisco Manuel dos Santos Foundation manages the PORDATA database, which compiles educational information sourced from public census records. The latter are published every ten years (2001 and 2011 for our analysis period); in our study, the data for the remaining years were obtained by linear interpolation.

### 3.2. Model specification

To analyse the spatial convergence in the Iberian regions and the impact of human capital in this process, certain considerations should be taken into account. First, as pointed out above, panel data models will be used, and therefore spatial fixed or random effects will also be considered. Second, in order to model interactions between the spatial units in the dataset, we will use the spatial weight matrix described in the following section. Finally, the growth rate used is annual cumulative, with $T = 5$. As conditional explanatory variables, we consider the initial level of educational attainment, measured by the share of the population aged 15 years and over that has successfully completed primary, secondary and tertiary studies ($Pe_{t-5}, Se_{t-5}$ and $Te_{t-5}$ ,respectively). Hence, equation [1] is modified as follows:

$$\left(\frac{1}{5}\right) ln\left(\frac{y_t}{y_{t-5}}\right) = \alpha_t + \mu + W\left(\frac{1}{5}\right) ln\left(\frac{y_t}{y_{t-5}}\right)\delta + ln(y_{t-5})\beta_1 + Wln(y_{t-5})\theta_1 + ln(Pe_{t-5})\beta_2 +$$

$$Wln(Pe_{t-5})\theta_2 + ln(Se_{t-5})\beta_3 + Wln(Se_{t-5})\theta_3 + ln(Te_{t-5})\beta_4 + Wln(Te_{t-5})\theta_4 + u_t \tag{2}$$

$$u_t = \lambda W u_t + \varepsilon_t$$

Equation [2] is a GNS model, not SDM (when $\lambda$=0), and can be simplified to become SAR (when $\lambda$=0 and $\theta_1$=$\theta_2$=$\theta_3$=$\theta_4$=0) or SEM (when $\delta$=0 and $\theta_1$=$\theta_2$=$\theta_3$=$\theta_4$=0). Therefore, according to the above-noted advantages of taking the SDM model as a starting point, the equation to be estimated would read as follows:

$$\left(\frac{1}{5}\right) ln\left(\frac{y_t}{y_{t-5}}\right) = \alpha_t + \mu + W\left(\frac{1}{5}\right) ln\left(\frac{y_t}{y_{t-5}}\right)\delta + ln(y_{t-5})\beta_1 + Wln(y_{t-5})\theta_1 + ln(Pe_{t-5})\beta_2 +$$

$$Wln(Pe_{t-5})\theta_2 + ln(Se_{t-5})\beta_3 + Wln(Se_{t-5})\theta_3 + ln(Te_{t-5})\beta_4 + Wln(Te_{t-5})\theta_4 + \varepsilon_t \tag{3}$$

## 4. Exploratory spatial data analysis

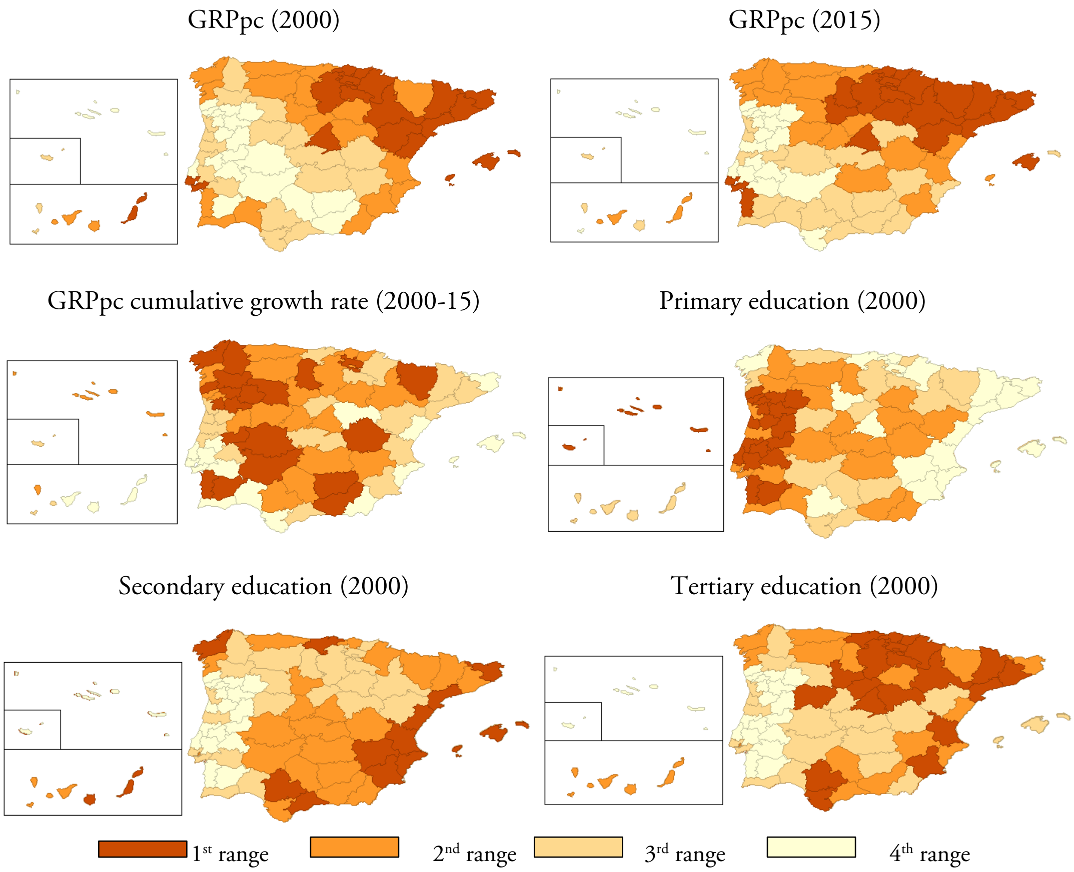
### 4.1. GRPpc and educational attainment level in Iberian regions: a preliminary analysis

From the quartile maps (see Figure 1), it is immediately apparent that in 2000 the GRPpc for all Portuguese regions except Lisbon, Algarve and Alentejo Litoral was in the third or fourth quartile. Within Portugal, the highest values were recorded for the coastal regions and those bordering Lisbon. However, with respect to the cumulative growth rate during the period 2000-2015, almost all of the Portuguese regions bordering Spain, especially those in the north-west, presented higher rates than the Spanish regions. This fact could indicate the presence of spatial autocorrelation between these regions and neighbouring ones in Spain.

In 2000, the levels of educational attainment were low in almost all Portuguese regions and, therefore, the secondary and tertiary levels were of less relative importance. The regions of Porto, Coimbra, Lisbon and Algarve presented the highest weights in the latter respect, but were still in the third quartile and therefore below most Spanish regions. The situation in Spain during this period was quite different: i) in 2000, no regions were in the fourth quartile for secondary and tertiary educational attainment; ii) the Spanish regions in the third quartile were mainly inland, in the north and south of the country, respectively, for both levels.

In general, the differences between Spanish and Portuguese regions in 2000 are evident; however, the disparities decreased during the study period, and the regional groupings based on national boundaries were less apparent. However, the strengthening relationship between Spanish and Portuguese regions, especially for the cross-border regions (e.g. Euroregions such as Euroace -Alentejo, Centro and Extremadura- or Galicia and northern Portugal) makes it necessary to consider alternative clusters that could include regions of both countries.

FIGURE 1.
**Quartile map of GRPpc and levels of educational attainment**



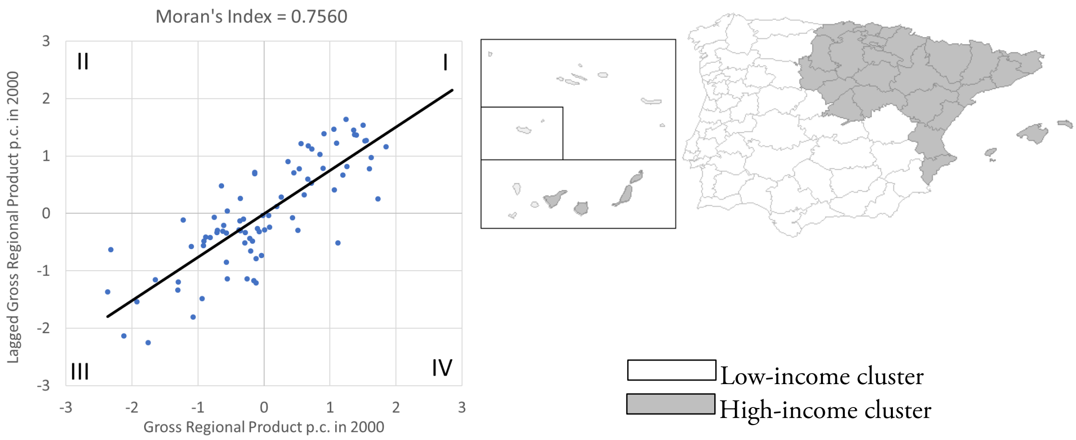

## 4.2. Selection of the regional clusters

In order to identify regional clusters, we followed the selection procedure described by Mella and Chasco (2006) in their study of urban growth in Spain. These authors used ESDA to detect spatial polarisation, expressed in terms of different spatial regimes. However, before applying this approach to the Iberian regions, it is necessary to select the most appropriate spatial weight matrix ($W$), comparing the model performance for each individual $W$. The first step in this process is to construct the $W$ that contains information on the "neighbourhood" structure for each location (Anselin, 2003). However, the correct specification of the elements of this matrix, $w_{ij}$ (which typically reflects the "spatial influence" of unit $j$ on unit $i$) is one of the most controversial methodological issues in spatial econometrics (Gibbons & Overman, 2012), reflecting the need to avoid spurious correlations, and therefore special care must be taken to choose appropriate spatial weights. As Leenders (2002, p. 26) says: "virtually any conclusion depends on the specification of $W$. It is therefore of vital importance to have justification for the $W$ applied in the research". In the present study, we considered specifications based on the geographical distance between the k-nearest neighbours ($k = 2$ to 10) computed from the distance between the centroids of the regions (Le Gallo & Ertur, 2003).

When ML estimation is used, the matrix that best describes the data is that corresponding to the model which presents the lowest parameter estimate of the residual variance (Elhorst, Zandberg, & De Haan, 2013). Thus, for the Iberian regions we used the 2-nearest neighbours, a matrix that obtained a much better fit than the alternatives.

Once the weight matrix had been selected, the next step in our study was to analyse the Moran scatterplot for GRPpc. As can be seen in Figure 2, the Moran index revealed positive spatial autocorrelation in Iberian regions for GRPpc in 2000. This is consistent with the fact that almost all regions were in quadrants I and III. In the first case, this indicates that high-income regions were surrounded by high-income neighbours, while in the second case, low-income regions were surrounded by similar neighbouring regions. In the map shown in Figure 2 (right), the regions located in quadrant I in 2000 are highlighted to identify spatial clusters (Mella & Chasco, 2006). It can be appreciated that most of these regions are located in the north-eastern quadrant of the Iberian Peninsula. By this approach, we established two subsets of observations: the regions located in quadrant I and other regions (henceforth, high-income and low-income clusters, respectively).

FIGURE 2.
**Moran scatterplot for GRPpc and clusters map by income level in 2000**




**Notes:** The spatial weight matrix used is 2-nearest neighbours.

Moran's index was calculated for the high-income and low-income clusters in 2000, obtaining 0.325 and 0.437, respectively. This result implies the presence of spatial heterogeneity in 2000, in the sense that the subset selected shows a different degree of spatial dependence. However, this is purely exploratory and does not guarantee the existence of a spatial regime. For this purpose, we also estimated a regression model to the standardised GRPpc (as the explanatory variable) and its spatial lag (as the dependent variable) for the clusters observed in 2000, subsequently applying the Chow test[5]. The test result (see Table 2) is highly significant for GRPpc clusters in 2000 and, therefore, we reject the null hypothesis that the coefficients of the linear regressions on different clusters in 2000 are equal. Therefore, in the rest of this paper we use two sub-samples: i) a high-income cluster, composed of the 30 regions highlighted in Figure 2 (right); and ii) a low-income cluster, composed of the 52 remaining regions.

Having identified the spatial regime present in the Iberian regions, we now repeat the spatial weight matrix selection procedure previously applied to these clusters in order to obtain the local indicators of spatial association (LISA). Finally, for the high-income and low-income clusters, considered separately, the matrices used were those for 3 and 2-nearest neighbours, respectively.

[5] Chow test is a particular case of the Wald statistic in which the constraint is applied according to the spatial regime structure adopted.

TABLE 2.
Chow test for clusters based on GRPpc (2000)

| Cluster | Intercept term | Estimated coefficient | Adj. $R^2$ |
|---|---|---|---|
| High-income cluster | 0.556*** (3.177) | 0.386** (2.481) | 0.180 |
| Low-income cluster | -0.271*** (-2.774) | 0.490*** (4.577) | 0.295 |
| Chow test for selected/unselected subsets: distrib. = F(2.78), ratio = 8.851, p-value = 0.000 | | | |

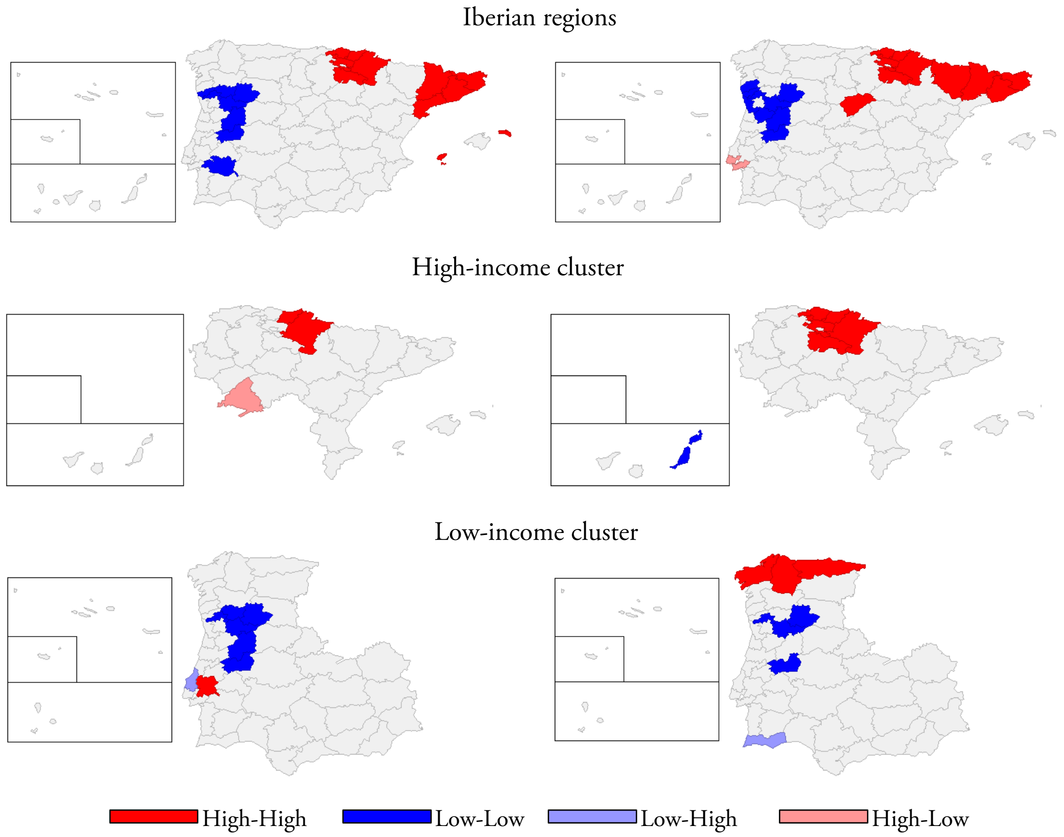
**Note:** T-statistics shown in parentheses. Statistical significance: * at 10% level, ** at 5% level, *** at 1% level.

### 4.3. Analysis of local spatial autocorrelation

There were remarkably few interactions between the Spanish and Portuguese regions when the 2-nearest neighbour matrix was adopted. For the Spanish regions, only five NUTS-3 units presented a spatial interaction with neighbouring Portuguese regions: Huelva with Baixo Alentejo, Salamanca and Zamora with Terras de Trás-os-Montes, Orense with Alto Tâmega and Pontevedra with Alto Minho. Among the Portuguese regions, only Alto Tâmega exerted a spatial influence (on Orense).

The LISA for GRPpc in 2000 for the Iberian regions revealed a positive autocorrelation of high values for Catalonia, Balearic Islands and the cluster formed of the Basque Country, Navarre and La Rioja, in Spain (see Figure 3). In Portugal, most of the inland regions (almost all bordering with Spain and in northern Portugal) showed a positive autocorrelation of low values. This can also be seen in 2015, but with certain differences, namely the positive autocorrelation of high values for all Spanish regions bordering France as well as for Segovia (near Madrid), and the negative autocorrelation of high values for Lisbon.

FIGURE 3.
LISA cluster map for GRPpc in 2000 (left) and 2015 (right)



Regarding the high-income cluster in 2000, three Spanish regions presented an autocorrelation of high values: this autocorrelation was negative for Madrid and positive for Guipuzcoa and Navarre. In the latter case, this situation was reinforced in 2015, since it is possible to identify a cluster of high values composed of Basque Country, La Rioja and Navarre NUTS-2 regions. In contrast, Lanzarote and Fuerteventura, two of the Canary Islands, presented a positive autocorrelation of low values.

The LISA cluster maps for the low-income cluster show that in 2000 many Portuguese regions (mainly Centro and Norte NUTS-2 regions bordering or very near Spain) presented a positive autocorrelation of low values. This reflects the existence of different patterns and behaviours between coastal and inland regions of continental Portugal. Two Portuguese regions near Lisbon showed autocorrelation but with different signs: positive of high values for Leiziria do Tejo and negative of low values for Oeste. The situation in 2015 was slightly different in two ways: i) most of the Portuguese regions bordering Spain did not show positive autocorrelation of low values (except for Trás-os-Montes, Douro and Beira Baixa); and ii) for the Spanish regions, the geographical distribution of the positive autocorrelation of high values reveals a spatial association in the coastal Atlantic regions. This would point to the existence of a strong economic relationship among the north-western regions of the Iberian Peninsula.

## 5. Empirical results

### 5.1. Model selection

In line with the methodological approach outlined in section 1, we estimated and analysed the alternative specifications underlying the panel data model defined in equation [3] by the ML estimator. To decide which spatial panel data model best describes the data, we applied the following selection framework developed by Elhorst (2010b): i) determine the significance of spatial and/or time-period fixed effects and whether they should be treated as fixed or as random effects; ii) determine which type of spatial interaction effects should be considered (observing whether the SDM model can be simplified in the SAR or SEM model).

Regarding the significance of spatial and/or time-period fixed effects, a non-spatial panel data model was estimated and the classic Lagrange Multiplier tests (and their robust versions) were applied, both for spatial errors and for omitted spatial lags in the panel data. These tests examine the residuals of the non-spatial model with and without spatial or time-period fixed effects, follow a chi-square distribution, and can take the form of a likelihood ratio (LR) test with N or T degrees of freedom, respectively. The corresponding LR test was performed to investigate the (null) hypothesis that the spatial or time-period fixed effects are jointly non-significant. The results obtained (see Table 3) indicate that both hypotheses must be rejected for the three regional clusters considered (with $p < 0.01$). Accordingly, the model can be performed with spatial and time-period fixed effects.

In the classical panel data literature, individual effects can be treated as fixed or random. To evaluate whether a spatial random effects model is more appropriate than a spatial fixed effects model, we estimated a spatial random effects model (with time-period fixed effects) by ML including spatially-lagged variables, both independent and dependent. The Hausman test compares random and fixed effects estimators and tests whether or not the random effects assumption is supported by the data (Millo & Piras, 2012). The test results (see Table 3) show that the probability value for all regional clusters is less than 0.1, and so the random effects model is rejected in favour of the fixed effects model.

Having determined the joint significance of spatial and time-period fixed effects, we then ascertained which type of spatial interaction effects should be accounted for in a SAR, SEM or SDM model. To do so, we first conducted a SDM estimation, supported by a Wald and LR test to verify whether the model can be simplified to a SAR or SEM model. The results obtained (see Table 3) suggest that the most suitable approach is a SDM model with fixed spatial and time-period effects for the Iberian regions and the low-income cluster, while for the high-income cluster a SAR model is most appropriate.

TABLE 3.
Model specification test

| | Iberian regions | | High-income cluster | | Low-income cluster | |
|---|---|---|---|---|---|---|
| Test | *Statistic* | *Prob. Value* | *Statistic* | *Prob. Value* | *Statistic* | *Prob. Value* |
| LR joint sig. spatial fixed effects | 1210.420 | 0.000 | 491.882 | 0.000 | 677.599 | 0.000 |
| LR joint sig. time-period fixed effects | 524.399 | 0.000 | 216.289 | 0.000 | 293.009 | 0.000 |
| Hausman test | 75.225 | 0.000 | 15.131 | 0.087 | 65.363 | 0.000 |
| Wald test for spatial lag model | 58.715 | 0.000 | 4.150 | 0.386 | 56.987 | 0.000 |
| LR SDM against SAR test | 62.737 | 0.000 | 3.684 | 0.451 | 60.274 | 0.000 |
| Wald test for spatial error model | 78.572 | 0.000 | 11.343 | 0.023 | 62.643 | 0.000 |
| LR SDM against SEM test | 85.742 | 0.000 | 12.495 | 0.014 | 67.633 | 0.000 |

**Notes:**
- LR joint significance spatial and/or time-period fixed effects with probability greater than 0.05 implies rejection of spatial and/or time-period fixed effects, respectively.
- LR spatial Durbin model against spatial lag/error model test with probability lower than 0.05 points spatial Durbin model cannot be simplified with respect to the spatial lag model or the spatial error model.

## 5.2. ESTIMATING THE DIRECT AND INDIRECT EFFECTS OF LEVELS OF EDUCATIONAL ATTAINMENT ON REGIONAL GROWTH

The contribution of educational attainment to GRPpc growth in the Iberian regions considered varies according to the determinants considered (see Table 4). Focusing on the initial GRPpc, the estimated coefficients for all regional groupings are negative (which is in line with the literature on regional convergence) with values ranging from -0.147 to -0.143, for the Iberian regions and the low-income cluster, respectively. The positive sign of the autoregressive parameter for these two regional clusters implies that when a region with initially low levels of per capita income has neighbours with high economic growth rates, spatial spillovers hinder growth in this region. Specifically, the value of the autoregressive parameter indicates that a 10% increase in GRPpc growth in a region produces an increase of 1.8% to 1.54% in the growth of neighbouring regions. On the other hand, the autoregressive parameter for the high-income cluster is negative (-0.133), indicating that regions with high economic rates exert a negative impact on the growth of neighbouring regions. This is consistent with the presence of increasing marginal returns in regions such as Madrid, Barcelona and Basque Country. In either case, the coefficients for the three clusters are significant at 1%.

Levels of educational attainment are important explanatory variables of regional economic growth in Iberian regions and low-income clusters, as reflected in the following results obtained (see Table 4):

a) The sign of the estimated coefficients is positive (which is consistent with previous research findings on economic growth) and significant at 1%, except in the low-income cluster for tertiary education in neighbouring regions.

b) Primary and secondary education levels are positively related to regional growth (significant at 1%) in the Iberian regions and especially in the low-income cluster. On the other hand, for the secondary educational level the coefficients obtained are greater than for the other educational levels, both for the regions in question and for their neighbours, at rates generally exceeding 50%. This indicates that the regions with a moderate educational level (or surrounded by others with a similar level) tend to grow faster than those with a higher educational level. Moreover, the coefficients obtained for a given region are lower than for its neighbours, suggesting that spatial effects have a significant impact on educational attainment.

c) The coefficients obtained for tertiary education are significant both for the region and for its neighbours. However, the values are low (around half those for the other education levels) and their impact on GRPpc growth is less significant.

Regarding the high-income cluster, a notable finding is the non-significance of the coefficients obtained for primary and secondary education. This means that only the coefficient for tertiary education is significant (at 5%) and it is negative, in contrast to the other clusters. The negative sign of the estimated coefficient for tertiary education indicates that regions with higher levels of human capital tend to grow less. Although this may seem contradictory, we must take into account that regions with high levels of human capital tend to have higher incomes and therefore it is more difficult to maintain high rates of growth.

In general, the initial GRPpc and the autoregressive component present the highest coefficients and significance. For the Iberian regions and the low-income cluster, the level of educational attainment seems to exert a positive influence on regional growth. We surmise that these interactions enhance the convergence effect, but this hypothesis is subject to confirmation by the analysis of direct and indirect spatial effects.

**TABLE 4.**
**Estimation results for conditional beta-convergence**

| Determinants | Iberian regions SDM | High-income cluster SAR | Low-income cluster SDM |
|---|---|---|---|
| log GRPpc | -0.147*** (-28.895) | -0.145*** (-23.032) | -0.143*** (-20.76) |
| log primary education | 0.017*** (5.398) | -0.003 (-0.563) | 0.031*** (5.124) |
| log secondary education | 0.020*** (3.936) | -0.014 (-1.526) | 0.031*** (4.522) |
| log tertiary education | 0.010*** (3.021) | -0.014** (-2.305) | 0.016*** (3.737) |
| W·GRPpc growth rate | 0.180*** (5.421) | -0.133*** (-2.811) | 0.154*** (3.659) |
| W·log GRPpc | 0.015* (1.810) | - | 0.027*** (2.688) |
| W·log primary education | 0.021*** (5.111) | - | 0.035*** (4.321) |
| W·log secondary educat. | 0.030*** (4.502) | - | 0.048*** (5.503) |
| W·log tertiary education | 0.017*** (4.300) | - | 0.012** (2.443) |
| $R^2$ | 0.898 | 0.918 | 0.895 |
| Corrected $R^2$ | 0.648 | 0.689 | 0.667 |
| Residual variance ($\sigma^2$) | 3.300E-05 | 2.400E-05 | 3.300E-05 |
| Log-likelihood | 3419.874 | 1305.585 | 2168.731 |
| Observations | 902 | 330 | 572 |

**Note:** T-statistics shown in parentheses. Statistical significance: * at 10% level, ** at 5% level, *** at 1% level.

The impact of the explanatory variables is interpreted by estimating their total effects, as the algebraic sum of the direct and indirect consequences. With regard to direct impacts, the following observations can be made (see Table 5):

a) For the GRPpc, the effects are significant (at 1% level) for the three regional clusters, with a greater effect for the Iberian regions, followed very closely by the high-income cluster (-0.1478 and -0.1452, respectively). In the first case, this means that when the initial GRPpc increases on average by 10%, its cumulative growth rate falls by 1.48%. This negative impact is slightly greater than the value of the parameter obtained for the Iberian regions and the high-income cluster (-0.009 and -0.005, respectively). In contrast, for the low-income cluster this impact is lower (0.006). In either case, the feedback effects between the growth of a region and that of its neighbours are not very important.

b) The direct effects of initial human capital are not very important, with parameter values (when significant) ranging from 0.0116 to 0.0341. For the Iberian and low-income clusters, the direct effects are positive and higher than the estimated coefficients, especially for secondary education in the latter cluster (0.003). This suggests that low-income regions with a growing share of the medium educational level tend to achieve higher rates of growth. With respect to tertiary education for the high-income cluster, the direct effect is negative, significant at 5% and very similar to the coefficient obtained, and therefore we conclude there are no feedback effects.

**TABLE 5.**
**Estimation of direct, indirect and total effects.**

| Variable | Direct effect | | Indirect effect | | Total effect | |
|---|---|---|---|---|---|---|
| *Iberian regions* | | | | | | |
| GRPpc | -0.1478*** | (-28.91) | -0.0135* | (-2.038) | -0.1613*** | (-22.899) |
| Primary education | 0.0184*** | (5.877) | 0.0272*** | (5.714) | 0.0456*** | (7.751) |
| Secondary education | 0.0223*** | (4.479) | 0.0379*** | (4.793) | 0.0603*** | (6.228) |
| Tertiary education | 0.0116*** | (3.493) | 0.0216*** | (5.034) | 0.0332*** | (6.993) |
| *High-income cluster* | | | | | | |
| GRPpc | -0.1452*** | (-22.625) | 0.0174*** | (2.812) | -0.1278*** | (-21.91) |
| Primary education | -0.0026 | (-0.566) | 0.0003 | (0.530) | -0.0023 | (-0.566) |
| Secondary education | -0.0138 | (-1.513) | 0.0017 | (1.289) | -0.0122 | (-1.511) |
| Tertiary education | -0.0144** | (-2.290) | 0.0018 | (1.652) | -0.0127** | (-2.315) |
| *Low-income cluster* | | | | | | |
| GRPpc | -0.1424*** | (-20.80) | 0.0062 | (0.683) | -0.1363*** | (-12.694) |
| Primary education | 0.0330*** | (5.641) | 0.0450*** | (5.335) | 0.0780*** | (9.174) |
| Secondary education | 0.0341*** | (4.928) | 0.0600*** | (6.165) | 0.0941*** | (7.729) |
| Tertiary education | 0.0169*** | (4.003) | 0.0162*** | (3.192) | 0.0331*** | (5.696) |

**Note:** T-statistics shown in parentheses. Statistical significance: * at 10% level, ** at 5% level, *** at 1% level.

The values for the indirect effects of GRPpc (i.e. their impact on the neighbouring regions as reflected in the region in question) are lower than those for the direct effects, while for educational attainment, in general, they are higher. The following major findings in this respect were noted:

a) GRPpc is significant at 1% for the high-income cluster, with a coefficient of 0.0174. In this case, the indirect effect of GRPpc suggests that increased GRPpc in neighbouring regions has a positive impact on the economic situation of the region, which seems intuitively plausible and is consistent with the presence of agglomeration economies. Consequently, for the high-income cluster, the (positive) indirect effect of initial GRPpc reduces the (negative) total effect by 12%.

b) The indirect effect of primary education in the Iberian and low-income clusters is positive, with values of 0.0272 and 0.045, respectively. In either case, this counteracts the indirect effect of GRPpc. The same applies to the case of secondary education, although this presents particularly high values in comparison with all educational levels. The indirect effect of tertiary education is weaker, especially in the low-income cluster. This finding reflects the importance of the synergies created in the low-income cluster when regions increase their human capital; in other words, when the value of human capital of a given region, or that of its neighbours, rises, this drives the growth of GRPpc of the neighbours or the region in question, respectively. In the high-income cluster, however, the indirect effect of any educational level is not significant.

Our analysis of indirect impacts, significantly different from zero, highlights the presence of omitted variables related to all educational levels in the low-income cluster (and, by extension, in the Iberian regions). This is consistent with the existence of additional factors that may affect regional growth (e.g. investment in educational systems, productive structure, productivity growth, innovation efforts, etc.).

In view of the above considerations, we conclude that educational attainment levels in high-income and low-income clusters play differing roles in their respective patterns of regional convergence. In the high-income cluster, improvements in tertiary education seem to have a limited negative impact on regional growth[6], while for the low-income cluster the positive effect is to a large extent achieved by improvements in secondary education. The total effect for primary education for the low-income cluster is positive and significant; its value is lower than for secondary education but around twice that for tertiary education.

## 6. Conclusions

Although GRPpc in the Iberian regions rose during the period 2000-2015, the regional distribution was uneven. Most Spanish regions grew at above-average rates, while the opposite was true for the Portuguese ones, where initial values were below the average for the Iberian regions (except for Lisbon, Alentejo Litoral and Algarve). A preliminary spatial analysis showed that the lowest GRPpc values were in the south-western third of the Iberian Peninsula. This spatial distribution is not random; Moran's index test reveals the presence of spatial autocorrelation. According to the LISA, most of the Portuguese regions bordering Spain present a positive autocorrelation of low values, while the regions with a positive autocorrelation of high values are Spanish, and mainly located in the north-eastern quadrant of the Iberian Peninsula. These results highlight the existence of differing behaviour patterns between these regions and the others (high-income and low-income clusters, respectively).

The impact of the explanatory variables on the growth of GRPpc is observed by estimating their total effects as the algebraic sum of the direct and indirect effects. For GRPpc, the effects for the high-income cluster are similar to those for the low-income cluster. In both cases, the direct effects are negative (which is in line with previous research findings) and significant. On the other hand, for the high-income cluster the indirect effects are non-significant and, therefore the spatial effects of GRPpc on regional convergence are irrelevant.

Analysis of the results for each national cluster reveals certain differences: firstly, for the low-income cluster the relationship between the level of educational attainment and the growth of GRPpc is positive, regardless of the level considered. Secondly, only tertiary education is significant for the high-income cluster, while for the low-income cluster the coefficients for secondary education present high values in comparison with all educational levels. In contrast, the indirect effect of tertiary education is weaker, especially in the low-income cluster. This finding reflects the importance of the synergies created in the low-income cluster when regions increase their human capital; in other words, when the value of human capital of a given region, or that of its neighbours, rises, this drives the growth of GRPpc of the neighbours or the region in question, respectively.

On balance, we conclude that for the high-income cluster there is a negative relationship between the initial level of tertiary education and the growth of GRPpc, which reflects the existence of spatial spillovers (especially around Madrid, Barcelona and Basque Country) which reinforce that of the negative effect of the initial GRPpc. In contrast, for the low-income cluster the positive effect of secondary and tertiary educational levels does not exceed the negative effect of the GRPpc. This shows the importance for poor regions of improving the level of educational attainment in the low-income cluster, particularly in secondary studies, because of the reinforcement of the convergence process.

[6] Sánchez de la Vega (2015) demonstrated the limited impact of tertiary studies on the productivity growth.

Regarding potential avenues for further analysis, it is important to consider other variables that might be related to GRPpc growth, such as unemployment rates (differentiated by level of education), the EU structural funds received by the regions or the level of public investment in the education system.

## References

Anselin, L. (1988). *Spatial econometrics: Methods and models*. Netherlands: Springer Science & Business Media. https://doi.org/10.1007/978-94-015-7799-1

Anselin, L. (1995). Local indicators of spatial association—LISA. *Geographical Analysis, 27*(2), 93-115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Anselin, L. (2003). *An introduction to spatial autocorrelation analysis with GeoDa*. Champagne-Urbana, Illinois: Spatial Analysis Laboratory, University of Illinois. http://www.utd.edu/~briggs/poec6382/geoda_spauto.pdf

Arbia, G. (2006). *Spatial econometrics: Statistical foundations and applications to regional convergence*. Berlin Heidelberg: Springer Verlag.

Badia-Miró, M., Guilera, J., & Lains, P. (2012). Regional incomes in Portugal: Industrialisation, integration and inequality, 1890-1980. *Revista De Historia Económica/Journal of Iberian and Latin American Economic History (New Series), 30*(02), 225-244. https://doi.org/10.1017/S0212610912000080

Bancaja Foundation, & Ivie (The Valencian Institute of Economic Research). (2014). *Capital humano en España y su distribución provincial*. January 2014. Database available at: http://www.ivie.es/es/banco/caphum/series.php

Barro, R. J., & Sala-i-Martin, X. (1990). *Economic growth and convergence across the United States*. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w3419

Barro, R. J., & Sala-i-Martin, X. (1992). Convergence. *Journal of Political Economy, 100*(2), 223-251. https://doi.org/10.1086/261816

Borsi, M. T., & Metiu, N. (2015). The evolution of economic convergence in the European Union. *Empirical Economics, 48*(2), 657-681. https://doi.org/10.1007/s00181-014-0801-2

Buendía Azorín, J. D., & Sánchez de la Vega, M.M. (2015). Efectos del capital humano sobre la productividad del trabajo bajo condiciones de dependencia espacial: El caso de las provincias españolas. *Información Comercial Española,* (883), 183-195. http://www.revistasice.com/index.php/ICE/article/view/1769/1769

Cardoso, C., & Pentecost, E. J. (2011). *Regional growth and convergence: The role of human capital in the Portuguese regions*. Loughborough University Department of Economics Discussion Paper Series, *3*. http://www.lboro.ac.uk/departments/sbe/RePEc/lbo/lbowps/CardosoandPentecost.pdf

Crespo Cuaresma, J., Doppelhofer, G., Huber, F., & Piribauer, P. (2018). Human capital accumulation and long-term income growth projections for European regions. *Journal of Regional Science, 58*(1), 81-99. https://doi.org/10.1111/jors.12339

Crespo Cuaresma, J., Havettová, M., & Lábaj, M. (2013). Income convergence prospects in Europe: Assessing the role of human capital dynamics. *Economic Systems, 37*(4), 493-507. https://doi.org/10.1016/j.ecosys.2013.02.004

Elhorst, J. P. (2003). Specification and estimation of spatial panel data models. *International Regional Science Review, 26*(3), 244-268. https://doi.org/10.1177/0160017603253791

Elhorst, J. P. (2010a). Applied spatial econometrics: Raising the bar. *Spatial Economic Analysis, 5*(1), 9-28. https://doi.org/10.1080/17421770903541772

Elhorst, J. P. (2010b). Spatial panel data models. In M. M. Fischer, & A. Getis (Eds.), *Handbook of applied spatial analysis. Software tools, methods and applications* (pp. 377-408). New York: Springer. https://doi.org/10.1007/978-3-642-03647-7_19

Elhorst, J. P. (2014). *Spatial econometrics: From cross-sectional data to spatial panels*. New York: Springer Heidelberg. https://doi.org/10.1007/978-3-642-40340-8

Elhorst, J. P., Zandberg, E., & De Haan, J. (2013). The impact of interaction effects among neighbouring countries on financial liberalization and reform: A dynamic spatial panel data approach. *Spatial Economic Analysis, 8*(3), 293-313. https://doi.org/10.1080/17421772.2012.760136

Ertur, C., & Koch, W. (2007). Growth, technological interdependence and spatial externalities: Theory and evidence. *Journal of Applied Econometrics, 22*(6), 1033-1062. https://doi.org/10.1002/jae.963

Ezcurra, R., & Rios, V. (2015). Volatility and regional growth in Europe: Does space matter? *Spatial Economic Analysis, 10*(3), 344-368. https://doi.org/10.1080/17421772.2015.1062123

Fingleton, B., & López-Bazo, E. (2006). Empirical growth models with spatial effects. *Papers in Regional Science, 85*(2), 177-198. https://doi.org/10.1111/j.1435-5957.2006.00074.x

Fleisher, B., Li, H., & Zhao, M. Q. (2010). Human capital, economic growth, and regional inequality in China. *Journal of Development Economics, 92*(2), 215-231. https://doi.org/10.1016/j.jdeveco.2009.01.010

Geppert, K., & Stephan, A. (2008). Regional disparities in the European Union: Convergence and agglomeration. *Papers in Regional Science, 87*(2), 193-217. https://doi.org/10.1111/j.1435-5957.2007.00161.x

Gibbons, S., & Overman, H. G. (2012). Mostly pointless spatial econometrics? *Journal of Regional Science, 52*(2), 172-191. https://doi.org/10.1111/j.1467-9787.2012.00760.x

Gómez-Antonio, M., & Fingleton, B. (2012). Regional productivity variation and the impact of public capital stock: An analysis with spatial interaction, with reference to Spain. *Applied Economics, 44*(28), 3665-3677. https://doi.org/10.1080/00036846.2011.579068

Guerreiro, G. (2013). (2013). Regional income convergence in Portugal (1991-2002). Paper presented at the *Fifth Meeting of the Society for the Study of Economic Inequality (ECINEQ).* Italy: University of Bari. https://doi.org/10.1108/S1049-258520140000022011

Kubis, A., & Schneider, L. (2012). *Human capital mobility and convergence: A spatial dynamic panel model of the German regions*. Nuremberg, Germany: Technical report, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Discussion Paper. http://doku.iab.de/discussionpapers/2012/dp2312.pdf

Kutan, A. M., & Yigit, T. M. (2007). European integration, productivity growth and real convergence. *European Economic Review, 51*(6), 1370-1395. https://doi.org/10.1016/j.euroecorev.2006.11.001

Lacombe, D. J., & LeSage, J. P. (2015). Using Bayesian posterior model probabilities to identify omitted variables in spatial regression models. *Papers in Regional Science, 94*(2), 365-383. https://doi.org/10.1111/pirs.12104

Le Gallo, J., & Ertur, C. (2003). Exploratory spatial data analysis of the distribution of regional per capita GDP in Europe, 1980– 1995. *Papers in Regional Science, 82*(2), 175-201. https://doi.org/10.1007/s101100300145

Leenders, R. T. A. (2002). Modeling social influence through network autocorrelation: Constructing the weight matrix. *Social Networks, 24*(1), 21-47. https://doi.org/10.1016/S0378-8733(01)00049-1

LeSage, J. P. (2008). An introduction to spatial econometrics. *Revue D'Économie Industrielle,* (123), 19-44. https://doi.org/10.4000/rei.3887

LeSage, J. P., & Fischer, M. M. (2008). Spatial growth regressions: Model specification, estimation and interpretation. *Spatial Economic Analysis, 3*(3), 275-304. https://doi.org/10.1080/17421770802353758

LeSage, J. P., & Pace, R. K. (2009). *Introduction to spatial econometrics (statistics, textbooks and monographs)* CRC Press. https://doi.org/10.1201/9781420064254

Ligthart, J. E. (2002). Public capital and output growth in Portugal. an empirical analysis. *European Review of Economics and Finance, 1*(September), 3-30. https://www.imf.org/~/media/Websites/IMF/imported-full-text-pdf/external/pubs/ft/wp/2000/_wp0011.ashx

Lopez-Bazo, E. (2017). Growth and convergence across economies: The experience of the European regions. In B. Fingleton, A. Eraydin, R. Paci (eds.) (Ed.), *Regional economic growth, SMEs and the wider Europe* (pp. 65-90) London: Routledge. https://doi.org/10.4324/9781315197869-3

López-Bazo, E., Vayá, E., Mora, A. J., & Surinach, J. (1999). Regional economic dynamics and convergence in the European Union. *The Annals of Regional Science, 33*(3), 343-370. https://doi.org/10.1007/s001680050109

Marelli, E. (2007). Specialisation and convergence of European regions. *The European Journal of Comparative Economics, 4*(2), 149-178. http://eaces.liuc.it/18242979200702/182429792007040203.pdf

Martinho, Vítor João Pereira Domingues. (2011). *Net migration and convergence in Portugal. an alternative analysis.* MPRA Paper 32801. Germany: University Library of Munich. https://mpra.ub.uni-muenchen.de/32801/1/MPRA_paper_32801.pdf

Melchor-Ferrer, E. (2018). Regional convergence and productive structure in Iberian regions: A spatial approach. *Portuguese Review of Regional Studies,* (47), 5-20. http://www.apdr.pt/siteRPER/numeros/RPER47/47.1.pdf

Mella, J., & Chasco, C. (2006). Urban growth and territorial dynamics: A spatial-econometric analysis of Spain. In A. Reggiani, & P. Nijkamp (Eds.), *Spatial dynamics, networks and modeling* (pp. 325-366). New York: Edward Elgar. https://doi.org/10.4337/9781781007471.00024

Millo, G., & Piras, G. (2012). Splm: Spatial panel data models in R. *Journal of Statistical Software, 47*(1), 1-38. https://doi.org/10.18637/jss.v047.i01

Naveed, A., & Ahmad, N. (2016). Technology spillovers and international borders: A spatial econometric analysis. Journal of Borderlands Studies, 31(4), 441-461. https://doi.org/10.1080/08865655.2016.1188669

Quah, D. T. (1996). Regional convergence clusters across Europe. *European Economic Review, 40*(3-5), 951-958. https://doi.org/10.1016/0014-2921(95)00105-0

Ramos, R., Suriñach, J., & Artís, M. (2010). Human capital spillovers, productivity and regional convergence in Spain. *Papers in Regional Science, 89*(2), 435-447. https://doi.org/10.1111/j.1435-5957.2010.00296.x

Rey, S. J., & Montouri, B. D. (1999). US regional income convergence: A spatial econometric perspective. *Regional Studies, 33*(2), 143-156. https://doi.org/10.1080/00343409950122945

Tortosa-Ausina, E., Pérez, F., Mas, M., & Goerlich, F. J. (2005). Growth and convergence profiles in the Spanish provinces (1965–1997). *Journal of Regional Science, 45*(1), 147-182. https://doi.org/10.1111/j.0022-4146.2005.00367.x

Viegas, M., & Antunes, M. (2013). Convergence in the Spanish and Portuguese NUTS 3 regions: An exploratory spatial approach. *Intereconomics, 48*(1), 59-66. https://doi.org/10.1007/s10272-013-0445-z

## ORCID

*Elías Melchor Ferrer* https://orcid.org/0000-0002-4474-1623