HUMAN CAPITAL SPILLOVERS AND REGIONAL ECONOMIC GROWTH IN SPAIN*

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Abstract (100 words)

The paper analyses the differential effect of human capital on regional economic productivity and growth depending on its composition. The potential existence of geographical spillovers of human capital is also considered applying spatial panel data techniques. The empirical analysis of Spanish provinces between 1980 and 2005 confirms the positive effect of secondary and tertiary studies on both growth and productivity, but we find very weak evidence of positive geographical spillovers of human capital. In fact, only in some specifications the spatial lag of primary studies has a positive effect on productivity, while tertiary studies seems to have the contrary effect both on productivity and growth.

Keywords

Regional economic growth, human capital composition, geographical spillovers.

JEL Classification

O18, O47, R23

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Human capital spillovers and regional economic growth in Spain

1. Introduction and objectives

The role of human capital on economic growth has been highlighted by different authors. Mankiw *et al* (1992) augmented the Solow model with human capital as an additional production factor while endogenous growth models (Lucas, 1988; Romer, 1990) directly relate human capital and technology adoption. The main conclusion of this strand of the literature is that countries and regions with higher levels of human capital are supposed to expect higher growth rates than territories with lower levels. However, despite the theoretical predictions of these models, empirical evidence has not been conclusive with studies finding non-significant or even negative effects of human capital on growth (De la Fuente, 2006).

Different explanations have been provided by the literature, but the main criticism is that most works basically rely on human capital stock, which is usually proxied by the average number schooling of years or the percentage of population with secondary or tertiary studies[1]. Some recent papers have also suggested that different schooling levels can have different effects on growth. In particular, Petrakis and Stamatakis (2002) show that primary and secondary education matter more for growth in less developed countries as opposed to more developed economies, where higher education becomes more important. Similar results are found by Vandenbussche *et al* (2006) and by Pereira and St. Aubyn (2009). The only study to our knowledge that has considered this issue at the regional level is Di Liberto (2008). Focusing on Italian regions, she finds that primary education seems to be important in the South while a negative impact of tertiary studies is found for Northern regions. These results suggest that Italy has not been able to capture the positive returns from higher levels of education since economic growth has been associated to low-tech activities where a highly skilled labour force did not play a significant role. But, the role of human capital is not only confined to one particular territory: human capital in one region can also influence the neighbouring ones. Different studies in the field of Urban (Rauch, 1993 or Rosenthal and Strange, 2008) and Regional (Fingleton and López-Bazo, 2006 or López-Bazo *et al* 2004) Economics have confirmed the existence of positive human capital externalities, but other studies such as Adamson *et al* (2004) or Olejnik (2008) have found the opposite result. In particular, Olejnik (2008) has found that the level of human capital in neighbouring locations has a negative influence on the level of per-capita income in a given region. According to this author, one possible explanation for this is that an increase in the level of human resources in one

[1] The quality of data has also been questioned (De la Fuente and Doménech, 2006).

region is caused mainly by migration of the educated population between neighbouring regions, which will have a negative effect for them.

Taking this previous research as a starting point, the objective of the paper is twofold: first, to test the influence of different schooling levels on regional economic growth and, second, to analyse if there are differences in the effect of human capital on neighbouring regions depending on its composition. Our study focuses on the Spanish continental NUTS III regions (47 provinces) for the period 1980-2005. The role played by human capital in promoting Spanish economic growth has been analysed in different studies, although the evidence is mixed. For example, while Gorostiaga (1999) found that the estimated coefficient of human capital is negative and significant, Serrano (1999) and Galindo-Martín and Alvárez-Herranz (2004) found that human capital enters positively into the production function. Moreover, additional regional analysis, such as de la Fuente (2002) or Freire-Serén (2002) have used NUTS-II data (Autonomous communities) which probably is not the most appropriate regional dimension to test the existence of geographical spillovers. An additional contribution of the paper is related to the application of recently developed spatial econometric panel data techniques. The main advantage of this approach in relation to the use of cross-sectional data is that it permits to control for unobservable heterogeneity by the inclusion of region and time fixed effects.

The rest of the paper is structured as follows. First, the methodology used in the study is described. Next, in the third section, details on data sources and variable definitions are provided while the empirical results are shown in the fourth section. Last, the paper concludes summarising the main findings and policy implications.

2. Methodology

In order to analyse the contribution of human capital to the growth of regional productivity, we rely on the model developed by de la Fuente (2002) and that has been extensively used in the literature on regional growth and human capital (de la Fuente *et al*, 2003 for Spain, Ciccone, 2004 for Italy and Committee of the Regions, 2005 for France and Germany). The model is built around a regional production function and a technical progress relation that allows for the diffusion of technical know-how across regions. In particular, we assume that the educational attainment of the population is one of the inputs in a constant-returns Cobb-Douglas aggregate production function. Taking into account the availability of statistical sources that will permit the use of panel data, the log specification of the production function is the following one:

$$y_{it} = \beta_k k_{it} + \beta_h h_{it} + \alpha_t + \mu_i + \varepsilon_{it} \tag{1}$$

where y_{it} is the log of output per employed worker in region i at time t, k_{it} is the log of the stock of physical capital per employed worker and h_{it} is the log of the average number of schooling years. α_t are time specific effects that control for all common shocks to the considered regions[2] while μ_t are spatial specific effects[3] that control for all unobservable region-specific time invariant effects. The regional fixed effects may capture permanent differences in relative total factor productivity that will presumably reflect differences in R&D investment and other omitted variables. Last, ε_{it} is an independently and identically distributed error term for i and t with zero mean and variance σ^2. β_k and β_h are the parameters that summarise the factor contribution to regional productivity.

Taking into account that our objective is to analyse the impact of the different schooling levels, we decompose the log of the average number of schooling years into three components that indicate the relative contribution of primary (p_{it}), secondary (s_{it}) and tertiary (t_{it}) studies to the level of human capital of a particular region. Equation (1) is then modified to take into account the potentially different effect of each of these components:

$$y_{it} = \beta_k k_{it} + \beta_p p_{it} + \beta_s s_{it} + \beta_s t_{it} + \alpha_t + \mu_i + \varepsilon_{it} \qquad (2)$$

As highlighted by Fingleton and López-Bazo (2006), most empirical analysis taking as the starting point the estimation of production functions at the regional level, is that regions have been considered isolated economies. However, theoretical and empirical arguments suggest that regions, as well as not being homogeneous, are also not independent. If the influence of spatial location on the process of growth is ignored, results could be biased and hence conclusions could be misleading. For this reason, equation (2) is augmented specifying the interaction between the different regions. In particular, the interactions can be specified by including a spatially lagged dependent variable (spatial lag model) or a spatial autoregressive process in the error term (spatial error model).

In the spatial lag model, the endogenous variable depends on the set of explanatory variables observed in the same region and on the values of the endogenous variable observed in neighbouring regions. In particular, the spatial lag model based in equation (2) will be the following:

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[2] We have chosen to control for time period fixed effects although we are conscious that, as highlighted by Elhorst (2009), applied researchers often find weak evidence in favour of spatial effects when time-period fixed effects are also accounted for. The explanation is that most variables tend to increase and decrease together in the different regions along time (i. e., in the presence of a common business cycle).

[3] The spatial specific effects may be treated as fixed effects or as random effects. As usual in the literature, in our empirical analysis the decision of including fixed or random effects will be taken on the basis of the results of the Hausman test. Its joint significance will also be tested using Likelihood Ratio (LR) tests.

$$y_{it} = \partial \sum_{j=1}^{N} w_{ij} y_{jt} + \beta_k k_{it} + \beta_p p_{it} + \beta_s s_{it} + \beta_s t_{it} + \alpha_t + \mu_i + \varepsilon_{it} \tag{3}$$

where δ is the spatial autoregressive coefficient and w_{ij} is each of the elements of the spatial weights matrix W that describes the spatial arrangement of the different regions. In our empirical analysis, we will use a first-order binary contiguity matrix for the 47 continental Spanish provinces. The spatial lag model is usually seen as the formal specification for the equilibrium outcome of a spatial interaction process in which the value of the dependent variable for one region is jointly determined with that of the neighbouring ones (Elhorst, 2009).

The spatial error model, however, assumes that the error terms are correlated across space as shown in the system formed by equations (4) and (5)

$$y_{it} = \beta_k k_{it} + \beta_p p_{it} + \beta_s s_{it} + \beta_s t_{it} + \alpha_t + \mu_i + \varepsilon_{it} \tag{4}$$

$$\phi_{it} = \rho \sum_{j=1}^{N} w_{ij} \varphi_{jt} + \varepsilon_{it} \tag{5}$$

where ϕ_{it} denotes the spatially autocorrelated term and ρ is the spatial autocorrelation coefficient[4]. This model is a particular case of a nonspherical error covariance matrix and is consistent with a situation where unobserved shocks follow a spatial pattern.

Both models can also be enlarged with spatially lagged independents variables that will permit to analyse the existence of geographical spillovers among the considered regions. In particular, the spatial lag model including physical capital and human capital spillovers will be as follows:

$$\begin{aligned} y_{it} = {} & \partial \sum_{j=1}^{N} w_{ij} y_{jt} + \beta_k k_{it} + \beta_p p_{it} + \beta_s s_{it} + \beta_s t_{it} + \\ & + \gamma_k \sum_{j=1}^{N} w_{ij} k_{jt} + \gamma_p \sum_{j=1}^{N} w_{ij} p_{jt} + \gamma_s \sum_{j=1}^{N} w_{ij} s_{jt} + \gamma_t \sum_{j=1}^{N} w_{ij} t_{jt} + \\ & + \alpha_t + \mu_i + \varepsilon_{it} \end{aligned} \tag{6}$$

[4] In both, the spatial lag and the spatial error model, stationarity requires that δ and ρ are constrained to the smallest and largest characteristic roots of the matrix W, which in most cases implies to be inside the interval [-1,1]. For more details, see the discussion on Elhorst (2009, page 4).

and the spatial error model:

$$\begin{aligned} y_{it} &= \beta_k k_{it} + \beta_p p_{it} + \beta_s s_{it} + \beta_s t_{it} + \\ &+ \gamma_k \sum_{j=1}^{N} w_{ij} k_{jt} + \gamma_p \sum_{j=1}^{N} w_{ij} p_{jt} + \gamma_s \sum_{j=1}^{N} w_{ij} s_{jt} + \gamma_t \sum_{j=1}^{N} w_{ij} t_{jt} + \\ &+ \alpha_t + \mu_i + \varepsilon_{it} \end{aligned} \tag{7}$$

$$\phi_{it} = \rho \sum_{j=1}^{N} w_{ij} \varphi_{jt} + \varepsilon_{it} \tag{8}$$

Equation (6) and the system formed by equations (7) and (8) can also be transformed to derive convergence equations, where growth in a region over a given period is inversely related to its initial income as a result of the mechanism of convergence towards its steady state caused by decreasing returns to capital accumulation. Additional variables in the specification (physical capital and human capital) control for factors determining differences in the steady states across regions. In particular, the convergence equation in the context of the spatial lag model will be as follows:

$$\begin{aligned} y_{it} - y_{it-1} &= \partial \sum_{j=1}^{N} w_{ij} (y_{it} - y_{it-1}) + \beta_y y_{it-1} + \beta_k k_{it-1} + \beta_p p_{it-1} + \beta_s s_{it-1} + \beta_s t_{it-1} + \\ &+ \gamma_k \sum_{j=1}^{N} w_{ij} k_{jt-1} + \gamma_p \sum_{j=1}^{N} w_{ij} p_{jt-1} + \gamma_s \sum_{j=1}^{N} w_{ij} s_{jt-1} + \gamma_t \sum_{j=1}^{N} w_{ij} t_{jt-1} + \\ &+ \alpha_t + \mu_i + \varepsilon_{it} \end{aligned} \tag{9}$$

and the spatial error model specification for the convergence equation is the following one

$$\begin{aligned} y_{it} - y_{it-1} &= \beta_y y_{it-1} + \beta_k k_{it-1} + \beta_p p_{it-1} + \beta_s s_{it-1} + \beta_s t_{it-1} + \\ &+ \gamma_k \sum_{j=1}^{N} w_{ij} k_{jt-1} + \gamma_p \sum_{j=1}^{N} w_{ij} p_{jt-1} + \gamma_s \sum_{j=1}^{N} w_{ij} s_{jt-1} + \gamma_t \sum_{j=1}^{N} w_{ij} t_{jt-1} + \\ &+ \alpha_t + \mu_i + \varepsilon_{it} \end{aligned} \tag{10}$$

$$\phi_{it} = \rho \sum_{j=1}^{N} w_{ij} \varphi_{jt} + \varepsilon_{it} \tag{11}$$

As Temple (2001) highlights, this specification is preferred to the analysis of the relation between the change in output and the change in education as in this case causality could run from output (or anticipated output) to education, and not *vice versa*. As long-run changes in average educational attainment are driven by government policy, it seems plausible that as output and tax revenues increase, governments will often allocate more resources to education, and attainment will rise for a transitional period. This critique does not apply to the specification between output growth and the initial level of human capital as considered here. Moreover, the use of schooling years (instead of enrolment rates) and panel data makes more unlikely that reverse causation could explain a positive and significant effect of human capital and growth (de la Fuente and Domenech, 2006).

In the fourth section of the paper, we will estimate both the production function in levels and the convergence equation in order to test the direct impact of human capital and through geographical spillovers on regional development. In both cases, the selection between the spatial lag and the spatial error models will be based in statistical criteria, such as the Lagrange Multiplier (LM) spatial dependence tests by Anselin *et al* (1996). Fingleton and López-Bazo (2006) found that the empirical evidence on growth models with spatial dependence suggests that, especially when no additional variables are included in the list of regressors, the spatial error model is more often than not the chosen specification, a result that could be related with the omission of spatially autocorrelated regressors. In this sense, it is not clear if it is better to test whether spatially lagged independent variables must be included and then whether the model should be extended to include a spatially lagged endogenous variable or a spatially autocorrelated term or instead it will be better to adopt an unconstrained model and then test if the model could be simplified. Using simulated data, Florax *et al* (2003) showed that when using cross-sectional data the general-to-specific approach provided worst results than the alternative approach. However, the relative merits of both approaches when using panel data have not been analyzed yet (Elhorst, 2009) and, for this reason, we will compare the results obtained by both procedures using the LM tests developed for spatial panels by Anselin *et al* (2006). In fact, since each spatial specification produces rather different interpretations, the policy implications for the process of economic growth will be substantially different.

Regarding the estimation procedure, we will apply Maximum Likehood (ML) procedures for the estimation of spatial panel data models as implemented in the MATLAB routines by Elhorst (2009)[5]. One advantage of the ML procedures in relation to the Instrumental Variables/Generalized Method of Moments (IV/GMM), as the ones proposed by Kelejian *et al* (2006), is that instruments usually include spatially lagged independent variables, a requirement that will not permit to test the influence of spatial spillovers.

[5] These routines are freely available at http://www.regroningen.nl/elhorst/software.html

3. Data sources, variable definition and preliminary analysis

As stated above, we will consider the influence of human capital on Spanish regional economic development during a period in which there was a marked accumulation of education and physical capital together with its trade opening after the integration into the European Union.

We have yearly data for Gross Domestic Product (GDP), productive capital stock, employment and human capital indicators for the Spanish 47 continental provinces (NUTS III regions) for the period 1980-2005.

The source for GDP is the *Instituto Nacional de Estadística* (INE)[6]. INE Regional Accounts statistics only provide provincial GDP data in nominal terms, but we have used provincial Consumer Price Indexes (CPI) from the same source as deflators. The period covered by the data is 1980-2008, but we will extend our analysis only until 2005 as preliminary estimates for the last years are usually subjected to important revisions at the provincial level. Provincial data on net productive capital stock in real terms are available from "*El stock y los servicios del capital en España y su distribución territorial*", by the FBBVA-IVIE[7] for the period 1964-2006. The source for provincial employment and different human capital indicators is "*Capital Humano en España y su distribución provincial*" by IVIE-Bancaja[8] In particular, the availability of detailed information on the average number of schooling years of the working population[9] and the relative share of the different schooling levels has made possible to decompose this variable into three components: the average number of years of primary, secondary and tertiary studies in each region.

Figure 1 shows the evolution between 1980 and 2005 of the standard deviation of the log of regional GDP per worker, the usual tool to check for sigma-convergence. As we can see, regional disparities in labour productivity have substantially decreased in the analysed period: the value of the coefficient of variation has dropped from values around the 8% in 1980 to 3% in 2005. A similar conclusion is obtained when annualized growth rates of GDP per worker between 1980 and 2005 are regressed on the initial levels. As shown in figure 2, the results reinforce the idea of regional convergence with a speed of 2.6%. These results are in line with the ones obtained by previous studies.

FIGURES 1 and 2

[6] http://www.ine.es/
[7] http://www.fbbva.es/TLFU/microsites/stock08/fbbva_stock08_index.html
[8] http://www.ivie.es/banco/caphumser07.php

[9] Two different calculations of the average number of schooling years are provided in the dataset in order to take into account the reforms carried out in 1990. The data used in the paper are based on the

An analysis of the evolution of capital stock per worker and human capital indicators shows that both factors have positively influenced growth between 1980 and 2005 (figures 3 and 4), but the reduction of regional differences has been much more intense in terms of schooling indicators. While the speed of convergence for the capital stock is around 1.8%, the value for the average number of schooling years is above 8%. The average number of schooling years of employed workers increased from 6.53 in 1980 to 10.56 by 2005.

FIGURES 3 and 4

As it can be seen in figure 5, in 1980, more than 75% of the average number of schooling years was attributable to primary studies while less than one year was due to secondary studies and only a half year to tertiary studies. The situation, however, has substantially changed between 1980 and 2005. In this last year, the contribution of primary studies was only 1.9 years; while secondary studies represented around the 60% of the total with more than 6 years and tertiary studies contributed with more than 2 years.

FIGURE 5

The preliminary analysis of data seems to confirm the results by de la Fuente (2002) on the relevance of physical and human capital accumulation as a source of convergence between Spanish regions in the considered period. In the next section, we estimate the models discussed in section 2 in order to confirm this preliminary evidence.

4. Results

In this section, we present the results of estimating the models discussed in section 2 using the data for the 47 Spanish continental provinces between 1980 and 2005. As previously mentioned, in our empirical analysis, the spatial interaction between regions has been specified using a binary first-order contiguity matrix.

The results of estimating the production function in levels are shown in table 1, while the results of estimating convergence equations are shown in table 2. In both cases, we have started estimating a basic specification, without spatial lags of the endogenous or the exogenous variables including spatial and time-period fixed effects. A Hausman test to select between fixed and random effects and the joint significance of the effects have been the criteria for the choice of the model shown in the first column of both tables.

Second, we have computed the LM and robust LM statistics proposed by Anselin *et al* (2006) in order to test for the null hypothesis of no spatial lag and no spatial error in the models. In the case that both groups of tests lead to the non rejection of the null hypothesis, this will imply that there are no geographical spillovers in the production function and the convergence equation. However, in case the null hypothesis of no spatial lag or no spatial error are rejected, then it will be necessary to include a spatial lag of regional productivity or to consider the existence of spatial autocorrelation, respectively.

As previously mentioned, it is not clear, however, if the selection between the spatial lag model and the spatial error model should be based before or after the inclusion of spatially lagged variables. For this reason, the second column of tables 1 and 2 show the estimates of the production function and the convergence including the spatial lags of the log of physical capital stock per worker, the log of the average years of primary studies, the log of the average years of secondary studies and the log of the average years of tertiary studies. Again, the LM and robust LM statistics are computed in order to select the most appropriate model between the spatial lag and the spatial error model.

Column 1 of table 1 shows the results of estimating the basic specification of the production function including spatial and time-period fixed effects while column 2 shows the results obtained when including spatial lags of the explanatory variables. In both cases, a Hausman test for choosing between the random and the fixed effect specification clearly discriminates in favour of the latter and the LR tests clearly rejects the hypothesis of the no joint significance of the spatial fixed effects. According to these estimates, we find that both physical capital stock and the average number of schooling years for the different levels enter the equation with positive and significant coefficients. The magnitude of the coefficient for physical capital is around 0.6 which is clearly higher than estimates in previous studies (i.e., de la Fuente et al. 2003 estimated the effect of physical capital around 0.3). The inclusion of spatial lags of the explanatory variables does not substantially affect the results. As it can be seen in column 2 of table 1, geographical spillovers of physical capital and primary studies exert a positive and significant effect while a high level of tertiary studies in neighbouring regions affects negatively the productivity of the considered region.

TABLE 1

If we look at the results of the LM and robust LM tests, in column 1, where no spatial lags of the explanatory variables are included, the LM test for no spatial lag is more significant than the LM test for no spatial error and the robust test for no spatial lag rejects the null at the 1% significance level while the robust test for no spatial error rejects it a higher significance level. Taking these results into account, and looking at the Hausman tests to select between random and fixed effects model, model in column 5 of table 1 where random effects are included would be more appropriate. As we can see from this column, there is clear evidence of geographical spillovers (the spatial lag of the endogenous variable is clearly significant) but, these spillovers will not be associated to human capital or physical capital.

However, if we look at the results of the LM and robust LM tests in column 2 (the basic model with spatial lags of the explanatory variables), the results are quite different. The LM test for no spatial error is more significant than the LM for no spatial lag, while the robust LM test for no spatial error is significant and the robust LM test for no spatial lag is not. In this case, and taking into account the result of the Hausman test, model in column 3 of table 1 (where spatial autocorrelation and fixed effects are included) may be selected. The results are quite different from the previous ones: geographical spillovers associated to physical capital and to primary studies are positive and significant, although the spatial autocorrelation coefficient is also significant, showing the relevance of omitted spatial variables.

Column 1 of table 2 shows the results of estimating the basic specification of the convergence equation spatial and time-period fixed effects while column 2 shows the results obtained when including spatial lags of the explanatory variables. As with the production function, in both cases, a Hausman test has clearly discriminated in favour of fixed effects. As we can see from this table, the coefficient associated to the initial level of GDP per worker is negative and statistically significant, a result that reinforces our previous evidence of the existence of a convergence process between Spanish regions in the considered period. The value of this coefficient is, however, significantly higher to the "usual" 2%, but this is a common result in the studies using panel data (Islam, 1995) and focusing on smaller regions (Higgings *et al*, 2006). Physical capital stock and the different human capital indicators have a positive and statistically significant influence on regional economic growth. However, the number of average years of primary studies is only significant at the 10% level. As before, the inclusion of spatial lags of the explanatory variables does not substantially affect the results, although the human capital indicators are less significant. As it can be seen in column 2 of table 2, primary studies are no longer significant at the usual levels and tertiary studies are only significant at the 10% level. Regarding geographical spillovers, physical capital stock exerts a positive and significant effect on growth while a high level of tertiary studies in neighbouring regions affects negatively the growth rate of the considered region, a similar result to the one obtained in the production function specification.

TABLE 2

If we look at the results of the LM and robust LM tests, the conclusion for both models (column 1 and 2) is that the spatial error model should be preferred in statistical terms to the spatial lag models. The fixed effects model is also preferred to the one with random effects. The results in column 4 of table 2 confirms that, even when spatial autocorrelation is controlled for, geographical spillovers associated to physical capital are positive and significant while the role of the human capital of neighbouring is less clear. The spatial lag of the average number of tertiary studies is negative but only significant at the 10% level. The spatial lags associated to the other human capital variables (primary and secondary studies) are not statistically significant.

Summarising, the empirical analysis in this section permits to affirm that the accumulation of physical capital has a positive effect on regional productivity and growth, not only for the considered region but also for the neighbouring ones. Regarding human capital, the results depend on the considered level: secondary and tertiary studies have a significant and positive effect on productivity and growth regardless of the selected specification. Primary studies exert a positive influence on productivity but not on growth. The evidence on human capital geographical spillovers is not so clear. In the production function specification, and once the spatial dependence on the endogenous variable is controlled for, secondary and tertiary studies do not seem to have a direct effect on the productivity of the neighbouring regions. However, the evidence from spatial error models highlights the positive role of primary studies on neighbouring regions while spatial lag models clearly reject this positive influence. The results from growth models are more robust regarding the negative geographical spillovers from tertiary studies. One possible explanation of the negative effect of tertiary studies on the neighbouring's region growth (in a context of reduced geographical mobility of workers) is that they compete for highly qualified jobs in high added value sectors (Olejnik, 2008; Di Liberto, 2008).

Last, it is worth mentioning, that this evidence confirms our initial hypothesis of the different effect of the three considered levels. The results are in line with the findings of Di Liberto (2008) for Italy and Pereira and St Aubyn (2009) for Portugal. Moreover, an additional interesting result from our analysis is that further research is required to establish an appropriate modelisation strategy in the context of spatial panel econometric models. In particular, the conclusions by Florax *et al* (2003), who showed that when using cross-sectional data the general-to-specific approach provided worst results than the alternative approach, should be confirmed by specific studies for panel data. Our results have confirmed that using one or the other strategy provide substantially different results (and policy implications).

5. Final remarks

This paper has considered the effects of human capital spillovers in the Spanish regions in the period 1980-2005. In particular, we have first tested the influence of different schooling levels on regional economic growth and, second, we have analysed if there are differences in the effect of human capital on neighbouring regions depending on its composition.

With this aim, we have specified a standard production function and convergence equation and we have applied recently developed spatial panel econometric techniques to estimate the considered relationships. We have detected a positive influence of physical capital on regional productivity and growth, not only for the considered region but also for the neighbouring ones. The composition of human capital is also relevant for improving regional productivity and growth. While secondary and tertiary studies have a significant and positive effect on productivity and growth regardless of the selected specification, the role of primary studies is less clear. The evidence is less clear for human capital geographical spillovers. The most robust result in the context of the convergence equation is the existence of negative geographical spillovers from tertiary studies. The policy implications of this result are, however, not straightforward. As previously mentioned, one possible explanation is that regions compete for highly qualified jobs in high added value sectors or that neighbouring regions attract qualified workers to exploit agglomeration economies. Further research will be devoted to the analysis of the mechanisms behind these results.

From a methodological point of view, the paper has also suggested some possible directions for future research. In particular, the specification strategy for spatial panel data models is not clear. Is it better to first test whether spatially lagged independent variables must be included and then whether the model should be extended to include a spatially lagged dependent variable or a spatially autocorrelated error term or should it be the other way round? Our empirical analysis has shown that the results (and the implications) from both approaches are different. Their relative merits in the context of a simulation study remains a topic of further research.

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7. Data sources, variable definition and preliminary analysis

Figure 1. Sigma-convergence in regional GDP per worker between 1980 and 2005

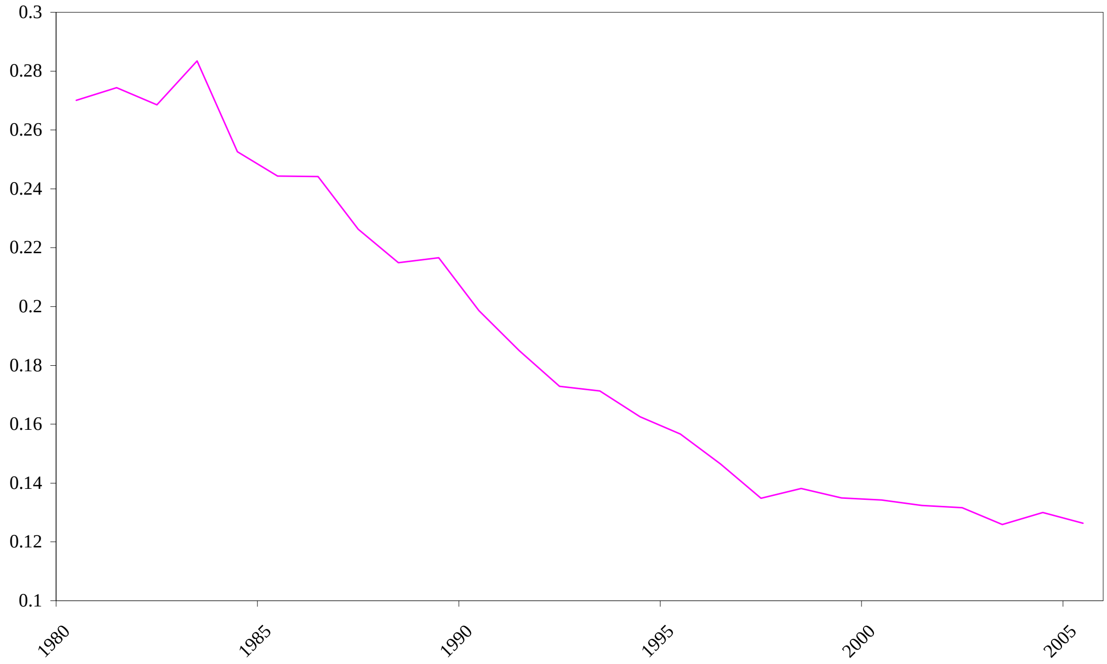


Figure 2. Beta-convergence in regional GDP per worker between 1980 and 2005

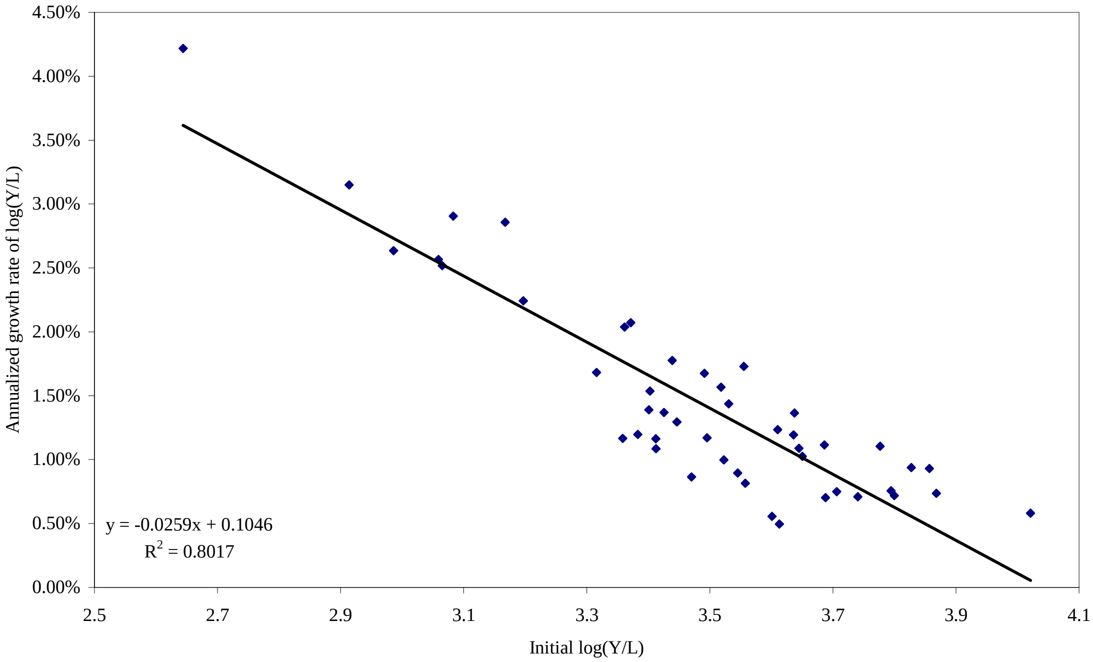


Figure 3. Beta-convergence in regional capital stock per worker between 1980 and 2005

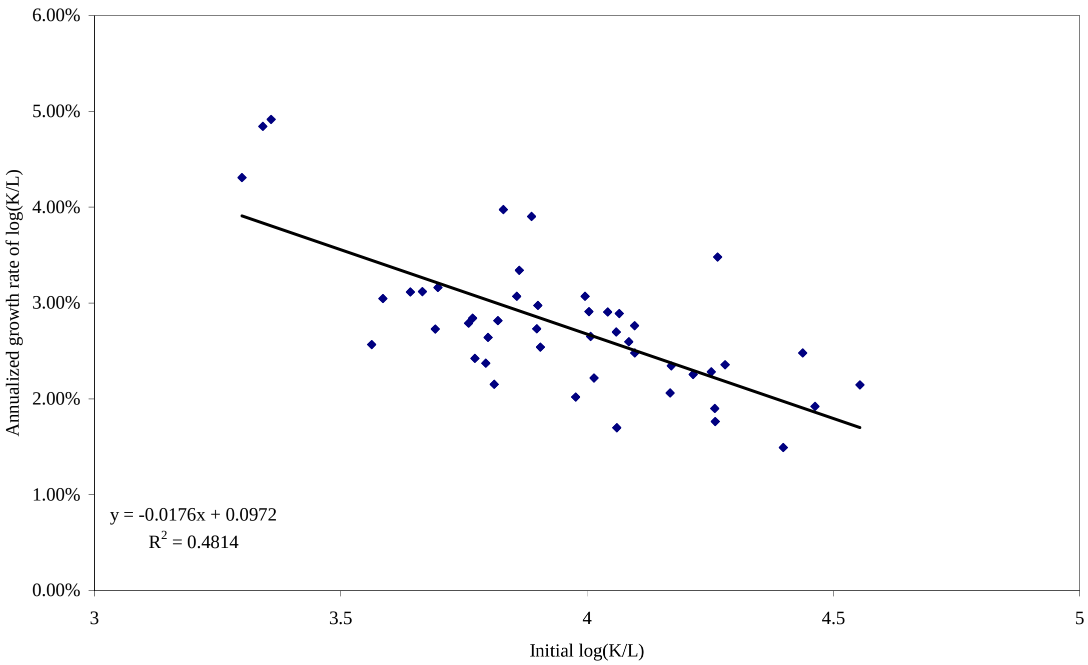


Figure 4. Beta-convergence in the average years of schooling between 1980 and 2005

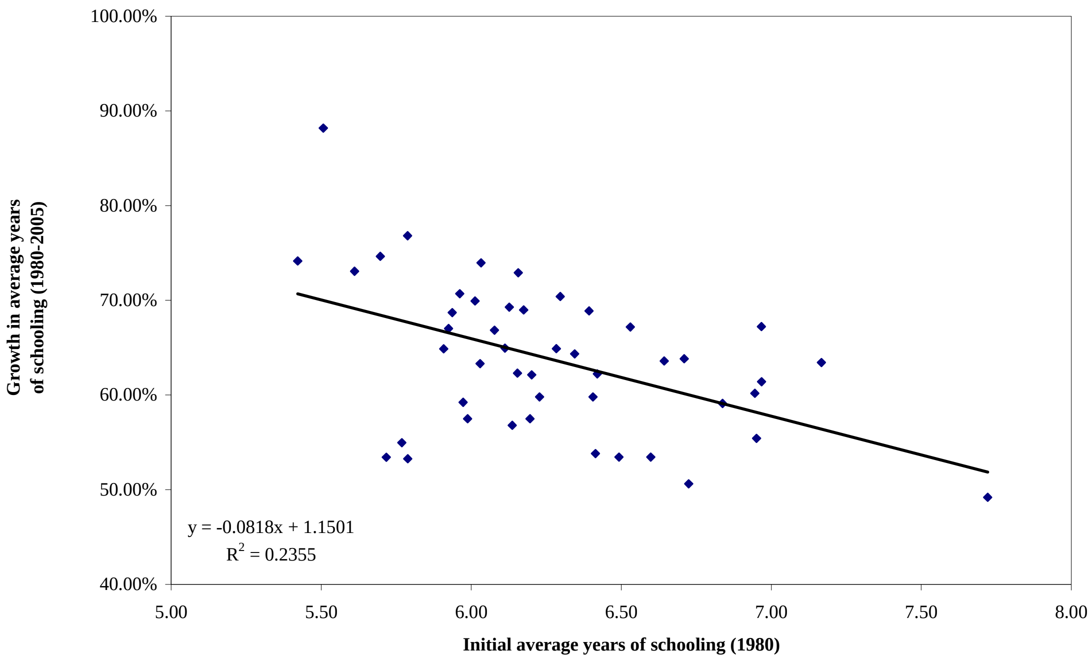
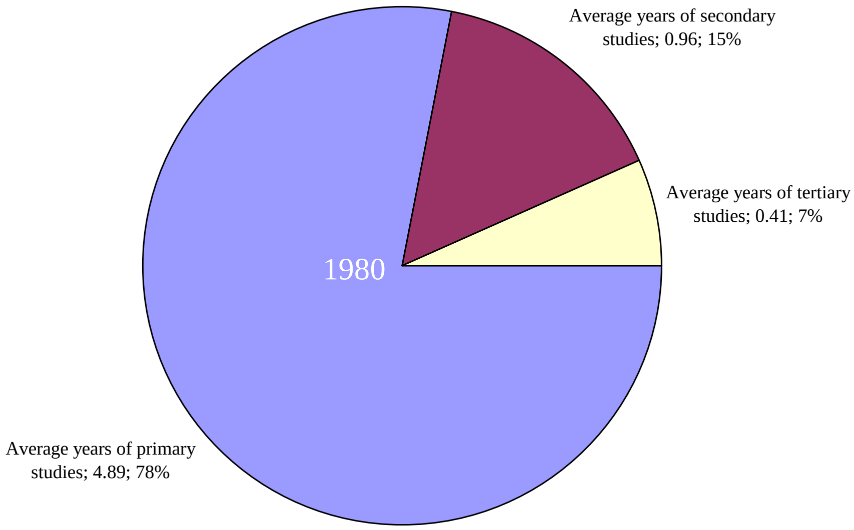


Figure 5. Decomposition of the average years schooling into different levels (1980 and 2005)



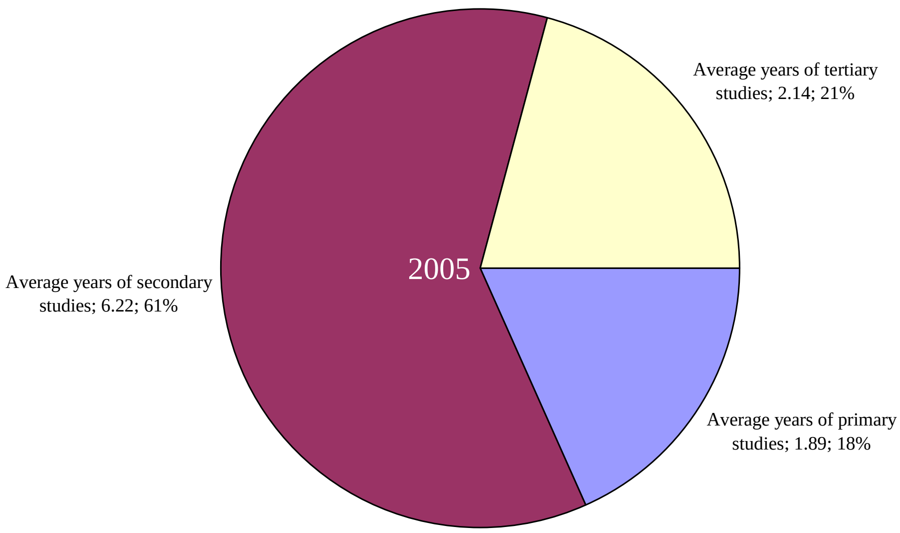


Table 1. Production function estimates

$Log(GDP/L)_t$	Spatial fixed effects				Spatial random effects	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log(physical capital stock per worker)$_t$	0.633***	0.592***	0.549***	0.588***	0.527***	0.559***
Log(average years of primary studies)$_t$	0.066***	0.057***	0.052***	0.067***	0.054***	0.071***
Log(average years of secondary studies)$_t$	0.090***	0.068***	0.061***	0.084**	0.073***	0.106***
Log(average years of tertiary studies)$_t$	0.065***	0.059*	0.057***	0.062***	0.068***	0.078***
Spatial lag physical capital stock		0.049***	0.0140	0.026***	-0.004	-0.008**
Spatial lag primary studies		0.011***	0.049	0.016***	0.004	0.016***
Spatial lag secondary studies		-0.005	0.002	0.005	0.007	0.016***
Spatial lag tertiary studies		-0.012**	-0.008	-0.009	-0.003	0.001
Spatial autoregressive			0.147***		0.298***	
Spatial autocorrelation				0.334***		0.380***
R-squared	0.874	0.878	0.951	0.948	0.949	0.951
Corr-squared			0.877	0.877	0.614	0.578
Observations	1175	1175	1175	1175	1175	1175
LM test no spatial lag	93.903***	50.697***				
Robust LM test no spatial lag	21.428***	0.927				
LM test no spatial error	76.342***	56.284***				
Robust LM test no spatial error	3.867**	6.513**				
LR-test spatial fixed/random effects	1811.37***	638.02***	1849.841***	1862.425***	1561.381***	1558.313***
Hausman test-statistic	49.02**	126.51***	27.637	163.38***		

All models include time period fixed effects
*** p<0.01; ** p<0.05; * p< 0.1

Table 2. Convergence equation estimates

$Log(GDP/L)_t - log(GDP/L)_{t-1}$	Model 1	Model 2	Spatial fixed effects		Spatial random effects	
			Model 3	Model 4	Model 5	Model 6
Log(GDP per worker)$_{t-1}$	-0.194***	-0.205***	-0.205***	-0.217***	-0.088***	-0.093***
Log(physical capital stock per worker)$_{t-1}$	0.054***	0.052***	0.052**	0.059***	0.014**	0.012**
Log(average years of primary studies)$_{t-1}$	0.014*	0.012	0.012	0.013*	0.004	0.004
Log(average years of secondary studies)$_{t-1}$	0.043***	0.038***	0.039***	0.041***	0.036***	0.033***
Log(average years of tertiary studies)$_{t-1}$	0.020***	0.019*	0.020**	0.020**	0.016***	0.017***
Spatial lag physical capital stock		0.017**	0.019***	0.014**	0.002	0.001
Spatial lag primary studies		0.001	0.001	0.001	-0.004*	-0.004
Spatial lag secondary studies		-0.003	-0.003	-0.002	-0.004	-0.003
Spatial lag tertiary studies		-0.008*	-0.008*	-0.008*	-0.014	-0.001
Spatial autoregressive			0.147***		0.139***	
Spatial autocorrelation				0.183***		0.163***
R-squared	0.223	0.229	0.267	0.255	0.222	0.227
Corr-squared			0.225	0.228	0.209	0.211
Observations	1175	1175	1175	1175	1175	1175
LM test no spatial lag	11.032***	12.268***				
Robust LM test no spatial lag	20.694***	11.939***				
LM test no spatial error	19.860***	17.543***				
Robust LM test no spatial error	29.521***	17.214***				
LR-test spatial fixed effects	62.840**	68.240**	112.160***	117.826***	42.146***	48.386***
Hausman test-statistic	42.100**	52.050**	51.513**	49.464**		

All models include time period fixed effects
*** $p<0.01$; ** $p<0.05$; * $p< 0.1$