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Investigaciones Regionales

Education, Catch-up and Growth in Spain

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ABSTRACT: The debate over the impact of education on economic growth has recently led to disagreement when, at the empirical level, the effect of average human capital on economic growth has been found to be weak. With this paper we revisit these results by arguing how different educational attainment levels (rather than the average human capital stock) impact heterogenously different regions' economic performance. We build and test a catch-up model where technology adoption takes place as a function of each region's human capital composition. We show for 50 NUTS3 Spanish provinces in between 1965 and 1997, how convergence to the frontier is driven by higher education and, to a lesser extent, by vocational training. Both theoretical and empirical results are alternative to the well known formalization proposed by Vandenbussche, Aghion and Meghir (2006). Severe endogeneity issues, as well as small sample biases, are tackled by using system GMM estimators and the correction proposed by Windmeijer (2005).

JEL Classification: I25, 030, 040.

Keywords: Human capital composition, regional growth, convergence, adoption.

La educación, Catch-up y crecimiento en España

RESUMEN: El debate sobre el impacto de la educación en el crecimiento económico ha recientemente evidenciado la escasa significatividad empírica del efecto del capital humano medio sobre el crecimiento económico. Con este trabajo nos proponemos revisar estos resultados con el objetivo de analizar cómo inciden los diferentes niveles educativos (más que el *stock* de capital humano promedio) sobre el crecimiento económico de las regiones. Con este objetivo construimos y analizamos un modelo de *technology catch-up* en el que la adopción de tecnología

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se lleva a cabo en función de la composición del capital humano de cada región. Nuestros resultados demuestran para 50 provincias españolas (NUTS3) cómo la convergencia hacia la frontera tecnológica se debe mayoritariamente a la educación superior y, en menor medida, a la formación profesional entre los años 1965 y 1997. Tanto los resultados teóricos como los empíricos son una alternativa a la formalización del modelo propuesto por Vandenbussche, Aghion y Meghir (2006). Los importantes problemas de endogeneidad, así como los sesgos debidos al uso de una muestra pequeña, se abordan mediante el uso de estimadores *system* GMM y de la corrección propuesta por Windmeijer (2005).

Clasificación JEL: I25, 030, 040.

Palabras clave: Composición capital humano, crecimiento regional, convergencia, adopción.

1. Introduction

Education and its impact on economic growth has been the focus of economic literature for a long time. From a theoretical point of view, starting from the seminal contribution of new growth theory by Romer (1990), human capital has been argued to be one of the main long-run determinants of economic growth at the country level since it would foster technology creation or, as in Behnabib and Spiegel (2005), the adoption of foreign technology.

Similarly, more dynamic regions are usually those fully taking advantage of technological opportunities and renewing their productive structures by technology implementation. Acemoglu and Dell (2009) argue how «between-municipality [regional] differences in labor income are about twice the size of between-country differences» such that «similar to the residual in cross-country exercises, these regional residual differences can be ascribed to differences in the efficiency of production across sub-national units-i.e. to “technology differences”».

What matters for regional economic growth is, hence, the relative efficiency with which economic agents in each region are capable of implementing and adopting the available know-how (technology) and taking advantage of it profitably. Hence, education is usually argued to be the channel through which technology is exploited also at the regional level leading to growth differentials across regions.

Nonetheless, recently, some doubts on the positive impact of human capital on economic growth have arisen as pointed out by de la Fuente and Doménech (2006), Pritchett (1996) and Krueger and Lindhal (2001) who argue how, especially in dynamic panel data context, the econometric relation between human capital and economic growth is almost null or very weak.

On the one hand, an explanation to this odd result has led to questioning the quality and homogeneity of the data on international educational levels used in growth regressions [see Cohen and Soto (2007)]. It is difficult, however, to argue that this may be an important element when the analysis is run at the regional level. Other strands of literature point, instead, to the uneven (non-linear) impact that education may have on economic growth and catch-up [see Vandenbussche, Aghion and Meghir (2006)] such that different types of human capital may be better suited to the technological needs of regions differring in their development stage. In particular, Vandenbussche, Aghion and Meghir (2005) argue how «a marginal increase in the stock of unskilled human capital enhances productivity growth all the more the economy is further away from the technological frontier» [1].

We insert directly into this literature and examine the role played by different educational attainment levels on the economic growth (the catch-up) of Spanish NUTS3 regions over a long period of time, 1965-1997. Different studies have yet examined the role played by human capital on spanish regional economic growth. Nonetheless, their results are mixed. On the one hand, the work by Cuadrado Roura and García Greciano (1995) examine the role played by different educational categories on productivity growth, finding a positive effect for 17 NUTS2 spanish regions. Similarly, the work by Bajo Rubio (1998) finds a positive impact played by human capital on regional growth for the period 1967-1991. Also, more recently, de la Fuente and Vives (2002) highlight the important role of human capital in the explanation of regional inequality for Spain. Similarly to these results, but with micro data, Motellon *et al.* (2010) show how regional heterogeneity in wages can be attributed to differences in the return and endowment of human capital while Lopez-Bazo and Moreno (2008) show the importance of human capital for economic activity and for the accumulation of private physical capital.

On the other hand, however, other studies do not succed in finding a strong relation between average human capital and economic activity. Dolado *et al.* (1994) and by de la Fuente and da Rocha (1994) do not find empirical evidence of a positive effect of human capital on regional economic growth and convergence. Dolado *et al.* (1994) examine both flows and stocks average measures of human capital finding a non significant relation between these proxies and economic growth. A similar result is found by de la Fuente and da Rocha (1994) who argue that average measures of human capital (proxied by the average years of education per region) are not actually able to explain Spanish economic growth, while instead, the stock-fraction of skilled workers seemt to be strongly associated to economic convergence. Also, Serrano (1996) finds evidence of a positive impact of human capital on regional economic growth only when the fractions of highly educated workforce rather than average

[1] See Vandebussche, Aghion and Meghir (2004), proposition 1: «Under assumption (A1), a marginal increase in the stock of skilled human capital enhances productivity growth all the more the economy is closer to the world technological frontier. Correspondingly, a marginal increase in the stock of unskilled human capital enhances productivity growth all the more the economy is further away from the technological frontier». Their result is puzzling to us and we believe it to be counter-intuitive since it suggests that any decrease in educational levels would be growth beneficial for the less developed regions (and countries), and all the more they are under-developed. This is like saying that poor regions should oddly compete one another by lowering (rather than increasing) their educational levels.

years of education are used as regressors. With a similar purpose, de la Fuente and Domenech (2006) elaborate a detailed database at the regional level for Spain of different educational categories and attainment levels for the period between 1960-2000.

Also, Diliberto (2008) for Italy and Ramos *et al.* (2009) for Spain show mixed results regarding the impact of human capital composition on regional economic growth. For Italy, Diliberto (2008) finds, similarly to Vandenbussche, Aghion and Meghir (2006), that primary education (rather than secondary or tertiary) is more important in those regions which are already lagging far behind the frontier. Ramos *et al.* (2009), instead, show that especially tertiary education has been the leading force behind the regional convergence process in Spain over the last decades.

Previous empirical literature, hence, seems to suggest that the ability of exploiting the available know-how may be tightly linked to the education of the active workforce. With this contribution we ask what type of education is better conductive to economic growth and to the adoption and creation of technology by analyzing over a panel of 50 Spanish provinces different educational attainment levels and their impact on the process of economic catch-up at the regional level. Our identifying assumption is that regions endowed with more skilled workforce will be able to implement and absorb technology faster than other regions.

The theoretical background on which we base our analysis is then similar to Vandenbussche, Aghion and Meghir (2005) since it does analyzes the impact on growth of different educational attainment levels. It crucially differs from them, instead, by assuming that skilled workers rather than unskilled ones are better suited to activities such as technology adoption or implementation. For this reason, in the present contribution we propose an alternative theoretical explanation of our results by exploiting a modification of Manca (2009) catch-up model. In this, we relax some of the counter-intuitive assumptions made by Vandenbussche, Aghion and Meghir (2005) and show how technology catch-up is driven by educated workforce rather than by an uneducated one.

We empirically test the relation among different educational attainment levels, social capital and GVA catch up. These relations may severely suffer from endogeneity. Hence we deal carefully with simultaneity issues by estimating a dynamic panel making use of system GMM estimators as proposed by Arellano and Bond (1991) and Arellano and Bover (1995). We also correct for small sample biases by applying the two-step optimal estimation procedure proposed by Windmeijer (2005). Results show the positive role of tertiary education (and partly of vocational training) on the reduction in the GVA gap across Spanish provinces.

The remainder of the paper is as follows. In section 2 we give the basic setup of the model focusing on the main variables which will be analyzed throughout the paper. In section 3 we depict the process of technology adoption and state the main conclusions of the revisited theoretical model. Section 4 describes the data used while section 5 address the endogeneity issues between economic performance and human capital accumulation. Section 6 proposes the empirical results for both a linear and non-linear human capital specification. At the end some conclusions.

2. Setup of the model

This section has the aim of proposing a technology catch-up model in which the human capital composition of each region shapes the ability of adopting the available technology frontier. For simplicity of exposition we will focus the discussion on a representative follower region even if the model could be generalized to a setting where a finite number of follower regions exists with no changes to the main results presented in this contribution.

Regions produce output by means of a Spence (1976)/Dixit and Stiglitz (1977) production function as follows:

$$Y_i = A_i(L_{yi})^{1-\alpha} \sum_{j=1}^{N_1} (X_{ij})^{\alpha} \qquad (1)$$

where i takes value 1 for the leader and 2 for the representative follower. As for the variables in eq. (1), Y_i is output, X_{ij} is the quantity of the jth nondurable intermediate good used in the production by region i. As in Barro and Sala-i-Martin (1997) we use the variable N_i to proxy for the technological level of region i such that the relative development stage of each follower region w.r.t. the leader will be defined as:

$$0 < \frac{N_2}{N_1} \leqslant 1 \qquad (2)$$

Consistently with empirical evidence, we assume that the follower lags behind the frontier w.r.t. other macroeconomic fundamentals. First, the follower is endowed with relatively worse institutions. In the model, A represents institutional quality of regional governments. This variable captures the quality of the of local institutions. These are particularly important in a country such as Spain which delegates many of its central powers to its Comunidades Autonomas which have large powers in budgetary and economic matters. With A we also capture all other unobservable differences across regions that are not explicitly modeled such as infrastructures and so on [2]. Hence, more formally, we assume that the leader owns more developed institutions than the followers as:

$$A_1 > A_2 \qquad (3)$$

[2] In our empirical investigation we will proxy A_i by making use of an index of social capital defined as the degree of those «relationships that evolve in the economic sphere, particularly in employment, financial or investment markets, in which long-lasting relationships exist in contexts of uncertainty and strategic interdependence». See IVIE, http://www.ivie.es/banco/ksocial.php.

Second, and more importantly, we assume differences in human capital composition across regions. In both regions a fraction of population will be of the low skill type, namely L_{yi}, and employed in the production of the final good Y_i as in eq. (1). The remaining fraction of the workforce in each region, namely L_{ri} represents the high skilled workers which will be employed in the technological sector. At the frontier, L_{r1} will be employed in the creation of new blueprints (new technology know-how) while, in the case of the follower regions, L_{r2} will be the fraction of workforce devoted to the adoption and adaptation of the technologies discovered at the frontier.

Consistently with empirical evidence, the follower regions are populated by a relatively larger share of low skilled workers (over their total populations) and by a lower share of high skilled workers w.r.t. the region at the frontier. These conditions can be restated more formally as follows:

$$L_{r1} > L_{r2} \tag{4}$$

and, conversely

$$L_{y1} < L_{y2} \tag{5}$$

such that the condition for the differences in human capital composition across regions reads as:

$$\frac{L_{r1}}{L_{y1}} > \frac{L_{r2}}{L_{y2}} \tag{6}$$

The following general condition for the total workforce is also satisfied:

$$L_i = L_{yi} + L_{ri} \tag{7}$$

where L_i is normalized to 1.

3. The cost of technology adoption and education

As argued by Maskus (2000), technology imitation usually takes the form of adaptations of existing technologies to new markets. In order to adopt a new product (or a process) the follower usually need to adapt the new technology to its market or productive needs. Hence, managerial as well as technical skills are necessary for the follower in order to adopt and «adapt», for example, a newly discovered process innovation [3]. Managerial and technical skills are also important when the follower

[3] For example, in the last Community Innovation Survey (CIS) carried out by the European Commission the definition of «process innovation is the implementation of a new or significantly improved production process, distribution method, or support activity for your goods or services. The innovation (new or improved) must be new to your enterprise, but it does not need to be new to your sector or

has to choose which innovation (within the large pool of available ones) has to be to implemented and adopted. The profitability of the adoption then will be a function of the manager's judgment of the innovation market potentials as well as of the capabilities of workers of adopting the new technologies.

The basic assumption on the costliness of technology adoption is very much in line with the theoretical framework by Nelson and Phelps (1966) [4]. Following this rationale, our formalization implies that the cost of imitation will be lower the larger the share of skilled workforce in the follower. More formally we can restate the cost function for imitation as follows:

$$V_2 = \psi(L_{r2})^{-1}\left(\frac{N_2}{N_1}\right) \tag{8}$$

where v_2, represents the cost of adopting and correctly implementing a new technology in the follower region. The technology adoption cost, v_2, is assumed to be a negative function of the skill intensity of the follower region, that is of L_{r2} [5]. In the fashion of Connolly and Valderrama (2005) and Barro and Sala-i-Martin (1997) we assume the cost of technology adoption to be also an increasing function of the proximity of the imitator w.r.t. the technological frontier. When it exists a large pool of innovations (blueprints) from which an imitator can copy, the cost of imitation tends to be low and viceversa.

Technology spillovers and the adoption of new technologies developed at the frontier, in fact, do not take place spontaneously nor they can be thought as a free lunch. The costliness of imitation is widely observed and acknowledged in theoretical and empirical literature. Maskus, Saggi and Puttitanun (2004), Mansfield, Schwartz and Wagner (1981), Coe and Helpman (1995) or Behnabib and Spiegel (2005) argue that the cost of the adaptation and imitation of technologies discovered at the frontier (or in other technological sectors) is usually positive but relatively lower than the cost of innovation.

Once a new technology is discovered at the frontier this will be potentially available for adoption by any agent in region 2. Assuming that consumers maximize the same Ramsey-type utility utility and solving for the stream of profit to the

market. It does not matter if the innovation was originally developed by your enterprise or by other enterprises».

[4] They argue how «it is clear that the farmer with a relatively high level of education has tended to adopt productive innovations earlier than the farmer with relatively little education [...] for he is better able to discriminate between promising and unpromising ideas [...] The less educated farmer, for whom the information in technical journals means less, is prudent to delay the introduction of a new technique until he has concrete evidence of its profitability».

[5] Crucially, if two follower regions were to stand equally distant from the frontier (at the same development stage), the one endowed with a larger share of skilled workforce would be able to better distinguish between profitable and unprofitable technologies being able to better use the available technologies in the production chain, facing a relatively lower cost of adoption and eventually catching up with the frontier faster than the region with endowed with lower skills.

adopter we can finally define the growth rate for the follower region as a function of its human capital composition through the parameters L_{y2}, v_2 and of institutional quality, A_2.

$$\gamma_2 = (1/\theta)(\pi_2/v_2 - \rho) = (1/\theta)[(1-\alpha)L_{y2}A_2^{1/1(1-\alpha)}\alpha^{(1+\alpha)/(1-\alpha)}v_2^{-1} - \rho] \quad (9)$$

As we can notice from eq. (9), the growth rate of the follower is tightly linked to the composition of its human capital rather than to its average level. On one hand, γ_2 is a positive function of the unskilled share of the workforce which is needed in order to produce the final good and employed in the production, that is of L_{y2}. However, the engine of growth lies in the technology absorptive capacity of the economy, that is, in its ability to exploit technology spillovers. The second crucial parameter is, in fact, v_2, the cost of technology adoption, which enters at the denominator of the expression in eq. (9). It is easy to recall how the cost of adoption is, itself, a negative function of the skilled fraction of the workforce as in eq. (8) such that if an increase in L_{r2} reduces by definition the value of L_{y2} (negatively impacting growth), it will at the same time boost the capacity of the follower to adopt technology reducing the adoption cost. This scenario is analyzed in the following proposition.

Proposition: *A rise in the share of the workforce with a higher level of education (skilled workers) is growth enhancing for the follower region reducing the cost of technology adoption and increasing its rate of return. Conversely, a rise in the fraction of population with low skills is shown to be growth diminishing. The result (which depends on the relative composition of human capital in each economy) is stronger the smaller the initial share of skilled workers over the total population and it holds under plausible values for the model parameters and of human capital composition.*

By inspection of the growth rate in eq. (9) we can notice that, everything else being equal, the growth rate of the economy is a function of the level of skilled over unskilled workers in the economy. Taking the partial derivative of the growth rate w.r.t. L_{r2} and imposing this to be greater than zero yields to the following:

$$\frac{\partial \gamma_2}{\partial L_{r2}} = (1/\theta)[(1-\alpha)A_2^{1/1(1-\alpha)}\alpha^{(1+\alpha)/(1-\alpha)}v_2^{-1} - \rho](1 - 2L_{r2}) \quad (10)$$

Due to the standard assumptions made on the model parameters in order to ensure positive growth, the term $(1/\theta)[(1-\alpha)A_2^{1/1(1-\alpha)}\alpha^{(1+\alpha)/(1-\alpha)}v_2^{-1}-\rho]$ will be always greater than zero. This leads to the following:

$$\frac{\partial \gamma_2}{\partial L_{r2}} > 0 \quad \Leftrightarrow \quad L_{r2} < 1/2 \quad (11)$$

An increase in the skilled fraction of workforce is then shown to be growth enhancing while, conversely, an increase in the share of unskilled workers will end up being growth detrimental to the follower [6]. The condition expressed in eq. (11), in fact, holds for $L_{y2} > 1/2$ such that, for catching up to take place, basic education (along with higher education) has to be ensured.

4. Data

On one hand, the data that we use to proxy for economic activity (proxied by the Gross Value Added, GVA) comes from the Fundación BBVA. Our sample will consist on a 4-years dynamic panel for 50 NUTS3 Spanish provinces. We compute the distance from the frontier of each province as a ratio to the leader province which is taken to be Madrid in all points in time of our panel. Our analysis will focus on a long time period, 1965-1997, for which data for all the relevant variables are available in a panel setting.

On the other hand, we proxy for education (and especially for the different educational attainment levels) by using the the «Human capital series» provided by the IVIE in collaboration with Bancaja [7]. Data on education refer to the following nominal categories: (HK1) illiterate, (HK2) primary schooling, (HK3) compulsory secondary schooling, (HK4) pre-university education (HK5) higher education. We summarize the different educational categories in the table here below:

Table 1. Educational attainment levels

Label	*Category*	*Attainment levels*
HK1	Analfabetos	—
HK2	Sin estudios y estudios primarios	Primary Schooling, EGB
HK3	Estudios medios	Secondary Schooling, Vocational Training (FP1 and 2)
HK4	Estudios anteriores al superior	Diplomas in Humanities, Engineering, Social Sciences and Law etc.
HK5	Estudios superiores	University degrees and PhD carrers

Since we are interested in the specific effect played by human capital composition on the convergence process, human capital variables have been computed as the share of the active population in each educational attainment level over the total

[6] It is important to notice, however, how the positive marginal effect of an increase in the share of skilled workers on economic growth encounters diminishing returns as in standard endogenous growth models (see for example Romer, 1990) due to the possible duplication effect in the technological sector and the so called «stepping on toes» effect. The non-linear impact of human capital composition on growth also highlights the role played by lower education for growth, which is itself necessary for the basic result to hold.

[7] See: http://ivie.es/banco/capital.php?idioma=EN for more details.

active population in the region. Our study is also concerned with the role played by institutional quality. To the best of our knowledge, the best approximation for the Spanish case are the data for Social Capital provided by the IVIE in collaboration with the BBVA Foundation. In table A.1 in the appendix we provide the descriptive statistics of the different educational attainment levels at NUTS3 geographical disaggregation level. Along with the human capital variables we also provide the statistics for social capital and for both the initial GVA per capita gap and its growth rate [8].

4.1. Initial data investigation

As a first check of the hypothesis that different educational attainment levels may impact differently the economic performance of provinces in Spain we analyze, in table 2, the pairwise correlation matrix of the distance of each province w.r.t. the technology frontier (Madrid) against the different educational categories [9].

Table 2. Correlation Matrix

	GVA gap	*HK1*	*HK2*	*HK3*	*HK4*	*HK5*
GVA gap	1					
HK1	–0.59	1				
HK2	–0.41	0.51	1			
HK3	0.47	–0.63	–0.98	1		
HK4	0.36	–0.59	–0.90	0.88	1	
HK5	0.47	–0.58	–0.85	0.82	0.85	1

Note: GVA gap is expressed as the ratio of each province on the frontier. Educational attainment levels are detailed in table 1.

Simple correlation matrix shows how top margin educational categories are positively correlated to smaller GVA gap w.r.t. the technology frontier. The impact is, moreover, nonlinear since it seems to be stronger for the category HK3 (secondary and vocational training) and HK5 (university degree) while less important (even if positive) for the category HK4 (diplomas).

[8] As far as it concern the average illiteracy rate (HK0), the maximum value (8.68) is experienced by the province of Badajoz (Extremadura) while the lowest score (0.52) is attributed surprisingly to the province of Soria (probably due to recent decades dynamics). At the other side of the spectrum the highest average share of tertiary education (8.68) is, as expected, scored by the region of Madrid while the lowest share (1.74) is experienced by the province of Lugo (Galicia). The region of Madrid also scores the highest level in the average social capital index.

[9] The correlation is run on the panel without previously averaging not to loose information such that the maximum number of observation is 800 when no lags are analyzed.

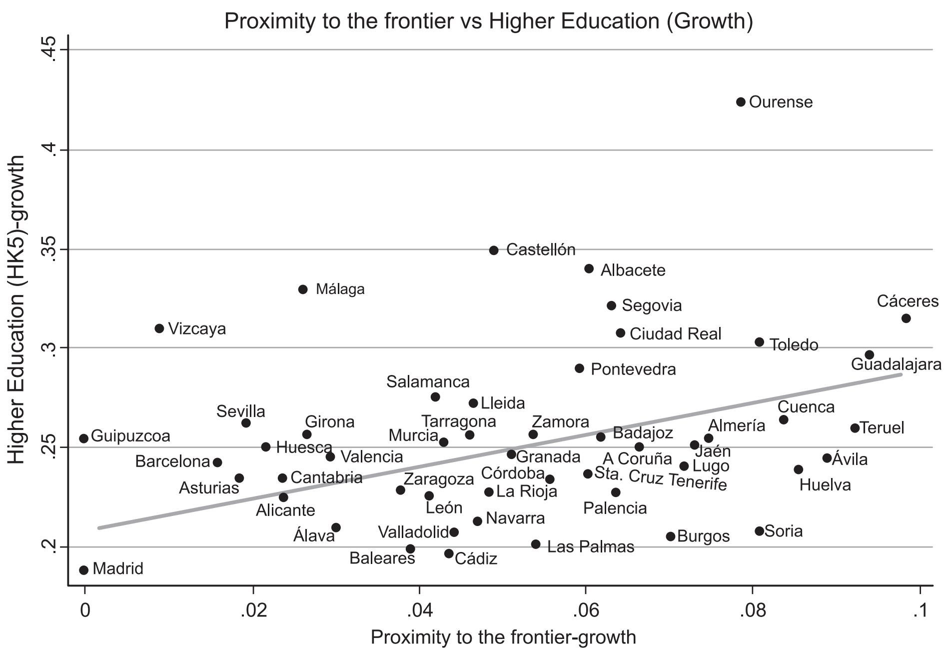
As we argued, however, the impact of education may not be immediate such that the lags (up to 3) of the educational categories have also been analyzed in table 3 here below.

Table 3. Correlation Matrix (lags of HK)

	GVA gap	
	(i)	*(ii)*
HK1	–0.57	–0.56
HK2	–0.35	–0.33
HK3	0.43	0.42
HK4	0.30	0.27
HK5	0.45	0.43

Note: (i), (ii) are 1st and 2nd lag of HK variables.
GVA gap is expressed as the ratio of each province on the frontier. Educational attainment levels are detailed in table 1

Again, the strongest impact on the reduction of the technology gap can be attributed to higher educational levels. Higher growth rates of the HK5 category are also associated to faster closure of the GVA gap w.r.t. the frontier as shown in the graph below:



5. Empirical approach and endogeneity issues

We acknowledge that the relation between education and economic growth is likely to be heavily affected by severe problems of endogeneity. As argued by Castelló (2006) educational variables are usually highly persistent over time. It is well known that system GMM estimators for dynamic panel data models generally perform better than standard first-difference estimators when variables are persistent. Blundell and Bond (1998) show that when the considered variables are close to random walk processes then the difference GMM estimators behave poorly because past levels of these variables convey little information about future realizations.

Improvements in econometrics theory now allow the researcher to use the so-called «two-step» System GMM estimator. The two-step variant of the System GMM, differently from the «one-step» version, makes use of an «optimal» weighting matrix which is the inverse of the estimate of Var[z'], where z is the instrument vector and the error term. This `optimal' weighting matrix it is argued it makes the two-step GMM asymptotically efficient. Even if asymptotically efficient and robust to whatever patterns of heteroskedasticity, a weakness of the two-step System GMM estimator has historically been that of producing standard errors that are severely downward biased (Arellano and Bond 1991; Blundell and Bond 1998). This problem is even more pronounced in the case of small samples and when the number of instruments is large. Windmeijer (2005) and Roodman (2006) ague how this problem may be as severe as to make two-step GMM useless for inference.

Windmeijer (2005) [10] proposes a correction to the two-step covariance matrix which is argued it can make the two-step robust estimation more efficient than robust one-step especially for system GMM which we use in our work.

5.1. The empirical model

As pointed out before, the theoretical model predicts that an increase in the fraction of skilled workforce will be growth enhancing and conductive to convergence in income levels across regions. Viceversa, increasing the unskilled content of the workforce will be growth detrimental and conductive to larger GVA gaps in the long run across regions with the follower converging towards lower GVA steady state levels.

We propose two alternative econometric specifications. Firstly we test a linear model where regional convergence is explained by the average human capital stock

[10] As pointed out by Roodman (2006), «the usual formulas for coefficient standard errors in two-step GMM tend to be severely downward biased when the instrument count is high. Windmeijer (2005) argues that the source of trouble is that the standard formula for the variance of FEGMM is a function of the "optimal" weighting matrix S but treats that matrix as constant even though the matrix is derived from one-step results, which themselves have error. He performs a one-term Taylor expansion of the FEGMM formula with respect to the weighting matrix, and uses this to derive a fuller expression for the estimator's variance». The correction has been made available in STATA by Roodman (2006).

of each region (and by a set of standard control variables and social capital). This is summarized by the following eq. (12):

$$GVAgap_{it} = c + \beta_1 GVA_{i,t-\tau} + \beta_2 AvSchool_{i,t-\tau} + \beta_3 SK_{i,t-\tau} + \beta_4 Z_{i,t-\tau} + \mu_i + u_{it} \quad (12)$$

Secondly, we test whether the specific composition of regional human capital stocks (rather than the average level) explain in a non-linear manner the process of regional economic convergence and unveils hidden dynamics. This is done through the following specification in eq. (13):

$$GVAgap_{it} = c + \beta_1 GVA_{i,t-\tau} + \beta_2 EduComp_{i,t-\tau} + \beta_3 SK_{i,t-\tau} + \beta_4 Z_{i,t-\tau} + \mu_i + u_{it} \quad (13)$$

where we define the GVA gap (in the two specifications) as the log of the ratio between the GVA per capita of each observed region w.r.t. to the value for Madrid which we assume to be our empirical leader region.

The initial GVA, is inserted in the two specifications in order to control for the initial development stage of each region as in standard growth models. This is to say that we control for initial income differences across regions in order to properly isolate the partial contribution of human capital composition in the definition of long run GVA gaps. In eq. (12) *AvSchool* proxies for the average years of education in each regions (the average human capital stock) while *EduComp* in eq. (13) proxies each one of the eduacational categories proposed in table1. In the latter, we will analyze whether different educational categories (starting from primary to tertiary education) play a different role in the catch-up of follower regions to the frontier as depicted in the theoretical model. As argued before, all the educational categories are expressed in relative terms as a fraction of the workforce in each educational category over the total active population. Also, SK represents Social Capital and it will be used in the province-level analysis to proxy for institutional quality. We augment these specifications by control variables such as regional physical capital stock, the employment level as well as its density in the region or their growth rate over the period.

6. Econometric results

6.1. Average years of education and regional catch-up

The baseline linear specification depicting the impact of average human capital on regional catch-up is presented in column (1) of table 4 below:

The estimated effect of the average number of years of education is not statistically significant and does not explain the process of regional catch-up for the period examined in the baseline specification proposed in column (1). Indeed, this result is in line with previous empirical evidence for Spain like the studies by de la Fuente and da Rocha (1994), Dolado *et al.* (1994) or Serrano (1996) who did not find a sig-

Table 4. Dependent Variable: GVA GAP per capita, NUTS3 (4-year span panel between 1965-1997)

	SYSGMM (1)	*SYSGMM (2)*	*SYSGMM (3)*	*SYSGMM (4)*	*SYSGMM (5)*	*SYSGMM (6)*	*SYSGMM (7)*	*OLS (8)*	*LSDV (9)*
Initial GVA per capita	0.317*** [0.030]	0.404*** [0.049]	0.280*** [0.032]	0.342*** [0.032]	0.582*** [0.087]	0.310*** [0.032]	0.571*** [0.109]	0.913*** [0.023]	0.419*** [0.020]
Average Years of Schooling	–0.010 [0.007]	–0.039*** [0.011]	–0.004 [0.008]	–0.003 [0.009]	–0.063*** [0.017]	–0.002 [0.008]	–0.068*** [0.020]	–0.118*** [0.007]	–0.032*** [0.005]
Employment			0.000*** [0.000]	0.000*** [0.000]	0.000 [0.000]	0.000*** [0.000]	–0.000 [0.000]		
Capital Stock		0.001*** [0.000]		–0.001** [0.000]	–0.000 [0.000]	–0.001*** [0.000]	0.000 [0.001]		
Social capital index					0.001*** [0.000]		0.001*** [0.000]		
Employment density						–0.000*** [0.000]	0.861* [0.476]		
Constant	–2.370*** [0.171]	–2.682*** [0.228]	–2.258*** [0.178]	–2.637*** [0.187]	–3.657*** [0.439]	–2.290*** [0.176]	–3.522*** [0.537]	–5.203*** [0.104]	–2.802*** [0.090]
Observations	400	400	400	400	250	400	250	400	400
R-Squared								0.851	0.777
Instruments	16	24	23	21	29	30	36		
Hansen	39.34	42.20	42.23	37.34	41.89	44.57	42.39		
Hansen p-value	0.000176	0.00260	0.00165	0.00188	0.00935	0.00654	0.0518		
AR(2)	0.254	0.0950	0.146	0.0466	0.0195	0.107	0.0582		
AR(2) p-value	–1.142	–1.670	–1.453	–1.990	–2.336	–1.611	–1.894		

Standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. System GMM estimates are two-step efficient and apply the small sample correction by Windmeijer (2005).HK are fractions of workforce in each educational attainment level over the total. The data source is IVIE (Instituto Valenciano de Investigaciones Economicas). Employment (thousand of people) comes from BBVA «La renta nacional de España y su distribución provincial: una publicación histórica del Servicio de Estudios del Banco de Bilbao» by Sánchez Asiaín and Urquijo de la Puente (2004). Capital Stock estimates come from IVIE and BBVA: «Capital stock in Spain and its distribution by territories (1964-2007)». Social Capital index comes from «Estimation del capital social en España. Series temporales por territorios», IVIE.

nificant impact of average human capital on regional economic growth. Interestingly, when we also introduce both capital stock and employment proxies to the baseline regression, the effect of average human capital (if statistically significant) is negative.

Even if at first sight surprising, the empirical estimates of the linear impact of average human capital on economic growth are in line with the so called Krueger and Lindhal's puzzle for which a variety of empirical studies found no correlation between economic growth and average human capital in a variety of settings and for different samples of countries and regions. A similar result is found by Pritchett (1996) who argues that «the estimated impact of growth of human capital [...] is large, strongly significant, and negative» or in the catch-up study by Benhabib and Spiegel (1994). Also, de la Fuente and Domenech (2006) highlight how «Educational variables frequently turn out to be insignificant or to have the "wrong" sign in growth regressions, particularly when these are estimated using first-differenced or panel specifications».

Results on the impact of average human capital on regional catch up are also robust to different econometric specifications such as the use of simple Ordinary Least Squares (OLS) in column (8) and of Least Squares Dummy Variable estimators (LSDV) in column (9). It is important to recall, however, that the endogeneity of the OLS regressor leads generally to an upward bias in the estimation of the coefficients. A solution to this bias can be that of transforming the data so as to remove the fixed effects by exploiting the Least Squares Dummy Variable (LSDV) approach. However, it has been shown that this transformation do not fully deal with the correlation of the endogenous regressor with the error term. In fact, the LSDV transformation still produces a negative correlation between the error term and the regressor which ends up biasing downwards the estimated coefficient. These problems, however, are solved when we apply system GMM estimators for which a reasonable coefficient of the lagged dependent variable should be found somewhere in between the OLS and LSDV estimates. Indeed, this is our case, which advocates for the use of SYSGMM as suitable estimator throughout our analysis while OLS and LSDV should be regarded as robustness checks of the baseline specification.

As argued before, the «wrong» sign of the average measure of human capital may be actually masking a deeper dynamic for which the composition of regional human capital stocks (rather than the average levels) may actually explain the process of catch-up. This is, indeed, the main hypothesis of our work and it is in line with the theoretical model predictions of our model. We turn to this analysis in the next section.

6.2. Human capital composition and regional catch-up

We now turn to the analysis of the impact of different educational categories on the process of regional GVA per capita catch-up. Results of the SYSGMM estimation in table 5 show a statistically significant effect of the share of active population with tertiary education on regional convergence. Over the period 1965-1997, data seem to

Table 5. Dependent Variable: GVA GAP per capita, NUTS3 (4-year span panel between 1965-1997)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
Initial GVA per capita	0.508*** [0.040]	0.436*** [0.041]	0.534*** [0.040]	0.508*** [0.052]	0.697*** [0.057]	0.434*** [0.036]	0.743*** [0.055]
HK5	0.055*** [0.012]	0.040*** [0.013]	0.045*** [0.011]	0.063*** [0.016]	0.031** [0.013]	0.034** [0.014]	0.017* [0.010]
HK4	–0.032* [0.016]	0.005 [0.016]	–0.020 [0.015]	–0.044* [0.024]	0.005 [0.017]	0.013 [0.019]	0.016 [0.012]
HK3	0.017*** [0.005]	0.021*** [0.006]	0.016*** [0.005]	0.013* [0.007]	0.020** [0.008]	0.017*** [0.006]	0.016** [0.007]
HK2	0.021*** [0.006]	0.025*** [0.007]	0.021*** [0.005]	0.016** [0.008]	0.025*** [0.008]	0.021*** [0.007]	0.022*** [0.007]
Employment		0.000*** [0.000]		0.000*** [0.000]	0.000 [0.000]		
Capital Stock			0.000* [0.000]	–0.002*** [0.001]	–0.000 [0.001]	–0.002** [0.001]	–0.000 [0.000]
Social capital index					0.001*** [0.000]		0.001*** [0.000]
Employment Density						3.246*** [0.947]	0.573 [0.370]
Constant	–5.48*** [0.558]	–5.57*** [0.613]	–5.64*** [0.480]	–5.08*** [0.710]	–7.24*** [0.715]	–5.24*** [0.659]	–7.27*** [0.631]
Observations	400	400	400	400	250	400	250
Instruments	40	47	48	36	47	43	47
AR(2)	–1.449	–2.297	–1.910	–1.356	–2.532	–2.440	–2.984
AR(2) p-value	0.147	0.0216	0.0561	0.175	0.0113	0.0147	0.00284
Hansen	45.01	47.29	48.12	42.35	47.93	46.10	48.86
Hansen p-value	0.0982	0.199	0.207	0.0402	0.130	0.0994	0.111

Standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. System GMM estimates are two-step efficient and apply the small sample correction by Windmeijer (2005).HK are fractions of workforce in each educational attainment level over the total. The data source is IVIE (Instituto Valenciano de Investigaciones Economicas). Employment (thousand of people) comes from BBVA «La renta nacional de España y su distribución provincial: una publicación histórica del Servicio de Estudios del Banco de Bilbao» by Sánchez Asiaín and Urquijo de la Puente (2004). Capital Stock estimates come from IVIE and BBVA: «Capital stock in Spain and its distribution by territories (1964-2007)». Social Capital index comes from «Estimation del capital social en España. Series temporales por territorios», IVIE.

confirm the importance of tertiary education as a driver of economic convergence. For all econometric specifications, the coefficient for higher education (HK5) show the expected sign and it is statistically significant at 1 or 5 percent confidence level. The marginal effect of an increase in the skill content of the followers workforce seem to drive the convergence towards the leaders GVA values and a reduction of the output gap.

Interestingly, our results show that the impact of «intermediate» education (HK4), proxying for non technical diplomas, seems to relatively slow down convergence. The interpretation to this result lies in the different technical and technological content of the heterogenous educational categories as highlighted by the theoretical model.

On the one hand, tertiary education usually provides individuals with more sophisticated tools in order to compete and create new opportunities which exploit the latest technological frontier and eventually boost economic growth. To put it in other words, when it comes to implement leading edge and more profitable technologies (as in the catch-up hypothesis) having more technical and specialized education (as in the case of tertiary education vs diplomas) is going to ease the implementation and adoption process similarly to what hypothesized by Nelson and Phelps (1966). The region with higher skills, in fact, will be adopting and implementing the latest (and more profitable) technology at a faster pace since its workforce (in relative terms) is more able to discern among profitable technologies and to adopt or modify them for its specific technology and productive needs.

Eventually, all regions will end up adopting this new technology frontier but the learning curve for the unskilled region will be longer than that for the skilled one, preventing the former to exploit a profitable technology for a considerable longer time (leading to a relatively slower growth). Our econometric work confirms this hypothesis showing robust evidence of the positive impact of tertiary education on the reduction of Spanish GVA per capita gaps.

On the other hand, hence, our results argue that those regions that accumulated larger shares of less technically educated workforce (as it may be argued it is the case of the category HK4) are comparatively less able to implement new technologies and transpose these new technologies into productivity gains. As a confirmation of this intuition, the estimated impact of secondary and vocational training (technical) education (HK3) is positive and statistically significant arguing that tertiary education (and especially vocational training) may be complementary in the productive chain. As argued by Easterly (2002), «Production is often a series of tasks. Think of an assembly line in which each worker successfully works on a product. The value of each worker's effort depends on the quality of all the other workers» [11]. This creates a strong incentive for the best workers (tertiary, technically educated) to match up with other very good workers (technical secondary education, vocational training) so that the work done by highly educated workers in early stages of the

[11] See Easterly (2002), «The elusive quest for growth», p. 155.

technology implementation does not go to waste due to mistakes, made later, in the productive chain.

Interestingly, social capital enters the regression with a positive and highly significant coefficient as expected. This result shows how, for those provinces in which trust and economic cooperation are more developed, the GVA convergence process is actually faster. The assumption is that a higher level of social capital will be growth beneficial and therefore associated to a reduction in the GVA gaps across provinces by decreasing transaction costs or, as in Hall and Jones (1999), by reducing the costs of social diversion: «Social institutions to protect the output of individual productive units from diversion are an essential component of a social infrastructure favorable to high levels of output per worker. Thievery, squatting, and Mafia protection are examples of diversion undertaken by private agents».

This pattern of results is robust to the introduction of various control variables such as capital stock, employment levels and the employment density (computed as the share of employed workforce over the regions area). The estimated coefficients for the different educational categories change only slightly after the introduction of additional control variables and argue for the robustness of the obtained results. Finally, as an additional robustness check, we re-estimate the baseline specification dropping conveniently pairs of educational categories in order to check the sensitivity of the estimated coefficients. Robustness checks are proposed in table 6 below.

Table 6. Dependent Variable: GVA GAP per capita, NUTS3 (4-year span panel between 1965-1997)

	(1)	*(2)*	*(3)*	*(4)*
Initial GVA per capita	0.504*** [0.043]	0.409*** [0.041]	0.380*** [0.038]	0.536*** [0.044]
HK5	0.058*** [0.015]	0.033** [0.013]		
HK4	–0.038* [0.021]	–0.050*** [0.015]	–0.027** [0.012]	
HK3	0.014** [0.007]		0.002 [0.002]	0.002 [0.003]
HK2	0.018** [0.008]			0.005* [0.003]
Constant	–5.171*** [0.685]	–2.942*** [0.253]	–2.792*** [0.239]	–4.272*** [0.403]
Observations	400	400	400	400
Instruments	31	19	19	19
AR(2)	0.188	0.276	0.134	0.00563

	(1)	*(2)*	*(3)*	*(4)*
AR(2) p-value	–1.318	–1.090	–1.498	–2.769
Hansen	42.42	30.32	33.62	44.24
Hansen p-value	0.0162	0.0108	0.00385	0.000101

Standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. System GMM estimates are two-step efficient and apply the small sample correction by Windmeijer (2005).HK are fractions of workforce in each educational attainment level over the total. The data source is IVIE (Instituto Valenciano de Investigaciones Economicas). Employment (thousand of people) comes from BBVA «La renta nacional de España y su distribución provincial: una publicación histórica del Servicio de Estudios del Banco de Bilbao» by Sánchez Asiaín and Urquijo de la Puente (2004). Capital Stock estimates come from IVIE and BBVA: «Capital stock in Spain and its distribution by territories (1964-2007)».

When we explain regional economic convergence by using only upper education (both tertiary and pre-tertiary education) we find confirmation of the positive impact of higher education (HK5) and of the negative impact (as in the full baseline model) of lower/intermediate education (HK4). It is important to stress that the obtained point estimates should not be directly compared to those of the full baseline model presented in table 5 since the base education category is now represented by all workforce with a education below the pre-tertiary level. However, even if not immediately comparable, point estimates are very close to those obtained in the full baseline. This argues in favor of the robustness of the empirical results. Also, when we only analyze intermediate education (both HK4 and HK3) we observe again the negative impact of pre-tertiary education and a not statistically significant (even if positive) effect of secondary education. Finally, we try to re-estimate the model by only using lower education (primary and secondary). Result show again a modest impact of primary education on regional convergence but with a coefficient much lower than the one estimated previously for tertiary education.

7. Conclusions

The impact of human capital on economic growth has been questioned by recent empirical literature. We start from these criticisms by pointing, similarly to other contributions, that what matters for growth is not the average stock of human capital but the specific composition which shapes the innovation and adoption technological possibilities of the economies.

We merged features from different previous contributions such as Behnabib and Spiegel (2005) and Vandenbussche, Aghion and Meghir (2005) in order to formalize the technology cost function and dynamics of the follower region. The relative easiness of adoption, its cost, has been assumed to be a function of the proximity to the technological frontier as well as of the quality of human capital devoted to adoption in the follower region.

Our identifying assumption, alternative to that by Vandenbussche, Aghion and Meghir (2005), implies that the increase in the high skill content of the follower's workforce reduces the cost of technology adoption. Regions more endowed with high skilled workers will be able to adopt the technology frontier faster and to take advantage of its productive possibilities.

Along with the follower's human capital composition, also the quality of regional institutions and of social capital play a fundamental role in defining the convergence condition. The model, consistently with previous empirical literature such as Hall and Jones (1999), shows how improvements in the quality of regional institutions and in social capital increase the long run proximity of follower economies to the technological frontier.

We test the main theoretical results of our model on 50 Spanish NUTS3 provinces for the period 1965-1997 by making use of a dynamic panel model. Our results seem to confirm the main hypothesis of the theoretical model for which average measures of human capital are not adequate proxies in order to unveil the catch-up dynamics properly. When we analyze the impact of average years of schooling on regional catch-up (at the NUTS3 level) we do not find positive and statistically significant evidence. If any, the contribution of average human capital to economic growth seems to be negative as highlighted also in previous empirical literature both at the country and regional level.

The impact of human capital on the reduction of GVA differential across regions is instead non-linear. Increasing the average human capital level (especially increasing intermediate and generalistic educations and diplomas) do not seem to lead to faster convergence. Instead, it is tertiary education and, mildly, vocational training and secondary education to lead to faster catch-up in our estimates. Empirical results are in line with the prediction of our theoretical model. Higher educational levels enter with a positive coefficient in our regressions indicating how increasing the high skill content of each regional workforce seems to be conductive to higher economic growth and convergence. Instead, intermediate and lower educational levels seem to negatively contribute to growth in the long run. The basic result is robust to different specifications and to the introduction of various control variables such as physical capital, employment (and its density in each province) as well as to social capital, which is shown to be one long-run determinant of economic convergence in Spain during the period examined.

Appendix 1

Table A.1. Descriptive statistics

NUTS2 and NUTS3 REGIONS	*Average HK1*	*Average HK2*	*Average HK3*	*Average HK4*	*Avera-ge HK5*	*Social Capital Index*	*Log annual GVA per capita growth*	*Initial GVA gap*
Almería	7.22	66.97	18.82	4.34	2.66	29.60	3.40	0.33
Cádiz	6.06	64.73	22.30	4.33	2.58	16.67	2.72	0.42
Córdoba	7.17	65.16	20.59	4.29	2.79	25.26	3.05	0.40

NUTS2 and NUTS3 REGIONS	*Average HK1*	*Average HK2*	*Average HK3*	*Average HK4*	*Avera-ge HK5*	*Social Capital Index*	*Log an-nual GVA per capita growth*	*Initial GVA gap*
Granada	7.80	61.75	21.33	4.90	4.21	23.27	2.94	0.34
Huelva	7.98	62.39	22.97	4.51	2.15	15.58	3.62	0.37
Jaén	7.89	65.69	20.19	4.12	2.12	15.58	3.46	0.35
Málaga	6.88	63.34	23.00	4.15	2.63	26.27	2.33	0.48
Sevilla	6.98	61.09	24.03	4.12	3.78	26.20	2.17	0.50
Huesca	1.08	66.40	24.16	5.02	3.33	68.15	2.22	0.70
Teruel	2.24	70.15	19.73	5.07	2.81	36.97	3.83	0.42
Zaragoza	1.46	60.70	28.24	4.91	4.69	69.51	2.64	0.68
Asturias	1.00	64.75	25.93	4.66	3.65	47.75	2.13	0.62
Cantabria	0.68	62.42	28.04	5.07	3.79	58.40	2.27	0.63
Albacete	4.05	67.84	21.72	4.02	2.36	39.33	3.13	0.36
Ciudad Real	7.85	63.75	21.77	4.12	2.51	24.60	3.22	0.39
Cuenca	5.15	67.79	20.12	4.57	2.37	48.61	3.65	0.33
Guadalajara	2.78	67.56	20.13	5.29	4.23	36.16	3.82	0.47
Toledo	5.39	67.99	21.24	3.04	2.34	43.44	3.57	0.37
Ávila	2.62	69.31	20.58	4.82	2.67	41.59	3.82	0.34
Burgos	0.87	63.87	27.04	4.68	3.54	50.85	3.37	0.53
León	1.69	66.12	23.93	5.02	3.25	50.85	2.71	0.48
Palencia	1.25	67.17	22.39	5.29	3.90	31.99	3.22	0.49
Salamanca	1.27	68.01	20.26	5.16	5.31	33.24	2.71	0.54
Segovia	0.95	65.91	23.77	4.98	4.39	60.35	3.20	0.45
Soria	0.52	67.06	22.90	5.40	4.11	55.63	3.61	0.42
Valladolid	1.15	60.82	27.93	5.37	4.73	32.12	2.77	0.59
Zamora	1.77	72.73	18.24	3.91	3.36	29.12	3.01	0.40
Barcelona	1.72	57.96	31.41	4.31	4.60	82.81	2.11	0.90
Girona	2.39	60.76	30.07	3.84	2.94	111.57	2.36	0.87
Lleida	1.61	65.80	24.85	4.51	3.23	101.58	2.83	0.64
Tarragona	3.27	62.58	27.40	3.78	2.97	58.65	2.78	0.68
Badajoz	8.68	64.25	20.52	4.20	2.36	18.34	3.21	0.32
Cáceres	4.99	70.94	17.12	4.37	2.58	26.19	4.04	0.33
A Coruña	2.35	70.74	20.04	3.85	3.02	57.16	3.28	0.42
Lugo	4.99	73.72	16.48	3.08	1.74	57.04	3.40	0.36

NUTS2 and NUTS3 REGIONS	*Average HK1*	*Average HK2*	*Average HK3*	*Average HK4*	*Average HK5*	*Social Capital Index*	*Log annual GVA per capita growth*	*Initial GVA gap*
Ourense	6.23	72.48	16.06	3.01	2.21	56.32	3.57	0.34
Pontevedra	4.99	68.07	21.36	3.24	2.34	62.93	3.12	0.43
Islas Baleares	3.95	61.67	27.57	3.65	3.16	93.00	2.62	0.81
Las Palmas	6.41	59.89	25.57	5.18	2.95	34.04	2.95	0.52
Sta. Cruz Tenerife	7.06	59.62	25.06	4.74	3.52	33.73	3.12	0.50
La Rioja	0.83	66.77	23.30	4.87	4.23	69.12	2.88	0.67
Madrid	1.59	50.38	33.86	5.49	8.68	154.42	1.72	1.00
Murcia	5.91	61.85	24.31	4.44	3.50	45.43	2.73	0.48
Navarra	1.18	58.70	29.47	5.70	4.96	64.18	2.85	0.68
Álava	0.93	57.94	31.88	4.98	4.27	69.85	2.43	0.89
Guipúzcoa	1.00	59.48	30.42	4.95	4.15	68.71	1.67	0.88
Vizcaya	0.92	55.62	31.61	5.66	6.18	68.71	1.93	0.88
Alicante	4.19	64.57	25.26	3.66	2.32	50.41	2.28	0.59
Castellón	2.97	68.43	22.42	3.53	2.65	57.85	2.90	0.63
Valencia	2.15	61.82	27.33	4.65	4.04	48.60	2.44	0.66
min	0.52	50.38	16.06	3.01	1.74	15.58	1.67	0.32
max	8.68	73.72	33.86	5.70	8.68	154.42	4.04	1.00
Average	3.48	64.16	24.28	4.53	3.55	53.39	2.87	0.56
S.D.	2.50	4.70	4.26	0.68	1.29	27.80	0.57	0.19

Legend: HK variables are the fraction of active population in each educational attainment level over the total. Data come from the IVIE (Instituto Valenciano de Investigaciones Economicas) is association with BBVA- Banco Bilbao Vizcaya Argentaria , http://www.ivie.es/downloads/caphum/2007/metodologia.pdf.
Social Capital index also comes from IVIE and BBVA: http://www.ivie.es/banco/ksocial.php?idioma=EN. GVA per capita series comes from BBVA in » La renta nacional de España y su distribución provincial: una publicación histórica del Servicio de Estudios del Banco de Bilbao«by Sánchez Asiaín and Urquijo de la Puente (2004). Initial GVA gap is computed as the ratio between each region and the leader, Madrid. Averages values are computed over the period 1965-1997 for both NUTS2 and NUTS3 regions.

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