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# Human Capital Composition and Economic Growth at the Regional Level

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## Abstract

This paper analyzes the impact of human capital composition on regional catch-up for Spain over the period 1960-1997. Empirical evidence shows that human capital has a non-linear impact on convergence at both NUTS2 and NUTS3 geographical disaggregation levels. Tertiary education drives regional catch-up while the accumulation of non-technical education slows down this convergence. When we control for the development stage of the regions, strong complementarities seem to arise between different types of skills. Closer to the frontier, the complementarities between tertiary education and secondary/vocational training drive the convergence process while the impact of intermediate education is weak for regions at lower development stages.

**Keywords:** Human capital composition, growth, catch-up

**JEL code:** O31, O33, I25, I21

## 1. Introduction

As pointed out by Acemoglu and Dell (2009), "*between-municipality [regional] differences in labor income are about twice the size of between-country differences*". These authors argue 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"*".<sup>1</sup>

Following Acemoglu and Dell's (2009) intuition we understand "technology", in a regional context, as the "*production possibility frontier facing a society, which we may refer to as [its] technological know-how*". What matters for regional economic growth is, therefore, the relative efficiency with which economic agents in each region are capable of

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2  
3 implementing and adopting the available *know-how* (technology) and taking advantage of it  
4  
5 profitably.  
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8 Growth literature (both theoretical and empirical) has usually looked at human capital as  
9  
10 one of the main factors behind the accumulation and implementation of new innovations  
11  
12 and technology, human capital being the proxy for the absorptive capacity of firms, regions  
13  
14 and countries.  
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16  
17 Nonetheless, recently, authors such as Krueger and Lindhal (2001) raised some doubts as to  
18  
19 the positive impact of average human capital stock on economic growth.  
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21  
22 In the search for an explanation for this puzzle, recent empirical evidence (de la Fuente and  
23  
24 Doménech (2006) and Cohen and Soto (2007) seriously questions the quality and  
25  
26 homogeneity of the data on international educational levels used in cross-country growth  
27  
28 regressions. This criticism, however, is on much weaker ground when we turn (as we do  
29  
30 here) to a regional context in which the data are far more homogenous than for cross-  
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32 country analyses.  
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35  
36 Recent influential contributions from Vandebussche, Aghion and Meghir (2006) and di  
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38 Maria and Stryszowski (2009) have also questioned the assumption that average human  
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40 capital measures can actually explain the growth process. The hypothesis, simple enough, is  
41  
42 that different types of human capital (low vs high skilled workers) may be differently suited  
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44 to economic growth depending on the development stage of the economy under  
45  
46 consideration, that is, on its distance to the technology frontier.  
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49  
50 Along a similar line of research, the work by Sequeira (2003) empirically shows the  
51  
52 specific contribution of high-tech human capital to economic growth as well as the  
53  
54 unexpected evidence of an inverted U-shaped relationship between tertiary education and  
55  
56 development and GDP per capita across countries while Simon (1998) focuses the analysis  
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3 at the city and MSAs level.

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5 With this paper we introduce into this line of research for which "*to solve the puzzle posed*  
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*by Krueger and Lindhal, we [...] need to focus attention both on an economy's distance to*  
*the technological frontier and on the composition of its human capital".*<sup>2</sup>

We depart from previous literature on a number of aspects. On the one hand, we start from the assumption that the adoption and implementation of technology (and of the *frontier technology know-how*) is indeed a "skill-costly" activity and, hence, it will be intrinsically better performed by skilled workers rather than unskilled ones. Even if at first sight it appears similar, our *human capital composition* hypothesis crucially differs from the results put forward by Vandebussche, Aghion and Meghir (2006) who suggest that "*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*"<sup>3</sup>. 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 less developed regions (and countries) all the more they are under-developed. We believe instead that better skills reduce the cost of technology adoption and speed up convergence rates. Our rationale is very much in line with the intuition of Nelson and Phelps (1966) who argue that "*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*".

On the other hand, we focus our analysis at the regional level where, as pointed out by Acemoglu and Dell (2009), far more variation in GDP per capita gaps is actually observed.

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3 However, to the best of our knowledge, few studies have considered these issues at this  
4 disaggregation level. Diliberto (2008) for Italy and Ramos et al. (2009) for Spain show  
5 mixed results regarding the impact of human capital composition. For Italy, Diliberto  
6 (2008) finds, similarly to Vandebussche, Aghion and Meghir (2006), that primary  
7 education (rather than secondary or tertiary) is more important in regions which are already  
8 lagging far behind the frontier. Ramos et al. (2009), instead, show that tertiary education  
9 has been the leading force behind the regional convergence process in Spain over the last  
10 few decades.  
11

12 The discrepancies seen in the results of these contributions represent an extra motivation  
13 for our work. In addition to that, we believe that recent studies do not always sufficiently  
14 control for the simultaneity bias arising between human capital and economic growth, a  
15 failing that may well affect the robustness of their econometric estimates.  
16

17 On the econometric side, therefore, we improve on previous empirical evidence by  
18 applying the system GMM estimators proposed by Arellano and Bover (1995). These  
19 estimators enable us to tackle simultaneity biases while also outperforming first-difference  
20 GMM estimators in the case of persistent explanatory variables, as it is the case for  
21 educational variables in our regressions. In addition to this, we also correct for small  
22 sample biases by applying the two-step optimal estimation procedure proposed by  
23 Windmeijer (2005).  
24

25 Our analysis is ran over different time periods and different human capital databases as well  
26 as on both NUTS2 and NUTS3 regional disaggregation levels for Spain. Empirical  
27 estimates show that regional economic convergence is robustly explained by the fraction of  
28 workforce with tertiary education for the period 1960-1997. Those regions which  
29 succeeded in changing the composition of their human capital by increasing the share of  
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3 highly educated workers (as a proportion of their total workforce) are shown to close the  
4 gap to the frontier faster. Conversely, an increase in the fraction of workforce with  
5 intermediate degrees (diplomas or non technical degrees) negatively affects the speed of  
6 regional convergence. Intuitively these results point to the different absorptive capacity of  
7 each educational attainment level when it comes to implementing new technologies  
8 implying that any redistribution of workers toward middle (rather than higher) levels of  
9 education will be likely to slow down the catch-up rate to the frontier<sup>4</sup>.

10  
11 Starting from these results, we examine whether these dynamics have changed over time as  
12 a consequence of the important productive and institutional shifts observed over the last  
13 few decades in the Spanish economy. Indeed, starting from the 80's, our results highlight a  
14 robust increase in the importance of secondary education and vocational training for  
15 economic convergence. Interestingly similar results are obtained when we split the regional  
16 sample into rich and poor regions. If tertiary education equally (and positively) affect both  
17 rich and poor regions' economic growth the impact of vocational training and secondary  
18 education is stronger in those regions which have already consistently closed part of their  
19 technology gap and are closer to the frontier. This result is driven by the complementarity  
20 links between tertiary and middle education categories which becomes stronger as regions  
21 move towards the technology frontier and catch-up. Finally, econometric estimates are  
22 shown to be robust to the introduction of a variety of controls such as physical capital and  
23 employment measures (both in levels and growth rates), social capital and employment  
24 density in the region.

25  
26 The remainder of the paper is as follows. In Section 2 we present the empirical model and  
27 the data used. There, we also discuss the important issues relating to the severe endogeneity  
28 between human capital and economic growth and the way we tackle them. In Section 3 we



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3 present the empirical results of both a linear and non-linear human capital specification at  
4 NUTS2 level. In Section 4 we analyze similar dynamics at NUTS3 level while we also  
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6 present the regression results of the development-specific effect of human capital  
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8 composition. In the last section we summarize the conclusions.  
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## 12 2. The empirical model

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15 The econometric specification that we implement aims to depict the relation between the  
16 evolution of regional GVA gaps (catch-up mechanism) and the composition of each  
17 region's human capital. In concise form, our empirical model is as below:  
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$$23 \quad GVAgap_{i,t} = c + \beta_1 EduAttain_{i,t} + \beta_2 Z_{i,t} + \mu_i + v_{i,t} \quad (1)$$

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26 where we define the *GVA gap* as the log of the ratio between the GVA per capita of each  
27 observed region w.r.t. to the value of Madrid which we assume to be our empirical leader  
28 region. *EduAttain* proxies for the human capital composition of each region. To this end, as  
29 pointed out before, we use the fraction of active population in each educational category as  
30 a proxy of the relative importance of the different human capital types in the catch-up  
31 process. In order to avoid multicollinearity problems we exclude the share of population  
32 with no education (HK0) from the estimations<sup>5</sup>.  
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47 Our specification differs from standard growth regressions due to the accuracy with which  
48 we try to depict the impact of human capital *composition* in the catch-up process. However,  
49 as happens with other growth regressions, in order to properly disentangle the magnitude  
50 (and effect) of each educational category on the growth process we also control for a set of  
51 other variables such as regional physical capital stock, the employment level as well as its  
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3 density in the region and their growth rate over the period. We also control for the initial  
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5 GVA per capita and for socio-economic difference across regions by making use of the  
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7 available proxy for social capital. In eq. (1) all these control variables are captured by Z.  
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## 10 2.1 Data

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12 Our analysis focuses on 17 autonomous communities (Comunidades Autonomas) in Spain<sup>6</sup>  
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14 as well as 50 Spanish NUTS3 regions. The time span chosen ranges from 1960 to 1995 for  
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16 the analysis carried out at NUTS2 level and from 1965 to 1997 for the analysis at NUTS3  
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18 level. For the former, our analysis exploits a 5-year dynamic panel model while for the  
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20 latter, due to a better match with other available series the dynamic panel will have a span  
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22 of 4 years. The GVA series, which we use in order to compute the gap in output levels of  
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24 each region w.r.t. the leader, are expressed in per capita terms and were made available by  
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26 the Fundación BBVA<sup>7</sup>.  
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31 As we mentioned above, because we are interested in the specific effect caused by human  
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33 capital composition on the convergence process, human capital variables have been  
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35 computed as the share of the active population in each educational attainment level over the  
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37 total active population in the region. The human capital data come from two different  
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39 sources enabling us to check the robustness of the results when different databases are used  
40  
41 to proxy for attainment levels.  
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46 At NUTS2 level we make use of the data proposed by de la Fuente, Domenéch (2006).  
47  
48 These data conveniently allow us to disaggregate the population aged 25 and over by  
49  
50 category of educational attainment. To be more specific we focus on the following  
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52 educational attainment categories<sup>8</sup>: (HK1) primary - *primaria, graduado escolar* which has  
53  
54 duration of 5 years, (HK1.2) lower secondary - *EGB, Bachiller elemental, ESO* which has  
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3 duration of 3 years, (HK2) upper secondary - *Bachillerato, COU, FP I and FP II* which has  
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5 duration of 4 years, (HK3) higher education, first level - *Diplomatura, Peritaje* which has  
6  
7 duration of 2 years and finally (HK4) higher education, second level - *Licenciatura* which  
8  
9 has duration of 3 years.  
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11  
12 Human capital data at NUTS3 level come instead from the "Human capital series" provided  
13  
14 by the Instituto Valenciano de Investigaciones Economicas (IVIE) in collaboration with  
15  
16 Bancaja<sup>9</sup>. This refers to the following nominal categories: (HK0) illiterate, (HK1) primary  
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18 schooling, (HK2) compulsory secondary schooling, (HK3) pre-university education and  
19  
20 (HK4) higher education<sup>10</sup>.  
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25 Along with human capital, recent growth literature has identified social capital as an  
26  
27 additional driver of economic growth. Higher levels of social capital, trust and confidence  
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29 in the rules are likely to increase the flow of information and collaboration among firms  
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31 and individuals and thus to smoothen technology spillovers. As pointed out by Hall and  
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33 Jones (1999), social capital helps "*to protect the output of individual productive units from*  
34  
35 *diversion [and this is] an essential component of a social infrastructure favorable to high*  
36  
37 *levels of output per worker. Thievery, squatting, and Mafia protection are examples of*  
38  
39 *diversion undertaken by private agents*". Sequeira and Ferreira-Lopes (2008) recently  
40  
41 studied the role played by social capital and its interactions with human capital<sup>11</sup>.  
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45  
46 Data proxying for social capital at NUTS2 and NUTS3 level are indeed very hard to find.  
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48 To the best of our knowledge, the best approximation for the Spanish case is provided by  
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50 the data of social capital produced by the IVIE in collaboration with the BBVA Foundation.  
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52 In particular, the approach followed in constructing the data for Spanish social capital  
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54 focused on the "*social relationships that evolve in the economic sphere, particularly in*  
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56 *employment, financial or investment markets, in which long-lasting relationships exist in*  
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3 contexts of uncertainty and strategic interdependence" for which "in a context of abundant  
4 social capital, transaction and supervision cost, together with uncertainty, will be lower  
5 than in other societies with lower social capital. This favorable environment will generate  
6 higher income levels than those that would correspond to the contribution of production  
7 function"<sup>12</sup>, i.e. it will increase technology spillovers. Along with the variables that capture  
8 human and social capital mentioned above, we enrich the analysis by controlling for the  
9 effect that capital and employment differences across regions may have on regional  
10 economic performance as in standard convergence literature. Both employment and capital  
11 stock data are provided by the IVIE and BBVA respectively in "*La renta nacional de*  
12 *España y su distribución provincial: una publicación histórica del servicio de estudios del*  
13 *banco de Bilbao*" and "*Capital stock in Spain and its distribution by territories (1964-*  
14 *2007)*".

15  
16 In Table 1 we provide the descriptive statistics for the different educational attainment  
17 levels at NUTS3 level as well as their aggregation (in shaded rows) at NUTS2 level<sup>13</sup>.  
18 Along with the human capital variables we also provide the statistics for social capital and  
19 both the initial GVA per capita gap and its growth rate.

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21  
22 [TABLE 1 ABOUT HERE]

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25 As far as the average illiteracy rate (HK0) is concerned, the maximum value (8.68) belongs  
26 to the province of Badajoz (Extremadura) while the lowest score (0.52) is attributed  
27 surprisingly to the province of Soria (Castilla y Leon, probably due to the dynamics of  
28 recent decades ). At the other end of the *spectrum* the highest average share of tertiary  
29 education (8.68) is, as expected, scored by the region of Madrid while the lowest share  
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3 (1.74) applies to the province of Lugo (Galicia). The region of Madrid also scores highest  
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5 in the average social capital index.  
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8 In Figures 1 to 7 we provide the geographical distribution across NUTS3 regions of  
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10 different variables of interest and their evolution over time. As expected the geographical  
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12 distribution of tertiary education (HK4) across Spain is shown to be quite uneven in 1965,  
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14 the first year of observation. Higher shares of skilled workers are concentrated in central-  
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16 northern regions (Fig.1) while the lowest concentration of tertiary education can be found  
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18 in central and southern regions. As we move to the dynamics of tertiary education (fig. 2), a  
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20 clear pattern of convergence in higher education seems to have taken place, with those  
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22 regions which started with very low values of tertiary education increasing their skill  
23  
24 intensity more than others. Interestingly, if we compare the geographical distribution of  
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26 tertiary education with that of GVA per capita (in fig. 3 and 4) we can notice some striking  
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28 similarities. Southern and central regions which started with low shares of tertiary  
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30 education were, at the same time, lagging far behind the frontier in terms of GVA in 1965.  
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32 However, the boost in the accumulation of tertiary education in southern regions such as  
33  
34 Extremadura, Castilla la Mancha and Murcia were followed by above the average GVA  
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36 growth and convergence over the period 1965-1997 (Fig. 4). At the same time, it also  
37  
38 seems that those northern regions which less increased on their initial shares of tertiary  
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40 education, contextually grew slower than the central and southern regions. The true  
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42 causality of this process is however difficult to be determined in this kind of statistical  
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44 analysis and it will be the focus of our econometric estimates in the following sections.  
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46 However, it is also interesting to notice how the geographical pattern of other educational  
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48 attainment levels' growth rate (of pre-tertiary education, HK3 and primary education, HK1,  
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50 for instance) do not resemble (at least not robustly) the level of GVA per capita growth  
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3 (Fig. 5, 6 and 7) suggesting that tertiary education may indeed have played a prominent role  
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5 in Spanish GVA convergence.  
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10 [FIGURES 1 TO 7 ABOUT HERE]  
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## 13 14 15 16 2.2 Econometrics issues and endogeneity treatment 17

18 The relation between education and economic growth is likely to be affected by severe  
19 endogeneity problems. In other words, the covariates may not be orthogonal to the error  
20 process and the resulting estimates may not be consistent. Within the dynamic panel  
21 settings this problem is usually addressed by making use of first-difference and system  
22 GMM estimators such as those proposed by Arellano and Bond (1991) or Arellano-  
23 Bover(1995)/Blundell-Bond (1998). These kinds of estimators allow to build internal  
24 instrumental sets relying on the moment conditions produced by exploiting lagged  
25 realizations of the variables in the model (both dependent and exogenous/endogenous ones)  
26 and have drastically improved on simpler OLS or LSDV estimators which, as shown in  
27 previous literature (see Nickell 1981, Kiviet 1995 or Bond 2002) are producing upward and  
28 downward biased coefficients respectively.  
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44 Apart from the endogeneity issues, our analysis faces another major statistical problem  
45 which relates to the use of educational variables as proxies for human capital composition.  
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47 As argued by Castelló (2006), educational variables are in fact usually highly persistent  
48 over time. It is well known that system GMM estimators for dynamic panel data models  
49 perform better than standard first-difference estimators when variables are persistent.  
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3 walk process the difference GMM estimators behave poorly because past levels of these  
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5 variables convey little information about future realizations.  
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8 To be slightly more specific, as pointed out by Roodman (2006), the Arellano and Bover  
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10 (1995) and Blundell and Bond (1998) estimators augment the standard Arellano and Bond  
11  
12 (1991) procedure by assuming that first differences of instrumenting variables are  
13  
14 uncorrelated with the fixed effects and by allowing the introduction of more instruments  
15  
16 which consistently improve the efficiency of the estimator.<sup>14</sup>  
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19  
20 The so called Difference GMM estimator relies on the transformation of all regressors,  
21  
22 usually by differencing them and, of course, makes use of the Generalized Method of  
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24 Moments (Hansen 1982) for estimation. The System GMM estimator, instead, relies on one  
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26 additional assumption that is that first differences of instruments are uncorrelated with the  
27  
28 fixed effects allowing the introduction of more instruments. This, as pointed out by  
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30 Roodman (2006), can dramatically improve efficiency especially when, as in our case, the  
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32 explanatory variables are likely to be persistent and to be weak instruments.  
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36 On the efficiency side, recent improvements in econometrics theory now allow the  
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38 researcher to use the so-called "two-step" System GMM estimator. Unlike the "one-step"  
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40 version, the two-step variant of the System GMM makes use of an "optimal" weighting  
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42 matrix which is the inverse of the estimate of  $Var[z'\varepsilon]$ , where  $z$  is the instrument vector  
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44 and  $\varepsilon$  the error term. It is argued that this 'optimal' weighting matrix makes the two-step  
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46 GMM asymptotically efficient although at the cost of producing severely downward biased  
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48 standard errors (Arellano and Bond 1991; Blundell and Bond 1998). This problem is even  
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50 more pronounced in the case of small samples and when the number of instruments is large.  
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55 As argued by Windmeijer (2005) and Roodman (2006), this problem may be as severe as to  
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3 make two-step GMM useless for inference.  
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6 Of course, in our specific analysis this may create severe estimation problems due to the  
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8 fact that the sample we are using for Spanish NUTS2 regions is not very large. Only  
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10 recently a correction to the downward bias of the two-step System GMM estimators has  
11  
12 been devised by Windmeijer (2005). In particular, Windmeijer (2005)<sup>15</sup> proposes a  
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14 correction to the two-step covariance matrix which it is argued can make the two-step  
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16 robust estimation more efficient than robust one-step especially for system GMM. For this  
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18 reason, we apply the correction to the two-step covariance matrix proposed by Windmeijer  
19  
20 (2005) to our estimations.  
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25 Another important issue, which is sometimes overlooked in the empirical literature, is  
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27 related to the possible overfitting of the endogenous variable by the creation of a too large  
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29 instrumental set. As pointed out by Roodman (2008), the software routines usually  
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31 employed for the computation of these estimators produce by default a very large number  
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33 of instruments which may actually overfit the endogenous variable in both Difference and  
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35 System GMM. The econometrician, therefore, must pay a great deal of attention to the  
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37 definition of the instrumental set. If the endogenous variable is overfitted by too many  
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39 instruments the estimator will produce implausibly good Hansen-test results with a P-value  
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41 very close to 1. As a rule of thumb it is argued that we should restrict the number of  
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43 instruments to be less than the number of individuals in the sample.  
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### 48 3. Econometric results

#### 49 3.1 Average human capital effect

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52 Before turning to the analysis of the non-linear effect that human capital has on regional  
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54 catch-up, it is useful to check whether average measures of human capital have any linear  
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3 impact on regional economic growth. The linear specification that we propose makes use of  
4  
5 average years of schooling to proxy for regional human capital stock. The results are  
6  
7 reported in Table 2.  
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12 [TABLE 2 ABOUT HERE]  
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17 Our proxy for the average years of education seems to explain robustly regional GVA  
18  
19 catch-up over the period 1960-1995. In Table 2 the results are reported using different  
20  
21 estimators in order to check the robustness of the SYSGMM estimator against the use of  
22  
23 simpler OLS or LSDV estimators. As pointed out by Kiviet (1995), Bond (2002) and  
24  
25 Roodman (2008), GMM estimators suffer from severe dynamic panel bias (see Nickell  
26  
27 1981) since the lagged realization of the dependent variable is correlated to the fixed effect  
28  
29 in the error term violating the necessary assumption for the OLS estimator to be consistent.  
30  
31 The endogeneity of the OLS regressor generally leads to an upward bias in the estimation  
32  
33 of the coefficient. A solution to this bias could be to transform the data so as to remove the  
34  
35 fixed effects by exploiting the Least Squares Dummy Variable (LSDV) approach.  
36  
37 However, it has been shown that this transformation do not fully deal with the correlation  
38  
39 of the endogenous regressor with the error term. In fact, the LSDV transformation does not  
40  
41 fully deal with the correlation between the error term and the regressor which ends up  
42  
43 biasing the estimated coefficient downwards. These problems, however, are solved by  
44  
45 applying system GMM estimators for which a reasonable coefficient of the lagged  
46  
47 dependent variable should be found somewhere in between the OLS and LSDV estimates.  
48  
49 Indeed, this is our case, which advocates for the use of SYSGMM as suitable estimator  
50  
51 throughout our analysis<sup>16</sup>. Both the Arellano and Bond (1991) test for autocorrelation in the  
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3 disturbance term and the Hansen test of overidentifying restrictions on the instrumental set  
4  
5 also perform well with statistics within the acceptable standard range.  
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8 The preliminary results on the linear effect of human capital on regional catch-up are also  
9  
10 robust to the introduction of capital stock and employment controls as well as to possible  
11  
12 changes in the observed dynamics over time<sup>17</sup>. When we split the sample into two  
13  
14 subperiods: "pre" and "post" 1981<sup>18</sup> the impact of human capital on regional convergence is  
15  
16 statistically significant over both subperiods even if it is shown to be stronger starting from  
17  
18 1981<sup>19</sup>. This said, however, the simple analysis of average human capital masks the  
19  
20 fundamental question of whether different educational categories have a specific effect on  
21  
22 the process of regional catch-up. We address this questions in the following sections.  
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### 26 27 3.2 Human capital composition effects, NUTS2 level. 28

29 We now turn to the analysis of the impact of different educational categories on the process  
30  
31 of regional GVA per capita catch-up. Results of the SYSGMM estimation in Table 3 show  
32  
33 a statistically significant effect of the share of active population with tertiary education on  
34  
35 regional convergence. Over the period 1960-1995, data seem to confirm the importance of  
36  
37 tertiary education as a driver of economic convergence at the regional level. Conversely,  
38  
39 our results show that the impact of "intermediate" education, proxying generally for non  
40  
41 technical diplomas (HK3), seems to relatively slow down convergence. The interpretation  
42  
43 of this (apparently robust) result lies in the different technical and technological content of  
44  
45 the heterogeneous educational categories.  
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48

49 On the one hand, tertiary education usually provides individuals with more sophisticated  
50  
51 tools to compete and create new opportunities which exploit the latest technological frontier  
52  
53 and eventually boost economic growth. In other words, when it comes to implementing  
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3 leading edge and more profitable technologies (as in the catch-up hypothesis) having a  
4 more technical and specialized education (as in the case of tertiary education vs diplomas)  
5  
6 will ease the implementation and adoption process as hypothesized by Nelson and Phelps  
7  
8 (1966).  
9

10  
11  
12 Technology spillovers and the adoption of new technologies do not in fact take place  
13 spontaneously and neither can they be thought of as a free lunch. The skill-costliness of  
14 imitation is widely observed and acknowledged in theoretical and empirical literature.  
15  
16 Mansfield, Schwartz and Wagner (1981), Coe and Helpman (1995) or Behnabib and  
17 Spiegel (2005) argue that the cost of the adapting and implementing technologies  
18 discovered at the frontier (or in other technological sectors) is usually positive and that it is  
19 tightly linked to the absorptive capacity of the economy in question. Mansfield, Schwartz  
20 and Wagner (1981) point out how, ranging over 48 different products in chemical, drug,  
21 electronics and machinery U.S. industries, the costs of imitation lay between 40% and 90%  
22 of the costs of innovation.  
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36 Interestingly, along with tertiary education also HK2, which proxies for the share of active  
37 population with secondary and vocational training, seems to reduce the gap to the frontier  
38 by easing the implementation and adoption of technology.  
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46 [TABLE 3 ABOUT HERE]  
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51 The baseline specification in column (1) is robust to the introduction of various control  
52 variables such as capital stock and employment levels as showed in column (2). Additional  
53 checks on the robustness of the results are presented in Table A.3 in the appendix, where  
54 we also control for the growth rate of capital stock and for changes in regional employment  
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3 levels (each computed over the 5-years time spans of our panel). Again, the instruments are  
4 valid as showed by the Arellano and Bond (1991) autocorrelation test and by the test on the  
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7  
8 overidentifying restriction in the Hansen statistics. The estimated coefficients for the  
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10  
11 different educational categories change only slightly after the introduction of additional  
12  
13 control variables and also when we drop specific educational categories from the regression  
14  
15 (namely *HK1.2* and *HK2* along with *HK0*).

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17  
18 In the last two columns of table 3, we control for possible changes in the catch-up dynamics  
19  
20 over time which may be related to the important institutional change that Spain underwent  
21  
22 in the early 80's<sup>20</sup> and which may have affected economic structure and growth patterns.  
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24  
25 Indeed, for the period before 1981, tertiary education seems to play a more important role  
26  
27 than later on<sup>21</sup>. Conversely, vocational training seems to be more important starting from  
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29 the early 80's. This result is likely to be related to the noticeable reduction in the regional  
30  
31 GVA per capita gaps which took place starting from the early 80's<sup>22</sup> and led to a stronger  
32  
33 complementarity between tertiary education and lower technical degrees such as those  
34  
35 proxied by secondary education and vocational training. The limited number of  
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37 observations at NUTS2 level does not allow us to split the sample so as to check the non-  
38  
39 linear effect of human capital composition at different development stages. We will discuss  
40  
41 this "development hypothesis", in the next sections of this paper when analyzing NUTS3  
42  
43 data.  
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### 48 3.3 Human capital composition effects, NUTS3 level.

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51 One of the main weaknesses of the NUTS2 level analysis is the limited number of  
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53 longitudinal observations available for the estimation. The analysis at NUTS3 level allows  
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55 us, instead, to exploit a larger database to which we compare the results obtained at  
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3 regional (NUTS2) level.

4  
5 The advantages for our analysis of using the NUTS3 data against the NUTS2  
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7  
8 disaggregation are various. On the one hand, we are able to introduce an additional control  
9  
10 variable proxying for social capital differences<sup>23</sup>. On the other hand, having four times  
11  
12 more observations than at the NUTS2 level, at the NUTS3 level we will also be able to split  
13  
14 our sample across different development stages (as well as split the sample over time) in  
15  
16 order to detect whether human capital composition plays a different role depending on the  
17  
18 specific development stage of each region.  
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21  
22 We start with our baseline specification in Table 4 which replicates the regional  
23  
24 specification used at NUTS2 level. Results confirm the important role played by tertiary  
25  
26 education on GVA per capita catch-up.  
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31 [TABLE 4 ABOUT HERE]  
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36 The estimated coefficient is slightly higher than the one obtained with the NUTS2 data<sup>24</sup>.  
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38 Interestingly, the coefficient for HK3 is also once again negative and statistically  
39  
40 significant, while the impact of secondary education and of vocational training (HK2) is  
41  
42 positive and statistically significant. Since the estimated model makes use of the shares of  
43  
44 workforce in each educational category as explanatory variables, the reported coefficients  
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46 are semi-elasticities, hence, they represent the percentage change in the dependent variable  
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48 to a unitary change of the explanatory variable. As suggested by Serrano (1996), it is  
49  
50 possible to retrieve the values of the coefficients' elasticities by noticing that  
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52  
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54  
55  $\gamma_{ed} = \beta \times \partial h / \partial \theta_{ed} \times \theta_{ed} / h$ , where  $\gamma$  represents the elasticity,  $\beta$  the estimated coefficient  
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3 and  $\theta$  and  $h$  respectively the share of population within a certain education category ( $ed$ )  
4  
5 and the years of schooling of that specific category. When we do this, the estimated  
6  
7 elasticity of HK4 in column (1) of Table 4 above would be 0.069<sup>25</sup>. This elasticity is in line  
8  
9 with previous empirical work such as the study by Ramos et al. (2010) on a similar NUTS3  
10  
11 sample of Spanish regions which finds an elasticity of 0.065. Similarly, for the HK1  
12  
13 variable, our implied elasticity would be close to 0.02, similarly to the statistically  
14  
15 significant coefficients estimated by Diliberto (2008) for primary education in Italy.  
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19 Overall, the results obtained at NUTS3 level are, hence, in line with those already shown at  
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21 the "Comunidad Autonoma" (NUTS2) level and are also robust to the introduction of  
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23 various control variables such as employment levels, capital stock and social capital  
24  
25 differences across provinces<sup>26</sup>.  
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29 Similarly to what we have done at NUTS2 level, in order to capture possible changes in the  
30  
31 catch-up dynamics over time, we re-run the analysis on two specific subperiods. The results  
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33 in table 5 confirm that tertiary education is again an important driver of economic  
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35 convergence. If anything, its impact is stronger in the first subperiod (1965-1981) than in  
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37 the second (1981-1997). This result is robust to different specifications and to the use of  
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39 various control variables.  
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46 [TABLE 5 ABOUT HERE]  
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51 Interestingly, when we analyze lower educational categories, we again detect their non-  
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53 linear impact on economic convergence. In particular, when we focus on the period in  
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55 between 1965 and 1981, intermediate education (HK3) scores a negative and statistically  
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57 significant coefficient while HK2 (the share of active population with completed secondary  
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3 education and vocational training) is never statistically significant. When we look instead at  
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5 the period between 1981 and 1997, HK2 becomes statistically significant (and positive) as  
6  
7 well as HK3<sup>27</sup>. We believe this result is closely linked to the development level reached by  
8  
9 regions in the early 80's and to the complementarity between tertiary (HK4) and  
10  
11 intermediate technical education (HK2) which is required at higher development stages. We  
12  
13 examine and discuss this hypothesis in the next section.  
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### 16 17 18 3.4 Human capital composition and development stage 19

20 In 1965, the initial year of observation, the average GVA of follower regions was about 50  
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22 percent lower than that of the leader. However, by the beginning of the 80's this gap was on  
23  
24 average only 25 percent as the result of fast economic convergence. In the previous sections  
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26 (at both NUTS2 and NUTS3 levels) we have already shown partial evidence of the  
27  
28 different importance played by intermediate and lower technical education starting from the  
29  
30 80's. Indeed, these results may be driven by the important institutional change which  
31  
32 followed the enactment of the spanish constitution in the early 80's which dramatically  
33  
34 increase in the Spanish trade openness as well as important changes in the Spanish  
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36 education system for which compulsory schooling, for example, was set to be until the age  
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38 of 16.  
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43 However, apart from this institutional change, it is especially the reduction in the GVA  
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45 gaps achieved at the beginning of the 1980's which is likely to explain the increasing  
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47 importance of different kinds of skills (along with the leading role of tertiary education) for  
48  
49 economic growth.  
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52 In order to confirm this hypothesis we re-run the analysis by splitting the sample according  
53  
54 to the relative development stage of the followers. A suitable way to proceed is to divide  
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3 the sample into richer regions and poorer ones (respectively above and below the average  
4 GVA gap for the whole period) in order to have panels of similar dimensions to be  
5 compared. We provide the results in Table 6 for both development sub-samples.  
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12 [TABLE 6 ABOUT HERE]  
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17 The estimated coefficient indicating the relative impact of tertiary education on economic  
18 convergence is again statistically significant and positive for both rich and poor regions.  
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20 When we look, instead, at the impact of intermediate education (HK3) and of secondary  
21 education and vocational training (HK2) on regions at different development stages, a more  
22 complex pattern seems to emerge.  
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29 If we focus on poorer regions, the presence of larger shares of people with intermediate  
30 education (HK3) seems to slow down economic convergence. At the same time, the impact  
31 of secondary education and vocational training (HK2), even if positive and statistically  
32 significant, is estimated to be lower if compared to the marginal contribution of tertiary  
33 education. Again, one could argue that tertiary education seems to be the most important  
34 driver of economic convergence when regions are far away from the frontier.  
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43 Interpreting the results is rather more complex and intriguing when we also analyse the  
44 richer regions which are closer to the frontier and had already experienced a good deal of  
45 technology convergence. Interestingly, closer to the technology frontier, the relative  
46 distance in the estimated coefficients between tertiary and secondary and vocational  
47 training decreases considerably. The estimated coefficient for tertiary education (HK4) is  
48 now only twice as big as the one estimated for secondary education and vocational training  
49 (HK2). This is due, in part, to the reduction in the estimated impact of HK4 but, mostly, to  
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3 the sharp increase in the importance of HK2 for regions closer to the frontier. It is  
4 important to stress that higher education is still a crucial driver of regional economic  
5 convergence but that other (relatively lower) educational categories play an increasingly  
6 important role when regions approach the technological frontier<sup>28</sup>.  
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12 The intuition behind this "development specific" result goes as follows. For simplicity,  
13 imagine that two regions are lagging at the same (substantial) distance from the  
14 technological frontier and that, at the same time, they are heterogenous in their skill  
15 endowments. One region is high-skill while the other low-skill. The region with higher  
16 skills will be adopting and implementing the latest (and more profitable) technology at a  
17 faster pace since its workforce (in relative terms) is more able to discern between profitable  
18 technologies and to adopt or modify them for its specific technology and productive needs.  
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Eventually, with time, both 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 from exploiting a profitable technology for a considerably 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.

Our results, however, highlight a deeper non-linear effect of human capital composition when it is analyzed jointly with the development stage of each region. Results in Table 6 show the increasing importance of medium/lower technical educational categories as regions move towards the technology frontier. For the sake of explanation, let us imagine that the two regions under consideration are now lagging at different distances from the frontier as is actually the case in our sample.

When closer to the technological frontier, economies generally produce more sophisticated

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3 products (either by adoption or innovation or a mix of these two activities). For this  
4  
5 sophisticated production to take place, two different kinds of workers are needed. On the  
6  
7 one hand, highly skilled workers with tertiary education are essential for setting up the idea  
8  
9 and for planning and implementing this new technology in the correct way.  
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12 As an example, we could think, as suggested by Easterly (2002), of the construction of a  
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14 space shuttle for which a considerable effort has to be made by very talented and  
15  
16 specialized workers with tertiary education to come up with the design of the new  
17  
18 technology or to adapt a similar one discovered in other regions.  
19  
20

21 On the other hand, in order to fully implement this new technology other types of skills are  
22  
23 also required. As argued by Easterly (2002) "*Production is often a series of tasks. Think of*  
24  
25 *an assembly line in which each worker successfully works on a product. The value of each*  
26  
27 *worker's effort depends on the quality of all the other workers*"<sup>29</sup>. This creates a strong  
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29 incentive for the best workers to match up with other very good workers so that the work  
30  
31 done by highly educated workers in the early stages of the technology implementation (let  
32  
33 us imagine the hard work to come up with the design of the space shuttle) does not go to  
34  
35 waste due to a fatal error subsequently made on the assembly line which results in the space  
36  
37 shuttle exploding on its first launch into space.  
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43 These kinds of incentives, those that link high to medium skilled workers to work together  
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45 in a productive manner are stronger the closer we are to the technology frontier and the  
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47 more sophisticated the technologies that have to be implemented actually are. Far from the  
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49 frontier, however, these links are weaker since these economies usually start implementing  
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51 the less sophisticated technologies first, those which are more "appropriate" (see Basu and  
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53 Weil, 1998) to their development, and then move on to more sophisticated ones at higher  
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55 development stages.  
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3 To give another example, instead of the construction of a space shuttle, we may think of the  
4 adoption of a new technology in the manufacturing industry for the production of T-shirts  
5  
6 on a large scale. As we argued before, if two competitors face the challenge of setting up  
7  
8 this new technology in their region, most probably it will be the one with the best  
9  
10 knowledge of the market and of the type of industry to succeed first, In other words,  
11  
12 rephrasing Nelson and Phelps's (1966) hypothesis, the more educated entrepreneur will  
13  
14 tend [ *to adopt productive innovations earlier than the one with relatively little education*].  
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20 When far from the technology frontier, the complementarity between tertiary and medium  
21  
22 educational categories will then be relatively weaker and so the impact of medium or low  
23  
24 educational categories in the process of regional catch-up, as shown by our empirical  
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26 results<sup>30</sup>.  
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#### 33 4. Conclusions

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36 The debate on the impact of education on economic growth is probably one of the most  
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38 recurrent in policy making. From a regional point of view the disparities in educational  
39  
40 attainments are sometimes very large with follower regions stuck at relatively low levels of  
41  
42 development.  
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45  
46 This said, the impact of average proxies of human capital on economic growth has been  
47  
48 recently questioned by theoretical and empirical literature which argues, however, that poor  
49  
50 cross-country data quality may be driving the weak empirical evidence. At the regional  
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52 level, however, this is not a strong argument since human capital data are usually more  
53  
54 robust and homogeneous than cross-country data.  
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58 Another influential strand of literature argues instead that what matters for growth is not the  
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3 average stock of human capital but its specific composition (high, medium and low skills)  
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5 which shapes the technological absorptive capacity of each economy in a non-linear way  
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8 according, also, to the development stage of the region under consideration. Recent  
9  
10 empirical evidence at regional level (see Diliberto 2008 for Italy and Ramos et al. 2009 for  
11  
12 Spain) provides mixed evidence of the impact of different educational categories on  
13  
14 economic growth. These discrepancies motivate our own contribution which aims to  
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16 improve on their analysis in different aspects.  
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20 On the one hand, unlike other recent empirical contributions, we examined the effect of  
21  
22 human capital composition by running our analysis at both NUTS2 and NUTS3  
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24 geographical disaggregation levels. In doing so, we also used two different human capital  
25  
26 databases for Spain. This enabled us not only to check for the robustness of the results  
27  
28 across different geographical units, but also for when different data sources and educational  
29  
30 aggregations are considered.  
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33  
34 On the other hand, the peculiar relation between human capital and economic growth  
35  
36 suffers from severe endogeneity problems which, we believe, have not been fully dealt with  
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38 in previous literature and that may drive the discrepancy in the results. We carefully tackled  
39  
40 the simultaneous relationship between human capital and economic growth by  
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42 implementing appropriate econometrics techniques, namely two-step System GMM  
43  
44 estimators to which we also apply the correction for small sample biases proposed by  
45  
46 Windmeijer (2005).  
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50 Our econometric estimates indicate that tertiary education strongly contributed to overall  
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52 Spanish regional convergence over the period 1960-1997. Conversely, other types of  
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54 human capital were not able to ignite the catch-up process as efficiently as tertiary  
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56 education did. This resulted in slower growth for those economies which mainly exploited  
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3 intermediate or lower education in their productive processes. This result is robust to the  
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5 introduction of various control variables and different specifications as well as when we  
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7 split the sample into different subperiods.  
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10 Crucially, however, as suggested by Vandebussche, Aghion and Meghir (2006), the  
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12 relative development stage of the economies plays a fundamental role in the impact that  
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14 human capital composition has on catch-up. Our analysis is able to disentangle the different  
15  
16 impact that specific educational categories have at different development stages for Spain.  
17  
18 Econometric analysis shows how tertiary education positively drives economic  
19  
20 convergence at both high and low development stages. Crucially, however, the way in  
21  
22 which medium/low skilled workers complement the work of skilled workers in the catch-up  
23  
24 process strongly depends on the economy's relative distance from the technology frontier.  
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29 When we analyze those regions that did experienced faster economic growth and  
30  
31 convergence up to the early 80's (mainly due to the fundamental contribution of tertiary  
32  
33 education), their new relative development stage (being closer to the frontier) led them to  
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35 exploit a wider combination of human capital inputs in a productive manner.  
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39 Empirical evidence indicate that, along with tertiary education, secondary and vocational  
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41 training also play an important role in the productivity catch-up of richer regions (while it  
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43 does not play substantial role for poorer regions). This evidence suggests that being closer  
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45 to the technology frontier implies having to rely on a different and specific combination of  
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47 human capital inputs in order to bring about growth and catch-up. Tertiary education is still  
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49 essential for the more specialized tasks of technology implementation/innovation but  
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51 secondary and vocational training are also increasingly needed to complement the work of  
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53 skilled workers as we approach the frontier.  
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58 Even if at first sight they appear similar, our results differ crucially from those of  
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3 Vandebussche, Aghion and Meghir (2006) when we look at the growth determinants of  
4 those regions far from the technology frontier at lower development stages. Our  
5 econometric estimates indicate that tertiary education positively stimulates economic  
6 convergence by increasing the technology absorptive capacity of a region and allowing it to  
7 take advantage (more quickly) of more profitable frontier technologies. This effect is  
8 relatively stronger the farther away the region is from the frontier.  
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12 In contrast, for those regions which did not succeed in closing the gap with the frontier by  
13 the early 1980's, lower educational categories played a very small role on economic growth  
14 and catch up while, in many cases, having accumulated larger shares of non-technical and  
15 intermediate education seemed to have actually reduced their speed of convergence.  
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38 views expressed herein are those of the author and not necessarily those of the affiliated  
39 institutions.  
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### Appendix

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**TABLE 1:**  
**Descriptive statistics**

<b>NUTS2 and NUTS3 REGIONS</b>	<b>Average HK0</b>	<b>Average HK1</b>	<b>Average HK2</b>	<b>Average HK3</b>	<b>Average HK4</b>	<b>Social Capital Index</b>	<b>Log annual GVA per capita growth</b>	<b>Initial GVA gap</b>
Andalucia	7.25	63.89	21.65	4.34	2.86	22.30	2.96	0.40
Almeria	7.22	66.97	18.82	4.34	2.66	29.60	3.40	0.33
Cadiz	6.06	64.73	22.30	4.33	2.58	16.67	2.72	0.42
Cordoba	7.17	65.16	20.59	4.29	2.79	25.26	3.05	0.40
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
Jaen	7.89	65.69	20.19	4.12	2.12	15.58	3.46	0.35
Malaga	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
Aragón	1.59	65.75	24.04	5.00	3.61	58.21	2.89	0.60
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
Castilla la Mancha	5.05	66.99	21.00	4.21	2.76	38.43	3.48	0.38
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
<b>Castilla y Leon</b>	<b>1.34</b>	<b>66.78</b>	<b>23.00</b>	<b>4.96</b>	<b>3.92</b>	<b>42.86</b>	<b>3.16</b>	<b>0.47</b>
Avila	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
Leon	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
<b>Cataluña</b>	<b>2.25</b>	<b>61.78</b>	<b>28.43</b>	<b>4.11</b>	<b>3.43</b>	<b>88.65</b>	<b>2.52</b>	<b>0.77</b>
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
<b>Extremadura</b>	<b>6.84</b>	<b>67.60</b>	<b>18.82</b>	<b>4.28</b>	<b>2.47</b>	<b>22.26</b>	<b>3.62</b>	<b>0.33</b>
Badajoz	8.68	64.25	20.52	4.20	2.36	18.34	3.21	0.32
Caceres	4.99	70.94	17.12	4.37	2.58	26.19	4.04	0.33
<b>Galicia</b>	<b>4.64</b>	<b>71.25</b>	<b>18.48</b>	<b>3.30</b>	<b>2.32</b>	<b>58.36</b>	<b>3.35</b>	<b>0.39</b>
A Coruna	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
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
<b>Islas Baleares</b>	<b>3.95</b>	<b>61.67</b>	<b>27.57</b>	<b>3.65</b>	<b>3.16</b>	<b>93.00</b>	<b>2.62</b>	<b>0.81</b>
<b>Islas Canarias</b>	<b>6.74</b>	<b>59.75</b>	<b>25.31</b>	<b>4.96</b>	<b>3.23</b>	<b>33.89</b>	<b>3.03</b>	<b>0.51</b>

Las Palmas	6.41	59.89	25.57	5.18	2.95	34.04	2.95	0.52
StacruzTenerife	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
Pais Vasco	0.95	57.68	31.30	5.20	4.87	69.09	2.01	0.88
Alava	0.93	57.94	31.88	4.98	4.27	69.85	2.43	0.89
Guipuzcoa	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
Valencia	3.10	64.94	25.01	3.95	3.01	52.28	2.54	0.66
Alicante	4.19	64.57	25.26	3.66	2.32	50.41	2.28	0.59
Castellon	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
<b>min</b>	0.52	50.38	16.06	3.01	1.74	15.58	1.67	0.32
<b>max</b>	8.68	73.72	33.86	5.70	8.68	154.42	4.04	1.00
<b>Average</b>	3.48	64.16	24.28	4.53	3.55	53.39	2.87	0.56
<b>S.D.</b>	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.

TABLE 2

	<i>Pooled OLS</i>	<i>Pooled OLS</i>	<i>SYSGMM</i>	<i>SYSGMM</i>	<i>LSDV</i>	<i>LSDV</i>	<i>PRE-1981 SYSGMM</i>	<i>POST-1981 SYSGMM</i>	<i>PRE-1981 SYSGMM</i>	<i>POST-1981 SYSGMM</i>
<b>Dependent Variable: GVA GAP per capita (5-year span panel between 1960-1995)</b>	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<b>Initial GVA per capita</b>	0.4329***	0.4835***	0.3103***	0.3508***	0.3247***	0.3495***	0.3824***	0.1180***	0.4624***	0.0607
	[0.024]	[0.031]	[0.030]	[0.031]	[0.016]	[0.019]	[0.041]	[0.035]	[0.045]	[0.060]
<b>Average Years of Schooling</b>	0.0052***	0.0053***	0.0044**	0.0059***	0.0015	0.0013	0.0046***	0.0055***	0.0068***	0.0066***
	[0.001]	[0.001]	[0.002]	[0.001]	[0.002]	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]
<b>Capital stock</b>		-0.0003**		-0.0001		-0.0001			-0.0005	0.0002**
		[0.000]		[0.000]		[0.000]			[0.000]	[0.000]
<b>Employment</b>		0.0000*		0.0000		-0.0001***			0.0001	-0.0000
		[0.000]		[0.000]		[0.000]			[0.000]	[0.000]
<b>Constant</b>	-1.8900***	-2.0392***	-1.4635***	-1.7223***	-1.2081***	-1.1965***	-1.6875***	-1.007***	-2.1398***	-0.9543***
	[0.066]	[0.088]	[0.170]	[0.178]	[0.183]	[0.169]	[0.181]	[0.220]	[0.240]	[0.173]
<b>Observations</b>	119	119	119	119	119	119	68	51	68	51
<b>R-squared</b>	0.858	0.867			0.832	0.871				
<b>Instruments</b>			14	26			8	14	9	9
<b>AR(2)</b>			-0.0344	-0.670			1.812	-1.841	1.790	-0.827
<b>AR(2) p-value</b>			0.973	0.503			0.0700	0.0656	0.0735	0.408
<b>Hansen</b>			16.64	16.70			10.15	14.93	5.598	6.940
<b>Hansen p-value</b>			0.119	0.729			0.0710	0.186	0.231	0.139

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).

Regional Average years of Schooling come from de la Fuente and Domenech (2006). 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) "

TABLE 3

**Dependent Variable:**  
**GVA GAP per capita**  
*(5-year span panel  
between 1960-1995)*

	SYSGMM	SYSGMM	SYSGMM	SYSGMM
	(1)	(2)	<i>PRE-1981</i>	<i>POST-1981</i>
			(3)	(4)
<b>Initial GVA per capita</b>	0.745*** [0.127]	0.729*** [0.110]	0.722*** [0.108]	0.449 [0.346]
<b>HK4</b>	0.022*** [0.006]	0.031** [0.012]	0.062* [0.033]	0.037 [0.023]
<b>HK3</b>	-0.087*** [0.024]	-0.081*** [0.020]	-0.061** [0.026]	-0.087** [0.038]
<b>HK2</b>	0.021*** [0.005]	0.019*** [0.004]	0.054 [0.044]	0.017*** [0.004]
<b>HK1. 2</b>	-0.006 [0.005]	-0.003 [0.005]	-0.043 [0.034]	0.002 [0.009]
<b>HK1. 1</b>	0.004*** [0.001]	0.006* [0.003]	0.002 [0.003]	0.005** [0.002]
<b>Employment</b>		0.000** [0.000]	0.000 [0.000]	0.000* [0.000]
<b>Capital Stock</b>		-0.000** [0.000]	-0.001 [0.001]	-0.000 [0.000]
<b>Constant</b>	-2.423*** [0.412]	-2.528*** [0.355]	-2.317*** [0.344]	-1.730* [0.951]
<b>Observations</b>	119	119	51	51
<b>Instruments</b>	19	17	22	17
<b>AR(2)</b>	1.466	1.095	.	-2.036
<b>AR(2) p-value</b>	0.143	0.273	.	0.0417
<b>Hansen</b>	14.37	11.02	10.14	9.634
<b>Hansen p-value</b>	0.278	0.201	0.682	0.292

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). Regression in column (6) includes time dummies. HK are fractions of workforce in each educational attainment level over the total. The data source is de la Fuente and Domenech (2006). 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)".

**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)
<b>Initial GVA per capita</b>	0.508*** [0.040]	0.436*** [0.041]	0.534*** [0.040]	0.508*** [0.052]	0.697*** [0.057]
<b>HK4</b>	0.055*** [0.012]	0.040*** [0.013]	0.045*** [0.011]	0.063*** [0.016]	0.031** [0.013]
<b>HK3</b>	-0.032* [0.016]	0.005 [0.016]	-0.020 [0.015]	-0.044* [0.024]	0.005 [0.017]
<b>HK2</b>	0.017*** [0.005]	0.021*** [0.006]	0.016*** [0.005]	0.013* [0.007]	0.020** [0.008]
<b>HK1</b>	0.021*** [0.006]	0.025*** [0.007]	0.021*** [0.005]	0.016** [0.008]	0.025*** [0.008]
<b>Employment</b>		0.000*** [0.000]		0.000*** [0.000]	0.000 [0.000]
<b>Capital Stock</b>			0.000* [0.000]	-0.002*** [0.001]	-0.000 [0.001]
<b>Social capital index</b>					0.001*** [0.000]
<b>Constant</b>	-5.48*** [0.558]	-5.57*** [0.613]	-5.64*** [0.480]	-5.08*** [0.710]	-7.24*** [0.715]
<b>Observations</b>	400	400	400	400	250
<b>Instruments</b>	40	47	48	36	47
<b>AR(2)</b>	-1.449	-2.297	-1.910	-1.356	-2.532
<b>AR(2) p-value</b>	0.147	0.0216	0.0561	0.175	0.0113
<b>Hansen</b>	45.01	47.29	48.12	42.35	47.93
<b>Hansen p-value</b>	0.0982	0.199	0.207	0.0402	0.130

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.

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**TABLE 5**

**Dependent Variable:  
GVA GAP per capita**

*NUTS3 (4-year span panel between 1965-1997)*

	SYSGMM	SYSGMM	SYSGMM	SYSGMM	SYSGMM	SYSGMM
	Pre1981	Post1981	Pre1981	Post1981	Post1981	Post1981
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Initial GVA per capita</b>	0.824***	0.572***	0.830***	0.697***	0.724***	0.726***
	[0.105]	[0.086]	[0.126]	[0.073]	[0.053]	[0.059]
<b>HK4</b>	0.051**	0.055***	0.044	0.034***	0.031***	0.031**
	[0.023]	[0.013]	[0.034]	[0.012]	[0.011]	[0.012]
<b>HK3</b>	-0.091***	0.042**	-0.091***	0.036**	0.003	0.001
	[0.030]	[0.020]	[0.033]	[0.015]	[0.014]	[0.022]
<b>HK2</b>	0.003	0.034***	0.002	0.024***	0.017**	0.016*
	[0.010]	[0.008]	[0.011]	[0.008]	[0.008]	[0.008]
<b>HK1</b>	0.013*	0.042***	0.013*	0.032***	0.023***	0.023**
	[0.008]	[0.009]	[0.007]	[0.008]	[0.009]	[0.009]
<b>Employment</b>			-0.000	-0.000		-0.000
			[0.000]	[0.000]		[0.000]
<b>Capital Stock</b>			0.000	0.001		0.000
			[0.002]	[0.001]		[0.001]
<b>Social capital index</b>					0.001***	0.001***
					[0.000]	[0.000]
<b>Constant</b>	-6.526***	-8.084***	-6.511***	-7.943***	-7.212***	-7.148***
	[0.447]	[0.841]	[0.497]	[0.670]	[0.767]	[0.799]
<b>Observations</b>	150	200	150	200	200	200
<b>Instruments</b>	15	40	20	55	47	47
<b>AR(2)</b>	.	-2.122	.	-2.954	-2.620	-2.621
<b>AR(2) p-value</b>	.	0.0338	.	0.00314	0.00880	0.00878
<b>Hansen</b>	22.29	44.91	25.59	48.35	48.47	48.19
<b>Hansen p-value</b>	0.00800	0.0999	0.0122	0.418	0.168	0.124

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.

TABLE 6

**Dependent Variable:**  
**GVA GAP per capita**

NUTS3 (4-year span panel between 1965-1997)

	SYSGMM Below	SYSGMM Above	SYSGMM Below	SYSGMM Above	SYSGMM Below	SYSGMM Above
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Initial GVA per capita</b>	0.554*** [0.034]	0.527*** [0.062]	0.514*** [0.035]	0.501*** [0.077]	0.478*** [0.038]	0.443*** [0.075]
<b>HK4</b>	0.046** [0.019]	0.053*** [0.015]	0.048** [0.019]	0.042*** [0.015]	0.052*** [0.017]	0.024* [0.014]
<b>HK3</b>	-0.060*** [0.021]	-0.008 [0.019]	-0.034* [0.019]	0.005 [0.015]	-0.023 [0.017]	0.035* [0.018]
<b>HK2</b>	0.006* [0.004]	0.020* [0.010]	0.015*** [0.005]	0.017* [0.009]	0.012** [0.006]	0.023** [0.010]
<b>HK1</b>	0.011** [0.004]	0.026** [0.011]	0.020*** [0.005]	0.023** [0.010]	0.018*** [0.006]	0.029** [0.011]
<b>Employment</b>			0.001** [0.000]	0.000* [0.000]	0.000 [0.000]	-0.000 [0.000]
<b>Capital Stock</b>			-0.003 [0.002]	-0.000 [0.000]	-0.002 [0.002]	-0.000 [0.000]
<b>Employment density</b>					3.970 [2.594]	2.961** [1.208]
<b>Constant</b>	-4.81*** [0.411]	-6.08*** [1.052]	-5.48*** [0.536]	-5.64*** [0.906]	-5.11*** [0.562]	-5.99*** [1.084]
<b>Observations</b>	187	213	187	213	187	213
<b>Instruments</b>	37	40	50	55	50	55
<b>AR(2)</b>	0.214	0.352	0.0692	0.196	0.214	0.359
<b>AR(2) p-value</b>	-1.244	-0.931	-1.817	-1.294	-1.243	-0.917
<b>Hansen</b>	41.76	44.90	36.21	43.99	36.79	42.45
<b>Hansen p-value</b>	0.0939	0.100	0.722	0.598	0.658	0.622

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)". Above and Below sub-samples refer to the mean GDP per capita of the sample.



**Table A.1: Educational attainment levels by NUTS disaggregation**

NUTS2	NUTS3	Category	Attainment levels
HK0	HK0	Analfabetos	-
HK1.1 HK1.2	HK1	Sin estudios y estudios primarios	Primary Schooling (also not completed), EGB, ESO.
HK2	HK2	Estudios medios	Secondary Schooling, Vocational Training (FP1 and FP2)
HK3	HK3	Estudios anteriores al superior	Diplomas in Humanities, Engineering, Social Sciences and Law etc.
HK4	HK4	Estudios superiores	University degrees and PhD carrers

**Table A.2****Post estimation checks**

	OLS (1)	LSDV (2)	SYSGMM (3)
<b>Dependent Variable:</b> <b>GVA GAP per capita</b> <i>(5-year span panel between 1960-1995)</i>			
<b>Initial GVA per capita</b>	0.769*** [0.029]	0.480*** [0.034]	0.745*** [0.127]
<b>HK4</b>	0.024*** [0.005]	-0.027*** [0.006]	0.022*** [0.006]
<b>HK3</b>	-0.061*** [0.008]	0.013 [0.008]	-0.088*** [0.024]
<b>HK2</b>	0.011*** [0.003]	0.014*** [0.003]	0.022*** [0.005]
<b>HK1.2</b>	-0.004 [0.003]	-0.008*** [0.002]	-0.006 [0.005]
<b>HK1.1</b>	0.004*** [0.001]	0.002* [0.001]	0.004*** [0.001]
<b>Constant</b>	-2.437*** [0.087]	-1.655*** [0.139]	-2.423*** [0.412]
<b>Observations</b>	119	119	119
<b>R-squared</b>	0.922	0.912	
<b>Instruments</b>			19
<b>AR(2)</b>			1.466
<b>AR(2) p-value</b>			0.143
<b>Hansen</b>			14.37
<b>Hansen p-value</b>			0.278

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 de la Fuente and Domenech (2006).

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<b>TABLE A. 3</b>	<b>SYSGMM</b>	<b>SYSGMM</b>	<b>SYSGMM</b>	<b>SYSGMM</b>
Additional Robustness checks NUTS2			<b>DROP HK1.2</b>	<b>DROP HK2</b>
<b>Dependent Variable:</b>	(1)	(2)	(3)	(4)
<b>GVA GAP per capita</b>				
<i>(5 -year span panel between 1960-1995)</i>				
<b>Initial GVA per capita</b>	0.844***	0.776***	0.835***	0.741**
	[0.088]	[0.099]	[0.096]	[0.279]
<b>HK4</b>	0.021***	0.025***	0.028*	0.037
	[0.006]	[0.007]	[0.014]	[0.026]
<b>HK3</b>	-0.099***	-0.065*	-0.076	-0.030
	[0.019]	[0.037]	[0.054]	[0.052]
<b>HK2</b>	0.020***	0.010**	0.012	
	[0.004]	[0.004]	[0.013]	
<b>HK1.2</b>	-0.007**	-0.006		0.004
	[0.003]	[0.005]		[0.014]
<b>HK1.1</b>	0.003***	0.003**	0.007	0.007
	[0.001]	[0.001]	[0.004]	[0.006]
<b>Employment</b>			0.000*	0.000
			[0.000]	[0.000]
<b>Capital Stock</b>			-0.000*	-0.000
			[0.000]	[0.000]
<b>Change in employment</b>		0.325**		
		[0.127]		
<b>Capital stock growth</b>	-0.111	-0.070		
	[0.088]	[0.071]		
<b>Constant</b>	-2.558***	-2.408***	-2.896***	-2.825***
	[0.226]	[0.199]	[0.304]	[0.680]
<b>Observations</b>	102	102	119	119
<b>Instruments</b>	22	25	22	15
<b>AR(2)</b>	-0.132	-0.245	1.684	0.887
<b>AR(2) p-value</b>	0.895	0.807	0.0923	0.375
<b>Hansen</b>	6.543	10.09	2.067	0.0762
<b>Hansen p-value</b>	0.951	0.862	0.979	0.782

Standard errors in brackets: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1..  
 HK are fractions of workforce in each educational attainment level over the total. The data source is de la Fuente and Domenech (2006). 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) ".

1 **Table A.4**  
2 **post estimation checks**  
3 **NUTS3**

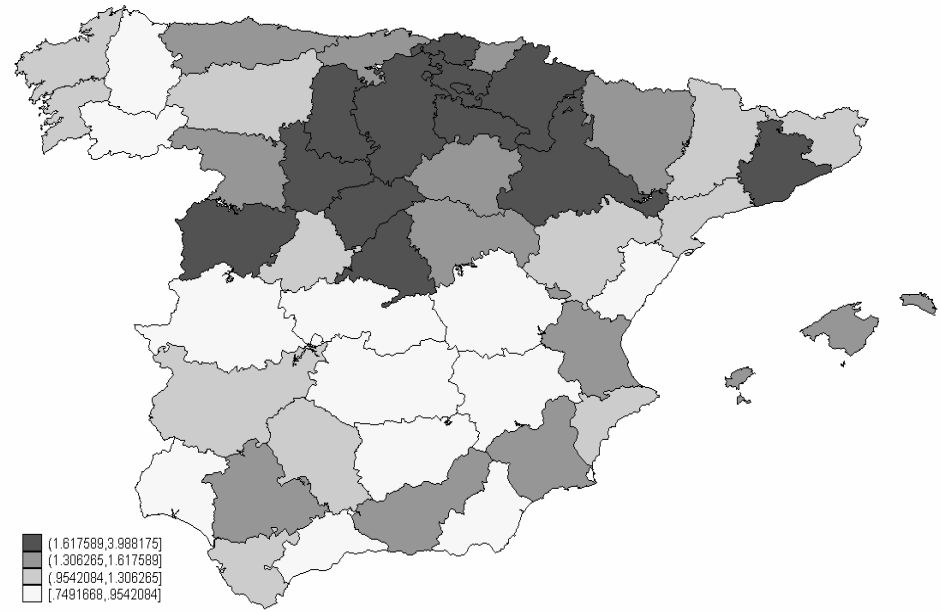
	OLS	LSDV	SYSGMM
<b>Dependent Variable:</b>	(1)	(2)	(3)
<b>GVA GAP per capita</b> (4-year span panel between 1965-1997)			
<b>Initial GVA per capita</b>	0.861*** [0.022]	0.412*** [0.020]	0.508*** [0.040]
<b>HK4</b>	0.019*** [0.004]	-0.005 [0.004]	0.055*** [0.012]
<b>HK3</b>	-0.025*** [0.005]	0.001 [0.004]	-0.032* [0.016]
<b>HK2</b>	-0.003 [0.002]	-0.002 [0.002]	0.017*** [0.005]
<b>HK1</b>	0.004** [0.002]	-0.000 [0.002]	0.021*** [0.006]
<b>Constant</b>	-6.134*** [0.173]	-2.998*** [0.178]	-5.489*** [0.558]
<b>Observations</b>	400	400	400
<b>R-squared</b>	0.884	0.778	
<b>Instruments</b>			40
<b>AR(2)</b>			-1.45
<b>AR(2) p-value</b>			0.147
<b>Hansen</b>			45.01
<b>Hansen p-value</b>			0.098

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, Human capital series.

Figures

Figure 1

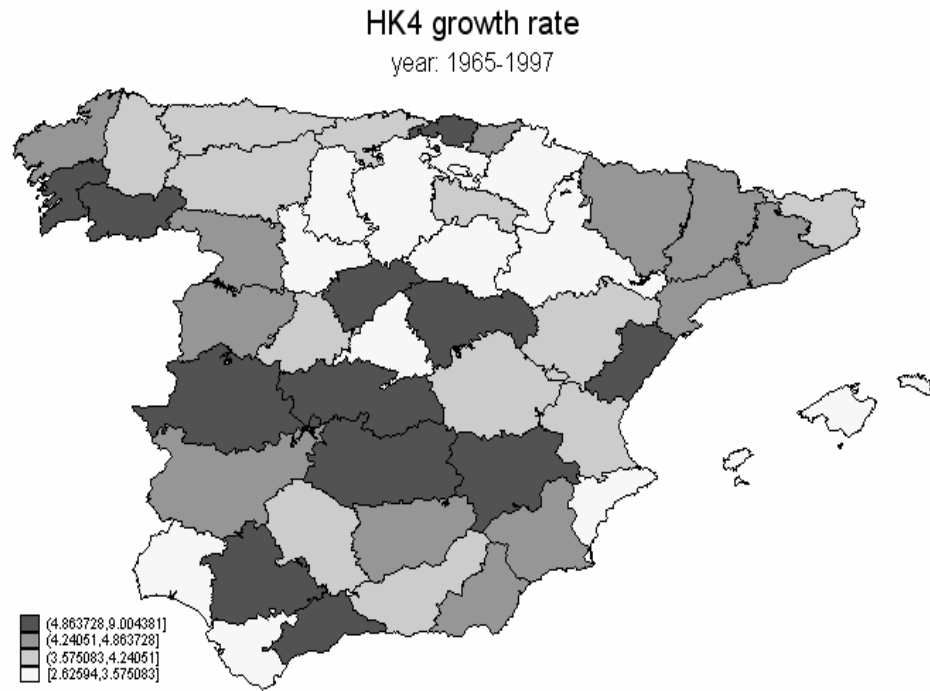
Human Capital (HK4) share of active population  
year: 1965



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Figure 2

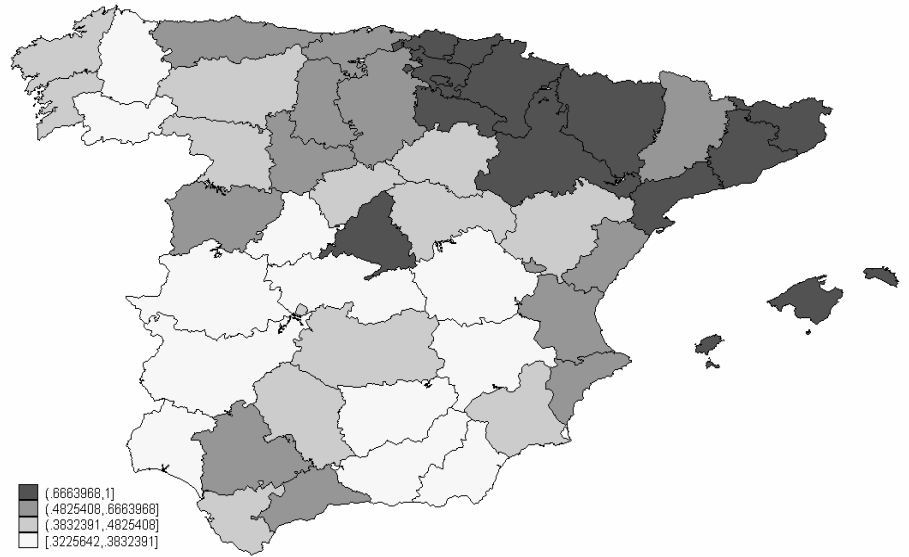


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Figure 3

Initial GVA per capita GAP  
year: 1965

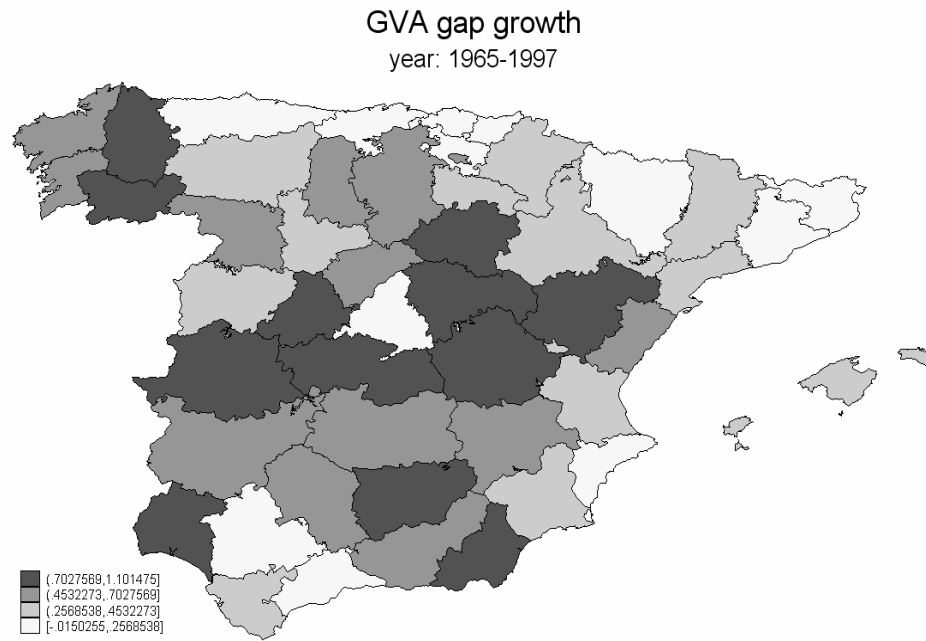


Darker regions are closer to the frontier

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Figure 4

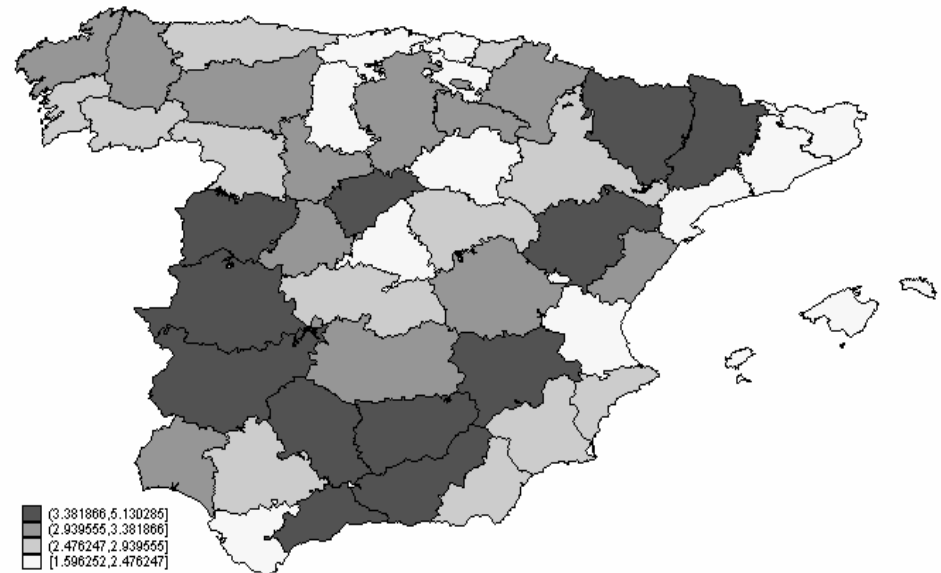


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Figure 5

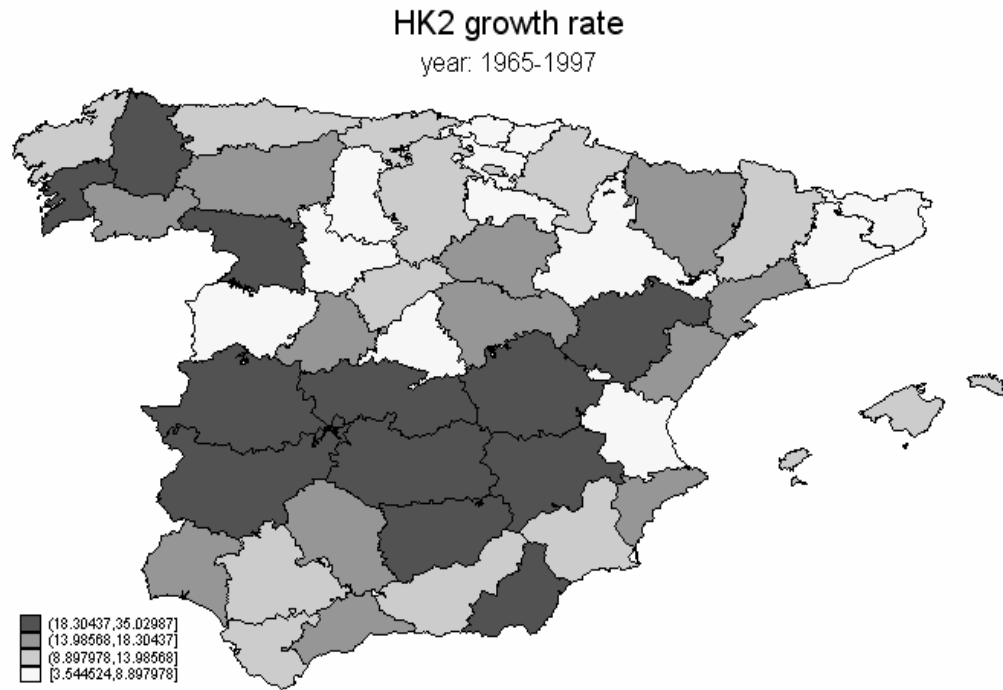
HK3 growth rate  
year: 1965-1997



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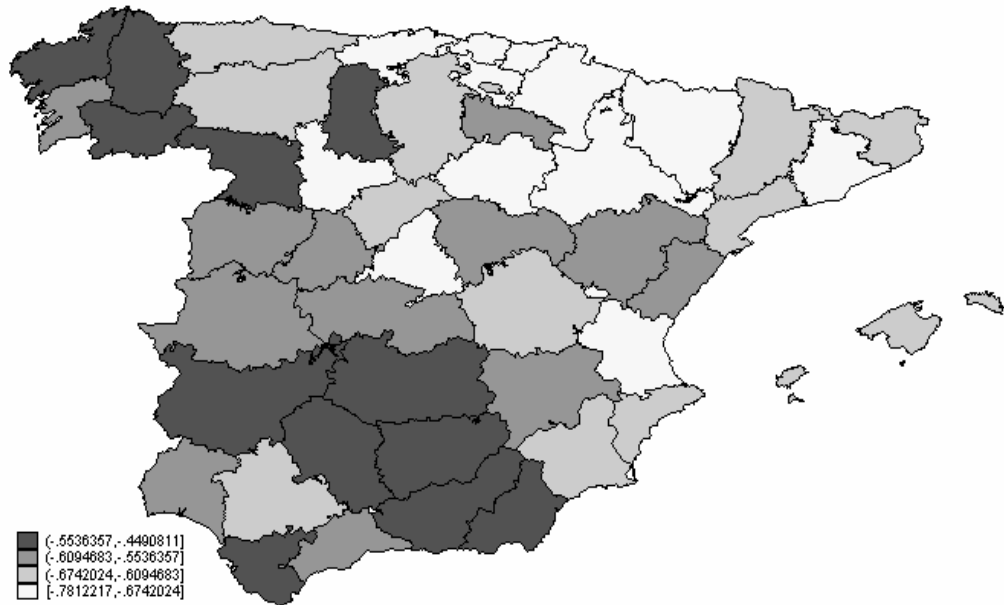
Figure 6



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Figure 7

HK1 growth rate  
year: 1965-1997



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## Endnotes

<sup>1</sup>See Acemoglu and Dell (2009).

<sup>2</sup>See Vandenbuscche, Aghion and Meghir (2006), pagg. 106-107.

<sup>3</sup>See Vandeussche, 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*".

<sup>4</sup>We thank an anonymous referee who pointed out to the likely presence of spatial dependence across regions which may affect the results. Indeed this may be an important issue to be considered. Nonetheless, up to this moment, the econometric analysis of dynamic spatial panel model is almost inexistent preventing us to correctly approach this problem. Additionally, the use of control variables such as employment, capital stock, employment density or social capital is also likely to lessen this problem by capturing, to a large extent, the substantive spatial dependence in our sample.

<sup>5</sup>Notice that using HK0 (illiteracy rate) as the base category for our analysis has the advantage of tackling the multicollinearity with the other educational categories and, at the same time, of allowing us not to loose explicitly any education category in the regressions.

<sup>6</sup>Our sample is Andalucía, Aragón, Asturias, Baleares, Canarias, Cantabria, Castilla y León, Castilla la Mancha, Cataluña, Comunidad Valenciana, Extremadura, Galicia, Madrid, Murcia, Navarra and Pais Vasco.

<sup>7</sup>See: "La renta nacional de España y su distribución provincial: una publicación histórica del Servicio de Estudios del Banco de Bilbao" by Sánchez and de la Puente (2004).

<sup>8</sup>HK0 represents the share of illiterate active population and has been dropped from all regressions.

<sup>9</sup>See: <http://ivie.es/banco/capital.php?idioma=EN> for more details

<sup>10</sup>If we compare the two human capital databases we can notice a slight different categorization of the human capital levels. This is summarized in table A.1 in the appendix for both NUTS2 and NUTS3 classifications.

<sup>11</sup>Due to the scope of this present contribution we will not explore these links but only use social capital proxies as additional control variables. We leave this interesting subject to future research.

<sup>12</sup>See IVIE, <http://ivie.es/banco/ksocial.php?idioma=EN>.

<sup>13</sup>For simplicity of exposition, and in order not to duplicate the number of tables, in table 1 we propose the descriptive statistics at the NUTS2 level coming from our own aggregation of the IVIE's NUTS3 human capital data. Similar analysis can be however found in de la Fuente and Domenech (2006) at NUTS2 level

for their set of data.

<sup>14</sup>Formally the system GMM estimator assumes the following:  

$$E[\Delta W_{i,t-1} \varepsilon_{i,t}] = E[\Delta W_{i,t-1} \mu_i] + E[W_{i,t-1} v_{i,t}] - E[W_{i,t-2} v_{i,t}] = 0 + 0 - 0$$
 where  $\mu_i$  are the fixed effects and  $v_{i,t}$  are the idiosyncratic shocks.  $W_{i,t}$  represents instead the endogenous regressors. If the condition above is satisfied then  $\Delta W_{i,t-1}$  is a valid instrument for the variables in levels.

<sup>15</sup>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)

<sup>16</sup>More robustness checks on this are also ran when we disaggregate human capital into specific educational categories in the table A.2 and A.4 in the appendix at the NUTS2 and NUTS3 level.

<sup>17</sup>The results of the linear specification at the NUTS3 level, instead, show a non significant effect of average human capital on province convergence. This result is not new in the literature which analyzed the spanish case. See for example the work by Dolado et al. (1994) or de la Fuente and da Rocha (1994).

<sup>18</sup>Recall that in 1978 a major political shift occured in Spain with the end of the dictatorship of Francisco Franco. The frequency of the regional data allows us to split the sample close enough to this historical date.

<sup>19</sup>Our preferred specifications are, hence, reported in columns (3), (4), (9) and (10).

<sup>20</sup>As we pointed out before, in 1978 the new democratic constitution was promulged.

<sup>21</sup>In fact, the coefficient for HK4 in column 4 is not statistically significant.

<sup>22</sup>A similar result is detected, in fact, when instead of splitting the sample into two time periods we divide it by using a GVA gap threshold level. We will discuss this result later in the paper when analyzing NUTS3 regions for which this disaggregation is possible to the the higher number of observations.

<sup>23</sup>Social capital series are only available starting from the 80's and, therefore, they could not be introduced in the NUTS2 level analysis due to the reduced number of observations which would have remained for estimation.

<sup>24</sup>We need to recall, however, that not only the regional disaggregation is a different one but that also the human capital data come from a different source as detailed in previous sections. As an additional robustness check, we estimated the baseline regression by OLS and LSDV (results are presented in table A.4 in the appendix).



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6<sup>25</sup>Serrano (1997) also argues that the difference in magnitude between the semi-elasticity and the implied  
7 true elasticity in a log-lin model is higher the smaller the fraction of population in the examined category.  
8 In our case, this means that the impact of the higher educational categories is greater than what reported  
9 by the semi-elasticity coefficient.  
10

11<sup>26</sup>Additionally, the same pattern of results, with only slight changes in the coefficients' point estimates, is  
12 confirmed when we control for employment change, capital stock growth rate, employment density or the  
13 size of the region. Results are available upon request to the author.  
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16<sup>27</sup>The results are robust to the introduction of additional control variables such as employment density or  
17 social capital. Results are available upon request to the author.  
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20<sup>28</sup>Results are again robust to the introduction of various standard control variables such as employment,  
21 capital stock or measures of agglomeration such as employment density. Results are available upon  
22 request to the author.  
23

24<sup>29</sup>See Easterly (2002), "The elusive quest for growth", p. 155.  
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27<sup>30</sup>Hence, even if the more appropriate technologies are easier to be implemented, they still require talented  
28 and specialized people (tertiary education) to set up the business, automatize the productive process and  
29 make the technology fully up and running but are less relying on the complementarity with medium skill  
30 workers. However, due to the fact the production of T-shirts is not as skill demanding as building a space  
31 shuttle, relatively less skilled workers may be employed in the assembly line while the marketing and  
32 managerial decisions will be still taken by very much qualified managers with tertiary education.  
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