Human Capital Composition and Economic Growth at the Regional Level

November 25, 2009

Abstract

With this paper we build a catch-up model where technology adoption takes place as a function of each region's human capital composition. We show how the high skill intensity of each region's workforce (rather than the average stock) determines convergence towards the income level of the leader region. The same applies to institutional quality which is conductive to higher growth in the long run. We test successfully our theoretical result over Spanish regions for the period between 1960 and 1997. We exploit system GMM estimators which allow us to correctly deal with endogeneity problems and small sample bias.

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*". Disparities in the endowment of physical capital across regions may only be a minor factor explaining these differences due to the relatively free mobility of capital within national boundaries. Hence, it is argued how "*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"*.[1]

When motivating the study of technology differences across regions (rather than across countries) one need to be somehow more specific in the definition attached to the word "technology". It may be difficult to argue, for instance, that major differences in technological levels are experienced between the region of Seville and that of Madrid in Spain. The two Spanish regions face indeed the same world technology frontier which, in principle, is easily accessible for the two of them. Following the intuition by Acemoglu and Dell (2009) we understand "technology", in a regional context, as the "*production possibility frontier facing a society, which we may refer to as technological know-how*". What matters for regional economic growth is, hence, the relative efficiency with which economic agents in each region are capable of implementing and adopting the available *know-how* (technology) and taking advantage of it profitably.

The literature focusing on technological change has already highlighted how the creation of an innovation generally implies considerable investments (in R&D) and risks. However, also the adoption of technology implies considerable costs which are related, for example, to the adaptation of the new product to the local market or of the new process to the old organizational paradigms which have to adjust to the new standards. Empirical evidence such as Mansfield, Schwartz and Wagner (1981) or Teece (2008) argue, directly or indirectly, to the "skill-costliness" of imitation and adoption of technologies. Differences in the cost of technology adoption hence, (as well as in the speed with which technology is adopted) are crucially linked to the ability of each individual, firm and region to react and take advantage of the available new technological frontier, that is to their "absorptive" capacity.

Closely related to these issues, the seminal contributions by Nelson and Phelps (1966) or more recent ones such as Behnabib and Spiegel (1995, 2005) base their results on the assumption that human capital enhances technology spillovers increasing the followers' absorptive capacities and decreasing the costs associated to technology adoption. Nonetheless, recently, some doubts on the positive impact of human capital on economic growth have arisen as pointed out by de la Fuente and Doménech (2006), and Krueger and Lindhal (2001). On one hand, an explanation to this odd result has led to questioning the quality and homogeneity of the data on international educational levels used in growth regressions (see de la Fuente and Domenech, 2006).

On the other hand, other influential contributions such as Vandenbussche, Aghion and Meghir (2005)[2] or di Maria and Stryszowski (2009) have been questioning the assumption that the average human capital stock may not actually exert a lineal impact on economic growth and that, instead, different types of human capital (low vs high skilled workers) may be differently suited to economic growth depending on the development stage of the region or country under consideration.

Our contribution inserts in this theoretical and empirical literature by building a model in which differences in human capital composition across regions play a fundamental role in the speed by which these are able to exploit technological spillovers coming from the frontier. At the regional level, interesting contributions are those by Diliberto (2006) for the Italian case and that by Ramos, Suriñach and Artis (2009) for the Spanish one.

We ground our work on a simple (but somehow overlooked) assumption: the adoption and implementation of technology (and of the *frontier technology know-how*) is a "skill-costly" activity and, hence, it is intrinsically better performed by skilled workers rather than unskilled ones. Better skills, then, reduce the cost of technology adoption. Our rationale is very much in line with the intuition by Nelson and Phelps (1966) who argue how "*it is clear that the farmer with a relatively high level of education has tended to adopt productive innovations earlier than the farmer with relatively little education [...] for he is better able to discriminate between promising and unpromising ideas [...] The less educated farmer, for whom the information in technical journals means less, is prudent to delay the introduction of a new technique until he has concrete evidence of its profitability*".

Even if at first sight similar, our identifying hypothesis crucially differs from that by Vandenbussche, Aghion and Meghir (2005) for which *"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"*[3]. Their result is puzzling to us and we believe it to be counter-intuitive since it suggests that any decrease in educational levels would be growth beneficial for the less developed regions (and countries), and all the more they are under-developed. This is like saying that poor regions should oddly compete one another by lowering (rather than increasing) their educational levels.

Our theoretical model, instead, shows how a marginal increase in the stock of skilled workers boosts convergence and economic growth. Differently from the already mentioned previous literature, the marginal effect of an increase in the stock of unskilled human capital will be growth detrimental rather than beneficial. The model shows faster convergence in those regions endowed with more qualified workforce which are then able to adopt technology more efficiently than regions with low skills.

Also, following an ever increasing deal of theoretical and empirical literature backing to Abramovitz (1986) and more recently to Hall and Jones (1999) and Acemoglu et. al (2001), our model also looks at the role played by institutional quality differences in the process of technology adoption under the hypothesis that better institutions increase the ability of regions of adopting leading edge technologies.

We empirically test the assumptions and results of the theoretical model on 17 NUTS2 Spanish regions (Comunidades Autonomas) and replicate the results at the county level for 50 NUTS3 Spanish *provincias*. The relation among human capital, institutional quality and economic growth may severely suffer from endogeneity. Hence we deal carefully with simultaneity issues by estimating a dynamic panel making use of both first-difference and system GMM estimators as proposed by Arellano and Bond (1991) and Arellano and Bover (1995). We find that system GMM outperform first-difference GMM estimators when persistent explanatory variables are used in the panel as it is the case for educational variables in our regressions. We also correct for small sample biases by applying the two-step optimal estimation procedure proposed by Windmeijer (2005). Results seem to confirm the theoretical assumptions made on the theoretical model.

The remainder of the paper is as follows. In section 2 we give the basic setup of the model focusing on the main variables which will be analyzed throughout the paper. In section 3 we analyze the dynamics of the follower regions when we assume that technology adoption is a skill costly activity and that regions differ in the endowment of human capital and in its relative composition. Here we derive the condition for technology catch up and for convergence in GDP levels as a function of human capital composition and of institutional quality differences across regions. Section 4 describes the empirical model as well as the estimation methodology. Here we also discuss the main empirical results obtained on NUTS2 and NUTS3 Spanish regions for the period in between 1960 and 1997. At the end some conclusions.

2 Setup of the model

This section has the aim of proposing a technology catch-up model in which the human capital composition of each region shapes the ability of adopting the available technology frontier. The fundamental assumption is that being endowed with a relatively larger share of high skilled workers will reduce the cost of technology adoption and increase the ability of the follower region to receive technology spillovers from the frontier.

For simplicity of exposition we will focus the discussion on a representative follower region even if the model could be generalized to a setting where a finite number of follower regions exists with no changes to the main results presented in this contribution.

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

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

where i takes value 1 for the leader and 2 for the representative follower. As for the variables in eq.(1), Y_i is output, X_{ji} is the quantity of the *jth* nondurable intermediate good used in the production by region i. N_i is the number of types of intermediates available in region i. As in Barro and Sala-i-Martin (1997) we use the variable N_i to proxy for the technological level of region i. By definition, the follower lags behind the frontier w.r.t. its technology level such that the following holds:

$$N_1(0) > N_2(0) \tag{2}$$

where the pool of blueprints (innovations) that are known at the frontier is strictly higher than that in the follower regions. The relative technological proximity of the follower w.r.t. the frontier is then expressed by the following ratio:

$$0 < \frac{N_2}{N_1} \leq 1 \tag{3}$$

Throughout the paper we will be using the measure in eq.(3) to define the relative *development stage* of the follower.

Consistently with empirical evidence, we assume that the follower lags behind the frontier w.r.t. other macroeconomic fundamentals.

First, the follower is endowed with relatively worse institutions. In the model, A_i represents institutional quality of regional governments. This variable captures the quality of the of local institutions at the regional level. These are particularly important in a country such as Spain which delegates many of its central powers to its *Comunidades Autonomas* which have large powers in budgetary and economic matters. With A_i we also capture all other unobservable differences across regions that are not explicitly modeled such as infrastructures and so on[4]. Hence, more formally, we assume that the leader owns more developed institutions than the followers as:

$$A_1 > A_2 \tag{4}$$

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

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

$$L_{r1} > L_{r2} \tag{5}$$

and, conversely

$$L_{y1} < L_{y2} \tag{6}$$

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

$$\frac{L_{r1}}{L_{y1}} > \frac{L_{r2}}{L_{y2}} \tag{7}$$

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

$$L_i = L_{yi} + L_{ri} \tag{8}$$

where L_i is normalized to 1.

3 Costly technology adoption

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

In particular, Mansfield, Schwartz and Wagner (1981) point out how, over 48 different products in chemical, drug, electronics and machinery U.S. industries, the costs of imitation lied between 40% and 90% of the costs of innovation. On the same line the empirical results of Teece (1977) who estimated the cost of technology transfer to be equal, on average, to 19% of total project expenditure.

As argued by Maskus (2000), imitation usually takes the form of adaptations of existing technologies to new markets. In order to adopt a new product (or a process) the follower usually need to adapt the new technology to its market or productive needs. Hence, managerial as well as technical skills are necessary for the follower in order to adopt and "adapt", for example, a newly discovered process innovation[5]. Managerial and technical skills are also important when the follower has to choose which innovation (within the large pool of available ones) has to be to implemented and adopted. The profitability of the adoption then will be a function of the manager's judgment of the innovation market potentials as well as of the capabilities of workers of adopting the new technologies.

The basic assumption on the costliness of technology adoption is very much in line with the theoretical framework by Nelson and Phelps (1966) who argue how "*it is clear that the farmer with a relatively high level of education has tended to adopt productive innovations earlier than the farmer with relatively little education [...] for he is better able to discriminate between promising and unpromising ideas [...] The less educated farmer, for whom the information in technical journals means less, is prudent to delay the introduction of a new technique until he has concrete evidence of its profitability*". Following this rationale, our formalization implies that the cost of imitation will be lower the larger the share of skilled workforce in the follower. More formally we can restate the cost function for imitation as follows:

$$\nu_2 = \psi(L_{r2})^{-1}\left(\frac{N_2}{N_1}\right) \tag{9}$$

where ν_2, represents the cost of adopting and correctly implementing a new technology in the follower region. The technology adoption cost, ν_2, is assumed to be a negative function of the skill intensity of the follower region, that is of L_{r2}. Crucially, if two follower regions were to stand equally distant from the frontier (at the same development stage), the one endowed with a larger share of skilled workforce would be able to better distinguish between profitable and unprofitable technologies being able to better use the available technologies in the production chain, facing a relatively lower cost of adoption and eventually catching up with the frontier faster than the region with endowed with lower skills. In the fashion of Connolly and Valderrama (2005) and Barro and Sala-i-Martin (1997) we assume the cost of technology adoption to be also an increasing function of the proximity of the imitator w.r.t. the technological frontier. When it exists a large pool of innovations (blueprints) from which an imitator can copy, the cost of imitation tends to be low and viceversa.

Once a new technology is discovered at the frontier this will be potentially available for adoption by any agent in region 2[6]. Following the intuition by Maskus (2000), the adoption of the leader's blueprint results in a new intermediate good X_{2j} which will be similar to the initial one X_{1j} discovered in the leader region but "ready-to-use" for production in the follower market. The adopter in the follower region, then, enjoys monopoly power over the use of the adopted good for production. Solving the model for the stream of monopoly profits gives, similarly to the solution by Barro and Sala-i-Martin (1995), the following:

$$\pi_{2j} = \pi_2 = (1-\alpha) L_{y2} (A_2) \alpha^{(1+\alpha)/(1-\alpha)} \tag{10}$$

which in turn, implies the following rate of return to technology adoption in the follower region:

$$r_2 = (L_{y2}/\nu_2) \left(\frac{1-\alpha}{\alpha} \right) (A_2)^{1/(1-\alpha)} \alpha^{2/(1-\alpha)} \tag{11}$$

We assume that consumers in all regions maximize the same Ramsey-type utility function as:

$$U_i = \int_0^\infty e^{-\rho t} \left[(C^{1-\theta} - 1)/(1-\theta) \right] dt \tag{12}$$

leading to the following expression for the growth rate of consumption:

$$\dot{C}_i / C_i = (1/\theta)(r_i - \rho) \tag{13}$$

which ultimately gives the growth rate for the follower region as a function of its human capital composition through the parameters L_{y2} and ν_2 and of institutional quality, A_2.

$$\gamma_2 = (1/\theta)(\pi_2/\nu_2 - \rho) = (1/\theta) \left[(1-\alpha) L_{y2} (A_2)^{1/(1-\alpha)} \alpha^{(1+\alpha)/(1-\alpha)} \nu_2^{-1} - \rho \right] \tag{14}$$

As we can notice from eq.(14), the growth rate of the follower region is tightly linked to the composition of its human capital rather than to its average level. On one hand, γ_2 is a positive function of the unskilled share of the workforce which is needed in order to produce the final good and employed in the production, that is of L_{y2}. However, the engine of growth lies in the technology absorptive capacity of the economy, that is, in its ability to exploit technology spillovers. The second crucial parameter is, in fact, ν_2, the cost of technology adoption, which enters at the denominator of the expression in eq.(14). It is easy to recall how the cost of adoption is, itself, a negative function of the skilled fraction of the workforce as in eq.(9) such that if an increase in L_{r2} reduces by definition the value of L_{y2} (negatively impacting growth), it will at the same time boost the capacity of the follower to adopt technology reducing the adoption cost. It is therefore the balance between these two effects which defines whether the marginal effect of an increase in the skilled fraction of the workforce will be growth beneficial or detrimental. This scenario is analyzed in the following propositions.

Proposition 1 *A rise in the share of the workforce with a higher level of education (skilled workers) is growth enhancing for the follower region reducing the cost of technology adoption and increasing its rate of return. Conversely, a rise* *in the fraction of population with low skills is shown to be growth diminishing. The result (which depends on the relative composition of human capital in each economy) is stronger the smaller the initial share of skilled workers over the total population and it holds under plausible values for the model parameters and of human capital composition.*

By inspection of the growth rate in eq. (14) we can notice that, everything else being equal, the growth rate of the economy is a function of the level of skilled over unskilled workers in the economy. Taking the partial derivative of the growth rate w.r.t. L_{r2} and imposing this to be greater than zero yields to the following:

$$\frac{\partial \gamma_2}{\partial L_{r2}} = (1/\theta)\left[(1-\alpha)(A_2)^{1/(1-\alpha)}\alpha^{(1+\alpha)/(1-\alpha)}\nu_2^{-1} - \rho\right][1 - 2L_{r2}] \tag{15}$$

Due to the standard assumptions made on the model parameters in order to ensure positive growth, the term $(1/\theta)\left[(1-\alpha)(A_2)^{1/(1-\alpha)}\alpha^{(1+\alpha)/(1-\alpha)}\upsilon_2^{-1} - \rho\right]$ will be always greater than zero. This leads to the following:

$$\frac{\partial \gamma_2}{\partial L_{r2}} > 0 \Leftrightarrow L_{r2} < 1/2 \tag{16}$$

An increase in the skilled fraction of workforce is then shown to be growth enhancing while, conversely, an increase in the share of unskilled workers will end up being growth detrimental by decreasing the rate of return of technology adoption impeding (or reducing) technology flows from the technological frontier to the follower. It is important to notice, however, how the positive marginal effect of an increase in the share of skilled workers on economic growth encounters diminishing returns as in standard endogenous growth models (see for example Romer, 1990) due to the possible duplication effect in the technological sector and the so called "stepping on toes" effect. The non-lineal impact of human capital composition on growth also highlights the role played by lower education for growth, which is itself necessary for the basic result to hold. The condition expressed in eq.(16), in fact, holds for $L_{y2} > 1/2$ such that, for catching up to take place, basic education (along with higher education) has to be ensured.

3.1 Long-run technology gap and human capital composition

Consistently with the result in the proposition above, it is possible to solve the model so as to define the long-run proximity of the follower w.r.t. the frontier (the gap with the frontier). Again, this can be shown to be a function of the human capital composition of the follower rather than of its average level as in standard growth models. This result is discussed in the next proposition.

Proposition 2 *The long-run technological proximity of the follower w.r.t. the technological frontier depends on the relative composition of human capital as well as on the quality of its institutions. Those regions managing to be endowed with larger shares of skilled workers (and with better institutions) will converge faster (and get closer) to the technological and output levels of the regions at the frontier.*

In steady state the two regions are expected to grow at the rate of expansion of the technology frontier. By definition, therefore, N_2 grows at the same rate as N_1 so that ν_2 remains constant in accordance with eq.(9). As argued by Barro and Sala-i-Martin (1997), the process of technology diffusion will end up equalizing the rate of returns in the two regions. The steady state value of the rate of return expressed in eq. (11) for region 2 will be equal to that of the leader region 1 as follows:

$$r_2^* = r_1 = \pi_1/\eta_1 \tag{17}$$

where the asterisk superscript denotes values in steady state for the follower and η_1 the cost for the leader of introducing a new innovation[7]. Hence, since $r_2^* = r_1$, and the leader performs innovation at the cost η_1 we can rearrange the following:

$$\pi_2/\nu_2^* = \pi_1/\eta_1 \tag{18}$$

where ν_2^* is the steady state value for the cost of imitation ν_2. By combining eq.(10) with eq.(18) we can express the steady state value for the cost of imitation as a function of the other variables of the model as follows:

$$\nu_2^* = \eta_1 (A_2/A_1)^{1/(1-\alpha)} (L_{y2}/L_{y1}) \tag{19}$$

Combining eq.(9) with eq.(19) we can derive a unique value for N_2/N_1 which satisfies the steady state condition as follows:

$$(N_2/N_1)^* = \left[\xi\,(\theta)^{1/(1-\alpha)}/\kappa\right] \tag{20}$$

where we redefined the variables as follows[8]:

$$\kappa = \eta_2/\eta_1 \tag{21}$$

$$\xi = (L_{y2}/L_{y1}) \tag{22}$$

$$\theta = A_2/A_1 \tag{23}$$

On one hand, the long run proximity the follower region w.r.t. technological frontier is an increasing function of the institutional quality endowment of the follower, namely of θ. The result is consistent with a great deal of empirical and theoretical literature which has become popular in the last decade starting from the contribution by Acemoglu et al. (2001) and Hall and Jones (1999). Better institutions in the follower regions are associated with higher technology levels in the long run.

A similar reasoning applies to the effect of an increase in the skilled fraction of the workforce in the follower which will increase the ratio ξ/κ increasing the long run proximity with the frontier. Hence, crucially, the technological distance between leader and follower shrinks as this latter increases the share of skilled workers devoted to technology adoption. Then, using eq.(20) with eqs.(10) and (1) we can solve for the long-run output gap of the follower w.r.t. the leader region as a function of human capital composition and of institutional quality as follows:

$$(Y_2/Y_1)^* = \left[\theta^{1/(1-\alpha)} \left(L_{y2}/L_{y1}\right) \left(N_2/N_1\right)^*\right] \tag{24}$$

where, smaller gaps in technological levels between the leader and the follower (as in eq. (20)) also imply smaller gaps in output levels in the long run as expected. Both convergence in GDP and in technology levels are therefore shown to be a function of institutional quality and of human capital composition with regions endowed with more skilled workers will converge to higher GDP in the long run.

3.2 Technology adoption vs innovation choice

The values of both the technology and output gap in steady state are computed under the assumption that the follower region implement technology adoption instead of innovation. The decision of whether to adopt technology or to innovate is tightly linked to the macroeconomic fundamentals of each region and, in particular, to the followers' human capital composition. Hence, given the assumptions of the model we can define under what general conditions technology adoption, rather than innovation, results to be an optimal activity for the follower *in the long run.*

Proposition 3 *The human capital composition of each region defines the optimal condition under which technology adoption is performed profitably instead of innovation. As long as the follower region is endowed with large shares of unskilled workers the cost of performing technology adoption will be lower than that of doing innovation such that the follower will be better off by technology adoption. Any increase in the endowment of skilled workers reduces the gap between the cost functions (ν_2^* and η_2) making imitation increasingly less profitable w.r.t. innovation. Sufficiently large shares of skilled workers in the follower region make innovation the most profitable activity and induce a switch from adoption to innovation.*

In order to compare the two situations (adoption *vs* innovation) we assume that if the follower region were to innovate it would face the following simple cost function:

$$\eta_2 = \omega(L_{r2})^{-1} \tag{25}$$

where we are assuming that, in order to produce innovation, the follower will make use of skilled workers in the R&D sector and that the relative cost of coming up with an innovation will be lower the more skilled workers are employed in R&D. This is the same assumption we have been using throughout the model for the leader region. Of course, then, in the case of innovation in the follower region, no spillover effects take place and so the cost of innovation is unrelated to the distance of the follower from the frontier.

Combining eq.(25) with eq.(19) we can define the condition for which the long-run cost of adoption is constrained to be lower than the correspondent cost of innovation defining the optimality condition for technology adoption as follows:

$$\nu_2^* < \eta_2 \Leftrightarrow (A_2/A_1)^{1/(1-\alpha)} L_{y2}/L_{y1} < \eta_2/\eta_1 \tag{26}$$

Rearrangement of the terms in eq.(26) in a more convenient way leads to:

$$\kappa > \xi\theta^{1/1-\alpha} \tag{27}$$

Crucially then, as long as the disequality in eq.(27) holds, the steady state cost associated to the adoption of technology will be strictly less than the correspondent cost of innovation η_2. Hence, in that case, the follower will always choose to adopt technology rather than being the direct producer of innovation. Adoption is then shown to be more profitable (if compared to innovation) for those economies which are scarcely endowed with highly skilled workers since they face competition in innovation from other regions with larger shares of skilled workers and already acting at the technological frontier.

As the follower approaches the frontier, the gap in the two activities' cost functions will shrink as it will the gap in rate of returns reducing the relative profitability of technology adoption w.r.t. innovation. It is possible to show, then, that given the follower's particular human capital composition, institutional quality and development stage a threshold level for the share of skilled workers in the follower region may be found such that the follower will be indifferent on whether performing technology adoption or innovation; $\tilde{L}r_2 \equiv (\xi/\kappa)^{1-\alpha} = \theta^{-1}$.

Interestingly, any accumulation of skilled workers above the threshold $\tilde{L}r_2$ would call for a switch to innovation activities making innovation a relatively more profitable activity once the critical mass of skilled workers $\tilde{L}r_2$ has been reached. This only happens if the switch from adoption to innovation is implemented once the follower has accumulated the necessary human capital (when $Lr_2 \geq \tilde{L}r_2$) such that this will be conductive to smaller technology and output gap with the frontier in the long-run.

Along with human capital composition differences, also institutional quality differences between the leader and follower, as expected, play a role in the definition of the conditions for which adoption rather than innovation results to be optimal in the long run. In particular it is easy to show how an increase in the quality of institutions of the follower (a rise in the parameter θ) leads the disequality (27) to be less likely to hold and so adoption to be increasingly less profitable w.r.t. technology adoption.

4 Empirical results

4.1 Data

This part of the paper will be devoted to the empirical test of the dynamics underlined in the theoretical model presented before. Our analysis will be focusing on the 17 Comunidades Autonomas Españolas [9] as well as on 50 Spanish provinces. The time span selected ranges from 1960 to 1995 for the analysis on the regions and from 1965 to 1997 for the analysis of the province case. The regional analysis exploits a 5-year dynamic panel model while for the case of the provinces, due to the higher frequency of the data, the dynamic panel will be of 4-years span. The GVA series, which we use in order to compute the gap in output levels of each region w.r.t. the leader, are expressed in per capita terms and is made available by the Fundación BBVA.

We use two different sources for the human capital proxy which allow us to check for the robustness of the results when different methodologies are used for proxying human capital. The data used for regional human capital stocks are those proposed by de la Fuente, Domenéch and Jimeno (2006). These data conveniently allow us to disaggregate the population of age 25 and over by categories of educational attainment. To be more specific we focus on the following educational attainment categories: (*HK1*) primary - *primaria, graduado escolar* whose duration is 5 years, (*HK21*) lower secondary - *EGB, Bachiller elemental, ESO* whose duration is 3 years, (*HK22*) upper secondary - *Bachillerato, COU, FP I and FP II* whose duration is 4 years, (*HK31*) higher education, first level - *Diplomatura, Peritaje* whose duration is 2 years and finally (*HK32*) higher education, second level - *Licenciatura* whose duration is 3 years.

The human capital series at the province level comes from the "Human capital series" provided by the IVIE in collaboration with Bancaja.[10] and refers to the following nominal categories: *(HK1)* illiterate, *(HK2)* primary schooling, *(HK3)* compulsory secondary schooling, *(HK4)* pre-university education *(HK5)* higher education. The data are here expressed in thousand of people employed (active population) for each branch of educational attainment.

If we compare the two human capital databases we can notice how the category *(HK3)* and *(HK4)* of the human capital series for the provinces refer to those educational attainment levels ranging from the secondary compulsory education (for the *HK3*) to the pre-university degrees. These two categories, therefore, correspond partly to those *(HK21)*, *(HK22)* and *(HK31)* of the regional classification given in de la Fuente, Domenéch and Jimeno (2006) database. *HK5*, instead, corresponds to the higher skill margin of the workforce in the province database while, in the regional case its correspondent is named *HK32.*

Our study is also concerned with the role played by institutional quality when this interacts with human capital levels in defining the growth path of the economies. Data proxying for the institutional quality at the regional and provinces level is very hard to find. To the best of our knowledge, the best approximation for the Spanish case are the data for Social Capital provided by the IVIE in collaboration with the BBVA Foundation. In particular, the approach followed in the construction of the data for Spanish social capital focused on the "*social relationships that evolve in the economic sphere, particularly in employment, financial or investment markets, in which long-lasting relationships exist in contexts of uncertainty and strategic interdependence*".[11]

4.2 Methodology

The relation between education and economic growth is likely to be heavily affected by severe problems of endogeneity. In other words, the covariates may not be orthogonal to the error process and the resulting estimates may not be consistent. Within the dynamic panel settings this problem is usually addressed by making use of first-difference GMM estimators such as those proposed by Arellano and Bond (1991) or Arellano-Bover(1995)/Blundell-Bond (1998). These estimators allow to build internal instrumental sets relying on the moment conditions produced by exploiting lagged realizations of the variables in the model (both dependent and exogenous/endogenous ones).

In our particular analysis, moreover, we face another problem related to the educational variables we are going to exploit. As argued by Castelló (2006) educational variables are usually highly persistent over time. It is well known that system GMM estimators for dynamic panel data models generally perform better than standard first-difference estimators when variables are persistent. Blundell and Bond (1998) show that when the considered variables are close to random walk processes then the difference GMM estimators behave poorly because past levels of these variables convey little information about future realizations.

To be slightly more specific, as pointed out by Roodman (2006), the Arellano and Bover (1995) and Blundell and Bond (1998) estimators augment the standard Arellano and Bond (1991) procedure by assuming that first differences of instrumenting variables are uncorrelated with the fixed effects and by allowing the introduction of more instruments which consistently improve the efficiency of the estimator.[12]

The so called Difference GMM estimator relies on the transformation of all regressors, usually by differencing them and, of course, makes use of the Generalized Method of Moments (Hansen 1982) for estimation. The System GMM estimator, instead, relies on one additional assumption that is that first differences of instruments are uncorrelated with the fixed effects allowing the introduction of more instruments. This, as pointed out by Roodman (2006), can dramatically improve efficiency especially when, as in our case, the explanatory variables are likely to be persistent and to be weak instruments in a simpler Difference GMM estimation.

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

Of course, in our specific analysis, this may create severe estimation problems due to the fact that the sample we are using for Spanish regions is not very large. Only recently a correction the downward bias of the two-step System GMM estimators has been devised by Windmeijer (2005). In particular, Windmeijer (2005)[13] proposes a correction to the two-step covariance matrix which is argued it can make the two-step robust estimation more efficient than robust one-step especially for system GMM. For this reason, we use the correction to the two-step covariance matrix proposed by Windmeijer (2005) even if, for completeness of the results and as a robustness check we will also provide, as it has been done in empirical literature up to now, also the results using the one-step System GMM estimator..

Finally, we tried to be extra-carefull with regards to another important issue which is nowadays overlooked in the empirical literature which makes use of Difference and System GMM estimators. This is the possible overfitting of the endogenous variable by a too numerous instrumental set. As pointed out by Roodman (2008), the software routines which are usually employed for the computation of these estimators produce by default a very large number of instruments which may actually overfit the endogenous variable both in Difference and System GMM. The econometrician, therefore, must pay a great deal of attention in the definition of the instrumental set. If the endogenous variable is overfitted by too many instruments the estimator will produce implausibly good Hansen-test results with a P-value very close to 1. As a rule of thumb it is argued we should constraint the number of instruments to be not more than the number of individuals in our sample.

4.3 The empirical model

As pointed out before, the theoretical model predicts that an increase in the fraction of skilled workforce will be growth enhancing and conductive to convergence in income levels across regions. Viceversa, increasing the unskilled content of the workforce will be growth detrimental and conductive to larger GDP gaps in the long run across regions with the follower converging towards lower GDP steady state levels. Also, an increase in the institutional quality of the region/province is expected to impact positively its GDP level and be conductive to convergence to the frontier's GDP levels.

The econometric specification we choose to use is a simplification of eq. (24) and takes the following form:

$$GDP\ gap_{i,t} \;=\; c + \beta_1 SK + \beta_2 Education_{i,t-\tau} + \beta_3 GDP_{i,t-\tau} + \mu_i + \upsilon_{i,t} \quad (28)$$

where we define the *GDP gap* as the log of the ratio between the GDP of each observed region w.r.t. to the value for Madrid which we assume to be our empirical leader region. The *initial GDP*, is inserted in our specification in order to control for the initial development stage of each region. This is to say that we control for initial income differences across regions in order to properly isolate the partial contribution of human capital composition in the definition of long run GDP gaps. *Education* will be the focus of our analysis proxying for regional and province differences in skill levels. Hence, we will analyze whether different educational categories (starting from primary to tertiary education) play a different role in the catch-up of follower regions to the frontier as depicted in the theoretical model. Also, SK represents Social Capital and it will be used in the province-level analysis to proxy for institutional quality.

4.4 Econometric results

4.4.1 Regional results: Pooled OLS

As a preliminary check of the theoretical results of our model assumptions we decided to run a pooled OLS regression of the specification proposed in eq. (28).

Table 1

Dependent Variable: Regional GDP gap			
	Pooled OLS	**Pooled OLS**	**Pooled OLS**
	(i)	*(ii)*	*(iii)*
Log Initial GDP	*.932*	*.916*	*.907*
	*(.023)****	*(.023)****	*(.023)****
HK32			
higher education, second	*-.017*	*.023*	*.031*
	(.019)	*(.010)***	*(.014)***
HK3			
higher education, first	*.029*		
	(.023)		
HK22			
upper secondary	*.007*		*-.044*
	(.031)		*(.017)***
HK21			
lower secondary	*-.044*	*-.044*	
	*(.020)***	*(.011)***	
HK1			
Primary	*-.052*		
	*(.019)***		
C	*.084*	*.028*	*.021*
	*(.028)***	*(.010)***	*(.010)***
R2	*0.97*	*0.90*	*0.97*
n. Obs	*119*	*119*	*119*

****, ** Statistically significant respectively at 1%, 5%*
Standard errors are corrected for heteroskedasticity and reported in parenthesis.

The dependent variable, the GDP gap of each region w.r.t. the leader, is regressed on the educational attainment levels and on initial GDP levels. Results are mixed and, at least in the full specification which uses all the educational categories, they seem to contradict the prediction of the theoretical model with the coefficient for higher education (*HK32*) showing a negative sign even if not statistically significant. Moreover, in column (i) *HK31* (higher education-first) and *HK22* (upper secondary) show positive coefficients differently from what expected and, still, not statistically significant.

When we drop some of the educational categories as in column (ii) and (iii), the coefficient for higher education *HK32* and for lower secondary education *HK21* (as well as *HK22*) seem to show the correct sign with good statistical significance. An increase in the skill intensity of the workforce (the partial effect of *HK32* on the GVA gap) seem to reduce the distance of the followers from the frontier as detailed in the results of the theoretical model. The opposite holds for an increase in the workforce with lower education.

This said, however, the econometric approach followed in this initial analysis - pooled OLS - is probably not adequate in our context due to the very likely presence of endogeneity of the explanatory variables, human capital categories, w.r.t. GVA levels. For this reason we move to the use of Difference and System GMM estimators which allow us to build internal instrumental set to address the problem of endogeneity of the regressors and provide consistent and unbiased estimates. In the next sections below we propose the results.

4.4.2 Regional results: System and Difference GMM estimations

For all econometric specifications (one-step and two-step system GMM estimations), the coefficient for second-higher education *(HK32)* show the expected sign and it is statistically significant at 1 percent confidence level. This result argues for the positive and important impact that the high skilled margin of the workforce would play in the process of GDP convergence at the regional level as hypothesized in the theoretical model. The marginal effect of an increase in the skill content of the followers workforce seem to drive the convergence towards the leaders GVA values and a reduction of the output gap.

Of much more difficult interpretation is the results of the "intermediate" educational categories. This is due to the fact that the available data for these categories do not own the adequate disaggregation so as to disentangle the effect of technical education, which as in our theoretical model may be better suited to technology adoption, from that of more general and "generalist" education.

In fact, if we analyze all the educational categories at once, coefficients for the intermediate educational levels are shown to be statistically significant even if, at a first sight, they appear with unexpected or mixed signs. The assumed educational ranking identifies *HK31* as a relatively higher category of education w.r.t *HK22*. This said, *HK31* shows a negative and statistically significant coefficient while *HK22* a positive one. The upper secondary category *(HK22)* proxies, however, for (i) high-school diploma but also for (ii) vocational training and (iii) lower technical education (FP I and FP II in the Spanish *nomenclature)*. The category *(HK31)* proxies for both (i) general Bachelor's degrees as well as for (ii) technical studies (Peritaje). Hence, differently from the straightforward interpretation of the educational categories at the bottom or top of our scale (such as in the case of the highest *HK32*), the interpretation of the growth effects of the intermediate educational categories results to be difficult due to the mixture in both *HK22* and *HK31* of technical and generalist skills. The data suggest, however, that the vocational training in category *HK22* may play a positive (and bigger) role in the process of technology catch-up than the technical education (Peritaje) of the *HK31* category.

Table 2

Dependent Variable: Regional GDP gap			
	System GMM one-step	**System GMM** one-step	**System GMM** two-step windmeijer robust
	(i)	*(ii)*	*(iii)*
Log Initial GDP	*.779* (.077)***	*.692* (. 056)***	*.701* (.200)***
HK32-higher education, second	*.022* (.006)***	*.025* (. 004)***	*.007* (.035)**
HK31-higher education, first	*-.094* (.077)***	*-.075* (.014)***	*-.024* (.009)**
HK22-upper secondary	*.016* (.002)***	*.014* (.003)***	*.006* (.002)***
HK21-lower secondary	*-.004* (.004)	*-.002* (.003)	*.005* (.008)
HK1-primary	*-.003* (.002)	*-.004* (.001)***	*-.001* (.001)
C	*-2.41* (.271)***	*-2.35* (.212)***	*-2.44* (.381)***
Arellano-bond test AR(2) p-values	*0.129*	*0.207*	*0.155*
Hansen test for Over-ID	*0.816*	*1.00*	*0.219*
n. Instruments	*25*	*42*	*19*
n. Obs	*119*	*119*	*119*

*Note: ***, **,* Statistically significant respectively at 1%, 5% and 10%.*
Robust standard error estimates are consistent in the presence of any pattern of heteroskedasticity and autocorrelation within panels standard errors and are reported in parenthesis. Two-step System GMM are corrected as in Windmeijer (2005) for finite-sample covariance matrix.

Due to the nature of the data, and in order to check for the robustness of the positive effect played by high skilled human capital on regional convergence, in Table 3 we aggregate the *HK22* and *HK31* educational categories into "intermediate education". The main result on the positive effect of skilled human capital (the top category *HK32*) still remains unchanged with strong statistical significance pointing to the growth beneficial contribution of skilled human capital in closing the gap with the frontier for follower regions. By aggregating the intermediate educational categories, the mixed effect of technical and generalist education averages out such that now the coefficient is not statistically different from zero while an increase in lower education (*HK21*) is shown to be growth detrimental as expected.

Table 3

Dependent Variable: Regional GDP gap		
	System GMM one-step	**System GMM** two-step windmeijer robust
	(i)	*(iii)*
Log Initial GDP	*.538*	*.468*
	*(.071)****	*(.109)****
HK32	*.019*	*.022*
higher education	*(.007)***	*(.009)***
HK31+HK22	*.003*	*.006*
Intermediate education	*(.005)*	*(.007)*
HK21		
Lower secondary education	*-.001*	*-.001*
	(.005)	*(.003)*
HK1		
Basic education	*.006*	*.007*
	*(.002)***	*(.002)***
C	*-2.17*	*-2.51*
	*(.182)***	*(.189)****
Arellano-bond test AR(2) p-values	*0.108*	*0.504*
Hansen test for Over-ID	*0.839*	*0.839*
n. Instruments	*26*	*26*
n. Obs	*119*	*119*

*Note: ***, **,* Statistically significant respectively at 1%, 5% and 10%.*
Robust standard error estimates are consistent in the presence of any pattern of heteroskedasticity and autocorrelation within panels standard errors and are reported in parenthesis. Two-step System GMM are corrected as in Windmeijer (2005) for finite-sample covariance matrix.

Finally, we re-do the exercise trying different aggregations of the educational categories and, in particular, by aggregating the two top categories (*HK32* and *HK31*) and those at the intermediate-bottom level (*HK22*, *HK21* and *HK1*). Education at the top of our scale is again find statistically significant and positive showing how the top margin of the scale (rather than unskilled workers) is driving convergence in output level.

Table 4

Dependent Variable: Regional GDP gap	**System GMM** one-step	**System GMM** one-step	**System GMM** two-step windmeijer robust
	(i)	*(ii)*	*(iii)*
Log Initial GDP	*.118*	*.791*	*.777*
	(.090)	*(. 047)****	*(.045)****
HK32+HK31	*.012*	*.005*	*.005*
higher education, (second+first)	*(.005)***	*(. 001)****	*(.001)***
HK22+HK21+HK1	*.003*	*-.000*	*.000*
Upper+Lower secondary + primary	*(.005)*	*(.000)*	*(.000)*
C	*-0.861*	*-2.56*	*-2.51*
	*(.416)***	*(.153)****	*(.137)****
Arellano-bond test AR(2) p-values	*0.054*	*0.338*	*0.319*
Hansen test for Over-ID	*0.297*	*0.783*	*0.783*
n. Instruments	*18*	*13*	*13*
n. Obs	*119*	*119*	*119*

*Note: ***, **,* Statistically significant respectively at 1%, 5% and 10%.*
Robust standard error estimates are consistent in the presence of any pattern of heteroskedasticity and autocorrelation within panels standard errors and are reported in parenthesis. Two-step System GMM are corrected as in Windmeijer (2005) for finite-sample covariance matrix.

4.4.3 Provinces results: System and Difference GMM estimations

Due to issue of data availability at the regional level, we were not able to introduce into the model any proxy of institutional quality differences across regions. The analysis at the province level allows us to address these two shortcomings by making use of a different (larger) database and therefore, also, to check the sensitivenness of the results to the change in the aggregation level as well as to the insertion of social capital data proxying for institutional quality. The assumption is that a higher level of social capital will be growth beneficial and therefore associated to a reduction in the GDP gaps across provinces by decreasing transaction costs or, as in Hall and Jones (1999), by reducing the costs of social diversion: "*Social institutions to protect the output of individual productive units from diversion are an essential component of a social infrastructure favorable to high levels of output per worker. Thievery, squatting, and Mafia protection are examples of diversion undertaken by private agents*".

In column (i) of table 5 we propose the one-step robust SysGMM estimation of the disaggregated human capital categories. The results show again the nonlineal impact of human capital educational levels on GDP convergence. Higher education (*HK5*) shows a positive and statistically significant coefficient estimated at 1 percent confidence level arguing again for the positive contribution of skilled workers to the catch-up process across Spanish provinces.

Again the interpretation of the intermediate educational level results more complicated. The category *HK4* proxies for pre-university degrees. Among these, we find technical studies along with other much more generalist subjects such as, for example, humanities and social sciences. The category *HK3*, instead, proxies for vocational and technical training but also for other degrees such as arts but also highschool degrees. In particular, *HK3* shows a positive coefficient even if not statistically significant while the pre-university degrees seem to impact negatively the convergence process. The positive (but not significant) coefficient for *HK3* may be interpreted again as data aggregation problem for which, vocational training which we expect to have a positive effect on growth, is averaged out by other types of degrees aggregated within the same educational category.

Interestingly, social capital enters, the regression with a positive and highly significant coefficient as expected. This result shows how, for those provinces in which trust and economic cooperation are more developed (proxying for the quality of provinces' institutions), the GDP convergence process is actually faster.

Table 5

Dependent Variable: Provinces GDP gap		
	System GMM ***one-step*** *(iii)*	**System GMM** ***two-step windmeijer robust*** *(iv)*
Log Initial GDP	*.592* *(.049)****	*.567* *(.050)****
HK5 higher education	*.227* *(.064)****	*.252* *(.070)****
HK4 pre-University Degrees	*-.379* *(.103)****	*-.403* *(.118)****
HK3 lower secondary	*.004* *(.057)*	*.006* *(.052)*
HK2-primary	*.186* *(.033)****	*.187* *(.034)****
Social Capital	*.001* *(.000)****	*.001* *(.000)****
C	*-4.82* *(.457)****	*-4.65* *(.426)****
Arellano-bond test AR(2) p-values	*0.566*	*0.789*
Hansen test for Over-ID	*0.202*	*0.202*
n. Instruments	*44*	*44*
n. Obs	*250*	*250*

*Note: ***, **,* Statistically significant respectively at 1%, 5% and 10%.*
Robust standard error estimates are consistent in the presence of any pattern of heteroskedasticity and autocorrelation within panels standard errors and are reported in parenthesis. Two-step System GMM are corrected as in Windmeijer (2005) for finite-sample covariance matrix.

Similarly to what we did for the regional case, we check whether the positive effect of the top margin of the educational scale on GDP catch-up holds also when we differently aggregate the educational categories. In column (i) and (ii) of table 6 we aggregate the categories *HK3* and *HK4* in the "intermediate education" one. Coefficient is now statistically significant and negative highlighting the non-lineal impact of human capital in the convergence process. In fact, the top category *HK5* is still statistically significant and positive (as well as the basic education, *HK2*) as predicted in the theoretical model contributing positively the closure of the gap with the frontier. Also, social capital still shows a positive and statistically significant coefficient in the SysGMM estimation while it does looses significance when we perform Difference GMM.

In columns (iii) and (iv), we try different human capital aggregation by merging together the top categories (*HK5* and *HK4*) and those at the bottom (*HK3* and *HK2*). The results show how the categories at the top positively contribute to GDP convergence of follower regions to the frontiers values. The coefficient for the bottom categories is instead not statistically different from zero in the preferred specification (the Sys GMM) and negative, instead, in the Difference GMM estimation.

Table 6

Dependent Variable: Provinces GDP gap	**System GMM** two-step windmeijer robust	**Difference GMM** two-step windmeijer robust	**System GMM** two-step windmeijer robust	**Difference GMM** two-step windmeijer robust
	(i)	*(ii)*	*(iii)*	*(iv)*
Log Initial GDP	*.777 (.055)****	*.131 (.062)***	*.111 (.047)****	*.007 (.029)*
HK5 Higher education	*.183 (.051)****	*.214 (.053)****		
HK4+HK5 Higher education, (second+first			*.049 (.024)***	*.129 (.025)****
HK3+HK4 Intermediate education	*-.698 (.123)****	*-.531 (.185)****		
HK2+HK3 secondary+ primary			*.062 (.051)*	*-.390 (.151)***
HK2 Basic education	*.550 (.079)****	*.241 (.097)****		
Social Capital	*.001 (.000)****	*.000 (.000)*	*.001 (.007)*	*-.006 (.009)*
C	*-4.19 (.438)****	-	*-1.56 (.368)****	-
Arellano-bond test AR(2) p-values	*0.155*	*0.380*	*0.660*	*0.419*
Hansen test for Over-ID	*0.254*	*0.862*	*0.038*	*0.531*
n. Instruments	*44*	*19*	*28*	*14*
n. Obs	*250*	*200*	*250*	*200*

*Note: ***, **,* Statistically significant respectively at 1%, 5% and 10%.*
Robust standard error estimates are consistent in the presence of any pattern of heteroskedasticity and autocorrelation within panels standard errors and are reported in parenthesis. Two-step System GMM are corrected as in Windmeijer (2005) for finite-sample covariance matrix.

5 Conclusions

The debate over education is probably one of the most recurrent in policy making. From a regional point of view the disparities in educational attainments are sometimes very large with follower regions stuck at relatively low level of development.

With this paper we studied the case of Spanish regions and provinces by building a simplified two-region theoretical model where follower regions adopt technology from the frontier. Technology spillovers are ignited by the recipient region's ability of adopting these technologies. As in previous literature, the follower's absorptive capacity is linked to the quality of its human capital which reduces the cost faced by followers when adopting an unknown technology.

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

We merged features from different previous contributions such as Barro and Sala-i-Martin (1997), Nelson and Phelps (1966), Behnabib and Spiegel (2005) and Vandenbussche, Aghion and Meghir (2005) in order to formalize the technology cost function and dynamics of the follower region. The relative easiness of adoption, its cost, has been assumed to be a function of the proximity to the technological frontier as well as of the quality of human capital devoted to imitation in the follower region. Also, the growth path of the follower economies is put in relation with its institutional and social capital levels. All these variables have been shown to be crucial in the definition of the optimal growth path for the follower region.

This said, even if at first sight based on similar grounds, our theoretical results crucially differ from previous contributions. In particular, our model shows, under broad conditions, that an increase in the share of skilled workers is growth enhancing for both the leader and the follower regardless of whether they are performing innovation or adoption.

The increase in the high skill content of the follower's workforce reduces the cost of technology adoption. As in the original Nelson and Phelps (1966) hypothesis, an increase in the follower's skills implies stronger technology spillover and catch-up making, among other things, technology adoption easier for the follower regions. At the same time, the accumulation of skilled workers in the follower makes innovation increasingly more profitable such that, for sufficient accumulation of skills, the follower will switch from technology adoption to innovation. Convergence in GDP and technological levels is, therefore, driven by the specific composition of human capital in each follower region.

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

We test the main theoretical results of our model on Spanish regions and provinces for the period 1960-1997 by making use of a dynamic panel model. We chose to use appropriate econometrics techniques, namely two-step Windmeijer small sample corrected System GMM estimators, to test the hypothesis that increases in the high skill content of regions' human capital stocks are conductive to higher growth and to a higher proximity with the leader in the long run.

Our results seem to confirm the main hypothesis of the theoretical model. The impact of human capital on the reduction of GDP differential across regions is non-lineal. Higher educational levels enter with a positive coefficient in our regressions indicating how increasing the high skill content of each regional workforce seems to be conductive to higher economic growth and convergence. Instead, intermediate and lower educational levels seem to negatively contribute to growth in the long run. The basic result is robust to different aggregations of the educational categories. Some weaker evidence is found for the positive impact of vocational and technical training as drivers of GDP convergence. However, the available disaggregation of the human capital data do not allow us to disentangle the marginal effect of technical studies from that of more generalist degrees (less useful for catch-up). Social capital shows, also, to be one long-run determinant of economic convergence for Spanish regions and provinces.

Notes

[1] See Acemoglu and Dell (2009).

[2] Two related contributions on regional economic growth which embrace this point of view are that by Diliberto (2006) for the Italian case and that by Ramos, Suriñach and Artis (2009) for the Spanish one.

[3] See Vandebussche, Aghion and Meghir (2004), proposition 1: "*Under assumption (A1), a marginal increase in the stock of skilled human capital enhances productivity growth all the more the economy is closer to the world technological frontier. Correspondingly, a marginal increase in the stock of unskilled human capital enhances productivity growth all the more the economy is further away from the techonological frontier*".

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

[5] For example, in the last Community Innovation Survey (CIS) carried out by the European Commission the definition of "*process innovation is the implementation of a new or significantly improved production process, distribution method, or support activity for your goods or services. The innovation (new or improved) must be new to your enterprise, but it does not need to be new to your sector or market. It does not matter if the innovation was originally developed by your enterprise or by other enterprises.*"

[6] To be more realistic we assume the follower faces a fixed (but relatively negligible) cost, ψ to acquire the license to use the inventor's idea. This is, for example, the cost paid to the innovator for licensing, using or adapting his/her idea in the follower's market. Hence, once the idea has been made available to the adopter, the speed and ability of each follower/adopter to implement and make profitable the new technology varies as a function of its skills as in eq.(9)

[7] We formalize the cost function for the production of innovation as $\eta_1 = \omega(L_{r1})^{-1}$, where η_1 represents the cost of coming up with a new blueprint. This is a function of L_{r1}, that is the share of high skilled workers employed in the R&D sector producing new knowledge.

[8] Notice that the new variables in eq.(27) are all expressed as the ratio of the follower's quantities over the leader's in order to make the analysis more readable.

[9] 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.

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

[11] See IVIE, http://ivie.es/banco/ksocial.php?idioma=EN. The data for social capital matches our sample at the regional and province level for the period in between 1981 and 1997. This is a shorter time span if compared to the data we have available on human capital and GDP. Due to the already small number of observations for the regional case the use of the social capital data in the context of the regional analysis has been therefore dropped. Its use, instead, for the provinces case reduce the sample from 400 observations to 250 observations so we decided to propose the empirical analysis of the impact of human capital composition either with and without controlling for institutional quality differences at the province level.

[12] Formally the system GMM estimator assumes the following: $E\left[\Delta W_{i,t-1}\varepsilon_{i,t}\right] = E\left[\Delta W_{i,t-1}\mu_i\right] + E\left[W_{i,t-1}\upsilon_{i,t}\right] - E\left[W_{i,t-2}\upsilon_{i,t}\right] = 0 + 0 - 0$ where μ_i are the fixed effects and $\upsilon_{i,t}$ are the idio-

syncratic 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.

[13] 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)

References

[1] Abramovitz, M. (1986). “Catching Up, Forging Ahead, and Falling. Behind”. Journal of Economic History 46, 385-406.

[2] Acemoglu, D. and Dell, M., "Productivity Differences between and within Countries". NBER Working Paper No. w15155.

[3] Acemoglu D., P. Aghion and F. Zilibotti (2006). "Distance to Frontier, Selection, and Economic Growth", Journal of the European Economic Association 4 (1), 37-74

[4] Acemoglu Daron, Simon Johnson and James A. Robinson (2001), "The Colonial Origins of Comparative Development: An Empirical Investigation", American Economic Review, volume 91, pp. 1369-1401.

[5] Acemoglu Daron, Simon Johnson and James A. Robinson (2005), "Institutions as the Fundamental Cause of Long-Run Growth", Handbook of Economic Growth (Philippe Aghion and Stephen Durlauf, eds., region 1 Holland)

[6] Aghion, P. and P. Howitt, (1992). “A Model of Growth Through Creative Destruction” Econometrica, 60 (2).

[7] Aghion, P. and P. Howitt (2005) "Appropriate Growth Policy,". Forthcoming in the Journal of the European Economic Association.

[8] Arellano, M. (2003a) Panel Data Econometrics, Oxford University Press, Oxford.

[9] Arellano, M. (2003b) ‘Modeling optimal instrumental variables for dynamic panel data models’, Working Paper 0310, Centro de Estudios Monetarios y Financieros, Madrid.

[10] Arellano, M., and S. Bond. (1991). 'Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations', Review of Economic Studies, Vol. 58, pp. 277–297.

[11] Arellano, M., and S. Bond. (1998). 'Dynamic panel data estimation using DPD98 for Gauss: a guide for users', available at ftp://ftp.cemfi.es/pdf/papers/ma/dpd98.pdf.

[12] Arellano, M., and O. Bover. (1995). 'Another look at the instrumental variables estimation of error components models', Journal of Econometrics, Vol. 68, pp. 29–51.

[13] Barro, Robert J., and Xavier Sala-i-Martin, (1997), "Technological Diffusion,Convergence and Growth," Journal of Economic Growth, 1, 1-26

[14] Barro, Robert J., and Xavier Sala-i-Martin, (1995), Economic Growth.

[15] Basu, Susanto, and David N. Weil, (1998), "Appropriate Technology and Growth," Quarterly Journal of Economics, November, 113(4), 1025-54.

[16] Benhabib, Jess and Mark M. Spiegel. (1994), "The Role of Human Capital in Economic Development: Evidence from Aggregate Cross-Country Data," Journal of Monetary Economics, 34, 143-173.

[17] Benhabib, J. and M. Spiegel. (2005). "Human Capital and Technology Diffusion", in Aghion P. and S. Durlauf (eds), Handbook of Economic Growth, Elsevier

[18] Bils, Mark, and Peter J. Klenow, (2000), "Does Schooling Cause Growth?," American Economic Review, December, 90(5), 1160-83.

[19] Blundell, R., and S. Bond. (1998). 'Initial conditions and moment restrictions in dynamic panel data models', Journal of Econometrics, Vol. 87, pp. 115–143.

[20] Blundell, R., and S. Bond. (2000). 'GMM estimation with persistent panel data: An application to production functions', Econometric Reviews, Vol. 19, pp. 321–340. 30

[21] Blundell, R., S. Bond, and F. Windmeijer. (2000). 'Estimation in dynamic panel data models: improving on the performance of the standard GMM estimator', in Baltagi B. (ed.), Advances in Econometrics, Vol. 15, Non-stationary Panels, Panel Cointegration, and Dynamic Panels, JAI Elsevier Science, Amsterdam.

[22] Caselli F. (2005). "Accounting for Cross-Country Income Differences," NBER Working Papers 10828, National Bureau of Economic Research

[23] Caselli, Francesco & Wilson, Daniel J., (2004). "Importing technology," Journal of Monetary Economics, Elsevier, vol. 51(1), pages 1-32, January

[24] Castelló, A. (2006). " On the distribution of Education and Democracy" Institute of international Economics, working paper, University of Valencia.

[25] Coe, David T. and Elhanan, (1995), "International R&D Spillovers," European Economic Review, May, 39(5), 859-87

[26] Connolly M. and D. Valderrama. (2005). "North-South technological diffusion and dynamic gains from trade," Working Papers in Applied Economic Theory, Federal Reserve Bank of San Francisco.

[27] de la Fuente, A. and Doménech R.(2006) "Human capital in Growth Regressions: How much difference does data quality make?" Journal of European Economic Association, 4(1), 1-36

[28] de la Fuente, A., Doménech R., and J.F. Jimeno (2003). "Human capital as a factor of growth and employment at the regional level. The case of Spain". IAE WP 610.04

[29] di Maria C. and Stryszowski P. (2009) "Migration, human capital accumulation and economic development", Journal of Development Economics, 90, 306-313.

[30] Diliberto, A. (2006). "Education and Italian Regional Development",Economics of Education Review, Vol. 27, No.1

[31] Dollar, D. and A. Kraay (2003). “Institutions, trade, and growth” Journal of Monetary Economics, Elsevier, vol. 50(1), pages 133-162

[32] Frankel J. and D. Romer, (1999), “Does Trade cause Growth? ”, American Economic Review. 89(3):. pp. 379-99.

[33] Gallini, N. (1992) "Patent Policy and Costly Imitation", The RAND Journal of Economics 23, 52-63

[34] Gerschenkron, A., (1962), Economic backwardness in historical perspective, Cambridge, Belknap Press of Harvard University Press

[35] Grossman, G. and Helpman E. "Innovation and Growth in the global economy". Cambridge MA:MIT press

[36] Hall, Robert E. and Charles I. Jones, (1999), “Why Do Some Countries Produce So Much More Output Per Worker Than Others?,” Quarterly Journal of Economics, February, 114(1), 83-116, 61, 1247-80

[37] Keefer P. and S. Knack. (1997). "Why Don’t Poor Countries Catch Up? A Cross-National Test of an Institutional Explanation". Economic Inquiry 35, 590-602.

[38] Keefer P. and S. Knack (2002). " Polarization, Politics and Property Rights: Links Between Inequality and Growth", Public Choice 111, 127-154.

[39] Krueger A. and Lindahl M. (2001). "Education for Growth: Why and for Whom?," Journal of Economic Literature, 39(4), pages 1101-1136

[40] Nelson, Richard R. and Edmund S. Phelps (1966), "Investment in Humans, Technological Diffusion, and Economic Growth," American Economic Review, 56, 69-75

[41] North, D. (1990)., "Institutions, Institutional Change, and Economic Performance, Cambridge", Cambridge University Press

[42] Olson M., N. Sarna and A. Swamy. (2000)."Governance and Growth: A Simple Hypothesis Explaining Cross Country Differences in Productivity Growth", Public Choice, 102, 341-364

[43] Parente, S. L., and E. C. Prescott (2000), Barriers to Riches, Cambridge, MA: MIT Press.

[44] Psacharopoulos, George. 1994. "Returns to Investment in Education: A Global Update", World Development 22(9):1325-43

[45] Ramos, R. Suriñach, J. and Artis M. (2009) "Human capital spillovers and regional economic growth in Spain" IAREG Working paper series, WP2/09

[46] Roodman, D (2006). "How to Do xtabond2: An Introduction to "Difference" and "System" GMM in Stata," Working Papers 103, Center for Global Development

[47] Roodman, D. (2007). "A Note on the Theme of Too Many Instruments," Working Papers 125, Center for Global Development.

[48] Sachs, Jeffrey. D. and Andrew M. Warner, (1997), "Fundamental Sources of Long-Run Growth,". American Economic Review, May, 87(2), 184-188.

[49] Windmeijer, F. (2005). 'A finite sample correction for the variance of linear efficient two-step GMM estimators', Journal of Econometrics, Vol. 126, pp. 25–51.