The farthest needs the best. Human capital composition and development specific economic growth.

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March 23, 2011

Abstract

In this study we provide robust and compelling evidence of the larger effect of tertiary education on the growth of less developed countries and of the relatively smaller impact on the growth of developed ones. This argues for the accumulation of high skills *especially* in technologically under-developed countries and, contrary to the common wisdom, independently of the fact that these economies might be initially producing low(er)-technology goods or performing technology imitation. Our results are robust to the different measures used to proxy for human capital and to the adjustment for cross-country differences in the quality of education. Country-specific insitutional quality, as well as other various indicators such as the legal origin, the religious fractionalization and openness to trade have been used to control for the robustness of the results. They are also shown to speed up technology convergence confirming previous empirical literature. Our estimates tackle endogeneity by applying a variety of techniques such as IV (both panel and cross-section) and two-step efficient system GMM.

1 Introduction

Where has all the education gone? With this question Lant Pritchett (2001) started wondering about the puzzling (weak) macroeconomic empirical evidence of the impact of human capital on economic growth. In fact, even if the predictions of endogenous growth theory have been consistently pointing to human capital as the engine of growth (Aghion and Howitt, 1992 or Romer, 1990), the estimated impact of education proxies on economic growth has been showed to be negative or, at best, null in a wide collection of empirical influential studies. The work by Krueger and Lindhal (2001), Benhabib and Spiegel (1994) or Temple (2001) are amongst those supporting this puzzling evidence and arguing that the role of human capital on economic growth might had been quite overstated. In panel data studies, Caselli, Esquivel and Lefort (1996) or Bond, Heffer and

Temple (2001) also failed to recover the expected positive coefficient of human capital on economic growth[1].

More recently, as a response to these empirical results, a new strand of literature has tried to redeem the role of education and human capital by pointing to various potential causes of this puzzling outcome. In two influential studies, de la Fuente and Domenech (2001) and Cohen and Soto (2006) argued that the human capital datasets used in previous growth regressions (and especially in panel data studies) were fairly unreliable and of poor quality. After having detected the presence of substantial measurement error in previous international estimates of average years of schooling, these authors have been able to produce more robust and consistent human capital proxies which now reasonably outperform other previous sources.

Contextually to the debate on the quality of the human capital proxies, an equally interesting and influential hypothesis has been proposed in the literature to explain the (lack of) empirical evidence of the impact of average measures of human capital on economic growth. In a recent paper, Vandenbussche, Aghion and Meghir (2006) (VAM henceforth) propose an original theoretical model in which different types of human capital (*resp.* skilled vs unskilled workers) would perform different tasks (*resp.* innovation vs imitation) depending on the relative distance of the economy to the technology frontier (*resp.* when close or farway from the technological leader).

The crucial dimension to be analyzed, hence, ends up being the relative "composition" (rather than the average level) of human capital in each country[2]. VAM's theoretical result is crucially based on a double-sided hypothesis. On the one hand, the elasticity of skilled labor is assumed to be higher the closer the economy is to the technology frontier (and hence, when innovation is performed). Consitently with this assumption, it is argued that "*a marginal increase in the fraction of skilled workers will enhance productivity growth all the more the economy is closer to the world technological frontier*". However, as a consequence of this assumption, for those countries which are found far from the frontier, it is also argued that "*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*"[3].

[1] The above mentioned studies are only some among others influential examples of a broader empirical literature that struggled in finding the expected positive effect of human capital on growth.

[2] This assumption is not completely new. Grossman and Helpman (1991) already pointed out how the skill composition of the workforce (rather than the average level) was able to explain differences in good or bad economic performances. In particular, their result is that high skilled labor is growth enhancing and *viceversa.*

[3] See Vandebussche, Aghion and Meghir (2006), 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*".

The second part of this theoretical result (the one related to the impact of unskilled labor on the growth of lagging economies) is rather troubling to us since it would suggest that, in order to catch up with the world technological frontier, developing countries should *reduce* rather than *increase* their skill endowement and that this reduction in skills would be beneficial the more these countries are under-developed[4]. To put it in other terms, VAM's theoretical results generates from the belief that imitation, being relatively easier than innovation, will be better performed by unskilled workers. Crucially, however, even if we agree that innovation is a more complex activity than imitation, there is no reason *a priori* to believe that skilled workers would be outperformed by unskilled workers in any of these activities, and hence, when it comes to imitation or technology adoption.

From an empirical point of view, VAM provide econometric evidence to their hypothesis. However, they do so on a reduced sample of 19 developed OECD countries (which, in practice, represent those developed countries already close to the world technology frontier) while they neglect the analysis of human capital composition on an equally (or more) important part of the available sample of countries: the developing and LDCs countries which are found considerably far from the technology frontier.

With our study we insert into this literature with the aim of challenging VAM's empirical and theoretical results by providing new robust macroeconomic empirical evidence of the alternative hypothesis for which skilled (rather than unskilled) labor contributes to growth and especially for the growth of those countries lagging far behind the technological frontier.

There are different reasons to argue that skilled workers may be fundamental for the growth of lagging countries that perform technology adoption. A large and robust microeconomic empirical evidence, in fact, (see Psacharopoulos (1994), Psacharopoulos and Patrinos (2002), Ichino and Winter-Ebmer (1999) or Cohn and Addison (1999)) points to the much larger returns to investment in education (and especially of investment in tertiary education) at lower development stages. The returns to tertiary education are estimated to be almost twice as big in LDCs than in OECD. These results somehow clash with the assumption made by VAM that skilled workers' elasticity on growth (*i.e.* tertiary education) should be any higher the closer an economy is to the world technology frontier (*i.e.* more developed).

As a fundamental reason grounding our hypothesis stands the fact that technology imitation is not a *free lunch*. On the contrary, technology imitation and

[4]Despite the puzzling implications of VAM's theoretical hypothesis for developing countries, recent empirical literature such as Acemoglu, Aghion and Zilibotti (2006), Aghion, Boustan, Hoxby and Vandenbussche (2009) or Acemoglu and Zilibotti (2001) embraced and shared similar assumptions on the elasticities of different types of human capital on economic growth.

adoption[5] are intrinsically skill demanding activities which are better performed by educated workers than uneducated ones. Other previous empirical literature has already stressed this point. Maskus, Saggi and Puttitanun (2004), Mansfield, Schwartz and Wagner (1981), Coe and Helpman (1995) or Behnabib and Spiegel (2005) argue, directly or indirectly, that the cost of the adaptation and imitation of technologies discovered at the frontier (or in other technological sectors) is positive[6] and that investments in human capital are hence needed in order to absorb this foreign-leading technology.

One might argue, in fact, that the growth challenge faced by developing countries is not that of producing large "quantities" of technologically imitated goods (task that could indeed be accomplished by lots of developing countries endowed with large shares of unskilled workers) but, rather, to uncrack the best ways to do it minimizing the process-imitation costs related to the adoption and imitation of these foreign technologies so as to be competitive in international markets against other imitators for which the frontier technology is also potentially available.

To put it differently, some technologies are indeed more difficult to be imitated than others[7] but, at the same time, they are also usually the most profitable ones. These technologies are not immediately available to everyone regardless of his/her skills. On the contrary, the imitation or adoption of leading edge and profitable technologies requires specialized labor that has to be able to do technical reverse engineering (during the imitation process), find the right product to be imitated and its market niche, understand market trends and, at later stages of the imitation process, to be able to trade the final imitated good in international markets. Instead, the lack of trained workforce will simply impede the imitation process to start and to develop optimally.

Ceteris paribus, those countries with better human capital will perform imitation activities better than those with relatively less skilled labor. Not only that, it can be argued that increasing the share (or the quality) of the workforce will induce better and more varieties of imitations to be performed such that the final imitated goods, sold in the international markets (or used in the domestic one), will be more in its quantity/variety and of higher economic

[5] In this context we make a slight differentitation between the terms "imitation" and "adoption". By imitation we refer to the process of unveiling a product's (or technology's) characteristics, of unpacking it and of physically reproducing it with the aim of reselling this technology at a cheaper price (and with a lower quality) in international and domestic markets. By technology adoption, instead, we refer to the process of unveiling and unpacking a foreign technology with the aim of using it in the domestic economy for production. One may think, for example to the adoption of a process technology (the way a certain process is optimized) when this process innovation can be adopted without having to pay the inventors for this organizational change.

[6] 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.

[7] See for instance, Basu and Weil (1998) or Barro and Sala-i-Martin (1997)

value. Rephrasing Calmfors, Corsetti, Flemming et al.(2003) "[skilled] *people may represent small numbers but have a critical economic significance*". This consideration applies also to developing countries, and especially in those countries where skilled and trained workers are indeed very scarce.

We depart from previous analyses under many respects by tackling, *altogether,* the different issues which we described above and that may affect the estimation of the causal relation between human capital and economic growth. Regarding the quality of the human capital data, we exploit the Cohen and Soto's (2006) international panel database for 88 countries for the period 1960-2000. This large dataset allows us to test the effect of different types of human capital on growth by differentiating between developed and developing countries. Hence, thanks to the rich disaggregation of the available human capital data we are able to check not only for the (likely) different impact that tertiary education may have on countries at different development stages (developed vs developing) but also to run this same analysis for secondary and primary education in order to rank the magnitude of their effects on growth.

We run our empirical model using, as human capital composition proxies, both (i) the average years of schooling in each education attainment level and (ii) the fractions of workforce for primary, secondary and tertiary education in each year while we test our hypothesis on both the TFP catch-up empirical specification used by VAM and on the logistic technology diffusion function proposed by Behnabib and Spiegel (2005).

From the econometric point of view, on the top of the data quality problems, another compelling issue has longly affected the correct estimation of the impact that human capital may have on economic growth. Bils and Klenow (2000) provide convincing evidence that part of the positive effect of intial schooling levels on economic growth might be attributed to reverse causality. We carefully tackle endogeneity by applying a variety of suitable econometric techniques. Hence we initially run our estimation by using fixed and random effects instrumental variables estimators in the fashion proposed by VAM. However, as pointed out by Aghion et al. (2009), the ability of correctly identifying the causal relation between human capital and economic growth is undermined by the use of lagged education spending as instruments which may be highly correlated over time within a country as well as correlated to other variables such as institutions. We overcome this issue under two aspects.

On the one hand, we control (in all specifications) for institutional quality adding this variable as an additional explanatory control into our catch-up specifications. We proxy for institutional quality by using the panel data provided in the Economic Freedom of the World index (EFW). However, since insitutional quality may itself be endogenous w.r.t. growth we also instrument for it by using exogenous characteristics of the countries which have been shown to be highly correlated with institutions such as their geographical location (Hall and Jones, 1999), their colonial and legal origin (Acemoglu et al. 2001, or la Porta et al., 2008) or their language or religious characteristics (Alesina et al. 2003). Results are again extremely robust and support our hypothesis.

On the other hand, however, since human capital data are quite persistent over time, the econometric literature suggests the use of different estimators able to deal with both the measurement error and the endogeneity of the regressors in a dynamic panel context. We re-run the our empirical model by applying the dynamic system GMM estimators proposed by Arellano and Bover (1995)[8]. In addition to this, we also correct for small sample biases by applying the two-step optimal estimation procedure proposed by Windmeijer (2005). Contrary to VAM theoretical predictions and empirical results, our estimates are extremely robust and unveil the fundamental role played by skilled labor (rather than unskilled labor) on economic growth for developing countries.

Interestingly, once we properly address endogeneity and identification issues, the estimated impact of tertiary education on the catch-up of developed countries turn out to be (somehow puzzlingly) negative. We argue there are various reasons able to explain this outcome. The most important one is that, when approximating human capital by average years of schooling we do not account for the quality of education inducing an under-estimation of the impact of tertiary education which may be potentially more severe at higher development stages. Hanushek and Woessman (2009) and Hanushek and Kimko (2000) argue, for example, that the use of average years of schooling as a proxy for human capital may still hide the effect of the differences in the *quality* of education systems across countries by imposing the same return to an additional year of education in the U.S. and, for instance, in Peru. The authors provide robust evidence of the statistical significance of cognitive skills (proxied by international achievement test scores) on economic growth arguing that adjusting for the quality of education helps restoring the (missing) positive relation between human capital and economic growth.

Hence, we also test whether the quality of education, rather than its quantity, has a statistically significant impact on economic growth and, crucially, if this impact differs for economies at different development stages. Our results are strikingly robust to changes in the specification and data used and show that tertiary education (or high-quality education) is a fundamental driver of productivity and economic convergence for developing countries. Adjusting the average years of schooling proxies for the quality of education also returns a positive impact of tertiary education on the growth of developed countries even if, consistently with our initial hypothesis, this effect is smaller the closer an economy is to the technology frontier.

Finally, we make an additional effort in trying to give a sound theoretical backgroud to our results. We modify the Barro and Sala-i-Martin's (1997) model so as to accomodate the assumption on human capital composition differences

[8]These estimators enable us to tackle simultaneity biases while also to outperform LSDV and first-difference GMM estimators in the case of persistent explanatory variables, as it is the case in our regressions.

across countries (the North at the technology frontier and the South, lagging behind). The model is calibrated on empirical evidence such that the South is endowed with a relatively lower share of skilled workers over its total population than the North. Differences in the quality of institutions are also accounted for in the model while we crucially link the cost of innovation and imitation activities (respectively performed at the technological frontier and far from it) to the human capital composition of each country (that is on their relative share of skilled over unskilled workers). Solving for the model growth rates and calibrating the theoretical result on numerically plausible model parameters we are able to show that a marginal increase in the share of skilled workers (tertiary or high-quality educated workers) boost economic growth. Contrary to previous theoretical models' results, the growth enhancing effect of an increase in the share of skilled workers is shown to be relatively larger the farther away an economy is found from the technology frontier and the smaller its initial endowement of skilled workers.

The policy implications of our results are crucially different from those proposed in previous literature and suggest that pro-development policies should favor the accumulation of skills in technologically lagging economies despite the fact that these economies are producing low-technology goods and performing little or null innovation. In contrast to much of the previously mentioned literature, our results show that skilled labor has a crucial impact in those countries that are less endowed with it (the developing countries) and that are currently struggling to catch-up with the technology frontier by means of technology imitation.

The remainder of the paper is as follows. In section 2 we describe the data collection and its sources while in section 3 we discuss our strategy to address endogeneity and simultaneity issues. In section 4 we provide the empirical results obtained by using different estimation techniques and the quantitative measures of human capital (average years of schooling and fractions of the workforce in each education level). In section 5 we discuss the evidence on the quality of education proxies and re-run our empirical estimates on both the quantity and quality human capital proxies. In section 6 we provide a simple theoretical model á la Barro and Sala-i-Martin (1997) grounding our empirical results. At the end some conclusions.

2 Data

In order to build our dataset we combine information coming from seven different sources and previous empirical literature. Our final dataset covers 88 countries (both developed and developing) for the period 1960-2000. As for the GDP data we make use of the Penn World Tables 6.1 provided by Heston, Summers and Aten (2002). Since capital stock data are not available in this database, a common solution is to build capital stock estimates by applying the Perpetual

Inventory Method (PIM) to time series investment data. Even if PIM is a well established method used in empirical literature, it is not without concern. This relates to the possible measurement error in the initial capital stock year which might arise if the investment data do not go back long enough in time[9]. In a recent study, Baier, Dwyer and Tamura (2006) build capital stock estimates by exploiting very long investment time series (in some cases dated to the 18th century) provided by B.R. Mitchell (1998a, b, c). Investment data prior to 1992 are measured by using the: (i) *International Historical Statistics: The Americas 1750-1993*, (ii) *International Historical Statistics: Africa, Asia and Oceania 1750-1993* and (iii) *International Historical Statistics: Europe 1750-1993*[10] such that the measurement error on the initial capital stock condition is of no concern in these estimates. We follow VAM and define Total Factor Productivity (TFP) as output per worker minus capital per worker times capital share[11] and compute the proximity to the technological frontier as the ratio of each country's TFP level to that of the U.S.[12].

Due to the aim of our study, the treatment of human capital data is of crucial importance for our analysis. As argued before, (one of) the most common approximations of human capital relies on computing average number of years of schooling[13] of the workforce in each country/period. Already available datasets make use of the data coming from the *UNESCO's Statistical Yearbook* as well as those provided in the *United Nations' Demographic Yearbook*. In principle, it is possible to categorize human capital datasets according to whether they make use of both census and enrollment data or only the latter. In the first group, which should be regarded as superior to the second one for the richness of the information used, we find the human capital database by Barro and Lee (1993 and 1996), as well as the more recent data coming from the work by de la Fuente and Domenech (2001) and that by Cohen and Soto (2001). In an interesting data comparison review, de la Fuente and Domenech (2006) show substantial measurement differences between, on the one hand, the data proposed by de la Fuente and Domenech (2001) or Cohen and Soto (2006) and, on the other hand, the widely used Barro and Lee (1993 and 1996) human capital series. De la Fuente and Domenech and Cohen and Soto's (2006) data are shown to better perform in panel data models due to the much smoother (and reasonable) dynamic behavior over time. As argued by de la Fuente and Domenech (2006) "*the*

[9] See Gollop and Jorgenson (1980), Jacob, Sharma and Grabowski (1997) or Caselli (2005).

[10] More recent investment data, starting from 1992 onwards, come from the World Development Indicators 2000.

[11] Our results are not affected by the choice of the growth accounting empirical specification. Results are robust to the computation of the TFP as proposed in Hall and Jones (1999).

[12] Again results are robust to the definition of the TFP gap, when this is computed as the ratio of each country's TFP to the highest TFP recorded in each year. Also, we will argue that results are robust to the computation of "development specific" TFP gaps computed as the ratio of each country's TFP to the highest TFP in each quartile of the distribution.

[13] See Kyriacou (1991), Lau, Jamisom and Louat (1991), Barro and Lee (1993) or Nehru, Swanson and Dubey (1995) as well as de la Fuente and Domenech (2001) and Cohen and Soto (2006), this last datasource used in our contribution.

difference in the range of [annualized growth rate of average years of schooling] *across data sets is enormous: while our annual growth rates range between 0.09% and 1.92% and those of Cohen and Soto between 0.27% and 3.27%, Barro and Lee's go from -1.35% to 6.13%; moreover, 19% of the observations in this last data set are negative, and 16.7% of them exceed 2%*"[14]. Hence, due to the better quality and the larger sample size of the Cohen and Soto's (2006) dataset[15] we opt to use this latter throughout our empirical analysis.

Another strand of literature (Hanushek and Kimko (2000) and Hanushek and Woessman (2009)) argue how the quality of the education systems, rather than the "quantity" of the formally completed education, represents a good (or better) approximation for human capital. They argue, in fact, that using quantitative measures related to the number of years of schooling would impose the same returns to education in countries which differ much in the quality of their education systems and schools. This would eventually bias and drive the (lack of) results on the impact of human capital on economic growth.

Hanushek and Woessman (2009) biuld a cross-country index of "cognitive skills" (available for 50 countries) which proxies for the average test scores in math and science of students (of primary through the end of secondary school) in internationally comparable tests[16]and provide compelling empirical evidence of the positive relation between average test scores and economic growth[17] arguing for the crucial importance of adjusting standard measures of average years of schooling for the differences in the quality of education.

To this end, we use the internationally comparable test score index proposed by Hanushek and Woessman (2009) to check the robustness of the results obtained using Cohen and Soto's (2006) quantitative education proxies. For this, we build a new composite indicator which adjusts the Cohen and Soto's (2006) years of schooling data for the differences in the quality of each country's educational system and we test again the robustness of our hypothesis with this new indicator.

Previous empirical literature has also put in relation economic growth and productivity convergence with each country's institutional quality. Hall and Jones (1999), Acemoglu et al. (2001), Easterly and Levine (1997), Glaeser, and Sheifler (2002) or La Porta et al. (1999) and Rodrik et al. (2004) point to the crucial role played by institutional quality on economic growth while

[14] See de la Fuente and Domenech (2001).

[15] With respect to the one by de la Fuente and Domenech (2001) for which only OECD countries are available.

[16] Twelve waves of Internationally comparable student achievement tests have been conducted in between the First International Mathematics Study (FIMS) in 1964 until the Programme for International Student Assesment (PISA) in 2003.

[17] In a previous study, however, Pritchett (2001) challenges Hanushek and Kim's (1995) results suggesting that not correcting the average years of education proxies for the differences in the quality of education cannot directly represent the cause of the widely observed negative effect of average years of education on economic growth. Pritchett (2001), p. 379.

Manca (2010) recently estimated the specific impact of different institutional arrangements on TFP catch-up across countries. The relationship between human capital and institutional quality has also been studied in previous empirical work. Starting from the suggestion by Lipset (1960), Glaeser et al. (2004) revisited the debate over whether institutions cause economic growth or if, instead, better human capital leads to institutional improvement and then to long-run economic growth, arguing that "*evidence suggests some skepticism about the viability of democracy in countries with low level of human capital*". However, one could also point that high levels of human capital may extract lower-than-expected economic returns if the institutional framework is a poor one. "*The incentives that are built into the institutional framework play the decisive role in shaping the kinds of skills and knowledge that pay off*", (North, 1990). Education and institutions are evidently very much linked. In our analysis we proxy for institutions by using the Economic Freedom of the World panel dataset which is itself based on survey data from two annual publications: the *Global Competitiveness Report* and the *International Country Risk Guide*. The index measures the degree of economic freedom between 1970 and 2000 in five major areas: (i) Size of Government: Expenditures, Taxes, and Enterprises, (ii) Legal Structure and Security of Property Rights, (iii) Access to Sound Money, (iv) Freedom to Trade Internationally and (v) Regulation of Credit, Labor, and Business. Within the five major areas, 21 components are incorporated into the index but many of those components are themselves made up of several sub-components[18]. In our analysis we use the chain-linked average index as a proxy for country specific institutional quality in each period. Institutions may however be potentially endogenous to economic growth. In order to instrument for institutions we exploit country specific and time invariant characteristics like the instruments suggested by la Porta et al. (1998) on the different legal origin of each country, the religious fractionalization proposed by Alesina et al. (2003) or a country's latitude, and the linguistic variables as in Hall and Jones (1999).

In Table 1 we present the descriptive statistics of the main variables of interest both for the whole sample and for the OECD and Developing countries' sub-samples. Summary statitistics show the substantial differences between the OECD and the Developing sub-samples. The average TFP proximity of the OECD sample w.r.t. the U.S. is 0.69[19] while it is only 0.22 for the Developing countries subsample. As expected, there exist also substantial differences in the human capital endowement across countries, with the average years of tertiary schooling in OECD being as of 0.51 against the 0.22 for the Developing sub-sample. Similarly, the OECD countries are shown to have better institutions (as expected) than developing economies as expected.

[Table 1 about here]

[18] Counting the various sub components, the EFW index uses 38 distinct pieces of data.

[19] The average TFP gap in VAM was slightly higher, 0.74.

3 The empirical model and the treatment of endogeneity

The empirical model that we test here is in the spirit of the ones proposed by VAM and by Benhabib and Spiegel (2005). Both empirical specifications are technology catch-up models which assume that human capital proxies for the economies' technology absorptive capacity[20]. We consider the following empirical specification:

$$g_{i,t} = \beta_{0i} + \beta_1 a_{i,t-1} + \beta_2 e_{i,t-1} + \beta_3 a_{i,t-1} * e_{i,t-1} + \beta_4 z_{i,t-1} + \epsilon_{i,t} \qquad (1)$$

where $g_{i,t}$ is country's i TFP growth rate, $a_i = A_{i,t-1}/\bar{A}_{t-1}$ represents the follower's proximity to the technology frontier ($\bar{A}$) in the previous period, $e_{i,t-1}$ represents human capital which (depending on the specification) will proxy for the (i) fraction(s) of the workforce with a specific education attainment level (tertiary, secondary or primary), for (ii) the averge number of years of schooling (in tertiary, secondary or primary), for (iii) the cognitive skill index (proxying for the quality of each country's education system) or for (iv) the composite human capital index built adjusting (i) and (ii) for the differences in education systems' quality. The term $a_{i,t-1} * e_{i,t-1}$ represents the interaction of human capital with the TFP gap. The empirical model in (1) resembles the one proposed by VAM and it only differs from Benhabib and Spiegel's (2005) logistic technology diffusion function due to the introduction of the additional term $\beta_1 a_{i,t-1}$ which aims at controlling for *"exogenous"* TFP catch-up, independent of each country's human capital absorptive capacity. To both VAM and Benhabib and Spiegel's (2005) specifications we also add an additional covariate proxying for each economy's institutional quality, $z_{i,t-1}$ as well as including time and continent dummies in all the econometric specifications.

The estimation of the empirical model in (1) poses different challenges. The most critical one is to deal with the potential endogeneity of education w.r.t. economic growth as pointed out by Bils and Klenow (2000). Instrumental variables techniques are a reasonable way to solve this endogeneity problem. For these, we need to find suitable instruments for our human capital proxy that need to be uncorrelated to the error process and satisfactorily correlated to the endogenous variable. Moreover, in our specific case, these instruments have

[20] As opposed to other empirical models that assume human capital to be a production factor which augments labor (Barro and Sala-i-Martin (1995), Aghion and Howitt (1992)), both VAM and Benhabib and Spiegel assume that the effect of human capital enables lagging economies to catch-up with the frontier enhancing technology spillovers. As pointed out by Benhabib and Spiegel (2005) "*the policy implications of distinguishing between the role of education as a factor of production and a factor that facilitates technology diffusion are significant. In the former, the benefit of an increase in education is its marginal product. In the latter, because the level of education affects the growth rate of total factor prouctivity and output, its benefits will be measured in terms of the sum of its impact on all output levels in the future*".

to be available for 88 amongst developed and developing countries. Following VAM's suggestion we treat all right hand side variables as endogenous and instrument them with their values lagged one period[21]. This applies also to the interaction term between human capital and the proximity to the frontier and to institutional quality. As for the choice among the available estimators able to cope with endogeneity, we initially run the model by applying both fixed and random effects instrumental variables and then test the goodness of one empirical model against the other. The results and the discussion of the best specification are given in the next section.

Indeed, however, as pointed out by Aghion et al. (2009) the estimates carried out by using panel data IV (either FE or RE) may still suffer from measurement and endogeneity problems due to omitted variables highly correlated over time and within a country (i.e. institutions). On the one hand, in order to solve for this problem (as well as to enrich the analysis) we introduce each country's institutional quality as an additional explanatory variable (as implicitly suggested by Aghion et al.(2009)). Nonetheless, this might not yet be sufficient to fully tackle endogeneity.

As an additional problem to omitted variables bias, in fact, education variables as well as institutions are quite persistent over time. In that case it is well known that system GMM estimators for dynamic panel data models perform better than standard first-difference estimators (Arellano and Bond (1991)) while also allowing to exploit internally built instrumental sets. Blundell and Bond (1998) show that when the considered endogenous variables are close to a random walk process the difference GMM estimators behave poorly because past levels of endogenous variables convey little information about future realizations. Arellano-Bover(1995)/Blundell-Bond (1998) system GMM 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) and have hence drastically improved on simpler OLS or LSDV estimators which, as shown in previous literature (see Nickell 1981, Kiviet 1995 or Bond 2002) might producing upward and downward biased coefficients respectively[22].

[21]In VAM the instruments are the explanatory variables lagged two periods instead than one. However, they use a 5 year panel (rather than a 10 years panel as we do) such that our lagged variables match exactly their same time span. VAM can also exploit information on per capita spending in education as instruments which is, instead, not available to us due to the our largest sample. However, they argue that their results on the OECD sample are unaffected by the use of this additional information.

[22]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.

On the efficiency side, recent improvements in econometrics theory now allow to apply the so-called "two-step" System GMM estimator. Unlike the "one-step" version, the two-step variant of the System GMM 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. It is argued, however, that this 'optimal' weighting matrix makes the two-step GMM asymptotically efficient although at the cost of producing severely downward biased standard errors (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. As argued by Windmeijer (2005) and Roodman (2006), the problem may be as severe as to make two-step GMM useless for inference. For this purpose, Windmeijer (2005)[23] proposes a correction to the two-step covariance matrix which it is argued can make the two-step robust estimation more efficient than the robust one-step especially for system GMM. Hence, we apply this modification of the system GMM estimator to the empirical model in (1) as regards this as our preferred econometric model.

4 Estimation results

4.1 Panel instrumental variables estimation

In what follows we provide a wide variety of results exploiting the different measures of human capital previously discussed. Also, we test the empirical model in (1) by making use of different estimators and controls for endogeneity as well as proposing different econometric models so as to accomodate both the VAM and the Benhabib and Spiegel (2005) specifications. All tests are then run on the whole sample as well as on the development-specific subsamples.

As a starting point we estimate VAM's empirical specification (human capital *fractions*) by using both "within groups" FE and RE instrumental variables estimators. We test the goodness of the fixed *vs* the random effect models under the null hypothesis that the individual effects are uncorrelated with the other regressors in the model (Hausman, 1978). The Hausman test (reported at the bottom of table 2 below) does not reject the null hypothesis arguing that the random effects should be preferred over the fixed effects specification. The Hausman statistics is run on different empirical models as a robustness check (namely, also, on the logistic diffusion function á la Benhabib and Spiegel) and

[23] 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)

when we also use either fractions or average number of years of schooling. The results[24] confirm that random effects IV estimators should be preferred to the fixed effect one in all the analyzed specifications.

[Table 2 about here]

Results in table 2 show the heterogenous impact of different education levels (expressed here by the fraction of the workforce of age 25 or more in tertiary, secondary or primary education) on the growth of countries at different development stages. In columns (1) to (3) we report the results of the estimated impact of tertiary education on TFP catch-up for the whole sample as well as for the OECD and developing countries' subsamples while in the remaining columns we analyze the impact of secondary and primary education respectively.

The impact of tertiary education on growth is statistically significant and precisely estimated only for the developed countries subsample. The coefficient associated to the share of skilled workers (tertiary education) shows a positive coefficient estimated at one percent confidence level. Similarly, the interaction term between the TFP gap and human capital shows a strong and negative statistically significant coefficient indicating that technology catch-up is enhanced by larger shares of tertiary educated workers. The result is in line with our hypothesis on the crucial role played by skilled workers for economic convergence at lower development stages.

When we look at the result for the OECD subsample the coefficients associated to tertiary education and to the interaction term are, instead, rather imprecisely estimated and not statistically significant while the proximity to the frontier term (*TFP gap*) shows the expected negative coefficient at five percent statistical significance level. Also institutional quality enters with a statistically significant and positive coefficient but only in the whole sample specification.

When we run the same model on secondary education (columns (4) to (6)) we find additional confirmation of the heterogeneity of the results when countries are analyzed at different development stages. The estimated coefficients of secondary education and of its interaction with the TFP gap are statistically significant for the whole sample as well as for the developing countries subsample (while, again rather imprecisely estimated for the OECD subsample) arguing for an important role of secondary education in TFP catch-up. Crucially, however, the magnitude of a marginal increase in tertiary education on growth is far stronger than that of either secondary or primary education arguing that increasingly higher education levels would lead to faster productivity convergence and that this effect would be stronger the farther away an economy is found from the technology frontier and the smaller its initial endowment of skills.

[24] Not reported but available upon request to the authors.

Related to the interpretation of the results, it is important to notice that, since the model estimated in table 2 relies on a specification where the education proxies enter as fractions over the total workforce, the reported coefficients represent semi-elasticities. As suggested by Serrano (1997), it is possible to retrieve the values of the coefficients' implied elasticities by noticing that $\gamma_{ed} = \beta \times \partial h/\partial\theta_{ed} \times \theta_{ed}/h$, where γ represents the elasticity, β the estimated coefficient on the education fraction and θ and h respectively the share of population within a certain education category (ed) and the years of schooling of that specific category. Crucially, it should be noticed that, when fractions are used as explanatory variables, the magnitude of the semi-elasticities' coefficients are systematically downward biased w.r.t. their implied elasticities. Moreover, the bias arising between the semi-elasticity and the implied true elasticity is larger the smaller the fraction of population in the examined category[25]. This implies that the differences in the impact on growth of tertiary, secondary or primary education is even greater than the one reported by the semi-elaticities. A similar reasoning would apply if we wanted to compare the magnitude of the tertiary education's elasticities between the Developing and the OECD subsamples, given the larger share of tertiary educated workers in the latter.

The results presented above are robust to alternative empirical specifications. In table 3 we test our hypothesis on a logistic diffusion function model. As argued by Benhabib and Spiegel (2005) there are both theoretical and empirical reasons to believe that an S-shaped diffusion function should be preferred over the (somehow more widely used) confined exponential diffusion (see Banks (1994) or Benhabib and Spiegel (1994)). The logistic formulation, in fact, "*allows for a dampening of the diffusion process so that the gap between the leader and the follower can keep growing*[26]" such that this formulation does not restrict the followers to grow at the speed of the leader from which they might also diverge in the long-run. This is particularly important when we analyze countries at very different development stages since it allows to account for the fact that the world technology frontier might not be immediately available to all followers (see Basu and Weil (1998)) and that divergence pattern might arise as a consequence of it. The empirical results, however, confirm our hypothesis and are in line with those obtained in table 2.

[Table 3 about here]

Both tertiary education and its interaction with the TFP gap are estimated to be statistically significant at one percent confidence level for the developing countries sub-sample. A similar result is now also recorded for the whole sample but, again, with a lower estimated coefficient. Secondary and primary education

[25] See Serrano (1997).

[26] See Benhabib and Spiegel (2005).

are also shown to have a positive, but relatively lower, impact on TFP convergence than tertiary education pointing that it is the top margin of education (tertiary levels) to speed up convergence the most.

Interestingly, the same results apply when, instead of using the OECD *vs* Developing countries sub-samples we run quartile regressions for the top 25% of the GDP distribution (proxying for developed countries) *vs* the bottom 75% or 50% (proxying for increasingly under-developed countries)[27]. The effect of tertiary education on growth becomes larger as the development stage of the countries decreases confirming the stronger effect of tertiary education on catch-up as we move far away from the frontier.

Similarly to VAM we also analyze the impact on growth of average years of education (in different educational category) as an alternative to the human capital shares proxies. To that end, we group human capital into two categories representing, on the one hand, average years of schooling in primary and secondary education and, on the other hand, average years of schooling in tertiary education[28]. The results are presented in table 4 where we pool together the different human capital proxies along with their interaction with the TFP gap and the inital gap alone as in VAM. To this specification, we then add instutional quality as an additional explanatory variable to check for the robustness of the results.

[Table 4 about here]

The results strongly confirm our initital hypothesis on the importance of tertiary education (as opposed to the weaker effect of primary and secondary education) for the catch-up of developing countries. Results are also robust to the introduction of institutional quality, which is however, only significant for the whole sample. If we repeat the same exercise on the logistic diffusion model (reported in table 5) the results are qualitatively the same with only a very minor change in the estimated elasticities of human capital proxies.

Somehow surprisingly, results in table 4 show a negative impact of average years of tertiary education on the growth of OECD countries. Our explanation to this result is twofold. On the one hand, part of this result might be driven by identification problems as argued by Aghion et al. (2009), that would be exacerbated by the small number of observations available for the OECD sample. We address this point in the next section by applying system GMM estimators which, however, only partially restore the expected positive impact of tertiary education on growth for the OECD sample while leaving, instead,

[27] The results are available upon request to the authors.

[28] Similar results are however obtained when we disaggregate human capital into primary, secondary and tertiary average years of schooling.

unaltered the other main results. On the other hand, however, the empirically weak significance of tertiary education for the catch-up of OECD countries may also be related to the way we approximate skills and education. As argued by Hanushek and Woessman (2009), by purely using quantitative measures to proxy for human capital we may under or over-estimate the contribution of human capital to growth. We argue that this problem is more pronounced for developed countries than for developing ones and show that, once we control for the quality of education we are able to restore the expected positive effect of tertiary education on the growth of these latter. We defer a deeper analysis of these results and the discussion of the arguments supporting this hypothesis to section 5.

4.2 System GMM estimations

As argued in section 3, there are different reasons to believe that panel instrumental variables techniques may not be sufficient to fully tackle endogeneity between education and growth. Hence, we now turn to our preferred econometric model which exploits system GMM estimators and that is able to tackle both measurement and endogeneity problems as well as the persistence of the human capital series. As before, we first analyze the basic VAM's specification by using, as explanatory variables, the fractions of tertiary, secondary and primary education and their interaction with the TFP gap.

[Table 6 about here]

Results in table 6 argue again for the heterogenous effect played by human capital composition on growth at different development stages. The coefficient for tertiary education (*fractions*) and that of its interaction with TFP gap show the expected signs for the developing countries' sub-sample and are estimated at five percent confidence levels[29]. Secondary education is also shown to positively impact the growth of developing countries but its impact is shown to be smaller than the one of tertiary education.

Indeed, the results for the OECD sub-sample are again in line with those already reported in table 4 and 5 before for which tertiary (fractions) education shows a negative impact on productivity catch-up. As argued by VAM, however, the "*occurrence of the IT revolution [may have had an] impact of the relationship between education and growth*". We test this additional hypothesis by runing the model for the post 1980 period only. The coefficients associated to tertiary education and its interaction with the TFP gap are not statistically different from zero for the OECD post-1980 sub-sample. On the contrary, for the

[29] The magnitude of the coefficients is however considerably lower if compared to the results of the IV estimations presented in the previous section but still points to the same qualitative results.

developing countries's subsample, along with the positive effect exerted by tertiary education on TFP catch-up, also the share of tertiary educated workforce is statistically significant[30]. These results are presented in the appendix.

When we turn to the estimation of the logistic diffusion function *á la* Benhabib and Spiegel (2005) we find again confirmation of the importance of tertiary education for the catch-up of developing countries. Results in table 7 show the expected (highly) significant negative coefficient of the interaction term between tertiary education and TFP gap for the developing countries' subsample pointing to the faster convergence of countries farther away from the frontier.

[Table 7 about here]

With regards to the OECD sub-sample, the interaction term between tertiary educated fraction and TFP gap for the OECD is now statistically significant (even if only at ten percent confidence level) and with a negative sign arguing for a likely positive impact played by tertiary education on growth. Crucially, however, when we compare the magnitude of the catch-up effect across different development stages, the effect of tertiary education on growth is again shown to be much stronger at lower development stages as reported by the far larger coefficient of the interaction term's reported for the developing countries' subsample. A similar reasoning applies to the results for secondary and primary education's specifications. Secondary education positively explains economic growth but with a relatively lower impact if compared to that of tertiary education at any development stage.

Our system GMM estimation are also robust when we proxy human capital composition by the average number of years of schooling in each education category. Again, tertiary education exerts a positive and statistically significant impact on the growth of developing countries while it would seem to negatively affect the growth of developed ones.

[Table 8 about here]

As an additional check, in table 9, we analyze tertiary and secondary education disjointly so as to compare their impact on growth at different dvelopment stages. Results are unchanged.

[Table 9 about here]

[30] Results are dependent on the introduction of differences in institutional quality across countries.

Developing countries are those enjoying the most from an increase in tertiary education. The results do not seem to be driven by any model mispecification or identification problems. As for the system GMM estimations, the robust Hansen overidentification tests on the joint significance of the instrumental set (built on the lagged levels and differences of the endogenous variables) does not reject the hypothesis of the goodness of the instruments. The same applies to the test developed by Arellano and Bond (1998) aimed at checking for the presence of autocorrelation in the disturbance term which is passed in all specifications (including the ones presented in previous tables).

As argued above, various institutional control variables have been introduced in all the specifications as suggested by Aghion et al. (2009) with the twofold aim of analyzing the impact of differences in institutions on growth and of overcoming the potential biases in the estimation when lagged realizations of human capital might be correlated to each country's institutional quality. From an econometric point of view, an advantage of system GMM over difference GMM estimators is the possibility of including time-invariant instrumentss into the system which may help the identification of endogenous variables while at the same time control for additional country specific characteristics related to economic growth. Glaeser et al. (2004) argue how "*Europeans brought their legal system into the countries that they conquered and colonized and that, therefore legal origin can be used as an instrument for the structure of various laws*". Also, la Porta et al. (1998) examine the relationship between the legal system and economic performance arguing that a country's legal origin can be viewed as indicators of the relative quality and power of the government. Similarly, various empirical works (see, among others, Easterly and Levine (2002), Alesina et al. (2003, 2008), la Porta et al. (1998) or Landes (1998)) have shown the relationship between religion (and religious fractionalization) and economic development. Landes (1998) argues specifically that catholic and muslim countries "*have tended to develop xenophobic cultures and powerful chuch/state bonds to maintain control, which hinders institutional and economic development*[31]". Following the empirical strategy proposed in similar contexts by Acemoglu et al. (2001) and la Porta et al. (1998) we instrument institutional quality by legal origin (whether a country's legal origin is either french, scandinavian, british or german) and by the religious fractionalization of each country (proxied by the fraction of catholic, muslim, protestant or neither of these over the total population). The results reported in tables 6 to 9 are hence robust to the introduction of all of these institutional controls[32].

Our results show that institutional quality is indeed an important driver of TFP growth in line with the empirical results of previous literature (see Hall and Jones (1999) or Acemoglu et al. (2001)). The elasticity associated to a 1 percent change in institutions ranges in between 0.09 and 0.15 percent of

[31] See also Easterly and Levine (2002).

[32] As an additional check we also run the empirical model by introducing the religion and legal origin proxies directly as explanatory variables. Results are unchanged and can be provided upon request to the authors.

overall TFP growth arguing that countries with better institutional quality are indeed converging faster to the world technology frontier and increasing their productivity.

5 Quality of education (?)

Remarkably, our previous estimates show a negative (or statistically not significant) impact of tertiary education on the growth of OECD countries. This result appears (rather persistently) in almost all the specifications and it deserves a special discussion. As we argued very briefly above, there are different reasons to believe that the estimated effect of tertiary education on the economic growth of OECD countries may turn out to be null or negative.

On the one hand, a weak(er) effect of tertiary education on the growth of developed countries is consistent with the evidence on the international returns to investment in education estimated in various influential studies. Psacharopoulos (1994) and Psacharopoulos and Patrinos (2002) provide evidence of the heterogeneity of the returns to investment in different education levels across countries at different development stages.

Psacharopoulos (1994) argues that "*social and private returns largely decline by the level of a country's per capita income*" and "*the declining pattern of the returns to education is also observed over time*". Interestingly, however, even larger differences can be detected when we specifically look at the returns to each education level. Returns to primary education, estimated by standard Mincer's (1974) wage equation, are shown to be quite homogeneous across very different development stages. Estimated private returns to investment in primary education, for instance, range in between 25.6 percent for the high-income group ($9,266 or more) to 27.4 percent for the middle income (up to $9,265) and 25.8 percent for low income countries (less than $755)[33]. The picture is extremely different, instead, when we look at the the estimated returns to secondary and tertiary education. Low income countries show the highest returns to both secondary and tertiary education while high-income countries experience the lowest returns. More specifically, the returns to secondary education range in between 12.2 percent for the high income sample to 18.0 and 19.9 percent for the middle and low income samples respectively. Even more striking, the estimated returns to secondary education are rather similar to those of tertiary education within each income group with the exception of the low income subsample which, instead, shows much higher returns to tertiary than to secondary education. In the high-income sample, for instance, the estimated returns to secondary education (12.2 percent) are in line with those to tertiary education (12.4 percent) while, in the low income sample a substantial difference in returns between secondary (19.9 percent) and tertiary education (26.0 percent) is experienced. This evidence pinpoints the specific role played by tertiary (and partly of secondary) education for developing countries' growth.

[33] See Psacharopoulos and Patrinos (2002).

The heterogeneity in the returns of tertiary education at different development stages might explain, at least in part, the weak impact of tertiary education on the catch-up of advanced economies and corroborate our strong results for the developing countries. However, along with this evidence, we believe that another crucial issue plays a (joint) role in the explanation of the weak relation between growth and tertiary education for developed countries. As argued by Hanushek and Woessman (2009), the usual proxies used to account for cross county differences in human capital do not account for the differences in the quality of the human capital but only for their relative quantity. Hence, it is argued that the raw number (quantity) of graduates students in each economy may not properly *signal* the skill intensity of the workforce and that this would lead to underestimate the role of tertiary education on the catch-up of, especially, developed countries.

Crucially, in fact, the "human capital quantity-signaling" bias may be more severe in developed countries than in developing ones once we acknowledge for the fact that the access to tertiary education in OECD countries has steadily increased over time and that completion and access to tertiary education is relatively much easier in the OECD countries than in less developed regions of the world.

As argued by Hanushek and Zhang (2009), "*the school and college selectivity has gone down over time [...] if school continuation is related to ability, people with lower innate ability on average have been promoted to greater schooling levels over time*" and "*if so, contributions of more recent cohorts' schooling will be underestimated*"[34]. Indeed, if we examine our sample, the difference between the tertiary enrollment rate in OECD and in developing countries has been steadily rising (rather than falling) during the last decades. The average share of tertiary educated workers in the OECD countries grew from 0.05 in 1960 to an average of 0.19 percent in 2000. Instead, the share of tertiary educated workforce in developing countries grew from an initial value of 0.01 percent in 1960 to 0.06 in the year 2000 diverging from the OECD tertiary growth path.

If any, hence, one might argue that having completed tertiary education is likely to "signal" less about the workforce's "true" human capital in OECD countries than it does in developing countries simply because the access to tertiary education in OECD countries is far more universal increasingly allowing less talented students to formally complete tertiary education. In developing countries, instead, the access and completion of tertiary education is likely to give stronger signals about the skills of the average tertiary educated worker w.r.t. the average human capital of the population, due to the relatively harder entry selection to tertiary education.

Indeed, if we investigate the relation between quantity-based human capital measures (average years of schooling or fractions of tertiary educated workers)

[34] See Hanushek and Zhang (2009).

and quality based measures as proposed by Hanushek and Woessman (2009) a positive and statistically significant relation emerges when we regress international test scores achievements in math and science (proxying for the quality of education) on the quantitative measures of tertiary education. This positive and statistically significant relation appears, however, only for developing countries while a negative but non significant relation is shown for OECD countries when we also control for cross countries differences in institutional quality[35]. Far from being a sound empirical proof, this simple test (along with the empirical evidence of decreasing returns to tertiary education/development stage) gives a hint on the validity of the hypothesis that the human capital signaling bias might be stronger at higher development stages and that this may be one of the causes of the weak coefficient associated to average years of tertiary schooling for OECD countries estimated up to now[36]. Conversely, this also argues that the results obtained for developing countries are, instead, likely to be confirmed when we adjust the human capital proxies for the quality of the education systems.

Hanushek and Woessman (2009) provide two different indexes for a cross-section of 50 among developed and developing countries which proxy for the quality of education. The "Cognitive skill index" refers to the average score in math and science of students who took internationally comparable tests in between 1963 and 2003. The "Top skills index" refers to the scores of only the top-performing students for the same time period. The correlation between the two indexes is high (0.73) and the regression results below are qualitatively very similar[37].

The data provided by Hanushek and Woessman (2009) proxy for the quality of the education systems and, in principle, allow to compare the quality of education and of human capital across countries. Indeed, as argued by the authors, "*variations in cognitive skills can arise from various influences - families, culture, health and ability*". This said, the authors also claim to be able to provide robust evidence that schools are one of the major channels affecting and shaping the quality of education outcome in each country.

It is interesting to notice that the quantitative and qualitative human capital measures do convey information which is rather different one another[38]. Out of the first ten countries with the highest average number of tertiary years

[35] Results are presented in the appendix.

[36] On a similar line of reasoning, Gary Becker and Richard Posner in their blog argue that, for developed countries, "there probably are diminishing returns to providing higher education, because IQ provides a ceiling beyond which educational effort is wasted on students. The United States may be in that position today. Many colleges offer what amounts to a remedial high school education, postponing the students' entry into the work force. If we had better high schools, we might have fewer colleges (or more-if better high schools improved intellectual motivation and performance). With ever-increasing specialization of the workforce, there is an argument for making education increasingly vocational.

[37] Results can be provided upon request to the authors.

[38] The overall correlation index between the quantitative and qualitative human capital indexes is of 0.53.

of schooling nine countries belong to the OECD sample. However, when we look at the student performances (education quality, *cognitive skills*) only six OECD countries enter in the top-ten ranking. If, instead, we focus only on the developing countries sub-sample smaller differences in the rankings can be observed[39].

When we also cross this information with GDP per worker a negative relation emerges between quality of education and GDP per worker at high development levels while, conversely, the relation between the quantity of tertiary education and GDP per worker is slightly positive at higher development level. If instead we only focus on the 10 best performing developing countries, the relation between human capital quality (cognitive skills) and development is (weakly) positive and the same is shown for the relation between years of tertiary schooling and GDP per worker[40].

[Figure 1 about here]

[Figure 2 about here]

As a first test on the impact of education quality on TFP catch-up we regress TFP growth on the cognitive skills index and its interaction with the TFP gap as well as on institutional quality differences. The results are presented in table 10.

[Table 10 about here]

As expected, the quality of education plays a fundamental role on growth at all development stages. The interaction term's coefficient is statistically significant for all the different development's subsamples indicating that increasing the quality of education leads to faster catch-up to the world technology frontier. Crucially, however, the magnitude of the effect is very much heterogenous as in our previous results. Developing countries are shown to be those which benefit the most from a marginal increase in the quality of education with a coefficient which is almost the double than the one estimated for OECD countries. Endogeneity between quality of education and growth might be affecting again our estimates. We employ both robust OLS estimators (in columns (1) to (3)) and two-step efficient generalized method of moments (GMM) estimator to address endogeneity issues (in columns (4) to (6)). Due to cross-country comparability, the cognitive skill index is only available as an average over the period examined

[39] Out of the 10 countries with higher average years of tertiary schooling, only 5 countries are also present in the ranking of highest cognitive skills.

[40] This additionally confirms that the potential bias between the quantitative and qualitative measures of human capital might be stronger for OECD countries than for developing ones as suggested above.

such that we cannot directly instrument its with lagged realizations in the GMM estimations. Instead, for it, we use past realizations of the average tertiary years of schooling variable which however lead to a poor identification of for the whole and OECD sample as detected by the Kleibergen and Paap (2006) instrumental test[41]. Results are instead satisfactory for the developing countries' subsample with an average bias of the IV estimator less than 10 percent w.r.t. the OLS estimation.

This said, it is not only the quality but also the quantity of education which matters for growth. In table 11 we regress the average growth of TFP over the period on our quality adjusted measure of human capital (which interacts the cognitive skill index[42] with the quantity human capital measures), on its interaction with TFP and on institutional quality as an additional control variable. As for previous estimations, we acknowledge the very likely presence of simultaneity issues in the OLS estimations and re-run our test by implementing the two-step efficient generalized method of moments (GMM) estimator in the last three columns of table 11.

[Table 11 about here]

Once again, the magnitude of the impact of human capital (quality adjusted) is quite heterogeneous across countries at different development stages. Interestingly, the effect of human capital is positive (negative in the coefficient associated to the interaction term) for all countries and hence for the OECD sample as well at one percent confidence level in the GMM estimation. This is in contrast to the results based solely on quantitative measures of human capital. Crucially, hence, on the one hand our quality adjusted-human capital measure restores the expected positive role of tertiary education on the growth of all countries while, on the other hand, the magnitude of the catch-up impact on OECD countries still ranges in between 4 and 5 times less the same impact for developing countries. The results confirm our initial assumptions on the key role played by tertiary education on the catch-up of developing countries. As for the two-step GMM estimation, both institutions and human capital are assumed to be endogenous variables and are hence jointly instrumented in all the IV estimations.

Regarding the (over)-identification of very different sub-samples of countries, this called for a careful thinking of the suitable instruments to be used. Instruments have to be highly correlated to the two endogenous variables being, at the same, time capable of conveying information about the relative differences within more or less homogenous sub-groups of countries as well as across very

[41] Results improve only slightly when we also instrument by percapita spending in education.

[42] Empirical tests have been also run on the Top skill index and its interaction with TFP. Results are available upon request to the authors.

different development stages. On the one hand we employ a common set of instruments for both the OECD and developing countries' subsample in order to be able to draw meaningful comparisons across different development stages and subsamples. For this we make use again of the legal origin and religious fractionalization indexes already employed in the system GMM estimations above. However, the over-identification of the (homogenous) institutions within the OECD subsample calls for the use of additional information. Hence, to the OECD instrumental set we also add the logarithm of the Frankel and Romer trade predicted shares[43] and the Government Anti-Diversion Policy (GADP)[44] index proposed by Hall and Jones (1999). As for the human capital, we instrument it with the average per capita expenditure in education[45] and, when data were not available, with the lagged average years of tertiary schooling.

Overall, the Hansen over-identification test is passed in all specifications pointing to the joint significance of our instruments. However, as pointed out by Stock, Wright and Yogo (2002), weak instruments may still be a problem if their "relavance" to the endogenous variable(s) is only scarce. This problem exacerbates when more than one endogenous regressors are jointly analyzed such that weak identification might result. This might indeed be our case, since both human capital and institutions are treated as endogenous variables. We control for this problem by applying the generalized weak identification Wald statistics proposed by Kleibergen and Paap (2006) which have the advantage over the Cragg and Donald's (1993) F-tests of being valid to non-i.i.d. errors. Our statistics confirm the validity of the instrumental set used. Both in the case of the OECD and of the developing countries sub-samples the reported F-statistics confirm that the bias of the estimation perfomed by GMM using the proposed instrumental set is no more than, respectively, 5 and 10 percent of the inconsistency of an OLS estimation.

As an additional robustness check of the results we also correct the average number of years of schooling for human capital quality and re-run the estimations. Again, the interaction term between human capital and the TFP gap shows a statistically significant coefficient in all specifications as well as when we also control for endogeneity by exploiting two-step efficient GMM estimators. Also, the difference in the magnitude of the effect of human capital on the catch-up is very similar to our previous results and highlights the stronger effect of tertiary education on the growth of countries farther away from the technology frontier.

[43] The log predicted trade share of an economy is based on a gravity model of international trade that only uses a country's population and geographical features and for this reason can be accounted for as an exogenous instrument (see Hall and Jones (1999)).

[44] The GADP index is an equal-weighted average of the following sub-indicators: (i) law and order, and (ii) bureaucratic quality as well as of three categories relate to the government's possible role as a diverter: (iii) corruption, (iv) risk of expropriation, and (v) government repudiation of contracts.

[45] These data come from the UNESCO statistical yearbook (1999).

[Table 12 about here]

Overall, results confirm the validity of the hypothesis for which tertiary education (either raw-quantity or quality-adjusted measured) heterogenously affect the catch up of countries at different development stages by benefitting the most those that are farther away from the frontier and whose intial stock of high-skills is relatively lower.

6 Theoretical background

6.1 Hypotheses of the model

This section has the aim of proposing a technology catch-up model able to theoretically ground the empirical results obtained in previous sections and to depict the links and the dynamics between human capital composition, development stage, institutional quality, economic growth and catch-up. A natural option is to rely on the very well established theoretical framework proposed by Barro and Sala-i-Martin (1997) and to augment it so as to accomodate the new assumption on the heterogeneity of human capital types (*human capital composition*) and to capture their link with technology imitation and innovation at different development stages.

The theoretical model proposed here is similar to VAM's but grounded on a very different hypothesis about the way technology imitation should be linked to human capital composition. VAM's theoretical results generates from the assumption that imitation, being relatively easier than innovation, is going to be better performed by unskilled workers (rather than skilled ones). On the contrary, we believe there is no reason to think that unskilled workers should outperform skilled ones also (or especially) when it comes to perform innovation or imitation. Instead, we assume that both innovation and imitation are skill costly activities (even if the former may be indeed more skill demanding than the latter) and that, for this reason, that they will be both better performed by skilled workers.

As argued by Maskus (2000), technology imitation usually takes the form of adaptations of existing technologies to new markets. In order to adopt a new product (or a process) the follower usually needs to adapt the new technology to its market or productive needs. Managerial and technical skills are important for instance, when the follower has to choose among 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 follower'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 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*".

6.2 Set up of the model

We assume that the world consists of 2 countries denoted by i=1,2 where country 1 represents the North and country 2 the South. The output in the two countries is expressed by means of a Spence (1976)/Dixit and Stiglitz (1977) production function as follows:

$$Y_i = A_i(L_{yi})^{1-\alpha}\sum_{j=1}^{N_i}(X_{ij})^{\alpha} \tag{2}$$

where $0 < \alpha < 1$, Y_i is output and X_{ji} is the quantity of the *jth* nondurable intermediate good used in the production by country i. N_i is the number of types of intermediates available (known) in country i. The variable N_i proxies for the technological level of country i. The technology shown in eq. (2) can be accessed by all agents in country i and production occurs under competitive conditions.

A_i represents institutional quality[46] of country i. Following the empirical evidence, we assume that the North is endowed with better institutions than the South as follows:

$$A_1 > A_2 \tag{3}$$

L_{yi} is the fraction of the labor force employed in the production of output Y_i[47].

6.2.1 Human capital composition

We assume that labor in the 2 countries is heterogeneous in skill endowment. In both countries a fraction of population will be of the low skill type, namely L_{yi},

[46] Some authors such as Keefer and Knack (2002), Alesina et al. (1992) or Levine and Renelt (1991) point to the process of democratization and to the political stability of a country as the main features of a country's institutional quality. Others, such as Mauro (1995), or Barro (2000) also emphasize the role of corruption and criminality as distortions to the correct functioning of a country's institutional framework.

[47] Trade in final goods is assumed to be balanced between the two countries such that the domestic output is equal to the total of domestic expenditures which go for consumption of goods, C_i, production of intermediates, X_{ji}, and R&D aimed at discovering new blueprints and varieties of intermediates. Since final goods are tradable internationally, market size does not influence the results. This setting is very similar to the one proposed by Barro and Sala-i-Martin (1997).

and employed in the production of the final good Y_i. The remaining fraction of the workforce, namely L_{ri}, represents the high skilled workers that will be employed in the innovation or imitation activities of country 1 and 2. The following general condition is hence satisfied:

$$L_i = L_{yi} + L_{ri} \tag{4}$$

where L_i is the total workforce. Noticeably, North and South differ in the *composition* of their human capital stocks. The North, consistently with empirical evidence reported in table 1 is populated by a relatively larger share of high skilled workers (over its total population) than the South. Conversely, the South, is largely populated by low skilled workers and only a relatively small fraction of its total workforce is of the high skill type. This condition can be restated more formally as follows:

$$L_{r1} > L_{r2} \quad \text{and} \quad L_{y1} < L_{y2} \tag{5}$$

6.3 The leader country

We assume the North to be the technological leader. This is implied by the following:

$$N_1(0) > N_2(0) \tag{6}$$

where the pool of blueprints (or intermediates) that are known in country 1 is strictly higher than that in the technological follower country 2. The relative technological proximity between country 2 and country 1 is expressed by the following ratio:

$$0 < \frac{N_2}{N_1} \leq 1 \tag{7}$$

Throughout all the paper we will be using the measure in eq.(7) to define the relative *development stage* of country 2 w.r.t. the leader[48].

One of the crucial assumptions of our formalization is that both innovation and imitation/adaptation are skill-costly activities. Hence, instead of assuming a fixed cost for innovation as in Barro and Sala-i-Martin (1997) we assume, somehow more realistically, that the cost of inventing a new blueprint, namely η_i, is a decreasing function of the fraction of workforce endowed with high skills within each economy. This assumption reads as follows:

$$\eta_i = \psi(L_{ri})^{-1} \tag{8}$$

Notice that combination of eq. (8) with eq. (5) imply the following:

[48] Empirically, this would proxy for the TFP gap of the followers to the technology frontier.

$$\eta_2 \geq \eta_1 \tag{9}$$

The different composition of human capital stocks in the two countries shapes their relative innovation possibilities[49]. The country endowed with a higher fraction of high skilled labor ends up being relatively more efficient in producing innovation due to the more educated and talented researchers employed in R&D. Interestingly, this is a result that we share with VAM's formalization. In what follows, however, we will show that assuming that high-skill workers perform innovation more efficiently than unskilled ones does not also imply the opposite, that is, that unskilled workers will better perform imitation activities than skilled workers.

6.3.1 Innovation production in the leader country

When a new intermediate good is introduced (invented) in country 1, the innovator retains monopoly power over the use of this good for production *within country 1*[50]. Since the intermediate good j is priced in country 1 at P_{1j} the flow of monopoly profit to the inventor is given by:

$$\pi_{1j} = (P_{1j} - 1)X_{1j} \tag{10}$$

where the 1 inside the brackets represents the marginal cost of producing the intermediate X_{ij}. The marginal product of the jth intermediate is instead given by:

$$\partial Y_1 / \partial X_{1j} = A_1 \alpha L_{y1}^{1-\alpha} (X_{1j})^{\alpha - 1} \tag{11}$$

This, in turns, leads to the demand function for the intermediate j from all producers of goods in country 1:

$$X_{1j} = L_{y1}(A_1 \alpha / P_{1j})^{1/1-\alpha} \tag{12}$$

Substituting eq.(12) into eq.(10) we get the monopoly price, which is the same for all types of intermediates:

$$P_{1j} = P_1 = 1/\alpha > 1 \tag{13}$$

which in turns implies that the total quantity of the jth intermediate that country i will be producing amounts to the following:

$$X_{1j} = X_1 = L_{y1}(A_1)^{1/(1-\alpha)} \alpha^{2/(1-\alpha)} \tag{14}$$

[49] We assume here, for simplicity, that ψ is a linear function. This may not be the case however and more complexity may be added to the model by assuming a non linear relation between the cost of innovation and the share of skilled workers employed in R&D. The results will not change qualitatively.

[50] As pointed out by Barro and Sala-i-Martin (1997), it is however simple to allow the good to become competitive with an exogenous probability p per unit of time.

From this we finally get country's 1 total output by substituting eq.(14) into eq.(2) which gives:

$$Y_1 = (A_1)^{1/(1-\alpha)} \alpha^{2/(1-\alpha)} L_{y1} N_1 \tag{15}$$

By substituting eq.(13) and eq.(14) into eq.(10) one can get the flow of monopoly profit from sales to the owner of the rights of intermediate j as follows:

$$\pi_{1j} = \pi_1 = (1-\alpha) L_{y1} (A_1)^{1/(1-\alpha)} \alpha^{(1+\alpha)/(1-\alpha)} \tag{16}$$

As argued by Barro and Sala-i-Martin (1997) the present value of profits for the jth innovator is simply π_{1j}/r_1 where r_1 is the rate of return in country 1. When free entry is assumed into the R&D sector (and the quantity of R&D is nonzero) it must be that the present value of profits must equal the constant cost of invention η_1 at each point in time. Hence, rearrangement of the free-entry condition implies the following rate of return for economy 1:

$$r_1 = (L_{y1}/\eta_1) \left(\frac{1-\alpha}{\alpha} \right) (A_1)^{1/(1-\alpha)} \alpha^{2/(1-\alpha)} = \pi_1/\eta_1 \tag{17}$$

where the rate of return r_1 is the ratio of π_1, the flow of monopoly profit given in eq.(16), to the cost η_1 of obtaining this profit flow. We assume that consumers maximize utility over infinite horizons through a standard Ramsey type utility function as follows:

$$U_1 = \int_0^\infty e^{-\rho t} \left[(C^{1-\theta} - 1)/(1-\theta) \right] dt \tag{18}$$

where, as usual $\rho > 0$ represents the rate of time preference and $\theta > 0$ the magnitude of the elasticity of the marginal utility of consumption[51]. If we maximize the utility function subject to a standard budget constraint we obtain the usual expression for the consumption growth rate:

$$\dot{C}_1/C_1 = (1/\theta)(r_1 - \rho) \tag{19}$$

The growth rate of C_1 is constant due to the constancy of r_1 as in eq.(17). Hence, the growth rate of the leader economy is given by:

$$\gamma_1 = (1/\theta)(\pi_1/\eta_1 - \rho) = (1/\theta) \left[(1-\alpha) L_{y1} (A_1)^{1/(1-\alpha)} \alpha^{(1+\alpha)/(1-\alpha)} \eta_1^{-1} - \rho \right] \tag{20}$$

where the parameters of the model are such that $\pi_1/\eta_1 \geq \rho$ ensures positive growth. As expected, the inspection of eq.(20) reveals that the growth rate of the leader is a positive function of institutional quality and of its human capital composition.

[51] This implies the intertemporal elasticity of subsitution being equal to $1/\theta$.

6.4 The follower country

As we argued above, the skill-costliness of technology imitation is widely observed and acknowledged in theoretical and empirical literature. We build on this previously mentioned literature and express the cost function of technology adoption as a function of the follower's skills and of its development stage:

$$\nu_2 = \psi (L_{r2})^{-1} \left(\frac{N_2}{N_1} \right) \tag{21}$$

where ν_2, represents the cost of adopting and correctly implementing a new technology in the follower country. The technology adoption cost, ν_2, is assumed to be a negative function of the skill intensity of the South, that is of L_{r2}. Crucially, if two followers 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, to better use those profitable technologies in the production chain, to do better and more efficient reverse engineering and, ultimately, to face a relatively lower cost of adoption eventually leading to catch up with the frontier at a faster speed than the country endowed with relatively lower skills. The cost of technology adoption is also linked to the relative distance from the frontier. In the fashion of Connolly and Valderrama (2005) and Barro and Sala-i-Martin (1997) we assume this cost to be an increasing function of the proximity of the imitator w.r.t. the technological frontier such that, 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.

Similarly to the original model by Barro and Sala-i-Martin (1997), once a new technology is discovered at the frontier it will be potentially available for adoption by the follower[52]. Assuming that consumers in the South maximize a similar Ramsey-type utility function as in the leader country and solving for the stream of profit to the adopter we can define 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. The equation leading to the solution for the growth rate of the follower are symmetric to the one of the leader from eq. (10) to (20) such that we can express its growth rate as follows:

$$\gamma_2 = (1/\theta)(\pi_2/\nu_2 - \rho) = (1/\theta) \left[(1-\alpha) L_{y2} (A_2)^{1/(1-\alpha)} \alpha^{(1+\alpha)/(1-\alpha)} \nu_2^{-1} - \rho \right] \tag{22}$$

As we can notice from eq.(22), the growth rate of the follower is tightly linked to the composition of its human capital. More specifically, the follower's

[52]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.(21)

engine of growth lies in its technology absorptive capacity, that is, in its ability to receive the technology spillovers coming from the frontier. The crucial parameter is, in fact, ν_2, the cost of technology adoption, which enters at the denominator of the expression in eq.(22). It is easy to recall that the cost of adoption is, itself, a negative function of the skilled fraction of the workforce as in eq.(21) such that an increase in L_{r2} will boost the capacity of the follower to adopt technology (reducing the adoption cost) but, at the same time reducing the share of workforce employed in the physical production of the final imitated good L_{y2}. This latter effect is however compensated by the former under general conditions and especially at lower development stages or when the initial skills of the followers are relatively low. This outcome of this scenario is analyzed in the following proposition.

Proposition 1 *A marginal increase in the share of the workforce with a higher level of education (L_{r2}, skilled workers) is growth enhancing for the followers, reducing the cost of technology adoption. Conversely, a rise in the fraction of population with low skills is shown to be growth diminishing and to lead to slower technology convergence. The result (which depends on the relative composition of human capital in the follower economy) is stronger the farther away the follower economy is from the technology frontier as well as the smaller the initial share of skilled workers.*

Proof. The results follow the examination of the partial derivative of eq. (22) w.r.t. L_{r2} and its numerical calibration. ■

Taking the partial derivative of the growth rate in eq.(22) w.r.t. L_{r2} and imposing this to be greater than zero yields to the following expression:

$$\frac{\partial \gamma_2}{\partial L_{r2}} = \frac{1}{N_2 \theta} \left(L_{r2} N_1 \alpha - L_{r2} N_1 \right) \chi + \frac{1}{N_2 \theta} \left(N_1 - L_{r2} N_1 - N_1 \alpha + L_{r2} N_1 \alpha \right) \chi > 0 \tag{23}$$

where $A_2^{\frac{1}{1-\alpha}} \alpha^{\frac{\alpha+1}{1-\alpha}} = \chi$. It can be easily shown that, following the standard assumptions made on the model parameters in order to ensure positive growth, the term $(1/\theta) \left[(1-\alpha)(A_2)^{1/(1-\alpha)} \alpha^{(1+\alpha)/(1-\alpha)} v_2^{-1} - \rho \right]$ will be always greater than zero leading to the following simplification of $\partial \gamma_2 / \partial L_{r2} > 0 \Leftrightarrow L_{r2} < 1/2$. Hence, as long as the share of skilled workers is less than the average workforce a marginal increase in the top margin skill will be growth beneficial.

In order to grasp the magnitude of a marginal increase in L_{r2} on growth, and since eq.(23) is rather complex, we explicitly calibrate its parameters and solve it numerically in figure 3 below.

[Figure 3 about here]

Our numerical simulation reports the impact of a marginal increase in L_{r2} for different scenarios of the initial levels of the share of skilled workers (0.3 and 0.35) and at different development stages. In figure 3 we plot the solutions for $\partial\gamma_2/\partial L_{r2}$ against increasing values of the proximity to the technology frontier. Larger positive effects of a marginal increase in L_{r2} are experienced when far away from the frontier as argued in proposition 1. Similarly, holding constant the distance from the frontier, a marginal increase in L_{r2} has a larger impact when the initial values of the skilled workforce is smaller. In both cases, the theoretical predictions and the results of the numerical calibration of our modified growth model match the empirical evidence presented in previous sections. Developing countries (those farther away from the frontier and endowed with relatively smaller fraction of skilled workers) experience the largest marginal effect of an increase in tertiary education on growth. Conversely, countries endowed with relatively larger shares of skilled workers (the OECD countries for instance) experience smaller (and diminishing) returns to the the change in tertiary education.

7 Conclusions

Our contribution provides compelling and robust evidence of the heterogenous impact of human capital composition on the growth of countries at different development stages. Tertiary education is shown to be the engine of productivity convergence at all development stages while secondary and especially primary education are only marginally related to economic growth.

More importantly, and in contrast to previous theoretical and empirical literature[53] which argued for the "primacy" of high skills at higher development stages, our results show that tertiary education plays a fundamental role for the growth, in particular, of developing countries while its impact on developed economies is shown to be substantially weaker.

The policy implications stemming from our results suggest that pro-development policies should foster the accumulation of high skills *especially* in technological under-developed countries and, contrary to the common wisdom, independently of the fact that these economies might be initially producing low(er)-technology goods or performing technology imitation. The effect of tertiary education on the rate of productivity growth and technology convergence is in fact shown to be substantially larger in developing countries than in developed ones by sensibly reducing the cost of technology adoption and implementation in lagging economies.

We argue that our empirical evidence overcome that of previous literature that dealt with these issues under a variety of aspects. In order to test the impact of diverse education levels on the growth of economies at very different

[53] See Vandenbussche, Aghion and Meghir (2006), Acemoglu and Zilibotti (2001) or Aghion et al. (2009) among others.

development stages we built a large panel database for 88 among developed and developing countries for the years in between 1960 and 2000 by combining information from several sources. Previous studies, instead, tended to focus on smaller samples not being able to provide a more comprehensive evidence of the impact of different education levels on the growth of very diverse economies.

We followed the suggestions by de la Fuente and Domenech (2001) or Vandenbussche, Aghion and Meghir (2006) who stressed the importance of using robust human capital proxies. This is especially important for panel data estimations for which poor quality data had driven previous empirical results. For this, on the one hand, we rely on the Cohen and Soto's (2006) human capital database which has been shown to over-perform other previously existing databases and to provide more consistent estimates of education levels both across countries and over time.

On the other hand, however, another influential strand of literature (see Hanushek and Kimko (2000) and Hanushek and Woessman (2009)) argue how the quality of the education systems, rather than the "quantity" of the formally completed education, would represent a better approximation for human capital.

Our empirical results are strikingly robust to the use of both quantity[54] and/or quality-human capital proxies. The impact of a marginal increase in either of the two proxies leads to faster convergence overall. However, and in contrast to the results by Vandenbussche, Aghion and Meghir (2006) and others, this effect is shown to be much larger for those economies which are farther away from the technology frontier and endowed with smaller initial stocks (or lower the quality) of tertiary education. In order to prove the robustness of our results we additionally built a composite human capital indicator by exploiting jointly the quantitative and qualitative information on cross-country human capital. Results are again in line with our initial assumption.

Interestingly, adjusting the human capital indicators by the quality of education reduces the gap in the estimated returns of tertiary education between developed and developing countries. We argue that this results might be related to the lower signalling power of quantitative measures of human capital (such as, for instance, average years of schooling) for developed countries which, in turn, could be attributed to the observed decrease in school and college selectivity over time which would impede to capture the true nature of the developed countries' workforce's human capital.

We provide some empirical evidence supporting the hypothesis for which "quantitative" measures of human capital such as the average years of schooling measures would tend to underestimate the impact of tertiary education on the

[54] The Cohen and Soto's data provide data on the relative stock (quantity) of education in each country/year approximated by both the average years of schooling in primary, secondary and tertiary education as well as by the fraction of the workforce in each education category.

growth of countries at higher development stages. Our main results reconcile with the microeconomic evidence of decreasing returns to investment in tertiary education at higher development stages as shown by Psacharopoulos (1994) or Psacharopoulos and Patrinos (2002) among others. A more formal analysis of this hypothesis is however left for future research.

The evidence on the heterogenous impact of tertiary education at different development stages is also robust to a wide array of controls and, especially, to the introduction of differences in country's institutional quality indicators. Institutions, as expected, are generally shown to increase the speed of economic convergence in line with previous empirical literature such as Hall and Jones (1999) or Acemoglu et al. (2001). In our study we control for differences in the legal origin and in religious fractionalization across countries in line with the empirical evidence by la Porta et al. (2008) or Alesina et al. (2003) as well as for differences in legal systems, openness to trade and other institutional sub-indicators included in the EFW index. Also, our results are fully corrected for the likely presence of endogeneity by applying a wide array of estimators such as Instrumental Variables (both for the panel and cross section analysis) and two-step efficient system GMM estimators.

To conclude, and to support our empirical evidence, we presented a simple modified version of the technology catch-up model by Barro and Sala-i-Martin (1997) which accomodates the assumption on human capital heterogeneity across countries at different development stages. We linked the cost of innovation and imitation to each country's human capital composition. Solving the model for both the leader and followers' growth rates and calibrating its parameters as in our raw descriptive statistics (endowing the leader with higher skills and better institutions than the follower) we find additional confirmation of the validity of our empirical results and of the greater marginal effect of tertiary education on growth at lower development stages.

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TAB 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ALL					
TFP gap	412	0.34	0.27	0.00	1.00
Institutions	307	5.84	1.17	2.9	8.6
Mean Years Tertiary	440	0.23	0.27	0.00	1.40
Mean Years Secondary	440	0.72	0.78	0.00	3.36
Mean Years Primary	440	1.43	1.12	0.04	5.13
Tertiary Fraction	440	0.06	0.07	0.00	0.35
Secondary Fraction	440	0.12	0.13	0.00	0.56
Primary Fraction	440	0.24	0.19	0.01	0.85
OECD					
TFP gap	104	0.69	0.17	0.21	1.00
Institutions	84	6.9	0.75	5.3	8.6
Mean Years Tertiary	105	0.51	0.32	0.04	1.40
Mean Years Secondary	105	1.53	0.89	0.08	3.36
Mean Years Primary	105	2.32	1.33	0.18	5.13
Tertiary Fraction	105	0.13	0.08	0.01	0.35
Secondary Fraction	105	0.25	0.15	0.01	0.56
Primary Fraction	105	0.39	0.22	0.03	0.85
DEVELOPING					
TFP gap	297	0.22	0.17	0.00	0.90
Institutions	216	5.38	1.00	2.9	7.5
Mean Years Tertiary	323	0.14	0.17	0.00	1.30
Mean Years Secondary	323	0.46	0.54	0.00	2.89
Mean Years Primary	323	1.13	0.88	0.04	4.54
Tertiary Fraction	323	0.03	0.04	0.00	0.32
Secondary Fraction	323	0.08	0.09	0.00	0.48
Primary Fraction	323	0.19	0.15	0.01	0.76

TAB. 2:
TFP GROWTH EQUATION,
FRACTIONS

Dependent Variable:
TFP growth rate

	ALL	OECD	DEVELOPING	ALL	OECD	DEVELOPING	ALL	OECD	DEVELOPING
TFP gap	-0.040	-0.268**	0.034	-0.045	-0.362*	0.020	-0.001	0.017	-0.011
	[0.026]	[0.133]	[0.039]	[0.029]	[0.188]	[0.039]	[0.042]	[0.124]	[0.050]
Tertiary Fraction	0.195	-0.802	0.871***						
	[0.145]	[0.524]	[0.289]						
TFP gap*Tertiary Fraction	-0.261	1.003	-2.827***						
	[0.198]	[0.642]	[0.884]						
Secondary Fraction				0.237***	-0.363	0.542***			
				[0.075]	[0.357]	[0.121]			
TFP gap*Secondary Fraction				-0.260**	0.525	-1.426***			
				[0.102]	[0.477]	[0.418]			
Primary Fraction							0.222***	0.460	0.135*
							[0.086]	[0.324]	[0.072]
TFP gap*Primary Fraction							-0.335**	-0.652	-0.272
							[0.151]	[0.437]	[0.197]
Institutional Quality	0.015**	0.013	0.009	0.015**	0.021	0.009	0.018*	0.012	0.008
	[0.007]	[0.022]	[0.009]	[0.007]	[0.020]	[0.008]	[0.009]	[0.018]	[0.008]
Constant	-0.072*	0.136	-0.053	-0.080**	0.119	-0.061	-0.118**	-0.075	-0.046
	[0.040]	[0.126]	[0.050]	[0.041]	[0.155]	[0.047]	[0.054]	[0.162]	[0.051]
Observations	198	62	131	198	62	131	198	62	131
Number of id	84	21	61	84	21	61	84	21	61
R2	0.106	0.341	0.138	0.149	0.290	0.234	0.164	0.401	0.130
Hausman X(3)	3.39								
P-value	0.334								

Note: Random effect IV estimations are performed. Instruments are the 2nd lag of the explanatory variables. Standard Errors in brackets. Time dummies are included in all specification but not reported. *** p<0.01, ** p<0.05, * p<0.1.

TAB. 3:
TFP GROWTH EQUATION,
FRACTIONS

Dependent Variable: TFP growth rate	ALL	OECD	DEVELOPING	ALL	OECD	DEVELOPING	ALL	OECD	DEVELOPING
Tertiary Fraction	0.248*	0.144	0.838***						
	[0.149]	[0.279]	[0.271]						
TFP gap*Tertiary Fraction	-0.378*	-0.173	-2.606***						
	[0.195]	[0.322]	[0.769]						
Secondary Fraction				0.280***	0.122	0.513***			
				[0.083]	[0.182]	[0.102]			
TFP gap*Secondary Fraction				-0.340***	-0.181	-1.282***			
				[0.109]	[0.200]	[0.292]			
Primary Fraction							0.240***	0.452**	0.174**
							[0.080]	[0.181]	[0.070]
TFP gap*Primary Fraction							-0.382***	-0.648***	-0.352**
							[0.132]	[0.236]	[0.150]
Institutional Quality	0.008	-0.011	0.012	0.007	-0.004	0.010	0.020**	0.013	0.005
	[0.006]	[0.021]	[0.010]	[0.007]	[0.018]	[0.008]	[0.008]	[0.018]	[0.012]
Constant	-0.038	0.109	-0.069	-0.042	0.062	-0.066	-0.135**	-0.073	-0.038
	[0.036]	[0.147]	[0.060]	[0.042]	[0.129]	[0.046]	[0.057]	[0.148]	[0.073]
Observations	198	62	131	198	62	131	198	62	131
Number of id	84	21	61	84	21	61	84	21	61
R-Sq	0.0773	0.0700	0.152	0.124	0.0915	0.243	0.159	0.390	0.113

Note: Random effect IV estimations are performed. Instruments are the 2nd lag of the explanatory variables. Standard Errors in brackets. Time dummies are included in all specification but not reported. *** p<0.01, ** p<0.05, * p<0.1.

TAB. 4:
TFP GROWTH EQUATION,
AVERAGE YEARS OF SCHOOLING

Dependent Variable: TFP growth rate	ALL	OECD	DEVELOPING	ALL	OECD	DEVELOPING
TFP gap	-0.067	0.456*	-0.035	-0.085	0.335	-0.093
	[0.041]	[0.261]	[0.049]	[0.054]	[0.278]	[0.067]
Tertiary Schooling	0.004	-0.066***	0.008**	0.001	-0.071**	0.010*
	[0.004]	[0.022]	[0.004]	[0.005]	[0.028]	[0.005]
Primary+Secondary Schooling	0.003	0.419**	-0.003	0.013	0.357**	-0.003
	[0.007]	[0.167]	[0.008]	[0.010]	[0.153]	[0.012]
TFP gap* Tertiary Sch.	0.003	0.135**	-0.208**	0.009	0.130**	-0.238**
	[0.026]	[0.059]	[0.098]	[0.032]	[0.065]	[0.120]
TFP gap* Prim.+Sec. Sch.	0.005	-0.086**	0.005	-0.001	-0.074**	0.013
	[0.005]	[0.037]	[0.010]	[0.006]	[0.036]	[0.014]
Institutional Quality				0.018*	0.017	0.006
				[0.010]	[0.024]	[0.012]
Constant	0.035*	-0.778**	0.050***	-0.087	-0.763**	0.025
	[0.018]	[0.330]	[0.019]	[0.064]	[0.335]	[0.082]
Observations	226	62	158	196	62	129
Number of id	86	21	63	84	21	61
R-Sq	0.0626	0.486	0.0936	0.123	0.455	0.150

Note: Random effect IV estimations are performed. Instruments are the 2^{nd} lag of the explanatory variables. Standard Errors in brackets. Time dummies are included in all specification but not reported. *** p<0.01, ** p<0.05, * p<0.1.

TAB. 5:
TFP GROWTH EQUATION,
AVERAGE YEARS OF SCHOOLING

Dependent Variable: TFP growth rate	ALL	OECD	DEVELOPING	ALL	OECD	DEVELOPING
Tertiary Schooling	0.002	-0.053**	0.007*	-0.001	-0.072***	0.008
	[0.003]	[0.022]	[0.004]	[0.004]	[0.028]	[0.006]
Primary+Secondary Schooling	0.007	0.199**	-0.001	0.011	0.230**	0.002
	[0.007]	[0.085]	[0.007]	[0.008]	[0.092]	[0.012]
TFP gap* Tertiary Sch.	0.001	0.145**	-0.222**	-0.017	0.151**	-0.247*
	[0.028]	[0.063]	[0.097]	[0.027]	[0.064]	[0.143]
TFP gap* Prim.+Sec. Sch.	-0.002	-0.032***	0.000	-0.004	-0.035***	0.002
	[0.003]	[0.012]	[0.007]	[0.004]	[0.012]	[0.011]
Institutional Quality				0.011	0.026	-0.000
				[0.007]	[0.022]	[0.016]
Constant	0.016	-0.295**	0.042***	-0.061	-0.555**	0.040
	[0.015]	[0.143]	[0.016]	[0.049]	[0.277]	[0.107]
Observations	226	62	158	196	62	129
Number of id	86	21	63	84	21	61
R-Sq	0.0466	0.441	0.0870	0.0947	0.427	0.0960

Note: Random effect IV estimations are performed. Instruments are the 2nd lag of the explanatory variables. Standard Errors in brackets. Time dummies are included in all specification but not reported. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TAB. 6:
TFP GROWTH EQUATION, FRACTIONS

Dependent Variable: TFP growth rate	(SYSGMM)			(SYSGMM)			(SYSGMM)		
	ALL	OECD	DEVELOPING	ALL	OECD	DEVELOPING	ALL	OECD	DEVELOPING
TFP gap	-0.058***	-0.269***	-0.029***	-0.063***	-0.237**	-0.037***	0.008	-0.007	-0.066***
	[0.008]	[0.074]	[0.010]	[0.008]	[0.094]	[0.012]	[0.012]	[0.035]	[0.020]
Tertiary Fraction	0.008	-0.958**	0.306***						
	[0.067]	[0.399]	[0.100]						
TFP gap*Tertiary Fraction	0.036	1.170**	-1.033***						
	[0.091]	[0.525]	[0.200]						
Institutional Quality	0.015***	0.017*	0.009***	0.008***	-0.000	0.005**	0.015***	-0.006	0.010***
	[0.002]	[0.010]	[0.003]	[0.002]	[0.006]	[0.002]	[0.002]	[0.006]	[0.002]
Secondary Fraction				0.218***	-0.406	0.348***			
				[0.042]	[0.242]	[0.056]			
TFP gap*Secondary Fraction				-0.156***	0.583*	-0.743***			
				[0.057]	[0.307]	[0.121]			
Primary Fraction							0.142***	0.190***	0.128***
							[0.023]	[0.051]	[0.024]
TFP gap*Primary Fraction							-0.234***	-0.268***	-0.150**
							[0.029]	[0.065]	[0.060]
Constant	-0.063***	0.110	-0.043**	-0.033**	0.198*	-0.030**	-0.092***	0.085	-0.055***
	[0.014]	[0.106]	[0.017]	[0.014]	[0.100]	[0.013]	[0.011]	[0.057]	[0.016]
Observations	286	83	196	317	83	226	317	83	226
Number of id	87	21	64	87	21	64	87	21	64
Hansen P-value	0.0211	0.570	0.349	0.0587	0.403	0.242	0.00566	0.888	0.189
Hansen Stat	55.24	13.42	37.64	40.58	12.54	31.73	50.52	18.49	33.24
Instr. count	44	23	43	35	19	34	35	34	34
AR (2)- Pvalue	0.241	0.354	0.197	0.255	0.497	0.248	0.448	0.405	0.334
AR (2)- Stat	1.173	-0.927	1.290	1.139	-0.679	1.155	0.758	-0.833	0.966

Note: Two-step efficient Dynamic Panel System GMM estimations are performed by correcting for small sample biases. Standard Errors in brackets. Time dummies are included in all specification but not reported. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. IV controls………

TAB. 7:
TFP GROWTH
EQUATION, FRACTIONS

Dependent Variable: TFP growth rate	(SYSGMM)			(SYSGMM)			(SYSGMM)		
	ALL	OECD	DEVELOPING	ALL	OECD	DEVELOPING	ALL	OECD	DEVELOPING
Tertiary Fraction	0.116	0.195	0.479						
	[0.214]	[0.122]	[0.334]						
TFP gap*Tertiary Fraction	-0.303	-0.372*	-1.577**						
	[0.283]	[0.199]	[0.735]						
Institutional Quality	0.011**	0.004	0.008	0.005	0.001	0.005	0.015***	-0.006	0.010**
	[0.005]	[0.016]	[0.006]	[0.006]	[0.009]	[0.006]	[0.003]	[0.012]	[0.005]
Secondary Fraction				0.275***	0.061	0.419***			
				[0.098]	[0.063]	[0.137]			
TFP gap*Secondary Fraction				-0.351***	-0.136*	-1.037***			
				[0.121]	[0.074]	[0.237]			
Primary Fraction							0.136*	0.198**	0.163*
							[0.074]	[0.074]	[0.082]
TFP gap*Primary Fraction							-0.220***	-0.278**	-0.305***
							[0.083]	[0.099]	[0.097]
Constant	-0.051*	0.013	-0.045	-0.031	0.038	-0.035	-0.095***	0.078	-0.071**
	[0.030]	[0.106]	[0.037]	[0.035]	[0.062]	[0.033]	[0.024]	[0.094]	[0.027]
Observations	286	83	196	286	83	196	286	83	196
Number of id	87	21	64	87	21	64	87	21	64
Hansen P-value	0.0121	0.403	0.108	0.0117	0.674	0.274	0.0384	1.000	0.200
Hansen Stat	59.04	16.73	23.20	59.18	12.99	40.61	53.55	13.40	42.87
Instr. count	44	23	23	44	23	43	44	43	43
AR (2)- Pvalue	0.0723	0.244	0.205	0.124	0.181	0.116	0.923	0.515	0.311
AR (2)- Stat	1.797	1.164	1.266	1.537	1.337	1.573	-0.0970	-0.651	1.013

Note: Two-step efficient Dynamic Panel System GMM estimations are performed by correcting for small sample biases. Standard Errors in brackets. Time dummies are included in all specification but not reported. *** p<0.01, ** p<0.05, * p<0.1.

TAB. 8:
TFP GROWTH EQUATION, AVERAGE
YEARS OF SCHOOLING

Dependent Variable: TFP growth rate			
	(SYSGMM)		
	ALL	OECD	DEVELOPING
TFP gap	-0.088	0.316	-0.205**
	[0.060]	[0.297]	[0.085]
Tertiary Schooling	0.006	-0.055**	0.015*
	[0.006]	[0.021]	[0.008]
Primary+Secondary Schooling	0.012	0.119	0.015
	[0.013]	[0.081]	[0.016]
TFP gap* Tertiary Schooling	-0.001	0.052	-0.039**
	[0.012]	[0.052]	[0.016]
TFP gap* Prim.+Sec. Sch.	-0.006	-0.171	-0.015
	[0.028]	[0.130]	[0.039]
Institutional Quality	0.013**	0.019	0.008
	[0.005]	[0.025]	[0.006]
Constant	-0.040	-0.346	0.014
	[0.050]	[0.235]	[0.060]
Observations	284	83	194
Number of id	87	21	64
Hansen P-value	0.189	0.946	0.374
Hansen Stat	60.77	11.76	53.62
Instr. count	62	31	61
AR (2)- Pvalue	0.673	0.580	0.226
AR (2)- Stat	0.422	-0.553	1.210

Note: Two-step efficient Dynamic Panel System GMM estimations are performed by correcting for small sample biases. Standard Errors in brackets. Time dummies are included in all specification but not reported. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

TAB. 9:
TFP GROWTH EQUATION, AVERAGE
YEARS OF SCHOOLING

Dependent Variable: TFP growth rate	(SYSGMM)			(SYSGMM)		
	ALL	OECD	DEV	ALL	OECD	DEV
TFP gap	-0.083**	0.002	-0.199***	-0.079**	-0.063	-0.150***
	[0.033]	[0.034]	[0.065]	[0.031]	[0.045]	[0.036]
Tertiary Schooling	0.008	-0.063**	0.015*			
	[0.005]	[0.023]	[0.009]			
TFP gap* Tertiary Schooling	-0.005	0.076**	-0.041**			
	[0.010]	[0.028]	[0.017]			
Secondary Schooling				0.009	-0.043*	0.020
				[0.007]	[0.023]	[0.012]
TFP gap*Secondary Schooling				0.011	0.069***	-0.036
				[0.015]	[0.024]	[0.023]
Institutional Quality	0.009*	0.007	0.002	0.008	-0.009	0.005
	[0.005]	[0.012]	[0.005]	[0.006]	[0.013]	[0.009]
Constant	0.000	-0.029	0.059	-0.002	0.143	0.023
	[0.037]	[0.087]	[0.053]	[0.040]	[0.106]	[0.062]
Observations	284	83	194	282	83	192
Number of id	87	21	64	87	21	64
Hansen P-value	0.0810	0.917	0.395	0.0168	0.875	0.135
Hansen Stat	48.41	8.160	36.60	56.28	9.056	44.30
Instr. count	44	23	43	44	23	43
AR (2)- Pvalue	0.296	0.703	0.142	0.551	0.918	0.198
AR (2)- Stat	1.045	-0.381	1.468	0.597	0.103	1.289
	IV controls	IV controls	IV controls	IV controls	IV controls	IV controls

Note: Two-step efficient Dynamic Panel System GMM estimations are performed by correcting for small sample biases. Standard Errors in brackets. Time dummies are included in all specification but not reported. *** p<0.01, ** p<0.05, * p<0.1.

TAB: 10
TFP GROWTH EQUATION
EDUCATION QUALITY

	(1) ALL	(2) OECD	(3) DEVL.	(4) ALL	(5) OECD	(6) DEVL.
	OLS	OLS	OLS	GMM	GMM	GMM
Cognitive Skills index	0.018***	-0.032	0.013*	0.018**	-0.016	0.015**
	[0.004]	[0.038]	[0.006]	[0.007]	[0.026]	[0.006]
Cogn* TFPGap	-0.012***	-0.012**	-0.018***	-0.015***	-0.011***	-0.022***
	[0.002]	[0.004]	[0.004]	[0.005]	[0.002]	[0.005]
Institutional Quality	0.003	0.006	0.003	0.012	0.003	0.012**
	[0.005]	[0.007]	[0.008]	[0.010]	[0.006]	[0.005]
Constant	-0.052**	0.189	-0.024			
	[0.024]	[0.159]	[0.044]			
Observations	43	20	21	43	20	21
R-squared	0.396	0.551	0.515	0.312	0.319	0.381
Hansen J-stat				7.133	6.352	6.44
Pvalue				0.3087	0.3849	0.2657
Kleibergen-Paap rk Wald F statistic				4.791	2.995	15.816
Stock-Yogo's Critical Value *20, **10, ***5% maximal relative bias				4.73	4.73	9.92**

Robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1. Institutions and Human capital variables are taken as endogenous and instrumented by country specific legal origin, religion fractionalization and average education expenditures over the period (for OECD) and lagged human capital as detailed in the text. Continent dummies are added in all specification but not reported.

TAB: 11
TFP GROWTH EQUATION
EDUCATION QUALITY

	(1) ALL	(2) OECD	(3) DEVL.	(4) ALL	(5) OECD	(6) DEVL.
	OLS	OLS	OLS	GMM	GMM	GMM
Cognitive Tertiary (Fraction)	0.016	0.024	0.048	0.021	0.016	0.054
	[0.026]	[0.020]	[0.061]	[0.021]	[0.013]	[0.043]
Cognitive Tertiary fraction *TfpGap	-0.051*	-0.040*	-0.184**	-0.084***	-0.053***	-0.180***
	[0.028]	[0.022]	[0.078]	[0.028]	[0.013]	[0.059]
Institutional Quality	0.006	-0.010	0.002	0.009	-0.005*	0.001
	[0.004]	[0.009]	[0.007]	[0.008]	[0.003]	[0.008]
Constant	-0.004	0.101	0.018			
	[0.028]	[0.064]	[0.046]			
Observations	43	20	21	43	20	21
R-squared	0.152	0.375	0.301	0.197	0.337	0.206
Hansen J-stat				4.175	11.104	5.054
Pvalue				0.6531	0.0852	0.4094
Kleibergen-Paap rk Wald F statistic				4.278	23.725	15.83
Stock-Yogo's Critical Value *20, **10, ***5% maximal relative bias				4.73	17.7***	9.92**

Robust standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1. Cognitive Tertiary (fraction) is the "Cognitive index adjusted measure" of Tertiary fraction of workforce. Institutions and Human capital variables are taken as endogenous and instrumented by country specific legal origin, religion fractionalization and average education expenditures over the period (for OECD) and lagged human capital as detailed in the text. Continent dummies are added in all specification but not reported.

TAB: 12
TFP GROWTH EQUATION
EDUCATION QUALITY

	(1) ALL	(2) OECD	(3) DEVL.	(4) ALL	(5) OECD	(6) DEVL.
	OLS	OLS	OLS	GMM	GMM	GMM
Cognitive Tertiary (Years schooling)	0.004	0.006	0.012	0.005	0.004	0.014
	[0.007]	[0.005]	[0.015]	[0.005]	[0.003]	[0.011]
Cognitive Tertiary (Years)* TFP Gap	-0.013*	-0.010*	-0.046**	-0.021***	-0.013***	-0.045***
	[0.007]	[0.006]	[0.020]	[0.007]	[0.003]	[0.015]
Institutional Quality	0.006	-0.010	0.002	0.009	-0.005*	0.001
	[0.004]	[0.009]	[0.007]	[0.008]	[0.003]	[0.008]
Constant	-0.004	0.101	0.018			
	[0.028]	[0.064]	[0.046]			
Observations	43	20	21	43	20	21
R-squared	0.152	0.375	0.301	0.197	0.337	0.206
Hansen J-stat				4.175	11.104	5.054
Pvalue				0.6531	0.0852	0.4094
Kleibergen-Paap rk Wald F statistic				4.278	23.725	15.83
Stock-Yogo's Critical Value *20, **10, ***5% maximal relative bias				4.73	17.7***	9.92**

Robust standard errors in brackets.*** p<0.01, ** p<0.05, * p<0.1. Cognitive Tertiary (Years schooling) is the "Cognitive index adjusted measure" of Tertiary years of schooling. Institutions and Human capital variables are taken as endogenous and instrumented by country specific legal origin, religion fractionalization and average education expenditures over the period (for OECD) and lagged human capital as detailed in the text. Continent dummies are added in all specification but not reported.

Appendix 1
OLS: Cognitive skills regression

VARIABLES	(1) cognitive	(2) cognitive	(3) cognitive
Average years of Tertiary education in 1960	0.408	-0.707	4.184**
	[0.621]	[0.505]	[1.669]
Institutional quality	0.292***	0.207**	0.295*
	[0.081]	[0.078]	[0.173]
Constant	2.717***	3.347***	2.630**
	[0.514]	[0.478]	[1.007]
Observations	50	21	27
R-squared	0.759	0.678	0.655
r2	0.759	0.678	0.655
F	14.01	6.311	5.161

Robust standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1.
Continental dummies are included but not reported.

Figure 1

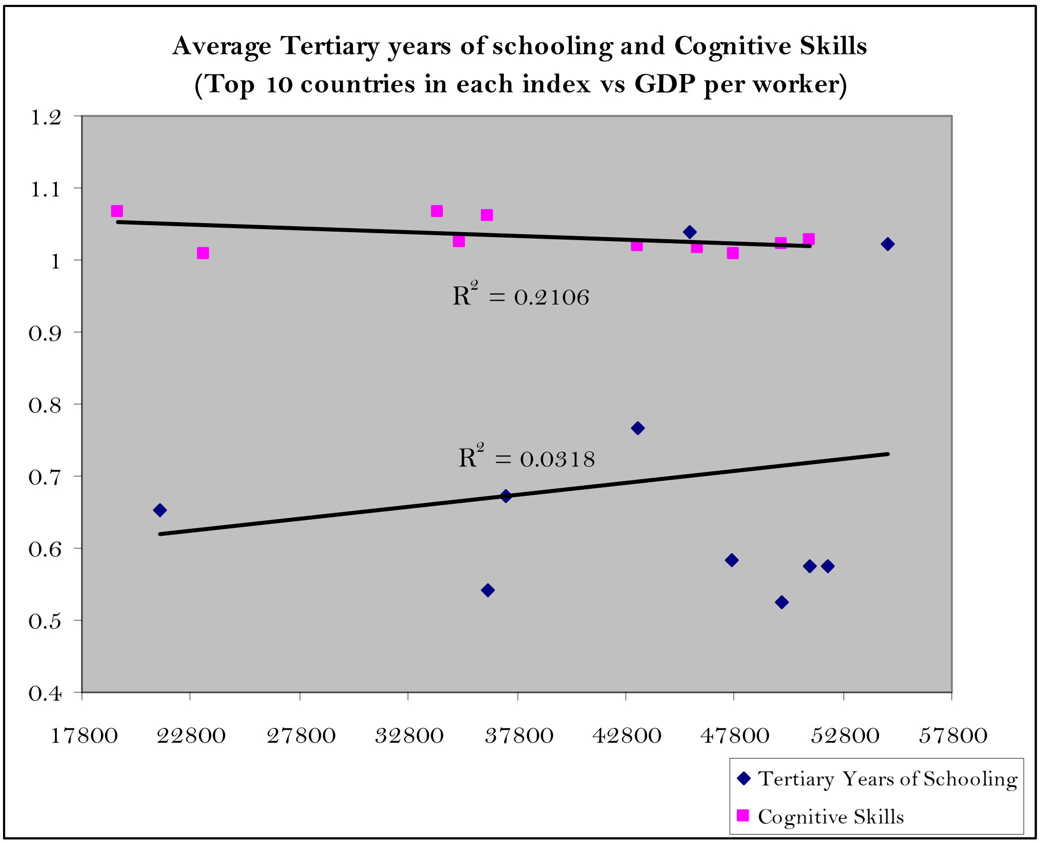
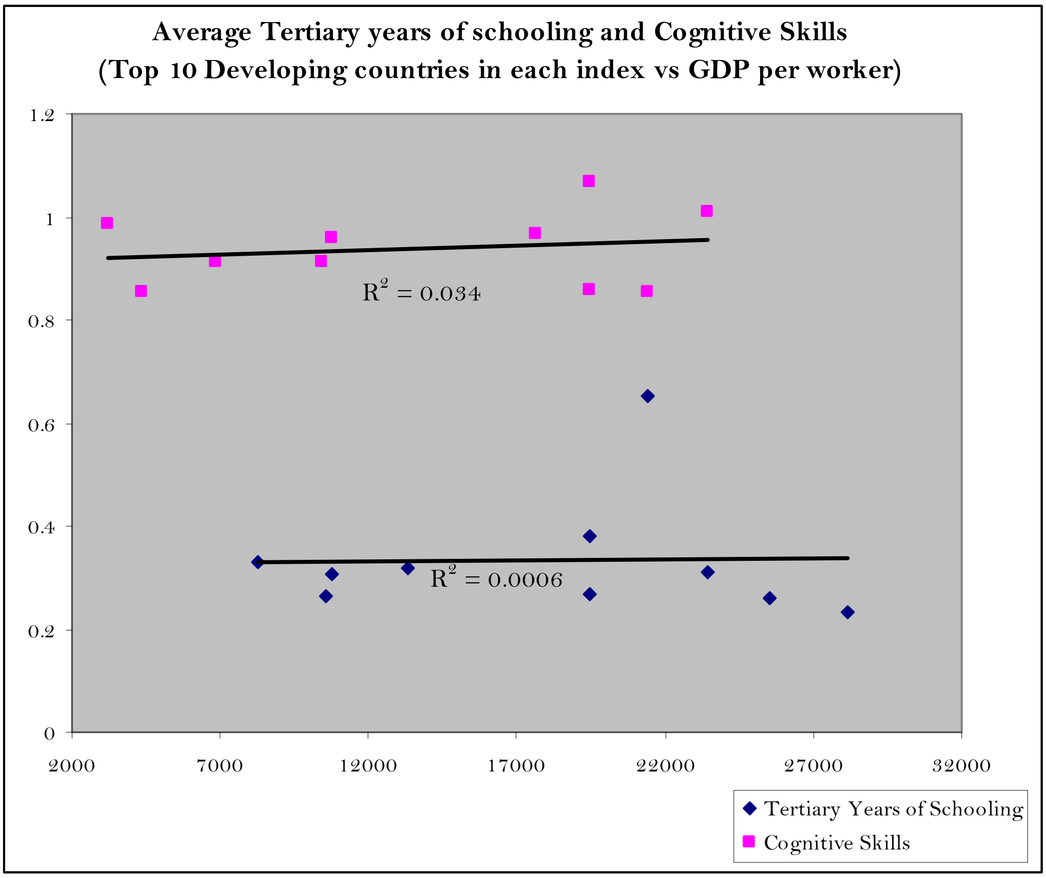


Figure 2



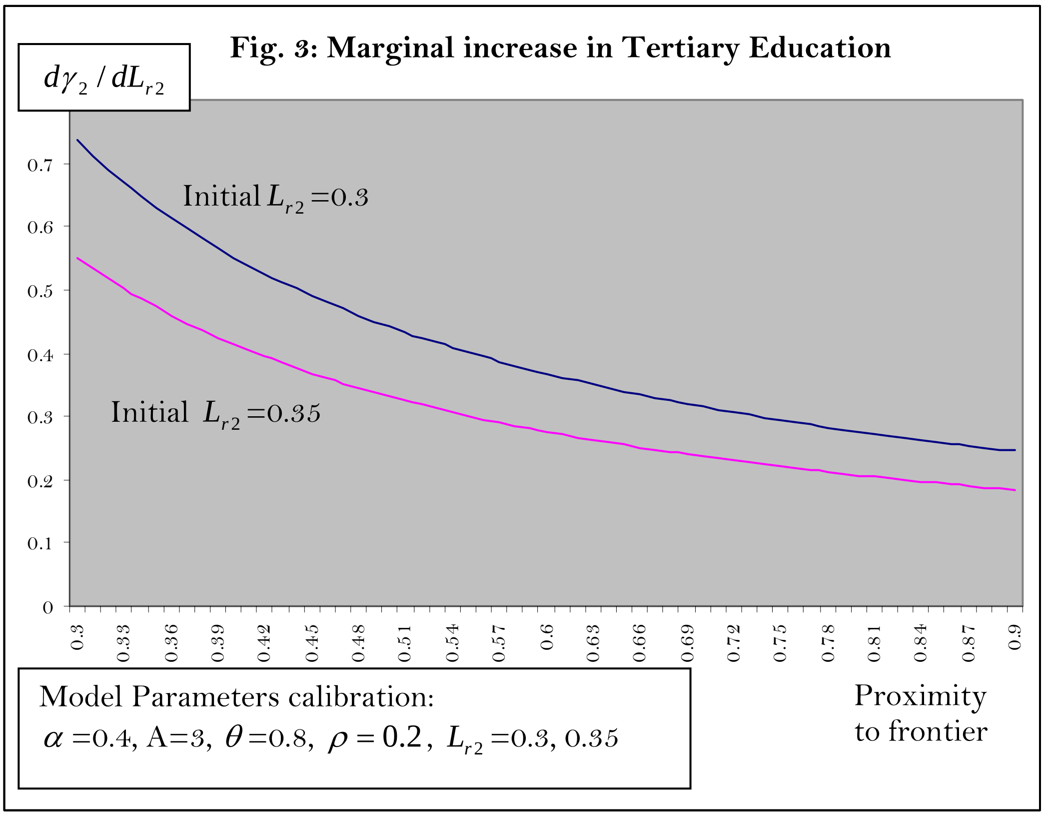


Fig. 3: Marginal increase in Tertiary Education
$d\gamma_2 / dL_{r2}$
Initial L_{r2}=0.3
Initial L_{r2}=0.35
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0.3
0.33
0.36
0.39
0.42
0.45
0.48
0.51
0.54
0.57
0.6
0.63
0.66
0.69
0.72
0.75
0.78
0.81
0.84
0.87
0.9
Model Parameters calibration:
α=0.4, A=3, θ=0.8, $\rho = 0.2$, L_{r2}=0.3, 0.35
Proximity
to frontier