Growth in emerging economies: is there a role for education?

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Abstract

We study the relationship between human capital and growth using a model which encompasses previous specifications and estimates the short and the long-run effects of human capital accumulation. We adopt an empirical framework which accounts for countries' heterogeneity and cross-sectional dependence in a dynamic panel. Results for a sample of 14 Asian countries reveal a large and positive long-run impact of human capital on growth in the 1960-2013 period. Looking at different types of education we find that the diffusion of primary and secondary education has a positive long-run impact, while the long-run effect of tertiary education is negative. Low proportion of people educated at the tertiary level, lack of opportunities for highly educated workers and the brain drain phenomenon could explain this result. These results support policies directed towards increasing investments in primary and secondary education rather than focusing on a minority educated at the tertiary level.

Keywords: growth, human capital, cross sectional dependence, error correction model.

JEL codes: C4, O4, O5

"The experience of the developing world actually makes it all too clear that education cannot guarantee growth". (Alison Wolf, 2002)

1. Introduction

In 2001 Lant Pritchett asked 'Where has all the education gone?' The question refers to the weak empirical macroeconomic evidence on the effect of investment in education on growth, which is in stark conflict with the theory and with results at the microeconomic level (Pritchett, 2001). In theory, the role of human capital on growth is indisputable. Since the seminal contributions by Becker (1964) and Schultz (1981), followed by a wave of endogenous growth models such as Lucas (1988) and Romer (1986; 1990), investments in human capital have been identified as a key policy instrument to improve productivity growth both directly, as skilled workers are more productive, and indirectly as human capital increases countries' ability to absorb new knowledge and to generate externalities (Cohen and Levinthal, 1989; Nelson and Phelps, 1966; Griffith et al., 2004; Vandenbussche et al., 2006).

While microeconomic studies have reached a consensus on the size of the effect of schooling on wages (Krueger and Lindahl, 2001)[1], at the macro level the assessment of the impact of human capital (usually measured in terms of enrolment into education or educational attainment) on output growth has produced mixed results. Studies based on cross-country growth regressions have produced evidence of the positive impact of education on growth (Barro, 1991; Barro, 2001; Levine and Renelt, 1992; Mankiw et al., 1992). However, studies based on panel data have not been able to find a meaningful role for human capital in growth regressions (De Gregorio, 1992; Knight et al., 1993; Caselli et al., 1996; Hamilton and Monteagudo, 1998; Madsen et al., 2010). This outcome is surprising. In an era of fast

[1] Since the seminal contribution of Mincer (1974), the Mincerian wage regression has become a yardstick to estimate the returns to education and experience. A survey of the empirical evidence concludes that the average returns to education for both developing and developed countries are about 10 percent for each additional year of education (Card, 1999).

technological development, education should be crucial in pushing the frontier forward in developed countries and in promoting the adoption of foreign technologies in emerging economies (Vandenbussche et al. 2006). Nevertheless, even for the latter, opinions are divided as to whether investments in education are worth the effort (Wolf, 2002).

This paper investigates the role of human capital on growth using an innovative analytical framework, with the main objective of bringing some resolution to the mixed evidence and shed light on some of the unresolved issues that still plague the applied macroeconomic literature. First, it is still unclear whether the accumulated stock or the growth of human capital plays the main role in accounting for growth, or whether they should both be included in the growth equation (Sunde and Vischer, 2015). Here we adopt an Error Correction Model (ECM) representation, which controls for the long-run (accumulation effect) and short-run (growth effect) of human capital on growth. This approach also provides a more general way of specifying the role of human capital, and allows us to test directly the validity of the restrictions imposed by some of the most commonly used empirical models.

Second, the empirical analysis in this paper makes use of recently developed econometric techniques that account for cross-sectional heterogeneity and cross-sectional dependence in panel data. As discussed above, heterogeneity across countries has been frequently acknowledged in the literature and is usually addressed with the introduction of country dummies, assuming common slope coefficients (Temple, 1999; Krueger and Lindahl, 2001; Vandenbussche et al., 2006; Al-Yousif, 2008; Zhang and Zhuang, 2011). In this paper, we use a mean group estimator, while contemporaneously controlling for the presence of unobserved common factors that can create dependencies across units (Eberhardt and Presbitero, 2015; Eberhardt and Teal, 2013). Examples of such unobserved factors include global shocks, such as the recent financial crisis (Chudik et al., 2011) and the presence of spillovers (Eberhardt *et* al., 2013). Omitting the impact of these common factors can cause an omitted variable bias and produce inconsistent estimates.

The empirical analysis in this paper focuses on 14 Asian countries, observed over a period of 54 years (1960-2013), using data from the Penn World Table and the Conference Board. The strong economic performance of most countries in this area, together with increasing investments in education, provides an ideal setting to assess the role of human capital. Studies with a specific focus on emerging countries and with robust estimation techniques are still scarce, therefore this paper provides insights into a relatively less explored dimension of the relationship between human capital and growth. Our analysis will also answer the question of whether cross-country data can capture any effect of human capital on growth (Pritchett, 2006).

Our main human capital proxy is the average years of schooling for the population aged 15 and over (Barro and Lee, 2010). We compare results based on this measure with the educational variable in the Penn World Tables (PWT), which adjusts the Barro-Lee (BL) indicator by the assumed returns for primary, secondary and tertiary education, as in Caselli (2005). In addition, we examine how the different levels of education (primary, secondary and tertiary) affect growth. This analysis is particularly meaningful for emerging economies where a large share of the population is only educated at the primary level. Despite the imperfections of these human capital proxies (De la Fuente and Domenech, 2006; Mason et al., 2012), they have the advantage of being available for most countries and allowing comparisons with existing studies. Finally, to account for endogeneity, we adopt ARDL modelling framework which allows us to obtain consistent estimates (Pesaran and Shin, 1999).

Our results provide evidence that investments in human capital have contributed to Asian countries' economic performance over the 54 year-period. This result is robust to the use of different econometric techniques, and to the introduction of controls for cross-sectional dependence. Using our preferred specification, the long-run human capital coefficient ranges between 0.4 (using the BL measure) and 1.2 (using the PWT measure). Our study also shows that previous models used for the analysis of human capital and growth are restricted versions of an ECM specification and these restrictions are rejected in our analysis, implying that some of the results found in the related literature might be affected by an omitted variable/specification bias. When we account for different education levels, we find that the number of years of primary and secondary education have an important effect on growth, while the long-run effect of tertiary education is negative. We provide three main reasons for this result: low proportion of people educated at the tertiary level (Lau, 2010), lack of adequate job opportunities for highly educated workers, who might end up working in low-productivity sectors (Pritchett, 2001) and the brain-drain phenomenon (Beine et al., 2008).

Our paper contributes to the existing literature on the human capital – growth nexus in three ways. First, it contributes to the debate on how to best model the impact of human capital on growth, which has a longstanding tradition in the growth literature, starting from Solow (1956) and Lucas (1988) and including Benhabib and Spiegel (1994), Temple (1999), and Sundae and Visher (2015), among others. We propose a more general modelling strategy that encompasses previous specifications, hence addressing this important debate. Second, our study offers an alternative empirical framework to the analysis of the role of human capital on growth, contributing to a discussion initiated with Islam (1995), who advocated the use of panel data as opposed to cross sectional data, and further developed in Sianesi and Van Reenen (2003) and Mason et al. (2012). To our knowledge, this is the first application of dynamic panel estimation techniques, with controls for cross-sectional dependence, to the analysis of the human capital – growth relationship. Third, we further the understanding of the role of human capital in emerging economies, where incentives to increase investments in education have been particularly strong in recent years. More specifically, by considering different levels of education, we contribute to the debate of whether resources should be directed towards the diffusion of primary and secondary education, or whether should be aimed at educating a smaller proportion of the population at the highest level (Castelló-Climent and Mukhopadhyay, 2013). Our results indicate that the first option is to be preferred.

The rest of the paper is organised as follows. In the next section we provide some background features of investments in education and growth in Asian countries, comparing their performance with the US. Section 3 introduces our analytical framework while section 4 describes the data and the econometric framework. Section 5 presents the results of our empirical analysis and section 6 concludes the paper.

2. Background

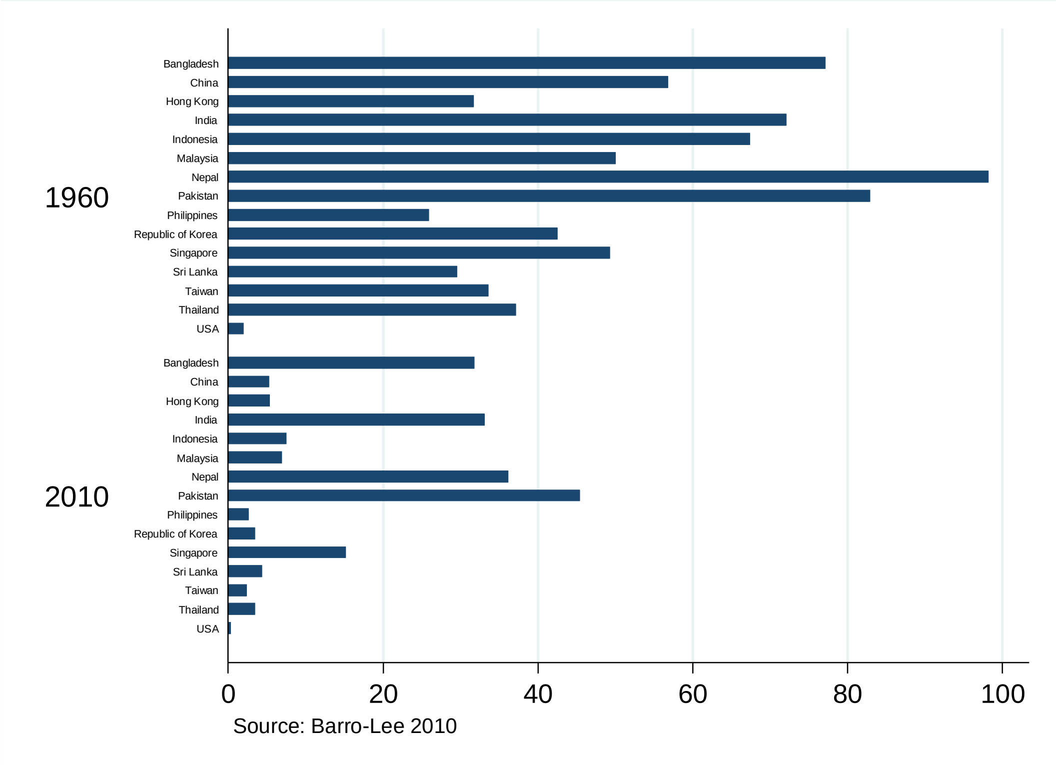
Asian countries have made large investments in education, particularly in primary and secondary education, in recent years. This has substantially reduced the proportion of the population with no schooling. The top half of Figure 1 shows that in 1960 the proportion of the population aged 15 and over with no schooling amounted to nearly 100% in Nepal, 80% in Bangladesh and Pakistan and over 40% in most of the other countries. Lower proportions were observed in Hong Kong, Philippines, Taiwan, Thailand and Sri Lanka, but even these countries compare quite poorly next to the US, where the proportion of the population with no education was very close to zero in 1960.

The picture changes dramatically in 2010[2], with a substantial drop in the proportion of the population with no schooling. Many governments have invested heavily in education since the year 2000 to achieve the Millennium Development Goals of universal primary education for all children by 2015 and this has contributed to the trend depicted in Figure 1 (Dundar et al., 2014). Countries like Taiwan, Republic of Korea and the Philippines, which started to invest in education at an earlier stage compared to other Asian countries, caught up with the

[2] The Barro & Lee data is available until 2010. In the empirical analysis we will extrapolate this variable until 2013.

Western world's standards, while in the rest of the sample the proportion of population without schooling has more than halved between 1960 and 2010.

Figure 1
Percentage of population aged 15 and over with no schooling: Asian Countries and the USA



In Table 1 we compare the proportion of the population aged 15 and over with secondary and tertiary education in Asia and in the US, in 1960 and in 2010. All countries in Asia increased investments in secondary education over the period under consideration, catching up with the USA. Investments in tertiary education have also increased but at a much slower pace. Large differences still persist in 2010 in the proportion of the population with tertiary education, which is substantially lower in Asia compared to the US, particularly in countries like Bangladesh, Nepal and Pakistan.

The last 3 columns of Table 1 show the (logarithmic) rate of output growth over the period 1960-2010 and over two sub-periods, 1960-1980 and 1981-2010. Around the 1980s most of these countries underwent major institutional reforms[3], which have had a strong impact on their economic performance. Asian countries' growth performance has been in many cases higher than in the USA. The period 1960-1980 witnesses the emergence of the Asian tigers (Hong Kong, Republic of Korea, Singapore and Taiwan), that enjoyed rates of growth above 8% per annum, compared to a 3.54% in the US. In the most recent period (1981-2010) the predominance of these four countries slightly declines and although their rates of growth are still high compared to Western World standards, other countries take the lead. For example, China is one of the top performing economies, with rates of value added growth in the later periods of nearly 7%. We also see the emergence of other late developers, like Bangladesh and India, gradually catching up with the leaders in the area.

Despite this exceptional growth performance, accompanied by strong investments in primary and secondary education, empirical studies of the relationship between human capital and growth in Asian countries are scarce. Generally, existing contributions show that the impact of human capital is positive although its importance differs across countries. In some cases, results show that Hong-Kong, Korea, Singapore and Taiwan have greatly benefited from increasing investments in education, while in the rest of Asia the impact of education is weaker (Park, 2012). A more positive view is found in the study by Birdsall et al. (1999), where human capital contributes to growth in East Asia both directly, via its role on productivity, and indirectly via a reduction in income inequality, which also leads to improved growth performance. Self and Grabowski (2004) focus on India and they find that primary education has played an important role in enhancing growth during the 1966-1996 period.

[3] China has been going through a political and economic revolution since the introduction of gradual reforms towards a market economy in 1978 (Wang and Yao, 2003; Wu, 2011). Similarly, the liberalisation policy in India has been adopted since 1980 although it took place in 1991 (Panagari ya, 2005).

Table 1

Education and output growth: USA and Asian Countries

Country	Secondary		Tertiary		Output growth		
	1960	2010	1960	2010	1960-2010	1960-1980	1981-2010
USA	48.79	42.96	15.73	53.94	3.05%	3.54%	2.71%
Bangladesh	5.77	41.74	0.33	4.09	2.67%	1.32%	3.59%
China	12.81	66.47	0.67	4.48	5.37%	3.37%	6.72%
Hong Kong	18.98	59.62	4.49	18.05	6.75%	9.36%	5.06%
India	2.53	41.53	0.57	8.50	4.71%	2.92%	5.92%
Indonesia	3.50	41.94	0.10	6.40	5.30%	6.57%	4.48%
Republic of Korea	17.78	45.28	2.60	41.64	7.59%	8.77%	6.80%
Malaysia	10.04	56.25	1.47	18.60	6.45%	7.66%	5.69%
Nepal	1.06	29.81	0.15	2.94	3.43%	2.05%	4.31%
Pakistan	8.02	31.67	0.80	5.70	4.67%	5.18%	4.32%
Philippines	14.33	47.04	6.28	23.21	4.27%	5.15%	3.66%
Singapore	22.12	40.17	1.54	37.61	8.53%	9.60%	7.83%
Sri Lanka	23.39	64.56	0.37	14.23	3.33%	0.51%	5.23%
Taiwan	20.25	46.17	3.62	38.03	6.80%	9.37%	5.05%
Thailand	7.04	34.11	0.66	13.00	6.37%	8.19%	5.16%

Source: proportion of the population aged 15 and over with secondary and tertiary education (Barro and Lee, 2010). Output growth is the logarithmic rate of growth computed using PWT series.

These contributions are quite heterogeneous in terms of model specification and estimation techniques and the results are not easily comparable with the evidence based on OECD countries. The reminder of the paper will provide a rigorous investigation of the relationship between human capital and growth in Asian countries, using the approach more typical of the mainstream analysis applied to advanced economies. We will compare different model specifications that have been commonly used in the literature, as well as proposing an alternative model that can account for both short and long run impact of human capital. The use of up-to-date econometric techniques will produce results that are robust to several key specification errors, hence providing an important contribution to the understanding of the role of human capital in emerging economies.

3. Analytical framework

In this section, we introduce and discuss the models that form the backbone of our empirical analysis. We begin with three well known specifications of the relationship between human capital and growth and then continue with an alternative approach that focuses on the dynamic process that drive the co-movements of output, physical and human capital.

3.1. Traditional specifications of the relationship between human capital and growth.

Our analysis of the relationship between human capital and output growth starts from Solow's (1956) growth model. Under this theoretical framework, economic growth within a country is determined by factor accumulation, including physical and human capital, and technological progress:

$$Y_{it} = A_{it}\, F_i(L_{it}, K_{it}, H_{it}) \tag{1}$$

Where Y_{it} is value added, L_{it} is the total number of workers and H_{it} is human capital. i denotes countries, t indexes time and A_{it} is the Hicks-neutral Multi Factor Productivity (MFP) indicator. Assuming a Cobb-Douglas production function with diminishing returns to factor inputs and constant returns to scale in production technology, we can re-write Equation (1) in per-worker term as follows[4]:

$$y_{it} = a_{it} k_{it}^{\beta 1} h_{it}^{\beta 2} \tag{2}$$

[4] We prefer to express both output and fixed capital in per-worker term rather than in per capita terms as this mirrors countries' effective productive capacity, in an area where labour force participation among women is still quite low. For example, the female labour force participation rate in South Asia is 33 percent as compared to 64 percent in high income countries (World Bank, 2012).

where $y_{it} = Y_{it}/L_{it}$, $k_{it} = K_{it}/L_{it}$ and $h_{it} = H_{it}/L_{it}$. Hence equation (2) expresses average labour productivity as a function of physical capital per worker and human capital per worker. Taking the logarithmic transformation and first differencing, we can re-write equation (2) as follows:

$$\Delta lny_{it} = \Delta a_{it} + \beta_1 \Delta lnk_{it} + \beta_2 \Delta lnh_{it} + \varepsilon_{it} \qquad (3)$$

The error term ε_{it} is initially assumed to be normally distributed, with zero mean, homoscedastic variance and serially uncorrelated.

Equation (3) is in the spirit of the standard neoclassical theory, which predicts that the main role of human capital is to slow down the convergence to the steady state by counteracting the effects of decreasing returns to physical capital accumulation (Solow 1956; Mankiw et al., 1992; Aghion and Howitt, 1998). This specification has been widely used in related studies, but it often predicts a negative and/or insignificant role of education, contradicting the theoretical predictions (Islam, 1995; Mason et al., 2012; Sunde and Vischer, 2015). Competing reasons have been proposed to explain these results, including the possibility that the first difference model is not suitable to capture the relationship between human capital and growth, particularly when estimated for a large number of highly heterogeneous countries. Following the intuition of Nelson and Phelps (1966), Benhabib and Spiegel (1994) develop a model where human capital influences growth via two channels: by affecting the country's ability to produce new technologies and by facilitating the catching-up process with the technology leader (see also Romer, 1990). Their model assumes that the stock of human capital should enter the specification, next to a variable that captures the proximity of a country to the frontier. Following Mason et al. (2012), we measure proximity with the lagged level of output per worker:[5]

[5] Benhabib and Spiegel (1994) also estimate the first difference specification adding the lagged level of output but this still produces a negative and insignificant human capital coefficient.

$$\Delta lny_{it} = \Delta a_{it} + \beta_1 \Delta lnk_{it} + \gamma lnh_{it-1} + \lambda lny_{it-1} + \varepsilon_{it} \quad (4)$$

The lagged level of output per worker is expected to be negatively signed as countries with lower levels of output (farther away from the frontier) will grow faster.

A recent extension of equation (4) is discussed and estimated in Sunde and Vischer (2015). They argue that previous analyses of the relationship between human capital and growth fail to jointly account for the two channels of impact: human capital as a factor of production, as in Lucas (1988), and as a means that facilitates the diffusion and adoption of technologies, as in Nelson and Phelps (1966). Independently accounting for human capital accumulation, as in equation (3), and human capital stock, as in equation (4), could introduces a serious misspecification if both channels are important in explaining output growth. In fact, if this is the case, models (3) and (4) suffer from an omitted variable problem. To address this issue, Sunde and Vischer (2015) propose the following specification, which includes growth (Δlnh_{it}) and levels ($lnh_{i,t-1}$) of human capital:

$$\Delta lny_{it} = a + \beta_1 \Delta lnk_{it} + \beta_2 \Delta lnh_{it} + \gamma lnh_{i,t-1} + \lambda lny_{it-1} + \varepsilon_{it} \quad (5)$$

The estimation of this extended specification, expressed in long differences over the period 1970-1990, for a sample of approximately 90 countries, produces results that provide support for the presence of the two channels, i.e. the stock and the accumulation of human capital are positive and statistically significant when they are both included in the same model (Sundae and Vischer, 2015).

3.2. Extension to a full dynamic specification

Models (3) - (5) are all theoretically sound but they do not fully account for the dynamic relationship between output, physical and human capital. In fact, the role of physical capital has often been given little consideration; however, the modelling issues discussed above in relation to human capital can easily be extended to physical capital. For example, if both the accumulation and the stock of physical assets are important for growth, including only one of the mechanisms can result in a mis-specification problem.

An alternative way of looking at the relationship between human capital and growth is to assume that such relationship follows an autoregressive distributed lag model, which we assume for simplicity to be of the first order, ARDL (1,1,1):

$$\ln y_{it} = \mu_{it} + \delta_{10i} \ln k_{it} + \delta_{11i} \ln k_{it-1} + \gamma_{10i} lnh_{it} + \gamma_{11i} lnh_{it-1} + \lambda lny_{it-1} + \varepsilon_{it} \qquad (6)$$

Equation (6) explains movements in output per worker using contemporaneous and lagged values of all inputs and the lagged levels of the dependent variable. Equation (6) can be specified as an error correction model (ECM) as follows:

$$\Delta\ln y_{it} = \phi_i(lny_{it-1} - \theta_{0i} - \theta_{1i} \ln k_{it-1} - \theta_{2i} lnh_{it-1}) + \delta_{10i}\Delta \ln k_{it} + \delta_{20i}\Delta lnh_{it} + \varepsilon_{it} \qquad (7)$$

This is a convenient specification as it allows the analysis of the long-run and the short-run impacts of human capital on growth. Specifically, the coefficient θ_{2i} captures the stock effect of human capital, or its long-run impact, while the effect of short run adjustments is controlled for by the first difference coefficient δ_{20i}. Fixed capital per worker is also allowed to affect growth both in the short and in the long run, via the coefficients θ_{1i} and δ_{10i} , respectively. The coefficient ϕ_i is the speed of adjustment to the long-run equilibrium.

Equation (7) encompasses the models discussed in the previous section. If $\phi_i = 0$ equation (7) becomes a first difference specification; if $\theta_{1i} = 0$ and $\delta_{20i} = 0$ we obtain the Benhabib and Spiegel (1994) model. If $\theta_{1i} = 0$ we obtain the Sunde and Vischer's (2015) model. Hence, equation (7) provides a more general construct for the analysis of the relationship between human capital and growth and allows us to discriminate across different theoretical approaches. In addition, given the availability of a panel of countries with a long-time dimension, this modelling framework will take full advantage of the characteristics of our dataset.

4. Data and empirical implementation

4.1. Data

This study uses annual data on 14 Asian countries observed over the 1960-2013 period. We include five South Asian economies (Bangladesh, India, Nepal, Pakistan, and Sri Lanka) eight East Asian countries (Hong Kong, Indonesia, Malaysia, Philippines, Singapore, South Korea, Thailand and Taiwan) and China. The main data source for this study is the Penn World Tables (PWT) version 8.0 (Feenstra et al., 2015), which provides data on real GDP at current PPPs (in mil. 2005 US$) and capital stock at current PPPs (in millions of 2005 US$) for all countries in our sample. We supplement this data with employment series from The Conference Board (2014) as they provide a wider coverage for our sample of countries, compared to the PWT.

We employ two main measures of human capital: first, we make use of the Barro and Lee (2010) human capital indicator, which is one of the most commonly used measures of human capital in the macro literature on emerging countries.[6] We use the average years of schooling for the population aged 15 and over. We rely on the latest version of the Barro and Lee data set, which provides information at 5-year intervals. Missing values are computed by interpolation.

[6] Islam (1995), Krueger and Lindahl (2001) and Park (2012). An alternative measure of human capital is based on students' scores of cognitive abilities tests (PISA). Hanushek and Woessman (2011) claim that this measure better captures the impact of education on growth because it provides a more accurate representation of the outcome of the education system in different countries. However, this measure has a limited coverage of Asian economies and it is limited to few observations in the time dimension. In addition, Pistaferri (2011) doubts the superiority of the PISA scores compared to the more commonly used measure of average years of schooling. In fact, the PISA scores are based on few areas of the school curriculum (reading, maths and science); students have little incentives to provide correct answers as the outcome of the tests has no consequence on their school attainment.

The Barro and Lee data set also provides information on the average number of years of primary, secondary and tertiary education. We will use these measures in our analysis to account for the fact that, in a sample of Asian countries where levels of education are, in some cases, still below developed countries' standards, changes in basic education could have a large impact on growth performance.

In addition to the BL data, we also use the human capital series from the PWT. This provides an aggregate measure of educational attainment, assuming different returns to primary, secondary and tertiary education, following Hall and Jones (1999) and Caselli (2005). This measure is derived using the following formula:

$$h = e^{\varphi s}$$

where h stands for human capital, s is average years of schooling and the function $\varphi(s)$ is a piecewise linear function with slopes equal to 0.13 for $s \leq 4$, 0.10 for $4 > s \leq 8$ and 0.08 for $s > 8$. Appendix Table A1 presents summary statistics of all variables used in the empirical analysis.

4.2. Econometric issues

The empirical implementation of our analysis involves considering different estimation techniques, which will allow us to check the robustness of our results, compare them with the existing evidence as well as addressing several issues that can bias the estimated impact of human capital on growth. As discussed in the introduction, one of these issues is cross-sectional heterogeneity, i.e. the possible bias in the results caused by cross-country differences that are not properly accounted for in the analysis. We first address this issue by including country and time dummies.

Using a sample of countries located in the same geographical area might help to reduce the relevance of the heterogeneity problem. However, assuming the same returns to factor inputs in, for example, China and in Bangladesh is clearly a strong assumption.[7] The use of standard panel data techniques can only partially address this issue under the assumption that cross-country differences are fixed over time. A much more flexible estimation strategy is to allow the technology parameters to vary by estimating separate equations for each country and then derive the mean of individual estimates, as in the Mean Group (MG) estimator, discussed in Pesaran and Smith (1995), Pesaran et al. (1999) and further developed in Bond and Eberhardt (2013).

Furthermore, an issue that has been ignored in the human capital literature so far relates to the assumption of cross-sectional independence, i.e. each cross-section unit (country) is treated as an isolated entity with no impact on other countries' technologies. This assumption is hard to defend in the presence of increasing globalisation, common shocks and international spillovers, including human capital and more general productivity spillovers, particularly when using panels characterised by a long-time dimension. The literature is still divided over the presence of human capital spillovers.[8] However, if spillovers are present but unaccounted for, the estimation of equations (3) - (5) can lead to biased coefficient estimates. In the absence of spillovers, controlling for the presence of cross-sectional dependence accounts for any other unobserved common effects (Eberhardt et al., 2013).

Referring for simplicity to equation (3):

$$\Delta lny_{it} = \Delta a_{it} + \beta_1 \Delta lnk_{it} + \beta_2 \Delta lnh_{it} + \varepsilon_{it} \tag{3.a}$$

We can model the impact of cross-sectional dependence by assuming the following multi factor structure for the error term:

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[7]The discussion in Eberhardt and Teal (2013), provides a concise yet detailed account of this issue, linking theoretical contributions of the 'new growth' literature with recent empirical evidence supporting the presence of heterogenous technologies in cross-country growth regressions.

[8] Vandenbussche et al. (2006) find evidence of a positive impact of human capital on Total Factor Productivity TFP) growth, which can be interpreted as a spillover effect. A study by Inklaar *et al*. (2008) claims that the finding of human capital spillovers disappear when using a measure of TFP corrected for differences in labour quality and in the number of hours worked. Mason *et al*. (2012) find a weak evidence of human capital spillovers.

$$\varepsilon_{it} = \sum_{j=1}^{m} \gamma_j f_{jt} + u_{it}$$

where f_{jt} is a set of unobserved common factors. A similar error structure can be specified for the explanatory variables in our model, as both the error term and the covariates may contain a given number of common factors. Failing to account for these multiple factors causes an endogeneity problem that is often referred to as transmission bias in the productivity literature (Griliches and Mairesse, 1995; Eberhardt and Helmers, 2010; Marsh et al., 2017). Following Pesaran's (2006) Common Correlated Effect (CCE) estimator, to capture the impact of unknown common factors, we augment equation (3) with cross section averages of the dependent variable and regressors.[9] In this case equation (3) can be re-written as:

$$\Delta lny_{it} = \Delta a_{it} + \beta_1 \Delta lnk_{it} + \beta_2 \Delta lnh_{it} + \gamma_1 \overline{\Delta lny_t} + \gamma_2 \overline{\Delta lnk_t} + \gamma_3 \overline{\Delta lnh_t} + \varepsilon_{it} \qquad (3.b)$$

where a bar over a variable identifies the cross-sectional mean.

For the estimation of the dynamic model (equation 7), we adopt the Pesaran et al. (1999) Pooled Mean Group estimator. This allows short run coefficients and error variances to vary across countries, while imposing common long-run coefficients. This means that technology parameters will converge to common values in the long-run, while they differ in the short run, a reasonable assumption when countries have access to similar technologies. Imposing common long run coefficients increases the efficiency of the estimates and it is therefore preferred in this setting. This estimation framework also allows us to test directly for the presence of cointegration, based on the significance of the error correction term (the speed of adjustment). To account for cross sectional dependence, we extend the PMG estimator to include the common factors in the specification of the short-run dynamics (Binder and

[9] Extensions of this methodology include exogenous factors (Chudik et al., 2011) and allowing the common factors to follow a unit root process (Kapetanios et al., 2011).

Offermanns, 2014)[10]. Assuming for simplicity an ARDL(1,1,1) process, we can rewrite model (7) as follows:

$$\Delta \ln y_{it} = \phi_i(lny_{it-1} - \theta_{0t} - \theta_{1i}\ln k_{it} - \theta_{2i}lnh_{it}) + \delta_{10i}\Delta\ln k_{it} + \delta_{11i}\Delta\ln k_{it-1} + \delta_{20i}\Delta lnh_{it} + \delta_{21i\Delta}lnh_{it-1} + \sum_{j=1}^{m}\Delta\gamma_j f_{jt} + \varepsilon_{it} \quad (8)$$

Finally, a common problem in the estimation of production functions is the endogeneity of both fixed and human capital per worker (Griliches and Mairesse, 1995). In fact, as a country grows it will increase the demand for inputs, which makes the estimation of the causal effect of human (and physical) capital particularly challenging. A convenient way of addressing this issue is to use 'internal instruments' i.e. lagged levels of the endogenous variables as in the Generalised Method of Moments by Arellano and Bond (1991). However, in panels characterised by a long-time dimension and a relatively small cross-sectional dimension the GMM estimator can produce inconsistent estimates (Pesaran et al., 1999). In our study the adoption of the ARDL modelling framework will produce consistent estimates even in the presence of endogenous regressors, as discussed in Pesaran and Shin (1999). In addition, by adding controls for cross-sectional dependence, we account for an additional source of omitted variable bias.

5. Results

5.1. Estimation of the traditional models

We start our analysis by conducting tests for the stationarity of all covariates. If series are non-stationary the analysis will produce unreliable results for the impact of human capital on growth. We run the Im et al., (2003) and the Pesaran (2003) panel unit root tests. Both tests are built around the null hypothesis of non-stationary series, hence rejection of the null implies

[10] We thank Markus Eberhardt for suggesting this extension.

that the series are stationary.[11] The Pesaran (2003) test also controls for the presence of cross sectional dependence. Results for both tests, based on a maximum lag order of 4, are presented in Appendix Table A2. The null hypothesis of non-stationarity cannot be rejected for the variables in levels at the 5% significance level (columns 1 and 2). Taking first differences addresses the stationarity problem as the null hypothesis is rejected by both tests at standard significance levels (columns 3 and 4), which validates our use of the first difference model. For specifications that include variables in first differences and in levels we test for the stationarity of the residuals (cointegration) - see Table 2 below.

Studies have also shown that time series data for Asian countries may suffer from structural breaks, as discussed in Narayan et al. (2010). Testing for unit roots without accounting for structural breaks could lead to the wrong conclusion regarding the stationarity of our series. In addition, given the length of our time series (54 years), it is important to check consistency between panel and individual country's unit root test. Appendix Table A4 and Table A5 presents results for the Narayan and Popp (2013) test, which allows for the presence of two structural breaks. Results are consistent with the panel data testing procedure as they indicate non-stationarity for the variable in levels and stationarity for the variables in first difference. In sum, these stationarity tests support the use of panel data techniques.

Table 2 presents results of the estimation of equations (3) – (5), under the assumption of exogenous regressors and cross-sectional independence. We include time dummies in all specifications to account for common shocks that have a homogeneous impact across countries. At the bottom of the Table we report residual tests for unit root (Im et al., 2003; Pesaran, 2003) and cross-sectional dependence (Pesaran, 2004). Appendix Table A3 presents results of the Pesaran (2004) test for cross-sectional dependence for the individual series.

[11] Both tests represent an extension of the Dickey Fuller (DF) and Augmented Dickey Fuller (ADF) tests to heterogenous panels and they are constructed by averaging the DF and the ADF for individual cross-sectional units.

Table 2

Human capital and growth: common technologies and cross-sectional independence

VARIABLES	First Difference		Benhabib and Spiegel (1994)		Sunde and Vischer (2015)	
	B&L	PWT	B&L	PWT	B&L	PWT
	[1]	[2]	[3]	[4]	[5]	[6]
Δlnk_{it}	0.670***	0.664***	0.638***	0.617***	0.647***	0.620***
	(0.073)	(0.073)	(0.074)	(0.079)	(0.080)	(0.082)
Δlnh_{it}	0.198**	0.606**			0.248**	0.507*
	(0.082)	(0.234)			(0.102)	(0.259)
lnh_{it-1}			-0.006	0.060	0.004	0.077
			(0.005)	(0.062)	(0.009)	(0.060)
Proximity (lny_{it-1})			-0.023***	-0.021***	-0.021**	-0.019**
			(0.006)	(0.007)	(0.007)	(0.007)
Constant	-0.021	-0.022	0.071***	0.001	0.040	-0.022
	(0.016)	(0.017)	(0.022)	(0.052)	(0.030)	(0.052)
Im et al. (2003)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Pesaran (2003)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Pesaran (2004)	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]	[<0.001]
[p value]						
Observations	714	714	714	714	714	714
R-squared	0.311	0.311	0.321	0.323	0.326	0.325

Notes: Dependent variable: value added per worker in log first differences. Estimation is based on a fixed effect estimator and all specifications include time and country dummies. Im *et al*. (2003) is a test for unit root in panel data. Pesaran (2003) tests for unit roots in panel data with controls for cross-sectional dependence. I(0) indicates stationarity, I(1) indicates the presence of a unit root. Pesaran (2004) is the test for cross sectional dependence in panel data. Standard errors in brackets. * = significant at 10%, ** = significant at 5%, ***= significant at 1%.

The first difference specification (columns 1 and 2) predicts a positive and statistically significant human capital effect. This differs from the evidence presented in a large number of studies on human capital and growth, based on country and industry level data (Islam, 1995; Barro and Sala-i-Martin, 1997; Behabib and Spiegel, 1994; De la Fuente, 2011; Mason et al., 2012; Sunde and Vischer, 2015). The use of a group of countries at a similar stage of development and with similar pattern of human capital accumulation is likely to explain this result. The human capital estimates differ across the two proxies for human capital. The impact of the PWT measure is three times as large as the BL measure, suggesting that accounting for differential returns to education can sensibly increase the role of human capital in growth regressions. This is consistent with existing evidence at the industry and country level (Mason et al., 2012; Hanushek and Kimko, 2000).

In columns (3) and (4) we present a specification in the spirit of Benhabib and Spiegel (1994), which includes the lagged level of output and lagged level of human capital as explanatory variables. This is aimed at capturing the impact of human capital stock on output growth and it usually produces positive and statistically significant coefficients of human capital (Mason et al., 2012). This is not the case for our sample of Asian countries. The lagged level of output is negative and statistically significant, as expected, implying that the growth of value added per worker will be higher in laggard countries. However, the lagged level of human capital is never statistically significant. One possible explanation is that the stock of human capital is still too low in the countries included in our sample for it to play a major role in assisting growth (Lau, 2010). Another more likely justification lies in the incomplete dynamics in our model, an issue that we will address below.

Columns (5) and (6) present estimates based on the specification in Sunde and Vischer (2015) and include both levels and growth of human capital, while allowing for countries' catching up processes. The inclusion of the lagged level of human capital increases the estimated effect of human capital accumulation when using the Barro-Lee educational measure (from 0.198 in column (1) to 0.248 in column (5)) while decreasing the PWT coefficient. However, the lagged level of human capital is never statistically significant.

5.2. Accounting for heterogeneity and cross-sectional dependence

As discussed in the methodology section, there are two concerns with the results presented in Table 2: the imposition of the same technology coefficients across all countries and the assumption of cross-sectional independence. Tests for cross-sectional dependence, presented at the bottom of Table 2, clearly shows that the null hypothesis of cross-sectional independence is rejected in all specifications. The same test carried out for the individual variables reaches the same conclusion (see Appendix Table A.3).

To account for these issues, we re-estimate the models discussed in the previous section using a mean group estimator with controls for cross sectional dependence (Pesaran 2006). Results are presented in Table 3. Overall, we find support for the positive impact of human capital accumulation on growth. Compared to the results in Table 4, accounting for heterogeneous technology parameters and CSD the first difference specification produces an even larger impact of human capital, ranging between 0.465 (BL) and 1.086 (PWT). The level of human capital in the Benhabib and Spiegel (1994) model is positive, and the PWT measure is statistically significant. However, the stationarity tests at the bottom of Table 3 do not reject the null of non-stationary residuals hence results based on this model can be misleading. Results for the Sunde and Vischer (2015) model reveal that stock and accumulation of human capital are important for growth, but only when using the PWT human capital measure.

Table 3
Human capital and growth: heterogeneous technologies and cross-sectional dependence

VARIABLES	First Difference		Benhabib and Spiegel (1994)		Sunde and Vischer (2015)	
	B&L	PWT	B&L	PWT	B&L	PWT
	[1]	[2]	[3]	[4]	[5]	[6]
Δlnk_{it}	0.720***	0.714***	0.578***	0.699***	0.592***	0.682***
	(0.109)	(0.089)	(0.144)	(0.121)	(0.154)	(0.131)
Δlnh_{it}	0.465	1.086**			0.624*	2.138*
	(0.286)	(0.464)			(0.339)	(1.260)
lnh_{it-1}			0.109	0.389*	0.149	0.471*
			(0.124)	(0.219)	(0.138)	(0.277)
Proximity (lny_{it-1})			-0.171***	-0.203***	-0.169***	-0.207***
			(0.026)	(0.029)	(0.032)	(0.034)
Im et al. (2003)	I(0)	I(0)	I(1)	I(1)	I(0)	I(1)
Constant	0.006	-0.004	0.008	-0.003	-0.024	-0.029
	(0.013)	(0.010)	(0.098)	(0.067)	(0.099)	(0.080)
Observations	714	714	714	714	714	714

Notes: Dependent variable: value added per worker in log first differences. All specifications are augmented with cross-section averages (not reported). Im *et al*. (2003) is a test for unit root in panel data. I(0) indicates stationarity, I(1) indicates the presence of a unit root. Standard errors in brackets. * = significant at 10%, ** = significant at 5%, ***= significant at 1%.

Our analysis so far shows that, when controlling for heterogeneity and CSD, both the accumulation and the stock of human capital are important for growth, although results differ across the two measures of education. Accounting for different returns to education, as in the PWT proxy, predicts stronger effects. The coefficients on human capital are higher in Table 3, compared to those presented in Table 2. If the unknown common factors were capturing positive spillover effects we would have expected the fixed effect estimates to be upward rather than downward biased, as shown in Eberhardt et al. (2013). Results in our study suggest that, when we account for CSD, we might be controlling for factors that decrease the effect of human capital, such as political and religious conflicts, militarism, corruption and other institutional factors.

5.3. Human capital and growth in a heterogeneous dynamic panel framework.

This section extends the analysis to the fully dynamic model, equation (7). As discussed in section 4, the introduction of the lagged level of value added per worker in Tables 4 and Table 5 already introduces some dynamics in the model. However, a more complex dynamic specification could be estimated that uses an ECM framework. In this model, the level of human capital will capture its long-run impact on growth and provides an alternative way of modelling the role of human capital accumulation and human capital stock.

Results presented in Table 4 are based on the Pooled Mean Group estimator (Pesaran et al., 1999). We impose the same long run coefficients across the 14 Asian countries, but we allow the short-run adjustments to be country-specific. The first two columns present results based on the assumption of cross-sectional independence, columns (3) and (4) presents results based on equation 8, where the correction for CSD is included in the short-run specification, as in Binder and Offermanns (2014).

In all specifications, the error correction term has the expected negative sign and it is statistically significant, testifying to the validity of our modelling framework, and it predicts a similar speed of adjustment across the different models. Every year, Asian countries will close approximately 10% of the gap between short-run and long-run equilibrium. The statistical significance of the error correction term and of the long-run coefficient for physical capital per worker implies that the specifications discussed in the previous section are affected by an omitted variable problem. Changes in output per capita are positively related to changes in human and physical capital, particularly when using the BL human capital measure. This indicates that the accumulation of human and physical assets is important in promoting growth in Asian countries

The main difference across the different models lies in the role played by human capital. The most conservative estimates for the BL measure of human capital are those based on the uncorrected PMG (column 1). Here the long-run elasticity is about 0.3, but the short-run impact is not statistically significant. The impact of human capital increases to 0.4 when correcting for CSD (columns 3 and 5). Similar to previous results, PWT human capital measure predicts a stronger effect, ranging between 0.8 (column 6) and 1.2 (column 4). Results are robust to the specification of a different lag orders.

Table 4, columns (3) and (5) also shows that the impact of physical and human capital on growth is larger in the short-run compared to the long run. This may be capturing the slowdown of the catching-up process over time, i.e. the returns to capital decrease when countries get closer to the frontier. For example, estimates of the (long-run) human capital elasticity of around 0.4 (as in column 5) are in fact closer to the elasticities estimated for developed countries, which is where eventually developing countries will converge to.

How do these estimates compare with related studies? Given that, in competitive factor markets, the coefficients of the Cobb-Douglas production function represent factor shares of national income, the coefficient on human capital represents the part of labour share due to education.

Table 4
Pooled mean group estimator of the relationship between human capital and growth

VARIABLES	B&L [1]	PWT [2]	B&L [3]	PWT [4]	B&L [5]	PWT [6]
	No correction for CSD ARDL(1,1,1)		Correction for CSD ARDL(1,1,1)		Correction for CSD ARDL(2,2,2)	
Long-run parameters						
lnk_{it}	0.432***	0.233***	0.542***	0.341***	0.560***	0.557***
	(0.052)	(0.073)	(0.050)	(0.084)	(0.040)	(0.042)
lnh_{it}	0.269**	1.387***	0.430**	1.197***	0.411***	0.823***
	(0.114)	(0.277)	(0.152)	(0.363)	(0.140)	(0.229)
EC	-0.108***	-0.103***	-0.115***	-0.088***	-0.111***	-0.106***
	(0.036)	(0.033)	(0.040)	(0.036)	(0.037)	(0.035)
Short-run parameters						
Δlnk_{it}	0.737***	0.763***	0.666***	0.887***	0.847***	0.802***
	(0.152)	(0.177)	(0.104)	(0.109)	(0.141)	(0.132)
Δlnh_{it}	-0.249	0.076	0.542***	0.012	0.755***	0.256
	(0.465)	(0.940)	(0.400)	(0.925)	(0.319)	(0.453)
Constant	0.034**	0.029*	-0.032***	-0.003	-0.025	-0.018
	(0.014)	(0.016)	(0.030)	(0.018)	(0.030)	(0.018)
Observations	714	714	714	714	700	700

Notes: Dependent variable: value added per worker in log first differences. EC stands for Error Correction coefficient. Specifications (3) - (6) are augmented with cross-section averages (not reported). Standard errors in brackets. * = significant at 10%, ** = significant at 5%, ***= significant at 1%.

There are different ways of computing this share, as discussed in Pritchett (2001). Starting from the assumption of constant returns to scale and considering different assumptions on the wage increment due to education, he computes the educational share of the wage bill to be between 0.35 and 0.7. Assuming a labour share of 0.6, these imply a range of values for the human capital coefficient of 0.21-0.42. This range is consistent with earlier predictions by Mankiw *et al*. (1992), who estimate a human capital coefficient of 0.3 for developed and emerging countries.

Sunde and Vischer's (2015) estimates range between 0.3 and 0.6 (see Table 2) for a sample of approximately 90 countries. Our estimates are within that range, particularly those based on the Barro and Lee data. Estimates based on the PWT are higher, suggesting that accounting for the quality of human capital produced larger effects, as discussed in the previous section. The only caveat to this result is that it is based on hypothetical returns to primary, secondary and tertiary education, which can be quite different from the actual returns, particularly in emerging economies. Hence, results based on the PWT measure should be interpreted with caution.

Improving the model specification, accounting for heterogeneity and cross-sectional dependence we find a much stronger effect of human capital on growth in emerging economies compared to existing studies. For example, in Collins and Bosworth (1996) the estimated human capital effect in seven East Asian countries ranges between 0.16 and 0.25 but it is not statistically significant when including country dummies. Baldacci et al. (2008) include both changes and levels of education, and they obtain a coefficient of approximately 0.1 for a sample of 118 developing countries. Park (2012) focuses on 12 Asian economies and finds that the effect of educational capital is approximately equal to 0.02 and it is robust to the inclusion of controls such as openness and R&D. Although differences in sample composition prevents a direct comparison, our specification predicts a more important role for human capital compared to existing estimates, which is consistent with the theoretical expectations and provides stronger support for policies aimed at increasing investment in education in emerging economies. This also implies that existing estimates showing a negative impact of education on growth might understate the importance of education, particularly in developing countries. Other drivers of growth, such as R&D, product variety and product quality, are certainly important but it is only by investing in education and skills that improvements in quality and variety can be achieved. In addition, human capital promotes the absorption of foreign technologies, a factor that is particularly important in developing countries where imitation, rather than innovation can promote economic growth.

5.4. A look at investments in primary, secondary and tertiary education

An important policy issue is which level of education mostly affects growth. As shown in figure 1, illiteracy rates in some Asian countries are still very high (over 30% in Nepal, India, and Pakistan) and this raises the dilemma of whether the education policy should focus on extending (lower level) education to the whole population or directing resources towards a minority well educated elite. Castello'-Climent and Mukhopadhyay (2013) have investigated this issue in India and found that tertiary and secondary education give the strongest contribution to growth, while there is no effect from primary education. This result contradicts previous work by Petrakis and Stamatakis (2002) and Psacharopoulos and Patrinos (2004), who find that returns are higher for low levels of schooling and raises doubts on the effectiveness of the Millennium Development Goal, which supports mass education at the primary level[12]. To investigate this point we estimate

[12] In developed countries, which are characterised by a high proportion of the population educated at the tertiary level, the impact of tertiary education is not always consistent across studies. Vandenbussche et al. (2006) find that tertiary

equation (7) using information on the average number of years of education at the primary, secondary and tertiary level, from the BL data set.[13]

Table 5 presents results based on our preferred specification, the pooled mean group estimator with corrections for CSD, using two ARDL models to check for the robustness of our results to different lag structures. Our estimates reveal that increasing investments in primary and secondary education has a positive long-run impact on growth, with primary education showing the strongest contribution. Conversely, we find that the long run impact of tertiary education is negative and statistically significant, a somewhat unexpected outcome. Following Pritchett (2001), a possible explanation for this result is that highly skilled workers are mainly employed in low productivity sectors (e.g. government) and hence they do not contribute to productivity growth. This suggests that increasing investments in higher education needs to go hand in hand with expansion of high tech manufacturing and services, where highly educated workers can use their skills in more growth-enhancing activities. This could also contribute to a reduction of the *brain drain*, the migration of highly educated individuals in search of better job opportunities abroad[14]. This phenomenon is in large part driven by the emigration of highly skilled immigrants from developing countries (Beine et al., 2008). Assuming that it may take some time for workers to relocate abroad, the brain drain would also explain why the long-run impact is negative, while the short-run effect of tertiary education is positive.

education is particularly important for growth for countries closer to the frontier, while Hanushek and Woessman (2011) do not find a strong effect.

[13] The three definitions are entered separately in the specification to avoid collinearity problems, an issue also raised in Castello'-Climent and Mukhopadhyay (2013).

[14] We wish to thank an anonymous referee for suggesting this explanation.

Table 5
The impact of primary, secondary and tertiary education
(Dynamic specification with correction for CSD)

	ARDL (1,1,1)			ARDL (2,2,2)		
Long-run parameters	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary
lnk_{it}	0.540***	0.648***	0.772***	0.595***	0.621***	0.794***
	(0.038)	(0.053)	(0.051)	(0.027)	(0.046)	(0.039)
lnh_{it}	0.387**	0.137*	-0.188***	0.211*	0.151**	-0.190***
	(0.157)	(0.071)	(0.054)	(0.123)	(0.076)	(0.051)
EC	-0.115***	-0.102**	-0.102***	-0.118***	-0.103***	-0.110***
	(0.040)	(0.039)	(0.028)	(0.039)	(0.039)	(0.031)
Short-run parameters						
Δlnk_{it}	0.718***	0.613***	0.679***	0.857***	0.819***	0.819***
	(0.112)	(0.122)	(0.107)	(0.151)	(0.140)	(0.161)
Δlnh_{it}	0.387**	0.169	0.181**	0.545	0.374*	0.163***
	(0.157)	(0.305)	(0.077)	(0.400)	(0.228)	(0.055)
Constant	0.002	-0.007	-0.077**	0.014	0.008	-0.077*
	(0.028)	(0.016)	(0.034)	(0.029)	(0.022)	(0.031)
Observations	714	714	714	700	700	700

Notes: Dependent variable: value added per worker in log first differences. Human capital indicators are the average number of years of primary, secondary and tertiary education. EC stands for Error Correction coefficient. All specifications are augmented with cross-section averages. The ARDL (2,2,2) specification also includes the lagged dependent variables and lagged first difference terms. Standard errors in brackets. * = significant at 10%, ** = significant at 5%, ***= significant at 1%.

An alternative explanation is that the supply of workers educated at the tertiary level needs to reach a certain threshold level before having a positive long-run impact on growth. Lau (2010) discusses this issue in relation to Chinese provinces. His results show the presence of non-linearities between human capital and growth, as only high levels of human capital affect growth. In fact, primary schooling, which is highly diffused, has a positive impact while his analysis does not reveal any role for secondary and tertiary education[15]. Our descriptive analysis in section 2 (see Table 1) shows that in 2010, the proportion of the population educated at the tertiary level is less than 10% in six Asian countries, which could hardly have driven the growth performance of large countries such as China and India. This result is also consistent with Vandenbussche et al. (2006), where high skill labour has a greater growth enhancing effect in countries closer to the technology frontier, while countries further away from the frontier get greater value from low and intermediate skills. [16]

Overall our findings are consistent with existing contributions that have emphasised the importance of primary education in emerging economies (Keller, 2006; Self and Grabowski, 2004); in addition, we provide evidence that increasing investments should be devoted to the provision of secondary education, which contributes positively to the growth prospects in the area. The increasing supply of workers educated at the primary and secondary level will allow all countries to increase the proportion of the population with higher education, which is important in promoting growth once countries approach the productivity frontier. At the same time, more effort should be directed to provide opportunities for highly skilled workers, which are likely to be still quite limited in several Asian countries.

[15] In Lau (2010) growth dynamics is also related to trade with other regions.

[16] Next to these possible explanations there is also a related data issue. Summary statistics presented in Table A1 show that the average number of years of tertiary education in our sample is 0.2, with a much lower standard deviation compared to primary and secondary education. This low variation in our key explanatory variable implies that it is difficult to precisely estimate the effect of tertiary education in Asian countries. It is also possible that there might be a more serious reverse causality issue for the decision to invest in higher skills, whereby higher rates of growth favour increasing enrolment in higher education (Loening, 2004).

5.5. Robustness checks

In this section we undertake a series of sensitivity checks to ensure that our results are robust to the presence of structural breaks and to changes in sample composition. As mentioned in section 5.1, Asian economies have experienced economic shocks and important transformation during the period of our analysis, such as the two World oil price shocks (1973-1974 and 1979-1980), the massive devaluation of most Asian currencies (1987-2004) (Narayan et al. 2010) and several political reforms (Wang and Yao, 2003; Wu, 2011). The Narayan and Popp unit-root test, presented in Tables A4 and A5, identifies structural breaks in the early 80s, mid 90s and late 90s for most of the countries included in our analysis. To investigate whether the presence of structural breaks affects the relationship between human capital and growth, we follow Stiroh (2002) and O'Mahony et al. (2008) in using the break dates at the country-level to re-estimate the impact of human capital on growth in the panel dimension, allowing the coefficients to vary over time by means of interaction dummies. Results are presented in Appendix Table A6. We report a subset of results which consider structural breaks at six different points in time. Statistical significance of the interaction term would indicate a significant change in the coefficients. In all specifications, however, our results show that all the interacted terms are not statistically significant, indicating that the presence of structural breaks does not affect our coefficient estimates.

Although our estimation method accounts for countries' heterogeneity, there might still be country differences that affect our results. We check whether the impact of human capital changes when eliminating in turn the four tiger economies (Hong Kong, Singapore, Taiwan and the Republic of Korea), India and China. Results in appendix Table A7 show that the parameter estimates for the long-run impact of education are consistent with our main set of results; the only exception is the coefficient for the Barro and Lee human capital measure in China, which does not display a significant coefficient. Appendix Table A8 reports estimates for the impact of primary, secondary and tertiary education in the three different samples. When excluding the Tiger economies and India, results are consistent with those discussed in the main body of the paper (Table 5), i.e. we find a positive long-run impact of primary and secondary education and a negative impact of tertiary education. When excluding China, both secondary and tertiary education play a negative role. This could be the results of two factors. First, this result suggests that in China investments in education have been particularly effective in driving growth within the country; second, China has likely affected performance in neighbouring countries via a spillover effect, which is captured by the inclusion of corrections for cross-sectional dependence.

6. Conclusions

This paper provides a new contribution on the impact of human capital on growth focusing on Asian countries. Differences across countries in this area are large and we deal with this heterogeneity using new developments in panel data analysis. Our results show that investments in education have played an important role in rising productivity growth, a conclusion that is supported by the different model specifications we have used in our analysis. Our preferred model, which is based on an ECM framework, predicts that in the long-run a 1% increase in educational attainment increases growth by 0.4% when using the BL measure and around 1% when using the PWT measure. The latter adjusts information on educational attainment with different returns for primary, secondary and tertiary education and generally produces larger coefficients, suggesting that accounting for the quality of education gives an even stronger human capital effect.

We also investigate whether different types of education are more relevant for growth, using the average number of years of primary, secondary and tertiary education. These results highlight the importance of primary and secondary education, providing support to recent policies, which focus on the diffusion of primary education in developing countries, such as the UN Millennium Development Goal (Sachs, 2005) and the recent UN Sustainable Development Goals. More surprising is the finding of a negative impact of tertiary education. We suggest that the lack of opportunities for highly skilled workers, low level of workers educated at the tertiary level and the brain drain phenomenon could explain this result. This is an interesting issue which deserves further investigation.

This work also shows that the use of aggregate data can capture the effect of human capital on growth, particularly when using a fully dynamic specification and controlling for countries' heterogeneity and the impact of unknown common factors. Further work is needed to investigate whether results for Asian countries hold for other groups of emerging economies or whether they are confined to this specific area. Different environmental factors, institutions and quality of education across countries imply that the role of human capital can differ. This has implications for policy interventions that should consider countries' specific needs, particularly when aiming to develop the provision of secondary and tertiary skills.

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APPENDIX

Table A1
Summary Statistics

Variable	Obs.	Mean	SD	Min	Max
Real GDP per worker (Y/L)	756	15.09	18.27	1.23	89.97
Real capital stock per worker (K/L)	728	43.80	63.31	2.04	303.63
Barro and Lee: avg. years of schooling	756	5.59	2.76	0.13	12.08
Primary education	756	3.65	1.54	0.08	5.82
Secondary education	756	1.73	1.23	0.05	5.06
Tertiary education	756	0.21	0.25	0.00	1.20
Avg. years of schooling, returns adjusted (PWT)	728	2.03	0.58	1.02	3.35

Source: Real GDP is computed at current PPPs (expenditure side), while real physical capital stock is cumulated investment in structures and equipment, using asset-specific geometric depreciation rates (Feenstra et al., 2015). All values are in millions of 2005US$. Both are from the Penn World Tables, version 8.0. Per-worker figures are obtained by dividing real GDP and real capital by the total number of workers (Conference Board database). Barro-Lee indicators of educational attainment are from the Barro-Lee dataset (2010). The Average years of schooling data, adjusted for returns to primary, secondary and tertiary education, is from the Penn World Tables, version 8.0.

Table A2
Unit root test for panel data

	Levels		First Differences	
	Im et al. (2003)	Pesaran (2003)	Im et al. (2003)	Pesaran (2003)
Output per Worker (lny_{it})	-0.873	-1.379	-4.753***	-2.877***
	(0.192)	(0.949)	(<0.001)	(<0.001)
Physical Capital per worker (lnk_{it})	3.415	-1.152	-2.243***	-2.324***
	(0.994)	(0.995)	(0.013)	(0.014)
Human capital (*lnhit* B&L)	-1.076	-1.805	-4.027***	-2.684***
	(0.141)	(0.460)	(<0.001)	(<0.001)
Human capital (*lnhit* PWT)	-1.052	-1.969	-1.521*	-2.107*
	(0.146)	(0.221)	(0.064)	(0.092)

Notes: probability values in brackets. B&L stands for Barro & Lee, PWT stands for Penn World Tables.

Table A3

Test for the presence of cross sectional dependence in variables

Variable	CD-test	p-value
Δlny_{it}	9.08	<0.001
Δlnk_{it}	5.43	<0.001
Δlnh_{it} *B&L*	11.39	<0.001
Δlnh_{it} PWT	5.63	<0.001

Notes: BL stands for Barro & Lee, PWT stands for Penn World Tables.

Table A4
GDP per worker (levels): Two-break unit root test. Narayan and Popp (2010)

		M1				M2			
Nr.	Country	test statistic	TB1	TB2	k	test statistic	TB1	TB2	k
1	Bangladesh	-2.399	1970	1972	1	-2.533	1972	1983	5
2	China	-2.038	1975	1988	5	-1.540	1971	1983	5
3	Hong Kong	-0.477	1973	1975	0	-4.175	1973	1997	1
4	India	-2.246	1973	1978	0	-2.438	1974	1978	0
5	Indonesia	-3.274	1978	1997	1	-4.110	1985	1997	0
6	Malaysia	-2.836	1972	1985	3	-2.509	1974	1985	0
7	Nepal	-3.079	1997	2000	0	-1.359	1997	2001	1
8	Pakistan	-1.653	1970	1996	0	-4.097	1974	1996	0
9	Philippines	-2.840	1977	2000	1	-2.914	1977	1986	0
10	Republic of Korea	0.238	1972	1979	0	-1.719	1979	1984	0
11	Singapore	-2.721	1999	2001	1	-1.284	1997	1999	0
12	Sri Lanka	-2.167	1978	1980	3	-1.167	1980	1996	0
13	Taiwan	1.736	1973	1985	4	-5.059*	1973	2000	1
14	Thailand	-2.386	1988	1996	0	-0.268	1970	1996	0

Note: The critical values for this test are based on Table 3, of Narayan and Popp (2010).

Table A5
GDP per worker (First differences): Two-break unit root test. Narayan and Popp (2010)

		M1				M2			
Nr.	Country	test statistic	TB1	TB2	k	test statistic	TB1	TB2	K
1	Bangladesh	-6.823***	1972	1988	2	-4.056	1973	1983	2
2	China	-6.395***	1983	1988	1	-6.945***	1971	1983	0
3	Hong Kong	-6.485***	1973	1997	1	-6.838***	1973	1997	1
4	India	-4.958**	1973	1975	0	-7.340***	1974	2000	0
5	Indonesia	-4.549**	1978	1997	4	-3.792	1978	1997	4
6	Malaysia	-7.405***	1974	1985	0	-7.020***	1974	1997	0
7	Nepal	-9.968***	1997	2000	0	-5.495**	1997	2001	3
8	Pakistan	-9.636***	1989	1996	0	-7.456***	1976	1996	1
9	Philippines	-5.518***	1977	1997	0	-4.706	1977	1985	0
10	Republic of Korea	-8.636***	1972	1979	0	-9.771***	1973	1979	0
11	Singapore	-4.943**	1999	2001	0	-5.187**	1997	1999	0
12	Sri Lanka	-4.549**	1978	1980	0	-4.782	1980	1996	5
13	Taiwan	-6.189***	1973	1985	3	-6.765***	1973	2000	3
14	Thailand	-6.719***	1988	1996	0	-7.013***	1988	1996	0

Note: the critical values for this test are based on Table 3, of Narayan and Popp (2010). *, **, *** indicate rejection of the null hypothesis of non-stationarity at the 10%.

Table A6

Testing for the presence of structural breaks in the human capital-growth relationship in Asian countries.

	1973 [1]	1978 [2]	1988 [3]	1997 [4]	2000 [5]	2004 [6]
Δlnk_{it}	0.356	0.631**	0.584*	0.646***	0.624***	0.712***
	(0.333)	(0.246)	(0.308)	(0.190)	(0.181)	(0.143)
Δlnh_{it} *B&L*	3.562**	2.245**	0.582	0.514	0.589**	0.488*
	(1.626)	(0.985)	(0.472)	(0.320)	(0.297)	(0.297)
Δlnk_{it} * *year*	0.435	0.181	0.295	-0.007	-0.047	-0.094
	(0.347)	(0.306)	(0.381)	(0.229)	(0.238)	(0.531)
Δlnh_{it} **year*	-2.410	-0.729	0.532	0.717	-0.456	-8.860
	(1.579)	(0.932)	(0.971)	(3.855)	(2.726)	(18.128)
Year dummy	0.003	-0.019	-0.050	-0.018	0.000	0.114
	(0.076)	(0.079)	(0.053)	(0.058)	(0.045)	(0.122)
Constant	-0.009	0.010	0.043	0.023	0.018	0.008
	(0.070)	(0.064)	(0.036)	(0.025)	(0.019)	(0.018)
Observations	714	714	714	714	714	714

Note: These results refer to a first difference specification (column 1, table 3) with correction for cross-sectional dependence, augmented with shift and interaction dummies to capture the impact of structural change on our coefficient estimates. The year at the top of each column indicated the time of the structural break. The coefficients on *Δlnkit* and *Δlnhit* represent estimates pre-break, while the coefficients on the interacted terms (Δlnk_{it} * *year* and Δlnh_{it} **year*) captures differences over time. Lack of significance of these terms indicates that there are no significant changes of the coefficients over time. All results in this table are based on the Barro & Lee human capital measure. The use of the PWT human capital produces similar results.

Table A7

Long-run relationship between human capital and growth, different sample compositions (Dynamic specification with correction for CSD)

	Excluding Tiger Economies		*Excluding India*		*Excluding China*	
Long-run parameters	B&L	PWT	B&L	PWT	B&L	PWT
lnk_{it}	0.538***	0.183*	0.546***	0.343***	0.435***	-0.0574
	(0.047)	(0.099)	(0.051)	(0.085)	(0.116)	(0.211)
lnh_{it}	0.333**	1.578***	0.404***	1.322***	-0.090	2.244***
	(0.143)	(0.43)	(0.151)	(0.377)	(0.087)	(0.726)
EC	-0.122**	-0.103***	-0.124***	-0.091**	-0.071***	-0.043***
	(0.056)	(0.038)	(0.041)	(0.039)	(0.016)	(0.014)
Constant	-0.036	0.010	-0.031	-0.009	0.076***	0.027*
	(0.023)	(0.021)	(0.027)	(0.020)	(0.020)	(0.016)
Observations	510	510	663	663	663	663

Notes: Dependent variable: value added per worker in log first differences. EC stands for Error Correction coefficient. All specifications include corrections for cross-section dependence. Standard errors in brackets. * = significant at 10%, ** = significant at 5%, ***= significant at 1%. Tiger economies are Hong Kong, Singapore, Taiwan and the Republic of Korea.

Table A8
The impact of primary, secondary and tertiary education, different sample compositions
(Dynamic specification with correction for CSD)

Long-run parameters	Excluding Tiger economies			Excluding India			Excluding China		
	Primary	Tertiary	Secondary	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary
lnk_{it}	0.525***	0.627***	0.588***	0.548***	0.655***	0.800***	0.358***	0.857***	0.753***
	(0.042)	(0.056)	(0.092)	(0.039)	(0.054)	(0.056)	(0.104)	(0.078)	(0.063)
lnh_{it}	0.238*	0.145**	-0.130*	0.396**	0.159**	-0.228***	0.051	-0.357***	-0.197***
	(0.131)	(0.069)	(0.068)	(0.165)	(0.072)	(0.064)	(0.114)	(0.078)	(0.052)
EC	-0.117**	-0.139***	-0.103***	-0.118***	-0.118***	-0.100***	-0.068***	-0.056***	-0.075***
	(0.056)	(0.051)	(0.025)	(0.043)	(0.038)	(0.029)	(0.0167)	(0.019)	(0.014)
Constant	-0.001	-0.013	-0.030	-0.002	-0.006	-0.092**	0.076***	-0.028*	-0.048**
	(0.017)	(0.017)	(0.021)	(0.027)	(0.016)	(0.039)	(0.027)	(0.016)	(0.020)
Observations	510	510	510	663	663	663	663	663	663

Notes: Dependent variable: value added per worker in log first differences. Results are from an ARDL(1,1,1) model. Human capital indicators are the average number of years of primary, secondary and tertiary education. EC stands for Error Correction coefficient. All specifications are augmented with cross-section averages. Standard errors in brackets. * = significant at 10%, ** = significant at 5%, ***= significant at 1%. Tiger economies are Hong Kong, Singapore, Taiwan and the Republic of Korea.