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Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

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JEL Classification: I25, O47, O15, I20

Keywords: Education and Economic Development, Empirical Studies of Economic Growth, Human Capital

Assaf Sarid - assaf.sarid@gmail.com
The University of Haifa

Zvi Eckstein - zeckstein@idc.ac.il
The Interdisciplinary Center Herzliya – IDC and CEPR

Yuli (Yael) Tamir - yuli@shenkar.ac.il
Shenkar College

Do cognitive skills Impact Growth or Levels of GDP per Capita?[☆]

Zvi Eckstein[a], Assaf Sarid[b,*], Yuli (Yael) Tamir[c]

[a] *Tiomkin School of Economics, The Interdisciplinary Center (IDC), Israel*
[b] *Department of Economics, The University of Haifa, Mount Carmel, Haifa, 3498838, Israel*
[c] *Shenkar College, Israel*

Abstract

Incredible policy attention has been given to the claim that an increase in the quality of education as measured by international tests (e.g. PISA tests) has a significant impact on the GDP long-run growth rate (Hanushek and Woessmann, 2015). This study is based mostly on aggregate data from the second half of the century, and never addresses the question of the current paper, which is whether the impact of the quality of cognitive skills affects the level of GDP per capita or the long run growth rate. Focusing on this question, we construct a variant standard growth model in which cognitive skills have theoretically both a level and growth rate effects by assumption. Estimating this model using standard cross-country data and panel data, cognitive skills measured by the methodology of Hanushek and Woessmann (2015) have a significant level effect on GDP but not a growth effect. Therefore, the cognitive skills improvement impact economic growth is bounded.

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1. Introduction

This paper reconsiders the impact of investment in human capital on long-run economic growth. In order to analyze this question, we start from an aggregate production function, and generate a growth equation, which we estimate with cross country and panel data, as accepted in the literature (Durlauf et al., 2005). An important feature of our paper is that we use a proxy for the quality of human capital, which is based on the average achievement in international tests in math and sciences, as in Hanushek and Woessmann (2015) (HW). HW used cross country data and concluded that:[1]

> "A rise of one standard deviation in cognitive skills of a country's workforce is associated with approximately two percentage points higher annual growth in per-capita GDP."

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[*] Corresponding author
URL: assaf.sarid@gmail.com (Assaf Sarid)
[1] This argument was first presented in Hanushek and Kimko (2000), and was also repeated in Hanushek and Woessmann (2012) & Hanushek et al. (2013).

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In this paper we test if this argument is true.

The literature on the impact of investment in human capital on economic growth is vast, and so are the variety of measures used to proxy human capital. Some measures consist on the quantity of human capital, such as literacy rates (e.g., Mankiw et al. (1992)) or average years of schooling (e.g. Cohen and Soto (2007) and Barro and Lee (2013)). While these measures find a positive correlation between human capital and growth, they do not include any information on the quality of human capital, and as such their result may be biased.

Recently, a new proxy for human capital – which consists on quality rather than quantity – has been developed in Hanushek and Kimko (2000), and is used in HW. They attempt to proxy cognitive skills using the average achievement of students in international tests in math and sciences. The contribution of this measure is important for understanding differences in income levels, as indeed, as HW argue, this measure is more correlated than previous measures of human capital with the average annual growth rate of different economies around the globe. As a result, HW argue that improvement in the average achievement in these tests is crucial for long-run growth.

It is hard to emphasize the importance of the HW results, as they have been adopted by the PISA (Programme for International Student Assessment) analysts, as well as by The World Bank and OECD experts as a justification for imposing a testing policy contested by most educational experts. In an age that sees education through economic prism this seems to be a very convincing argument. Indeed, nowadays the World Bank uses these tests as a policy device to stimulate economic growth.[2] As a result, the number of participating countries in these exams has risen in the past two decades from slightly less than 30 to approximately 100 countries around the globe, and educational reforms have taken place in an attempt to succeed in these tests at the expense of other educational goals. Nevertheless, these policies are contested by many educational experts, who claim that the testing regime demeans education and harms the lives of hundreds of millions of children.[3] The consequences are far beyond the scope of an academic debate.

A key aspect in the analysis of HW is that cognitive skills have a causal impact on long run growth rates.[4] Indeed, HW mention three views in the literature that support the notion that human capital is vital to growth. First, in a neoclassical growth model, human capital is a factor of production; investment in education increases the human capital of the labor force, and thus shifts the economy from one steady state to a higher one. Note that according this view, investment in education affects the level of output per capita, but not its long run growth. The second argument raised by HW comes from the endogenous growth literature, namely that growth is driven mainly by innovation, and the latter depends on the cognitive skills of entrepreneurs. As such, investment in education,

[2] François Bourguigono, World Bank's Senior Vice President (2007) wrote in a World Bank research publication written by Hanushek and Woessmann, that "The Bank will contribute to ensuring that the measurement of learning achievements is undertaken in a more systematic way and is properly taken into account in the Bank's dialogue with partner countries", [World Bank, 2007].

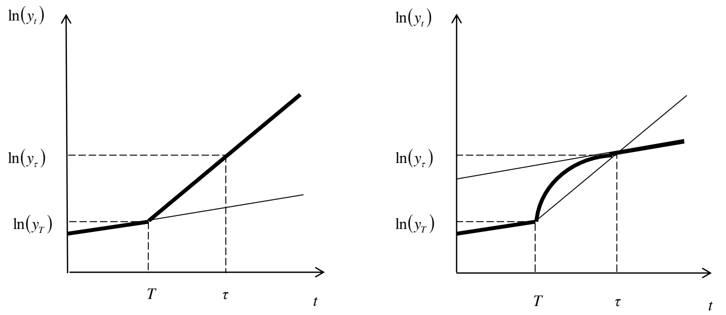
[3] See, Ravitch (2013), and "OECD and PISA Tests are Damaging Children Worldwide, An Open Letter to Dr. Andreas Schleicher, the Guardian 6 may 2014."

[4] HW explain in detail the identification strategy they use to establish a causal effect of cognitive skills on growth (See chapter 4). Consequently, we do not focus on establishing such a causal connection, but rather on the nature of this connection.

which raises the cognitive skills of entrepreneurs, affects the long-run growth rate of the economy. Last but not least, according to a third view, investment in education assists the economy in absorbing new technologies.[5] Referring to these three views, HW argue that:

> "All these approaches have in common a view of human capital as an ingredient vital to growth. The latter two stress its impact on long-run growth trajectories. This is the notion we build on."

We question if this is correct, or whether cognitive skills have a level effect. Figure 1 illustrates the question at stake. Let us consider the following exercise, similar to the one presented in Hanushek et al. (2013) (HPW) and in HW: Suppose that a country is on its steady state growth path. At period T the economy experiences an educational reform that increases its cognitive skills level, and hence output per capita grows at a higher rate for a certain period (between period T and τ). If investment in cognitive skills has a growth effect, this economy will experience this high growth rate for all future periods, as the left part of the figure shows. This is also the interpretation of HW. If, on the other hand, investment in cognitive skills has a level effect, then the spike in the growth rate is temporary; it will decline eventually to its original rate of growth, and the impact of such a reform on output per capita will be substantially lower, as shown in the right part of the figure.



a. A growth rate effect caused by an educational reform at time *t*.

b. A level effect cause by an educational reform at time *t*.

Figure 1: A growth rate effect (left) and a level effect (right) of an educational reform

To answer this question, we construct a neoclassical growth model in which investment in cognitive skills has a level effect by assumption. We use a common methodology in the literature to generate our first estimated equation. We estimate our model using data from Penn World Tables (Feenstra et al., 2015) and from HW. Our first specification replicates the main specification of HW, and indeed, our results are very similar to theirs. Yet since in our case this specification springs from a model in which cognitive skills have a level effect by assumption, we question whether HW really capture a growth effect.

In our second specification we add to the model other components that according to the growth theory and our model may have an impact on output per worker in the long run, such as the average growth rate of population

[5] This idea was highlighted by Nelson and Phelps (1966).

and the average investment rate in physical capital. As a result, the coefficient of the investment in cognitive skills declines, suggesting that not only do the results of HW capture only a level effect, but also that their coefficients are biased upwards.

Finally, we show that the coefficient of investment in cognitive skills is statistically significant only when initial output per worker is one of the regressors, suggesting that the positive effect documented in HW is significant *conditional* on the initial output per capita level. This is consistent with the conditional convergence hypothesis, according to which investment in human capital has a level effect. We conclude from this result, and from the fact that in this model cognitive skills have a level affect by assumption, that investment in cognitive skills has a level effect, as part of the conditional convergence hypothesis.

We then show the quantitative differences of our results and those reported in HW. We show that while HW argue that 90 years after an educational reform, output per capita will be 26% higher than its no-reform counterpart, our estimations suggest that after 90 years, output per capita will exceed its no-reform level by about 10%. Furthermore, the difference between the results of HW and ours increases over time. These results call for a new consideration of the educational reforms throughout the world.

As a robustness check, we extend the model and allow investment in cognitive skills to have a growth effect. In this model, each country converges to a globally stable steady state. Yet, unlike our basic model, in this model, even in the steady state countries may differ in their growth rates, since the growth rate of each economy depends on its level of cognitive skills. We estimate this model, and show that the model does not fit the data, suggesting that the data do not support the growth effect hypothesis.

So far, our analysis relied on cross country data. A more powerful approach is to use panel data, because such data follow an economy for a long period of time, and hence they enable a better identification of the level and growth effects. Furthermore, panel data allow to account for country specific fixed effects, and this way to disentangle the potential bias caused by some omitted variables that are country specific.

We use data for 13 OECD countries, which participated in the international tests since they initiated. We follow the methodology of HW and construct the measure of cognitive skills for these countries since the onset of the international tests. The construction of the level of cognitive skills over time reveals that none of the countries has experienced a sharp increase in the average achievements of it students in the international tests. These findings raise two questions: first, whether the level of cognitive skills is bounded from above, and as such so is its impact on the level of GDP per worker. Second, whether the countries in the sample that experienced a higher growth rate of cognitive skills indeed experienced a higher growth rate of GDP per capita as well.

In order to answer these questions, we construct a model based on a standard production function, in which the level of human capital affects both the level of output per worker. We also assume that the level of human capital affects the growth rate of technology. Hence, the model includes both the level effect *and* the growth effect. We develop from the production function the growth rate of output per worker, which in turn depends on both the level and the change of cognitive skills, capturing both the growth effect and the level effect, respectively.

We estimate the model described above, using data from PWT and our calculations of cognitive skills. Since most of the international tests are taken at the age of 14, we use in our estimations a five year lag of the cognitive skills level. As mentioned above, if cognitive skills have a growth effect, then their *level* should be positively correlated with the growth of GDP per capita, while if they have a level effect then their *change* should be correlated with the growth rate of GDP per capita.

We first measure the model assuming that cognitive skills have a growth effect alone. The coefficient of the level of cognitive skills on GDP per worker growth rate is not statistically significant. We then test the hypothesis of the level effect alone (assuming that there is no growth effect of cognitive skills on growth), and indeed the coefficient of the change in cognitive skills is positive and statistically significant.

Finally, we do not restrict the model, and allow both level effect and growth effect play a role. Consistent with our previous results, the level of cognitive skills is not correlated with the growth rate of output per worker, whereas the change in the level of cognitive skills (which captures the level effect) is positive and statistically significant. We conclude from this analysis that consistent with the cross country analysis, the panel data support the level effect hypothesis, rather than the growth effect hypothesis.

The rest of the paper is constructed as follows: Section 2 presents our baseline model, where the accumulation of cognitive skills and physical capital are determined endogenously, and technology advances in an exogenously given rate. In section 3 we describe the data we use; In Section 4 we present the results of estimating our baseline model. In Section 5 we discuss the quantitative difference between our results and the results obtained by HW, and in Section 6 we relax our assumption of exogenous technical change. Section 7 presents our panel data results, and Section 8 concludes.

2. A Baseline Model

In this section we construct a simple model in which cognitive skills have a level effect by assumption. The model is a standard neoclassical growth model, in which the accumulation of physical capital and cognitive skills are determined endogenously, while the rate of technical change is exogenously given. Consider a closed economy, in which the production function of a single homogenous good is of the form:

$$Y_t^i = K_t^{i\alpha}\left(A_t^i h_t^i L_t^i\right)^{1-\alpha}, \tag{1}$$

where Y_t^i is the output at period t in country i, A_t^i is the (labor augmenting) technology level in country i at period t, K_t^i is the capital employed in production in country i at period t, h_t^i is the average cognitive skills of a worker in country i at period t and L_t^i is the raw labor employed in production in country i at period t; $0 < \alpha < 1$. This is a standard production function, used in many empirical growth studies (e.g., Fernald and Jones (2014)).

2.1. The Dynamics of the Model

We assume that the technological parameter, A_t^i, increases in an exogenously given constant rate, λ. This assumption is common in the neoclassical growth literature (e.g., (Mankiw et al., 1992)).[6] We also assume that the population grows at a constant rate, n^i. The physical capital formation follows a usual law of motion, which implies that the physical capital stock at the next period equals the stock of capital that is left from the present period (after depreciation) plus the investment in physical capital:

$$K_{t+1}^i = (1-\delta)K_t^i + s_K^i Y_t^i, \tag{2}$$

where δ is the depreciation rate and s_K^i is the investment rate in physical capital in country i, both assumed to be constant over time.

We assume that the cognitive skills evolve due to the investment rate in cognitive skills, s_H^i, according to the following equation:

$$h_{t+1}^i = \overline{h}^i + s_H^i \cdot h_t^i, \tag{3}$$

where $\overline{h}^i$ is a measure of time-invariant level of cognitive skills (but perhaps country-specific), which does not require investment in cognitive skills. The investment rate, s_H^i, which yields the increase in cognitive skills over time, may be a consequence of public expenditures on education, parental investment in education (either time dedicated to education or private monetary expenditures), or the quality of the education system. Note that this dynamic equation is different from the one used in Mankiw et al. (1992), but shares important properties for our purpose. With $0 < s_H^i < 1$, the dynamic equation converges into a unique steady state, with a declining growth rate of cognitive skills.[7] This, in turn, generates a model in which investment in cognitive skills, as captured by s_H^i has a level effect, and not a growth effect, by assumption.

2.2. Steady State

A steady state in this economy is a state in which output per worker, $y_{i,t} \equiv Y_{i,t}/L_{i,t}$ grows at a constant rate. In order to find the steady state, we develop the dynamic equation of capital per effective labor, $\tilde{k}_{i,t} \equiv \frac{K_{i,t}}{A_{i,t}L_{i,t}}$, and find its steady state level, $\tilde{k}_i^*$. Finally, we find the constant rate at which output per worker grows.

For $\tilde{k}^{i,*}$ to be constant, the average level of cognitive skills has to be constant as well. That is, $h^{i,*} = \frac{\overline{h}^i}{1-s_H^i}$. Consequently, $\tilde{k}^{i,*}$ becomes:[8]

$$\tilde{k}^{i,*} = \left(\frac{s_K^i}{n^i+\lambda+\delta}\right)^{\frac{1}{1-\alpha}} h^{i,*}. \tag{4}$$

[6] As discussed above, we relax this assumption below.

[7] Another way of modeling the dynamic equation of cognitive skills accumulation could be $h_{t+1}^i = \overline{h}^i \cdot (h_t^i)^{s_H^i}$. Note that this function shares the same characteristics of declining growth rates over time if $0 < s_H^i < 1$. We prefer a more tractable functional form.

[8] The development of this equation is detailed in Appendix A.

Characteristics of the Steady State. Capital per worker is given by:

$$k_t^i = A_t^i \tilde{k}^{i,*} = A_t^i \left(\frac{s_K^i}{n^i + \lambda + \delta} \right)^{\frac{1}{1-\alpha}} h^{i,*}. \tag{5}$$

It is straightforward that capital per worker grows at a constant rate λ and so does output per worker. Note that countries with higher $\overline{h}^i$, or with a higher investment rate in cognitive skills have higher *levels* of $\tilde{k}^{i,*}$ and *levels* of output per worker, yet they share the same GDP per worker growth rate.

2.3. Generating Average Growth Rates

Our last step towards estimating the relation between the level of cognitive skills and output growth rate is to generate the growth rate towards the steady state. We follow the methodology of Durlauf et al. (2005), and plug (5) in the production function of output per worker, take logs and subtract output per worker at a base year (in logarithmic scale) from both sides of the equation. This yields the following equation:[9]

$$g_{y_t^i} = \lambda + \frac{\ln A_0^i}{t} + \alpha \frac{\ln s_K^i}{t} - \alpha \frac{\ln(n^i + \lambda + \delta)}{t} + \frac{\ln(h^{i,*})}{t} - \frac{\ln y_0^i}{t}, \tag{6}$$

where $g_{y_t^i}$ is the growth rate of output per worker in the time span between period 0 and t. Hence, according to the model, the growth rate of output per worker is an increasing function of the exogenous technical change, the initial level of technology, the investment rate in physical capital as well as in cognitive skills; it is a decreasing function of the growth rate of population and of the initial level of output per worker.

One may be tempted to conclude from this specification that the investment rate in cognitive skills affects the long-run growth rate of output per worker. This is, in fact, the interpretation in HW. However, this interpretation is not consistent with the model described above. To see this, note that as t converges to infinity, and the economy converges to its steady state, the only element that affects the growth rate of the economy is the exogenous technical change. This is, in fact, the only element in neoclassical model that has a growth effect, whereas all other economic variables, including cognitive skills investment have a level effect. As suggested below, this model generates an identical specification analyzed in HW, and hence it raises the question whether HW indeed capture a growth effect, as they argue.

2.4. The Estimated Equation

We estimate equation (6), under the assumptions that the exogenous growth rate of technology, λ, is common to all countries; we also assume, as in Mankiw et al. (1992) that $A_0 \sim N(\overline{A}_0, \sigma^2)$. Hence, we estimate the following equation:

$$g_{y_t^i} = \lambda + \frac{\ln \overline{A}_0}{t} + \alpha \frac{\ln s_K^i}{t} - \alpha \frac{\ln(n^i + \lambda + \delta)}{t} + \frac{\ln(h^{i,*})}{t} - \frac{\ln y_0^i}{t} + \epsilon^i. \tag{7}$$

[9] The mathematical procedure is detailed in Appendix B.

where ϵ^i is the random residual from the distribution of A_0. Note that the constant includes both the average level of initial technology and the exogenous growth rate of technology, λ.

Note that this equation is similar to the one in Mankiw et al. (1992) or Durlauf et al. (2005) (in Sections 3 and 4). HW estimate a similar equation, but they exclude the impact of investment in physical capital as well as the impact of population growth rate on output per capita growth rate. This specification is vulnerable to identification problems, as omitted variables may affect both growth and cognitive skills. To overcome these problems, Hanushek and Woessmann (2012) implement an instrumental variable approach: They use institutional characteristics of the school system (such as the percentage of private schools, the existence of external exit exam systems etc.) and show that their results are not affected by these instruments. HW also argue that the problem of reverse causality is absent in their study, as they show that if they focus on tests that took place before the period studied, the coefficient of the level of cognitive skills increases, rather than declines, as one would expect if the problem of reverse causality existed in the data.

3. Data

We use data on GDP per capita and population size from 1960 to 2010 for 51 countries from Penn World Tables version 8.1 (PWT) (Feenstra et al., 2015). All these countries did not belong previously to the Soviet bloc. We calculate the real GDP (on aggregate level) for these countries in these years, and then use data on the number of workers in these years from PWT as well to calculate output per worker in each year in the period 1960-2010, and its growth rate. We use data also from PWT to compute the average investment rate in physical capital for this period as the investment as a percentage of GDP. We assume that the exogenous growth rate of technology is 2% (as in Mankiw et al. (1992)), and that the depreciation rate is 4% (as suggested in the PWT (Inklaar and Timmer, 2013)). From the population in the ages of labor we compute for each country its average annual growth rate of the labor force, n^i. Finally, we use the measure of cognitive skills from HW as our cognitive skills measure. Table 1 summarizes the statistics of the variables we use for our estimations. All variables except the cognitive skills level are in percentage points.

Table 1: Summary statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Output per worker growth rate, 1960-2007	2.277	1.232	-0.721	5.165	51
Investment Rate	24.467	7.033	3.784	43.452	92
$n + \gamma + \delta$	7.76	1.355	5.933	14.067	90
Cognitive Skills level	4.506	0.727	0.562	5.452	75

4. Results

Table 2 presents the results of estimating equation (7). Column (1) includes only initial output per worker as a control variable. This regression is identical to the one reported in HW, and our results are very similar to the ones reported in their study. In their estimation, the coefficient of cognitive skills is close to 2, and the coefficient of initial output per capita is close to -0.3.[10] However, HW argue that their results capture a growth effect, whereas our estimated equation springs from a model in which investment in cognitive skills has merely a level effect. This by itself raises a concern whether their analysis identifies a growth effect. Furthermore, note that both in our estimation and in their estimation, the coefficient of initial output per worker is negative, supporting the conditional convergence hypothesis, according to which economies with similar characteristics converge to the same steady state.[11] This theory supports our hypothesis that investment in cognitive skills has a level effect.

Column (2) includes in addition the average investment rate in physical capital and the average population rate as independent variables. Their coefficients are positive and negative, respectively, exactly like the theory suggests. Note that once these variables are taken into account, the coefficient of investment in cognitive skills declines from 1.62 to 1.04, reducing further more the impact of investment in cognitive skills on economic growth. Note that this coefficient fits the model, according to which this coefficient is supposed to equal 1. This suggests that the coefficients reported in HW include also the complementarity between investment in physical capital and investment in cognitive skills, and the interaction between population growth and investment in cognitive skills.

Column (3) includes a restriction that the coefficients of s_K^i and $n^i + \lambda + \delta$ are equal with opposite sign, as the model suggests. This restriction yields three interesting results. First, the coefficient of the initial output level keeps a similar magnitude as in the previous estimations, suggesting that indeed initial output per worker has an exogenous impact on the growth rate. Second, the coefficient of the restriction is positive and equals 0.07. This suggests that marginal productivity of labor diminishes at a high rate (recall that this coefficient represents α from the production function). Third, the coefficient of investment in cognitive skills is 1.289, slightly more than one standard deviation from 1 (as the model suggests).

As described above, the negative coefficient of initial output per worker supports the conditional convergence hypothesis. According to this hypothesis, investment in cognitive skills has a level effect, and not a growth effect, as HW argue. Hence, in order to rule out the level effect hypothesis, the coefficient of the cognitive skills level should be positive and statistically significant even if initial conditions are not used as explanatory variables. This is the regression analyzed in column (4). Interestingly, the coefficient of the cognitive skills measure ceases to be statistically significant. This suggests that investment in cognitive skills affects economic growth *conditional* on the initial level of output per capita. This is consistent with the conditional convergence hypothesis, according to

[10] The quantitative difference between our results and theirs springs from the fact that we use output per worker, whereas they use output per capita.

[11] For more details on conditional convergence see, for example, Barro and Sala-i Martin (1992) and Durlauf et al. (2005).

which investment in cognitive skills has merely a level effect, and not a growth effect, as HW argue.

Table 2: Growth and Investment in Human capital and Physical Capital

	Output per Worker Growth, 1960-2007			
	(1)	(2)	(3)	(4)
$h^{i,*}$	1.62***	1.04***	1.29***	0.44
	(0.25)	(0.25)	(0.24)	(0.30)
y^i_{1960}	-0.71***	-0.69***	-0.62***	
	(0.13)	(0.11)	(0.11)	
$n^i + \lambda + \delta$		-0.42***		-0.23
		(0.14)		(0.18)
s^i_K		0.07***		0.09***
		(0.02)		(0.02)
$s^i_K - (n^i + \lambda + \delta)$			0.07***	
			(0.02)	
Adjusted-R^2	0.48	0.63	0.59	0.35
Observations	51	51	51	51

Notes: Standard error estimates are reported in parentheses; All regressions include a constant; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

5. Discussion

In this section we would like to highlight the quantitative differences between our results, as presented in Table 2 to the ones presented in HW. Figure 2 represents the impact of an educational reform, as presented in HW. The horizontal axis represents time from the beginning of the educational reform, while the vertical axis represents the ratio of GDP per capita after the reform, relative to a scenario of no reform. In this scenario, we follow HW and assume that the economy grows at a constant rate of 1.5%.

The reform has four stages:[12] In the first stage, the educational reform initiates, and the cognitive skills of students increase gradually, until the reform is fully enacted, after 20 years. Only then students begin to enjoy the highest level of cognitive skills. During the second stage, which lasts also 20 years, students – who, due to the first stage of the reform, have slightly higher cognitive skills than present workers – replace the workers in the labor force. In the third stage, new workers replace the old workers who were the first to enjoy the educational reform, and as such, do not have the highest cognitive skills available (recall that it took the reform twenty years to be enacted fully). Finally, after twenty years of the third stage, the economy reaches the fourth stage of the reform, in which all the labor force has the high cognitive skills.

HW interpret their result as an impact on the long run growth rate, and their estimation is depicted by the upper curve. Our simulation is based on the results above in Table 2, and they differ from the simulation of the results of HW in two aspects. First, the coefficient of the impact of such a reform on the change in the (short-run)

[12]For more information, see Chapter 7 in HW.

growth rate is 1.04, rather than 2, as used by HW. Second, unlike HW, we assume that the growth rate of GDP per capita converges towards 1.5%. Furthermore, we assume that the convergence rate is 2%, as in Barro and Sala-i Martin (1992) and Mankiw et al. (1992).

At the first stage of the reform, our result are very similar to the ones of HW. However, as the second stage of the reform initiates, differences between the two simulations emerge, and their curve becomes steeper than ours. Note that as the years go by, while the simulation of HW becomes steeper, ours becomes flatter. This is due to the forces of convergence, which are absent in HW. Finally, HW argue that 90 years after the reform, output per capita will be higher than its level without such a reform by about 26%. Our simulations do not support this viewpoint; they imply a much more moderate impact: after 90 years from the educational reform output per capita is only 10.4% higher than its level without a reform.

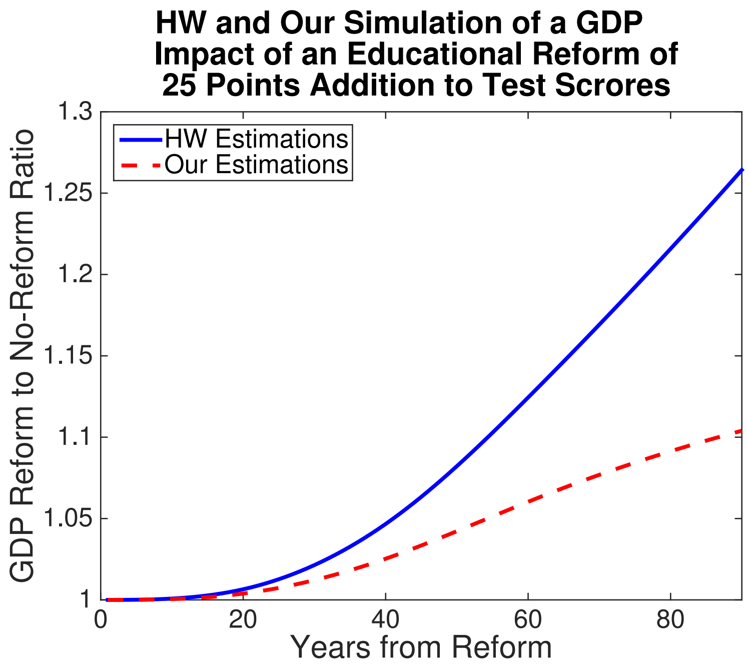


Figure 2: The ratio between GDP per capita after reform and without reform for our results and previous results.

6. Growth and Level Impact of Education

HW suggest channels that may generate the growth effect of cognitive skills. First, it might be that investment in cognitive skills accelerate R&D. Second, with higher cognitive skills, the economy may absorb better new technologies.[13] Both these channels imply that the technical change should depend on the level of cognitive skills.

[13] A third channel would be of cognitive skills externalities. Nevertheless, the evidence for such externalities are mixed. Acemoglu and Angrist (2001), for instance, find very weak evidence for such externalities.

This is the assumption we assume in this section. In this case:

$$g_{A_t^i} = \frac{A_{t+1}^i}{A_t^i} - 1 = \sqrt{h_t^i}. \tag{8}$$

This assumption, which suggests that the higher the average level of cognitive skills per worker, the higher the technical change, is consistent with the endogenous growth literature (e.g., Ha and Howitt (2007)),[14] and is similar to the assumption in Benhabib and Spiegel (1994). The rest of our model does not change. It turns out, that in the steady state, output per worker equals:

$$y_t^i = \left[\frac{s_K^i}{n^i + \sqrt{h^{i*}} + \delta}\right]^{\frac{\alpha}{1-\alpha}} h^{i*} \cdot A_t^i, \tag{9}$$

where, as in the previous model, $h^{i*} = \frac{\overline{h}^i}{1-s_H^i}$ is the steady state level of cognitive skills. It is straightforward that since in the steady state the level of cognitive skills is constant, so is the growth rate of technology. As a result, the term in the squared brackets is constant. This implies that in the steady state output per worker grows at a constant rate, $\sqrt{h^{i*}}$. The *level* of cognitive skills, on the other hand, may differ from one country to the other, as both the investment rate and initial level of cognitive skills may differ between countries. As a result, the *level* of cognitive skills, which has a growth effect in this model, may yield different growth rates in different countries, as HW suggest. To test this specification, we take logs from both sides of (9) and subtract from both sides $\log y_0^i$. Finally, we subtract and add to the right hand side of (9) $\log A_0$. This yields the following equation:

$$\ln(y_t^{i*}) - \ln(y_0^i) = \frac{\alpha}{1-\alpha} \ln\left[\frac{s_K^i}{n^i + \sqrt{h^{i*}} + \delta}\right] + \ln(h^{i*}) + \ln(A_t^{i*}) - \ln(A_0^i) - \ln y_0^i + \ln A_0^i. \tag{10}$$

Note that along the steady state, the technological level grows at a constant rate, which is a function of the steady state level of cognitive skills. Close to the steady state, the technological level grows also from the accumulation of cognitive skills. As a result, in (10), $\ln A_t^{i*} - \ln A_0^i \cong \sqrt{h^{i*}} + \sqrt{\Delta h_0^i}$, where $\Delta h_0^i \equiv h^{i*} - h_0^i$. Hence, the growth effect of the level of cognitive skills level is captured in two elements of this equation. First, in the expression in the squared brackets, $n^i + \sqrt{h^{i*}} + \delta$, and second, in the expression of convergence toward the steady state, $\sqrt{h^{i*}} + \sqrt{\Delta h_0^i}$.

In order to estimate this last equation, we assume, that $\ln A_0^i = \ln \overline{A}_0 + \epsilon^i$, where $\ln \overline{A}_0$ is the average level of $\ln A_0^i$. Consequently, (10) can be written as:

$$g_y^i = \frac{\alpha}{1-\alpha} \ln\left[\frac{s_K^i}{n^i + \sqrt{h^{i*}} + \delta}\right] + \ln(h^{i*}) + \left(\sqrt{h^{i*}} + \sqrt{\Delta h_0^i}\right) - \ln y_0^i + \ln \overline{A}_0 + \epsilon^i. \tag{11}$$

[14] Note that the endogenous growth theory does *not* rule out convergence. See, for instance, Howitt (2000).

Estimating Δh_0^i

The measure of cognitive skills developed by HW is calculated as an average of each country in the international tests it had participated in. Unfortunately, only 13 countries participated in these tests long enough to allow us to investigate its dynamics. In order to overcome this problem, we calculate the difference in the level of cognitive skills under different assumptions regarding the average schooling years, as reported in Barro and Lee (2013). First, for each country we estimate Δh_0^i by the difference in average schooling years. Second, we extrapolate the results in the international tests by using the growth rate of the average schooling years.

6.1. Results

Table 3 summarizes the results from estimating these two specifications. Columns (1) and (2) present the results of the estimations with our first and second specifications, respectively. As in the previous section, the average investment rate in physical capital is positive and close to 0.07; The coefficient of the initial level of output per worker in 1960 is negative, significant and close to its level in the Section 4. The coefficient of the level of cognitive skills is again close to 1, but recall that this impact is the *level* effect we found in the previous section, and not the *growth* effect we are attempting to estimate here.

The coefficients at stake are the coefficient of $n^i + g(h^{i*}) + \delta$ and the coefficient of the change in cognitive skills. The first coefficient is negative and statistically significant, just as in the previous section. Interestingly, its magnitude is similar to the one obtained in the previous section. This raises the question whether the level of cognitive skills indeed has an impact on the growth rate. In order to test this question we run two more regressions, reported in columns (3) and (4), where we omit $g(h^{i*})$ from the expression $n^i+g(h^{i*})+\delta$. Comparing the coefficients of $n + \delta$ in columns (3) and (4) to the ones of $n^i + g(h^{i*}) + \delta$ in columns (1) and (2) respectively, reveals that these coefficients are identical, suggesting that these regressions do not provide any evidence that cognitive skills indeed have a growth effect.

Finally, in none of the estimations reported, the effect of cognitive skills on the growth rate of TFP (the coefficient of the change in cognitive skills) is statistically significant. We conclude from all these results that we find no evidence in the data for the assumption that the level of cognitive skills has a growth effect.

7. Panel Data Analysis

In sections 4 - 6 we argued, using cross country data, that the data support the hypothesis that investment in cognitive skills has a level effect rather than a growth effect. In order to identify the model we assumed that all economies were at their steady states by 2010. Panel data follow a sample of countries over time and therefore they provide a better basis for testing the level vs. growth effect of cognitive skills. Furthermore, panel data allow us to account for time invariant country specific fixed effects, and this way to disentangle the potential bias caused by some omitted variables that are country specific.

Table 3: Output per Worker Growth in a Model of Endogenous Growth

	Output per Worker Growth, 1960-2007			
	A Model with $n+\lambda(h)+\delta$		A Model with $n+\delta$ alone	
	(1)	(2)	(3)	(4)
s_K^i	0.07***	0.07***	0.07***	0.07***
	(0.02)	(0.02)	(0.02)	(0.02)
$n^i+\lambda(h^{i*})+\delta$	-0.39**	-0.40**		
	(0.15)	(0.15)		
Cognitive Skills level	1.21***	1.16***	1.12***	1.07***
	(0.27)	(0.29)	(0.29)	(0.31)
y_{1960}^i	-0.72***	-0.70***	-0.72***	-0.70***
	(0.12)	(0.14)	(0.12)	(0.14)
CS change, first specification	-0.12		-0.12	
	(0.41)		(0.41)	
CS change, second specification		0.03		0.03
		(0.52)		(0.52)
$n^i+\delta$			-0.39**	-0.40**
			(0.15)	(0.15)
Adjusted-R^2	0.63	0.62	0.62	0.62
Observations	49	49	49	49

Notes: Standard error estimates are reported in parentheses; All regressions include a constant; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests.

7.1. Panel Data Specification

Consider, once again, a production function in country i:

$$\ln Y_t^i = \ln A_t^i + \alpha \ln K_t^i + \beta \ln(h_t^i L_t^i). \tag{12}$$

Assume also, as suggested by HW, that the growth rate depends on the level of human capital:

$$g_{A_t^i} = g_A(h_t^i) = \phi + \chi \cdot h_t^i, \tag{13}$$

where $g_{A_t^i}$ is the growth rate of TFP in country i at period t, which depends on two elements: an exogenous element, denoted by ϕ, and the level of human capital in country i. We assume that the relation between the level of human capital and the growth rate of TFP is linear and captured by χ. This equation is a reduced form of both justifications of HW for interpreting their results as a growth effect, namely: (i) endogenous growth theory; and (ii) a more skilled labor force can absorb technologies more easily.

Subtracting $\ln(L_t^i)$ from both sides of (12) and then subtracting two consecutive periods from one another yields the following equation:

$$g_{y_t^i} = g_A(h_t^i) + \alpha g_{K_t^i} - (1-\beta) g_{L_t^i} + \beta g_{h_t^i} = \phi + \chi \cdot h_t^i + \alpha g_{K_t^i} - (1-\beta) g_{L_t^i} + \beta g_{h_t^i},$$

where $g_{y_t^i}$ is the growth rate of GDP per worker in country i between two consecutive periods; $g_{K_t^i}$ is the growth rate of the capital stock in country i in two consecutive periods; $g_{L_t^i}$ is the growth rate of the number of persons employed in country i in two consecutive periods; h_t^i is the level of cognitive skills in country i at period t; and $g_{h_t^i}$ is the growth rate of cognitive skills in country i in two consecutive periods. Note that $\chi \cdot h_t^i$ represents the growth rate effect of cognitive skills, and $g_{h_t^i}$ represents the level effect. Hence, the panel provides us a simple specification to assess if cognitive skills have a level effect or a growth effect, without assuming any assumptions of the laws of motion of each factor of production as well as on the state of the economy. In this section, then, we estimate the following equation:

$$g_{y_t^i} = \phi + \chi \cdot h_t^i + \alpha g_{K_t^i} - (1-\beta) g_{L_t^i} + \beta g_{h_t^i} + \Delta^i + \epsilon_t^i, \tag{14}$$

where Δ^i is country time-invariant fixed effects and ϵ_t^i is an error term. If cognitive skills have a growth effect, one would find a positive and statistically significant estimator of χ, whereas if cognitive skills have a level effect, one would find a positive and statistically significant estimator of β. Note that most previous studies, which used panel data, attempted to estimate a neoclassical growth model and its convergence rate. As such, they used the level of output per worker as the dependent variable (e.g., Islam (1995)). We, on the other hand, try to identify the growth and level effects. Consequently, we use the growth rate of output per worker as our dependent variable.

7.2. Data

In the panel data analysis, we do not assume that the countries are in their steady state, nor we assume any laws of motion on any state variables. As a result, the data we use differ from the ones we used in the cross section analysis. In order to estimate (14), we use direct measures of the stocks of physical capital and employment rather than their average annual change within the entire period examined in the cross section.

We use data from PWT on the real capital and labor stocks, and real output for the countries in our sample for the period 1970-2005.[15] For each country, we calculate the annual level of output per worker. We then divide the entire period of 1970-2005 to 5 year long sub-periods. We calculate for each sub-period the average annual growth rate of output per worker, capital stock and labor stock. This approach, as well as the length of the sub-periods is very common in the literature (e.g., Islam (1995)).[16]

In order to construct a measure of cognitive skills for this period, we restrict our analysis only for countries that participated in the international tests long enough. The international tests were initiated in 1964, and since then they took place several times a decade. Table 4 presents the thirteen countries that participated either in the first tests in 1964, or in the second ones in 1970 and hence construct our sample. The table shows that these countries participated in at least five different tests (the average among these countries is 7.07). Note that all these countries are advanced, suggesting that we cannot analyze in this section different growth patterns of developed

[15] We restrict our analysis until 2005 in order to avoid some biases that may emerge due to the Great Recession.

[16] For a thorough survey of the literature using panel data in growth regressions, see Section VI.ii Durlauf et al. (2005).

and developing countries.

Table 4: Countries with Early Participation in International Tests
& Average Years of Schooling, 1970, 1990

Country	Year of First Participation	No. of Times Participated	Avg. Years of Schooling, 1970	Avg. Years of Schooling, 1990
Australia	1964	8	11.44	11.97
Belgium	1964	7	9.5	11.57
United Kingdom	1964	9	8.48	9.05
Finland	1964	7	8.66	10.15
France	1964	6	7.41	10.03
Germany	1964	5	4.2	11.35
Israel	1964	5	10.39	12.31
Italy	1970	6	7.38	10.74
Japan	1964	9	10.72	12.41
Netherlands	1964	8	9.1	11.43
New Zealand	1970	7	13.13	12.55
Sweden	1964	6	9.9	12.16
United States	1964	9	12.53	12.89

We use the methodology developed by HW to construct a measure of cognitive skills, yet unlike HW, we construct for each country a series of this measure.[17] For each of these countries, we calculate the measure for each year the country participated in the international tests. Since most countries did not participate in all the tests that took place, and since the tests did not take place in all the years in our sample, we linearly interpolate the results for these missing years. Figure 3 presents the cognitive skills measure in these countries over time. For most of the countries that participated in 1964, there is a sharp rise in the measure of cognitive skills between 1964 and 1970. However, after 1970 the dynamics are mixed: some countries experience a moderate increase (e.g. Australia); some experience a relative decline (e.g., Israel) and other countries do not have a specific trend (e.g., Sweden and Belgium). Note also that the measure of cognitive skills has not risen sharply for none of these countries. This raises the question whether an increase in cognitive skills much above the range presented in the figure is feasible. Furthermore, it is not clear whether those countries which experienced some increase in their cognitive skills indeed experienced a higher growth than those which did not.

The international tests are taken at the ages of 10, 14 and 17. Most of the exams are for the ages of 14 (45%) and 17 (31%).[18] Since we attempt to capture how variation in the test scores affected long run growth, we use the cognitive skills measure with a lag of 5 years, which means that the individuals who took the exams 5 years earlier are 15, 19 and 22 years old, respectively.

Table 4 explains why we use a five year lag. For the countries in our sample, the table provides the average years of schooling of the 20-24 year old cohort in 1970 and 1990, as well as the share of this cohort that graduated high school and college (in percentage points). As can be seen in the table, the average schooling years in 1970 for

[17] See Hanushek and Woessmann (2012) for a detailed explanation of the methodology.

[18] Most of the exams for 10 year old students took place towards the end of the 1990's and as such they form a small part in our sample.

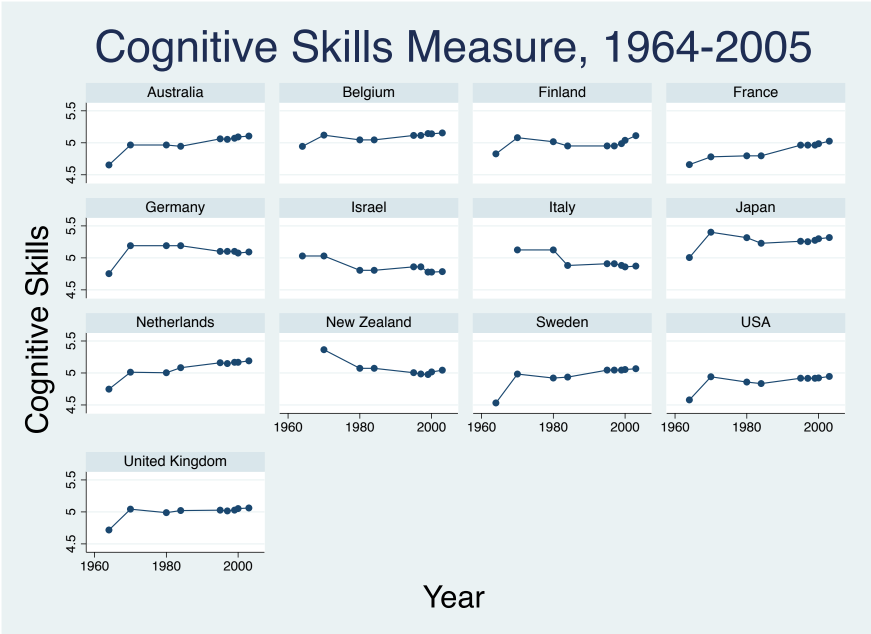


Figure 3: The measure of cognitive skills for countries which participated in international tests since 1964 or 1970

the cohort of 20-24 year olds was 9.5. This suggests that on average, individuals entered the labor force around the age of 17. This means, that students who participated in the international tests when they were 14 entered the labor force on average 3 years later. The same methodology reveals that in 1990 the average schooling years of the 20-24 year old cohort was 11.43, suggesting that on average students who took the test when they were 14, entered the labor force 5 years later. Note that a five year lag for all exams that had taken place at the age of 17, implies that the vast majority of the population is already in the labor force.[19]

7.3. Results

Our estimated model is a model with country fixed effects, as the Hausman test rejects the random effects model. Table 5 presents our results for estimating (14) using the data described above. In the first column we test whether there is a growth rate effect, without any controls (that is, assuming that β and α equal zero). The coefficient of the cognitive skills is negative and not statistically significant. In column (2) we add the change of physical capital, and labor stock, yet the coefficient of the level of cognitive skills is still negative and not significant. In column (3) we test whether cognitive skills have a level effect, without any controls (that is, assuming that χ and α equal zero). The coefficient is positive and statistically significant at the 1% level. In column (4) we add the controls of the change in capital and labor stocks. The coefficient of the change in cognitive skills declines in magnitude (from 1.37 to 0.86), yet it is still positive and statistically significant at the 5%. Finally, in columns (5) and (6) we include as independent variables both the change in the cognitive skills and its level, and only the

[19] As described above, exams for the 10 year old were not so prevalent during most of the period we analyze. Consequently, we emphasize more on individuals who took the exams when they were either 14 or 17.

change in cognitive skills is statistically significant at the 5%. In column (6) we add to the analysis back the change in the capital and labor stocks, and none of the coefficients of the cognitive skills is significant. We conclude from this table that the data supports the level effect hypothesis rather than the growth rate effect.

Table 5: Growth Rate vs. Level Effect Analysis

	Annual GDP per Capita Growth					
	Growth Effect Alone		Level Effect Alone		Both Effects	
	(1)	(2)	(3)	(4)	(5)	(6)
χ	-0.03	-0.03			-0.01	-0.02
	(0.02)	(0.02)			(0.02)	(0.02)
β			1.37***	0.86**	1.22**	0.63
			(0.44)	(0.34)	(0.45)	(0.36)
α		0.29***		0.25***		0.26***
		(0.07)		(0.07)		(0.07)
$1-\beta$		-0.09		-0.11		-0.09
		(0.16)		(0.15)		(0.16)
Adjusted-R^2	0.03	0.24	0.11	0.24	0.11	0.25
Observations	104	104	104	104	104	104

Notes: Standard error estimates clustered at the level of the country fixed effects are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests; All regressions include a constat.

Robustness. One concern with our results are that these are driven by the lag that we chose. Tables C.1, C.2 and C.3 in Appendix C provide evidence that this is not the case. These tables provide the results of estimating (14) with lags of 3, 6 and 10 years for our measure of cognitive skills (and their change), respectively. As can be seen, the level of cognitive skills (χ) is never positive and statistically significant. In fact in Table C.2 it is *negative* and statistically significant at the 5%. The change in the cognitive skills measure is always positive, and statistically significant either at the 1% or the 5% when the lag we use is either 3 or 6 years. It is not statistically significant when we use a 10 year lag. This, however, may be due to the decline in the sample of 13 observations that happens due to the large lag we impose in this table.

Another potential concern with a fixed effects model in panel data may arise due to the relatively small number of observations in each country. In such a case, since the between variation is not used for estimating the coefficients, the standard errors of the coefficients may be large.[20] In order to overcome this problem, we estimate a random effects model. Its results are presented in Table C.4. As can be seen in the table, not only are our result unaffected by the random effect model, but also their significance is higher.

[20] For a deep discussion of this problem, see Section VI.ii in Durlauf et al. (2005).

8. Conclusions

This study asks whether investment in cognitive skills has a growth effect or a level effect. In order to answer this question, we construct a simple neoclassical growth model, in which cognitive skills only has a level effect by assumption. We estimate our baseline model using data from PWT and HW, and show that the model supports the level effect hypothesis. Furthermore, we show that the data do not fit an extended model in which we assume that the level of cognitive skills has a growth effect.

We also use panel data based on 13 OECD countries to answer this question. The data reveal that the level of cognitive skills among these countries had mixed dynamics, and in all of the countries the level of cognitive skills is close to a certain level (of 5). This raises the question whether the level of cognitive skills is bounded from above.

Using the panel data, we test a model that incorporates both the level and the growth effects. We show that the data support only the level effect, and not the growth effect. Furthermore, we show that the results are robust for different potential concerns. We conclude from this analysis that there is no evidence that the level of cognitive skills affects the long run growth rate of output per worker. As a result, we show quantitatively that the impact of cognitive skills on output per worker is much smaller that under the assumption that it has a growth effect.

This study raises several question for future research that have some policy implications. First, it highlights the possibility that cognitive skills are bounded from above. If this is the case, policies that attempt to raise the average level of cognitive skills by increasing the level of all the students might overshoot their target. Instead, it may be better to target education policies to reduce the dispersion of students' achievements in the international tests. This may increase the average cognitive skills – and hence stimulate economic prosperity – by helping more the less abled students.

Second, this paper, as well as HW, emphasizes the role of cognitive skills in promoting economic prosperity. However, empirical evidence also sggest that high test scores result also from non-cognitive skills such as ambition, motivation and adequate personality traits.[21] While exploring the impact of these non-cognitive skills on economic development is beyond the scope of this study, we find it important for understanding the role of education in the process of development.

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AppendixA. Developing the Steady State for the Basic Model

In this Appendix we develop the steady states in the model presented in Section 2. Let us look at the dynamics of $\tilde{k}_t$. Dividing the physical capital formation equation by $A_t L_t$ yields:

$$\frac{K_{t+1}}{A_t L_t} = (1-\delta)\tilde{k}_t + s_K \cdot \tilde{y}_t, \tilde{y}_t \equiv \frac{Y_t}{A_t L_t} = \tilde{k}_t^{\alpha} h_t^{1-\alpha}. \tag{A1}$$

The LHS equals:

$$\frac{K_{t+1}}{A_t L_t} = \tilde{k}_{t+1} \left(1+\lambda\right) \left(1+n\right). \tag{A2}$$

Consequently, (A1) becomes:

$$\tilde{k}_{t+1} = \frac{(1-\delta)\tilde{k}_t + s_K \tilde{k}_t^{\alpha} h_t^{1-\alpha}}{(1+\lambda)(1+n)}. \tag{A3}$$

In the steady state, $\tilde{k}_{t+1} = \tilde{k}_t = \tilde{k}^*$, and (A3) becomes:

$$\tilde{k}^* = \left(\frac{s_K}{\lambda+n+\delta}\right)^{\frac{1}{1-\alpha}} h^*. \tag{A4}$$

Next, note that in the steady state, the cognitive skills is constant and equals:

$$h^* = \frac{\overline{h}}{1-s_H}. \tag{A5}$$

Substituting this expression into (A4) yields the value of $\tilde{k}^*$ as given in equation (4).

AppendixB. Generating Growth Rates Towards the Steady State

In this Appendix we log linearize the dynamic system around the steady state. In the first case, in which $s_H < 1$, output per worker is given by:

$$y_t = A_t \tilde{k}_t^{\alpha} \left(h_t\right)^{1-\alpha} = A_0(1+\lambda)^t \tilde{k}_t^{\alpha} h_t^{1-\alpha}. \tag{B1}$$

Let us assume that in period t the economy is in the steady state. Then (B1) becomes:

$$y_t = A_0(1+\lambda)^t \left(\frac{s_K}{n+\lambda+\delta}\right)^{\alpha} \frac{\overline{h}}{1-s_H}. \tag{B2}$$

Taking logs from both sides of (B2) yields:

$$\ln y_t = \ln A_0 + t\ln(1+\lambda) + \alpha \ln s_K - \alpha \ln(n+\lambda+\delta) + \ln \overline{h} - \ln(1-s_H). \tag{B3}$$

Subtracting $\ln y_0$ from both sides of the equation yields:

$$\ln y_t - \ln y_0 = \ln A_0 + t\ln(1+\lambda) + \alpha \ln s_K - \alpha \ln(n+\lambda+\delta) + \ln(\overline{h}) - \ln(1-s_H) - \ln(y_0). \tag{B4}$$

Dividing this equation by t, and using the approximation of $\ln(1+\lambda) = \lambda$ for small enough λ yields equation (6).

AppendixC. Robustness Checks for the Panel Data Analysis

Table C.1: Growth Rate vs. Level Effect Analysis Using 3 Year Lag of Cognitive Skills

	Annual GDP per Capita Growth					
	Growth Effect Alone		Level Effect Alone		Both Effects	
	(1)	(2)	(3)	(4)	(5)	(6)
χ	-0.02	-0.03			0.01	-0.01
	(0.03)	(0.03)			(0.03)	(0.03)
β			1.94***	1.27***	2.04**	1.10*
			(0.60)	(0.40)	(0.74)	(0.55)
α		0.31***		0.24***		0.25***
		(0.07)		(0.06)		(0.07)
$1-\beta$		-0.10		-0.10		-0.09
		(0.15)		(0.15)		(0.16)
Adjusted-R^2	0.00	0.22	0.14	0.25	0.13	0.25
Observations	104	104	104	104	104	104

Notes: Both levels and changes in cognitive skills are calculated with a 3 year lag. Standard error estimates clustered at the level of the country fixed effects are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests; All regressions include a constat.

Table C.2: Growth Rate vs. Level Effect Analysis Using a 6 Year Lag in Cognitive Skills

	Annual GDP per Capita Growth					
	Growth Effect Alone		Level Effect Alone		Both Effects	
	(1)	(2)	(3)	(4)	(5)	(6)
χ	-0.03*	-0.03*			-0.01	-0.02
	(0.02)	(0.01)			(0.01)	(0.02)
β			1.33***	0.86**	1.11**	0.55
			(0.42)	(0.34)	(0.41)	(0.35)
α		0.29***		0.25***		0.26***
		(0.07)		(0.07)		(0.07)
$1-\beta$		-0.09		-0.10		-0.09
		(0.16)		(0.15)		(0.16)
Adjusted-R^2	0.05	0.24	0.11	0.24	0.11	0.25
Observations	104	104	104	104	104	104

Notes: Both levels and changes in cognitive skills are calculated with a 6 year lag. Standard error estimates clustered at the level of the country fixed effects are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests; All regressions include a constat.

Table C.3: Growth Rate vs. Level Effect Analysis Using a 10 Year Lag in Cognitive Skills

	Annual GDP per Capita Growth					
	Growth Effect Alone		Level Effect Alone		Both Effects	
	(1)	(2)	(3)	(4)	(5)	(6)
χ	-0.01	-0.01			-0.01	-0.02
	(0.01)	(0.01)			(0.01)	(0.01)
β			0.13	-0.26	0.02	-0.49
			(0.34)	(0.31)	(0.37)	(0.31)
α		0.20***		0.21***		0.22***
		(0.06)		(0.07)		(0.06)
$1-\beta$		-0.06		-0.06		-0.02
		(0.15)		(0.14)		(0.14)
Adjusted-R^2	-0.00	0.11	-0.01	0.10	-0.01	0.11
Observations	91	91	91	91	91	91

Notes: Both levels and changes in cognitive skills are calculated with a 6 year lag. Standard error estimates clustered at the level of the country fixed effects are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests; All regressions include a constat.

Table C.4: Growth Rate vs. Level Effect Analysis in a Random Effects Model

	Annual GDP per Capita Growth					
	Growth Effect Alone		Level Effect Alone		Both Effects	
	(1)	(2)	(3)	(4)	(5)	(6)
χ	-0.01	-0.01			0.00	-0.00
	(0.01)	(0.01)			(0.01)	(0.01)
β			1.36***	0.87**	1.39***	0.83**
			(0.45)	(0.37)	(0.44)	(0.33)
α		0.31***		0.27***		0.28***
		(0.07)		(0.07)		(0.07)
$1-\beta$		-0.49***		-0.42***		-0.43***
		(0.11)		(0.11)		(0.12)
Adjusted-R^2						
Observations	104	104	104	104	104	104

Notes: Both levels and changes in cognitive skills are calculated with a 5 year lag. This table presents the estimates of a random effects model. Standard error estimates are reported in parentheses; *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level, all for two-sided hypothesis tests; All regressions include a constat.