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The Role of Cognitive Skills in Economic Development Revisited

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Abstract

Students' test scores at ages 9 to 15 are a measure of their skills as workers five to 55 years later. Using historic data on test scores and school attendance, I calculate the share of workers in 2005 that could have scored above 400 and above 600 in 45 countries. I find that the share above 400 and average schooling attainment cause national income, while the share above 600 and the share with post-secondary schooling do not. Implicitly the best long-term development strategy for poor countries is to increase the share of students who complete primary and secondary schooling.

JEL Codes: F43, I21, O11, O15

Key Words: World, Cognitive Skills, Human Capital, Education, Schooling, Economic Growth

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I. Introduction

Eric Hanushek has pioneered the use of students' average scores on international tests as a measure of nation's level of human capital. In conjunction with others he has used this measure to support his arguments that 1) a nation's average level of cognitive skill drives development, 2) both the share of students achieving a minimum level and the share reaching an advanced level contribute to growth, and 3) that it is this level of skill, rather than its average schooling attainment or the resources invested in schooling, that determines a nation's rate of growth. He has made this argument progressively in Hanushek and Kimko [2000], Jamison, Jamison, and Hanushek [2007], and Hanushek and Woessmann [2008 and 2009].

Hanushek and Woessmann (hereafter denoted HW) [2008] document that students' cognitive skills, as measured by test scores, are extremely low in developing countries, and they claim that schools in these countries do not raise students' cognitive skills "with sufficient regularity". They conclude that schooling policy in developing countries should change from a focus on schooling quantity (i.e, increasing coverage) to a focus on schooling quality, measured using standardized tests of students' skills.

HW's argument that the quality of a nation's schools determines economic development has considerable appeal. It seems obvious that students' mastery of relevant skills must be more important for a country's future development than the time students spend in school. And since students in poor countries score poorly on international tests, it seems reasonable to conclude that 1) the schools in these countries do not provide a quality education and 2) that the low quality of this schooling is preventing economic development.

But although HW's argument could be correct, Breton [2011] shows that the empirical evidence they present to support their argument is not valid. He points out that HW [2008] did not compare average test scores and average schooling attainment at the same point in time and that they used students' test scores from 1964 to 2003 to represent the cognitive skills of workers educated 45 years earlier. When he examines the relationship between these test scores, average schooling attainment and national income in 2000, he finds that differences in average schooling attainment explain differences in income better than differences in test scores. He also challenges HW's contention that low scores on tests necessarily mean that schools in developing countries are not educating students, since empirical studies consistently show that family characteristics are more important than school characteristics in explaining test scores.

But Breton's empirical findings are not definitive. Even though he used average test scores as a measure of workers' skills at a more appropriate date, these scores still do not represent the skills of workers who have little schooling. Since these workers are a large share of the adult population in developing countries, the test score measure of human capital is biased upward in these countries. In addition, Breton did not control for the endogeneity of schooling and average test scores, so the relationships he estimated cannot be considered causal.

HW [2009] provide additional tests to support the empirical results in HW [2008], including tests from different time periods and different levels of schooling. They also instrument their test score measures with institutional variables to control for endogeneity. They show that their earlier results are robust to these changes. HW [2011] show that the results in HW [2008] are not seriously biased due to sampling error in the student population.

But HW's more recent evidence does not address the principal deficiencies in their earlier analyses. Their additional empirical results still compare average schooling attainment and average test scores at different points in time. And they have not dealt with the principal problem with their test score data, which is that they are not representative of the skills of the work force.

In this paper I present the results of an analysis that remedies the deficiencies in the earlier analyses. First, I estimate the effect of test scores and average schooling attainment on income in 2005, so that the students' scores during 1964-2003 are more representative of the skills of the work force. Second, I use HW's [2008] estimates of the share of students that scored above 400 and 600, rather than average scores, as my measures of students' cognitive skills. Third, I convert these measures of students' skills to a measure of workers' skills by excluding the share of the population of working age in 2005 that was not in school long enough to have learned the skills evaluated on the tests. Fourth, I estimate the effect of these estimates of workers' skills on national income and use instruments for test scores and schooling attainment to control for endogenity.

Using these new measures I obtain estimates of the effect of test scores on national income that differ in important ways from HW's [2008 and 2009] and Breton's [2011] results. I find that the share of the work force with scores above 400 explains differences in national income very well, better than average schooling attainment and much better than students' average test scores. I also find that the share of the work force with scores above 600 has no relationship to national income. Subsequently, using instruments for these measures, I show that the share of the work force with scores above 400 and average schooling attainment cause national income and that students' average scores and the share of the work force with scores above 600 do not.

I then examine HW's conclusion that since cognitive skills are what matter, schooling policy in poor countries should change from a focus on quantity (coverage) to quality (test scores). I show that their conclusion is based on an incomplete analysis of the cognitive skills problem. They focused only on the student population aged 9 to 15, which in poor countries is a small fraction of the school age population, and they provided no evidence that children who are not in school can acquire the skills evaluated on international tests. I conclude that in the least educated countries the most reliable strategy for raising the cognitive skills of the work force is to increase the share of students who complete primary and secondary school.

The remainder of the paper is organized as follows: In section II I identify the fraction of the work force in 2005 that may have skills that correspond to the available test score data. I then present revised measures that are more representative of the capabilities of the entire work force. In Section III I present the income model used to estimate the effect of the various measures of human capital across countries. In section IV I estimate the income model in 2005 using the various human capital measures. In section V I examine the policy implications of the results. In section VI I conclude.

II. The Cognitive Skills of the Work Force

Scores on standardized tests are potentially a more accurate measure of human capital than schooling attainment because they measure the skills that students actually acquired inside and outside of school. In addition, test scores can provide information on the distribution of skills among students who have the same level of schooling.

But test scores also have their limitations. First, they measure skills that may not be representative of the human capital required for economic production. Second, they usually measure skills at a young age, so they do not include skills acquired in advanced schooling or on the job. Third, and most importantly, *they only represent the fraction of the population that was tested*. When the tests are conducted in schools, the scores only represent the fraction of the population that attends school, and they only represent this population if the students tested are a valid sample of the student population.

HW's measure of cognitive skills is the simple average of transformed mathematics and science scores over all the international tests of mathematics and science taken in each country by students between the ages of 9 and 15 during the period from 1964 to 2003. For some countries scores are available for the whole period, but for the majority, and particularly for countries with a less-educated population, scores are only available for the period between 1990 and 2003 [HW, 2009].

These scores do not measure the capabilities of the work force. Assuming that the typical individual begins work at age 20 and works for 40 years, an average score on a test of cognitive skills at age 9 is at best a rough indicator of an average student's capability to perform on the job 11 to 51 years later. Similarly, the average score on a test taken at age 15 would be an indicator of an average student's capability to perform 5 to 45 years later.

The implication is that for those countries with scores for the entire 1964-2003 period, if the scores over time are representative of the entire school age population and there is no growth in the population over the time period, then the average of these scores provides a measure of the relative human capital of the work force in about 2010. For countries with scores obtained only after 1990, the average of these scores is a rough measure of the relative human capital of the work force in about 2020.

These assumptions about the representativeness of the scores are at best only approximately correct. Rotberg [1998] has documented that in many countries the students tested in the international examinations are not representative of all students. Especially in the tests taken prior to 1990, in some countries only the better students participated. As a result, in the non-OECD countries, the average scores on international examinations are often an overestimate of the average student's level of skills. In addition, tests at age 9 to 15 do not measure skills acquired after age 15, and the population in more educated countries has a much higher share of workers with skills acquired after this age.

But the more serious sampling problem is that in countries that historically had low enrollment rates in primary and secondary school, a large share of the workers in 2010, or in 2020, are very unlikely to have skills comparable to the students previously tested at ages 9 to 15. As a consequence, the students' average test scores in these countries are an overestimate of the cognitive skills of the work force in 2010, or in 2020, and in most cases a very large overestimate.

HW [2008] analyzed the relationship between students' average test scores at ages 9 to 15 and the rate of economic growth from 1960 to 2000. Since the midpoint of this period is 1980, a reasonable test of whether the students' average scores are representative of the work force is to estimate the share of the work force in each country in that year that had any secondary schooling. Students without this schooling could not have been tested at ages 13 to 15 and are unlikely to have acquired the skills evaluated on tests at these ages.

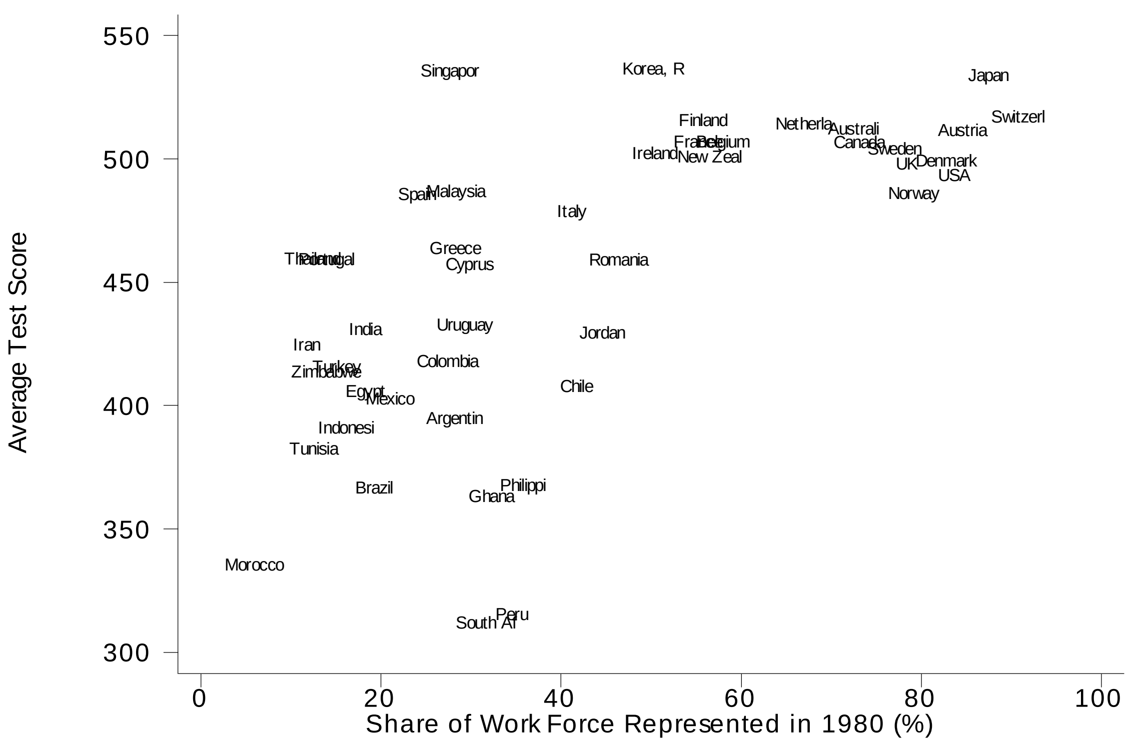
Cohen and Soto's [2007] data on the average schooling attainment of the population age 15 to 64 includes estimates of the share of the population over age 25 with primary, secondary, and post-secondary schooling and with no schooling in 1980 and 1990. These estimates can be used to calculate the share of the work force in 1980 that did not have any secondary schooling.

Using these data I calculated the share the population over age 25 in 45 countries that had no schooling or only primary schooling in 1985.[1] I use this share to represent the share of the population of working age in 1980 that did not have any secondary schooling. It includes the population over age 20 and excludes the fraction of the population in 1980 that did not survive until 1985. This excluded fraction is mostly the oldest share of the population that is likely to have been retired.

This calculation reveals that in these 45 countries, on average 57 percent of the work force in 1980 had no secondary schooling. Implicitly only 43 percent of the work force had remained in school until the ages of 13 to 15 when half of the test scores were obtained. More importantly, across these countries the share of the workers that had remained in school until these ages ranged from only six percent to 91 percent. These data are presented in Figure 1. Clearly in most countries HW's estimates of students' average test scores are not representative of the skills of the work force in 1980.

Figure 1

Average Test Scores and the Share of Workers in 1980 Represented by These Scores



[1] Cohen and Soto's data do not provide an estimate for 1985. I use the average of the shares in 1980 and 1990 for this estimate.

HW's average test scores are more representative of the work force in 2005 than in 1980, but in many countries they still are not very representative. Using the same methodology described above and Cohen and Soto's data for 2010, I estimated the share of the work force in 2005 that had no secondary schooling. These calculations indicate that on average about 35 percent of the work force in these 45 countries in 2005 still had no secondary schooling. In Morocco it was 80 percent, in India 70 percent, and in Greece and Spain 40 percent. Even in Sweden the workers without secondary schooling still comprised 15 percent of the work force. So in most countries HW's estimates of average test scores are still a substantial overestimate of the skills of the work force in 2005, and the degree of bias across countries is far from random.

These average scores cannot be adjusted to account for the workers who did not stay in school because it is impossible to estimate what their scores might have been if they had taken these tests. The scores on these tests are calibrated to maintain a score of 500 for comparable student achievement over time, and the variation in these scores is calibrated to provide a standard deviation of 100 points. There is no minimum score because the scores are imputed from an array of different tests taken by different students and the structure of these tests has varied over time [Martin and Mullis, 2012].

But there is another way to use the international test scores to measure a nation's cognitive skills. HW [2008] provide estimates of the share of students in each country that scored above 400 and above 600, one standard deviation below and above the standardized mean score of 500 in the highly-educated countries.

HW [2008] argue that these estimates are useful indicators of skill levels because 400 is considered a measure of basic literacy in the subjects tested and 600 is considered an indicator of exceptional performance. Importantly, the estimates of these shares in each country can be modified to account for the share of the work force that had no secondary schooling in 2005 by assuming that these workers would have had an average score below 400.[2] This is a very reasonable assumption for individuals who left school several years before the tests were given in secondary school. Even if these individuals scored above 400 at age 9, they would almost certainly have scored considerably below 400 at ages 13 to 15. As shown in HW [2008], in countries with low secondary school attendance, even the students who were in school at age 9 typically have low scores on these tests. The implicit average of these two scores at ages 9 and 15 for individuals who did not continue beyond primary school would almost certainly have been below 400.

[2] Thanks to Michael O. Martin and Ina V.S. Mullis, Executive Directors of TIMSS and PIRLS, for suggesting this method to create more representative test scores for countries with a large number of school drop-outs.

After adjusting HW's shares to account for the workers without secondary schooling, my estimates of the shares of the work force above 400 and above 600 are much lower than HW's estimates of the share of students scoring above these levels. As an example, HW estimate that in Morocco 35 percent of students score above 400, while my estimate for the work force is below 10 percent. They estimate that in Spain 80 percent of students score above 400, while my estimate for the work force is 50 percent. My reductions of their estimates considerably increase the difference in workers' skills between the most educated and the less educated countries.

Figure 2 shows the relationship between GDP/adult and HW's estimates of the share of students with scores above 400 in 45 countries. Figure 3 shows the same relationship with my estimates of these shares for the work force. In my estimates the correlation between national income and the share of the work force with scores above 400 is considerably higher than in HW's estimates, and this change has a large effect on the analysis of whether cognitive skills affect national income in section IV.

III. The Income Model and the Data Used in the Analysis

I use Mankiw, Romer, and Weil's [1992] augmented Solow model to estimate the effect of these measures of human capital (i.e., acquired skills) on national income:

(1) $$(Y/L)_{it} = (K/L)_{it}^{\alpha} (H/L)_{it}^{\beta} A_t^{(1-\alpha-\beta)}$$

In this model Y is national income, K is the physical capital stock, H is the human capital stock, L is the number of workers, and A is a common trend in world total factor productivity.

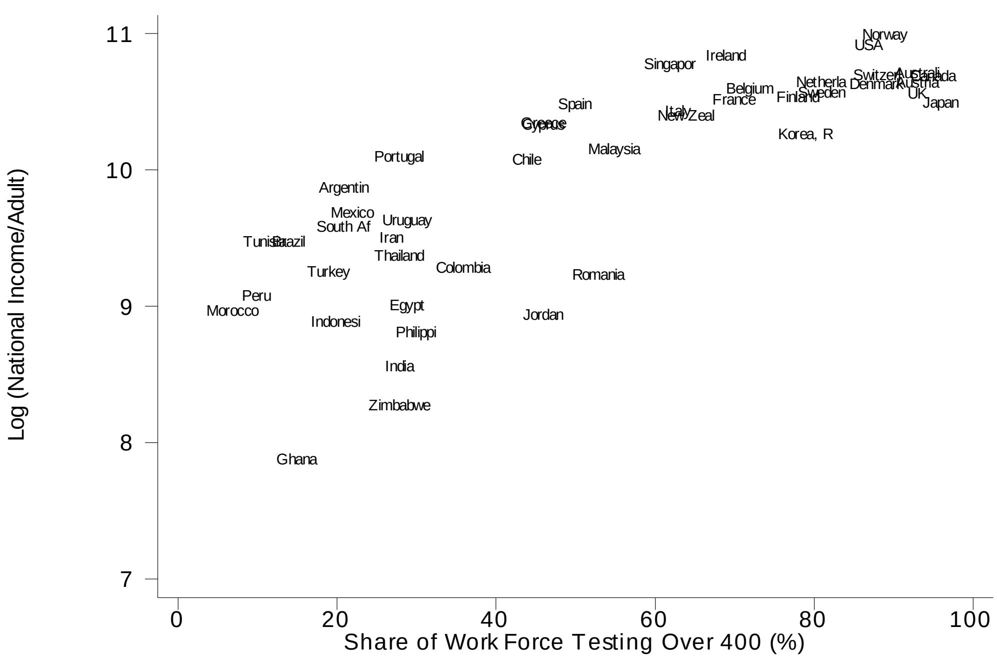
Breton [2012a] presents evidence that this model is a complete model of national income that does not omit any important national characteristics, and he demonstrates that its estimates of the effect of human capital are consistent with micro estimates of the effect of human capital on workers' earnings. This is the same model used in Breton [2011] to challenge HW's [2008] analysis.

Figure 2

National Income in 2005 and Share of Students with Scores Above 400

Figure 3

National Income in 2005 and Share of the Work Force with Scores Above 400



Given the high correlation between the stocks of physical capital and human capital and the greater measurement error in the measures of human capital, estimates of the income model in equation (1) tend to produce estimates of α that are biased upward and estimates of β that are biased downward. More accurate estimates of the effect of different measures of human capital are typically obtained using a reduced form of the model in which income is a function of the physical capital/output ratio (K/Y):

(2) $(Y/L)_i = (K/Y)_i^{\alpha/(1-\alpha)} (H/L)_i^{\beta/(1-\alpha)} A^{(1-\alpha-\beta)/(1-\alpha)}$

The data on average schooling attainment and average test scores cannot be used directly in the models in equations (1) and (2) because these data are not a linear proxy for the H/L variable in these models. The capital variables in the Solow model are capital stocks, which are financial measures created from cumulative investment over the relevant historic period. [Breton, 2012a] has shown that the relationship between the human capital stock and average schooling attainment is log-linear:

(3) $\beta \log(H/L) = \gamma$ attainment

The data in Figure 3 show that relationship between national income and the share of the work force with scores over 400 is approximately log-linear, so implicitly the relationship between the human capital stock and share of scores over 400 also is log-linear.[3] Taking the log of equation (2) and substituting these relationships into this equation yields:

(4) $\log(Y/L)_i = c_1 + (\alpha/(1-\alpha)) \log(K/Y)_i + \gamma/(1-\alpha)$ $\text{attainment}_i + \varepsilon_i$

(5) $\log(Y/L)_i = c_1 + (\alpha/(1-\alpha)) \log(K/Y)_i + \phi/(1-\alpha)$ $(\text{scores} > 400)_i + \varepsilon_i$

These mathematical relationships between income and schooling attainment or scores>400 are consistent with the standard Mincerian model of workers' salaries as a function of years of schooling [Krueger and Lindahl, 2001].

I estimate the regression models for 2005 using data for 45 of the 50 countries that HW [2008] used in their analysis. I excluded four of the countries because Cohen and Soto [2007] do not provide data for them. I also excluded China because the average test score is for Shanghai, which is not representative of the entire country. These 45 countries are those shown in the earlier Figures.

I estimated the (net) physical capital stock in these countries using the perpetual inventory method over the 1965 to 2004 period, annual investment rates, annual GDP/capita and population data, and a geometric depreciation rate of 0.06. OECD [2001] provides

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[3] I estimated the log-log relationship between income and test scores>400 and found that it is less statistically significant than a log-linear relationship.

documentation for this method. Caselli [2004] provides documentation for this depreciation rate. The average test score data are from HW [2009] and the student shares over 400 and 600 are from HW [2008]. I obtained Cohen and Soto's [2007] data on average schooling attainment data from Marcelo Soto. I averaged the schooling attainment data for 2000 and 2010 to create an estimate for 2005. The income measure is GDP/adult in 2005, calculated from data for GDP/capita (rgdpch) and GDP per equivalent adult (rgdpeqa) in Penn World Table (PWT) 6.3 [Heston, Summers, and Aten, 2009]. The annual rates of investment in physical capital (ki) are also from PWT 6.3. The data used in the analyses are presented in the Appendix. I used data from PWT 6.3 rather than PWT 7.0 because the historic data in PWT 6.3 appear to be more accurate for calculating physical capital stocks [Breton, 2012b].

One serious concern with the income models in equations (4) and (5) is that average schooling attainment and the various test score measures may be endogenous variables. These variables are predetermined in 2005, but across countries their value may be affected by a country's level of income, and if so, the OLS estimates of the coefficients on these variables could be biased in a cross-country regression.

Breton [2012a] uses the Protestant share of the population 20 years earlier as an instrument for the human capital stock in Mankiw, Romer, and Weil's income model. He provides extensive documentation that Protestant affiliation has been consistently correlated with the level of schooling across and within countries for centuries, evidently due to the Protestants' emphasis on literacy to enable their members to read the Bible. In addition, numerous researchers have rejected the hypothesis that Protestant affiliation affects national income through mechanisms other than schooling [Iannaccone, 1998]

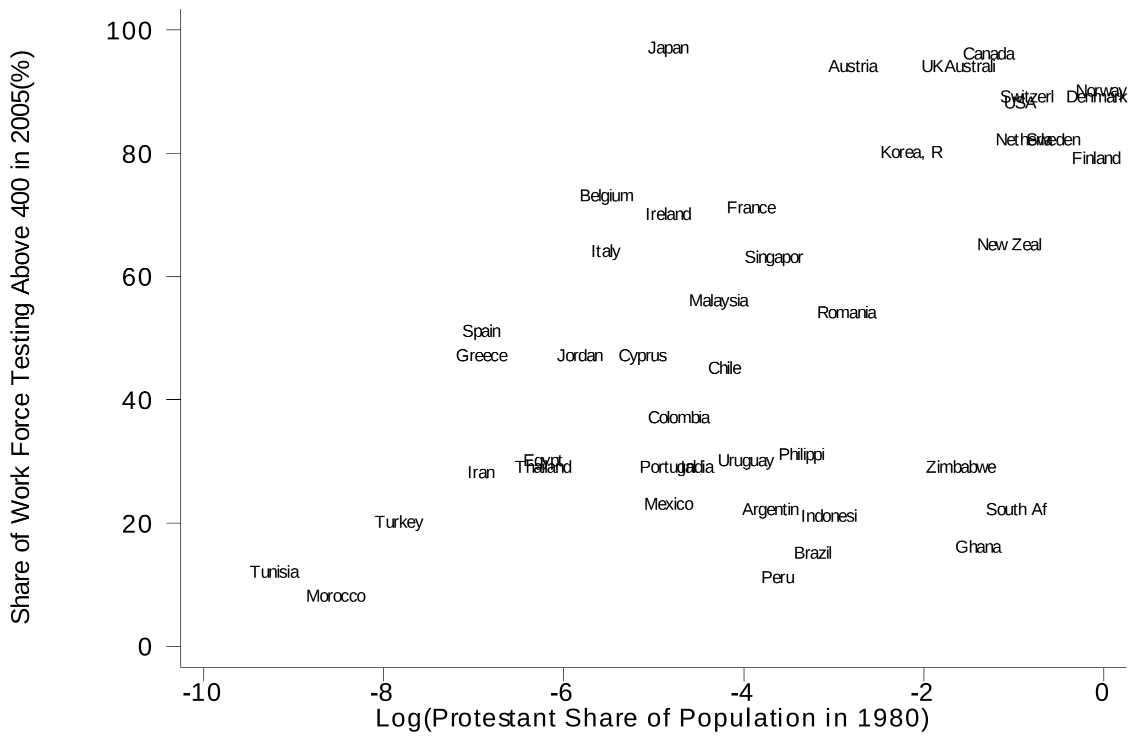
Figure 4 shows the relationship between the share of workers testing above 400 in 2005 and log(Protestant share) in 1980 for the 45 countries in the data set. The data in 1980 correspond to the mid-point of the period over which the 2005 work force obtained its schooling. The correlation between these two variables is 0.54. Since the models with two variables for human capital require two instruments, in my 2SLS estimates of the income model, I also include a country's latitude as a second instrument. Latitude is related to temperature, which has affected education through the influence of European colonial settlement and culture [Bolt and Bezemer, 2009]. I obtained the Protestant share data from Barrett [1982] and the latitude data from La Porta, Lopez-de-Silanes, Shleifer, and Vishny [1999]. The data are shown in the Appendix.

IV. Empirical Results

Table 1 presents the OLS estimates of the relationship between log(GDP/adult) and the various measures of human capital in 2005. The implied value of α, the effect of physical capital on national income, is shown to monitor whether its estimated value is acceptable in each model. In a valid augmented Solow model, α is physical capital's share of national income [Mankiw, Romer, and Weil, 1992]. Bernanke and Guynarak [2001] show that across countries this share is consistently about 0.35.

Figure 4

Share of Work Force Testing Above 400 and Protestant Affiliation



Columns 1 to 3 confirm Breton's [2011] results showing that when average schooling attainment is compared to students' average test scores, average schooling attainment explains more of the variation in national income and is more statistically significant. Columns 4 and 5 examine the relationships between national income and the share of students above 400 and the share of workers above 400. The coefficient on the share of students is positive and statistically significant at the 5% level. The coefficient on the share of workers is positive and statistically significant at the 1% level. The model with the share of workers above 400 provides a slightly better estimate of α (0.33 rather than 0.39) and explains much more of the variation in national income (0.71 vs. 0.59).

Column 6 shows the results when average schooling attainment is included in the model with the workers' share above 400. In this model the coefficient on the workers' share above 400 is smaller, but it remains statistically significant at the 5% level, while the coefficient on average schooling attainment is not significant and the explained variation in national income is unchanged. This result supports HW's claim that it is the cognitive skills of the work force that explain national income, not the time they spent in school.

Table 1
Effect of Test Scores and School Attainment on National Income in 2005
[Dependent variable is log(GDP/adult)]

	1	2	3	4	5	6	7	8	9	10
Technique	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Observations	45	45	45	45	45	45	45	45	43	45
Log(K/Y)	0.41 (.33)	0.51 (.24)	0.29 (.31)	0.64 (.34)	0.50 (.25)	0.47 (.25)	0.52 (.32)	0.51 (.27)	0.53 (.26)	0.51 (.25)
Average Test Scores/100	0.77* (.23)		0.40 (.23)							
Student Share>400				1.61 (.65)			0.98 (.62)			
Student Share>600							5.40 (2.98)			
Worker Share >400					1.69* (.33)	1.28 (.60)		1.73* (.39)	1.25* (.39)	1.49* (.31)
Worker Share >600								-0.28 (3.32)	4.59 (3.59)	
Avg School Attainment		0.18* (.04)	0.14* (.04)			0.06 (.06)				
Post-Second Share										0.72 (.77)
R^2	.64	.68	.71	.59	.71	.71	.63	.71	.73	.71
Implied α	.29	.34	.22	.39	.33	.32	.34	.34	.35	.34
Implied γ		.12								

*Statistically significant at the 1 percent level.
Note: Robust standard errors in parentheses

But a comparison of the results in columns 2 and 5 shows that average schooling attainment alone explains differences in national income almost as well as the share of workers above 400 (0.68 vs. 071). This result should not be surprising because the share of workers above 400 and average schooling attainment have a correlation coefficient of 0.92. Due to the methodology used to estimate the share of the work force scoring above 400, countries with a large share above 400 have a high level of average schooling attainment. If workers did not remain in school until age 15, by assumption they cannot have scored above 400.

Nevertheless, the difference in the empirical results between columns 2 and 5 is meaningful. If cognitive skills did not matter, the effect of the revised share of the work force with scores over 400 would be less statistically significant than the effect of average schooling attainment, and the model with the share of workers above 400 would explain less of the variation in national income.

Columns 7 to 9 examine the relationships between national income and the shares of students and workers above 600. In column 7 the estimated coefficients on the shares of students above 400 and above 600 are both positive but neither is statistically significant at the 5% level. In column 8 the estimated coefficient on the share of workers above 400 is positive and statistically significant at the 1% level, while the coefficient on the share above 600 is negative and not statistically significant. These results reject HW's [2008] findings that a high share of high performers positively affects national income.

Figure 5 shows the relationship between national income and the share of workers with scores above 600. South Korea and Japan have a larger share of high performers on the tests than other countries, but they do not have the highest national income. Students in these countries make an enormous effort, which includes intensive tutoring, to raise their test scores to gain access to elite schools [Dang and Rogers, 2008]. Although these efforts clearly raise their scores, it does not appear that this achievement contributes to economic output.

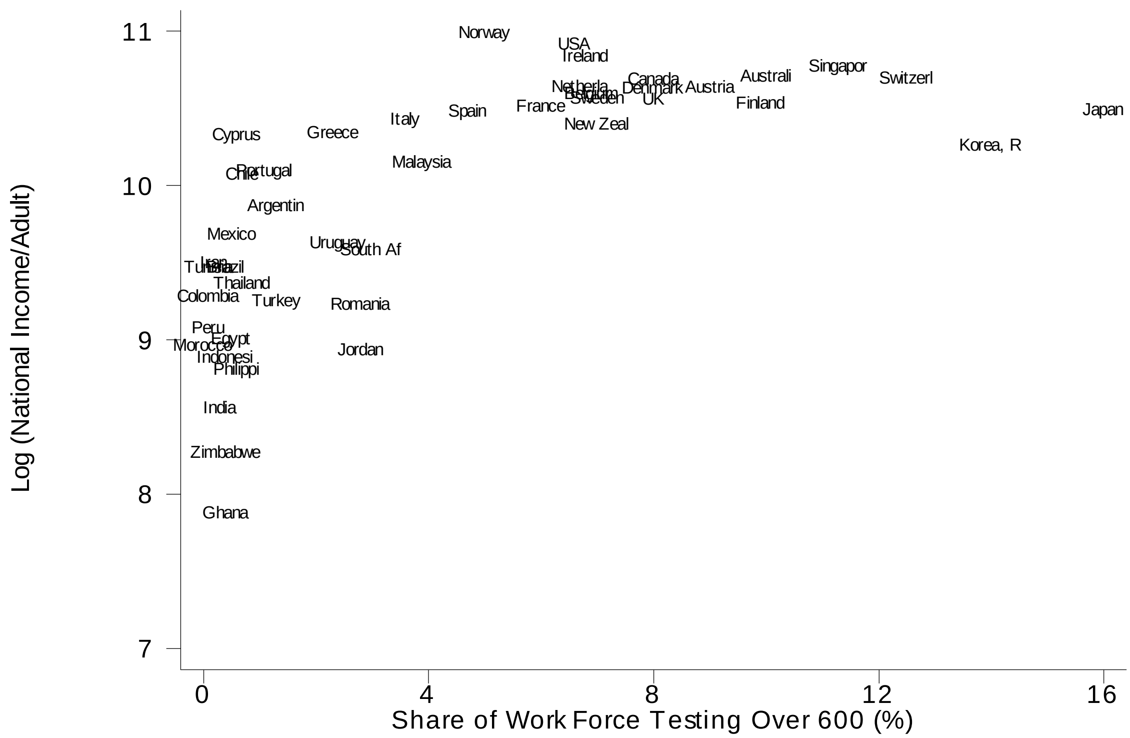
Column 9 shows the results for the same model when Japan and South Korea are removed from the data set. The coefficient on the share of workers above 600 becomes positive, but it is not statistically significant. Again the hypothesis that high performers on these tests raise national income is rejected.

In addition to their high share of scores above 600, Japan and South Korea students have an average score of 532, which is 32 points above the average international score on these tests. But while these scores are substantially above those in other countries, they are well within the increase in scores that normally accompanies continued secondary schooling.

Juerges and Schneider [2004] document that when 7th and 8th grade students took the same TIMSS 1995 test of mathematics, the 8th grade students scored 32 points higher. Fuchs and Woessmann [2006] document that when 9th and 10th grade students took the same PISA 2000 tests of science and mathematics, the 10th grade students scored 31 points higher. Woessmann [2003] estimates that, controlling for other factors, 8th grade students score 43 points higher than 7th grade students on the TIMSS 1995 tests of science and mathematics. He also estimates that when students in the final year of secondary school in Sweden and Switzerland took these same tests, they scored 103 points higher than students in 7th grade.

Figure 5

National Income and Revised Share of the Work Force with Scores Over 600



These examples indicate that students in Japan and South Korea score one year ahead of the international mean on international tests, but they also indicate that each additional year of schooling beyond ages 13 to 15 typically has a large effect on students' science and mathematics skills. It seems likely that the observed Japanese and South Korean advantage on these tests is temporary, so it does not affect national income.

In contrast, the graph in Figure 3 shows that increases in the share of the work force with scores above 400 contribute positively to economic output up to a share of 100%. The implication is that students who fail to achieve a basic literacy in mathematics and science skills at ages 9 to 15 never catch up, either because they do not continue in school or because they are too far behind to comprehend what is being taught in class.

A potential problem with using the share of workers above 400 as a measure of a country's human capital is that it does not account for skills learned after age 15. Column 10 examines whether schooling beyond this age has an additional effect on national income by adding the share of the working population with any post-secondary schooling to the model. With this addition the estimated coefficient on the share of workers above 400 declines slightly but remains statistically significant at the 1% level. The estimated coefficient on the post-secondary share is positive but not statistically significant, and overall the explained variation in national income is the same. These results indicate that the share of workers with scores above 400 fully captures the cognitive skills that workers acquire in post-secondary schooling. Implicitly the share of workers above 400 at ages 9 to 15 is a good predictor of the share that subsequently pursues more advanced schooling.

Table 2 presents 2SLS estimates of the same models shown in Table 1 to control for endogeneity bias. All of these models are estimated using log(Protestant share) and latitude as instruments for the various human capital measures. Columns 1, 3, 4, and 7 show the results using HW's estimates of the various student test score variables. The hypothesis that these measures cause national income is rejected in all of these models because the estimated coefficient on physical capital is consistently negative.

In contrast, the 2SLS effects of average schooling attainment and the share of workers with scores above 400 on national income in the various models are consistent with the OLS results. The model with the share of workers above 400 provides the best results. In this model the estimated coefficient is positive and statistically significant at the 1% level, and the implied value of $\alpha = 0.35$, which matches physical capital's average share of national income.

As in the OLS results, the share of workers above 400 and average schooling attainment are very similar in their capability to explain income variation in the 2SLS results. But again the model with the share of workers above 400 explains a slightly larger share of the variation in national income. And again when both measures are in the same model (column 6), the share of workers above 400 provides conceptually and statistically superior results.

As in the OLS results, the hypothesis that the share of workers above 600 affects national income is rejected in the 2SLS results. The estimated coefficient on this variable is negative with and without Japan and South Korea in the model. The hypothesis that the share of the work force with post-secondary schooling has an additional effect on national income also is rejected.

The clear conclusions from these two sets of results and the consistently higher average test scores for students with more secondary schooling are 1) raising the share of the work force who previously scored above 400 at ages 9 to 15 raises national income and 2) raising the share of the school age population that remains in school through age 15 is required to attain a high share of workers with this level of cognitive skills.

Table 2
Effect of Test Scores and School Attainment on National Income in 2005
[Dependent variable is log(GDP/adult)]

	1	2	3	4	5	6	7	8	9	10
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Observations	45	45	45	45	45	45	45	45	43	45
Log(K/Y)	-0.56 (.80)	0.63* (.21)	-1.76 (2.90)	-0.31 (.60)	0.54 (.25)	0.59 (.37)	-0.34 (.79)	0.90 (.45)	0.74 (.43)	0.31 (1.44)
Average Test Scores/100	1.76* (.65)		3.80 (4.41)							
Student Share>400				4.58* (1.52)			5.96 (3.85)			
Student Share>600							-6.8 (14.5)			
Worker Share >400					1.59* (.34)	4.44 (2.08)		3.98 (3.31)	4.87 (5.79)	9.0 (22.0)
Worker Share >600								-23.2 (28.8)	-30.0 (47.7)	
Avg School Attainment		0.15* (.04)	-0.23 (.44)			-0.33 (.24)				
Post-Second Share										-25.5 (74.1)
R^2	.39	.67	na	.25	.71	.48	na	na	.12	na
Implied α	-.23	.39	-.64	-.24	.35	.37	-.25	.47	.43	.24
Implied γ		.11								

*Statistically significant at the 1 percent level.
Note: Robust standard errors in parentheses

Table 3 presents the first stage regressions for the various measures of human capital. In these regressions the coefficient on the instrument log(Protestant share) is statistically significant at the 1% or 5% level for all of the measures. The share of workers scoring above 400 has an estimated coefficient on latitude that is significant at the 5% level. These results indicate that these two variables are valid instruments for the human capital measures.

V. Policy Implications

These empirical results indicate clearly that increasing the share of the population with scores above 400 at ages 9 to 15 raises national income when these students subsequently enter the work force. This share can be increased by 1) raising the share of students that remain in school until age 15 and 2) by raising the scores of the students that remain in school.

Table 3
First Stage Regressions for Human Capital Measures

	1	2	3	4	5	6	7
Measure	Avg Test Scores	Students > 400	Students > 600	Workers > 400	Workers > 600	School Attain	Post-Sec Share
Observations	45	45	45	45	45	45	45
Log(K/Y)	0.84* (.18)	0.25* (.06)	0.05* (.02)	0.25* (.07)	0.045* (.016)	2.57* (.62)	0.07 (.03)
Log(Protestant Share)	0.04 (.02)	0.013 (.007)	0.005* (.002)	0.05* (.01)	0.006* (.001)	0.50* (.09)	0.015* (.005)
Latitude	0.50 (.50)	0.24 (.17)	0.01 (.05)	0.48 (.19)	0.024 (.035)	2.36 (1.38)	0.11 (.09)
R^2	.63	.56	.47	.68	.52	.71	.37

*Statistically significant at the 1 percent level.
Note: Robust standard errors in parentheses

HW [2008] argue that schooling policy in developing countries should shift its focus from quantity (coverage) to quality (test scores). But their own summary of the literature indicates that in countries with low primary and secondary enrollment rates, this is not a promising development strategy. They state that most of the efforts undertaken to improve student achievement in developing countries have been unsuccessful.

Woessmann [2003] analyzed the relationship between TIMSS 1995 student test scores in science and mathematics at age 13 and factors potentially affecting these scores in 39 countries. He found that most of the differences in average scores between countries were due to family characteristics (education and wealth) and to the institutional characteristics of national education systems. These characteristics are very difficult to change through policy interventions.

In contrast, governments are capable of increasing the share of the population of student age that enters and stays in school. There are many ways to do this, and particularly in recent years, most countries have successfully increased enrollment rates in primary and secondary school. Even if the share of students scoring over 400 at ages 9 to 15 does not change, the future share of the work force with scores over 400 will increase if more students remain in school. In addition, since student scores are affected by the education of their parents, keeping students in school longer is the first step in raising the cognitive skills of the next generation.

VI. Conclusions

There is considerable evidence that human capital plays an important role in economic development. Hanushek and Woessmann [2008] have argued that it is the cognitive skills of the work force that drive this development, not average schooling attainment. In this study I examine whether average schooling or measures of students' or workers' cognitive skills better explain the differences in national income across countries.

I begin by estimating the share of the work force that previously scored above 400 and above 600 at ages 9 to 16 on international tests of science and mathematics. I find that the share of workers that scored above 400 and average schooling attainment cause national income, while average test scores and the share of workers that scored above 600 do not. I also find that the share that scored above 400 explains income differences across countries slightly better than average schooling attainment. But these two measures have a correlation coefficient of 0.92, implying that workers obtain scores above 400 by previously remaining in school until age 15.

In addition, there is ample evidence that students' cognitive skills, as measured by test scores, continue to increase if they stay in school until the end of secondary school. As a result, it is clear that a nation's level of cognitive skills is largely determined by its average level of schooling attainment. Given the difficulty of raising the test scores of existing students in poor countries, these findings indicate that the most reliable strategy for raising the share of the work force with scores above 400 is to increase the share of the school age population that remains in primary and secondary school.

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Appendix

Table A-1
Data Used in the Analysis

Country	TestSc	School	GDP/A	Cap/A	St>400	Wk>400	St>600	Wk>600	PostSec	ProtSh	Lat
Argentina	3.920	8.55	18478	28067	0.49	0.21	0.030	0.013	0.089	0.025	0.378
Australia	5.094	13.17	42755	104082	0.93	0.93	0.100	0.100	0.251	0.227	0.300
Austria	5.089	11.57	39826	114654	0.93	0.93	0.090	0.090	0.162	0.062	0.524
Belgium	5.041	11.13	38313	106596	0.93	0.72	0.090	0.069	0.249	0.004	0.561
Brazil	3.638	7.85	12417	15641	0.35	0.14	0.010	0.004	0.114	0.040	0.111
Canada	5.038	13.19	41996	94158	0.95	0.95	0.080	0.080	0.510	0.280	0.667
Chile	4.049	10.36	22688	33497	0.62	0.44	0.010	0.007	0.159	0.015	0.333
Colombia	4.152	7.47	10278	10657	0.64	0.36	0.001	0.001	0.146	0.009	0.044
Cyprus	4.542	9.30	29349	71613	0.82	0.46	0.010	0.006	0.099	0.006	0.389
Denmark	4.962	12.26	39595	102287	0.88	0.88	0.080	0.080	0.236	0.938	0.622
Egypt	4.030	7.40	7808	4787	0.57	0.29	0.010	0.005	0.106	0.002	0.300
Finland	5.126	11.98	36016	99839	0.95	0.78	0.120	0.099	0.286	0.925	0.711
France	5.040	11.04	35276	88931	0.93	0.70	0.080	0.060	0.214	0.020	0.511
Ghana	3.603	5.45	2518	1265	0.41	0.15	0.010	0.004	0.007	0.250	0.089
Greece	4.608	10.32	29742	77203	0.79	0.46	0.040	0.023	0.201	0.001	0.433
India	4.281	4.83	4980	4626	0.92	0.28	0.010	0.003	0.066	0.011	0.222
Indonesia	3.880	7.62	6913	8634	0.46	0.20	0.010	0.004	0.068	0.048	0.056
Iran	4.219	6.00	12783	23452	0.72	0.27	0.005	0.002	0.056	0.001	0.356
Ireland	4.995	10.38	48718	101554	0.91	0.69	0.090	0.068	0.230	0.008	0.589
Italy	4.758	10.68	32406	103127	0.87	0.63	0.050	0.036	0.124	0.004	0.472
Japan	5.310	12.86	34533	133304	0.96	0.96	0.160	0.160	0.303	0.008	0.400
Jordan	4.264	10.23	7273	8032	0.66	0.46	0.040	0.028	0.305	0.003	0.344
Korea, Rep.	5.338	12.84	27287	88384	0.96	0.79	0.170	0.140	0.335	0.119	0.411
Malaysia	4.838	9.77	24588	33007	0.86	0.55	0.060	0.039	0.095	0.014	0.026
Mexico	3.998	8.19	15352	27948	0.48	0.22	0.010	0.005	0.142	0.008	0.256
Morocco	3.327	4.04	7497	8725	0.35	0.07	0.001	0.000	0.076	0.000	0.356
Netherlands	5.115	11.42	39980	98314	0.96	0.81	0.080	0.067	0.238	0.418	0.581
N Zealand	4.978	12.29	31287	67056	0.91	0.64	0.100	0.070	0.399	0.355	0.456
Norway	4.830	12.60	56863	143250	0.89	0.89	0.050	0.050	0.262	0.976	0.689
Peru	3.125	8.67	8366	11940	0.18	0.10	0.001	0.001	0.202	0.027	0.111
Philippines	3.647	8.28	6380	7139	0.48	0.30	0.010	0.006	0.200	0.035	0.144
Portugal	4.564	7.59	23185	75425	0.8	0.28	0.030	0.011	0.091	0.008	0.437
Romania	4.562	10.50	9761	29363	0.77	0.53	0.040	0.028	0.140	0.058	0.511
Singapore	5.330	10.50	45778	128041	0.94	0.62	0.170	0.113	0.298	0.026	0.014
S Africa	3.089	8.09	13901	10557	0.36	0.21	0.050	0.030	0.106	0.386	0.322
Spain	4.829	9.89	34093	98613	0.85	0.50	0.080	0.047	0.217	0.001	0.444

Sweden	5.013	11.92	37119	79113	0.93	0.81	0.080	0.070	0.272	0.574	0.689
Switzerland	5.142	12.65	42257	142869	0.92	0.88	0.130	0.125	0.216	0.429	0.522
Thailand	4.565	8.01	11175	28358	0.85	0.28	0.020	0.007	0.183	0.002	0.167
Tunisia	3.795	4.82	12425	14717	0.45	0.11	0.003	0.001	0.072	0.000	0.378
Turkey	4.128	6.57	9968	16114	0.58	0.19	0.040	0.013	0.065	0.000	0.433
UK	4.950	13.23	36901	72414	0.93	0.93	0.080	0.080	0.233	0.150	0.600
Uruguay	4.300	8.67	14571	21503	0.61	0.29	0.050	0.024	0.145	0.019	0.367
USA	4.903	12.94	52670	112635	0.92	0.87	0.070	0.066	0.445	0.400	0.422
Zimbabwe	4.107	8.56	3734	10098	0.68	0.28	0.010	0.004	0.072	0.206	0.222