# Cross-Country Differences in the Quality of Human Capital*

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**Abstract**

This paper constructs a new measure of the quality of years of schooling based on international test scores. The main finding is that there are large cross-country differences in the effectiveness of one year of schooling - one year of schooling in the U.S. is equivalent to three or more years of schooling in a number of low-income countries. The quality measure is then used in a development accounting exercise. This leads to a second important finding which is that although quality differences are large, they only imply a moderate increase in our understanding of world income differences. A third important result is that, because of the complementarity of quality and quantity of human capital, an increase in either years of schooling or quality of schooling alone will only equalize world income differences minimally. Thus, policy reforms aimed at increasing human capital levels in developing countries should focus on both areas.

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# 1 Introduction

How important is human capital in determining income per capita? Most of the literature on development accounting (e.g. Hall and Jones (1999), Caselli (2005)) agree that human capital is an important determinant of income, but that the lion's share of the gap in income between poor and rich countries is not attributable to differences in human capital or physical capital endowments. Instead, the main cause of the world income differences lies in differences in a residual productivity term which remains unexplained. However, recent work by Hanushek and Woessman (2009) and Manuelli and Seshadri (2006) suggest that the role of human capital may be under appreciated. The central charge is that the literature hitherto has has ignored differences in human capital quality.

In the development accounting literature, the human capital stock is usually computed using average years of schooling as the only input. Thus, this approach implicitly assumes that one year of schooling is equally productive everywhere. This paper challenges this assumption by allowing schooling quality to differ across nations. One year of education in Ghana does not result in the same amount of learning and thus human capital as one year of education in the U.S.

This could potentially have ramifications for the ability of human capital stocks to motivate income per capita differences. In particular, one might expect that in a country with low education quality the average years of schooling will tend to be low as well; including the quality of schooling may thus increase the variation in human capital stocks, and therefore enhance the model's ability to account for per capita income differences.

The main contribution of this paper is to construct a cross-country series for the quality of education using data on international test scores. In this paper, the quality of education (or quality of human capital) is defined as all factors which affect education outcomes besides years of schooling. These factors could be parental human capital, institutions, health of children, quality of schools - the list of possible determinants is extensive. There is no attempt, in this paper, to quantify the contributions of each different factor. Rather, the quality measure estimated below is a single number encompassing all of these factors.

The basic approach is to assume that tests scores are produced using a combination of years of schooling and quality of schooling in a specific functional form. A cross-section series for the quality is then estimated jointly with production function parameters. The main finding is that differences in human capital quality are large. For example, four years of education in Yemen correspond to one year in the U.S.

A limitation of using test scores data is that it is only available for 65 countries and most of these are high-income countries, which means that the same holds for the estimated quality series. This is a problem if the estimates are to be used in e.g. cross-country analysis of income per capita differences since the countries are not representative of the world. To solve this problem a number of variables are found which are highly correlated to the quality data, and which are available for 174 countries. These variables can then be used to extend the sample by generating a proxy measure for the countries where test score data is not available.

The next step is to incorporate the quality data in a development accounting framework to investigate the importance of quality differences for income per capita differences. The main finding is that accounting for differences in the quality of education only increases the fraction of explained income differences by a moderate amount.

However, the paper has a third, important conclusion: A reform which increases the years of schooling does not increase the human capital stocks a lot if it is not accompanied by an increase in the quality of human capital. Reforms aiming at reducing world income differences by increasing the human capital of low-income countries should therefore focus on both the quantity and the quality of human capital. In particular, the Millenium Goals set by the United Nations aim at providing a primary education for all children by 2015, and focuses singlehandedly on the quantity of education. While this may be convenient in terms of measurement and policy evaluation it is likely that it will not be very effective at reducing world income differences.

The paper proceeds as follows. The next section defines human capital quality and discusses the literature. Section 3 estimates the quality of human capital. In section 4, these estimates are used in a development accounting exercise. Section 5 checks the results for robustness to selection of more able students. The final section concludes.

# 2 The concept of human capital quality and related literature

There are several ways to think of the quality of human capital, and it is important to establish which definition to follow before we delve into the main section. Traditionally, in the development accounting literature, the human capital stock is constructed using only years of schooling - a variable which is relatively easy to define and measure. Defining the quality of education, however, is less straightforward. Clearly, better schools, more books and better teaching methods improves the effectiveness of learning. But imagine a new type of knowledge is discovered which replaces old knowledge. An example is the notion that the earth is round. Should this be counted as an increase in quality of education?

According to the definition used in this paper, the answer is no. I will distinguish between technological advance and changes in the quality of human capital. Technology is the total amount of knowledge which can be learned at a given point in time - *what* there is to be learned. The quality of education measures the effectiveness of learning - *how fast* knowledge is aquired. Thus, the notion that the world is round would not be counted as an increase in the quality of education but as a technological advance. This definition implies that the quality of education is always defined relative to the present technological level. The type of knowledge learned in Harvard in 1950 is probably not worth a lot in todays labour market. But this is mostly because students in a school in 1950 did not learn a lot about computers and other important modern technologies. It might still have been a good school in 1950 in the sense that Harvard graduates were up to date with the technological frontier as it was back then.

With this definition in our hands it is useful to look at how other scholars view and define the quality of education. To my knowledge no other papers have produced cross-country data on schooling quality using international test scores. However, two recent studies do generate human capital stocks incorporating the quality of human capital.

Manuelli and Seshadri (2006) set up a model where quality and quantity of human capital are endogenously chosen. The model is calibrated to match U.S. data and is then used to produce human capital stocks for a number of countries. The exogenous variables which generate different choices of quality and quantity and hence stocks of human capital are the retirement age, the fertility rate, life expectancy and total factor productivity[1]. Using data on the first three of these variables and the calibrated model they generate human capital stocks and show that human capital and physical capital accounts for a very large share of income differences. They also show that differences in the quality of human capital are crucial for explaining the variation in income. The method used relies heavily on theory and is very different from the one used in this paper. It is difficult to compare the two, but an important difference lies in the definition of quality of human capital. In Manuelli and Seshadri (2006), human capital quality is

[1] In a revised version of Manuelli and Seshadri (2006), Manuelli and Seshadri (2009) endogenize fertility but basically use the same methodology.

determined by early childhood investments, market goods and human capital. This implies that human capital is perpetually reinforcing itself - with investments today feeding into human capital tomorrow. In principle this process can continue unlimited. Under the definition used in the present paper the quality of human capital is bounded above. The physiological capacities of the brain will simply put an upper bar to the effectiveness of learning. Limitless increases in the quality of human capital are hard to imagine unless one uses a broad definition encompassing technological change.

Hendricks (2002) also examines the significance of human capital quality in accounting for differences in labour productivity. He assumes that average human capital is an aggregate of the human capital stocks of different skill groups. The human capital stock of each skill group is then quantified using wage differentials. To quantify quality differences he uses immigrant wage data. The idea is that since the skills of workers are evaluated at the same labour market, differences in wages between two workers of the same skill level can be attributed to differences in the quality of human capital. Thus, the human capital stocks of two countries may differ for two reasons: 1. because the composition of skill groups is different (the quantity of human capital differs) 2. because the efficiency within each skill group is different (the quality of human capital differs). Contrary to Manuelli and Seshadri (2006) his results are in the same ballpark as the standard finding in the literature: over half of the variation in income remains unexplained.

A number of other papers do not estimate the quality of human capital directly, but are related to this paper in other ways. Hanushek and Kimko (2000) note that international test scores are highly correlated to growth rates in income per capita and that this correlation survives the inclusion of several other prominent correlates of growth. However, as Hanushek and Kimko (2000) point out, their OLS results may not capture the causal impact of human capital quality on growth. Hanushek and Woessman (2009) attempt to solve this issue by using a set of institutional determinants to instrument for the quality of education, and find a strong causal impact close to the OLS estimate. Still, the required exclusion restriction questionable[2]. In his handbook chapter, Caselli (2005) incorporates international test scores directly into the measure of human capital, and finds that this does not increase the fraction of explained income differences markedly. Weil (2007) looks into another aspect of human capital, namely health. He accounts for the causal effect of

[2] Hanushek and Woessman (2009) use as instruments several institutional features of the education system such as existence of external exit exams systems, the share of privately owned schools and centralization of decision-making. It is likely that these variables are correlated with other institutional variables which might affect the growth process.

health on income and finds a considerably lower effect than studies which only measure the cross-country correlation. The method of using proxy variables to extend the data used in this paper is also borrowed from Weil (2007).

# 3 Estimating the quality of human capital

This section falls in four subsections. The first subsection presents the data. The next presents the methodology. The third subsection contains the main estimation results, while the final subsection expands the estimated human capital quality data to a larger number of countries.

## 3.1 The data

Trends in Math and Science Study (TIMSS) is a series of science and math tests conducted in schools in a number of countries in the years 1995 to 2007 by the International Association for the Evaluation of Educational Achievement (IEA). In each of the years 1995, 1999, 2003 and 2007, four tests - one science and one math test in primary school, one math and one science test in secondary school - were administered in a varying number of countries[3]. In the following these four classifications will be denoted as *test types*.

Great care was taken in constructing the tests so that they matched an international curriculum, and the tests were randomly assigned to a large number of students in each country (ususally over 5000 students per test). In 1995, the same test was given to different grades which will prove to be invaluable in the estimation of the quality of education.

In all of the TIMSS programs, each student is given a multiple choice test where the answers are ranked according to correctness. The grading of the tests is done separately for each test type, and is based on item responce theory (IRT) which is an intricate method used to convert answers into a test score. This conversion method is designed so that the resulting test scores are placed on a certain predetermined metric. In TIMSS, it is decided that the pooled sample of test scores from students of all countries in 1995 should have a mean of 500 and a standard deviation of 100. A detailed description of the method is given in Chapter 11 of TIMSS (2007).

[3] In 1999, tests were only given to 8th graders.

Even though different tests were constructed from year to year some of the questions were repeated, which allows the IEA to temporally link the scaling of test scores such that all of the scores are placed on the 1995-metric. This way, the test scores are actually compatible with the quality definition given in the previous section. Over time, technology advances causing new knowledge to replace old knowledge in the curriculum. The repeat questions are "core knowledge" which are an important part of the curriculum in all periods. Those questions thus serve as a measuring stick, allowing the quality to be compared over time. Thus, test scores are comparable over time but not between test types.

Table 1 gives an overview of the availibility of the data. All of the test scores data used in the following are country averages. The maximum number of participating countries in one type of test is 46 (secondary math test, 2007), and the total number of countries which participated in at least one test is 65.

| | Test type | Math primary | | Science primary | | Math secondary | | Science secondary | |
|---|---|---|---|---|---|---|---|---|---|
| | Grade | 3 | 4 | 3 | 4 | 7 | 8 | 7 | 8 |
| Year | Publication | | | | | | | | |
| 1995 | TIMSS (1997a,b) | 25 | 25 | 25 | 25 | 38 | 38 | 38 | 38 |
| 1995 | TIMSS (2008) | 0 | 25 | 0 | 25 | 0 | 38 | 0 | 38 |
| 1999 | TIMSS (2008) | 0 | 0 | 0 | 0 | 0 | 22 | 0 | 21 |
| 2003 | TIMSS (2008) | 0 | 20 | 0 | 20 | 0 | 31 | 0 | 30 |
| 2007 | TIMSS (2008) | 0 | 35 | 0 | 32 | 0 | 46 | 0 | 43 |

Table 1: Availibility of TIMSS test scores data. The table shows the number of participating countries for each test type and each year.

As shown in the table, the data is collected from two different sources, TIMSS (1997a,b) and TIMSS (2008). The TIMSS (2008) publication includes test score data from 1995 but only for the 4th and 8th grade, not for the 3rd and 7th grade. Fortunately, TIMSS (1997a,b) contain test scores from 1995 for all four test types and all four grades. However, the test scores for the 4th and 8th grades from TIMSS (1997a,b) are not directly comparable with the test scores for the corresponding grades and test types from TIMSS (2008). Although the scores are based upon the same underlying test answers, the tests are scaled differently. In TIMSS (1997a,b), the mean and standard deviation of the pooled sample of both grades of a particular test type are set to 100 and 500, respectively. For example, all the secondary science test answers given to 7th and 8th graders in all countries are pooled, and the scaling of this test type is chosen such that the moments of the pooled distribution reach the above mentioned values. In TIMSS (2008) the data is scaled slightly differently. The scaling is still chosen such that the mean and standard deviation of the grades of a particular test type are 500 and 100, respectively, but all tests given to students in 3rd and 7th grade are excluded. Even though the test scores data from the two different data sources are not directly comparable it is possible to rescale the TIMSS (2008) data using a simple linear method.

Details of the rescaling are given in the appendix. In the end, we have 544 observations from 65 countries which are fully comparable across countries and time.

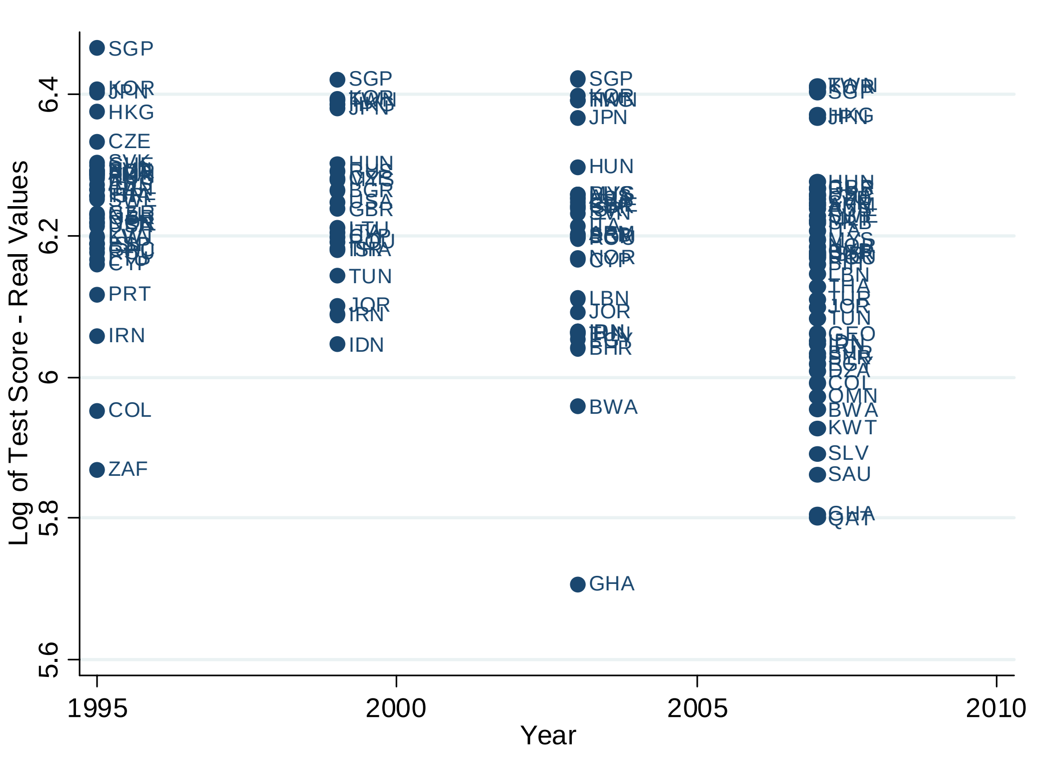


**Figure 1:** Rescaled TIMSS test scores for mathematics in 8th grade.

Figure 1 shows the rescaled test scores over time for the period 1995-2007 for mathematics tests of 8th graders. At the high end of the spectrum we find East Asian countries such as Korea, Japan and Singapore. The Western industrialized countries lie in the middle, while low-income countries such as Colombia, South Africa and Ghana are amongst the countries with the lowest test scores; the picture for the other test types is very similar.

### 3.2 The model and the empirical specification

Assume that the test score $T_{k,i,s,t}$ of test type $k$, country $i$, grade $s$ and in year $t$ is "produced" using:

$$T_{k,i,s,t} = f\left(s \times q_i, \Gamma_k\right), \tag{1}$$

where $q_i$ is the quality of years of schooling, and $\Gamma_k$ is a vector of parameters. Thus, $T_{msec,US,8,2003} = f\left(8 \times q_{US}, \Gamma_{msec}\right)$ is the 8th grade math test score of the U.S. in 2003. It is produced with 8 years of schooling and the quality of U.S. education as input and the production function parameters are those of the math secondary schooling test type.

Below I will assume a specific functional form for (1) and estimate $q_i$ and $\Gamma_k$ jointly using the test scores data. Note, that $\Gamma_k$ vary by test type since test scores cannot be compared across types, but it is constant over countries since, for each year, the same test was given to all countries. It is also constant over time since the test scores from year to year are comparable. Thus, cross-country differences in test scores can only come from differences in $s$ and $q_i$. It is reasonable to think of $q_i$ as the general level of the quality of human capital in the years 1995-2007, hence $q_i$ is restricted to be constant over time and test types. Indeed, in the estimation below, it turns out that the standard deviations of all estimated $q_i$'s are low, so this seems like a reasonable assumption. $f(\cdot)$ is, of course, increasing in inputs $s \times q_{k,i,t}$. Another reasonable prior would be that $f'(\cdot)$ is decreasing in $s \times q_{k,i,t}$. A justification for this statement is that there is a cognitive limit to how much knowledge the human brain can process, implying that the marginal product decreases as inputs increase[4]. However, decreasing returns are not a necessary precondition for the estimation. Rather, the results below confirms this prior.

A functional form which potentially satisfies these assumptions and turns out to provide a good fit is:

$$T_{k,i,s,t} = \beta_k \left(s \times q_i\right)^{\gamma_k}, \tag{2}$$

where $\beta_k$ and $\gamma_k$ are a scaling parameter and an elasticity parameter, respectively.

[4] One could argue that increasing the quality of education by learning 'better' or more correct knowledge (i.e. the notion that the earth is flat vs. the notion that the earth is round) does not necessarily put a strain on the physiological capabilities of the human brain. However, according to the definition given in Section 2, this is considered a technological advancement and not an increase in $q$.

A convenient way to estimate (2) is to use the following empirical specification:[5]

$$\ln T_{k,i,s,t} = \eta_{0,k} + \eta_{1,k}\left[\tilde{s} + \sum_{j\in J} D_{ji}\ln \eta_{2,i}\right] + e_{k,i,s,t}, \tag{3}$$

where $\eta_{0,k} = \ln \beta_k$, $\eta_{1,k} = \gamma_k$, $\tilde{s} = \ln s$, $D_{ij}$ is a country dummy which is one if $j = i$, $J$ is the set of 65 countries, $\eta_{2,i} = q_i$ and $e_{k,i,s,t}$ is an error term. (3) is estimated using non-linear least squares. Even though the number of participating countries is 65 and each country potentially can have up to 18 different test scores, the total number of observations is limited to 544 since a lot of countries participated in only one or two years.

To identify $\beta_k$ and the $q_i$'s separately it is necessary to fix one of the $q_i$'s before estimating. I choose to set the $q_i$ of U.S. to one ($q_{US} \equiv 1$). Thus, $q_{US}$ acts as a numeraire allowing us to interpret $1/q_i$ as the years of education it takes for the average school child in country $i$ to obtain the same amount of education as the average U.S. school child gets out of one year of schooling. $s \times q_i$ is then denoted quality-adjusted years of schooling or U.S.-equivalent years of schooling (the multiplication sign is included to underline that $s \times q_i$ is the product of two separate variables, but will be suppressed from now on as will the index $i$).

## 3.3 Results

The resulting dataset of $q$'s spans 65 countries and is shown in the appendix which also provides standard errors for each estimated $q_i$. The mean standard deviation of the estimated $q$'s is 0.04 and it does not exceed 0.07 for any one country - a fairly high degree of precision[6]. It also indicates that the assumption that the $q$'s do not vary too much over time seems very reasonable.

Figure 2 shows a scatter plot of log GDP per worker and the quality of human capital for the 41 countries for which both data series were available. The figure shows a great

[5] (2) could, for example, also be estimated using OLS as:

$$\ln T_{k,i,s,t} = \ln \beta_k + \gamma_k \ln s + \sum_{j\in J} D_{ji} x_{k,i} + e_{k,i,s,t},$$

where $x_{k,i} = \gamma_k \ln q_i$. The estimates of $q_i$ could then be inferred from the estimates of $x_{k,i}$ and $\gamma_k$. However, this method would not give us the standard deviations of the estimated $q_i$'s directly as estimation output.

[6] The $\beta_i$'s and $\gamma_i$'s are also estimated with large precision. The estimates with standard deviations in parenthesis are: $\hat{\beta}_{matpri} = 5.63$ (0.04), $\beta_{scipri} = 5.63$ (0.04), $\beta_{mat\sec} = 5.31$ (0.06), $\beta_{sci\sec} = 5.43$ (0.05), $\gamma_{matpri} = 0.49$ (0.03), $\gamma_{scipri} = 0.49$ (0.03), $\gamma_{mat\sec} = 0.47$ (0.03), $\gamma_{sci\sec} = 0.41$ (0.02).

deal of variation in $q$, which is also evident from looking at the appendix table. It also shows a strong positive relationship between $q$ and log income per worker. Regressing $q$ on log income gives a slope of 2.03 with an $R^2 = 0.59$, although nothing causal can be inferred from this finding.

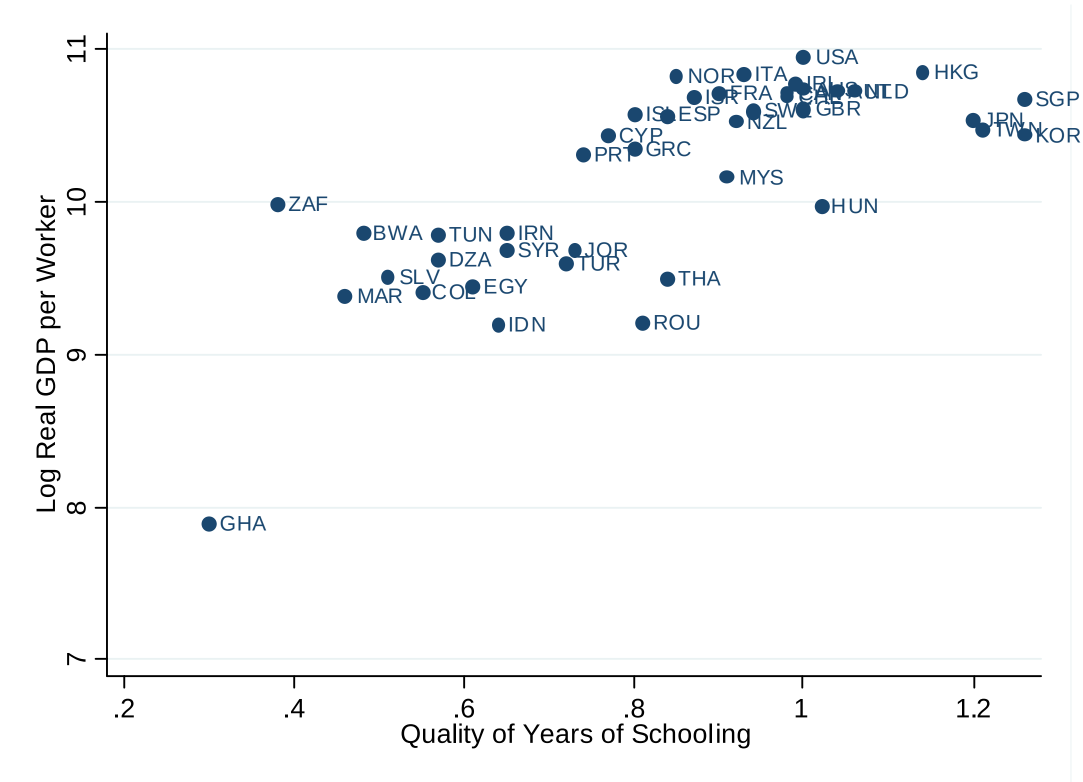


**Figure 2:** Log of GDP per worker, 1995 and quality of years of schooling, around 2000.

Source: Penn World Table 6.1 and own calculations based on TIMSS (1997a), TIMSS (1997b) and TIMSS (2008).

## 3.4 A larger dataset of quality-adjusted years of schooling

The dataset created in the previous section consists of only 65 countries with a strong over-representation of high-income countries. Therefore, this section extends the sample of $q$'s. The method used to do so is taken from Weil (2007).

First, the quality of education estimated in the previous section is regressed on a set of variables. Second, the predicted values from this regression are then used as $q$'s for 107 countries which do not have estimated data for $q$.

When choosing which variables to include in the regression I focus mainly on finding variables which are highly correlated to $q$ and for which data is available for a large number of countries. Three variables which fulfill these conditions are: the birth rate (number of children born per 1000 inhabitants in 1990, extracted online from UNdata), the percentage of households with a television in 2005 (from UNESCO (2008)) and the population density (population per 100 $m^2$ in 2000, extracted online from UNdata). Table 2 shows the results of regressing $q$ on these three variables. Region dummies are included in the regression but not shown in Table 2[7].

Dependent variable: quality of education. $R^2 = 0.79$. 58 observations

| | Estimate | Std. dev |
|---|---|---|
| Constant | 0.7770 | 0.1750 |
| Birth rate | -0.0082 | 0.0036 |
| % households with television | 0.0024 | 0.0015 |
| Population density | 0.0054 | 0.0021 |

Table 2: Regression of quality of education on various proxy variables. Region dummies are included but not shown.

Nothing causal can be inferred from the results in Table 2, the only purpose of the regression is to extend the sample. Thus, the main thing to notice is that the included variables explain a high fraction of the variation in $q$. It might seem obvious that GDP per worker and years of schooling should be added to the regression. However, including these variables drastically lowers the sample size and does not increase the $R^2$ by a significant amount. Figure 3 plots the actual values against the predicted values, and shows that the regression line provides a reasonable fit, also in the case of countries with lower $q$.

[7] The nine regions are: Asia, Middle East and North Africa, Europe, North America, Central America and the Caribbean, South America, Africa (Sub-Saharan Africa and Intra-Saharan Africa), Oceania.

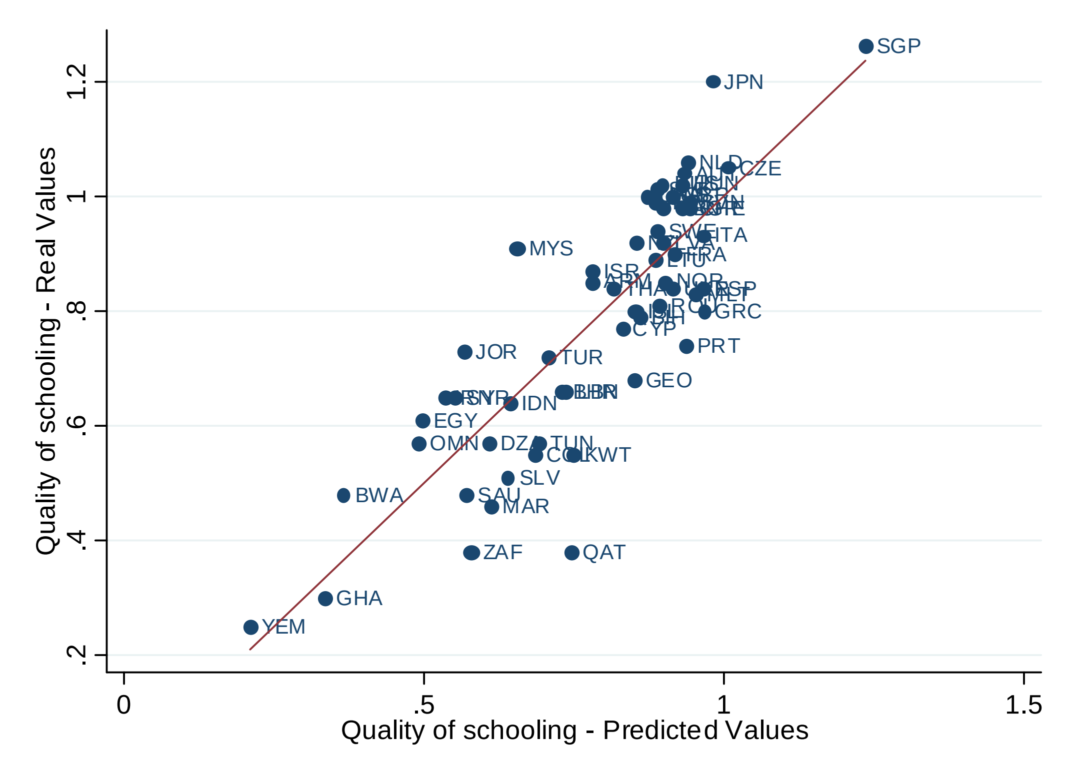


**Figure 3:** Predicted and actual values of quality of schooling. Predicted values are based on a linear regression - see the main text for a description of included variables and their sources.

The above regression results are now used to predict $q$'s for 107 countries resulting in a dataset containing $q$ for 171 countries shown in Table A1 in the appendix. Figure 4 plots $q$ against income per worker. As in Figure 2, there is a lot of dispersion in the $q$'s. Notice, that for countries with a $q$ below 0.25 (the $q$ of Yemen), data is extrapolated and should only be used for further analysis with caution. For our purposes, the $q$'s will only be used in conjunction with years of schooling to generate quality-adjusted years of schooling. Since years of schooling in the first place is close to zero in all of the low-$q$ countries (in all countries under 2 and in many countries under 1), the adjustment does not change a lot for these countries, so this is less of a problem. Again, there is a strong positive relationship between log GDP per worker and $q$.

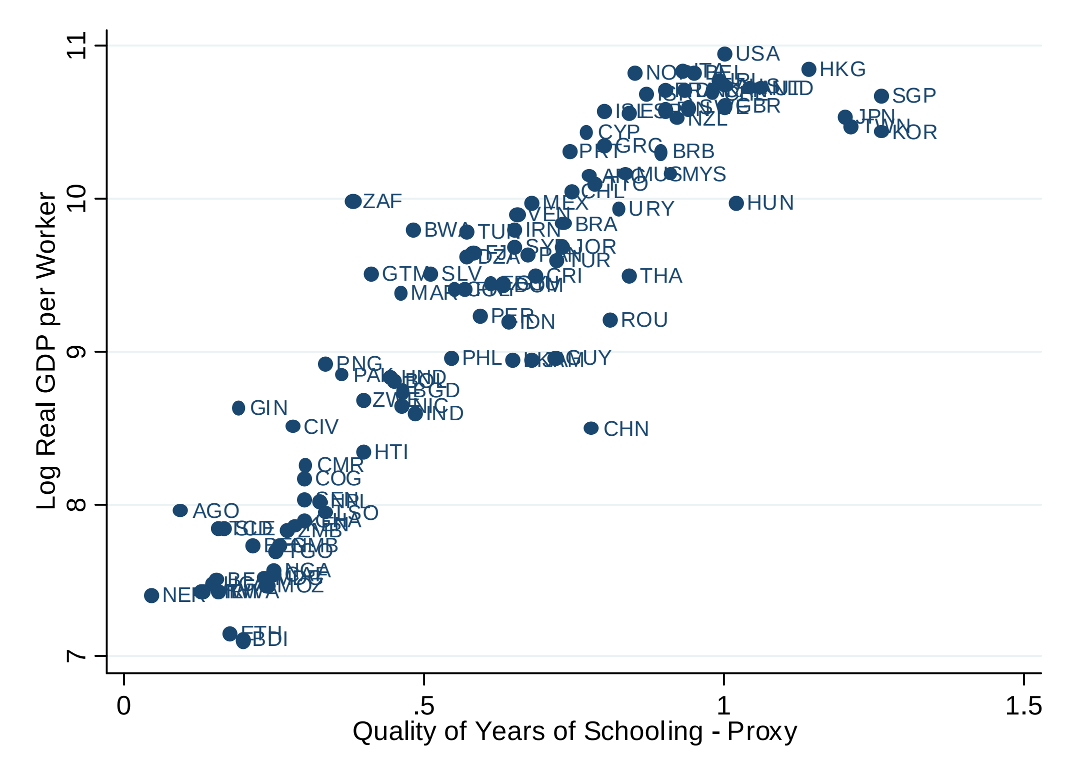


**Figure 4:** Log of GDP per worker, 1995 and quality of years of schooling, imputed, around 2000.

# 4 Quality-adjusted years of schooling and world income differences

## 4.1 Development Accounting

Per capita production is on the usual Cobb-Dougals form[8]:

$$y = Ak^{\alpha}h^{1-\alpha}, \tag{4}$$

[8]This analysis does not take into account the effect of human capital on income levels through externalities as e.g. technology. Altough such effects potentially could be important, there is no relliable estimates of the magnitude of such effects, so they are left out of the analysis.

where $A$ is total-factor productivity, $k$ is physical capital per worker and $h$ is human capital per worker given by

$$h = e^{\phi(sq)}. \tag{5}$$

In the following, two different calibrations of $\phi(sq)$ are used, and it is shown that they give approximately the same results with respect to world income differences. The first assumption is that the return to one U.S. equivalent year of schooling is 0.1 which corresponds to the finding of recent studies using different econometric techniques to isolate the causal effect of years on wages[9]. The second assumption acknowledges Psacharopolous' (1994) finding that returns to schooling are lower in countries where the average years of schooling are lower, thus $\phi(sq)$ is piecewise linear with the slope decreasing when $sq$ increases.

First, it is assumed that $\phi(sq) = 0.1sq$ implying that the return to log-wages of an increase in $sq$ is 0.1. Using this calibration along with data for years of schooling from Caselli (2005) and the quality data estimated in the previous section gives a cross-country series for human capital. (4) implies that

$$var[\ln y] = var[\ln A] + var[\ln \hat{y}] + 2Cov[\ln A, \ln \hat{y}], \tag{6}$$

where $\hat{y} = k^{\alpha}h^{1-\alpha}$[10]. To compare with the case of no differences in $q$, a second series of human capital stocks is constructed under the assumption that $q = 1$ and $\phi(s) = 0.1s$[11]. The data for output per capita, capital and years of schooling is taken from Caselli (2005) and all variables are from 1995. Even though the estimation results in Section 4 indicated that the there is little variability over time in $q$, the average human capital stock in 1995 entails the human capital of a broad range of workers, many of which got their education

[9] Card (1999) reviews the literature of the effect of education on earnings.

[10] This is not the only way to decompose the variance of log income. Hall and Jones (1999) and Klenow and Rodriguez-Clare write output as

$$y = \left(\frac{k}{y}\right)^{\frac{\alpha}{1-\alpha}} hA^{\frac{1}{1-\alpha}}.$$

They then define $\hat{y}_{HJ} = \left(\frac{k}{y}\right)^{\frac{\alpha}{1-\alpha}} h$ and decompose the variance as in (6) with $\hat{y}_{HJ}$ replacing $\hat{y}$. In a Solow model, higher $A$ generates more savings and thus higher $k$ while $k/y$ is unaffected by $A$. Therefore, they look at differences in $k/y$ rather than differences in $k$. This puts less emphasis on the role of physical capital lowering the fraction of income explained by differences in $k$. Qualitatively, the results in this section are not affected by changes in the method.

[11] Although this is not Caselli's (2005) benchmark callibration, he actually assumes this in a robustness check and finds a very small change compared to the main results where returns are decreasing and piece-wise linear.

decades before 1995. This problem should be kept in mind, especially if the data is used for specific country analysis. In the context of variance decomposition, the individual country measurement error arising from this issue may be less of a problem provided there has not been large changes in the variability of the quality of human capital.

Table 3 shows the decomposition of log income assuming constant returns and $\alpha = 1/3$. The first two columns pertain to the case of the small sample where all $q$'s are estimated, while columns 3 and 4 contain numbers for the large sample where $q$'s are imputed using the method described in Section 4. Within each set of columns the benchmark case of $q = 1$ is compared to the case of different $q$'s. The first row shows the variance of log income. The second row contains the variance of predicted log income, whereas the third row shows the covariance term. The last two rows contain two different measures of the fraction of variance in income explained by the model. There is no consensus in the literature about how to assign the covariance term. In the fourth row, the covariance term is assigned to TFP. This is Caselli's (2005) preferred measure. The last row follows Klenow and Rodriguez-Clare (1997) in splitting the covariance term equally between TFP and input factors.

| | Small Sample ($N = 40$) | | Large Sample ($N = 93$) | |
|---|---|---|---|---|
| | $q = 1$ | different $q$'s | $q = 1$ | different $q$'s |
| $var\left[\ln y\right]$ | 0.424 | 0.424 | 1.231 | 1.231 |
| $var\left[\ln \hat{y}\right]$ | 0.225 | 0.284 | 0.485 | 0.537 |
| $2cov\left[\ln A, \ln \hat{y}\right]$ | 0.124 | 0.073 | 0.519 | 0.493 |
| $var\left[\ln \hat{y}\right]/var\left[\ln y\right]$ | 0.531 | 0.671 | 0.394 | 0.436 |
| $\left(var\left[\ln \hat{y}\right] + cov\left[\ln A, \ln \hat{y}\right]\right)/var\left[\ln y\right]$ | 0.677 | 0.757 | 0.605 | 0.636 |

Table 3: Decomposition of the variance of log GDP pr worker. $h$ is constructed under the assumption that $\phi\left(sq\right) = 0.1sq$.

For the case of $N = 93$ and $q = 1$, $var\left[\ln y\right]$ and $var\left[\ln \hat{y}\right]/var\left[\ln y\right]$, and $\left(var\left[\ln \hat{y}\right] + cov\left[\ln A, \ln \hat{y}\right]\right)/var\left[\ln y\right]$ are very close to the corresponding numbers in Caselli (2005) even though the human capital stocks are produced using a different assumption about the return to years of schooling. For both samples, including the quality of education raises the explained fraction of the variance of income. In the small sample the increase is substantial, but in the large sample it is a lot smaller. These findings hold for both measures of the fraction of explained variance in log-income.

Since returns to schooling are usually higher in low-income countries, the assumption that returns to schooling are constant might be unrealistic. The following sub-section thus assumes that returns are decreasing in $sq$. Based on Psacharopolous' (1994) survey of Mincerian wage regressions, Hall and Jones (1999) assume that the return of years of schooling is 13.4% for the first four years, 10.1% for the next four years and 6.8% for years beyond the 8th, based on the average return in Sub-Saharan Africa, the whole world and OECD countries, respectively. I will now follow them in assuming the piece-wise linear relationship, but will adjust the slope to fit the framework with differences in $q$. Using (5) and (4) the return to log wages of years of schooling:

$$\frac{\partial \ln w}{\partial s} = q\phi' (sq) . \tag{7}$$

(7) is used to backwards infer the shape of $\phi (sq)$, as follows:

1. The estimated $q$'s of the three Sub-Saharan African countries in the small sample, Botswana, Ghana and South Africa are 0.59, 0.40 and 0.47, respectively. Hence, in the following $q = 0.5$ will be taken as an average value for Sub-Saharan Africa. For the return to schooling to be 13.4% for the first 4 years of schooling in Sub-Saharan Africa, the return to $sq$ must be 26.8% ($\phi' (sq) = 0.268$) for the first 2 units of $sq$.

2. The mean $q$ for the 65 countries in the dataset is 0.86. This implies that the return to the next 3 quality-adjusted years will be 11.7%.

3. For the OECD countries, $q = 1$ seems reasonable implying that the return to all quality-adjusted years beyond the 5th will be 6.8%[12].

Using this calibration a third series of human capital stocks is produced. It seems reasonable to compare this to the case where there are no differences in $q$ and returns are piecewise linear. Thus, a fourth series of $h$ is produced under the assumption that $q = 1$ and the return is calibrated as in Hall and Jones (1999)[13]. The results of the variance decomposition for the small dataset and the full imputed dataset, respectively, are given in Table 3.

[12] The exact specifications for $\phi (sq)$ is
$\phi (sq) = 0.268sq$ if $sq < 2$, $\phi (sq) = 0.536 + 0.117 (sq - 2)$ if $2 < sq < 5$, $\phi (sq) = 0.887 + 0.068 (sq - 5)$ if $sq > 5$.

[13] The exact specifications for $\phi (s)$ is
$\phi (s) = 0.134s$ if $s < 4$, $\phi (s) = 0.536 + 0.101 (s - 4)$ if $4 < s < 8$, $\phi (s) = 0.940 + 0.068 (s - 8)$ if $s > 8$.

| | Small Sample, $(N = 40)$ | | Large Sample, $(N = 93)$ | |
|---|---|---|---|---|
| | $q = 1$ | different $q$'s | $q = 1$ | different $q$'s |
| $var\left[\ln y\right]$ | 0.424 | 0.424 | 1.231 | 1.231 |
| $var\left[\ln \hat{y}\right]$ | 0.211 | 0.258 | 0.492 | 0.582 |
| $2cov\left[\ln A, \ln \hat{y}\right]$ | 0.137 | 0.103 | 0.517 | 0.473 |
| $var\left[\ln \hat{y}\right]/var\left[\ln y\right]$ | 0.498 | 0.608 | 0.400 | 0.473 |
| $\left(var\left[\ln \hat{y}\right] + cov\left[\ln A, \ln \hat{y}\right]\right)/var\left[\ln y\right]$ | 0.660 | 0.729 | 0.610 | 0.665 |

Table 4: Decomposition of variance of differences in log GDP pr worker. $h$ is constructed under the assumption that $\phi\left(sq\right)$ is piecewise linear, see the main text for the full specification.

In the large sample, the numbers for the benchmark case of no quality differences are again very close to Caselli's (2005). The increase in explained variance is somewhat larger than in the case of constant returns for the large sample. Still, the lion's share of income differences remains unexplained by the model.

What can we conclude from Tables 3 and 4? Taking into account the quality of human capital increases our understanding of world income differences, but only by a modest amount. An important reason for this finding is probably that the years of schooling and thus the human capital of many developing countries are very low in the first place. Thus, adjusting for quality only entails a minimal change for these countries. On this background, it is perhaps not so surprising that accounting for the quality of human capital only changes the fraction of explained variance in log income by a moderate amount.

## 4.2 Policy Experiments

In terms of policy conclusions it turns out to be very important to take into account the quality of human capital. Table 5 investigates the effect on the ratio of explained income differences of three different policy experiments: 1. Eliminating differences in human capital all together (row 1). 2. When only differences in $s$ are eliminated (row 2) 3. When only differences in $q$ are eliminated (row 3). The measure used in Table 5 is $\left(var\left[\ln \hat{y}\right] + cov\left[\ln \hat{y}, \ln A\right] - var\left[\ln \hat{y}_e\right] - cov\left[\ln \hat{y}_e, \ln A_e\right]\right)/var\left[\ln y\right]$, where subscript $e = sq, s, q$ refers each of the three experiments[14]. Thus, the table displays how large of a

[14] $\left(var\left[\ln \hat{y}\right] - var\left[\ln \hat{y}_e\right]\right)/var\left[\ln y\right]$ could have been used instead. This does not change the conclusions of this subsection.

fraction of todays income differences will vanish, respectively, if we equalize the different components of human capital.

The columns divide each case up according to the relevant assumption about returns to education (constant or decreasing) and sample size (large or small). Holding $sq$ constant will set the third term in (6) and all related covariance terms to zero nomatter what value $sq$ is set to. However, when one sets either of $s$ or $q$ constant without changing the other variable, the particular value to which the variable is set constant will affect $var[\ln \hat{y}]$. I concentrate on the extreme experiments where $s = 12$ (close to the U.S. value of 12.8) and $q = 1$.

| | constant returns to $sq$ | | decreasing returns to $sq$ | |
|---|---|---|---|---|
| change compared to full model | $N = 40$ | $N = 93$ | $N = 40$ | $N = 93$ |
| $sq$ constant | -0.272 | -0.181 | -0.245 | -0.210 |
| $s = 12$ | -0.079 | -0.031 | -0.069 | -0.055 |
| $q = 1$ | -0.055 | 0.014 | -0.091 | -0.071 |
| complimentarity, $1. - 2. - 3.$ | -0.138 | -0.163 | -0.085 | -0.084 |

Table 5: The change in $(var[\ln \hat{y}] + cov[\ln \hat{y}, \ln A])/var[\ln y]$ resulting of the three scenarios: eliminating all differences in $sq$ (row 1), eliminating all differences in years of schooling by setting $s = 12$ for all countries (row 2) and eliminating all differences in quality of schooling by setting $q = 1$ for all countries (row 3). The fourth row is computed as the first row minus the second and the third row. The columns divide the numbers up into two different assumptions about the returns to $sq$ and two different samples.

The first row of Table 5 shows that eliminating all differences in the human capital stock significantly decreases world income differences. This holds for all columns although moreso in the small sample cases. Meanwhile, the second and third rows show that changing either $s$ or $q$ alone has a relatively small effect. This is because of the complimentarity between the two human capital variables. A way to measure the complimentarity effect of changing both effects at once is to subtract rows 2 and 3 from row 1. This is done in row 4 which shows that this effect is large in all cases. Inspecting (7) will shed some light on how the complimentarity effect works intuitively. When $\phi'(sq) = 0.1$ it is clear that $\partial \ln y / \partial s$ is increasing in $q$, thus $q$ and $s$ thus are complementary. When $\phi(sq)$ is piecewise linear this is less clear, since changing $q$ will also change change $\phi'(sq)$. As shown in row 4 this will mitigate the complimentarity effect but not set it off completely.

If the years of schooling increase in a developing country with a very low quality of schooling it has little effect on the human capital of that country. Thus, political reforms aimed at increasing human capital should focus on both areas. One of the targets of UN's Millenium Development Goals is to achieve universal primary education, that is, to secure that all school-age children complete primary education. While this goal may have many motives and its completion may have many effects on the welfare of low-income countries, this section has shown that it might not have a huge effect on income unless it is followed by an increase in the quality of education.

# 5 Selection of More Able Students

A potential problem for the estimation of the quality of schooling is that, in countries where a low fraction of students are in primary or secondary school, there might be a selection of good students. This may not necessarily be a problem: Since we are interested in estimating the average $q$ of children enrolled in school and not of all children of school age, children out of school should not be counted as contributing to the human capital of the country.

However, selection might still be a problem for the following three reasons: Firstly, in a country where the fraction of children continuing from primary to secondary schooling is low, the ability of children in secondary school might be a lot higher than those in primary because of selection. This will not bias the estimate as long as secondary schooling tests are weighted less than primary. However, since the estimation procedure puts equal weight on primary and secondary school observations, the $q$ will be biased upwards for those countries. Secondly, if test scores are only availible in secondary school grades, the estimated $q$ will only reflect the ability of secondary school children and the estimate might be even more upwards biased. Finally, it is not evident that it is always the average $q$ of children in school which is the variable of interest. In particular, the $q$ of children not in school is interesting in the case of a policy experiment

This section shows that selection seems to be a small problem. The approach is to first construct two separate measures of $q$ for each country, one for primary and one for secondary school. There can be many reasons for these measures to differ. In some countries, relatively more ressources might be diverted to primary than secondary school compared to the rest of the countries, causing differences in the ratio of primary to secondary $q$'s.

By inspecting how this ratio covaries with other variables I conclude that selection does not seem to be a problem.

In the following, the $q$'s from primary and secondary school, $q_{PRI,i}$ and $q_{SEC,i}$, respectively, are calibrated using the estimated production functions from Section 3. I will focus on calibrating the $q$'s using test scores data from 4th and 8th grade since 3rd and 7th grade observations are only availible in a limited cross-section of countries. Thus, in the following, all 3rd and 7th grade observations are excluded. Using (2), an estimate of $q$ can be backed out for each country, year and test type:

$$q_{k,i,t} = \frac{1}{s}\left(\frac{T_{k,i,s,t}}{\hat{\beta}_k}\right)^{1/\hat{\gamma}_k},$$

for $i \in J$, $k = mpri$, $spri$, $msec$, $ssec$ and $t = 1995$, 1999, 2003, 2007. This gives a total number of 426 different $q$'s. The $q$'s for primary and secondary school are then simply computed as averages of the relevant sub-categories. That is, for country $i$, $q_{PRI,i}$ is the average of $q_{mpri,i,1995}$, $q_{mpri,i,1999}$, $q_{mpri,i,2003}$, $q_{mpri,i,2007}$, $q_{spri,i,1995}$, $q_{spri,i,1999}$, $q_{spri,i,2003}$ and $q_{spri,i,2007}$, and $q_{SEC,i}$ is the average of $q_{msec,i,1995}$, $q_{msec,i,1999}$, $q_{msec,i,2003}$, $q_{msec,i,2007}$, $q_{ssec,i,1995}$, $q_{ssec,i,1999}$, $q_{ssec,i,2003}$ and $q_{ssec,i,2007}$. Of, course for many countries, one or more $q$'s are missing since there is no data for the corresponding test score. In that case, the average is just computed without considering the missing value.

41 countries have data for both $q_{PRI}$ and $q_{SEC}$. Figure 5 below plots the ratio $q_{PRI}/q_{SEC}$ against the $q$ estimated in section 3. If there are significant selection problems, one would expect them to be larger in countries where school enrollment is lower. Indeed, if both primary and secondary school enrollment are close to 100% there can be no selection problems. Moreover, one would expect that enrollment is lower in low $q$ countries. Thus, if selection is a problem, Figure 5 should display a positive relationship between $q_{PRI}/q_{SEC}$ and $q$. Regressing $q_{PRI}/q_{SEC}$ on $q$ yields a positive but insignificant slope. Nevertheless, there are a couple of countries with a very low $q_{PRI}/q_{SEC}$ which also have a low quality of schooling.

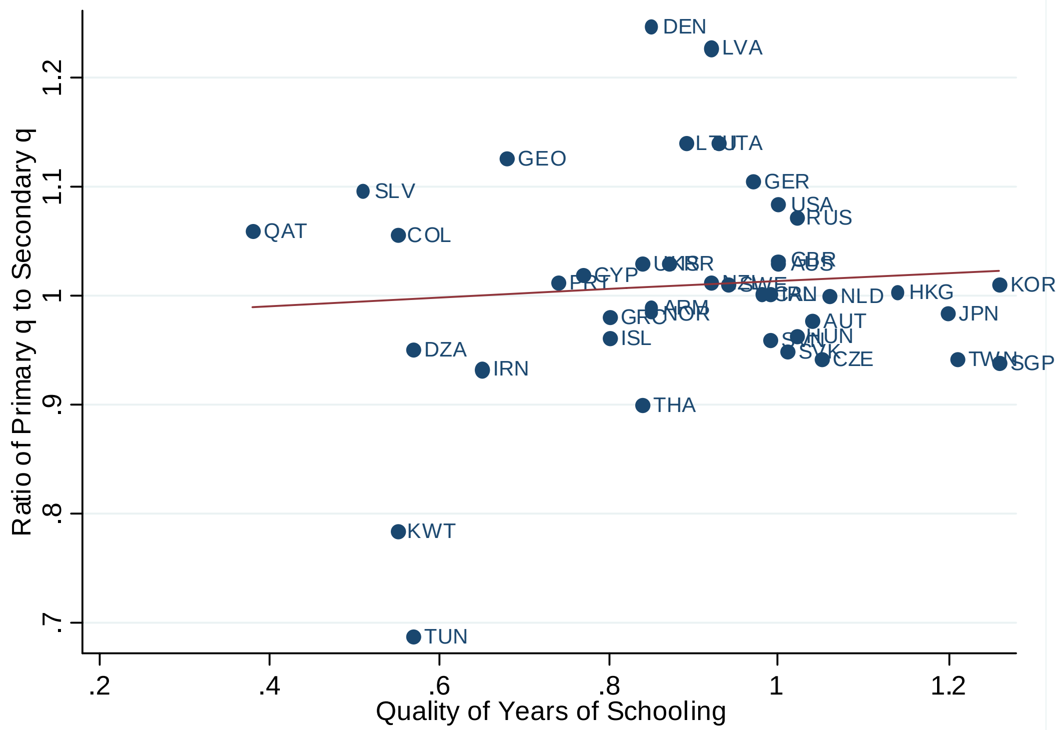


**Figure 5:** The ratio of $q_{PRI}$ to $q_{SEC}$, constructed as described in the text and the overall level of $q$ estimated in Section 3. Line estimated by OLS. The slope is insignificant with a p-value of 0.61.

Another, more direct, way of checking if there is a selection problem is to examine whether $q_{PRI}/q_{SEC}$ is relatively low in countries where a very low fraction of students transition from primary to secondary schooling. Figure 6 plots $q_{PRI}/q_{SEC}$ against the ratio of the primary school enrollment ratio to the secondary school enrollment ratio. Only in Tunisia, which has a low $q_{PRI}$ $q_{SEC}$ ratio and a low rate of transition from primary to secondary schooling, does selection seem to be a problem. However, in Kuwait, the country with the second lowest $q_{PRI}$ $q_{SEC}$ ratio, the transition rate is very close to one. Moreover, judging from its high $q_{PRI}$ $q_{SEC}$ ratio, Colombia does not not seem to have problems with selection even though the transition rate is very low.

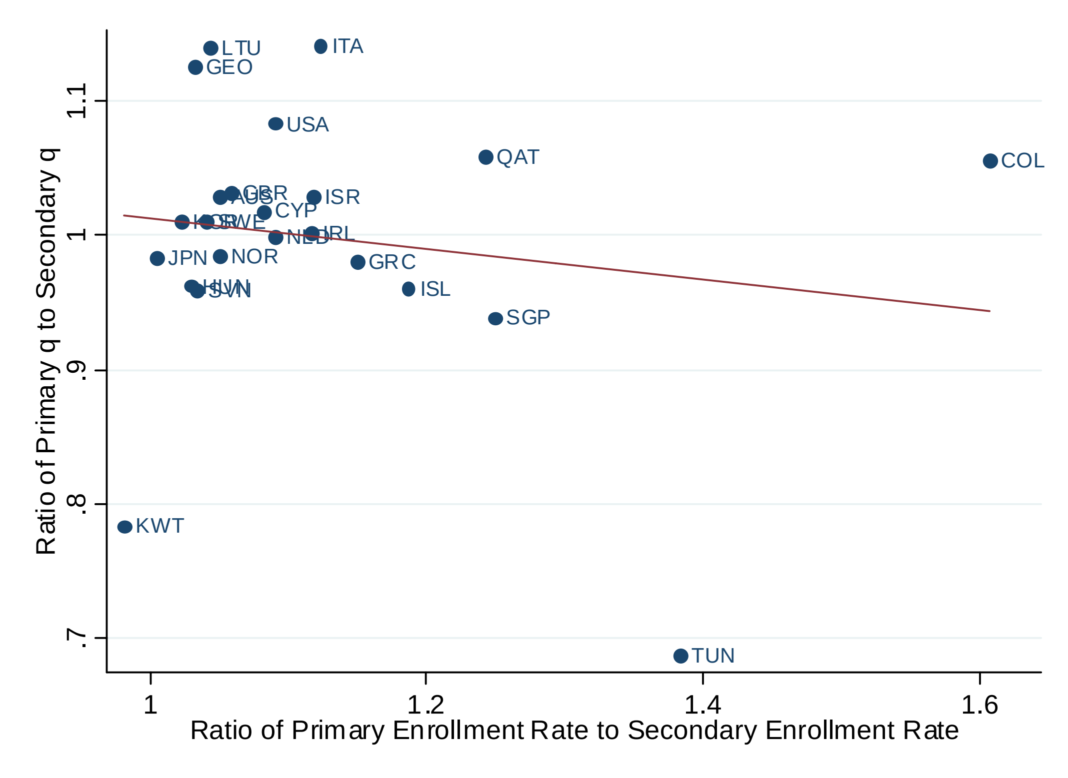


**Figure 6:** The ratio of $q_{PRI}$ to $q_{SEC}$, constructed as described in the text and the ratio of primary school enrollment rate to secondary school enrollment rate. Line estimated by OLS. The slope is insignificant with a p-value of 0.47.

There are signs of selection problems in some countries, but this is not a systematic pattern. Thus both figures in this sub-section show that selection is probably not a very big issue.

# 6 Conclusion

With a few exeptions, so far the development accounting literature has implicitely assumed that education is equally effective across countries. That is, one year of education in the U.S. and one year of education in Ghana create the same amount of knowledge. This paper challenges this assumption. I use test scores data to estimate the differences in human capital quality. I find that there are large differences in the quality of education throughout the world. Including human capital quality in a development accounting exercise increases the fraction of the variance in income explained by the model, but only by a moderate amount. A large share of income differences remain unexplained.

The paper also holds an important lesson for policy makers: Efforts to increase schooling quantity and quality should complement each other. Focusing only on one aspect of human capital will increase income equality by a much smaller amount.

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# 8 Appendix A: Rescaling of Test Scores

First, four separate linear regressions are run, one for each test type, with the TIMSS (1997a,b) version of the 1995 test scores as left-hand side variables and the TIMSS (2008) version of the 1995 test scores as right-hand side variables:

$$T^{97}_{k,i,95} = B_k + b_k T^{08}_{k,i,95} + \varepsilon_i, \tag{8}$$

where $k = mpri$, $spri$, $msec$, $ssec$ refers to test type and $i$ refers to country and thus observation. In all four regressions, the fit is very nice with $R^2$'s in the range of $0.85 - 0.93$. The next step is to use the regression results to convert the TIMSS (2008) version of the test scores from 1999, 2003 and 2007 into the scale of TIMSS (1997a,b). This is done by simply replacing the TIMSS (2008) values of test scores from 1999, 2003 and 2007 with the predicted values from the regressions, i.e.

$$\hat{T}^{97}_{k,i,t} = \hat{B}_k + \hat{b}_k T^{08}_{k,i,t}. \tag{9}$$

# 9 Appendix B: Table of the Quality of Human Capital for a Cross-Section of Countries

| Country | Iso | q | Std. dev. | q, imputed |
|---|---|---|---|---|
| Afghanistan | AFG | | | 0.22 |
| Angola | AGO | | | 0.18 |
| Albania | ALB | | | 0.80 |
| United Arab Emirates | ARE | | | 0.62 |
| Argentina | ARG | | | 0.61 |
| Armenia | ARM | 0.85 | 0.03 | 0.85 |
| Australia | AUS | 1.00 | 0.03 | 1.00 |
| Austria | AUT | 1.04 | 0.04 | 1.04 |
| Azerbaijan | AZE | | | 0.66 |
| Burundi | BDI | | | 0.24 |
| Belgium | BEL | | | 0.93 |
| Benin | BEN | | | 0.26 |
| Burkina Faso | BFA | | | 0.21 |
| Bangladesh | BGD | | | 0.67 |
| Bulgaria | BGR | 0.98 | 0.04 | 0.98 |
| Bahrain | BHR | 0.66 | 0.04 | 0.66 |
| Bahamas | BHS | | | 0.57 |
| Bosnia and Herzegovina | BIH | 0.79 | 0.06 | 0.79 |
| Belarus | BLR | | | 0.90 |
| Belize | BLZ | | | 0.48 |
| Bolivia | BOL | | | 0.38 |
| Brazil | BRA | | | 0.58 |
| Barbados | BRB | | | 0.67 |
| Brunei Darussalam | BRN | | | 0.86 |
| Bhutan | BTN | | | 0.67 |
| Botswana | BWA | 0.48 | 0.03 | 0.48 |
| Central African Republic | CAF | | | 0.26 |
| Canada | CAN | 0.98 | 0.04 | 0.98 |
| Switzerland | CHE | 0.98 | 0.05 | 0.98 |
| Chile | CHL | | | 0.58 |
| China | CHN | | | 0.90 |
| Côte d'Ivoire | CIV | | | 0.31 |
| Cameroon | CMR | | | 0.31 |
| Congo, the Dem. Rep. of the | COD | | | 0.20 |
| Congo | COG | | | 0.29 |
| Colombia | COL | 0.55 | 0.03 | 0.55 |
| Comoros | COM | | | 0.30 |
| Cape Verde | CPV | | | 0.42 |
| Costa Rica | CRI | | | 0.54 |
| Cuba | CUB | | | 0.58 |
| Cyprus | CYP | 0.77 | 0.03 | 0.77 |
| Czech Republic | CZE | 1.05 | 0.03 | 1.05 |
| Denmark | DEN | 0.85 | 0.04 | 0.85 |
| Germany | DEU | | | 0.93 |
| Djibouti | DJI | | | 0.46 |
| Denmark | DNK | | | 0.92 |
| Dominican Republic | DOM | | | 0.50 |
| Algeria | DZA | 0.57 | 0.03 | 0.57 |

| Country | Iso | q | Std. dev. | q, imputed |
|---|---|---|---|---|
| Ecuador | ECU | | | 0.51 |
| Egypt | EGY | 0.61 | 0.04 | 0.61 |
| Eritrea | ERI | | | 0.30 |
| Spain | ESP | 0.84 | 0.05 | 0.84 |
| Estonia | EST | | | 0.89 |
| Ethiopia | ETH | | | 0.22 |
| Finland | FIN | | | 0.89 |
| Fiji | FJI | | | 0.76 |
| France | FRA | 0.90 | 0.05 | 0.90 |
| Gabon | GAB | | | 0.43 |
| United Kingdom | GBR | 1.00 | 0.03 | 1.00 |
| Georgia | GEO | 0.68 | 0.04 | 0.68 |
| Germany | GER | 0.97 | 0.04 | 0.97 |
| Ghana | GHA | 0.30 | 0.03 | 0.30 |
| Guinea | GIN | | | 0.24 |
| Gambia | GMB | | | 0.28 |
| Guinea-Bissau | GNB | | | 0.26 |
| Equatorial Guinea | GNQ | | | 0.31 |
| Greece | GRC | 0.80 | 0.03 | 0.80 |
| Guatemala | GTM | | | 0.35 |
| Guyana | GUY | | | 0.57 |
| Hong Kong SAR | HKG | 1.14 | 0.04 | 1.14 |
| Honduras | HND | | | 0.37 |
| Croatia | HRV | | | 0.92 |
| Haiti | HTI | | | 0.32 |
| Hungary | HUN | 1.02 | 0.03 | 1.02 |
| Indonesia | IDN | 0.64 | 0.03 | 0.64 |
| India | IND | | | 0.69 |
| Ireland | IRL | 0.99 | 0.04 | 0.99 |
| Iran, Islamic Republic of | IRN | 0.65 | 0.02 | 0.65 |
| Iceland | ISL | 0.80 | 0.03 | 0.80 |
| Israel | ISR | 0.87 | 0.03 | 0.87 |
| Italy | ITA | 0.93 | 0.04 | 0.93 |
| Jamaica | JAM | | | 0.52 |
| Jordan | JOR | 0.73 | 0.04 | 0.73 |
| Japan | JPN | 1.20 | 0.04 | 1.20 |
| Kazakhstan | KAZ | 1.08 | 0.07 | 1.08 |
| Kenya | KEN | | | 0.29 |
| Cambodia | KHM | | | 0.60 |
| Korea, republic of | KOR | 1.26 | 0.04 | 1.26 |
| Kuwait | KWT | 0.55 | 0.03 | 0.55 |
| Lao People's Democratic Republic | LAO | | | 0.57 |
| Lebanon | LBN | 0.66 | 0.04 | 0.66 |
| Libyan Arab Jamahiriya | LBY | | | 0.54 |
| Saint Lucia | LCA | | | 0.54 |
| Sri Lanka | LKA | | | 0.70 |
| Lesotho | LSO | | | 0.31 |
| Lithuania | LTU | 0.89 | 0.03 | 0.89 |
| Luxembourg | LUX | | | 0.92 |

| Country | Iso | q | Std. dev. | q, imputed |
|---|---|---|---|---|
| Latvia | LVA | 0.92 | 0.03 | 0.92 |
| Morocco | MAR | 0.46 | 0.03 | 0.46 |
| Moldova, Republic of | MDA | | | 0.82 |
| Madagascar | MDG | | | 0.26 |
| Maldives | MDV | | | 0.79 |
| Mexico | MEX | | | 0.87 |
| Macedonia, former Yugoslav Rep. of | MKD | | | 0.87 |
| Mali | MLI | | | 0.21 |
| Malta | MLT | 0.83 | 0.06 | 0.83 |
| Myanmar | MMR | | | 0.64 |
| Mongolia | MNG | | | 0.73 |
| Mozambique | MOZ | | | 0.26 |
| Mauritania | MRT | | | 0.32 |
| Mauritius | MUS | | | 0.68 |
| Malawi | MWI | | | 0.20 |
| Malaysia | MYS | 0.91 | 0.04 | 0.91 |
| Namibia | NAM | | | 0.34 |
| Niger | NER | | | 0.15 |
| Nigeria | NGA | | | 0.29 |
| Nicaragua | NIC | | | 0.38 |
| Netherlands | NLD | 1.06 | 0.04 | 1.06 |
| Norway | NOR | 0.85 | 0.03 | 0.85 |
| Nepal | NPL | | | 0.57 |
| New Zealand | NZL | 0.92 | 0.03 | 0.92 |
| Oman | OMN | 0.57 | 0.04 | 0.57 |
| Pakistan | PAK | | | 0.41 |
| Panama | PAN | | | 0.52 |
| Peru | PER | | | 0.48 |
| Philippines | PHL | | | 0.75 |
| Papua New Guinea | PNG | | | 0.58 |
| Poland | POL | | | 0.88 |
| Portugal | PRT | 0.74 | 0.03 | 0.74 |
| Paraguay | PRY | | | 0.47 |
| Palestinian Territory, Occupied | PSE | | | 0.51 |
| Qatar | QAT | 0.38 | 0.03 | 0.38 |
| Romania | ROU | 0.81 | 0.03 | 0.81 |
| Russian Federation | RUS | 1.02 | 0.03 | 1.02 |
| Rwanda | RWA | | | 0.21 |
| Saudi Arabia | SAU | 0.48 | 0.04 | 0.48 |
| Sudan | SDN | | | 0.30 |
| Senegal | SEN | | | 0.32 |
| Singapore | SGP | 1.26 | 0.04 | 1.26 |
| Solomon Islands | SLB | | | 0.54 |
| Sierra Leone | SLE | | | 0.22 |
| El Salvador | SLV | 0.51 | 0.03 | 0.51 |
| Somalia | SOM | | | 0.28 |
| Serbia | SRB | 0.84 | 0.05 | 0.84 |
| Sao Tome and Principe | STP | | | 0.37 |
| Suriname | SUR | | | 0.52 |

| Country | Iso | q | Std. dev. | q, imputed |
|---|---|---|---|---|
| Slovakia | SVK | 1.01 | 0.04 | 1.01 |
| Slovenia | SVN | 0.99 | 0.03 | 0.99 |
| Sweden | SWE | 0.94 | 0.04 | 0.94 |
| Swaziland | SWZ | | | 0.30 |
| Syrian Arab Republic | SYR | 0.65 | 0.05 | 0.65 |
| Chad | TCD | | | 0.21 |
| Togo | TGO | | | 0.28 |
| Thailand | THA | 0.84 | 0.03 | 0.84 |
| Tajikistan | TJK | | | 0.72 |
| Tonga | TON | | | 0.68 |
| Trinidad and Tobago | TTO | | | 0.59 |
| Tunisia | TUN | 0.57 | 0.03 | 0.57 |
| Turkey | TUR | 0.72 | 0.05 | 0.72 |
| Chinese Taipei | TWN | 1.21 | 0.05 | 1.21 |
| Tanzania, United Republic of | TZA | | | 0.27 |
| Uganda | UGA | | | 0.21 |
| Ukraine | UKR | 0.84 | 0.04 | 0.84 |
| Uruguay | URY | | | 0.63 |
| United States | USA | 1.00 | | 1.00 |
| Saint Vincent and the Grenadines | VCT | | | 0.54 |
| Venezuela, Bolivarian Republic of | VEN | | | 0.53 |
| Viet Nam | VNM | | | 0.81 |
| Vanuatu | VUT | | | 0.57 |
| Samoa | WSM | | | 0.79 |
| Yemen | YEM | 0.25 | 0.02 | 0.25 |
| South Africa | ZAF | 0.38 | 0.03 | 0.38 |
| Zambia | ZMB | | | 0.29 |
| Zimbabwe | ZWE | | | 0.37 |