

# The causal effect of education on aggregate income

Marcelo Soto\*

Instituto de Analisis Economico, Campus UAB, 08193 Bellaterra,  
Barcelona, Spain

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## Abstract

Empirical studies assume that the macro Mincer return on schooling is constant across countries. Using a large sample of countries this paper shows that countries with a better quality of education have on average relatively higher macro Mincer coefficients. As rich countries have on average better educational quality, differences in human capital between countries are larger than has been typically assumed in the development accounting literature. Consequently, factor accumulation explains a considerably larger share of income differences across countries than what is usually found.

**Keywords:** *Human capital; income growth; GMM estimation; development accounting.*

**JEL Codes:** O11, O47, C33.

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# 1 Introduction

A recurrent question that characterizes the debate on economic growth refers to the effect of schooling on income per capita. Pritchett (2001) argues that the poor institutional framework, low quality and excess supply of schooling in developing countries causes it to have a virtually null marginal effect on income per worker. Evidence reported by Temple (2001) supports the *Pritchett hypothesis*. Paralleling these results a number of panel data studies have also failed to find any significance of schooling in standard growth regressions (Bond, Hoeffler and Temple, 2001; Caselli, Esquivel and Lefort, 1996; Islam 1995).

The purpose of this paper is to produce fresh estimates of the social return on schooling. This is not a paper about why changes in years of schooling cannot explain per capita income growth between 1960 and a later date, as first noted by Benhabib and Spiegel (1994). This has already been addressed by Krueger and Lindahl (2001) and Cohen and Soto (2007) who single out measurement error in years of schooling as the central cause behind this finding. Instead, the focus here is on how to compute reliable estimates of the social return on schooling given the estimation problems found in the literature.

Here the term ‘return’ calls for a clarification. In the same way that the micro Mincer coefficient from wage regressions cannot be interpreted as the internal rate of return of education but as the causal effect of schooling on wages (Card, 1999; Heckman, Lochner and Todd, 2005), in this paper the macro Mincerian return is interpreted as the effect of schooling on GDP per worker. So the terms ‘effect of schooling’ or ‘return on schooling’ will be used interchangeably.

In part due to econometric difficulties, the literature has recently turned more attention to development accounting (Caselli, 2005; Hall and Jones 1999). This approach relies on the use of unknown parameters describing the returns on physical and human capital. Although this paper is complementary to this literature, the estimated returns on schooling found here are different from those typically used in development accounting. In particular, richer countries tend to display higher social returns as a consequence of better education quality.

Assuming return homogeneity across countries, the benchmark estimate of the income response to one additional year of schooling is 8.3%. This is in the range of

the micro-Mincerian returns reported by Psacharopoulos (1994) and Psacharopoulos and Patrinos (2004). The average social return exceeds the standard private return found in micro studies only if physical capital is assumed to respond to changes in human capital.

The average return conceals substantial heterogeneity across countries. Two additional results emerge from the data. First, the macro Mincer coefficients bear no relationship with the micro coefficients reported by Psacharopoulos. In particular, schooling has no significant effect on aggregate income for the group of countries with the highest micro Mincer coefficients. And second, schooling has no significant effect on income in countries with low educational quality. This result leads to the finding that factor accumulation explains a larger share of income differences across countries than generally reported in the development accounting literature. This finding is consistent with Hanushek and Woessmann (2008) who argue that the actual levels of human capital in developing countries are less favourable than usually depicted in studies that do not account for educational quality differences.

In summary, contrary to earlier findings, the causal effect of education on income is positive and statistically significant in countries with relatively high schooling quality as reported by Hanushek and Kimko (2000). But on average the macro Mincer coefficients are not higher than private ones. This last result is in line with the findings of Heckman, Layne-Farrar and Todd (1996), Acemoglu and Angrist (2001), Pritchett (2006) or Ciccone and Peri (2006), who following a different (i.e. micro) approach do not detect significant externalities to schooling.

The paper is organized as follows. Section 2 presents the benchmark estimation assuming that the return on schooling is constant across countries. The estimates from GMM regressions are significant and consistent with results from labour studies. Section 3 allows for return heterogeneity across countries and assesses the effects of educational quality. It is found that in low educational quality countries the returns are not statistically significant whereas in countries with high quality the return is consistent with those found in labour studies. Section 4 presents an income accounting decomposition using the returns of schooling estimated in this paper. It is found that factor accumulation has a substantially larger role in explaining income differences across countries than what is usually described in the literature. Section

5 sets this paper in the context of the earlier literature. Section 6 concludes.

## 2 Benchmark Estimation

The benchmark estimation is inspired by Topel (1999) and Cohen and Soto (2007). From a standard Cobb-Douglas production function with physical and human capital and constant returns we can write:

$$\ln y_{it} = \alpha \ln k_{it} + (1 - \alpha) \ln h_{it} + \eta_i + \tau_t + e_{it} \quad (1)$$

where  $y_{it}$ ,  $k_{it}$  and  $h_{it}$  respectively represent income, physical capital and human capital per worker. The disturbance  $\eta_i$  represents an unobserved time-invariant country-specific effect,  $\tau_t$  is a time-specific effect and  $e_{it}$  is residual. Suppose that the representative level of human capital per worker is such that:

$$\ln h_{it} = rS_{it} + \varepsilon_{it} \quad (2)$$

where  $S$  is the average number of years of schooling for the working-age population and  $\varepsilon$  captures other determinants of human capital <sup>1</sup>. Therefore (1) yields the following estimable equation:

$$\ln y_{it} = \alpha \ln k_{it} + (1 - \alpha) rS_{it} + \eta_i + \tau_t + \epsilon_{it} \quad (3)$$

with  $\epsilon_{it} \equiv (1 - \alpha) \varepsilon_{it} + e_{it}$ .

To eliminate collinearity between physical and human capital Topel (1999) suggests reparametrizing the model. By subtracting  $\alpha \ln y$  from both sides of equation (3) and dividing by  $(1 - \alpha)$  we obtain,

$$\ln y_{it} = \frac{\alpha}{1 - \alpha} \ln \left( \frac{k}{y} \right)_{it} + rS_{it} + \tilde{\eta}_i + \tilde{\tau}_t + \tilde{\epsilon}_{it} \quad (4)$$

where a tilde denotes variables divided by  $(1 - \alpha)$ .

Note that the parameter  $r$  is not directly comparable with micro Mincer returns because it is a parameter that converts years of schooling into human capital and not into income. Indeed, the micro-Mincer coefficient is defined as the percentage

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<sup>1</sup>The original Mincerian equation also includes labour experience, which is not explicitly accounted for here.

increase in wages given an increase in years of schooling, leaving the remaining determinants of wages constant. From equation (4) it is clear that  $r$  represents the effect of schooling on income allowing for an endogenous change in physical capital so that the  $k/y$  ratio remains constant. Consequently, in macro regressions it is the coefficient  $(1 - \alpha)r$  which should be compared with the estimates of the effect of schooling on wages (see equation 3). However most of the existing literature compares the estimates of  $r$  with the Mincer coefficient from labour studies. The appendix formally shows that in the absence of externalities the private return is equal to  $(1 - \alpha)r$ .

In all subsequent regressions the period covered is 1960-1990 and the data is from PWT 5.6 in order to maintain the same income and growth data studied in the earlier literature. The physical capital series are from Easterly and Levine (2001) and the data for years of schooling is from Cohen and Soto (2007). The number of countries with full information for at least three decades is 83<sup>2</sup>.

The reparametrisation (4) introduces new endogeneity problems to the estimation as the income level now appears on both sides of the equation. Topel (1999) has already estimated equation (4) by constraining the coefficient  $\alpha$  to specific values (he chooses 0.35 and 0.5) or by assuming that the ratio  $k/y$  is constant for each country over time. Under this last assumption he treats  $k/y$  as a country specific effect and estimates (4) by fixed-effect and OLS methods. Heckman and Klenow (1997) also estimate a constrained version of (4) by OLS.

In Cohen and Soto (2007) we estimate an unconstrained version of equation (4). For benchmark purposes such regressions are replicated for the larger sample available here. The main results are reported in Table 1. The OLS estimation in levels (column 1) results in an implausibly low coefficient for the capital-output ratio. Indeed, the implicit share of physical capital in total output is  $0.221/1.221 = 0.181$ <sup>3</sup>. This negative bias is the consequence of the presence of  $y$  in the capital-output ratio. By contrast, the coefficient for schooling is large (21.7%) and highly significant. This value reflects the return on schooling that allows physical capital to adjust to changes in  $S$  so that the ratio  $k/y$  stays constant. However, as discussed above, the Mincerian-comparable return of one additional year of schooling –i.e. the increase

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<sup>2</sup>The full data set used here is available at <http://soto.iae-csic.org/Data.htm>

<sup>3</sup>No statistical inference is performed on  $\alpha$  since the standard errors refer to the estimated  $\alpha/(1 - \alpha)$ .

in income per worker that would be obtained without an endogenous response of  $k$  is  $0.217 \times (1 - 0.181) = 17.8\%$ . This figure is still large and its size is in part due to the low coefficient for the capital-output ratio. Similar problems apply for the estimation in first-differences (column 2), which explains a negative  $\alpha$ .

Blundell and Bond (1998) and Blundell, Bond and Windmeijer (2000) show that in finite samples a system GMM estimation, i.e. the simultaneous estimation of the equation in levels and in first differences with suitably chosen lags of explanatory variables used as instruments, provide more precise estimates and lower biases than traditional estimators. Columns (3) and (4) report results from system GMM regressions that use two different sets of instruments. In both regressions the instruments used for the equation in first differences are a constant and the level of explanatory variables lagged one period. For the equation in levels the instruments are a constant and the first-difference of explanatory variables lagged one period (regression 3) or one and two periods (regression 4).

The GMM estimation produces significant coefficients for both the capital-output ratio and years of schooling. Not surprisingly the implicit share of physical capital (around 46.0%) is higher than the one obtained in OLS estimation. It is also larger than the typical capital share used in the literature. The implicit social Mincerian returns (between 7.4% and 8.3%) are larger than those reported by Topel (1999; table 2, column 5) who, conditioning on a physical capital share of 35%, finds a marginal effect of schooling equal to 5.5%. On the other hand, the results found here imply that the marginal effect of schooling at a macro level is slightly lower than the standard private return observed in labour studies. For instance, from around seventy country-level studies, Psacharopoulos (1994) and Psacharopoulos and Patrinos (2004) report, respectively, a world average Mincerian return equal to 10.1% and 9.7%. Consequently, if micro returns are taken at face value, these results indicate an absence of externalities to schooling<sup>4</sup>. This finding is consistent with Heckman, Layne-Farrar and Todd (1996), Acemoglu and Angrist (2001), Pritchett (2003) and Ciccone and Peri (2006), among others.

On the other hand, if an increase in the level of human capital induces an expansion of physical capital such that  $k/y$  remains constant the macro return to schooling

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<sup>4</sup>There is a large amount of literature on whether the micro returns are properly estimated but this topic goes far beyond the scope of this paper. The micro Mincer coefficients are used only as a reference.

would be higher than the typical private one. Indeed, under this assumption the total return to schooling ranges between 13.6% and 15.5% depending on the regression. However, this larger long-term Mincerian return does not represent externalities in the sense offered by Lucas (1988). In Lucas’s model, the social marginal product of human capital is higher than the private marginal product in the short-run –i.e. without taking into consideration any hypothetical endogenous response of physical capital. Therefore in order to analyse whether these externalities show up in the data we must compare the short-run return with the typical micro Mincerian coefficient. And the results in Table 1 indicate the absence of such externalities.

If the explanatory variables are endogenously determined the assumption of no autocorrelation in the residuals  $\epsilon_{it}$  is crucial for the validity of the instruments. Otherwise past values of explanatory variables, which are used as instruments, would not be exogenous. When the residuals are not serially correlated the first order correlation of differenced residuals  $\epsilon_{it} - \epsilon_{it-1}$  is negative and the second order correlation is equal to zero. Tests for second order serial correlation reject the hypothesis that such correlation is present in the residuals. As an additional test of the validity of instruments Table 1 reports Sargan tests of overidentifying restrictions. In neither regression is the validity of the instruments rejected.

### 3 Return Heterogeneity

The previous section assumes, consistently with most of the earlier literature, that the macro return on schooling is the same across countries. However there are theoretical and empirical reasons to believe that the social returns on schooling differ across countries. On the theoretical ground, the hypothesis that human capital has decreasing returns with the level of schooling has been put forward by Bils and Klenow (2000). Similarly, Hall and Jones (1999) and Caselli (2005) assume decreasing Mincerian returns to build human capital stocks for their income accounting analyses.

The decreasing return hypothesis is in fact founded on the private Mincerian returns reported by Psacharopoulos (1994) and Psacharopoulos and Patrinos (2004). These studies report major differences across world regions with, on average, richer and better educated countries having lower private returns. However this is far from

being a perfect regularity and there are a number of exceptions. For instance, according to Psacharopoulos and Patrinos the latest estimates for Japan and Singapore are 13.2% and 13.1%, respectively, whereas those for South Africa and Egypt are 4.1% and 5.5%, respectively. Although private and social Mincerian returns are not necessarily connected, there is still a chance that they are. If so, the observed heterogeneity in labour studies would indicate major differences in Mincerian returns at the aggregate level.

Another piece of empirical evidence suggesting return heterogeneity is provided by Hanushek and Kimko (2000). There the authors report substantial differences in schooling quality across countries. Differences in schooling quality may lead to differences in labour productivity and thus cause return heterogeneity. Pritchett (2001) supports this idea by arguing that the low quality of schooling is one major cause of the lack of significance of schooling variables in cross-country growth regressions<sup>5</sup>.

Let's introduce heterogeneity by assuming that the parameter  $r_i$  is given by:

$$r_i = \bar{r} + \nu_i \tag{5}$$

where  $\bar{r}$  is the world average return and  $\nu_i$  is the country deviation from the world average.

In order to assess the effects of return heterogeneity it is convenient to illustrate its consequences for cross-section regressions. When the income level is regressed on years of schooling a potential source of bias of the estimated  $\bar{r}$  emerges as the term  $\nu_i S_i$  is present in the residual of the equation. The sign of the bias depends on the sign of the correlation  $\sigma_{\nu,S}$  between  $\nu_i$  and  $S_i$ . According to the micro evidence presented by Psacharopoulos (1994) and Psacharopoulos and Patrinos (2004) the return on years of schooling is on average lower in countries with higher levels of education. This would suggest that  $\sigma_{\nu,S}$  is negative. This, in turn, would imply that cross-country regressions that do not account for differences in returns across countries produce downwardly biased estimates of  $\bar{r}$ .

A different scenario has been put forward by Pritchett (2001, 2003) who argues that the social return on schooling is relatively lower in developing countries be-

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<sup>5</sup>Note that in that case, countries with higher levels of schooling –which are also those with better quality– should display higher returns. This is contradicted by Psacharopoulos's numbers.



cause of their limited educational quality, among other reasons. On similar lines, Hanushek and Kimko (2000) highlight that schooling quality differs considerably among countries and in general it is lower in the poorer and less educated ones. Under this hypothesis, since more educated countries benefit from higher schooling quality their  $r_i$  should be relatively high. In that case  $\sigma_{\nu,S}$  would be positive and the estimated  $\bar{r}$  would be upwardly biased.

Of course this analysis neglects the potential endogeneity of  $S$ , which would also positively bias the estimated  $\bar{r}$  in growth regressions. As is well known instrumental variable methods do not solve the endogeneity problem introduced by heterogeneity since any instrument that is correlated with  $S_i$  is also correlated with  $\nu_i S_i$  (Heckman and Vytlačil, 1998).

To assess the effects of return heterogeneity in panel regressions let's write  $S_{it} = \bar{s}_i + d_{it}$  where  $\bar{s}_i$  is the sample average of years of schooling and  $d_{it}$  is the deviation from the average. Suppose that  $r_i$  is given by (5). Then equation (4) can be rewritten as,

$$\ln y_{it} = \frac{\alpha}{1-\alpha} \ln \left( \frac{k}{y} \right)_{it} + \bar{r} S_{it} + v_i (\bar{s}_i + d_{it}) + u_{it} \quad (6)$$

Now a new source of bias is introduced by the presence of the term  $v_i d_{it}$  (the term  $v_i \bar{s}_i$  is part of the country's specific effect and thus can be accounted for with standard econometric techniques). Neglecting other possible sources of bias it can readily be shown that the sign of the bias introduced by the presence of heterogeneity is equal to the sign of  $E(v_i \sigma_i^2)$ , where  $\sigma_i^2$  is country  $i$ 's sample variance of years of schooling. As before, the use of instruments does not solve the bias problem since any variable correlated with  $S_{it}$  is also correlated with  $v_i d_{it}$  (see Garen, 1984).

### 3.1 Evidence from micro returns

As a first attempt to deal with heterogeneity we will exploit results from labour studies. Psacharopoulos (1994) and Psacharopoulos and Patrinos (2002) report private Mincerian coefficients for 55 of all countries used here. The average Mincerian coefficient for these countries is 10%. In addition there is little variation in returns over time which is consistent with a time-invariant  $r_i$  as in (5). In order to study whether the private returns convey information about the social returns, the sample

is divided into groups of countries according to their private returns. Then a specific social return for each group can be estimated as follows:

$$\ln y_{it} = \frac{\alpha}{1 - \alpha} \ln \left( \frac{k}{y} \right)_{it} + \sum_{j=1,2,3} r_j D_j S_{it} + u_{it} \quad (7)$$

where  $D_j$  is a dummy variable that takes value 1 depending on whether the private Mincer return of country  $i$  is "low", "medium" or "high". The thresholds defining these three groups are respectively (and arbitrarily) 8%; from 8% to 11%, and over 11%<sup>6</sup>.

Table 2 reports the main results with system GMM estimation. For benchmark purposes, the first regression ignores heterogeneity. This is the same as regression 4 in table 1 but for the smaller sample of 55 countries for which private Mincerian coefficients are available. The results are similar to those obtained with the full sample, with a point estimate for  $\bar{r}$  equal to 13.9% (the implicit social Mincerian return is equal to 7.2%). The low p-value for the Sargan statistic hints at high heterogeneity among the countries in this smaller sample. In regression 2 the groups with low and moderate private returns display highly significant coefficients for schooling and respectively equal to 12.9% and 13.8%. The implicit social Mincerian returns are, respectively, 7.8% and 8.3%. These are "close" to the observed private returns for these two groups (respectively, 6.3% and 9.5%). In contrast, countries with high private returns yield, paradoxically, a low and non-significant coefficient. The implicit social Mincerian return for this group of countries is 4.9%, which is almost 10 percentage points lower than their average private return. Regression 3 pools group 1 and 2 together but the results are not significantly modified.

The findings in table 2 suggest that the micro returns are not related to the social ones. Indeed, the group of countries with relatively large micro-returns has lower than average social returns in the sample. Finally, it is important to highlight that return heterogeneity across countries is considerable, as is suggested by the low p-values in Sargan tests. In fact, it is possible that countries classified into group 3 are themselves highly heterogeneous. This could be one reason, among others, for a non-significant estimate for these countries.

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<sup>6</sup>Other thresholds were tried but the results reported below did not change qualitatively.

### 3.2 Quality of education

One natural candidate to explain heterogeneity in social Mincerian returns is the quality of education. As noted above, Pritchett (2001) justifies the lack of significance of schooling in cross-country growth regressions by the low quality of education in developing countries. Consistently with this Hanushek and Kimko (2000) find that education quality has a strong explanatory power for growth.

The following regressions explore how the quality of education may impact on the social return on schooling. Hanushek and Kimko (2000) construct two different measures of schooling quality from a number of international tests of student achievement in mathematics and science carried out during the 1965-1991 period. The authors argue that schooling quality varies slowly over time in a given country, which allows them to combine the results of the tests from different years. The two measures that they build differ in the way the various tests conducted in each country are merged into a single score (see Hanushek and Kimko, 2000, pp. 1186-1187 for further details). Since the authors report a high correlation between the two measures (0.92), in this paper the simple average of the two quality scores reported by Hanushek and Kimko (2000, pp. 1206-1207) is computed. Furthermore, to facilitate the interpretation of the results the measure of quality is scaled to 1 for the country with the highest score in the sample (Singapore). The quality measure  $q_i$  for each country  $i$  obtained in this way is shown in the appendix.

The first regression in Table 3 is the baseline estimation for the smaller sample of 67 countries with available data on education quality and years of schooling. In this regression the coefficient for schooling is constrained to a common value for all countries in the sample. The Blundell and Bond (1998) system GMM estimator is performed. The instruments are the same as before: for the equation in first differences, a constant and the level of explanatory variables lagged one period; and for the equation in levels, a constant and up to two lags of explanatory variables in first differences. Regression 1 shows that there are no important differences with respect to the full-sample results. Namely, the coefficient for schooling in both regressions are not statistically different. The implicit social Mincerian return is 8.4% which is virtually the same as in the benchmark regression in table 1. Note however that according to the Sargan statistic the exogeneity of the instruments

is rejected at a 10% level. As discussed before, the instruments are rendered non significant when parameter heterogeneity occurs (Heckman and Vytlačil, 1998).

Next countries are classified into different groups depending on their quality level  $q_i$  so that a different coefficient for schooling can be estimated for each group. Such an estimation offers the advantage of not needing to specify how quality affects the return on schooling<sup>7</sup>. On the other hand, this approach supposes that all countries in a quality group have the same return. The criteria for the number of groups and the limits of  $q$  that define each group are obtained endogenously from the data. More specifically, the sample is first divided into two groups, one with countries with low  $q$  and the other with high  $q$ . Initially the low- $q$  group has the smallest number of countries needed for estimation and the remaining countries go into the high- $q$  group. After estimation the lowest quality country from the high- $q$  group is moved into the low- $q$  group and a new estimation is performed. This procedure is applied recursively. As noted above, when parameter heterogeneity is not accounted for, any instrumental variable correlated with the explanatory one will be correlated with the residual. Thus, under heterogeneity the Sargan statistic should reject the exogeneity of the instruments. Therefore, if the Sargan statistic worsens significantly between two consecutive estimations it is a sign that the country that has just been moved into the low- $q$  group is better placed among the high- $q$  group.

Figure 1 displays the probability values of the Sargan statistic obtained with this recursive procedure. Each point represents the p-value obtained when the corresponding country is included in the low- $q$  group. There are at least two instances in which there is an almost vertical drop in Sargan's p-values. This suggests estimating different coefficients for three groups of countries: a group with "low" education quality (up to Iraq's level); a group with "intermediate" quality (from Syria up to Cameroon); and a group with "high" quality (equal to or higher than Jordan's).

This analysis leads to an estimation similar to (7) but now the  $D_j$  dummy is conveniently redefined according to each country's  $q$ . Regression 2 shows that the low and intermediate quality groups (respectively groups 1 and 2) display non-significant coefficients. In contrast, schooling is significant for the high-quality group (group 3). For this group the long-term return is about 10% which is around 40% less than

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<sup>7</sup>In Gundlach, Rudman and Wossmann (2002) a quality measure is multiplied by the number of years of schooling  $S_{it}$ . That approach assumes that quality and quantity are perfect substitutes.

the value obtained when heterogeneity is ignored (see regression 1). As discussed earlier in this section, the positive bias observed when heterogeneity is ignored is an indication that countries with larger increases in average years of schooling in the sample correspond on average to countries with relatively high social returns.

On the other hand, the improvement in the Sargan statistic (its p-value is equal to 25.5%) suggests that accounting for heterogeneity in this way produces more accurate estimates. The lack of significance of the schooling variable for groups 1 and 2 may be due to a small sample bias. But when the countries in those groups are pooled together (regression 3), the results do not show major changes. Schooling for group 2 is significant only if it is merged with group 3 (regression 4). But the substantial fall in Sargan's p-value raises doubts about the suitability of such pooling. Finally, when group 3 is itself split into two groups (regression 5)<sup>8</sup> the coefficient for schooling is virtually the same for both high quality groups and is not significant for the remaining countries in the sample.

Overall, these results suggest that years of schooling are significant for countries with a relatively high quality of education whereas it is not significant for countries with low levels of schooling quality. We can measure the difference between the social returns implicit in table 3 and the private returns reported by Psacharopoulos (1994) and Psacharopoulos and Patrinos (2004) in order to obtain a crude assessment of the "excess" return in each country. If the coefficients for schooling from regression 5 are transformed into Mincerian-equivalent values (by multiplying them by  $(1 - \alpha)$ ) we obtain 0.4%, 3.6%, 8.1% and 8.1% respectively for the lowest to highest quality groups. Thus the externality associated to schooling can be measured as the difference between these numbers and the private returns. Average excess returns by groups of countries are reported in table 4. The results for each country are reported in the appendix. In general, private returns are higher than the macro ones.

Regarding the coefficient for the  $k/y$  ratio, it is significant at a 10% level in all regressions except for the number 3. Among the regressions where it is significant, the implicit share of physical capital varies from 37.1% to 42.1%. This is consistent with the typical estimates for the capital share.

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<sup>8</sup>Group 3a is contains countries with quality lower than Fiji's. The remaining countries are in group 3b. The rationale for this classification is the drop in Sargan's p-value when Fiji goes to the lower quality group (see figure 1).

To summarize these findings, schooling quality appears to be an important determinant of the social return on schooling. The results in table 3 show that there is a high degree of heterogeneity. Countries with better quality display, on average, higher coefficients for years of schooling.

## 4 Income Accounting

The income accounting literature decomposes the differences in levels of income per worker across countries into differences in factor accumulation and productivity. To do so income per worker is typically expressed as a Cobb-Douglas:  $y = Ak^\alpha h^{1-\alpha}$  where  $A$  is total factor productivity (Hall and Jones, 1999; Caselli, 2005)<sup>9</sup>. The main finding in the literature is that factor accumulation explains only a minor share of income disparities across countries. For instance Caselli (2005) shows that factor accumulation only explains between 30% and 40% of cross-country income variance. This result is robust to a number of checks and is consistent with earlier findings by Hall and Jones (1999). One key assumption of these papers is that in the human capital function  $h = e^{rS}$  the parameter  $r$  is supposed to decrease with the numbers of years of schooling. This is based on the estimated micro returns on schooling, which are on average lower for countries with relatively higher educational attainment.

As seen in the previous section, there is no evidence of a link between private and aggregate returns on schooling. In particular, the data does not reveal that countries with higher levels of schooling have lower macro returns. Moreover, the estimates above suggest that education quality plays an important role in the determination of the macro returns on schooling. Earlier attempts to incorporate direct measures of quality in development accounting are found in Gundlach, Rudman and Woessmann (2002) and Woessmann (2003). However these papers also use the micro evidence as proxies for the macro returns on schooling.

This section decomposes income per worker by incorporating the macro returns obtained in the previous section. This is a key difference with respect to the previous literature because here the parameters are endogenously determined by macro data. More concretely based on regression 5 in table 3 human capital  $h$  in year 1990 is such that  $r = 0.7\%$  for  $q < 0.450$ ,  $r = 5.7\%$  for  $0.450 \leq q < 0.635$  and  $r = 12.8\%$

<sup>9</sup>Caselli and Coleman (2006) go beyond this standard framework by assuming imperfect substitution between skilled and unskilled labour.

for  $q \geq 0.635$ . Let's call this measure of human capital  $h_s$ . As a benchmark let's also construct  $h$  assuming the piecewise linear returns of Hall and Jones (1998) and Caselli (2005) and call it  $h_p$ . These two approaches are fundamentally different because  $h_s$  is obtained by assuming that  $r$  depends positively (and exclusively) on the quality of schooling, whereas  $h_p$  is obtained by assuming that  $r$  depends negatively (and exclusively) on years of schooling. In spite of this difference the correlation between  $h_s$  and  $h_p$  is 92% (the correlation for  $\ln h$  is 88%).

Caselli (2005) defines two measures to gauge the capacity of production factors to account for income differences across countries. The first measure is

$$success_1 = \frac{var(\ln y_{kh})}{var(\ln y)}$$

where  $\ln y_{kh} \equiv \alpha \ln k + (1 - \alpha) \ln h^{10}$ . Thus  $success_1$  is the share of the income variance across countries that can be explained by differences in factor accumulation. When human capital is measured by  $h_p$ ,  $success_1$  takes the value 0.37. In other words, factor accumulation is able to explain only 37% of income variance across countries. This is slightly lower than the value obtained by Caselli (2005) with a different data set and year (he finds  $success_1 = 0.39$ ). In contrast if human capital is measured by  $h_s$ ,  $success_1$  increases to 0.64. Thus by using measures for  $r$  based on macro estimation, the ability of factor accumulation to explain cross-country income differences improves substantially. These results are summarized in table 5.

As variances are sensitive to outliers Caselli (2005) proposes computing an alternative measure that is less affected by such a problem. This measure is defined as:

$$success_2 = \frac{y_{kh}^{90}/y_{kh}^{10}}{y^{90}/y^{10}}$$

where  $x^p$  is the  $p$ th percentile of the distribution of  $x$ . Thus if the output gap were totally explained by differences in factors  $success_2$  would be equal to 1. When  $success_2$  is calculated using  $h_p$  it takes the value 0.32 (in Caselli's paper it is 0.34). But if human capital is measured by  $h_s$ ,  $success_2$  takes the value 0.51. Again,

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<sup>10</sup>As in Caselli's paper I assume that  $\alpha = 1/3$

the data suggests that factor accumulation plays a larger role in explaining income disparities across countries than is usually thought.

Note that although the use of macro returns in development accounting substantially improves the role of factor accumulation in explaining cross-country income differences a substantial share of such differences is still unaccounted for. This is consistent with Caselli and Coleman (2006) who argue that technological choice plays a large role in explaining income differences across countries.

## 5 Earlier Evidence

The availability of historical data since the mid-nineties on both physical and human capital stocks made it possible to directly estimate a production function. As is well known, Benhabib and Spiegel (1994) were the first to show that schooling provides non-significant coefficients in cross-country growth regressions. They estimate

$$\hat{y}_i = \hat{A}_i + \alpha \hat{k}_i + \beta \hat{h}_i \quad (8)$$

where  $\hat{y}_i$ ,  $\hat{k}_i$  and  $\hat{h}_i$  respectively stand for the growth rate of income, physical capital and human capital per worker and  $\hat{A}_i$  represents the growth rate of total factor productivity over the 1965-1985 period. Human capital is represented by the labour force's average years of schooling whether measured with Kyriacou (1991) or Barro and Lee (1993) data. None of these measures turn out to be significant in Benhabib and Spiegel's (1994) regressions. In contrast they find that the level of schooling is positively, though not always significantly, correlated with growth<sup>11</sup>.

In Benhabib and Spiegel (1994) the income growth rate is regressed on the change in the logarithm of years of schooling. Pritchett (2001) replicates these regressions but with an expression for human capital inspired by Mincer (1974). He uses OLS and instrumental variable methods to estimate regression (8). As in Benhabib and Spiegel (1994), Pritchett finds a non-significant  $\beta$ , implying that changes in schooling have had no impact on economic growth. Furthermore, a level regression for year

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<sup>11</sup> The findings by Benhabib and Spiegel (1994) produced an empirical literature that postulates a growth-on-level formulation. This literature, which is not addressed in this paper, is well represented by informal growth regressions à la Barro. In these regressions the educational level is sometimes seen as a state variable, i.e. a variable measuring the proximity to the steady state (Barro and Sala-i-Martin, 1995) and sometimes as a determinant of the steady-state itself (Barro, 1997). More recently, Sala-i-Martin, Doppelhoefer and Miller (2004) found that primary school enrollment in 1960 is strongly correlated with growth during the 1960 – 1996 period.



1985 also rejects the significance of  $\beta$ . However, the interpretation of this result is different from the one given by Benhabib and Spiegel. Pritchett highlights the institutional characteristics where increases in education have taken place and argues that: i) the education provided has low quality and so it has not generated increases in human capital; ii) the expansion in the supply of educated labour has surpassed demand, leading to a decrease in the return on education; and iii) educated workers may have gone into privately lucrative but socially unproductive activities.

However, even if all these phenomena are taking place simultaneously, they can hardly be the reason behind the apparent lack of productivity of education in macro empirical studies. First, it is difficult to believe that the provision of education has been of such a low quality in some countries that on average the world return is zero. Moreover, as discussed in section 3, if countries with higher levels of schooling benefit from better quality and productivity of schooling, then standard cross-country regressions would produce positively biased world average returns. So an argument based on differences in quality goes against Pritchett's (2001) hypothesis. Second, even assuming that the supply of education has increased more rapidly than demand, this cannot in itself imply that one additional year of schooling leads to a null increase in production. And third, the hypothesis that most of the increases in education have been devoted to socially unproductive activities around the world—which would be necessary to explain a null global return—is simply at odds with reality: we do observe that more educated people are employed in better-remunerated activities, which themselves are registered in the national account systems. Again, this simple observation does not mean that all skilled workers are devoted to socially productive activities, but the opposite is not true either.

Temple (2001) has revisited Pritchett's results with different assumptions about the human capital function. However none of these yielded significant coefficients at standard levels of confidence. Temple concludes that “[...] *the aggregate evidence on education and growth, for large sample of countries, continues to be clouded with uncertainty*”.

The systematic failure of cross-country regressions to display positive effects of education has led to some researchers to question about the quality of the data on education. Topel (1999) and Krueger and Lindahl (2001) argue that measurement

error in the number of years of schooling is a major cause of the apparent lack of significance of changes in schooling in growth regressions. In these papers the authors report panel data results for various specifications of growth regressions. The years of schooling variable is from Barro and Lee (1993), which according to Krueger and Lindahl, has less measurement error than Kyriacou's (1991) data. Consistent with the earlier literature they find that changes in schooling are significant only when physical capital is omitted from the regressions or when its coefficient is constrained. Krueger and Lindahl argue that measurement error in years of schooling is exacerbated by the inclusion of physical capital, hence the lack of significance of schooling in the regression with physical capital. Thus they conclude that: *“Overall, unless measurement error problems in schooling are overcome, we doubt that cross-country growth equations that control for capital growth will be very informative insofar as the benefit of education is concerned”*.

Cohen and Soto (2007) present a new data set for years of schooling for a broad group of countries. They also provide preliminary evidence that the new series provide significant results for schooling in a panel of countries, while in the same regressions with Barro and Lee's (2001) data the schooling variable is not significant.

One key point that is not accounted for in the empirical literature is that there is substantial heterogeneity in the returns across countries. Moreover, based on labour studies results the development accounting literature assumes that the macro returns are relatively higher in countries with lower levels of schooling (Hall and Jones, 1999; Caselli, 2005). This hypothesis is rejected by the evidence presented here.

## 6 Conclusions

This paper has revisited the empirical link between years of schooling and GDP per worker. In the borderline panel regression for 83 countries the coefficient for schooling is highly significant. When the estimates are converted into a Mincer-equivalent coefficient we obtain a return equal to 8.3%. This coefficient must not be interpreted as an internal rate of return of schooling but as the causal effect of schooling on income per worker, for a given level of physical capital per worker. With this caveat in mind the estimates suggest the absence of externalities to education, which is consistent with the findings based on wage regressions by Heckman, Layne-

Farrar and Todd (1996), Acemoglu and Angrist (2001) or Ciccone and Peri (2006). This is also consistent with the macro regressions of Heckman and Klenow (1997), Topel (1999) and Cohen and Soto (2007).

However, these regressions conceal the fact that there is substantial return heterogeneity across countries. When the regressions allow for return heterogeneity depending on the quality of schooling as measured by Hanushek and Kimko (2000) countries with higher quality have on average higher returns whereas the coefficient for the lowest quality group is virtually equal to (and not statistically different from) zero.

On the other hand, when countries are classified according to the private returns on schooling as measured by Psacharopoulos (1994) and Psacharopoulos and Patrinos (2004), the social Mincer coefficient is not higher in countries with higher private Mincer coefficients. This suggests that private and social returns on education bear little or no relationship.

One important implication of these results is that the income accounting literature that uses micro returns to build measures of aggregate human capital stocks underestimates the role of human capital in explaining income differences across countries. For instance Hall and Jones (1999) assume a piecewise linear return, which is decreasing in the number of years of schooling. This leads them to find that human capital in India is 45.4% of the US level in 1988. With the estimates in table 5 –where a country like India gets a much lower return than the US– the ratio of human capital in India to the US falls to about 26%. Consequently this paper provides empirical support for schooling quality as an important determinant of income disparities across countries.

## References

- [1] Acemoglu, A., Angrist, J., 2001. How Large Are Human-Capital Externalities? Evidence from Compulsory Schooling Laws. NBER macroeconomics annual 2000, 9-59.
- [2] Barro, R., 1997. Determinants of economic growth: A cross-country empirical study. MIT Press, Boston.

- [3] Barro, R., Lee, J., 1993. International Comparisons of Educational Attainment. *Journal of Monetary Economics* 32(3), 363-94.
- [4] Barro, R., Lee, J., 2001. International Data on Educational Attainment: Updates and Implications. *Oxford Economic Papers* 3, 541-563.
- [5] Barro, R., Sala-i-Martin, X., 1995. *Economic Growth*. McGraw-Hill, New York.
- [6] Benhabib, J., Spiegel, M., 1994. The role of human capital in economic development: Evidence from aggregate cross-country data. *Journal of Monetary Economics* 34, 143-73.
- [7] Bils, M., Klenow, P., 2000. Does schooling cause growth? *The American Economic Review* 90(5), 1160-1183.
- [8] Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics* 87, 115-143.
- [9] Blundell, R., Bond, S., Windmeijer, F., 2000. Estimation in dynamic panel data models: Improving on the performance of the standard GMM estimator, in Baltagi, B. (Ed.), *Nonstationary Panels, Panel Cointegration, and Dynamic Panels*. *Advances in Econometrics* 15. JAI Press, Elsevier Science, Amsterdam.
- [10] Bond, S., Hoeffler, A., Temple, J., 2001. GMM Estimation in Empirical Growth Models. CEPR Discussion Paper 3048.
- [11] Card, D., 1999. The causal effect of education on earnings. In Ashenfelter, O. and Card, D., (Eds.), *Handbook of Labor Economics, Volume 3, Part 1*, 1999, Elsevier Science, Amsterdam, 1801-1863.
- [12] Caselli, F., Esquivel, G., Lefort, F., 1996. Reopening the convergence debate: A new look at cross-country growth empirics. *Journal of Economic Growth* 1, 363-389
- [13] Caselli, F., 2005. Accounting for cross-country income differences. In Aghion, P. and Durlauf, S. (Eds.), *Handbook of Economic Growth*.
- [14] Caselli, F., Coleman, W., 2006. The world technology frontier. *The American Economic Review* 96(3), 499-522.

- [15] Ciccone, A., Peri, G., 2006. Identifying human capital externalities: Theory and applications. *The Review of Economic Studies* 73(2), 381-412.
- [16] Cohen, D., Soto, M., 2007. Growth and human capital: Good data, good results. *Journal of Economic Growth* 12(1), 51-76.
- [17] Easterly, W., Levine, R., 2001. It's not factor accumulation: Stylized facts and growth models. *The World Bank Economic Review* 15(2), 177-219.
- [18] Garen, J., 1984. The Returns to Schooling: A Selectivity Bias Approach with a Continuous Choice Variable. *Econometrica* 52(5), 1199-1218.
- [19] Gundlach, E., Rudman, D., Woessmann, L., 2002. Second thoughts on development accounting. *Applied Economics* 34(11), 1359-1369.
- [20] Hall, R., Jones, C., 1999. Why do some countries produce so much more output per worker than others?, *The Quarterly Journal of Economics* 114(1), 83-116.
- [21] Hanushek, E., Kimko, D., 2000. Schooling, labor force quality, and the growth of nations. *The American Economic Review* 90(5), 1184-1208.
- [22] Hanushek, E., Woessmann, L., 2008. The role of cognitive skills in economic development. *Journal of Economic Literature* 46(3), 607-668.
- [23] Heckman, J., Klenow, P., 1997. Human capital policy. Unpublished manuscript.
- [24] Heckman, J., Layne-Farrar, A., Todd, P., 1996. Human capital pricing equations with an application to estimating the effect of schooling quality on earnings. *Review of Economics and Statistics* 78(4), 562-610.
- [25] Heckman, J., Lochner, L., Todd, P., 2005. Earnings functions, rates of return and treatment effects: The Mincer equation and beyond. NBER Working Paper 11544. Draft chapter for the *Handbook of the Economics of Education*.
- [26] Heckman, J., Vytlacil, E., 1998. Instrumental Variables Methods for the Correlated Random Coefficient Model: Estimating the Average Rate of Return to Schooling When the Return Is Correlated with Schooling. *Journal of Human Resources* 33(4), 974-987.

- [27] Islam, N., 1995. Growth empirics: A panel data approach. *The Quarterly Journal of Economics* 110(4), 1127-1170.
- [28] Krueger, A., Lindahl, M., 2001. Education for growth: Why and for whom? *Journal of Economic Literature* 39, 1101-1136.
- [29] Kyriacou, G., 1991. Level and Growth Effects of Human Capital: A cross-country study of the convergence hypothesis. NYU Economic Research Report: 91-26.
- [30] Lucas, R., 1988. On the mechanics of economic development. *Journal of Monetary Economics* 22, 3-42.
- [31] Mankiw, G., Romer, D., Weil, D., 1992. A contribution to the empirics of economic growth. *Quarterly Journal of Economics* 107(2), 407-437.
- [32] Mincer, J., 1974. *Schooling, experience and earnings*. Columbia University Press, New York.
- [33] Pritchett, L., 2001. Where has all the education gone? *The World Bank Economic Review* 15(3), 367-391.
- [34] Pritchett, L., 2006. Does Learning To Add Up Add Up? The Returns To Schooling In Aggregate Data, *Handbook of The Economics of Education*, Vol. 1, Elsevier Science, 635-695.
- [35] Psacharopoulos, G., 1994. Returns to investment in education: A global update. *World Development* 22(9), 1325-1343.
- [36] Psacharopoulos, G., Patrinos, H., 2004. Returns to investment in education: A further update. *Education Economics* 12(2), 111-134.
- [37] Sala-i-Martin, X., Doppelhoefer, G., Miller, R., 2004. Determinants of long-term growth: A Bayesian averaging of classical estimates (BACE) approach. *The American Economic Review* 94(4), 813-835.
- [38] Summers, R., Heston, A., 1991. The Penn World Table (Mark 5): An Expanded Set of International Comparisons, 1950-1988. *The Quarterly Journal of Economics* 106(2), 327-368.

- [39] Temple, J., 2001, Generalizations that aren't? Evidence on education and growth. *European Economic Review*, 45(4-6), 905-918.
- [40] Topel, R., 1999. Labor markets and economic growth. In Ashenfelter, O. and Card, D., (Eds.), *Handbook of Labor Economics*, Volume 3, Part 3, Elsevier Science, Amsterdam, 2943-2984.
- [41] Woessmann, L., 2003. Specifying human capital. *Journal of Economic Surveys* 17(3), 239-270.

## Appendix A

In section 2 it is argued that in order to evaluate the presence of externalities in years of schooling we must compare the private Mincerian return with  $(1 - \alpha)r$ . To illustrate this result let's consider for simplicity a large number of identical firms operating under perfect competition and absence of externalities. In this case a unit of human capital is paid its marginal productivity  $\frac{\partial Y}{\partial H}$  where  $Y$  and  $H$  are respectively aggregate output and human capital. Thus a worker  $j$  with  $h(S^j)$  units of human capital gets a salary  $w^j = \frac{\partial Y}{\partial H} h(S^j)$ . With the production function  $Y = AK^\alpha H^{1-\alpha}$  the salary perceived by worker  $j$  is such that:

$$\ln w^j = \ln(1 - \alpha) + \ln(A) + \alpha \ln K - \alpha \ln H + \ln h^j$$

Suppose that there are  $n$  workers and that total human capital is such that  $H = \sum_{l=1}^n h^l$ . So the equilibrium salary for worker  $j$  can be written as:

$$\ln w^j = \ln(1 - \alpha) + \ln(A) + \alpha \ln K - \alpha \ln \sum_{l \neq j}^n h^l + (1 - \alpha) \ln h^j \quad (9)$$

Expression (9) represents the salary that worker  $j$  gets under perfect competition and lack of externalities. In such a context the marginal effect of schooling on  $\ln w^j$  is equal to  $(1 - \alpha) \frac{\partial \ln h^j}{\partial S^j}$ .

On the other hand the standard wage equation is a function of years of schooling  $S$  and experience  $x$  as follows (see for example Heckman, Lochner and Todd, 2005):

$$\ln w^j = a_0 + \rho S^j + \beta_0 x^j + \beta_1 x^{j2} + e^j \quad (10)$$

Equation (10) describes the equilibrium salary received by a worker with schooling  $S^j$  and experience  $x^j$ . In this equation  $\rho$  is the micro Mincerian return on schooling, defined as the percentage increase in the wage caused by an increase in the level of schooling. Thus in the absence of externalities equations (9) and (10) are consistent only if

$$(1 - \alpha) \frac{\partial \ln h^j}{\partial S^j} = \rho$$

or equivalently,

$$\ln h^j = \frac{\rho}{(1 - \alpha)} S^j + \varepsilon^j \quad (11)$$

where  $\varepsilon^j$  is a residual independent from  $S^j$ . Therefore with an arbitrarily skewed distribution of schooling, average human capital per worker  $h$  is such that:

$$\ln h \approx \frac{\rho}{(1 - \alpha)} S + \varepsilon \quad (12)$$

where  $S$  is average schooling and  $\varepsilon$  is an aggregation of  $\varepsilon^j$ . Thus under the hypothesis of the absence of human capital externalities, from expression (12) and (2) we conclude that  $\rho = (1 - \alpha) r$ .



**Table 1: Benchmark Estimation**

Dependent variable is  $\ln(\text{GDP per worker})$   
(83 countries; 1960-1990)

	OLS (Levels) (1)	OLS (Differences) (2)	GMM (System 1) (3)	GMM (System 2) (4) - Baseline
Observations	313	230	313	313
<i>Log of capital-output ratio</i>	0.221 <sup>b</sup> (0.112)	-0.213 <sup>b</sup> (0.105)	0.843 <sup>b</sup> (0.340)	0.859 <sup>b</sup> (0.349)
<i>Years of schooling</i>	0.217 <sup>a</sup> (0.024)	0.093 <sup>b</sup> (0.044)	0.136 <sup>b</sup> (0.058)	0.155 <sup>a</sup> (0.054)
Implicit capital share	0.181	-0.271	0.457	0.462
Implicit Mincerian return	0.178	0.118	0.074	0.083
Sargan (p-values)	–	–	0.132	0.176
2 <sup>nd</sup> order serial correl. (p-values)	–	–	0.743	0.804

Notes: GDP per worker from Summers and Heston, PWT 5.6; stock of physical capital per worker from Easterly and Levine (2001); years of schooling from Cohen and Soto (2007). Time dummies included (not reported). Robust standard errors in parenthesis. 2-step GMM coefficients (one-step standard errors). See main text on the selection of instruments for GMM estimation.

a, b, c: coefficients are significant at a 1%, 5% and 10% respectively.

**Table 2: Effect of schooling by size of private Mincer coefficient ( $m$ )**

Dependent variable is  $\ln(\text{GDP per worker})$   
 (System GMM estimation, 55 countries, 1960-1990)

	(1)	(2)	(3)
<i>Log of capital-output ratio</i>	0.928 <sup>b</sup> (0.432)	0.661 <sup>c</sup> (0.347)	0.958 <sup>b</sup> (0.419)
<i>Years of schooling (all countries)</i>	0.139 <sup>a</sup> (0.051)		
<i>Years of schooling (countries with <math>m &lt; 0.08</math>)</i>		0.129 <sup>a</sup> (0.040)	
<i>Years of schooling (countries with <math>0.08 \leq m &lt; 0.11</math>)</i>		0.138 <sup>a</sup> (0.050)	
<i>Years of schooling (countries with <math>0.11 \leq m</math>)</i>		0.082 (0.056)	0.066 (0.060)
<i>Years of schooling (countries with <math>m &lt; 0.11</math>)</i>			0.120 <sup>b</sup> (0.048)
Implicit share of physical capital	0.481	0.398	0.489
Implicit social Mincerian coefficient in:			
<i>All countries</i>	0.072	--	--
<i>Countries with <math>m &lt; 0.08</math></i>	--	0.078	0.061
<i>Countries with <math>0.08 \leq m &lt; 0.11</math></i>	--	0.083	0.061
<i>Countries with <math>0.11 \leq m</math></i>	--	0.049	0.034
Sargan (p-values)	0.016	0.073	0.056
2 <sup>nd</sup> order serial correlation (p-values)	0.616	0.713	0.672

Notes: 214 observations. GDP per worker from Summers and Heston, PWT 5.6; stock of physical capital per worker from Easterly and Levine (2001); years of schooling from Cohen and Soto (2007); private Mincer coefficient ( $m$ ) from Psacharopoulos (2002) and Psacharopoulos and Patrinos (2004). Time dummies included (not reported). Robust standard errors in parenthesis. 2-step GMM coefficients (one-step standard errors). See main text on the selection of instruments.

a, b, c: coefficients are significant at a 1%, 5% and 10% respectively.

**Table 3: Effect of schooling by quality of education (q)**

Dependent variable is  $\ln(\text{GDP per worker})$   
 (System GMM estimation, 67 countries, 1960-1990)

	(1)	(2)	(3)	(4)	(5)
<i>Log of capital-output ratio</i>	0.726 <sup>c</sup> (0.416)	0.601 <sup>c</sup> (0.322)	0.506 (0.374)	0.643 <sup>c</sup> (0.361)	0.589 <sup>c</sup> (0.311)
<i>Years of schooling in:</i>					
<i>All countries</i>	0.145 <sup>b</sup> (0.057)				
<i>Countries with <math>q &lt; 0.450</math></i>		-0.023 (0.084)		0.024 (0.072)	0.007 (0.083)
<i>Countries with <math>0.450 \leq q &lt; 0.633</math></i>		0.030 (0.083)			0.057 (0.081)
<i>Countries with <math>0.633 \leq q</math></i>		0.104 <sup>b</sup> (0.046)	0.121 <sup>b</sup> (0.048)		
<i>Countries with <math>q &lt; 0.633</math></i>			0.032 (0.082)		
<i>Countries with <math>0.450 \leq q</math></i>				0.123 <sup>b</sup> (0.052)	
<i>Countries with <math>0.633 \leq q &lt; 0.835</math></i>					0.129 <sup>a</sup> (0.047)
<i>Countries with <math>0.835 \leq q</math></i>					0.128 <sup>a</sup> (0.040)
Implicit capital share	0.421	0.375	0.336	0.391	0.371
Sargan (p-values)	0.084	0.255	0.321	0.177	0.289
2 <sup>nd</sup> order serial correl. (p-values)	0.683	0.595	0.629	0.636	0.573

Notes: 257 observations. GDP per worker from Summers and Heston, PWT 5.6; stock of physical capital per worker from Easterly and Levine (2001); years of schooling from Cohen and Soto (2007); quality of education from Hanushek and Kimko (2000) as percentage of quality in Singapore. Time dummies included (not reported). Robust standard errors in parenthesis. 2-step GMM coefficients (one-step standard errors). See main text on the selection of instruments.

a, b, c: coefficients are significant at a 1%, 5% and 10% respectively.

**Table 4. Social and private Mincerian coefficients  
by quality of education**

Quality Group	Average social Mincer coefficient	Average private Mincer coefficient	Difference
$q < 0.450$	0.004	0.102	-0.098
$0.450 \leq q < 0.633$	0.036	0.112	-0.076
$0.633 \leq q < 0.835$	0.081	0.092	-0.010
$0.835 \leq q$	0.081	0.089	-0.008

**Table 5. Income decomposition (1990)**

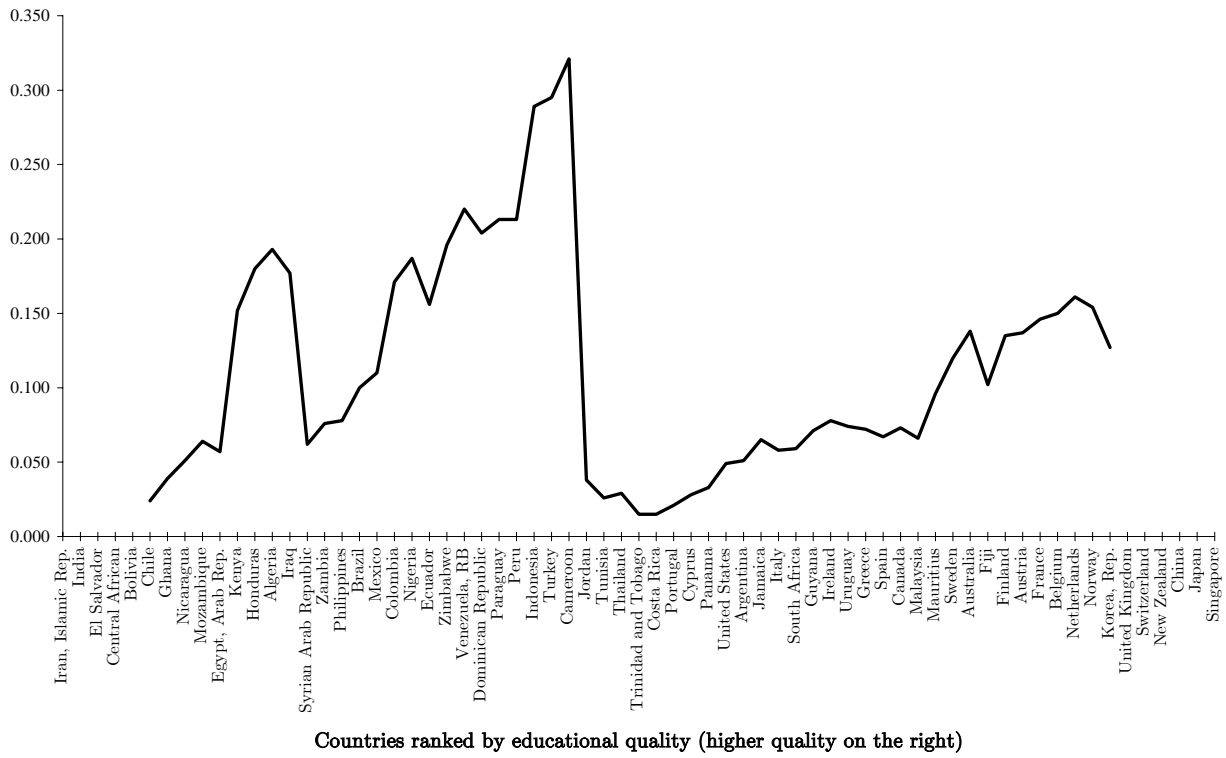
	Assuming $h_s$	Assuming $h_p$	Caselli (2005) estimation
$\text{Var}(\ln y_{kh})/\text{Var}(\ln y)$	0.64	0.37	0.39
$(y_{kh}^{90}/y_{kh}^{10})/(y^{90}/y^{10})$	0.51	0.32	0.34

$y_{kh}$  = factor accumulation;  $y$  = GDP per worker;  $x^p = p^{\text{th}}$  percentile of the distribution of  $x$ .

“Assuming  $h_s$ ”: Factor accumulation is calculated assuming that human capital is  $h_s$

“Assuming  $h_p$ ”: Factor accumulation is calculated assuming that human capital is  $h_p$

**Figure 1:** Sargan test (p-values) in recursive estimation



Note: A low p-value suggests that the country's return on schooling is significantly different from the average return in countries with lower educational quality.