The causal effect of education on aggregate income

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Abstract

Empirical studies find that changes in schooling are not correlated with changes in per capita income. The estimation in levels also produces minor coefficients for years of schooling. Low social returns and measurement error in educational variables have been invoked as possible explanations for such findings. This paper shows that collinearity between physical and human capital stocks seriously undermines the ability of educational indicators to display significance in panel data estimates. On top of that, failure to cope with endogeneity has produced biased estimates. As opposed to the earlier empirical literature, the social return on schooling is positive and significant, but no Lucas-type externalities are observed. Finally, the quality of education emerges as a significant determinant of heterogeneity in social returns across countries.

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JEL classification: C33, I20, O11

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1 Introduction

A recurrent question that has characterised the debate on economic growth during the last decade refers to the puzzling lack of correlation between years of schooling and income per capita in empirical research. This evidence has led to different examinations and reinterpretations of the role of education. Benhabib and Spiegel (1994) have put forward that the level of education should not be seen as a factor of production, but as a determinant of changes in total factor productivity. Also, in subsequent versions of an influential paper, Pritchett (2001) has argued that the poor institutional framework, low quality and excess supply of schooling in developing countries are all responsible for the lack of empirical link between changes in educational attainment and economic growth. Cross-country evidence reported by Temple (2001) supports the *Pritchett hypothesis*. Paralleling these results a series of panel data studies have also failed to find 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 try to reconcile the macro evidence with the micro findings on the returns to schooling. The paper argues that, although the *Pritchett hypothesis* may apply to some specific countries, it cannot explain the null or even negative coefficients for years of schooling. The causes of these findings must be found somewhere else.

This is not a paper about why changes in the schooling variable 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) 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.

In order to estimate the causal effect of schooling there are basically three issues that have to be considered. First, it must be defined how years of schooling should enter in a production function. The underlying question is how to relate the number of years of schooling to human capital. Put simply, this is a discussion on whether the macro-return to education should be evaluated in a log-log or log-linear formulation. This question can be settled empirically and has already been addressed by Bils and Klenow (2000). A second issue refers to the appropriate functional form to be estimated. As is shown later, a simple statistical problem of collinearity between physical and human capital stocks seriously undermines educational indicators' ability to display significance in regressions in levels. The third point refers to the consistency of the estimates. Empirical research has usually relied on ordinary least squares or fixed-effect estimation and therefore has overlooked endogeneity problems. On top of that, return heterogeneity in the macro return on schooling has been traditionally ignored. These omissions have probably led to inconsistent estimates.

Here the term 'return' calls for a clarification. In the same way as 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 Petra, 2005), in this paper the macro Mincerian return is interpreted as the effect of schooling on GDP per head. So the terms 'effect of schooling' or 'return on schooling' will be used interchangeably.

As many authors have noted, the discussion on why education fails to display positive effects in growth regressions is more an academic issue than one pertinent for policy decisions. The policy relevant question is whether schooling presents social returns that are higher than the private ones. The paper offers a range of values for the social return to years of schooling. Assuming return homogeneity the full sample estimate of the income response to one additional year of schooling is around 8.0%. This is in the range of micro-Mincerian returns reported by Psacharopoulos (1994) and Psacharopoulos and Patrinos (2002) for country-level studies. 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 hides substantial heterogeneity in the macro-Mincer coefficients 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 the group of countries with lowest quality levels of education. In addition it is found that ignoring return heterogeneity leads to a moderate overestimation of the average macro Mincer coefficient.

In summary, contrary to the earlier findings, the causal effect of education on income is positive and statistically significant. But on average the macro Mincer coefficients are not higher than the private ones. This last result is in line with the findings of Heckman, Layne-Farrar and Todd (1996), Acemoglu and Angrist (2001), Pritchett (2003) or Ciccone and Peri (2005), who following a different (i.e. micro) approach do not detect significant externalities to schooling.

The paper is organised as follows: the next section discusses the main results and the current debate about the macro-returns on schooling. This literature has given attention essentially to the estimation in first differences. From these estimates it has been concluded implicitly that the level of schooling does not affect the level of income or that it is not possible to gauge the impact of schooling due to the low quality of the data. Section 3 highlights the difficulties in estimating this return even in equations in levels and presents new empirical results. Section 4 explores the effects of return heterogeneity across countries and assesses the effects of quality of education. The main conclusions are presented in section 5.

2 Earlier evidence

In order to evaluate the causal effect of schooling on income the earlier literature has focused almost exclusively on the estimation of cross country growth regressions. In these regressions the income growth rate is regressed on enrollment rates or some measure of the change in years of schooling. Since it is found that the variations of schooling are not correlated with the changes of income, it has been inferred that whether the level of schooling does not affect the level of income or the data are too noisy to provide conclusive evidence about the social returns on schooling. Although the focus of this paper is not on the estimation in first differences, it is important to refer to this literature because it has determined the current conclusions regarding the impact of schooling on aggregate income.

One of the first attempts to assess the effect of schooling in macro growth regressions is done by Mankiw, Romer and Weil (MRW, 1992). There human capital is represented as a factor of production in an extended version of the Solow model as follows:

$$Y = AK^{\alpha}H^{\beta}L^{1-\alpha-\beta} \tag{1}$$

Here Y represents total output, K and H are total physical and human capital respectively, and L is the labour force. From equation (1) and standard laws of motion for K and H, MRW show that both, the output level and growth may be related to the investment rate in physical and human capital. These two equations represent, respectively, the steady state and convergence path of income. Then, in their empirical analysis, MRW show that human capital investment is significant in both equations. For human capital investment MRW use the secondary enrollment rate multiplied by the fraction of population aged 15 to 19 in the working age population.

The empirical results of this influential paper are nevertheless shadowed by the fact that MRW fail to control for the endogeneity of the investment rates and by the murkiness of their measure of human capital investment. Examples of papers that have tackled the endogeneity problem for testing the MRW model are Caselli, Esquivel and Lefort (1996) and Islam (1995). In both papers the schooling variable appears with the wrong sign.

The availability of data on both physical and human capital stocks has made possible the direct estimation of level-on-level or change-on-change regressions. Assuming a linear function between years of schooling human capital, Benhabib and Spiegel (1994) estimate

$$\hat{y}_i = \hat{A}_i + \alpha\hat{k}_i + \beta\hat{h}_i + \epsilon_i \tag{2}$$

where $y = Y/L$, $k = K/L$ and $h =$ average years of schooling for each country i and $\hat{g}$ stands for the log change of variable g over the period 1965-1985.

As is well known, Benhabib and Spiegel (1994) were the first to show that in regression (2) the change in schooling –whether measured by Kyriacou (1991) or Barro and Lee (1993) data– provides non-significant and sometimes even negative coefficients. On the other hand, they found that the level of schooling is positively, though not always significantly, correlated with growth. Undoubtedly, these results were the first to question empirically the view that human capital is to be treated as an additional factor of production[1].

In Benhabib and Spiegel (1994) the income growth rate is regressed on the change in the logarithm of schooling. Later Pritchett (2001) replicates these regressions but with a different measure of human capital. Based on Mincer (1974) wage equations, Pritchett builds a human capital index given by,

$$h = e^{rS} - 1 \tag{3}$$

where h is human capital per worker, r is the return to education (which Pritchett sets at 0.1) and S is the average number of years of schooling from Barro and Lee (1993). He then uses OLS and instrumental variable methods to estimate regression (2). As in Benhabib and Spiegel (1994), Pritchett finds a non-significant β, implying that changes in schooling have had no impact on economic growth. Furthermore, a level regression for year 1985 also rejects the significance of β. The interpretation of this result is however radically 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 supply of educated labour has surpassed demand, leading to a decrease in the return of education; and iii) educated workers may have gone to privately lucrative but socially unproductive activities.

[1] The findings of Benhabib and Spiegel (1994) produced an empirical literature that postulates a growth-on-level formulation. This literature, which is not adressed in this paper, is well represented by the 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, Doppelhofer and Miller (2004) find that primary school enrollment in 1960 is strongly correlated with growth during the period $1960 - 1996$.

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 it is shown later, if countries with higher levels of schooling benefit from better quality and productivity of schooling, then standard cross-country regressions would provide world average returns biased upwards. So an argument based on differences in quality goes against the hypothesis of Pritchett (2001). Second, even assuming that the supply of education has increased more rapidly than demand, this cannot by 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.

More recently, Temple (2001) has revisited Pritchett's results. He has explored the effects of estimating the MRW production function (1) by assuming different definitions for human capital. With the same database as Benhabib and Spiegel (1994), Temple estimates the following cross-country regressions:

$$\Delta \ln Y_i = \mathbf{C}_0 + \alpha \Delta \ln K_i + \beta \Delta f(S_i) + \gamma \Delta \ln L_i + \Delta \varepsilon_i \tag{4}$$

where $f(S_i)$ is a function of the number of years of schooling. In particular, Temple reports results for $f(S_i) = rS_i$ and for $f(S) = c_0 + c_1 ln(S_i) + c_2(1/S_i)$. None of these yielded significant coefficients at standard levels. 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 from 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 ΔS in growth regressions. In both papers the authors report panel data results for the following equation for country i in year t:

$$\Delta \ln y_{it} = \pi_1 S_{it-1} + \pi_2 \Delta S_{it} + \pi_3 \ln y_{it-1} + \Delta \tau_t + \Delta \varepsilon_{it} \tag{5}$$

where τ_t represents a time-specific effect. 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. Topel and Krueger and Lindahl estimate (5) by using different data frequencies. They find that in high frequency regressions (i.e. panel data with 5-year observations) ΔS is not significant, while in lower frequency regressions (10 or 20-year observations), ΔS becomes significant. The authors argue that in short periods of time ΔS has a low informational content relative to the measurement error and this is why in 5-year data regressions the significance of ΔS is rejected. In longer periods of time, the argument goes, true changes in S are more likely to predominate over measurement errors. Furthermore, Krueger and Lindahl show that if the estimate of π_2 (in the regressions with 20-year observations) is adjusted by taking into account the downwards bias induced by the measurement error in S, its magnitude shoots from 0.18 to 0.30. Topel finds a non-adjusted π_2 as high as 0.25 in a similar regression. These values suggest huge returns to education, and if taken at face value, they would imply large positive externalities.

Yet, these findings must be considered with some caution for three reasons. First, the regressions are not based on a specific growth model. The use of lagged income suggests that equation (5) represents a convergence path towards steady state. But in that case it is hard to justify the presence of both, the change and the level of schooling simultaneously. Indeed, the MRW augmented model states that in a convergence path, income growth depends on the investment rate of human capital (not on its level or change).

Second, in almost all the regressions reported, the endogeneity of years of schooling is ignored. This variable is likely to be endogenous since as a country gets richer it may afford more investment in education, hence a higher level of education. Not dealing with the endogeneity of S means that its coefficient is likely to be biased upwards. The few regressions reported by Krueger and Lindahl that were estimated with instrumental variables methods make use of Kyriacou's series as instruments (as a solution to the measurement error problem). However, this instrument does not represent a solution to endogeneity since it is itself an endogenous variable. Krueger and Lindahl argue that the attenuation bias introduced by measurement error is higher than the upwards bias inherent to the endogeneity of S. But this argument, by itself, does not justify not using suitable instruments –like lagged values of endogenous variables– to overcome the measurement error or endogeneity problems. A straightforward estimation method that deals with both sorts of biases looks as a much more natural method of estimation.

A third reason to be cautious about these results is that ΔS is significant only when the change in the stock of physical capital is omitted from the regressions. When Krueger and Lindahl include $\Delta \ln(k)$, ΔS loses its explanatory power, while physical capital growth gets a coefficient as high as 0.8. This is much higher than the standard share of physical capital in total income –which is thought to have a ceiling at around 0.5 (see Gollin, 2002)– and consequently is a clear sign of endogeneity problems. Only when the coefficient associated to $\Delta \ln k$ is constrained to 0.35, ΔS recovers its significance. Krueger and Lindahl 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*".

To illustrate the effects entailed in the omission of physical capital consider table 1. Columns 1 and 2 reproduces the estimates of equation (5) reported by Krueger and Lindahl (2001) and Topel (1999) for the regressions based on 10-year observations (over the period 1960-1990). Series for GDP per capita and per worker are from World Penn Table Mark 5.6 and years of schooling are from Barro and Lee (1993). These results show that both, the change and the initial level of years of schooling have a positive effect on economic growth. The differences in point estimates are due to the different methods of estimation. Krueger and Lindahl's results are obtained by OLS, while Topel uses the Within estimator.

From these results the authors conclude that schooling has a positive effect on growth although they acknowledge that the estimates may be biased due to the omission of physical capital and the presence of measurement error in schooling series. The consequences of omitting physical capital are illustrated in the rest of the table. Columns 3 and 4 replicate these regressions by using Cohen and Soto (2001) series on years of schooling, for 83 countries[2]. The results are very close to those of Krueger and Lindahl, whether GDP per capita or per worker is used. Namely, the coefficients on

[2] Cohen and Soto (2001) show that their series of schooling have better reliability ratios than Barro and Lee (1993 and 2001) series. The complete database on years of schooling and educational attainment is available at: http://www.oecd.org/dataoecd/33/13/2669521.xls

years of schooling are almost the same. This shows that at least in these regressions the change of the series of schooling is not affecting the results.

However, when the change in capital stock is included[3] in column 5 the coefficient on the change in years of schooling falls dramatically and becomes insignificant. The further inclusion of the initial level of physical capital stock causes the initial level of schooling to lose its significance as well. On the other hand, the large coefficient on physical capital reflects that endogeneity is biasing upwards this coefficient. Yet, endogeneity of physical capital by itself may not be the cause behind the vanishing effect of schooling. Moreover, if countries invest more on education as they become richer, schooling would also be affected by an upwards simultaneity bias.

Krueger and Lindahl argue that measurement error in S is exacerbated by the inclusion of physical capital, hence the lack of significance of schooling in the regression with $\Delta \ln k$. However, the next section shows that even the estimation in levels –which is less subject to measurement error problems– produces non-significant coefficients for years of schooling. Therefore, something in addition to measurement error is affecting the estimation of the social return to schooling, unless Pritchett was right in his assessment about the fact that education has not promoted economic growth in the last decades.

The main message of the earlier evidence is that the social return on schooling is low or not significant or that the data available are too noisy to yield information regarding the social returns on schooling. The next section provides new evidence in the framework of a standard production function.

3 Rediscovering education

The previous section highlights the difficulties that the earlier studies have found in trying to estimate the social return on schooling from equations in first differences. A natural solution in order to gauge this return is to run regressions in levels or a combination of levels and first-differences. Assuming constant returns on K and H, and setting $\ln h = rS$ [4], equation (1) yields the following equation:

$$\ln y_{it} \quad = \quad \alpha \ln k_{it} + (1-\alpha)\, rS_{it} + \eta_i + \tau_t + \epsilon_{it}, \tag{6}$$

where η_i and τ_t are respectively country and time specific effects, and ϵ_{it} is a residual. The assumption of constant returns on K and H (i.e. $\alpha + \beta = 1$) allows the identification of r and has no implication on the results that are presented below. Indeed, the social Mincerian return is the semi-elasticity of income with respect to years of schooling. This can be estimated without any prior knowledge about factor shares in total income. In all subsequent regressions the period covered is 1960-1990 and the data are from PWT 5.6 in order to stick to the same income and growth data studied in the earlier literature.

Table 2 reports estimates for α and $(1-\alpha)r$ resulting from different methods of estimation. The first column shows the OLS estimates for the equation in levels (6). The physical capital variable is highly significant and its estimated share in total income is 0.60, larger than the 'conventional wisdom' about this variable. Conversely, years of schooling are not significant. Column 2 shows the results for the estimation of equation (6) in first-differences, which are similar to those obtained for the equation in levels. Namely, years of schooling are not significant, as earlier cross-country growth

[3]Physical capital stocks are from Easterly-Levine (2001).

[4]The original Mincerian equation also includes terms in labour experience and squared labour experience, which is not taken into account here.

regressions have already found[5]. As for the GMM estimates, none of them results in a significant coefficient for years of schooling[6]. The estimation in levels (regression 3), which uses lagged first-differences of the regressors as instruments, produces qualitatively similar results to the OLS estimates. What is more, the standard Arellano-Bond estimator (column 4) provides a negative coefficient –although not significant– for ΔS and an excessively high α. Blundell and Bond (1998) and Blundell, Bond and Windmeijer (2000) have shown that in finite samples the difference GMM estimator have a large bias and low precision when the series have a strong autoregressive component. This is certainly the case of the physical and human capital series. When the variables are strongly autoregressive the authors show that the system GMM estimator, which estimates simultaneously the equation in levels and in first differences, provides more precise estimates and lower biases in finite samples. Yet, the system GMM estimator yields a non-significant coefficient for years of schooling (column 5).

The fact that none of the regressions that make use of instrumental variables produces significant estimates for years of schooling suggest that the measurement error problem is not the only reason causing insignificant coefficients. Another econometric problem that may be behind this result is collinearity between physical capital stocks and years of schooling.

Figure 1 shows the relationship between years of schooling (S) and the logarithm of physical capital per worker (k). The correlation between both variables is considerable, as is shown by the large R^2 obtained from an OLS regression of $\ln k$ on S (without time dummies). An illustration that the high collinearity between physical and human capital is undermining the precision of the estimates can be made by regressing equation (6) without the physical capital variable. The results are shown in panel B of table 2. There, all the methods of estimation –except for the difference GMM estimator– result in significant coefficients for S. Even the equation in differences, when estimated by OLS, provides a non-null coefficient. Needless to say, these results are subject to inconsistency problems due to the omission of physical capital. This is patent from the implicit high return on schooling. But the fact that, by omitting physical capital, years of schooling become highly significant is a sign that collinearity may be affecting the precision of the estimation of equation (6) .

So why should collinearity affect more human capital than physical capital? Davidson and MacKinnon (1993, pp. 181-186) suggest a simple procedure to find out the variable whose significance is more affected by the presence of collinearity. Suppose that x_1 and x_2 are two collinear regressors and X represents the remaining regressors of the model to be estimated. If an OLS regression of x_1 on x_2 and X produces a higher R^2 than a regression of x_2 on x_1 and X then it is the significance of x_1 in the original model that will be more affected. The reason is that in this case x_1 is relatively well explained by x_2 and X. In the present context, if it is true that collinearity is the cause of the low significance of S, a regression of S on $\ln k$ and time dummies should produce a higher R^2 than a regression of $\ln k$ on S and time dummies. The R^2 of these two auxiliary regressions (not reported) are respectively 0.72 and 0.70. Although the difference is small it is consistent with the fact that physical capital is significant while human capital is not[7].

[5] Note that since estimation in first-differences implies the lost of the first observation, the results are not directly comparable to those of column 1.

[6] The standard errors reported for GMM correspond to one-step estimates. Indeed, Blundell and Bond (1998) and Blundell et al (2000) show that the two-step standard errors underestimate the true variability of the coefficients, and so the lead to under-rejection of non-significant coefficients. See Windmeijer (2000) for a correction of this problem.

[7] Obviously this is just a qualitative result. There is no theory that indicates how large the difference between the R^2 of the auxiliary regressions must be to cause only one of the regressors to

One way to get rid of the collinearity problem is to reparametrise the model. By subtracting $\alpha \ln y$ from both sides of equation (6) and dividing by $(1-\alpha)$ we obtain,

$$\ln y_{it} \;=\; \frac{\alpha}{1-\alpha} \ln \left(\frac{k}{y}\right)_{it} + rS_{it} + \frac{u_{it}}{1-\alpha} \tag{7}$$

where $u_{it} \equiv \eta_i + \tau_t + \epsilon_{it}$.

The lower scatter in figure 1 represents the relationship between years of schooling and the logarithm of the capital-output ratio. Although the correlation between $\ln(k/y)$ and S is still high it is lower than correlation between $\ln k$ and S.

This reparametrisation introduces additional endogeneity problems as the income level appears now in both sides of the equation. Although this is a common problem in growth econometrics few studies try to deal with it seriously. For instance, every convergence equation has the initial income level on both sides of the regression. Similarly any regression that has the GDP growth rate as a dependent variable and ratios like trade to GDP or financial development to GDP have the same problem. Only few studies recognize this by using instrumental variables, which is the proper solution.

Topel (1999) has already estimated equation (7) by constraining the coefficient α 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 (7) by fixed-effect and OLS methods. Heckman and Klenow (1997) also estimate a constrained version of (7) by OLS.

Table 3 presents unconstrained estimates for the equation (7). The OLS estimation in levels (column 1) results in an implausible low coefficient for the capital-output ratio. Indeed, the implicit share of physical capital in total output is $0.221/1.221 = 0.181$. This negative bias is the consequence of the presence of y in the capital-output ratio. By contrast, the coefficient on schooling is large (21.7%) and highly significant. This value reflects the return on schooling that allows for physical capital to adjust to changes in S so that the ratio k/y stays constant. Therefore it can be seen as a long-term return on schooling. However the Mincerian-comparable return of one additional year of schooling –i.e. the increase 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 is in part due to the low coefficient on the capital-output ratio. Similar problems apply for the estimation in first-differences (column 2), which explains a negative α. Note however that by dealing with the collinearity problem, the OLS estimations in both levels and in first-differences produce positive and significant coefficients associated with years of schooling.

The GMM estimation in levels produces significant coefficients for both the capital-output ratio and years of schooling (column 3). The estimated implicit share of physical capital in total income (46.4%) is slightly larger than its typical value while the estimated social Mincerian return (8%) falls in the range observed in micro studies. System GMM estimates display similar results. The capital share is estimated at 46.2% and the semi-elasticity of income with respect to years of schooling is equal to 8.3%.

These returns 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,

lose its significance. So we cannot say that the difference found here is "large" or "small".

Psacharopoulos (1994) and Psacharopoulos and Patrinos (2002) 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 point to an absence of externalities to schooling[8]. Moreover these preliminary results hint at the presence of signalling and screening effects of education. Under this hypothesis employers use education to screen employees' ability and so part of private the return on education is the value of the signal that it conveys. Therefore the presence of screening implies that the private return on schooling is higher than the aggregate return. Note however that the difference between private and social returns is small (less than 2 percentage points) and can be explained away by standard errors.

Finally, if an increase in the level of human capital induces an expansion of physical capital the total macro return to schooling would be higher than the typical private one. Indeed, under the assumption of a constant capital-output ratio the total return to schooling would fall in the range $15\% - 15.5\%$ depending on the method of estimation. However, this larger long-term Mincerian return does not represent externalities in the sense of Lucas (1988). In Lucas's model, the social marginal product of human capital is higher than the private marginal return in the short-run –i.e. without taking into consideration any hypothetical endogenous response of physical capital. Therefore in order to analyse if these externalities exist in the real world we must compare this short-run return with the typical micro Mincerian coefficient. And the results of table 3 point to the absence of this kind of externalities. On the other hand, what table 3 does show is that, contrary to the findings of most of the recent empirical literature, the neoclassical approach to human capital is strongly supported by the evidence, and years of schooling present a return surprisingly close to the standard value found in micro studies.

4 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 this assumption has been questioned recently. 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 motivated by the private Mincerian returns reported by Psacharopoulos (1994) and Psacharopoulos and Patrinos (2002). They report wide 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 respectively 13.2% and 13.1% whereas those for South Africa and Egypt are respectively 4.1% and 5.5%. Although private and social Mincerian returns are not necessarily connected, it is still possible that they are. If so, the observed heterogeneity in labour studies would point to important differences in Mincerian returns at the aggregate level.

Another piece of empirical evidence suggesting return heterogeneity is provided

[8] There is a huge literature on whether these micro returns are properly measured but this topic goes far beyond the scope of this paper. The micro Mincer coefficients are used only as a reference.

by Hanushek and Kimko (2000). They report substantial differences in schooling quality across countries –measured by test scores on mathematics and science. These differences may also be a cause of return heterogeneity. Pritchett (2001) backs this idea by arguing that the low quality of schooling is one major cause of the lack of significance of schooling variables in growth regressions[9].

Under the presence of heterogeneity each country's long-run return r_i can be expressed as:

$$r_i = \bar{r} + \nu_i \tag{8}$$

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

It is often stated that heterogeneity is not a problem in itself since the estimated parameter can be interpreted as the average across countries, i.e. $\bar{r}$. But, this is not necessarily the case. 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 introduced by this term depends on whether ν_i and S_i are positively or negatively correlated. According to the micro evidence presented by Psacharopoulos (1994) and Psacharopoulos and Patrinos (2002) the return on years of schooling is lower in countries with higher levels of education, so this would suggest that the correlation $\sigma_{\nu,S}$ between ν_i and S_i is negative. This, in turn, would imply that methods of estimation that do not account for differences in returns across countries produce estimates of $\bar{r}$ biased downwards.

On the other hand, it may be the case that higher levels of schooling are not matched by higher aggregate productivity, especially in developing countries, as put forward by Pritchett (2001, 2003). Moreover, 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. Therefore, 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 biased upwards. Of course this reasoning neglects the endogeneity of S inherent in growth regressions, which also bias the estimated $\bar{r}$ upwards. Note also that 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 $\nu_i S_i$.

To assess the effects of heterogeneity in panel regressions let's decompose country i's years of schooling into its sample average $\bar{s}_i$ and the deviation d_{it} from the average (i.e. $S_{it} = \bar{s}_i + d_{it}$). Suppose that the return on schooling is given by (8). Then equation (7) can be rewritten as,

$$\ln y_{it} = \frac{\alpha}{1-\alpha} \ln \left(\frac{k}{y}\right)_{it} + \bar{r} S_{it} + v_i \left(\bar{s}_i + d_{it}\right) + \frac{u_{it}}{1-\alpha} \tag{9}$$

Now the source of bias comes from the term $v_i d_{it}$ (the term $v_i \bar{s}_i$ is part of the country's specific effect). 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 $E\left(v_i \sigma_i^2\right)$, where σ_i^2 is country i's sample variance of years of schooling. Therefore, if countries with lower (higher) than average returns have more volatile levels of schooling then $\bar{r}$ will be estimated with a negative (positive) bias.

[9]However, as noted before, if better quality does have an impact on the return on education then countries with higher levels of schooling (which are also those with better quality) should present higher returns. This is contradicted by Psacharopoulos's data.

As before, the use of instruments does not solve the bias problem since any variable correlated with S_{it} is also correlated with $v_i d_{it}$. Conversely, if there is no correlation between return and volatility of education, then return heterogeneity would not bias the estimates of the average world return $\bar{r}$. The appendix reports the observed σ_i^2 for the countries in the sample.

A preliminary check of whether the heterogeneity in returns on schooling is biasing the estimated average return consists in analysing the exogeneity of instruments used in GMM estimation. The Sargan tests of table 3 reject the hypothesis of endogeneity of the instruments, which suggests that heterogeneity is not introducing bias. However the low p-values may be an indication that the instruments are in fact not exogenous.

4.1 Evidence from micro returns

An alternative way to deal with heterogeneity is to eliminate the source of bias by explicitly accounting for the term $v_i S_{it}$ in the regressions. If private returns p_i and aggregate returns are somehow related, the excess private return may be a good proxy for the excess macro return on schooling. In the absence of externalities to education $p_i \equiv (1-\alpha) r_i$. Thus under this assumption v_i would be equal to the excess private return divided by $(1-\alpha)$. But even if this extreme case does not apply, the private returns may contain some information about the aggregate returns on schooling. This suggests the use of micro evidence as a proxy for v_i.

Psacharopoulos (1994) and Psacharopoulos and Patrinos (2002) report private Mincerian coefficients for several countries, which are shown in the appendix. The average Mincerian coefficient for the 55 common countries available is 10%, which is almost identical to the mean of all countries reported by Psacharopoulos. We can check whether there is any relationship between the excess private return (defined as the private return minus 10%) and the variance of years of schooling in each country. Figure 2 shows that there is no apparent link between both variables and in fact their correlation is virtually equal to zero. Thus if the excess private returns calculated here are a good proxy for the excess social returns, the figure suggests that in panel regressions the presence of return heterogeneity does not introduce a significant bias in the estimation of $\bar{r}$.

Table 4 reports the regressions when private returns are used as proxies for social returns. The first regression shows the estimation of (9) without accounting for heterogeneity. This is the same regression as in table 3 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, although the Mincerian return falls to 7.2%. The low Sargan statistic hints at high heterogeneity among the countries in this smaller sample. Regression 2 incorporates the excess private return multiplied by schooling, which turns out to have a negative and significant coefficient. Recall that the expected coefficient on this variable, assuming that private and social returns are equal is $1/(1-\alpha)$.

These results show that the data reported by Psacharopoulos are a bad proxy for excess social returns. There are at least two possible reasons for this. First, it may be the case that private and social returns to education are unrelated, as claimed by Pritchett (2003). This may be caused by educational screening and signaling in the labour market, which affects a worker's salary but not his productivity. An alternative explanation is that the returns reported by Psacharopoulos are too noisy. An example of this is Jamaica, which has a micro-Mincerian return of 28.8% –or 4.5 standard deviations higher than the sample average. This is clearly an outlier that may be having a non negligible effect on the estimates of regression 2. Jamaica is dropped from the sample in regression 3. The major effect of this is the lost of significance of the excess private return. This is consistent with the fact that the high return of Jamaica is distorting the previous estimates. However, the other results are qualitatively the same as in regression 2. Namely, private returns still appear with the opposite sign and the Sargan test is too low. Thus, in summary, these results suggest that the excess private returns implicit in Psacharopoulos data are in fact a bad proxy for excess social returns.

As an alternative way to exploit the information from labour studies, the sample can be divided into different groups of countries according to their private returns and then estimate a separate macro return for each group. This is a natural way to proceed if micro and macro returns are correlated. This procedure has, in addition, the advantage that it avoids relying too heavily on the numbers reported by Psacharopoulos. Regression 4 shows the estimated macro returns for groups of countries with low, moderate and high private returns[10]. The group with low and moderate private returns display social returns respectively equal to 7.8% and 8.3%. These are not statistically different from the observed private returns for these groups (respectively 6.3% and 9.5%). By contrast, countries with high private returns have, paradoxically, the lowest macro return. It is estimated at 4.9%, which is almost 10 percentage points lower than their average private return. These results are summarised in table 5. One possible interpretation for these findings is that in countries where the private return on schooling is relatively high –for instance, due to important screening effects– a sub-optimally large share of the population goes to formal education. There is some evidence in favour of the screening hypothesis for specific countries as surveyed by Riley (2001). But the lack of more systematic evidence prevents exploring further this hypothesis. On top of the paucity of evidence, this hypothesis does not say why screening effects are more important in some countries than in others.

The weighted average social Mincerian return for the three groups is 7.2% or almost 3 percentage points lower than the average private return. Supposing that Psacharopoulos data properly measure the marginal effect of schooling on wages, these results point to an absence of positive externalities of education. Moreover, these findings show that there is no obvious relationship between micro and macro returns. More specifically, countries with relatively large micro-returns have lower than average macro returns.

Regarding the effects of heterogeneity on the estimated average macro return, table 4 provides mixed evidence. On the one hand, the point estimates that ignore heterogeneity (regression 1) are identical to those that best acknowledge it (regression 4). This suggests that the heterogeneity in social Mincerian returns across countries does not bias the estimated average return obtained when heterogeneity is ignored. But on the other hand, the low Sargan statistic may be an indication that heterogeneity is in fact affecting the estimates. Finally, it is important to highlight that regardless of whether the average return is estimated with a bias or not, it seems that return heterogeneity across countries is considerable. Thus even a good estimate of the "world" average return on schooling may be misleading about the magnitude of the social return in each country.

4.2 Quality of education

One candidate to explain heterogeneity in social Mincerian returns across countries is the quality of education. As noted above, Pritchett (2001) justify the lack of significance of schooling in cross-country growth regressions by the low quality of

[10] The thresholds are respectively returns up to 8%; from 8% to 11%, and over 11%.

education in developing countries. In similar regressions Hanushek and Kimko (2000) find that their indicators of education quality have a strong explanatory power for growth. As they argue, one possible reason for the implausible large coefficient on quality that they find is that quality determines the long-run income level.

To assess the effect of quality q_i on income levels we first compute the simple average of the two quality scores reported by Hanushek and Kimko (2000, pp. 1206-1207) for each country available. In order 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 q_i values obtained in this way are shown in the appendix. Then we can estimate the effect of quality by multiplying q_i by the number of years of schooling. This approach assumes that quality and quantity can be substituted by each other. On the other hand, multiplying the quality indicator by years of schooling captures the notion that the productivity of schooling increases with quality[11]. Under this approach the equation to be estimated is,

$$\ln y_{it} = \frac{\alpha}{1-\alpha} \ln \left(\frac{k}{y}\right)_{it} + r q_i^{\gamma} S_{it} + \frac{u_{it}}{1-\alpha} \tag{10}$$

where γ is a measure of the weight of quality in the determination of the return on schooling. Equation (10) indicates that the long-run return on schooling in country i is rq_i^{γ}.

Table 6 presents the main effects of quality of education for different values for γ. The first regression is the baseline estimation with the smaller sample of 67 countries for which the data on education quality and years of schooling is available. In this regression years of schooling is not weighted by quality (or equivalently $\gamma = 0$). There are no important differences with respect to the full-sample regression (see regression 4 of table 3). Namely, the point estimate for the social Mincerian return is virtually the same as before (8.4%). In regression 2, where $\gamma = 1$, the quality-weighted level of schooling enters with a larger and highly significant coefficient. The social Mincerian return implied in regression 2 for a country with $q = 1$ is $(1 - 0.632/1.632) \times 0.164 = 0.1$. Thus the sample average Mincerian return is simply 0.1 times the average quality across countries. The resulting return is 6.6%, which implies that neglecting education quality yields a return biased upwards by 1.8 points in this particular specification. Regressions 3 and 4 report the results for larger values of γ. As expected, the world average Mincerian return decreases as the importance of quality is assumed to increase.

We can measure the difference between the social returns in table 6 and the private returns reported by Psacharopoulos in order to obtain a crude assessment of the externality to education in each country. The implicit externalities assuming $\gamma = 1$ are shown in the appendix. In general, the high private returns observed in some countries are not accompanied by equivalently large social returns. This is so because empirically countries with high private returns on education have lower levels of quality (see figure 3) and a low quality implies a low macro Mincer coefficient. As a consequence the sample average of the macro Mincer coefficient is 3 percentage points lower than the private return.

One problem about the regressions 1-4 is that education quality is assumed to affect in a too specific way the return on schooling. Instead of multiplying quality by years of schooling a more parsimonious representation may be obtained by splitting the sample of countries according to their quality levels. Then a separate estimate can be obtained for each group of countries. Such estimation has the advantage that it

[11] A similar function for human capital was previously used by Gundlach, Rudman and Wossmann (2002).

does not need to specify how quality affects the return on schooling. But on the other hand, this approach has problems of its own since it supposes that all the countries in a group have the same return. Ignoring this last caveat, regression 5 shows the estimates when countries are split into three quality groups[12]. Countries in the low quality group have a low and non-significant coefficient on schooling. On the other hand countries with "moderate" and "high" quality have a significant coefficient on years of schooling. The implicit Mincerian returns for these countries are respectively 8.7% and 9.8%. However these are likely to be upper bounds since the share of physical capital is implausibly low in this regression. Note also that the Sargan statistic increases significantly, which may be an indication that regression 5 is dealing better with heterogeneity than regressions 1-4. Finally, regression 6 groups together countries with moderate and high quality of education. The coefficient on the k/y ratio is now significant at a 10% level and the implicit share of physical capital raises to 39%. This causes the Mincerian return of countries with better quality to fall to 7.5%. But the coefficient on schooling is still highly significant. By contrast, the return for countries with low quality is 1.5% and is not significantly different from zero.

To summarise these findings, schooling quality appears an important determinant of the social return on schooling. The results of table 6 show that ignoring quality of schooling leads to an overestimation of the average macro Mincer coefficient. The magnitude of this overestimation depends on how quality enters in the regressions. According to the regression 6, which yielded the largest Sargan test, this overestimation is around 2 percentage points.

5 Conclusions

This paper has revisited the findings of earlier empirical studies on schooling and income, a literature that has failed to find a role for schooling as an input in a standard production function. One particular issue that undermines the estimates of the coefficient on schooling in panel regressions is the collinearity between years of schooling and physical capital stocks. It is shown that when problems of model specification are properly dealt with, years of schooling fit well in a neoclassical production function. In the borderline panel regression for 83 countries the coefficient on schooling is highly significant and the point estimate for the macro Mincer return is 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. 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 (2005). This is also consistent with the macro regressions of Heckman and Klenow (1997) and Topel (1999).

This figure is an estimate of the cross-country average macro Mincer coefficient. However there seems to be substantial return heterogeneity across countries. Paradoxically, countries where the micro Mincer coefficients are relatively high display on average a low and non significant macro return. The other countries in the sample show social returns in line with the private ones. One possible explanation for this is that screening effects are pushing up the private returns on schooling in some

[12] The groups are formed by countries with quality lower than 0.45 (14 countries), between 0.45 and 0.67 (19 countries) and larger than 0.67 (34 countries). These thresholds were determined by the ocurrence of important differences in quality levels between two consecutive countries (when ranked by quality). This seems more reasonable and produced more sensible results than the option of having groups with the same number of countries.

countries. This in turn will encourage workers with low ability to invest in formal education. In this case high private returns on education may be accompanied with low macro Mincer coefficients. Labour studies, however, have not produced robust evidence about this kind of effects.

Paralleling these findings, schooling quality appears as a significant determinant of disparities in the social return on schooling across countries. The effect of quality depends on how it enters in the regressions. For instance, when the quality score multiplies the number of years of schooling the average social return falls to 6.6%. Under this setup the country with the highest quality in the sample (Singapore) has a social return on schooling equal to 10%, whereas in the country with the lowest quality (Iran) the macro Mincer coefficient is only 3%. If instead of explicitly including the quality score in the regressions countries are grouped according to their quality levels and a separate return is estimated for each group, similar results emerge. More specifically, the return in a group of countries with low schooling quality is virtually equal to zero. In countries with moderate and high levels of quality the average return is 7.5%. The average return for all three groups of counties obtained in this way is 6.2%.

The previous results show that when return heterogeneity is not taken into account in these regressions the average Mincer return is estimated with a positive bias of about 2 percentage points. Another implication of the results found here is that income accounting exercises that use micro Mincer returns to build aggregate human capital stocks may be seriously underestimating the role of human capital in explaining income differences across countries. For instance Hall and Jones (1999) assume a piecewise linear Mincerian 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. Caselli (2005) assumes a similar human capital function and not surprisingly obtains similar conclusions. Although he acknowledges that the human capital gap between rich and poor countries may be higher due to differences in quality he does not try to redo the calculations. The importance of taking into account the quality of education in income accounting has already been raised by Gundlach, Rudman and Wossmann (2002) and Wossmann (2003). With the estimates of table 6 –where a country like India gets a much lower Mincerian return than the US– the ratio of human capital in India to the US falls to 25% to 30%. So this paper provides empirical support for quality as a determinant of income disparities.

This leads us to the question of what allows countries to improve schooling attainment and schooling quality. Most empirical studies try to find out what the income elasticity to schooling is. But this provides precious little guidance on the policies that may lead to higher levels of educational outcomes. One interesting line of research is the role of health and life expectancy in the private decisions on schooling investment. In this respect, the theoretical works of Boucekkine, de la Croix and Licandro (2001) and of Kalemli-Ozcan, Ryder and Weil (2000), where increases in life expectancy raise investment in human capital are an important step ahead. Complementary empirical studies on this field would help to back this hypothesis.

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APPENDIX: Data Summary

Country Name	Average Years of schooling	Standard Deviation	Average Private Mincerian return	Social Mincerian return	Externality	Quality
Algeria	3.25	1.64		0.044		0.438
Argentina	7.03	0.39	0.103	0.071	-0.032	0.711
Australia	11.45	1.28	0.067	0.083	0.016	0.833
Austria	9.70	1.03	0.094	0.085	-0.009	0.854
Bangladesh	2.43	0.16				
Belgium	8.74	0.99		0.086		0.858
Benin	0.91	0.29				
Bolivia	5.39	1.96	0.089	0.039	-0.050	0.385
Brazil	4.39	1.71	0.147	0.055	-0.092	0.548
Burkina Faso	0.21	0.02	0.096			
Burundi	0.92	0.02				
Cameroon	3.00	0.80		0.063		0.632
Canada	10.86	1.51	0.071	0.079	0.009	0.794
Central African Republic	1.41	0.34		0.039		0.385
Chile	7.64	1.24	0.120	0.040	-0.080	0.397
China	4.09	0.64	0.086	0.096	0.010	0.962
Colombia	4.73	0.74	0.140	0.056	-0.084	0.565
Costa Rica	4.44	0.98	0.097	0.069	-0.028	0.686
Cote d'Ivoire	1.50	0.63	0.201			
Cyprus	6.75	0.84	0.081	0.069	-0.012	0.688
Denmark	10.43	0.88	0.045			
Dominican Republic	3.75	0.74	0.094	0.060	-0.034	0.597
Ecuador	5.73	1.22	0.118	0.058	-0.060	0.581
Egypt, Arab Rep.	2.63	2.28	0.052	0.041	-0.011	0.408
El Salvador	3.17	0.94	0.087	0.037	-0.049	0.373
Ethiopia	0.28	0.03	0.080			
Fiji	6.22	1.00		0.084		0.840
Finland	8.76	2.17	0.082	0.084	0.002	0.842
France	8.61	1.87	0.100	0.086	-0.014	0.856
Gabon	3.53	0.89				
Ghana	3.56	1.29	0.078	0.040	-0.038	0.398
Greece	7.28	1.08	0.052	0.078	0.026	0.777
Guatemala	2.53	0.78	0.149			
Guyana	6.26	0.89		0.076		0.756
Honduras	3.51	1.06	0.135	0.043	-0.092	0.428
India	2.22	0.55	0.078	0.033	-0.045	0.330
Indonesia	4.22	1.69	0.120	0.063	-0.057	0.629
Iran, Islamic Rep.	2.04	1.39	0.116	0.030	-0.086	0.304
Iraq	1.43	0.89		0.044		0.442
Ireland	8.43	0.76		0.076		0.760
Italy	7.42	1.52	0.025	0.073	0.048	0.731
Jamaica	6.48	1.61	0.288	0.072	-0.216	0.721
Japan	10.75	0.84	0.099	0.098	0.000	0.981
Jordan	6.14	6.37		0.063		0.635
Kenya	3.48	1.61	0.162	0.042	-0.120	0.421
Korea, Rep.	7.98	5.19	0.121	0.089	-0.031	0.892
Madagascar	2.18	0.36				
Malawi	2.49	0.23				
Malaysia	5.50	3.17	0.094	0.079	-0.015	0.794

Country Name	Average Years of schooling	Standard Deviation	Average Private Mincerian return	Social Mincerian return	Externality	Quality
Mali	0.65	0.07				
Mauritius	4.93	2.17		0.081		0.812
Mexico	5.46	1.31	0.109	0.056	-0.052	0.562
Morocco	1.37	0.46	0.158			
Mozambique	1.28	0.28		0.041		0.406
Netherlands	9.67	0.84	0.069	0.088	0.019	0.880
New Zealand	10.15	0.63		0.093		0.929
Nicaragua	3.52	1.41	0.109	0.040	-0.069	0.400
Nigeria	1.59	0.36		0.057		0.568
Norway	10.81	1.55	0.055	0.089	0.034	0.887
Panama	6.14	1.68	0.137	0.069	-0.068	0.690
Paraguay	4.94	0.52	0.115	0.061	-0.054	0.606
Peru	5.84	1.45	0.081	0.061	-0.020	0.614
Philippines	5.79	1.04	0.103	0.053	-0.050	0.528
Portugal	4.69	1.24	0.093	0.069	-0.024	0.686
Senegal	1.24	0.30				
Sierra Leone	1.94	0.53				
Singapore	6.23	0.34	0.133	0.100	-0.033	1.000
South Africa	4.98	0.24	0.041	0.075	0.034	0.751
Spain	7.05	0.99	0.072	0.079	0.007	0.788
Sweden	10.49	1.63	0.059	0.081	0.023	0.815
Switzerland	12.05	0.56	0.077	0.092	0.015	0.921
Syrian Arab Republic	4.27	1.21		0.048		0.481
Thailand	4.03	2.23	0.110	0.067	-0.043	0.669
Trinidad and Tobago	7.92	0.96		0.068		0.676
Tunisia	2.54	0.52	0.080	0.064	-0.016	0.640
Turkey	3.65	1.34		0.063		0.632
Uganda	1.93	0.24				
United Kingdom	10.82	1.46	0.068	0.091	0.023	0.906
United States	11.56	0.88	0.099	0.070	-0.029	0.701
Uruguay	6.47	0.78	0.097	0.077	-0.020	0.766
Venezuela, RB	4.96	1.52	0.089	0.059	-0.030	0.590
Zambia	4.29	0.85		0.052		0.522
Zimbabwe	5.05	1.75		0.059		0.588
Countries	83	83	55	67	49	67
Mean	5.230	1.131	0.100	0.066	-0.031	0.660
Standard Deviation	3.123	0.958	0.042	0.018	0.047	0.182

Table 1

The fading effect of schooling on growth

Dependent variable is annualised change in $\ln(y_{it})$

	K-L (per capita) (1)	Topel (per worker) (2)	This Paper (per capita) (3)	This Paper (per worker) (4)	This Paper (per worker) (5)	This Paper (per worker) (6)
Observations	292	290	230	230	230	230
ΔS_t	0.086	0.058	0.081	0.093	0.028	0.008
	(0.024)	(2.15)	(0.036)	(0.041)	(0.023)	(0.022)
S_{t-1}	0.004	0.009	0.003	0.003	1.6e-3	2.4e-4
	(0.001)	(2.35)	(0.001)	(0.001)	(0.6e-3)	6.7e-4)
$\ln(y_{t-1})$	-0.005	-0.050	-0.005	-0.006	-0.004	-0.016
	(0.003)	(6.45)	(0.004)	(0.003)	(0.002)	(0.004)
$\Delta\ln(k_{it})$					0.574	0.607
					(0.042)	(0.041)
$\ln(k_{it-1})$						0.011
						(0.003)
R^2	0.284	0.481	0.268	0.287	0.634	0.666

Notes: Time dummies included (not reported). Columns (1) and (2) are from Krueger and Lindahl (2001) and Topel (1999), respectively. OLS estimates, except for Topel, who reports fixed-effect estimates. Standard errors in parenthesis, except for Topel who reports t-statistics. 10-year observations for the period 1960-1990. Variables in changes are annualised. y_{it} is GDP per capita or per worker, from Summers and Heston, PWT 5.6; S_{it} is years of schooling from Barro and Lee (1993) in columns (1) and (2) and from Cohen and Soto (2001) in columns (3) to (6); k_{it} is stock of physical capital per worker from Easterly and Levine (2001).

Table 2

The effect of schooling in a standard production function

Dependent variable is $\ln(y_{it})$

Panel A: With physical capital

	OLS (Levels) (1)	OLS (Differences) (2)	GMM (Levels) (3)	GMM (Differences) (4)	GMM (System) (5)
Observations	313	230	313	230	313
$\text{Log}(k_{it})$	0.604 [a]	0.585 [a]	0.574 [a]	0.815 [a]	0.695 [a]
	(0.047)	(0.043)	(0.140)	(0.171)	(0.132)
S_{it}	0.010	0.024	0.033	-0.046	-0.016
	(0.018)	(0.022)	(0.059)	(0.108)	(0.056)
Sargan (p-values)	–	–	0.183	0.219	0.399

Panel B: Without physical capital (α=0)

	OLS (Levels) (1)	OLS (Differences) (2)	GMM (Levels) (3)	GMM (Differences) (4)	GMM (System) (5)
Observations	313	230	313	230	313
S_{it}	0.249 [a]	0.088 [b]	0.259 [a]	-0.312 [c]	0.253 [a]
	(0.018)	(0.041)	(0.031)	(0.169)	(0.031)
Sargan (p-values)	–	–	0.795	0.015	0.061

Notes: Time dummies included (not reported). Robust standard errors in parenthesis. 2-step results for GMM estimates. 10-year observations for the period 1960-1990. y_{it} is GDP per worker, from Summers and Heston, PWT 5.6; S_{it} is years of schooling from Cohen and Soto (2001); k_{it} is stock of physical capital per worker from Easterly and Levine (2001).
a, b, c: coefficients are significant at a 1%, 5% and 10% respectively.

Table 3

The effect of schooling after dealing with collinearity

Dependent variable is $\ln(y_{it})$

	OLS (Levels) (1)	OLS (Differences) (2)	GMM (Levels) (3)	GMM (System) (4) - Baseline
Observations	313	230	313	313
$\text{Log}(k/y)_{it}$	0.221 [b]	-0.213 [b]	0.865 [b]	0.859 [b]
	(0.112)	(0.105)	(0.422)	(0.349)
S_{it}	0.217 [a]	0.093 [b]	0.150 [b]	0.155 [a]
	(0.024)	(0.044)	(0.064)	(0.054)
Implicit α	0.181	-0.271	0.464	0.462
Mincerian return	0.178	0.118	0.080	0.083
Sargan (p-values)	–	–	0.363	0.176

Notes: Time dummies included (not reported). Robust standard errors in parenthesis. 2-step GMM coefficients (one-step standard errors). 10-year observations for the period 1960-1990. y_{it} is GDP per worker, from Summers and Heston, PWT 5.6; S_{it} is years of schooling from Cohen and Soto (2001); k_{it} is stock of physical capital per worker from Easterly and Levine (2001).
a, b, c: coefficients are significant at a 1%, 5% and 10% respectively.

Table 4

Accounting for Heterogeneity of Mincerian Returns

Dependent variable is ln(y_{it})

(System GMM estimation)

	(1)	(2)	(3)	(4)
Observations	214	214	210	214
ln(k/y)$_{it}$	0.928 [b] (0.432)	0.976 [b] (0.405)	0.904 [b] (0.434)	0.661 [c] (0.347)
S_{it}	0.139 [a] (0.051)	0.089 [c] (0.050)	0.094 [c] (0.054)	
Excess private return × S_{it}		-0.612 [a] (0.196)	-0.651 (0.449)	
S_{it} *(Low priv. return)*				0.129 [a] (0.040)
S_{it} *(Moderate priv. return)*				0.138 [a] (0.050)
S_{it} *(High priv. return)*				0.082 (0.056)
Implicit α	0.481	0.494	0.475	0.398
Social Mincerian Return	0.072	0.045	0.049	0.072
Sargan (p-values)	0.016	0.041	0.027	0.073

Notes: Time dummies included (not reported). Robust standard errors in parenthesis. 2-step GMM coefficients (one-step standard errors). 10-year observations for the period 1960-1990. y_{it} is GDP per worker, from Summers and Heston, PWT 5.6; S_{it} is years of schooling from Cohen and Soto (2001); k_{it} is stock of physical capital per worker from Easterly and Levine (2001). Excess private returns from Psacharopoulos (1994) and Psacharopoulos and Patrinos (2002). Regression 3 excludes Jamaica.
a, b, c: coefficients are significant at a 1%, 5% and 10% respectively.

Table 5

Mincerian returns by group of countries

Private return	Countries	Average private return	Social return
Up to 0.08	17	0.063	0.078
Between 0.08 and 0.11	22	0.095	0.083
Higher than 0.11	16	0.147	0.049

Private returns from Psacharopoulos (1994) and Psacharopoulos and Patrinos (2002).

Table 6

The effects of quality of education

Dependent variable is ln(y_{it})

(System GMM estimation)

	(1) $\gamma = 0$	(2) $\gamma = 1$	(3) $\gamma = 3$	(4) $\gamma = 10$	(5)	(6)
Observations	257	257	257	257	257	257
$ln(k/y)_{it}$	0.726 [c]	0.632	0.575	0.933 [b]	0.406	0.643 [c]
	(0.416)	(0.433)	(0.424)	(0.386)	(0.381)	(0.361)
$q^{\gamma} S_{it}$	0.145 [b]	0.164 [a]	0.178 [a]	0.168 [a]		
	(0.057)	(0.050)	(0.046)	(0.054)		
S_{it} *(Low q)*					0.011	0.024
					(0.080)	(0.072)
S_{it} *(Moderate q)*					0.122 [c]	
					(0.064)	
S_{it} *(High q)*					0.138 [a]	
					(0.045)	
S_{it} *(Mode. & high q)*						0.123 [b]
						(0.052)
Implicit α	0.421	0.387	0.363	0.483	0.289	0.391
Average Mincerian return	0.084	0.066	0.040	0.010	0.076	0.062
Mincerian return for country with q = 1	0.084	0.100	0.113	0.087	0.098	0.075
Sargan (p-values)	0.084	0.082	0.105	0.076	0.156	0.177

Notes: Time dummies included (not reported). Robust standard errors in parenthesis. 2-step GMM coefficients (one-step standard errors). 10-year observations for the period 1960-1990. y_{it} is GDP per worker, from Summers and Heston, PWT 5.6; S_{it} is years of schooling from Cohen and Soto (2001); k_{it} is stock of physical capital per worker from Easterly and Levine (2001); q is the quality score of a country relative to the score of Singapore (from Hanushek and Kimko (2000)).

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

Figure 1

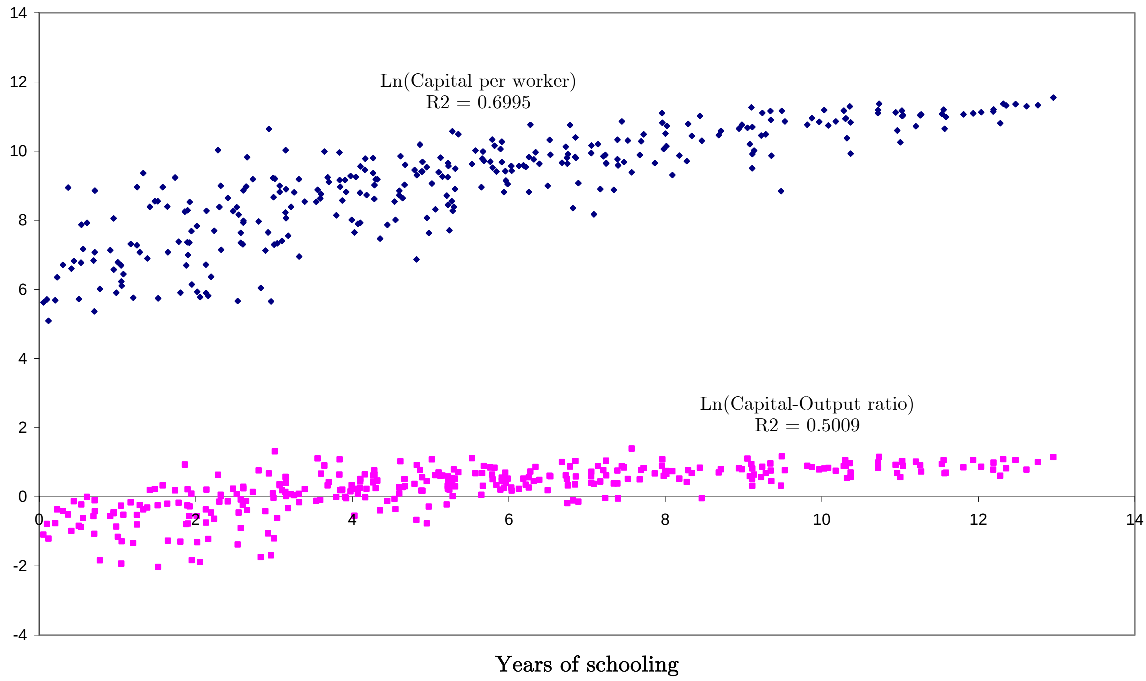
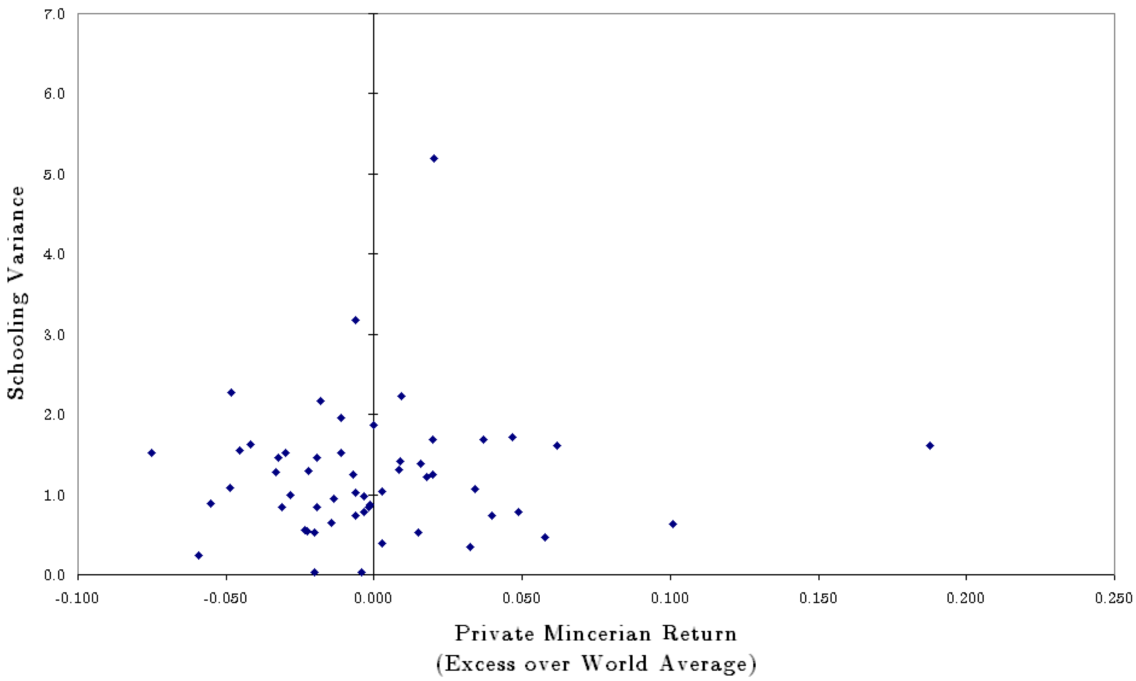
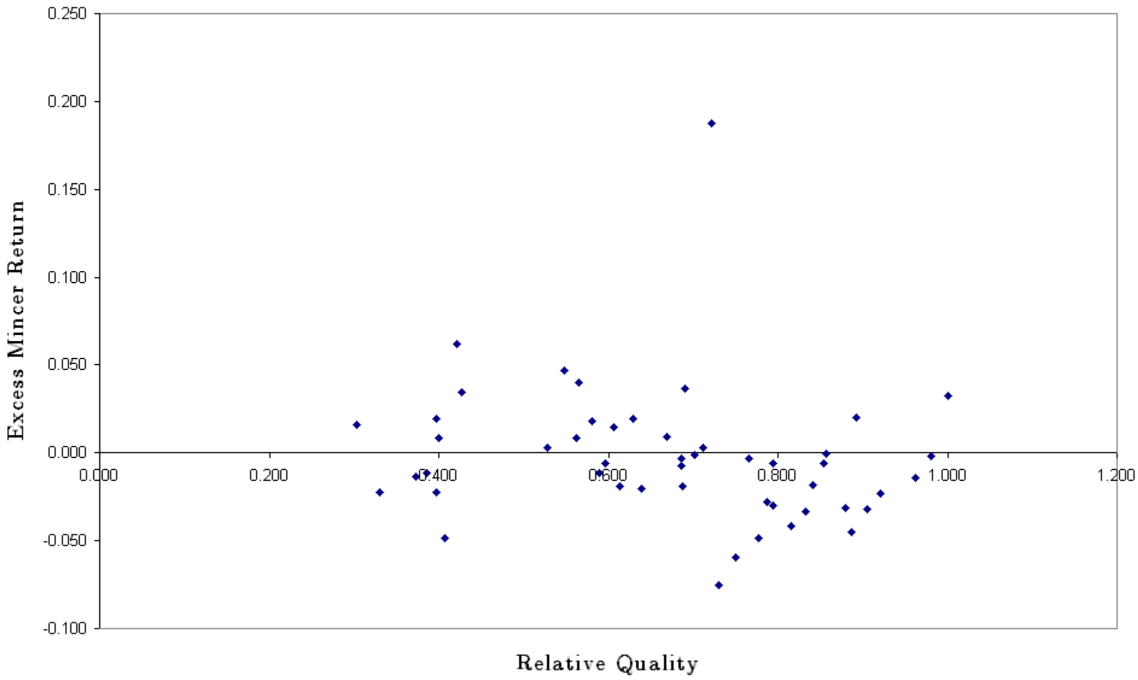

14
12
10
8
6
4
2
0
-2
-4
0
2
4
6
8
10
12
14
Ln(Capital per worker)
R2 = 0.6995
Ln(Capital-Output ratio)
R2 = 0.5009
Years of schooling

Figure 2



Schooling Variance
7.0
6.0
5.0
4.0
3.0
2.0
1.0
0.0
-0.100
-0.050
0.000
0.050
0.100
0.150
0.200
0.250
Private Mincerian Return
(Excess over World Average)

Figure 3



0.250
0.200
0.150
0.100
0.050
0.000
-0.050
-0.100
Excess Mincer Return
0.000
0.200
0.400
0.600
0.800
1.000
1.200
Relative Quality