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DIRECTLY UNPRODUCTIVE SCHOOLING: HOW COUNTRY CHARACTERISTICS AFFECT THE IMPACT OF SCHOOLING ON GROWTH

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Directly Unproductive Schooling: How Country Characteristics Affect the Impact of Schooling on Growth *

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Abstract

The rapid rise in schooling in developing countries in recent decades has been dramatic. However, many cross-country regression analyses of the impact of schooling on economic growth find low and insignificant coefficients. This empirical 'puzzle' contrasts with theoretical arguments that schooling, through raising human capital, should raise income levels. This paper argues that poor results are to be expected when regression samples include countries that vary greatly in their ability to use schooling productively. Data on corruption, the black market premium on foreign exchange and the extent of the brain drain for developing countries are used as indicators of an economy's productive use of schooling. Regression analysis shows that the impact of secondary schooling on economic growth is substantially higher in countries that are adjudged to use schooling productively.

Keywords: Schooling, human capital, corruption, brain drain, economic growth.

J.E.L. Classification: I21, O15, O40

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1 Introduction

The rapid rise in schooling in developing countries over the last few decades has been impressive. Between 1965 and 1995 the average years of secondary schooling in developing countries rose by more than threefold.[1] Many microeconomic studies find high private rates of return for additional years of schooling, as measured by increases in wages, implying that the rise in schooling should raise GDP. Equally, many growth economists, from old or new traditions, would assert that increases in human capital – for which stocks of schooling are often used as a proxy – should raise GDP. However, empirical studies of economic growth across a range of countries have often found a low, and often insignificant, coefficient on the growth of schooling. This has prompted some to ask 'where has all the schooling gone?' (Pritchett, 2001). This paper provides some empirical evidence on this question.

The basic hypothesis behind this paper is that schooling does not automatically find its way into productive use (i.e. activities that add to value added in the domestic economy). I expect many economists, especially those interested in development, would suspect such an outcome. Nevertheless, many influential empirical studies on the impact of schooling on growth fail to incorporate such modifications in the estimation procedure, although they sometimes acknowledge the general issue. This paper uses data on corruption, the black market premium on foreign exchange and the extent of the brain drain as proxies for the economy's productive use of schooling. The testable hypothesis is that the impact of schooling on growth will vary across countries according to the values of these variables. The results find support for this hypothesis.

The structure of the paper is as follows. The next section provides a short summary of the issues surrounding schooling, human capital and economic growth. The main message is that the link between schooling and growth is much more complex than empirical analysis normally allows for. In particular, there is no direct link between schooling and an increase in productive skills – or human capital – used in the

[1] Using Barro and Lee (2001) data on schooling stocks, and the World Bank definition of a developing country, the average years of secondary schooling in population over 25 increased from 0.33 years in 1965 to 1.16 years in 1995 (73 countries with data for both years).

economy. Section 3 summarises the standard empirical approaches to analysing how schooling and economic growth may be related. The existing literature distinguishes between two alternative mechanisms. The first is that changes in schooling affect growth rates, an assumption that reflects growth accounting studies and neoclassical growth models. The second assumes that the level of schooling may affect growth rates, an issue highlighted by endogenous growth models and also technological catch-up models. The dominant methodology for testing the importance of these mechanisms is cross sectional growth regressions, using data sources such as the Penn World Table and Barro and Lee (2001). In order to allow direct comparison with the existing literature, this paper also uses cross sectional regression analysis with growth in GDP per worker (1965-95) as the dependent variable. This does not imply that other econometric methods are not worthwhile, only a recognition of the need to explore the issue of unproductive schooling using the established methodology.[2]

The empirical analysis is spilt into two sections. The first considers data on corruption and the black market premium. The corruption data come from survey evidence and covers 31 developing countries in 1980-83. The black market premium has larger coverage (46 countries) and is a widely used measure for the conduciveness of macroeconomic and trade policy for growth, as well as institutional quality more generally. Both the corruption and black market premium data can be thought of as proxies for an economy's inability to use schooling in directly productive activities. If this hypothesis is true, the implication is that the impact of schooling on economic performance will vary with the levels of corruption and black market premium. To test this idea the corruption and black market premium data are used to rank countries and thereby create sub-samples of countries. A standard empirical growth analysis, with growth in GDP per worker (1965-95) as dependent variable and years of secondary schooling on adult population as the key independent variable, is then carried out on the different sub-samples. The evidence from cross country regressions

[2] Specifically, there has been an increase in the use of panel data estimators in growth regressions, which allow for country specific effects to be included (e.g. Casselli et al, 1996, Dowrick and Rogers, 2002). However, they require a shortening of the growth period to, normally, 5 or 10 year periods, which may be inappropriate for studying the impact of schooling on growth. Further, the problems of measurement error attenuating coefficient estimates may become more severe with panel estimators (Krueger and Lindahl, 2000).

on these sub-samples suggest that the impact of secondary schooling increases as the average level of corruption and the black market premium falls.

The second empirical section considers data on the extent of skilled migration to the US as a proxy for the brain drain. At one level, use of the brain drain data can be viewed as reducing measurement error in the data on schooling attainment. This should, in turn, improve coefficient estimates. However, at another level, relatively high rates of brain drain may reflect people's expectations about future economic conditions, which in itself is a proxy for whether the economy can use schooling productively. Again the data on levels of brain drain are used to rank countries and then regression analysis is conducted on different sub-samples. The results suggest that the impact of secondary schooling increases as the extent of the brain drain falls.

The penultimate section of the paper provides further testing and a discussion of the results. This section notes that the empirical results for countries with low corruption, black market premium or brain drain are much closer to those predicted by theory with respect to returns from human capital. In addition, further analysis indicates that the above results only hold for secondary schooling data: primary and tertiary education data show no significant association with economic growth. The last section concludes.

2 Schooling, human capital and growth: a synopsis

A number of papers have discussed in detail the possible links between human capital – defined in various ways – and economic growth. [3] A summary of the main mechanisms between schooling and growth is shown in Figure 1. The far left column highlights the familiar problem that there are many aspects to 'schooling' which could be important for growth. 'Years of schooling' has attracted much attention as a summary measure, but the issue of quality and effectiveness has also been the focus of analysis (Hanuschek, 2002, Hanuschek and Kimko, 2000, Pritchett and Filmer, 1999). The schooling column also includes a heading for 'socioeconomic and regional differences', which highlights the fact the distribution of schooling quantity and quality across social classes and regions may be important. For example, an objective

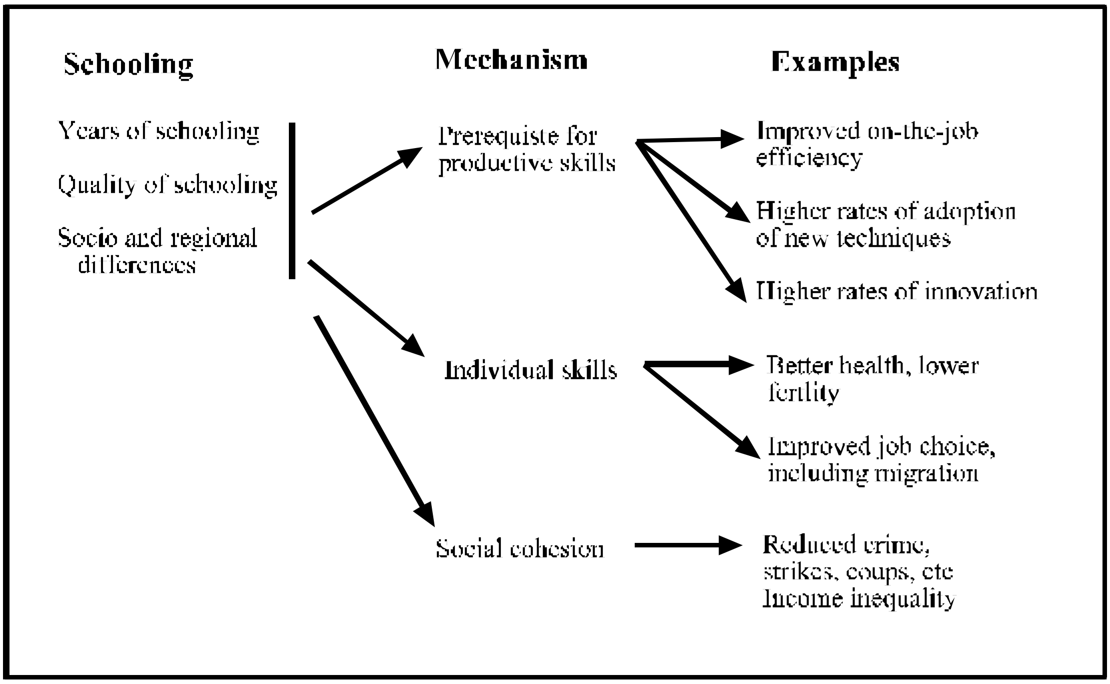
[3] A selection of recent contributions are Knowles et al (2002), Nelson and Nelson (2002), Piazza-Giorgi (2002), Barro (2001), Bils and Klenow (2000), Krueger and Lindahl (2000).

of schooling is to select and prepare students for appropriate careers, an aim which implies universal coverage, at least in early years.

The second column in Figure 1 shows three major mechanisms. The first mechanism – ‘prerequisite for productive skills’ – is probably the one most often cited by economists. This mechanism *assumes* that more ‘schooling’ directly raises the level of human capital employed by firms engaged in producing value added. The fact that this is an assumption has been made in discussions about ‘directly unproductive activities’ (DUPS), rent seeking, corruption and public sector employment policies, but is often neglected in empirical growth studies (Easterly, 2002). The major point is that increases in schooling are a necessary, but not sufficient, condition for increases in human capital. However, even with this caveat, testing hypotheses about education and growth is complex. For example, suppose literacy has the most impact on productive skills, then testing the partial correlation of, say, years of schooling with growth may reveal little association. Further, literacy itself might be the prerequisite for changes in firm-level work practices, which themselves require other conditions to be present (for example, a threshold level of certainty about future taxation, governmental and macroeconomic conditions).

The last column of entries in Figure 1 shows examples of the mechanisms. The first entry for ‘improved on-the-job efficiency’ represents a level effect (i.e. schooling, by improving productive skills, raises output per worker to a new level, causing only a short run growth effect). Schooling and human capital can, however, also have medium or long term growth effects. One possibility is that higher levels of human capital raise the rate of diffusion and adoption of new technology (Nelson and Phelps, 1966). Also, increased productive skills may raise the rate of innovation and technological change directly. The presence of both level and growth effects, the likelihood of threshold and interaction effects, and the difficulty of measuring the relevant aspect(s) of schooling, means that testing for the importance of schooling is complex.

Figure 1　Schooling and economic performance



Even though the 'productive skills' mechanism provides many challenges to empirical research, it is not the only mechanism by which schooling could affect performance. The two other mechanisms shown in Figure 1 – 'individual skills' and 'social cohesion' – add further complexity. The former acknowledges that research shows that education can have important influences on health and fertility outcomes which, apart from being important in their own right, may also influence economic growth (e.g. Becker et al, 1990). The 'social cohesion' mechanism is related to DUPS and corruption, but also to the prevalence of crime, strikes and civil unrest. These issues have links to research into the role of social capital (Gradstein and Justman, 2000, Knack and Kneefer, 1997).

The above discussion highlights the complexity of the link between schooling and economic performance. Given this, this paper has modest objectives. It focuses solely on the first mechanism – prerequisite for productive skills – and tests whether schooling is a necessary, but not sufficient, condition for economic growth. In particular, it takes the latest measures of years of schooling in the working population from Barro and Lee (2001) and tests whether the partial correlation of both the change in, and level of, schooling varies across sub-samples of countries. The sub-samples are chosen on the basis of three variables: an index of corruption, the black market premium on foreign exchange rates, and the extent of the 'brain drain' (i.e. out migration from the country).

3 Empirical specification and background

A basic production function is the most established, and simplest, starting point for growth analysis,

$$Y_t = A_t K_t^{a_k} H_t^{a_h} L_t^{a_l} \quad [1]$$

where A is technology, K is physical capital, H is human capital and L is (unskilled) labour input and Y is value added. Note that the parameter a_k should equal the share of capital in GDP and $a_h + a_l$ should equal the labour share (assuming constant returns to scale and that factors are paid their marginal products). Dividing [1] by L, and assuming constant returns to K, H and L, allows [1] to be written in per worker or intensive form,

$$y_t = A_t k_t^{a_k} h_t^{a_h} \quad [2]$$

where small capitals indicate values per worker. This specification is more appealing in that it 'merges' unskilled and skilled labour.[4] Perhaps the most important aspect of [2] is that it refers to the employment of factors in activities which can raise value added (GDP). If there are DUPS, these may well have a production function associated with them, but the output created is not 'value added', rather it is 'value neutral', or possibly even 'value reducing' as measured by national accounts.

Equation 2 can be logged and differentiated with respect to time to yield,

$$\hat{y}_t = \hat{a}_t + a_k \hat{k}_t + a_h \hat{h}_t \ , \quad [3]$$

where a hat indicates growth rate.

How should we proxy the growth in human capital? Human capital is defined as the skills useful in production that result from investment in education, training or experience. The growth of human capital is the result of the past investments in these activities and the interaction between these activities. For example, investment in

[4] Equation [1] implies that skilled and unskilled labour can be substituted, equation [2] suggests the critical aspect is the average skill per employee.

education may be a necessary but not sufficient condition for on-the-job training to be undertaken. On-the-job training may also require the presence of more experienced workers, or a stable economic environment, or certain labour market mobility conditions, etc. This means there are a host of thresholds, interactions and feedbacks in the accumulation of human capital – implying that empirical specifications will be crude representations of a complex process.

The complex process of human capital accumulation has been simplified by a focus on educational capital. Consider the following equation,

$$\log h_t = f \log h_{t-1} + rS_t \qquad [4]$$

where r is the return to an additional year of schooling and S is years of schooling. If f=0 then [4] is similar to the Mincerian approach to human capital, where ln(*wage*) is substituted for logh_t.[5] In this case the *growth* rate of human capital is proportional to the *change* in years of schooling.[6] This specification means that growth in human capital ceases in finite time, since years of schooling cannot increase without bound. Note that if f=1 then the growth of human capital is a function of the level of years of schooling, not the growth of years. More generally, if other determinants of human capital were included in [4], the growth of human capital would also depend on the levels of these variables. The latter specification is similar to the endogenous growth models of Lucas (1988) and Romer (1990), where the growth of human capital (or knowledge in Romer) can drive long run growth.

The distinction between f=0 and f=1 provides a way of classifying existing studies. Some studies, such as Pritchett (2001) and Bils and Klenow (2000), assume that f=0 (or that f<1, which yields the same asymptotic outcome). These types of studies, which are closely linked to the growth accounting tradition (e.g. Denison, 1967), enter the change of schooling as an explanatory variable in [3] (note that the change in schooling is a proxy for the growth in human capital from [4]). In particular, they

[5] More precisely, a microeconomic Mincerian approach would also include a range of other variables in regression analysis, such as experience, gender and race. Here we assume that these factors change little overtime for the workforce as a whole, although it would interesting to adjust for the change in experience for developing countries with rapidly changing population structures.

[6] The growth of human capital is logh_t - logh_{t-1} which equals $r\,\Delta S$ if r is constant and f=0.

draw motivation from microeconomic studies and weight the change of schooling by measures of wage premia (r) from microeconomic studies. This is in sharp contrast to studies in the Lucas/Romer tradition, which enter the level of schooling on the assumption that this may affect the growth of technology (e.g. Barro, 2001).

What have we learnt from empirical studies on the impact of schooling in growth? A major finding is that the partial correlation between the change in (or growth of) schooling and economic growth appears to be weak. Benhabib and Spiegel (1994), in an empirical study of 78 developing and developed countries (1965-85), found no evidence for a significant role for the growth of schooling, but did find that the level of schooling was important.[7] The influential Pritchett (2001) paper – which has been circulating as a working paper for at least 5 years prior to this – also found no evidence for the change of schooling years[8], prompting the title of his paper 'Where has all the schooling gone?' Pritchett notes that one explanation is that it has gone into 'privately remunerative but socially unproductive activities', but this explanation is not tested. Other studies investigate the robustness of the results on schooling, noting that the results are sensitive to sample changes (Temple, 1999) and the functional form used (Temple, 2001, Topel, 1999).

A contribution of this paper is to explain the weak association between schooling and growth in GDP per worker in terms of parameter heterogeneity. Put another way, the lack of robustness can be explained by the fact that schooling in the population does not map directly into the human capital measure in [3]. The same issue as stressed in section 2.

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[7] Their results suggest that the level of human capital raises growth through the technological catch-up mechanism for all countries, but also raises growth directly in the wealthiest countries.

[8] To be accurate, Pritchett (2001) considers the microeconomic model as $\ln(w_h) = \ln(w_{us}) + rS$, where subscript h is skilled wage and us is unskilled wage. The value of human capital is defined as the discounted sum of ($w_h - w_{us}$), and this implies the growth in human capital is $\ln(e^{rSt} - 1) - \ln(e^{rSt-1} - 1)$, assuming w_{us} and r are constant through time.

4 Corruption, black market premia and the unproductive use of schooling

4.1. Hypotheses

Distinguishing which economies use their schooling capital productively and unproductively appears to be a daunting task, requiring a great deal of microeconomic analysis of the labour market. However, there are empirical studies which use proxies for the extent of unproductive activities within a country. A well known example is the index of corruption used in Mauro (1995). Mauro finds that higher levels of corruption are associated with lower investment and economic growth in a cross section of 67 developing and developed countries. The interpretation is that high levels of corruption can reduce growth by diverting 'talented people' away from productive activities, as well as raising uncertainty. Murphy et al (1991, 1993) also provide some theory and evidence for this view. The direct implication of these results is that schooling should have less impact on economic growth when there are high levels of corruption:

Hypothesis 1 Countries with higher levels of corruption should exhibit a lower effect of schooling on growth.

The economic growth literature gives attention to the role of macroeconomic stability and trade openness. The main ideas are that economies with stable, well run macroeconomic policies are more conducive to investment and growth. Also, greater trade openness and reduced tariff barriers have been linked to economic growth, with the mechanisms being greater competition, economies of scale through export markets and reduced corruption. A widely available variable that proxies these elements is the black market premium on foreign exchange rates (Fischer, 1993). Further, the influential trade openness index proposed by Sachs and Warner (1995, 1997) uses the black market premium as a key element of their index. This leads to the following hypothesis:

Hypothesis 2 Countries with higher levels of black market premia should exhibit a lower effect of schooling on growth.

4.2. Data

The index of corruption used by Mauro is based on survey responses from correspondents of Business International in 1980-83.[9] The survey respondents selected an integer between 0 and 10 to rank a countries 'corruption' (where a '10' represents low corruption). Mauro points out that this index is correlated with other indices of the 'quality' of institutions, such as the extent of red tape, judiciary fairness and political stability. Given this, the corruption index can be considered as a proxy for institutional quality more broadly defined. In the empirics below, the analysis is restricted to countries defined as 'developing' by the World Bank (and with data for GDP per worker, capital and schooling, see Appendix). Table 1 shows some summary statistics by dividing the available sample of 31 countries into 'low' and 'high' corruption (based on the median value of the index). One, somewhat surprising, observation is that 'high' corruption countries managed to grow faster – this is largely a result of Indonesia and Thailand having high corruption ratings but also high growth rates. Both Indonesia and Thailand were relatively poor countries in 1965, hence some argue they may have benefited more from technological catch up, implying the need to control for this factor in empirical analysis. The Table also illustrates that low corruption is associated with higher levels of schooling (in 1965) and larger increases in secondary schooling stocks.

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[9] This index is now incorporated into the Economist Intelligence Unit's set of country indicators. Similar, but more recent, indexes are produced from surveys run by Transparency International and the World Competitiveness Report, amongst others (see Goettinger University Corruption Centre http://www.gwdg.de/~uwvw/icr.htm). Since the objective is to assess corruption over the 1965-95 period the more recent indexes, based on surveys in late 1980s and 1990s are deemed inappropriate.

Table 1 Summary statistics for sub-samples

	Growth of GDP per worker (65-95)	Growth of capital per worker (65-90)	Secondary schooling (1965 average years)	Secondary schooling (change of years 1965-95)	Log of GDP per worker (1965)
Corruption					
Low corruption Mean 7.6 (n=14)	1.09	2.95	0.54	1.23	9.15
High corruption Mean 4.0 (n=14)	1.57	2.19	0.32	0.98	8.51
Black market premia					
Low BMP Mean 6.9% (n=23)	1.40	3.13	0.37	0.95	8.70
High BMP Mean 203.6%(n=23)	0.85	1.85	0.37	0.86	8.65

Notes. There are 31 countries with corruption data. Three of these have values of 5.75, which is the median of the sample. In the above corruption statistics these three countries are omitted. The full sample of developing countries with black market premia data is 46, with the median exactly dividing the sample.

The lower panel in Table 1 shows summary statistics for countries classified by 'low' or 'high' black market premia (as defined by the median value), which is defined as the average value for the period 1965-90. A number of points can be made. First, the black market premium varies greatly across countries (the highest figure is for Indonesia, 2318%, which arises from a spectacularly high figure for 1965). Second, initial income and secondary schooling differences are small between the two samples. Third, differences between GDP per worker and capital per worker growth rates are large, despite the fact that Indonesia is included in 'high' black market countries (which will pull up the mean growth rate for this group).

4.3. Regression analysis

The regression analysis focusing on corruption is shown in Table 2. The first column shows a standard growth accounting specification for the 31 developing countries that have data for the corruption index. The dependent variable is the average annual growth in GDP per worker over the 1965 to 1995 period (see Appendix 1 for full details of variables). The results in column one indicate a positive and significant coefficient on the capital to worker growth variable, but an insignificant coefficient on change in years of secondary schooling in the adult population. This result is familiar from the work of Pritchett (2001). The next two columns of Table 1 run regressions for the sample of high and low corruption countries as defined in Table 1. For 'high' corruption countries the coefficient on capital is slightly higher and the coefficient on schooling is negative and significant. The implication is that a rise in schooling in these countries would have a detrimental effect on growth in value added. The regression for the sample of 'low' corruption countries shows a lower coefficient on capital growth (with a magnitude more in line with expectations), and a positive coefficient on the change in schooling years (although only significant at the 17% level).

The simple growth accounting specification can be criticised for assuming that the catch-up effect is constant across countries. Regressions 4, 5 and 6 include the log of the initial GDP per worker (1965) as an indicator of the size of the technology gap (with the assumption that poorer countries are able to grow faster *ceteris paribus*). In these regressions the coefficient on initial GDP per worker is significant and negative, confirming the catch-up interpretation.[10] Of more interest here is the fact that the coefficients on change in schooling years are now negative in the high corruption sample and positive in the low corruption sample. Again, the coefficient on the change in schooling is not significantly different from zero for the full sample.

Growth accounting has its limitations, not least that it assumes that the long run influence of human capital growth on output will tend to zero. The last three columns in Table 2 enter the level of years of secondary schooling as an explanatory variable. The results again suggest that dividing countries into low and high corruption samples has an impact on the coefficient on the level of schooling, although the results are weaker (specifically we do not reject the null hypothesis that the samples can be pooled). In conclusion, the implication of the results in Table 2 is that a failure to allow for coefficient heterogeneity in the impact of schooling arising from differences in corruption may bias empirical results.

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[10] There is a debate over whether the coefficient on initial GDP per worker indicates convergence to Solow-Swan steady state (e.g. Mankiw et al, 1992), or whether it indicates the presence of technological catch up (e.g. Dowrick and Nguyen, 1989). Here the inclusion of the growth in capital to labour ratio can be thought of as controlling for Solow-type convergence, allowing the technological catch up interpretation (Dowrick and Rogers, 2002).

Table 2 Regressions for schooling and corruption

Dependent variable: Growth in GDP per worker (1965-95)

	(1) Full sample	(2) High Corruption	(3) Low Corruption	(4) Full sample	(5) High Corruption	(6) Low Corruption	(7) Full sample	(8) High Corruption	(9) Low Corruption
Growth in capital to labour ratio	0.499	0.547	0.386	0.416	0.527	0.286	0.434	0.497	0.362
	(5.57)***	(9.64)***	(2.35)**	(5.36)***	(10.04)***	(3.32)***	(7.47)***	(6.34)***	(2.46)**
Change in secondary schooling years	-0.014	-0.697	0.275	0.160	-0.420	0.427			
	(0.10)	(4.97)***	(1.52)	(1.21)	(1.80)	(2.43)**			
Log of GDP per worker (1965)				-0.012	-0.007	-0.013	-0.012	-0.012	-0.011
				(4.35)***	(1.99)*	(3.42)***	(4.30)***	(3.74)***	(1.75)
Secondary schooling years (level 1965)							0.010	0.001	0.013
							(1.65)	(0.11)	(1.31)
Constant	0.001	0.026	-0.012	0.103	0.075	0.108	0.107	0.109	0.094
	(0.20)	(5.40)***	(1.12)	(4.53)***	(3.18)***	(3.63)***	(4.43)***	(4.04)***	(1.66)
Test of 'poolability' (prob)	0.00			0.03			0.54		
Observations	31	14	14	31	14	14	31	14	14
Adjusted R-squared	0.56	0.83	0.40	0.73	0.85	0.59	0.72	0.80	0.40

Note: * significant at 10%; ** significant at 5%; *** significant at 1%. Estimates are OLS with t-statistics based on robust standard errors. The 'poolability' test shows the probability of a Type II error for the null hypothesis of equal coefficients between the two samples (based on Chow test and F-statistic). The 'Growth of capital labour ratio' is the average annual growth for 1965-90. The 'Change in secondary schooling years' variable is the average annual change in years of secondary schooling, in population over 25 years of age, between 1965 and 1995. The 'Secondary schooling years (level 1965)' refers to the average years of secondary schooling in population over 25 in 1965.

Table 3 Schooling and black market premium regressions

Dependent variable: Growth in GDP per worker (1965-95)

	(1) Full sample	(2) High BMP	(3) Low BMP	(4) Full sample	(5) High BMP	(6) Low BMP	(7) Full sample	(8) High BMP	(9) Low BMP
Growth in capital to labour	0.451	0.516	0.372	0.407	0.496	0.304	0.445	0.495	0.393
ratio	(6.39)***	(4.80)***	(4.72)***	(5.80)***	(5.36)***	(4.09)***	(7.17)***	(5.52)***	(7.08)***
Change in secondary	0.106	0.011	0.195	0.234	0.147	0.328			
schooling years	(1.21)	(0.05)	(2.21)**	(2.57)**	(0.77)	(3.89)***			
Log of GDP per worker				-0.008	-0.010	-0.006	-0.007	-0.010	-0.004
(1965)				(3.16)***	(2.55)**	(2.01)*	(2.85)***	(2.28)**	(1.60)
Secondary schooling							0.010	0.004	0.021
years (level 1965)							(1.64)	(0.70)	(3.18)***
Constant	-0.003	-0.001	-0.004	0.060	0.08	0.050	0.058	0.085	0.031
	(0.91)	(0.17)	(1.06)	(2.89)***	(2.32)**	(1.77)*	(2.72)***	(2.24)**	(1.32)
Test of ‘poolability’ (prob)	0.70			0.43			0.24		
Observations	46	23	23	46	23	23	46	23	23
Adjusted R-squared	0.55	0.46	0.62	0.62	0.60	0.66	0.60	0.59	0.65

Note: * significant at 10%; ** significant at 5%; *** significant at 1%. All t-statistics based on robust standard errors. Other notes as per Table 2.

Table 3 shows a similar set of regressions, although this time the samples are based on a ranking of black market premia. Note that the black market premia data are available for more developing countries, raising the full sample size to 46. Hypothesis two stated that returns to schooling should be higher in countries with lower black market premium. Looking at the coefficients on the schooling variables, both on the change in, or the initial level of, years of secondary school, we can see that hypothesis 2 has support. The full sample regressions indicate schooling has an insignificant or negative coefficient, while the 'low' black market premia sub-sample regressions always find a positive and significant coefficient on secondary schooling. While the coefficient estimates support this economic interpretation, the statistical tests on the 'poolability' of the samples do not (i.e. the null hypothesis that all the coefficients are equal for both sub-samples is not rejected).[11]

Dividing developing countries into two sub-samples, based on whether a country is above or below the median, might be regarded as arbitrary. Perhaps slightly varying the sub-samples would greatly affect the results? One way of assessing this is to run a series of regressions on a 'rolling' sample of countries (i.e. start with the sample below the median, then add the country just above the median and delete the country with the lowest ranking, and so one). The results from this series of regressions map out how the coefficient changes between the two different samples shown in Tables 2 and 3. Graphs of the coefficients are shown in Appendix 2. The coefficients are marked with a circle and a vertical line shows the 95% confidence interval (i.e plus or minus 1.96 standard errors). The graphs indicate that the coefficient generally rises as the sub-sample moves from 'high' to 'low' corruption, or from 'high' to 'low' black market premium, indicating that the results in Tables 2 and 3 are not oddities. The graphs also show that the 95% confidence interval extends below zero in most cases, hence the graphs reinforce the point that coefficient estimates from this type of

[11] Testing for the equality of all coefficients could still hide the fact that the coefficient on schooling differs between samples. One way of testing for this is to create a dummy variable for 'low' black market premia and use this to create an interaction term with the schooling variable. The significance level of the coefficient on this interaction term can be interpreted as a statistical test of whether the coefficients are equal between sub-samples. Following this procedure we still do not reject the null hypothesis of equal coefficients on the change in schooling (10% level), but we can reject the equality of the coefficient on the level of schooling (5% level).

analysis are imprecise. Hence, even though using data to classify countries into whether they are more or less likely to use schooling productively improves the estimates, there is still imprecision. Given the discussion of the complexity of the link between schooling and economic growth, this is not that surprising.

5 The brain drain and the returns to schooling

5.1. Hypotheses

A long standing issue in development economics concerns the extent and impact of the migration of people with higher relative levels of human capital from developing to developed countries, referred to in short as the 'brain drain' (Bhagwati and Hamada, 1974). A survey of issues, a theoretical model and some empirical analysis are contained in Beine et al (2001). In this paper they note that the migration of people with higher stocks of schooling has, in theory, two effects on economic performance. First, migration may encourage more investment in schooling as people aim for higher levels in order to increase their chances of migrating. This may raise schooling levels in the country's working population if actual migration rates are below a threshold level. Thus, this 'incentive effect' may actually raise economic performance. Second, the actual migration of people with higher schooling may have a direct, detrimental effect on growth. This 'direct' effect is the one most commonly focused on. Testing these ideas requires data on migration flows. Beine et al (2001) use gross migration rates as a proxy for the 'brain drain', finding some support for the 'incentive effect' but, overall, that out migration is inimical for growth.

In this paper, the focus is on how the impact of schooling might vary across countries. In this regard, the extent of any brain drain is a potentially important conditioning variable. The most extreme example is when all of a country's secondary schooled students subsequently migrate! If this were the case, then one might expect the coefficient on secondary schooling to be zero or even negative (as such large scale out migrations of skilled labour might cause disruption, reduce investment and increase uncertainty). As will be discussed below, it is likely that the Barro and Lee (2001) schooling data do make some adjustments for out migration, although these adjustments are not perfect. However, even if these adjustments were perfect, there are two further reasons why we might be interested analysing brain drain data. First, it is possible that the people who migrate may have higher unmeasured levels of human capital than those that remain. Second, the extent of out migration is related to the current conditions and future prospects of the country. Normally, this provides a problem for empirical analysis, since the level of out migration is endogenous (i.e. higher migration reflects lower expectations for economic growth, hence a negative association between out migration and economic growth cannot be thought of as casual). Here, however, the data are used to divide the sample and then test the impact of schooling across sub-samples, hence the fact that out migration may reflect future opportunities within the country is not critical. Indeed, the corruption index was based on survey evidence from a small number of people, whereas the extent of out migration is based on people 'voting with their feet'. These observations suggest:

Hypothesis 3 Countries with higher levels of out migration of educated workers (brain drain) exhibit a lower effect of schooling on growth.

5.2. Data

As indicated above, a first issue is whether the secondary schooling data from Barro and Lee (2001) already account for out migration. The answer is both 'yes' and 'no'. Since the Barro and Lee data are benchmarked using census and survey data for particular years, these data should assess schooling stocks net of out migration. However, missing census or survey years are extrapolated using school enrolment data, a procedure that makes no allowance for differential rates of out migration between countries. This means that it is unclear how biased the schooling data are with respect to any brain drain effects.

The data used here for the extent of brain drain come from Carrington and Detragiache (1998). This paper uses data from the US Census (1990) on people over 25 to estimate the numbers of foreign born nationals who have migrated to the US. The data on migrants are broken down according to the highest level of schooling (primary, secondary or tertiary). Further, since the date when the person migrated to the US is recorded, it is possible to make educated guesses about where the education took place (the US Census does not directly ask this question). Hence, using the Barro and Lee (1993) data on schooling stocks in individual countries, the authors can estimate the percentage of country *i*'s stock of schooling that has out migrated. It should be stress that these percentages are *estimates*, for the reasons alluded to above and other measurement issues not mentioned here. Using the estimates of the percentage of secondary educated people to have migrated we can rank the countries from low to high.[12]

Table 4 Summary statistics for brain drain sub-samples

	Growth of GDP per worker (65-95)	Growth of capital per worker (65-90)	Secondary schooling (1965 average years)	Secondary schooling (Change in years 1965-95)	Log of GDP per worker (1965)
Low brain drain Mean 0.2% (n=24)	0.95	2.13	0.20	0.66	8.19
High brain drain Mean 12.1% (n=26)	1.01	2.71	0.49	1.03	9.12

Note: the 'low' brain drain is the sub-sample of 24 countries with the estimated % of secondary educated people in US below 0.6%. 'High' refers to sub-sample of countries with above 0.6%. The three countries with the median value are omitted.

Table 4 shows summary statistics for the two sub-samples, defined by above and below the median value. The data show that countries with a higher estimated rate of brain drain for secondary school educated people have a higher average growth rate, higher growth of secondary schooling and higher initial GDP per worker and the initial level of secondary schooling.

5.3. Regression analysis

Table 5 shows the results from regression analysis incorporating the brain drain data (there are 53 developing countries which have complete data). The full sample regression in column one shows that both growth of capital and change in years of secondary schooling are strongly significant for this sample of countries. This result, in comparison to the full sample regressions in Tables 2 and 3, highlights the fact that changes in the sample can greatly affect the regression results (Temple, 1999). The

[12] It is worthwhile noting some characteristics of the brain drain data (see Appendix 1). For example, small central American countries show the largest percentages of secondary schooled migrants to the US (e.g. El Salvador, 67%, Dominican Rep. 30%). Clearly these countries' social and political circumstances, combined with their political and geographical proximity to the US and their relatively small populations, interact to produce such high figures. Other countries may have higher out migration rates to European countries, something not captured by the data here. Carrington and Detragiache (1998) do estimate migration rates to OECD countries overall, but they stress these estimates are even more unreliable that the US estimates.

next two columns show regression results from the two sub-samples (i.e. those above and below the median value for brain drain). The coefficient on change in schooling in the 'low brain drain' sub-sample is positive and significant, and the magnitude is almost twice that in the full sample regression. In contrast, the coefficient on change in secondary schooling years for 'high brain drain' countries is insignificantly different from zero. This pattern of results is robust to including the initial income term. The results for the level of secondary schooling regressions also show a similar pattern of results, although the coefficient on schooling is not significant at standard significance levels for the 'low' brain drain sample. The robustness checks, using rolling regressions and plotting the coefficient on schooling, are shown in Appendix 2. These confirm the pattern of results shown in Table 5. In summary, the results find support for hypotheses three.

Table 5 Schooling and brain drain regressions

Dependent variable: Growth in GDP per worker (1965-95)

	(1) Full sample	(3) High brain drain	(2) Low brain drain	(4) Full sample	(6) High brain drain	(5) Low brain drain	(7) Full sample	(9) High brain drain	(8) Low brain drain
Growth in capital to labour ratio	0.434	0.721	0.413	0.391	0.599	0.394	0.431	0.614	0.397
	(6.25)***	(8.55)***	(4.87)***	(5.44)***	(8.00)***	(4.55)***	(5.79)***	(10.25)***	(3.93)***
Change in secondary schooling years	0.237	-0.011	0.428	0.347	0.050	0.499			
	(3.10)***	(0.12)	(3.07)***	(3.79)***	(0.51)	(3.01)***			
Log of GDP per worker (1965)				-0.006	-0.010	-0.004	-0.004	-0.011	0.002
				(2.47)**	(2.33)**	(0.67)	(1.41)	(2.43)**	(0.28)
Secondary schooling years (level 1965)							0.011	0.005	0.019
							(1.64)	(1.00)	(1.44)
Constant	-0.008	-0.009	-0.009	0.041	0.086	0.019	0.029	0.088	-0.017
	(2.47)**	(2.35)**	(1.86)*	(2.02)**	(2.20)**	(0.46)	(1.23)	(2.26)**	(0.35)
Test of 'poolability' (prob)	0.04			0.12			0.09		
Observations	53	26	24	53	26	24	53	26	24
Adjusted R-squared	0.52	0.72	0.55	0.55	0.75	0.54	0.47	0.76	0.43

Note: * significant at 10%; ** significant at 5%; *** significant at 1%. All t-statistics based on robust standard errors. Other notes as per Table 2.

6 Further discussion and analysis

The previous empirical literature has found that the magnitude and significance of the coefficient on schooling varies dramatically across different sub-samples of countries. As Temple (2001, p.916) has stated "the aggregate evidence on education and growth, for large samples of countries, continues to be clouded in uncertainty". Consider the first regression in each of Tables 2, 3 and 5, which use samples of 31, 46 and 53 countries respectively. The coefficient on the change in secondary schooling is -0.01, 0.11 and 0.24, with the last coefficient significant at the 1% level. This shows how changes in the sample of countries can have a dramatic effect on estimated coefficients, reinforcing the results of previous studies (Table 6 provides more information on three recent examples). The contribution of this paper is to show that such results are highly likely given that regressions do not control for the productive use of schooling, hence adding a few countries to a sample can make a dramatic difference.

Table 6 Recent estimates on change in schooling

Study	Coefficient on change in schooling	Coefficient on growth of capital	Description
Pritchett (2001)	-0.05^{ns}	0.52^{s}	OLS, 91 countries, 1960-85, Table 2 (1) p.375
Temple (2001)	0.01^{ns}	0.43^{s}	OLS, 78 countries, 1965-85, Table 1 (3) p.910
Topel (1999)	0.17^{s}	Na	OLS, 101 countries, 1960-90, Table 4 (10) p.2969 (No capital variable entered)

Note: s = significant ns = not significant

The regressions in Tables 2, 3 and 5 show that the coefficient estimate on secondary schooling increases if the sub-sample is restricted to those countries most likely to use schooling productively (as gauged by the relative value from the corruption, black market premia and brain drain data). The magnitude of the coefficient on the change in schooling varies from 0.20 to 0.50 in these 'productive use' sub-samples (the variation arises both from the nature of the sub-sample and the empirical specification). What coefficient magnitude should we expect? Pritchett (2001) provides a detailed discussion. In short, he expects the coefficient to be between 0.26

and 0.56.[13] Pritchett's estimate relate to the coefficient on growth of human capital which, according to equation [4], is $r\Delta S$. (i.e. 'rate of return' multiplied by change in schooling years). The analysis in Tables 2, 3 and 5 has implicitly set r=1, hence the results here are consistent with a 'rate of return' of around 100%. This means that the above results are compatible with very high rates of return to schooling for certain sub-samples of countries.[14]

Another way of interpreting the coefficients is to consider the effect of a one standard deviation in the (average annual) change in schooling (around 0.02 for the samples above), hence the coefficient estimates are associated with increases in growth of between 0.4% and 1% per annum (although, it should be acknowledged, this type of regression analysis does not prove causality).

The results on the empirical specification that uses the level of schooling in 1965 as an explanatory variable are also of interest. Barro (2001, Table 1) uses the average years of male secondary schooling as a dependent variable in a regression with 84 countries, finding a coefficient of 0.004, Topel (1999, Table 4) finds a similar coefficient on total years of schooling. This coefficient suggests a one standard deviation change (1 year for their sample) increases annual growth by 0.4%. In the above results the coefficient on initial level of secondary schooling for 'productive use' sub-samples is between 0.016 and 0.021, but the standard deviation is lower (around 0.3 years for the developing country sample), indicating an associated increase of between 0.5% to 0.6%.

Another way to view the results is to focus on the estimated coefficients for the sub-samples of countries with relatively high corruption, black market premia or levels of brain drain. The results are stark: no coefficient estimate is positive and significant, and some coefficients are negative and significant. The implication is that investments

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[13] The background is that there are various arguments for why the capital share should be around 0.4 and the total labour share should be around 0.6. Then Pritchett (2001) uses evidence on wage premia for schooling to estimate that the 'human capital' share of GDP will vary between 0.26 and 0.56 (see Table 1 in Pritchett, 2001).

[14] Use of the term 'rate of return' is standard, but it is also misleading in that there is no consideration of the costs of schooling.

in schooling in these sub-samples of countries have not been converted into human capital that is used productively.

Another aspect of the results of interest is that the coefficient on the growth of the capital to labour ratio is lower in the sub-samples most likely to use schooling productively. *A priori* we might expect that the coefficient on capital growth should equal the share of profits in GDP, commonly though to have a maximum of around 0.4 (Pritchett, 2001, Lucas, 1990). Thus, the results for the 'productive use' sub-samples, with capital coefficients between 0.29 and 0.41, are consistent with this expectation. In contrast, the coefficients on capital growth for the 'unproductive use' sub-samples appear too high (0.50 to 0.72). One possible explanation is that the marginal product of capital is much higher in these sub-samples, reflecting for example the higher levels of risk faced by investors.[15]

The above regression analysis has focused exclusively on secondary schooling. Do the above results hold for an analysis of primary or higher schooling? Overall, the answer is 'no', since the majority of coefficients on primary or higher schooling variables, when substituted for the secondary schooling variable in the above analysis, are insignificantly different from zero. This said, in the few cases where the coefficients are significant the results support the hypotheses above.

A further issue concerns the possibility that a group of influential observations are driving the results. The graphs in Appendix 2 indicate that influential observations are not a critical issue for the main hypotheses, but a further method of assessment is to use a robust regression technique (Temple, 1999, 2001). All the regressions above have been re-run using a robust estimator and the results are very similar, both in significance and magnitude of coefficients, to those shown above.[16] A related issue

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[15] The marginal product of capital is given by

$$\frac{dy}{dk} = a_k k^{a_k - 1} A h^{a_h},$$

based on equation [2], hence, *ceteris paribus*, if the estimate of a_k is higher, so is the marginal product.

[16] The robust regression estimates have the following procedure. Initially, the residuals from the OLS regression are analysed to give each observation a weight based on its residual's relative magnitude. A regression using the weighted data is then run. This procedure of re-weighting continues until no

concerns the influence of sub-Saharan African countries on the analysis. These countries have a poor record of economic growth, which sometimes leads to a separate analysis of sub-Saharan countries (e.g. Easterly and Levine, 1997). The regressions in Table 3 and 5 were re-run using sub-samples of sub-Saharan versus other countries (there are only 5 sub-Saharan countries in the sample in Table 2 preventing this approach for the 31 countries that have corruption data). The results show significant and positive coefficients for secondary schooling in the sub-sample of sub-Saharan countries, refuting the idea that the sub-Saharan countries drive the analysis.

7 Conclusion

This paper's central aim is to explore why the aggregate economic returns to schooling, as measured by increased value added, may vary across countries. The debate on the economic value of schooling is on-going, providing important background for policy work. A summary of econometric results to date is that economists often find low economic returns to schooling, with the estimates being sensitive to modelling approach and sample selection. The unexpectedly weak results are often tempered by comments on the wider value of schooling, in terms of health, fertility and quality of life issues. While these comments are, in the author's opinion, entirely justifiable, this paper shows that the failure to control for cross country variations in the ability to use schooling productively is critical. When regressions are run for countries that are more likely to use their schooling stocks productively, the economic impact of schooling is positive and, generally, statistically robust.

The specific approach and findings of the paper can be summarised as follows. Data on corruption, black market premia and brain drain to the US are used to divide developing countries into sub-samples. The hypotheses are that sub-samples with higher reported corruption, black market premia or brain drain will have a lower impact of schooling on economic growth. Cross country regressions for up to 53 developing countries, with GDP per worker growth (1965-95) as the dependent variable, are used to test the hypotheses. Empirical specifications for both the change

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'large' residuals exist. The procedure is described in more detail, with appropriate references, in STATA 7.0 reference manual under 'rreg' (www.stata.com).

in secondary schooling and the level of secondary schooling are used. The results show support for the hypotheses. In summary, the impact of secondary schooling on economic growth becomes more important if you control for the basic idea that not all schooling is used productively. The lesson is that investment in schooling creates a potentially powerful resource for raising economic growth, but it is possible to waste this resource.

Appendix 1 Data

Country	Growth	g(K/L)	logy	Δ sec	sec	bmp	corr	bd
Argentina	0.0024	0.0213	9.970	0.036	0.679	66.8	7.66	0.7
Bangladesh	0.0217	-0.0085	8.157	0.013	0.227	118.6	4	0
Benin	0.0015	0.0282	7.699	0.011	0.081	1.2	.	0.1
Bolivia	-0.0087	0.0019	9.056	-0.004	1.323	28.1	.	2.1
Brazil	0.0207	0.0316	9.099	0.008	0.653	21.2	5.75	0.7
Cameroon	0.0073	0.0546	8.232	0.008	0.267	1.2	7	0.1
Central African Republic	-0.0179	-0.0110	8.255	0.014	0.095	1.2	.	0.1
Chile	0.0105	0.0095	9.485	0.029	1.074	32.6	9.25	1
Colombia	0.0094	0.0176	9.115	0.030	0.599	10.4	4.5	3.6
Congo, Rep.	0.0175	0.0052	7.790	0.027	0.82	1.9	.	.
Costa Rica	-0.0004	0.0291	9.471	0.028	0.438	10.6	.	10.1
Dominican Republic	0.0162	0.0391	8.793	0.033	0.143	31.6	6.5	29.7
Ecuador	0.0164	0.0294	8.876	0.047	0.382	24.1	5.5	11.4
El Salvador	0.0000	0.0198	9.402	0.016	0.236	64.2	.	66.6
Gambia, The	-0.0034	0.0663	7.994	0.009	0.191	.	.	0.6
Ghana	-0.0124	-0.0263	8.199	0.036	0.146	125.9	3.66	0.3
Guatemala	0.0107	0.0161	9.121	0.012	0.16	16.6	.	29.1
Guyana	-0.0127	-0.0058	9.015	0.039	0.208	.	.	23.7
Honduras	0.0050	0.0130	8.690	0.019	0.161	16.6	.	15.7
India	0.0271	0.0280	7.769	0.026	0.12	35.5	5.25	0.1
Indonesia	0.0532	0.0804	7.603	0.033	0.116	2318.6	1.5	0.1
Iran, Islamic Rep.	0.0080	0.0376	9.186	0.036	0.21	449.9	3.25	1
Jamaica	-0.0064	-0.0055	8.968	0.050	0.287	19.6	5	23.4
Jordan	0.0230	0.0728	9.400	0.064	0.413	2.9	8.33	.
Kenya	0.0045	-0.0137	7.629	0.014	0.093	13.1	4.5	0.2
Korea, Rep.	0.0598	0.0998	8.530	0.098	0.974	4.4	5.75	1.2
Lesotho	0.0293	0.0940	7.626	0.011	0.062	9.9	.	0
Malawi	0.0057	0.0368	7.120	0.006	0.019	39.9	.	0.1
Malaysia	0.0393	0.0574	8.893	0.077	0.492	0.1	6	0.2
Mali	-0.0107	-0.0023	7.794	0.004	0.023	.	.	0.1
Mauritius	0.0376	0.0107	9.104	0.041	0.316	.	.	0.1
Mexico	0.0074	0.0288	9.712	0.050	0.277	8.2	3.25	20.9
Mozambique	-0.0275	0.0046	8.240	0.003	0.032	.	.	0.5
Nicaragua	-0.0276	0.0139	9.557	0.017	0.383	593.2	8.75	33.3
Pakistan	0.0238	0.0199	8.160	0.027	0.25	39.5	4	0.2
Panama	0.0129	0.0291	9.140	0.037	0.856	.	5	9.4
Papua New Guinea	-0.0011	0.0251	8.778	0.004	0.153	.	.	0.1
Paraguay	0.0210	0.0555	8.903	0.033	0.345	34.9	.	0.7
Peru	-0.0150	0.0092	9.511	0.053	0.497	29.3	7.25	2.3
Philippines	0.0072	0.0343	8.678	0.036	0.64	5.9	4.5	4.4
Rwanda	0.0119	0.0597	7.228	-0.001	0.11	.	.	0
Senegal	-0.0044	-0.0042	8.283	0.008	0.138	1.2	.	0.3
South Africa	0.0081	0.0210	9.690	0.053	0.79	2.3	8	0.1
Sri Lanka	0.0287	0.0500	8.151	0.037	0.988	57.7	7	0.1
Syrian Arab Republic	0.0274	0.0368	8.955	0.045	0.184	90.5	.	2.2
Thailand	0.0462	0.0559	7.971	0.022	0.285	-1.6	1.5	1.5
Togo	-0.0020	0.0430	7.888	0.020	0.042	1.2	.	0.1
Trinidad and Tobago	0.0121	0.0253	9.664	0.059	0.676	.	6.5	15.9
Tunisia	0.0206	0.0197	9.110	0.027	0.173	14.7	.	0.3
Turkey	0.0251	0.0450	8.760	0.025	0.32	10.1	6	0.7
Uganda	0.0127	-0.0037	7.095	0.012	0.04	293.2	.	0.6
Uruguay	0.0106	0.0160	9.548	0.042	0.797	10.6	8	2.3
Venezuela	-0.0087	-0.0025	10.050	0.031	0.299	18.1	5.75	0.6
Zambia	-0.0310	-0.0295	8.604	0.034	0.039	103.7	.	0.1
Zimbabwe	0.0065	-0.0223	8.369	0.039	0.094	64.8	8.75	0.3

Variables

Abrev.	Variable	Details and source
Growth logy	Growth and level of GDP per worker (1965-95)	Growth rate is coefficient from regression of log of GDP p.w. on constant and time trend. Penn World Table 6 (PWT6) (http://pwt.econ.upenn.edu/home.html)
g(K/L)	Growth of capital per worker (1965-90)	Average annual growth. From http://www.worldbank.org/research/growth/GDNdata.htm and discussed in Easterly and Levine (1999). (Note: PWT6 data on capital stocks are currently not available post-1990)
Δsec	Change in secondary schooling 1965-95	Average annual change in schooling years. These data are the average years of secondary schooling in working population over 25 years of age. Source: Barro and Lee (2001).
sec	Level of secondary schooling (1965)	As above for 1965.
bmp	Black market premium (%) (1965-90)	Average bmp of foreign exchange rate verses official rate (1965-90). Contained in data available at http://www.worldbank.org/research/growth/GDNdata.htm
corr	Corruption index	Index from 0 (bad) to 10 (good), based on survey data (1980-83). Mauro (1995).
bd	Brain drain	Estimated % of secondary schooling stock that has migrated to US. Carrington and Detragiache (1998).

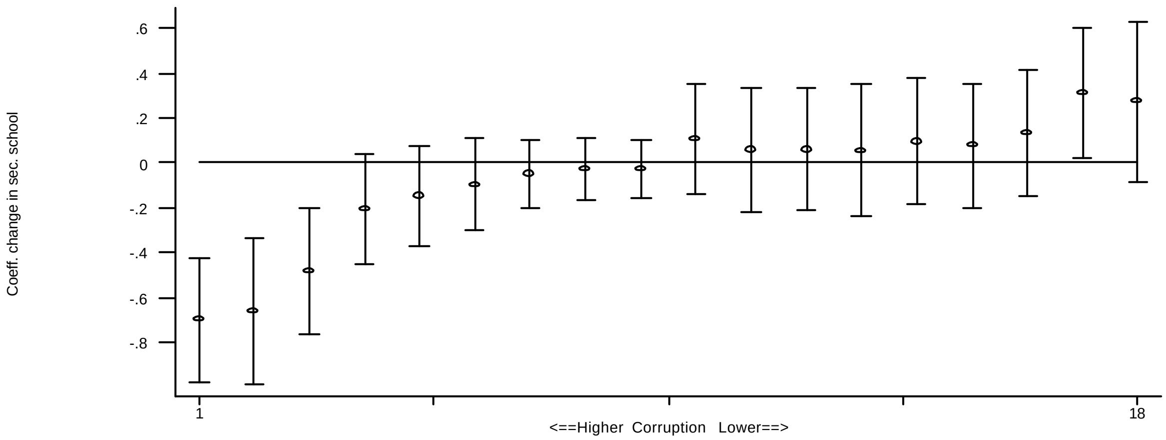
Notes: Definition of developing country taken from World Bank. See data available at:

http://www.worldbank.org/research/growth/GDNdata.htm.

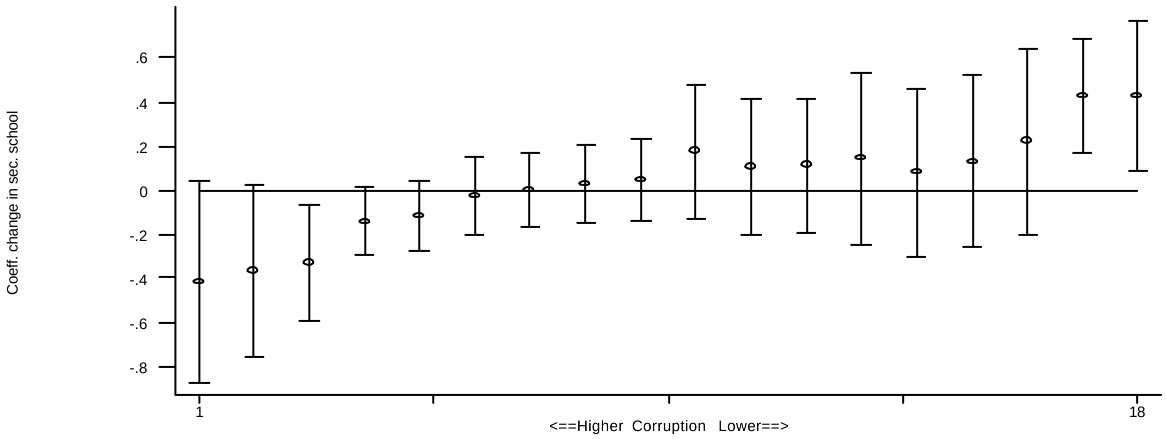
Appendix 2 Rolling sub-sample regression results

<u>Corruption samples</u>

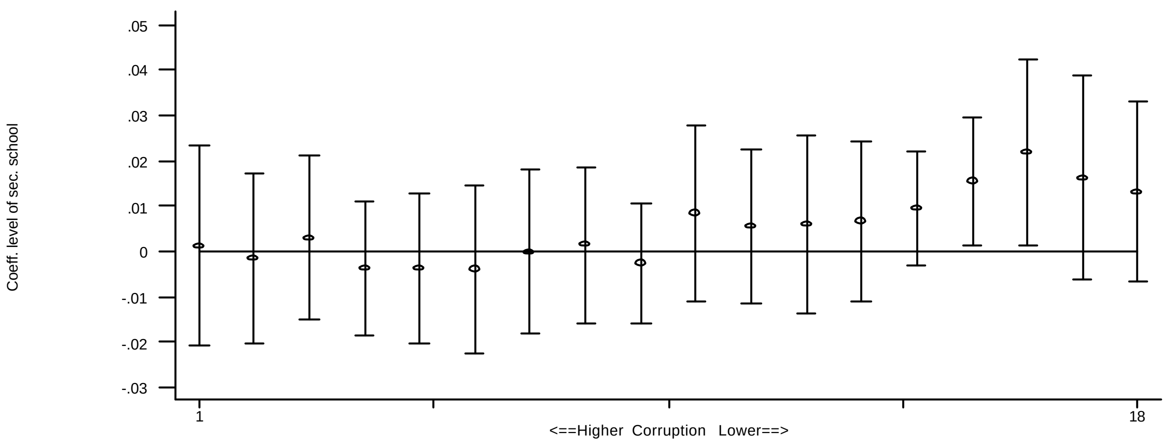
Coefficient on change in secondary schooling as n=14 sub-sample shifts from 'low' to 'high' corruption (regressions 2 and 3 in Table 2)



Coefficient on change in secondary schooling as n=14 sub-sample shifts from 'low' to 'high' corruption (regressions 5 and 6 in Table 2)

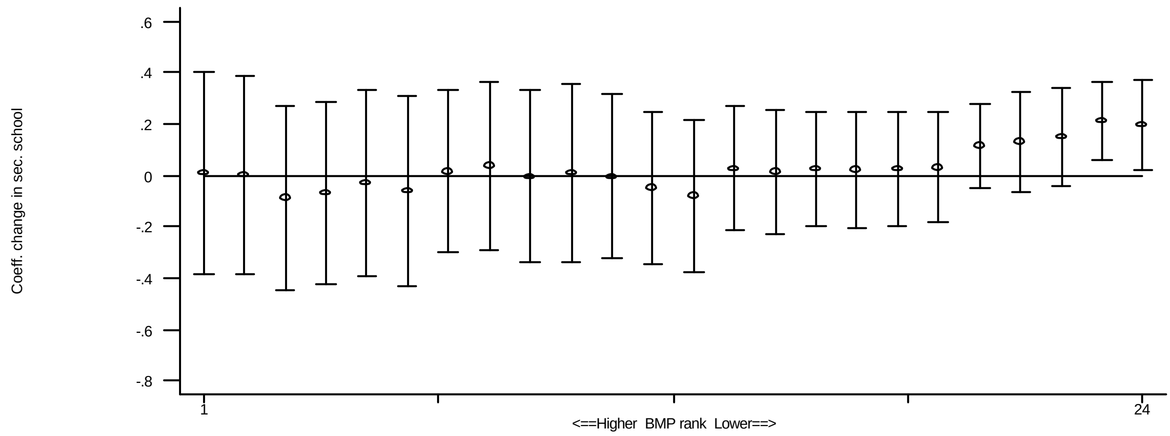


Coefficient on level of secondary schooling as n=14 sub-sample shifts from 'low' to 'high' corruption (regressions 8 and 9 in Table 2)

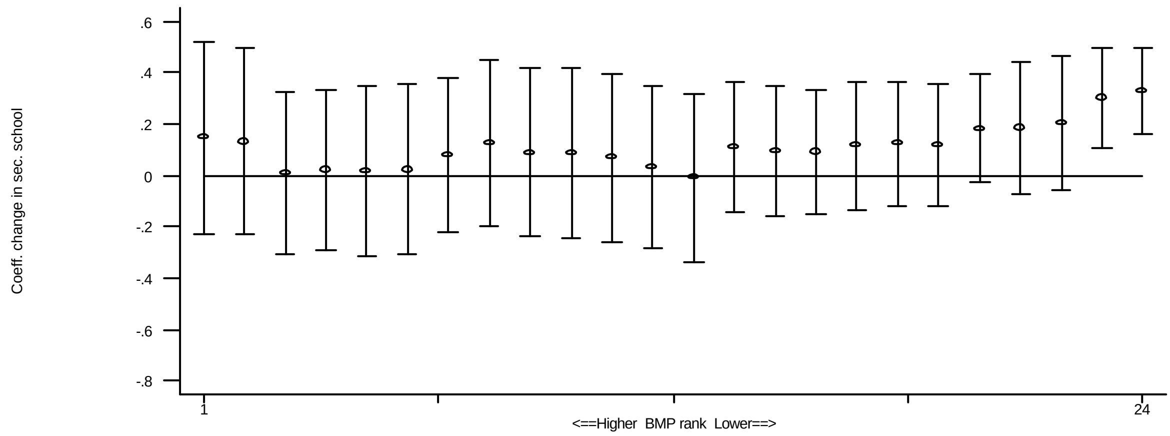


<u>Black market premium samples</u>

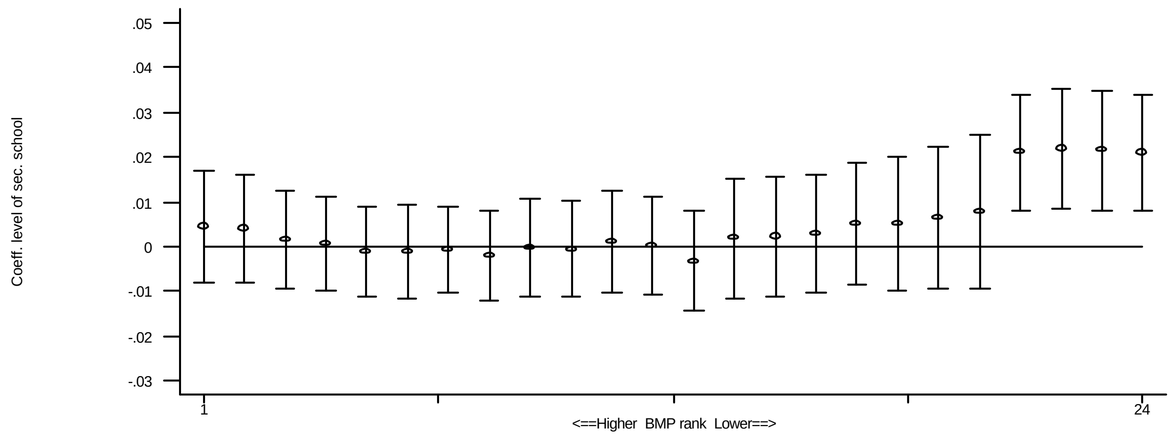
Coefficient on change in secondary schooling as n=23 sub-sample shifts from 'high' to 'low' premium (regressions 2 and 3 in Table 3)



Coefficient on change in secondary schooling as n=23 sub-sample shifts from 'high' to 'low' premium (regressions 5 and 6 in Table 3)

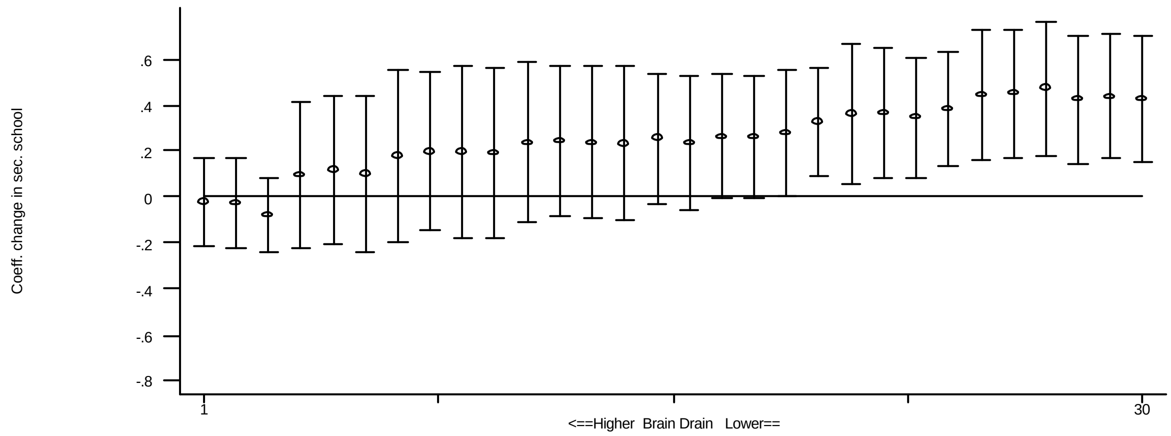


Coefficient on level of secondary schooling as n=23 sub-sample shifts from 'high' to 'low' black market premium (regressions 8 and 9 in Table 3)

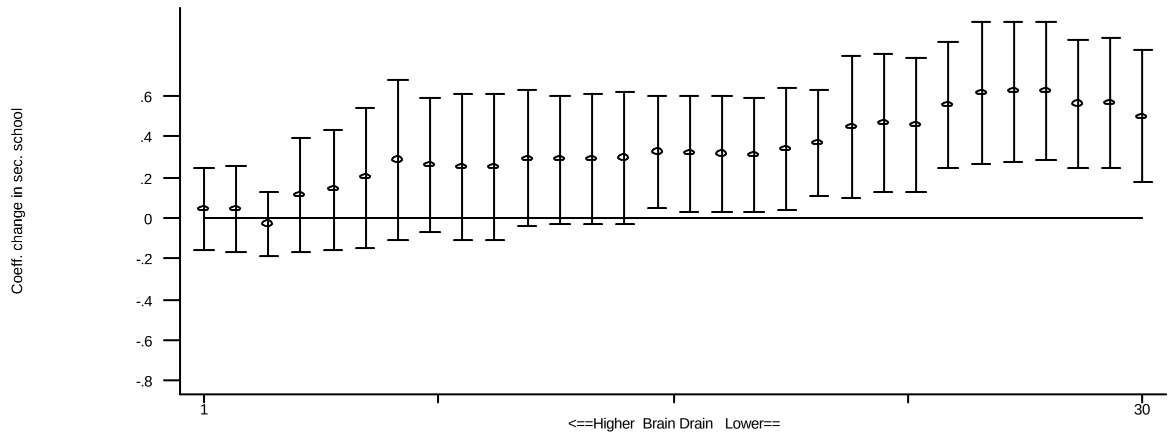


Brain drain samples

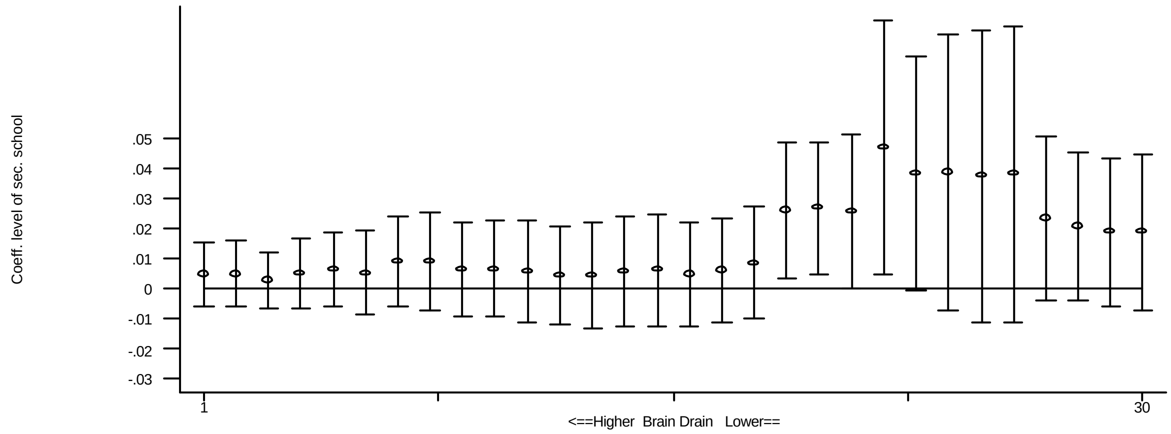
Coefficient on change in secondary schooling as n=24 sub-sample shifts from 'low' to 'high' brain drain (regressions 2 and 3 in Table 5)



Coefficient on change in secondary schooling as n=24 sub-sample shifts from 'low' to 'high' brain drain (regressions 5 and 6 in Table 5)



Coefficient on level of secondary schooling as n=24 sub-sample shifts from 'low' to 'high' brain drain (regressions 8 and 9 in Table 5)



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