

# Education and Growth

## Instrumental Variables Estimates

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### **Abstract**

This paper estimates cross-country production functions with first differenced unbalanced panel data. Least squares estimates find significant social returns to education and experience, even after controlling for physical capital accumulation. The estimated returns to human capital are slightly smaller than private returns estimated from micro-level data. The estimated returns to physical capital accumulation are much larger than estimates based on factor shares. Physical and human capital are subject to measurement error and endogeneity. To address these problems, I estimate the production function with instrumental variables based on the age structure of the population. Instrumental variables estimates find statistically significant returns to physical and human capital that are quite similar to private returns.

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## I. Introduction

This paper reports estimates from a first-differenced cross-country production function including physical and human capital. The purpose will be to provide estimates of the social returns to accumulating factors of production. Micro data (e.g., Gollin 2002, or Psachoropoulos, 1993) provides reasonably accurate estimates of the private returns to accumulating physical and human capital. Neo-classical theory argues that the social returns to accumulating capital are equal to the private returns. Many theories, following Arrow (1962), have assumed that the accumulation of physical or human capital creates externalities that cause social returns to deviate from private returns. There are also reasons, such as signaling (see Spence, 1974), that private returns to accumulating the factors of production may also exceed social returns. If social returns cannot be derived from factor payments, it is necessary to estimate the direct impact of these returns on aggregate productivity. Estimates of the returns to education are of special interest<sup>2</sup> because several prominent recent papers (for example, Benhabib and Spiegel 1994, and Pritchett, 1996) have encountered difficulties in finding any connection between growth in the stock of human capital and growth in productivity. Later work, by Topel (1999) and Krueger and Lindahl (2001), suggests specifications in which human capital changes can be seen to affect productivity, but also emphasizes the difficulties in jointly estimating the returns to physical and human capital.

The estimates here are based on cross-country production functions estimated with panel data, first differenced at 10-year frequencies. This estimation strategy is chosen for a number of reasons. First, using aggregate data at the national level allows us to identify the productive effects of education, as opposed to potential allocative effects within the nation. Second, a production function describes the other variables besides human capital, such as physical capital, that must be included in the regression. Omitting changes in physical capital increases the likelihood that the returns to education are subjected to bias. Since both physical and human capital may have social returns that differ from private returns, it is important to jointly estimate returns to both factors. Third, first differencing the production function is useful in dealing with endogeneity. In the long run, high productivity growth is likely to cause increases in schooling. As Temple (2000) points out, however, changes in education at sufficiently high frequency reflect

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<sup>2</sup> Estimates of the social returns to physical capital are also provided. As Griliches and Mairesse (1995) point out, deriving precise estimates of private returns to physical capital in first differenced production functions has also proved difficult in many cases.

demographics and policy decisions that are pre-determined by decisions made many years before. Fourth, the production function approach pins down the temporal relationship between education and output. Human capital is a *stock* that determines the *flow* of output. In first differences, the change in the stock of education determines the growth rate of output.

Neo-classical theory offers some a priori measures of the parameters of the production function. Under the neo-classical theory, factors are paid their marginal product and private returns are equal to social return. In this paper, I refer to the idea that the social returns to physical and human capital are equal to private returns as the neo-classical hypothesis. In a broad variety of countries, Gollin (2002) finds that the share of income not paid to labor ranges between 20 and 40%. Under the neo-classical hypothesis, this indicates the average elasticity of output with respect to capital should be in the same range. Psacharopoulos (1993) examines the elasticity of real wages with respect to years of education in a variety of countries, finding that each additional year of education increases wages between 5 and 15%. The neo-classical hypothesis would suggest that the social returns to education should also lie in that range. In this study, I find positive and significant social returns to education even when controlling for changes in physical capital. Least squares estimates of the returns to education lie in the low end of the range suggested by the neo-classical hypothesis. The estimated social returns to physical capital accumulation are large relative to capital's share in national income accounts.

Physical and human capital observations are likely to be subject to measurement error and endogeneity. Instrumental variables are the standard solution to both problems. I construct instruments based on the age demographics of the population. In theory, a country's age structure is an important determinant of both physical and human capital accumulation. Life cycle theories explain why physical capital investment would depend on the age structure of the population. Human capital increases as more highly educated young people enter the workforce and less-educated older people leave the workforce. When the share of the population at those points of the age distribution is high, changes in the education stock should also be high. Indeed, empirically, the average education level of the population increases most when the share of individuals in the population age groups entering and leaving the adult population is highest. Specification tests suggest that age demographics instruments are exogenous and relevant, explaining 10% of the independent variation in changes in the human capital stock.

The 2SLS estimates of the returns to accumulating physical and human capital are consistent with the neo-classical hypothesis. Estimates of the response of productivity to physical capital are statistically significant and marginally larger than the range suggested by factor payments (though within a standard error of that range). Estimates of the response of productivity to increases in education are statistically significant and within the range suggested by the neo-classical hypothesis (though near the high side of that range).

Human capital accumulation has long played a role in economic growth theory (see Lucas, 1988). The long run effect of education on output has been a central concern of the modern empirical growth literature since its inception and this study builds on much of that literature. Sianesi and Van Reenan (2000) is an excellent literature review that closely analyzes the strengths and weaknesses of various papers. In early contributions, Barro (1991) and Mankiw, Romer, and Weil (1992) find that enrollment rates are an important determinant of long-run growth after controlling for initial output. However, at low frequencies, enrollment rates are likely to be subject to substantial endogeneity. In the long run, rich nations can and will pay for more education for their citizens (see Bils and Klenow, 1998). At higher frequencies, enrollment rates may not be a useful proxy for human capital accumulation because of the long time to build process in education. Changes in the enrollment rates in any given period may not affect the actual education levels of the workforce for years or even decades. Thus, it may be more useful to examine the direct impact of changes in the education level on productivity. Several prominent studies including Benhabib and Spiegel (1994) and Pritchett (1996) notably find no relationship between growth rates of education and growth rates of productivity (after controlling for growth rates of physical capital). Temple (1999) finds that outliers may reduce the accuracy of OLS estimates and finds that robust regression estimates indicate a positive relationship between human capital growth rates and productivity growth rates. Temple (2001) performs an ad hoc nonlinear specification search and finds that the inclusion of non-linear terms can strengthen this relationship.

Topel (1999) argues that a correct specification of the relationship between education and productivity is vital. Labor economists model a constant relationship between the log of productivity and the level of years of education. In first differenced cross-country form, this indicates a constant relationship between changes in the average level of education and the growth rate of productivity. Using this specification, Topel (1999) finds a significant

relationship between changes in education levels and productivity growth. Krueger and Lindahl (2000) find that after controlling for capital growth, the relationship between changes in education levels and productivity growth is weak. However, they note that frequently used measures of education levels are subject to substantial measurement error that is likely to bias the estimates of the returns to education downwards. Moreover, they point out that the endogeneity of capital accumulation to unmeasured sources of output growth are likely to exaggerate the effect of capital growth on output.

A previous literature has used age demographic variables as an exogenous instrument for investment in physical and human capital. Higgins (1998) shows that the age profile of the population affects national savings and investment in cross-country data. Cook (1999) and Wilson (2000) show that demographic variables are relevant variables for factor inputs at the U.S. industry level. Ciccone and Peri (2000) use demographic variation as an instrument for U.S. city level changes in education levels.

## II The Model and the Data

The theoretical model assumes that each national economy's aggregate productivity, (output per worker) is a stochastic Cobb Douglas<sup>3</sup> function of physical and human capital per worker.

$$y_{it} = X_{it} k_{it}^{\beta^1} h_{it}^{\gamma}$$

Output per worker of economy  $i$  at time  $t$  is  $y_{it}$ ; stochastic technology level in country  $i$  at time  $t$  is  $X_{it}$ ; physical capital per worker is  $k_{it}$ ; and human capital per worker in country  $i$  and country  $t$  is  $h_{it}$ . Human capital per worker is itself an exponential function of the average number of years of experience of country  $i$ 's workers and the number of years of education

$$\ln h_{it} = \frac{\beta^2}{\gamma} school_{it} + \frac{\beta^3}{\gamma} ex_{it}.$$

The technology level has a country fixed effect  $\ln X_{it} = x_i + \varpi_{it}$ . In first differences, technology shocks have a worldwide time dependent component and a stochastic, idiosyncratic component.

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<sup>3</sup> Duffy and Papageorgiu (2000) find interesting evidence in favor of a more general CES production function. The study focuses on estimating the effect of changes in education levels on productivity growth rates. Thus, I choose data sources that can provide the broadest span of growth rate data across countries and time. This data however is not compatible with all types of comparisons in levels implying it may be difficult to extend the analysis to other types of non-Cobb-Douglas production functions.

$$\Delta \ln X_{it} = \Delta \varpi_{it} = \beta^0 + \varepsilon_{it}.$$

Productivity growth is written as:

$$\Delta \ln y_{it} = \beta^0 + \beta^1 \Delta \ln k_{it} + \beta^2 \Delta school_{it} + \beta^3 \Delta ex_{it} + \varepsilon_{it} \quad (1)$$

Equation (1) is the basic econometric model estimated throughout. The neo-classical model (in which factor payments reflect marginal productivity) along with microeconomic estimates of factor payments suggest some basic prior hypothesis about the parameters. In most industrial countries, capital income is substantially lower than one half of total income (see Gollin, 2002). If the neo-classical hypothesis holds, the parameter  $\beta^1$  should lie in the range .2-.4. A broad set of results from labor economics following Mincer (1974) shows that each extra year of education is associated with 5-15% higher wages in many countries; an extra year of work experience is associated with 4-5% higher wages. Bils and Klenow (2000) report microeconomic estimates for the effect of years of education and experience on wages in a wide variety of countries that is consistent with this range. The neo-classical hypothesis suggests that  $\beta^2$  and  $\beta^3$  should lie in the ranges .05 to .15 and .04 to .05 respectively.

Previous papers, such as Topel (1999) and Krueger and Lindahl (2001) that have estimated the returns to schooling using a specification similar to (1) have not controlled for changes in experience. Such an omission may bias the estimated effect of schooling on productivity downward as one cost of additional schooling is job experience.

Annual data on the level of output and capital stock for many countries are available from Nehru and Dhareshwar (1993). An advantage of this dataset is that it contains capital stock data for many countries as far back as 1950. A disadvantage is that the data has not been converted into purchasing parity form as in the Penn World Tables (see Heston and Summers, 1991). However, the models here will use exclusively first differenced data so comparisons will always be made between growth rates in productivity. Annual data on the number of workers in each period is from Easterly and Levine (1998). Five-year data on the average number of years of schooling of the population aged 15 and up is from the Barro and Lee (1993, 2000) dataset. Five-year data on the age profile of the population is available from United Nations (1994). I construct a measure of the average age of the workforce as the sum of the midpoint age of each 5 year age group between 15 and 64 multiplied by the share of the population aged 15 and 64 in that age group (i.e. *age* = *-17.5% of working age population aged 15-19* + *-22.5% of working age population aged 20-24* + ... + *-64.5% of working age*

*population aged 60-64*). Experience is the average age minus the average number of years of schooling of the population above 15 minus six.<sup>4</sup> I construct an unbalanced panel of 81 countries that will be used in each of the subsequent estimates.

One clear observation in the data is that the average growth rate of output per worker among countries in the sample has been falling over time. Table 1 shows that the average growth in output per worker in the 1960's was over 3% while the same figure was less than 2% in the 1970's and less than .5% in the 1980's. Meanwhile, the change in the level of average education was substantially higher in either the 1970's or the 1980's than in the 1960's. One explanation for this outcome is that education is either irrelevant or counter productive for growth (see Pritchett, 1996). Another is that worldwide technology growth happened to be higher in the earlier periods. Another interesting observation is in the differences between OECD and non-OECD countries. The change in the average education levels is virtually the same in the OECD and non-OECD countries until the 1980's when the education change in the developing world is slightly larger. However, productivity growth in the OECD countries is higher in every decade. Moreover, the sharp fall in productivity growth that occurs in the 1980's is concentrated in the developing world. Because of these observations, I allow the intercept term to vary across time as well as to differ across the OECD and non-OECD countries.

### III Estimates

#### A. Least Squares

Table 2, Column 1 reports the results from a least squares regression imposing the restriction that the intercept is constant across time and countries (standard errors are corrected for heteroskedasticity and autocorrelation). In this regression, physical capital growth is strongly correlated with labor productivity growth and statistically significant at the .1% level. The estimate of the capital intensity parameter,  $\beta^l$  is above .6. The human capital parameters are near zero and statistically insignificant at any reasonable critical value.

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<sup>4</sup> Wage regressions following Mincer (1974) include a squared experience term. In individual data, the variation of experience levels can be large. However, the spread of average experience across countries is much smaller. Changes in the squared average experience level are extremely co-linear with changes in the average experience level. There is little point in adding a squared term to country regressions.

There is strong evidence, however, that the intercept term varies across time and between developed and developing economies. Column 2 shows the estimates when time dummies are included. The time dummies are separately and jointly significant at the .1% critical value. The inclusion of the time dummies slightly reduces the estimate of the coefficient on physical capital. Most interestingly, the inclusion of the dummies increases the correlation between changes in the level of human capital and average productivity growth. The estimate of the effect on productivity of a change in the years of schooling is approximately six percent. The estimate is significantly different from zero at the 5% critical level. This estimate is on the low side of the range suggested by the neo-classical hypothesis. The estimate of the returns to a year of experience is approximately 3%, which is significantly different from zero at the 10% critical value. This estimate is again small relative to the neo-classical hypothesis, but the difference is less than a standard error. Column 3 reports the results from a regression in which OECD dummy variables are also included. The OECD-time interactive dummies are jointly significant at the 1% critical value. The results for the coefficients on factor accumulation are otherwise similar. Returns to schooling remain significant at the 5% critical value. Column 4 reports the results when interactive dummy variables for Latin American and African are included. The size of the effect of education changes on growth is slightly smaller and is only significant at the 6% critical value.

Benhabib and Spiegel (1994) find that the initial level of average education per worker is a significant determinant of output growth. They argue that education levels make the adoption of technology easier. I estimate the production function model while controlling for the initial education level at the beginning of each 10-year period. The results of this estimation are reported in Column 6. In this specification, the coefficient on initial education is small and statistically insignificant. The inclusion of initial education has little impact on the other coefficient estimates. Changes in average education are still significant at the 5% critical level.

## **B. Instrumental Variables Estimates**

There are familiar reasons that the above estimates may be biased. First, factor accumulation may be endogenous to random technology shocks. The fact that the coefficient on physical capital significantly exceeds the standard notion of capital's share of income may reflect this endogeneity. High unobserved technology growth may cause capital growth to be high

either by increasing the returns to investment or producing more output that is available for use as investment. Positive correlation between the residual and capital growth is likely to bias the estimate of the returns to capital upward. Second, data on physical and human capital are likely mis-measured along with their first differences. The classical solution for both endogeneity and measurement error is instrumental variables. In this section, I include some estimates of the production function using instrumental variables. Table 3 shows the 2SLS coefficient estimates along with some post-estimation specification tests.

Given the panel nature of the data, a natural instrument might be lags of the right hand side variables. The data has levels of capital for many countries from 1950 onwards. Moreover, lagged capital growth is a powerful instrument for current capital growth. The simple  $R^2$  from a regression of current capital growth on lagged growth is above .3. Unfortunately, data on education stocks goes back only to 1960 so using lagged schooling or experience changes would eliminate nearly one third of the observations. Moreover, schooling changes do not seem to have great persistence. The simple  $R^2$  from a regression of schooling change on its lag is approximately .001. A Wald F test fails to reject the hypothesis that lagged schooling has no predictive power at even the 60% critical value. Thus, lagged schooling would be a poor instrument.

The age demographic profile of the population offers a useful instrument for the coefficients. There is a clear a priori connection between the age profile of the population and the accumulation of human and physical capital that is exogenous to unobserved technology growth (the error term in the regression). Life cycle theory suggests that savings should be high when a large share of the population is in the prime working years, as would be the marginal product of capital. This suggests that demographics affect investment in physical capital. Education occurs at specific age. A large share of the population at school age is likely to be followed by rapid growth in the average educational level of the population. The connection between experience and age demographics is also clear. Moreover, the demographic data is used to construct the experience variable, so the variable is available at 10-year frequencies for each observation.

Both the levels and the growth rates of the demographic data may impact the right hand side variables. I construct an instrument list consisting of the lags of the share of the population in each 5-year age group from 0-4 to 75-79 and the lagged growth rate of each of those age groups relative to the sum population. Define  $agesh^j$  as the share of the population aged  $(j-1)*5$  to

$(j-1)*5+4$  (for example,  $agesh^1$  is the share of the population aged 0-4,  $agesh^2$  is the share of the population aged 5-9 and so on). Following Dominguez and Fair (1991), I force the 16 coefficients on the lagged age share variables in the first stage regressions to lie on a 4<sup>th</sup> degree polynomial. I also force the 16 coefficients on the lagged growth rates to lie on a separate 4<sup>th</sup> degree polynomial. Each first stage regression also includes lagged capital growth as an instrument.

Instruments with no relevance for the endogenous variables are likely to give biased results, especially in small samples. An examination of the data shows that this instrument list is relevant for the endogenous right hand side variables. For instruments to have sufficient power to identify the parameters in a multivariate regression, as Shea (1997) points out, the instruments must be relevant for linearly independent variation in each of the endogenous variables. Shea (1997) offers the partial  $R^2$  between the instruments and the endogenous variables as a measure of the ability of the instruments to explain the linearly independent variation in the endogenous variables. Table III lists the partial correlation of the instruments for each of the endogenous variables. In the benchmark regression, the partial correlations range between .1 for the schooling change, .35 for capital growth rates, and .6 for experience. In a univariate context, Nelson and Startz (1990) argue that skepticism should be applied toward instruments when the first stage  $R^2$  multiplied by the sample size is less than 2. Here the *partial*  $R^2$  times the sample size ranges between 20 and 120. Thinking of this product as a chi-squared Wald test statistic with 9 degrees of freedom corresponding with the 9 instruments, each of these is significant at the 5% level. Hall, Rudebusch, and Wilcox (1996) propose a test of the significance of instruments in the first stage regressions of the multiple right hand-side variables. The  $\chi^2$  HRW test is a likelihood ratio test that the smallest canonical correlation between the instrument list and the right hand side variables is zero. The HRW test for the multivariate irrelevance of the instruments is rejected at the 10% critical value.

All of the instruments precede the instrumented variables in time; idiosyncratic technology shocks cannot cause changes in the instruments. It is clear that, in the long run, demographic variables are endogenous to economic conditions (see Bloom, Canning, and Sevilla, 2001, for a review of the interrelation between demographics and growth). However, there is no obvious link between the demographic profile of a country and *subsequent* unobserved technology growth at 10-year frequencies (though, of course, it is impossible to rule out a priori).

To understand the channels through which demographics do, in fact, affect education levels, it may be interesting to examine the first stage regressions of changes in education on the instruments. To capture the linearly independent variation in change in schooling levels explained by the demographic instruments, I regress  $\Delta school_{it}$  on  $\Delta lnk_{it}$  and  $\Delta ex_{it}$ , and the instruments<sup>5</sup>. Figure 1 shows the estimated coefficients on the levels of the age share variables. Dotted lines show the 95% confidence intervals. The coefficients on the age share variables are positive. The coefficient on the age share between 0 and 5 is the smallest; coefficients increase rapidly until reaching a local peak at the age 15 to 20 age group. The coefficients decline until the over 55-age group and increase again. This pattern fits with the a priori story. Increases in the average education level of the adult population occur when younger, more educated workers enter adulthood and when older, less educated workers exit the adult population. Figure 2 shows the coefficients on the growth rates of the age shares. Rapid growth amongst the youthful population has a negative effect on education growth. This might suggest that rapid growth in the student age population results in less education for each one due to bottlenecks in the educational system. The effect of growth in older age shares is not statistically significantly different from zero.

Estimates of the 2SLS regression specification are reported in Table 3, Column 1. All of the coefficients are significantly different from zero at the 5% critical value. The 2SLS estimate of the coefficient on physical capital is smaller than the OLS estimates. The 2SLS estimates of the coefficients on human capital are larger than the OLS estimates. This result is consistent with the idea that the OLS estimate of the effect of capital is biased upward due to endogeneity while the OLS estimate of the coefficient on human capital is biased toward zero due to measurement error. The 2SLS estimates narrow the difference between the estimates and the neo-classical hypothesis. I include Hausman tests of the difference between the OLS and 2SLS errors. A Hausman test of the hypothesis that the 2SLS and OLS estimates are equal is rejected at the 10% critical value.

Hall et.al. (1996) point out that first stage tests of the relevance of instruments are likely to reject the null of irrelevance in the case when the instruments are correlated (in sample) with the second stage residuals. This result emphasizes the importance of additional specification tests of the

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<sup>5</sup> This is equivalent to the coefficients of the short regression of that element in schooling changes which is orthogonal to the other endogenous variables on the element of the instruments that is orthogonal to the endogenous variables.

exogeneity of the instruments. Davidson and McKinnon (1993) point out that over-identifying restrictions tests are a joint test of the model specification and the exogeneity of the instruments. I test the over-identifying restrictions of each 2SLS regression using the test described in Davidson and McKinnon (1993). The over-identification restrictions are rejected at the 5% level, presenting fairly strong evidence that the model is either mis-specified or the instruments are correlated with unobserved technology growth.

It would appear that the misspecification concerns the intercept term alone, however. Column 3, Table 3 reports some results from the specification that includes interactive OECD dummy variables. In the 2SLS regression, the interactive dummy variables are jointly significant at the 1% critical value. The inclusion of these dummy variables does not greatly change the point estimates of the returns to capital, education or experience. The coefficients on capital growth and education changes are significantly different from zero at the 5% critical value. Experience is only significant at the 10% critical value when OECD-time interactive dummies are included. In this specification, the over-identifying restrictions are not rejected at the 30% critical value. The inclusion of the OECD dummies does not affect the relevance of the instruments. The HRW likelihood ratio test of the smallest canonical correlation rejects the irrelevance of the instruments at the 10% critical value. Each of the partial  $R^2$  is above .10. Again, the Hausman tests reject the consistency of the OLS estimates at the 10% critical value. Column 4 shows the results when Latin American and African interactive dummies are included. Both capital and schooling changes remain significant at the 5% critical value. Experience changes are not significant at the 10% critical value when the continent dummies are included. The HRW test statistic rejects the hypothesis that the instruments are not relevant at the 10% critical value. The over-identification restrictions are not rejected at the 30% critical value. In this specification, it is not possible to reject the hypothesis that the OLS estimates are consistent at the 15% critical value using the Hausman test.

A potential omitted variable is the initial schooling level. As it seems unlikely that subsequent technology growth determines the level of the initial average schooling, I model initial schooling as exogenous. The HRW statistic demonstrates that the instrumental variables are relevant for the instrumented. The hypothesis that the smallest canonical correlation between the instruments and the instrumented variables is zero is rejected at the 5% critical value. Conditioning on initial schooling, the coefficient on the change in education levels is near .17 and is significant at the 5% level. The coefficient on initial education is similar in size to the estimate from the OLS

regression. A Hausman test rejects the hypothesis that the OLS and 2SLS estimates are equal at the 5% critical value. The over-identifying restrictions are not rejected at the 60% level.

### C. Sub-samples

The inclusion of intercepts that vary across time and across countries raises the question whether other parameters may also vary across sub-samples. Durlauf (2000) argues that production functions are likely to differ across countries.

#### 1. *OECD vs. Developing Countries*

Table 4 presents OLS and 2SLS parameter estimates for OECD and non-OECD countries separately. The OLS and 2SLS estimates for OECD countries are nearly identical. In each case, the coefficient on physical capital is large and significant at the 1% critical value. The coefficients on education and experience are near zero and statistically insignificant. The HRW instrument relevance statistic shows that it is impossible to reject the hypothesis that the instruments do not explain independent variation in the instruments at even the 80% critical value. The demographic instruments simply do not explain differences in schooling within the developed countries sufficiently to identify any of the effect of schooling independently from the effect of physical capital. The Hausman test fails to reject the hypothesis that the OLS and 2SLS estimates are different at the 75% critical value. The over-identifying restrictions are not rejected at the 25% critical value.

The effect of schooling changes on growth is easier to identify within the developing world. In both the 2SLS and OLS estimates, the effect of schooling changes on growth is positive and statistically significant at the 5% level in the non-OECD sample. OLS estimates suggest that an extra year of schooling translates into 8% higher productivity. Two stage least squares estimates suggest that an extra year of schooling translates into 15% higher productivity. Both are in the range of the neo-classical hypothesis. There is substantially more evidence that the instruments are relevant within the developing countries. The HRW test rejects the hypothesis that the instruments are irrelevant at the 5% level. The over-identifying restrictions are not rejected at the 25% critical value. In this case, the Hausman test cannot reject the consistency of the OLS estimates at the 15% critical level. In both the OLS and 2SLS case, heteroskedasticity, auto-correlation consistent Chow tests do not reject the hypothesis that the coefficients are equal across sub-samples at the 15% level.

#### 2. *Time Varying Parameters*

In Table 5, I report decade-by-decade OLS and 2SLS estimates of the production function. The OLS and 2SLS estimates of the capital intensity parameter range between .40 and .6. The standard errors tend to be larger than in the whole sample, which is unsurprising given the reduced sample size. In the OLS regression, the returns to education are positive and significant only in the 1980's. In many countries, estimates of education levels might be improving over time, reducing measurement error in this sub-sample. In the 2SLS regressions, the variables are significant only during the 1960's and 1970's. The returns to education are positive but not significant during the 1980's. Here, the HRW test rejects the irrelevance of the instruments only within the 1990's sample. However, the over-identifying restrictions are also rejected at the 10% level within this sub-sample. A Chow test for the equality of the coefficients on the inputs across time does not reject the equality of the parameters at even the 85% critical value.

#### **D. Fixed Effects Regressions**

The possibility that the intercepts are country specific should also be considered given the broad range of countries in the sample. Table 6 reports OLS and 2SLS estimates estimated using country specific intercepts. Column 1 reports the Within (fixed effect) estimates. In the Within-OLS regression, the inclusion of the country fixed effects reduces all of the coefficients in size relative to their counterparts in Table 2. Though, capital remains significant at the 1% critical value, the schooling and experience parameters are insignificant. Column 3 reports the Within-2SLS estimates. The inclusion of fixed effects sharply increases the standard errors relative to their counterparts in Table 3. None of the coefficients are significantly different than zero at the 10% critical value though the parameter estimates on physical capital and education are economically large. The estimate of the returns to education of .13 is similar in size to the estimates without country dummies. The Hausman test rejects the consistency of the Within-OLS estimates at the 1% critical value. The Over Identifying restrictions are not rejected at the 30% critical value.

Given that the time dimension of the panel is small and the cross-sectional dimension is large, the estimate of a fixed effect for each country is likely to be inaccurate. In addition, the large number of additional parameters estimated reduces the efficiency of the coefficients of interest. The inclusion of fixed effects reduces the power of the instruments. The HRW test does not reject the hypothesis that the instruments are irrelevant at the 15% critical value. Besides the loss of accuracy that comes from including fixed effects,

there is little statistical evidence that fixed effects are important in these regressions. In each regression, I estimate an F test of the hypothesis that the country fixed effects are jointly zero. The results of these F tests are reported in Column 1 and 3. In neither case is the hypothesis rejected at even the 85% critical value. As the Within-2SLS estimates are similar to the more efficient estimates in Table 3, there seems little reason to ignore the extra precision of the latter.

I also estimate the parameters of each equation using a between r. The Between-OLS estimates are reported in Table 6, Column 2. All coefficients are significant at the 5% critical value. The coefficients on education and experience are slightly larger than their counterparts in Table 2. The Between-2SLS estimates are reported in Column 4. Again all coefficients are significant at the 5% critical value. The HRW test rejects the irrelevance of the instruments at the 10% level. The over-identifying restrictions are not rejected at the 15% level. The Between-2SLS estimates of the coefficient on education and experience are large relative to their counterparts in Table 3.

#### IV. Discussion

An unbalanced cross-country panel estimate of an aggregate production function finds that physical capital, education, and experience all have positive and significant coefficients. The estimated physical capital intensity of the international production function is higher than common estimates of physical capital shares of income. The estimated returns to human capital are on the low side of the range of estimates of private returns. It is likely that unobserved technology growth (the theoretical residual in a first differenced Cobb-Douglas production function) could cause endogenous movements in capital growth biasing the estimates. Moreover, measurement error in both human and physical capital inputs could be a source of bias. I estimate 2SLS regressions using readily available instruments based on the age demographic structure of the population, which in theory have strong correlation with input growth through channels exogenous to technology growth. The instruments are highly relevant to the input growth in the data. Estimates of capital intensity from the 2SLS regressions are much closer to estimates from factor income measures. Instrumental variables estimates of the returns to education are statistically significant and quantitatively on the high side of estimates of private returns.

It is important to estimate the returns to productivity and factors using aggregate data, as this can identify potential returns from externalities as well as identifying whether the private returns to education are truly due

to productivity effects. One drawback of using cross-country data is that the size of datasets is inherently limited. As a result, estimates might lack precision especially when instrumental variables are used. The use of regional data may be useful in increasing sample sizes. An example from U.S. data is Acemoglu and Angrist (1999). De la Fuente and Domenech (2000) use detailed country data to construct alternate measures of education in the OECD, reducing measurement error. However, both of these strategies rely on access to data that is unlikely to become available soon for it remains to be seen how soon this strategy will become useful for many developing countries with less data availability. My instrumental variables estimates draw much of their power from variation within developing economies. A strength of this paper is the finding that human capital positively affects productivity is driven by data from developing countries, given the centrality of education in development strategies (see Easterly, 2001).

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Figure 1. Effect of Demographics on Human Capital Accumulation

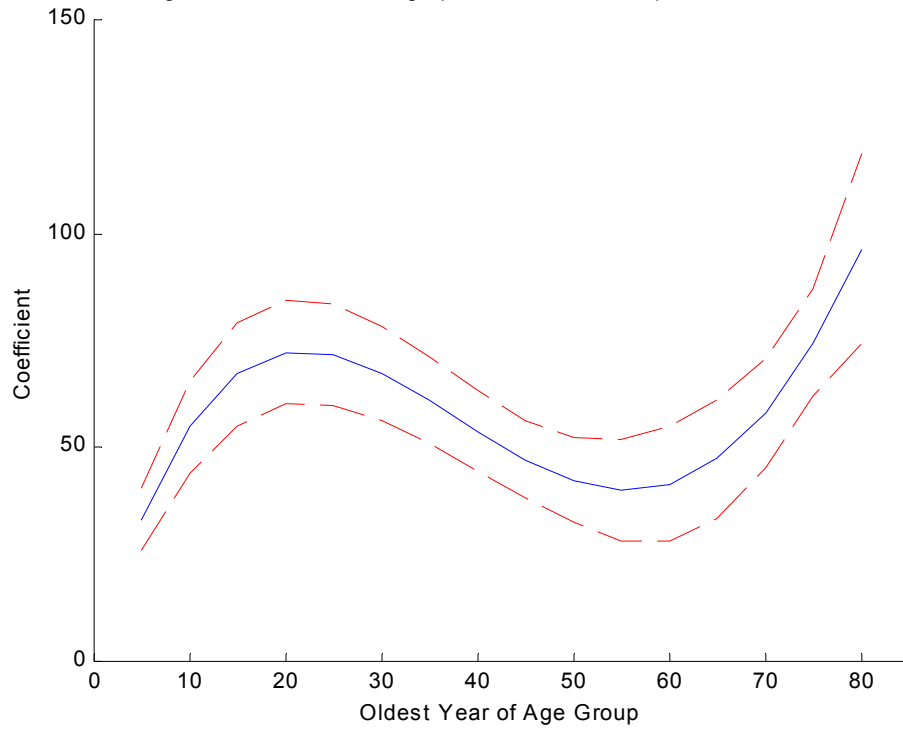
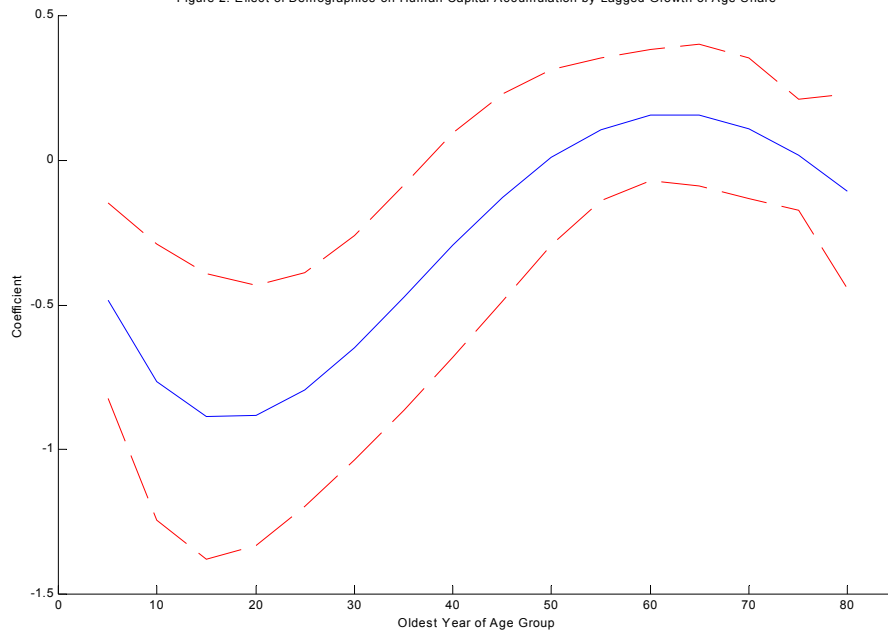


Figure 2. Effect of Demographics on Human Capital Accumulation by Lagged Growth of Age Share



**Table 1: Sample Means by Decade [Annual Rates]**

	$\Delta \ln y$			$\Delta school$		
	All	OECD	Non-OECD	All	OECD	Non-OECD
1960-1970	.031	.040	.028	.051	.054	.050
1970-1980	.020	.021	.019	.091	.093	.090
1980-1990	.004	.016	-.001	.077	.070	.080

**Table 2. OLS Estimates of the Production Function**

	Independent Variable: $\Delta \ln y$ (HAC Standard Errors)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln k$	.616 <sup>♥</sup> (.041)	.541 <sup>♥</sup> (.050)	.536 <sup>♥</sup> (.050)	.517 <sup>♥</sup> (.054)	.545 <sup>♥</sup> (.033)	.537 <sup>♥</sup> (.042)
$\Delta school15$	.004 (.018)	.059 <sup>♠</sup> (.022)	.055 <sup>♠</sup> (.023)	.048 <sup>♠</sup> (.025)	.045 <sup>♠</sup> (.017)	.054 <sup>♠</sup> (.023)
$\Delta expy$	-.008 (.012)	.029 <sup>♠</sup> (.016)	.023 (.018)	.019 (.019)	.025 <sup>♠</sup> (.011)	.020 (.018)
$school15_{-1}$						.000 (.001)
<b>Dummies</b>						
time	no	yes	yes	yes	yes	yes
time × OECD	no	no	yes	yes	yes	yes
time × latin&africa	no	no	no	yes	no	no
R <sup>2</sup>	.533	.587	.599	.587	.730	.599
Sample Size	232	232	232	232	218	232

♥ Significant at .1% Level, ♠ Significant at 1% Level, ♦ Significant at 5% Level, \* Significant at 10% Level

**Table 3. Instrumental Variables Estimates of the Production Function**

	Independent Variable: $\Delta \ln y$ (HAC standard errors)			
	(1)	(2)	(3)	(4)
	<i>Coefficients</i>			
$\Delta \ln k$	.460 <sup>♥</sup> (.104)	.456 <sup>♥</sup> (.084)	.426 <sup>♥</sup> (.098)	.461 <sup>♥</sup> (.084)
$\Delta school$	.133 <sup>♦</sup> (.065)	.147 <sup>♦</sup> (.062)	.126 <sup>♦</sup> (.057)	.167 <sup>♠</sup> (.057)
$\Delta ex$	.052 <sup>♦</sup> (.025)	.040 <sup>♠</sup> (.022)	.034 (.024)	.034 (.023)
$school15_{-1}$				.000 (.001)
time dummies	yes	yes	yes	yes
time × OECD	no	yes	yes	yes
time×latin&africa	no	no	yes	no
	Specification Tests (p-value)			
Over Identifying Restrictions	12.728 <sup>♠</sup> (.0475)	7.288 (.295)	6.455 (.374)	6.612 (.642)
Hausman Test	7.20 <sup>♠</sup> (.066)	7.46 <sup>♠</sup> (.059)	5.14 (.162)	9.35 <sup>♦</sup> (.025)
Hall Rudebusch Wilcox Test	13.571 <sup>♠</sup> (.059)	13.49 <sup>♠</sup> (.063)	13.649 <sup>♠</sup> (.058)	14.665 <sup>♦</sup> (.041)
	First Stage Partial R <sup>2</sup>			
$\Delta \ln k$	.310	.340	.336	.346
$\Delta school$	.100	.105	.111	.119
$\Delta ex$	.602	.631	.616	.583
R <sup>2</sup>	.589	.600	.604	.576
Sample Size	203	203	203	203

♥ Significant at .1% Level, ♠ Significant at 1% Level, ♦ Significant at 5% Level, ♠ Significant at 10% Level

Table 4. OECD and Developing World Subsamples

	Independent Variable: $\Delta \ln y$ (HAC standard errors)			
	OLS		2SLS	
	(1) OECD	(2) Developing	(3) OECD	(4) Developing
$\Delta \ln k$	.618 <sup>♥</sup> (.050)	.518 <sup>♥</sup> (.055)	.610 <sup>♥</sup> (.060)	.454 <sup>♥</sup> (.097)
$\Delta school$	.006 (.015)	.078 <sup>♦</sup> (.032)	.061 (.048)	.148 <sup>♦</sup> (.063)
$\Delta ex$	-.000 (.009)	.030 (.024)	.000 (.012)	.046 (.029)
time dummies	yes	Yes	yes	yes
	Specification Tests (p value)			
Over Identifying Restrictions			7.663 (.264)	7.535 (.274)
Hausman Test			1.04 (.792)	4.93 (.179)
Hall Rudebusch Wilcox Test			3.89 (.826)	15.62 <sup>♦</sup> (.029)
Chow Test		5.13 (.163)		2.97 (.401)
R <sup>2</sup>	.856	.550	.856	.596
Sample Size	66	166	66	137

♥ Significant at .1% Level, ♦ Significant at 1% Level, ♦ Significant at 5% Level, ♦ Significant at 10% Level

Table 5. Decade by Decade Sub-samples

	Independent Variable: $\Delta \ln y$ (HAC standard errors)					
	OLS			2SLS		
	1960-70 (1)	1970-80 (2)	1980-90 (3)	1960-70 (4)	1970-80 (5)	1980-90 (6)
$\Delta \ln k$	.401 (.402)	.689 <sup>♥</sup> (.126)	.510 <sup>♥</sup> (.098)	.538 <sup>♥</sup> (.075)	.528 <sup>♦</sup> (.216)	.573 <sup>♥</sup> (.150)
$\Delta school$	.020 (.031)	.020 (.034)	.094 <sup>▲</sup> (.019)	.164 <sup>♦</sup> (.072)	.157 <sup>♦</sup> (.076)	.054 (.069)
$\Delta ex$	.021 (.017)	-.017 (.030)	.046 (.033)	.039 <sup>♦</sup> (.019)	.021 (.054)	.015 (.036)
OECD dummy	yes	yes	yes	yes	yes	yes
Specification Tests (p-value)						
Over Identifying Restrictions				4.88 (.588)	3.876 (.693)	12.45 <sup>★</sup> (.067)
Hausman Exogeneity Test				2.88 (.423)	4.80 (.187)	1.17 (.766)
Hall Rudebusch Wilcox Test				5.41 (.682)	10.21 (.1780)	16.99 <sup>♦</sup> (.022)
Chow Test	5.94 (.438)			2.46 (.870)		
R <sup>2</sup>	.726	.496	.536	.688	.423	.560
Sample Size	76	78	77	52	76	75

♥ Significant at .1% Level, ▲ Significant at 1% Level, ♦ Significant at 5% Level, ★ Significant at 10% Level

**Table 6. Panel Estimates**

	Independent Variable: $\Delta \ln y$ (HAC standard errors)			
	OLS		2SLS	
	(1) Within	(2) Between	(3) Within	(4) Between
$\Delta \ln k$	.572 <sup>♥</sup> (.119)	.565 <sup>♥</sup> (.041)	.652 (.552)	.395 <sup>♠</sup> (.145)
$\Delta school$	.036 (.036)	.076 <sup>♠</sup> (.028)	.137 (.14)	.242 <sup>♠</sup> (.081)
$\Delta ex$	.010 (.027)	.051 <sup>♦</sup> (.022)	.016 (.051)	.087 <sup>♦</sup> (.028)
<b>Dummies</b>				
time dummies	yes	--	yes	--
OECD dummy	--	yes	--	yes
time × OECD	yes	--	yes	--
	Specification Tests (p-value)			
Over Identifying Restrictions			6.455 (.374)	5.16 (.523)
Hausman Exogeneity Test			12.89 <sup>♠</sup> (.005)	5.24 (.155)
HRW			9.884 (.195)	12.21 <sup>♠</sup> (.094)
Fixed Effect F-test	.80 (.864)		.61 (.991)	
R <sup>2</sup>	.856	.550	.856	.596
Sample Size	232	81	206	81

♥ Significant at .1% Level, ♠ Significant at 1% Level, ♦ Significant at 5% Level, \* Significant at 10% Level