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Openness and Human Capital as Sources of Productivity Growth: An Empirical Investigation

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Abstract

Do openness to trade and higher levels of human capital promote faster productivity growth? That they do is a key implication of several versions of endogenous growth theory. To answer the question we use panel data on 93 countries spanning the 1970-2000 period. Controlling for fixed effects as well as endogeneity, the results show a significant effect of openness on productivity growth. If the level of openness of an economy is doubled the underlying rate of technical progress will increase by 0.8 per cent per annum. We find an effect, significant at the ten per cent level, of the level of human capital on the level of income but no effect on underlying productivity growth. Our preferred estimator combines high and low frequency differences of the data. We discuss reasons why this estimator is well suited for empirical analysis of economic growth.

JEL classification: F43, O11.

Keywords: Productivity, openness, human capital, growth, panel data.

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1 Introduction

There has been much dispute as to whether economies that are open and those with more human capital grow faster. The economic success stories of the post-war period, the East Asian NICs, had both higher levels of human capital and, by some measures, a more outward orientation than their less successful contemporaries. Such a congruence of policies makes it difficult disentangling which, if either, of the two elements - openness or human capital - was the source of higher growth rates. The evidence for either effect has been a matter of considerable contention.

Much of the large literature on growth stemming from the work of Barro (1991, 1997) has focused on some measure of human capital as a determinant of growth. However, as noted by Temple (2001, p.905), “the empirical evidence that education matters for growth is surprisingly mixed”. Pritchett (1999) shows that variation in the change in average schooling plays little role in explaining cross-country variation in growth rates. In contrast Gemmell (1996) finds both the levels of human capital and their growth rates to be important in explaining growth. Benhabib and Spiegel (1994) investigate whether education influences rates of technological progress and Temple (1999a) shows that their inability to produce a significant coefficient on human capital may be due to the influence of outliers. Temple (2001) revisits the data and for two of his empirical investigations concludes that it is hard to reject the Pritchett view that large investments in education have yielded a very small pay-off in developing countries. Pritchett is not alone. Bills and Klenow (2000) ask if the observed correlation between school enrolments in 1960 and growth over the period from 1960 to 1990 can be interpreted as causal. They argue that it cannot.

The evidence relating trade to growth has been equally contentious. Dollar (1992), Sachs and Warner (1995), Edwards (1998), Frankel and Romer (1999), Irwin and Terviö (2002) and Greenaway et al. (2002) all argue that trade, or trade reform, is an important determinant of differences in either incomes or growth. Krugman (1994), Rodrik (1995) and Rodriguez and Rodrik (1999) question whether much of the empirical evidence is convincing.

Our objective in this paper is to test whether human capital and trade impact causally on the rate of technological progress. That they do is a key implication of several versions of endogenous growth theory. One obvious difficulty we are faced with in this investigation is that human capital and trade are likely to be endogenous. The two most common ways of attempting to deal with endogeneity in the context of growth equations is instrumental variable estimation and panel data methods. Finding valid instruments for growth regressions is a difficult task (see Durlauf and Quah, 1999, pp. 281-3). Krueger and Lindahl (2001) focus on measurement errors in the cross-country education data as one possible source of bias, but do not address other forms of endogeneity arising due to, for instance, unobserved labour quality. As recognised by these authors, the practice common in the microeconomic literature of forming instruments based on natural experiments does not carry over easily to macro equations. In the trade literature, Frankel and Romer (1999) and Irwin and Terviö (2002) use measures of countries' geographical characteristics as instruments for the trade share. Durlauf and Quah (1999, p. 281) criticise this procedure, arguing that geographical characteristics may be correlated with factors omitted from the income equation, in which case the instrumental variable approach breaks down.

If the endogeneity is such that the part of the residual that is correlated with the explanatory variables is constant over time within countries, then standard panel data estimators such as the within or the differenced estimator are attractive (Harrison, 1996; Miller and Upadhyay, 2000). If the time varying part of the error term is correlated with the regressors, then there remains an endogeneity problem even with controls for fixed effects. This is recognised by Caselli et al. (1996), Bond et al. (2001), Hoeffler (2002) and Beck (2002) who estimate growth equations using instrumental variable estimators for panel data. Panel data methods, however, have problems of their own, as discussed by Barro (1997, pp.36-42) and Temple (1999b, p. 132). There is much empirical evidence that the use of differencing can take away by the increase in measurement error what is gained in terms of eliminating fixed effects. Further, even if measurement error bias is a negligible problem, the differencing procedure is often associated with a considerable efficiency loss.

Our basic model is a production function differenced over five year intervals. We estimate the parameters of the model using an instrumental variable estimator that allows for unobserved heterogeneity across countries in underlying rates of technological progress and other forms of endogeneity. Our preferred econometric results are based on an estimator proposed by Griliches and Hausman (1986), which combines high and low frequency differences of the data. We argue that this estimator is well suited for empirical analysis of economic growth.

The remainder of the paper is structured as follows. The next section outlines the analytical framework and how we propose to model the growth rate. Section 3 discusses the sources of data. Section 4 presents the results for a growth equation, which is used to interpret comparative growth performance in section 5. A final section concludes.

2. Modelling productivity growth

The starting point for our analysis is the Cobb-Douglas production function common in the literature:

$$[1] \quad \ln Y_{it} = \ln A_{it} + \alpha \ln K_{it} + \beta \ln L_{it},$$

where i, t denote country and time period, respectively, Y is real income, K is physical capital, A is technology, L is the number of workers and α, β are technology parameters. Drawing on theories of endogenous growth we hypothesise that technological progress, defined as $g_{it} \equiv \Delta \ln A_{it}$, is driven by openness, the average level of human capital, a set of unobserved country specific and time invariant characteristics captured by a fixed effect μ_i , and a set of time varying factors represented by a residual v_{it} :

$$[2] \quad g_{it} = \omega_1 \cdot \Delta T_{it} + \omega_2 \cdot T_{i,t-1} + \omega_3 \cdot \Delta h_{it} + \omega_4 \cdot h_{i,t-1} + \mu_i + v_{it},$$

where T_{it} denotes openness, h_{it} is the average years of education and $\omega_1 - \omega_4$ are coefficients.¹ We allow both the changes and the levels of openness and human capital to affect technological progress. Given that g_{it} is a growth rate, the coefficients on ΔT_{it} and Δh_{it} are interpretable as effects of openness and human capital on the *level* of technology. The coefficients on T_{it} and h_{it} , on the other hand, are interpretable as effects of openness and human capital on the *growth* of technology. Specified in this way, a permanent change in the trade share or human capital will have a permanent effect on the growth rate, while a temporary change will have a temporary effect on the growth rate but a permanent effect on income. Taking first differences of the production function [1] and rewriting the equation in per capita terms yields

$$[3] \quad \Delta \ln(Y/L)_{it} = \alpha \cdot \Delta \ln(K/L)_{it} + (1 - \alpha - \beta) \cdot \Delta \ln L_{it} + \omega_1 \cdot \Delta T_{it} + \omega_2 \cdot T_{i,t-1} + \omega_3 \cdot \Delta h_{it} \\ + \omega_4 \cdot h_{i,t-1} + \mu_i + v_{it}.$$

This specification forms the basis for our empirical analysis. Before turning to estimation issues we discuss alternative approaches for modelling growth. Our purpose here is not to review the large empirical growth literature (see Durlauf and Quah, 1999, and Temple, 1999b, for excellent surveys), but rather to establish how our empirical framework links to previous work in the area.

Alternative Models of Growth

The most widely used framework for analysing growth is the Solow (1956) model, and an often-cited paper adopting this framework is that by Mankiw et al. (1992). Under the assumptions that the production function is

$$\ln Y_{it} = \gamma_1 \ln(AL)_{it} + \gamma_2 \ln(hL)_{it} + (1 - \gamma_1 - \gamma_2) \ln K_{it},$$

¹ Feenstra (2003) provides an exposition of how trade can have endogenous growth effects (see also Krugman, 1987; Rodrik, 1988, 1991; Grossman and Helpman, 1991). Lucas (1988) and Romer (1990) discuss the roles of human capital for endogenous growth.

that the depreciation rate for physical and human capital is constant both over time and across countries at δ , and that the rate of technological progress is exogenous and constant across countries and over time, Mankiw et al. derive a convergence equation of the following form:

$$\begin{aligned} \ln \frac{Y_{it}}{L_{it}} - \ln \frac{Y_{i,t-1}}{L_{i,t-1}} = & \theta \ln A_{i0} + g \cdot (t - (t-1)e^{-\lambda}) - \theta \cdot \ln \frac{Y_{i,t-1}}{L_{i,t-1}} + \theta \frac{\gamma_1}{1 - \gamma_1 - \gamma_2} \ln s_{it}^k \\ & + \theta \frac{\gamma_2}{1 - \gamma_1 - \gamma_2} \ln s_{it}^h - \theta \frac{\gamma_1 + \gamma_2}{1 - \gamma_1 - \gamma_2} \ln(\delta + n_{it} + g), \end{aligned}$$

where s_{it}^k and s_{it}^h are the savings rates for physical and human capital, n is the growth rate of L , $\theta = 1 - e^{-\lambda}$ and $\lambda = (n + g + d)(1 - \gamma_1 - \gamma_2)$ is the rate of convergence to the steady state.²

In this model the productive effect of human capital is reflected in the coefficient on $\ln s_{it}^h$. Some economists focus on identifying the factors driving international differences in initial technology, and rewrite $\ln A_{i0}$ as a function of explanatory variables. This is known as the ‘augmented cross-section’ approach (Durlauf and Quah, 1999). Levine and Renelt (1992) consider measures of trade, or trade policy, as arguments of $\ln A_{i0}$. Other authors treat $\ln A_{i0}$ as an unobserved country specific effect and use panel data techniques to estimate the parameters of the model (Caselli et al., 1996; Bond et al., 2001; Hoeffler, 2002).

There are two reasons why we choose not to rely on the Solow model. First, because the model is derived under the assumption that technological progress is exogenous and constant it does not constitute a natural framework for the analysis of long run productivity growth effects of the kind implied by endogenous growth models. Second, because data on factor inputs are available (see Section 3) one may just as well estimate the production function directly (Temple, 1999b, pp. 124-25). Relying on the Solow model identifies no new parameters.

Some economists eschew the use of both the Solow framework and the differenced production function approach in favour of more parsimonious specifications. Analysing the

² Following Durlauf and Quah (1999), and unlike Mankiw et al., we write the convergence equation assuming panel data are available.

effect of schooling on growth, Krueger and Lindahl (2001) argue that the inclusion of physical capital in the regression aggravates measurement error bias to such an extent as to outweigh the reduction in omitted variable bias. They conclude that ‘...unless measurement error problems in schooling are overcome, we doubt the cross-country growth equations that control for capital growth will be very informative insofar as the benefit of education is concerned.’ (Krueger and Lindahl, 2001, p. 1126). Analysing the effects of trade on income, Frankel and Romer (1999) model per capita income solely as a function of trade, population and land area. The authors acknowledge that there are many other variables that may affect income, but argue that ‘...if we included other variables, the estimates of trade’s impact on income would leave out any effects operating through its impact on these variables. Suppose, for example, that increased trade (...) increases the saving rate. Then by including the saving rate in the regression, we would be omitting trade’s impact on income that operates via saving.’ (Frankel and Romer, 1999, p. 386). However, because the theoretical prediction that we wish to test for is whether human capital and trade have causal effects on *technological progress*, as distinct from overall effects on income levels or growth rates, for our purposes it is necessary to control for the factor inputs of the production function.

Estimation

In estimating the differenced production function [3] we are faced with the potential problem that the explanatory variables are endogenous, i.e. correlated with $\mu_i + v_{it}$, the unobserved part of the equation. For instance, high values of $\mu_i + v_{it}$ imply a high marginal product of capital and may therefore be associated with high physical capital investment. As a first step towards dealing with endogeneity we eliminate the time invariant component of the error term by differencing [3], yielding a double-differenced equation. Rather than limiting ourselves to high frequency (i.e. short) differences, we consider different orders of differences of the growth equation:

$$\begin{aligned}
[4] \quad \Delta_s \Delta_1 \ln(Y/L)_{it} &= \alpha \cdot \Delta_s \Delta_1 \ln(K/L)_{it} + (1 - \alpha - \beta) \cdot \Delta_s \Delta_1 \ln L_{it} + \omega_1 \cdot \Delta_s \Delta_1 T_{it} \\
&+ \omega_2 \cdot \Delta_s T_{i,t-1} + \omega_3 \cdot \Delta_s \Delta_1 h_{it} + \omega_4 \cdot \Delta_s \Delta_1 h_{i,t-1} + \Delta_s v_{it},
\end{aligned}$$

$s = 1, 2, \dots, S$, where $\Delta_s \chi_{it} \equiv \chi_{it} - \chi_{i,t-s}$. Thus, [4] is a system of S first differenced growth equations, $S-1$ second differenced growth equations, and so on up to one differenced growth equation with order of differencing equal to S . We estimate the equations of the system simultaneously, and therefore refer to the model as a difference combinations (DCOMB) estimator.

If the time varying residual, v_{it} , is correlated with the regressors, we need to use instruments to obtain consistent estimates. Following Griliches and Hausman (1986) we adopted a generalised method of moments (GMM; Hansen, 1982) framework. Provided there is no non-contemporaneous correlation between the regressors and the error term v_{it} , the explanatory variables in levels and first differences dated $t-2$ or earlier are potential instruments for first differenced equations ($\Delta_1 \chi_{it}$). For the longer differenced equations $\Delta_s \chi_{it}$, $s = 2, 3, \dots, S$, potential instruments are the explanatory in levels and first differences prior to $t-s$, and lags dated between $t-s$ and t . Any non-contemporaneous correlation between the regressors and the error term v_{it} , perhaps caused by serial correlation of v_{it} , would limit the set of potential instruments considerably. Standard tests for the validity of the overidentifying restrictions shed some light on whether instruments are orthogonal to the equation residual.³ For more details on the GMM estimator, see Appendix 1.⁴

³ The procedure outlined here of using different instrument sets for different equations has long been used for estimating dynamic panel data models (Arellano and Bond, 1991). It is likely that for some of the equations in [4] only a small number of instruments are available while for other equations the instrument set is richer, and clearly the more instruments that can be exploited, the more efficient is the estimator.

⁴ An alternative instrumental variable panel data model that has become increasingly popular in recent years is the system GMM estimator developed by Blundell and Bond (1998). This involves forming a two-equation system consisting of the first differenced equation and the original levels equation, and

There are two potential advantages of exploiting the information in the longer differences $s = 2, \dots, S$. First, there may be gains in efficiency since long differences are likely to exhibit a higher sample variance than short differences.⁵ Second, attenuation bias caused by measurement errors will be less severe if, which seems likely, the serial correlation in these errors is lower than that of the explanatory variables.⁶ These are potentially important advantages, as lack of efficiency and severe attenuation bias are common problems in standard panel data applications. For instance, Barro (1997, pp.36-42) thinks these problems are so severe as to make the cross-sectional results preferable to first-difference ones when estimating convergence equations.⁷

3 Data

We follow Benhabib and Spiegel (1994) and Miller and Upadhyay (2000) in combining data from the PENN World Tables (Heston et al., 2002) for income and the Barro and Lee (2000)

estimating the two equations simultaneously, subject to appropriate cross-equation restrictions that constrain the coefficient vectors in the two equations to be identical. Typically, lagged levels are used as instruments for contemporaneous differences and lagged differences are used as instruments for contemporaneous levels. Monte Carlo experiments reported by Blundell and Bond (1998) indicate that the system GMM estimator performs much better than the standard first differenced GMM estimator when the data are highly persistent. In the empirical growth literature the system GMM estimator has been used by Hoeffler (2002) and Beck (2002).

⁵ Whether or not there will be such efficiency gains hinges, *inter alia*, on the degree of serial correlation in the regressors relative to that of the error term. Notice that if the error term v_{it} is serially uncorrelated and homoskedastic then the variance of differences of v_{it} will not vary with the order of differencing.

⁶ See for instance Krueger and Lindahl (2001, p. 1115) for a derivation of this result and a discussion of the role of measurement errors in the context of estimating the effects of schooling on growth.

⁷ Similar estimation problems have been encountered in the literature on production function estimation based on micro data (Griliches and Mairesse, 1997; Blundell and Bond, 2000).

data set on human capital. Our only data innovation is the creation of a physical capital stock measure where we follow the methods proposed by Klenow and Rodríguez-Clare (1997). Using the most recent versions of these data sets it is possible to obtain a set of 93 countries for which there is information on output and human and physical capital inputs every five years from 1970 to 2000, giving us up to seven observations on each of the 93 countries (the countries included are given in Appendix 3). Table 1A shows the key variables on which we will focus averaged across regions for the years 1970 and 2000, Table 1B gives means for the whole sample to be used in the regressions reported below.

The key facts shown by the data are well known. Openness as measured in the PWT data as the shares of export and imports in GDP grew from an average of 54.2 to 77.0 per cent over the period 1970 to 2000. Among developing regions this rise was least for Latin America which saw a rise from 51.4 to 66.8 per cent. The average levels of openness differ markedly across regions and some authors have allowed for this by seeking to purge the trade share variable of the time invariant dimension of openness. Our procedure is to allow for fixed effects in the growth rate equation which will allow for those aspects of economic structure which cause small economies to have a higher trade share. Thus our method of estimation exploits the changes in the trade share to establish if these had an effect of the changes in underlying productivity growth.

The data in Table 1 shows that on average the rate of growth of human capital was similar across the regions. In terms of seeking to explain the differences in growth of incomes across the regions it is clear that by far the largest differences across regions are to be found in physical capital investment. The growth rate for a five year period averaged 11.5 for the whole sample. The figure for Africa is less than half this figure at 5.2 per cent while the capital stock in East Asia grew by 30.4 per cent per five year period. These large differences in the growth of physical capital stock are mirrored in the differential growth rates for income. Over the period the overall average was 7.1 per cent per five year period. Africa achieved 2.1 per cent while East Asia grew by 19.3 per cent. Our objective in the next section is to assess

how much of this remarkable divergence can be explained by the effect of human capital and trade on underlying productivity growth.

4 Empirical Analysis

In this section we present our empirical results. We begin by showing that our data can give similar results to that based on previous work exploiting only the cross sectional dimensions of the data. Table 2 column [1] is a regression of the log of per capita income on the trade share, the log of population and a constant using data for 1985. This specification is similar to that adopted by Frankel and Romer (1999), Table 3, columns 1 and 3, p. 387.⁸ Our results are in line with theirs. The estimated coefficient on the trade share is equal to 0.78, and highly significant, and the population coefficient is positive although not significant at conventional levels. The point estimate of 0.78 on the trade share implies that a one percentage point increase in the trade share results in an increase in per capita income of about 0.8 per cent. This is a very large effect indeed. As an illustration consider India, which has the smallest trade share in this sub-sample (13 per cent), and Singapore, which has the largest (338 per cent). With a trade effect of 0.78 the model predicts that if India somehow could change its trade share to the level of Singapore, there would be a twelve-fold increase in per capita income as a result, everything else held constant.

In Column [2] we add to the model the log of the capital-labour ratio and the average years of education in the population over 15 years of age. As a result the trade coefficient gets very close to zero and is far from significant. This is primarily driven by the capital-labour ratio, however the capital-labour coefficient is most likely upward biased. Capital's share in most countries is about 0.3 (Krueger and Lindahl, 2001), so if the technology is Cobb-Douglas and factor markets are competitive the coefficient on the capital-labour ratio in the

⁸ The only difference compared to Frankel and Romer is that we do not include a measure of country area as an explanatory variable. It is noted that the coefficient on country area is not significant in the regressions reported by Frankel and Romer.

income equation should equal its share. We obtain a point estimate of 0.54, which is not atypical compared to similar studies (e.g. Harrison, 1996) but clearly a long way from 0.3. The conventional explanation for this discrepancy is that capital is endogenous, and clearly the openness coefficient could be downward biased as a result. The estimated coefficient on education in this regression is 0.09 and significant at the one per cent level.

In Columns [3]-[6] we report regressions based on the panel of observations spanning every fifth year during the 1970-2000 period for 93 countries. Columns [3]-[4] show the same specifications as columns [1]-[2] and the results are largely consistent across the respective models. In column [5]-[6] we consider the effects of using the log of the trade share rather than the level. We do so because that the distribution of the trade share is highly skewed to the right⁹, and because it is possible that a given change in the trade share may matter more at relatively low shares. The estimated coefficient on the log of the trade share in column [5], interpretable as an elasticity, is 0.52 and highly significant. As before, when we include education and the capital-labour ratio in the model, column [6], the openness coefficient becomes very small and insignificant. The estimated education coefficient is 0.09 and highly significant. Testing for the presence of unobserved country effects using the method proposed by Wooldridge (2002), pp. 264-5, we reject in all cases at the one per cent level of significance the null hypothesis that there are no unobserved country effects.

Our investigation thus far confirms that the capital-labour ratio is highly correlated with per capita income and that there is strong evidence for unobserved country effects. Because the estimated coefficients on the capital-labour ratio are most likely upward biased we do not interpret the regression results in Table 2 as reflecting causal mechanisms. In Table 3 we probe the data further in order to assess the evidence on the causal effects of openness and human capital. We begin by estimating the differenced production function [3]. Results, reported in column [1], are similar to the previous regressions in that the capital coefficient is

⁹ The sample average of the openness measure is 67.6 per cent, the median is 58.3, the minimum is 7.6 and the maximum is 439.0.

about 0.5 and that the trade effect is insignificant, and different in that the estimated human capital levels effect is 0.03. There is no evidence of growth effects from either openness or human capital, as measured by the coefficients on the levels terms. Further, the test for presence of country effects suggests there is unobserved heterogeneity across countries in the underlying growth rates.

In column [2] we report fixed effects results, obtained by means of the standard within estimator. Rather surprisingly controlling for fixed effects has virtually no effect on the point estimate of the capital coefficient. The coefficient on the lagged trade share, however, increases dramatically in size and is now significant at the five per cent level. We interpret this as evidence that trade share *levels* vary across countries partly for reasons that have little to do with aspects of openness conducive to productivity growth. The point estimate on education collapses both in size and significance, and there is no evidence for a growth effect of lagged education. The country fixed effects are jointly significant at the one per cent level.

In columns [3]-[6] we treat the capital-labour ratio as endogenous and combine short and long differences of the data to form the GMM difference combinations estimator discussed in Section 2. In column [3] the remaining regressors in the model are treated as exogenous. As a result of allowing for the endogeneity of the capital-labour variable, the associated estimate of the coefficient shrinks to 0.35. This is a much more plausible estimate of the capital-labour coefficient for reasons already discussed. The coefficient on lagged trade share rises marginally to 0.07 and is now significant at the one per cent level. It thus seems the upward bias in the capital coefficient obtained in previous regression was accompanied by a downward (but moderate) bias in the openness coefficient. Recall that the latter coefficient is interpretable as the effect of the *level* of openness on the *growth* of productivity. The point estimate of 0.065 implies that an increase in the trade share by 20 per cent (e.g. from the sample median value of 0.58 to 0.70) increases the subsequent five-year growth rate by 1.3 percentage points. In contrast, the coefficient on the contemporaneous difference of openness, interpretable as the effect of the level openness on the level of income, is small and insignificant and so are the human capital coefficients. Based on the Sargan/Hansen

specification test we cannot reject the null hypothesis that the overidentifying restrictions are valid.

In column [4] we allow for endogeneity of the trade and the human capital variables. As expected this reduces the t -value associated with the lagged openness coefficient, but there is virtually no change in the point estimate. The coefficient on the contemporaneous difference of openness collapses from 0.03 with a t -statistic of 1.09 to 0.002 with a t -statistic of 0.06, which suggests there may be some contemporaneous correlation between openness and the residual. The two education coefficients are now negative but neither has a t -value larger than one so too much should not be made of this. There is a marginal increase in the estimated capital coefficient but at 0.38 it is still much lower than what we obtained when capital was assumed exogenous. The test for the validity of the overidentifying restrictions is easily passed.

The human capital coefficients have been insignificant in all our specifications that control for fixed effects. We proceed by dropping the lagged education term in order to see if we can obtain a precisely estimated coefficient on the change of human capital, reflecting a levels effect. Results are reported in columns [5]-[6] and the coefficients on openness and the capital-labour ratio are much the same as in columns [3]-[4] so we focus on the human capital coefficient here. In column [5] we treat the capital-labour ratio as endogenous and the remaining explanatory variables as exogenous. The resulting coefficient on human capital is 0.016 and significant at the ten per cent level. The implication of the point estimate is that a one year increase in education raises income by 1.6 per cent, which is a small effect. It is possible that the total effect on growth is considerably larger if human capital impacts positively on physical capital. This would not be interpretable as a productivity effect, which is what we are looking for. Further, some part of the productive effects of human capital is probably absorbed by the country fixed effects. However the human capital coefficient is relatively low in column [1], where there are no controls for fixed effects, so it appears the correlation between the fixed effects and human capital is not overly strong. In column [6] we

allow for endogeneity in the openness and human capital variables. As a result the human capital coefficient collapses to -0.009 and is far from significant.

5 Comparative Growth Performance

The results in Table 3 show a highly significant effect of trade onto productivity growth. Is this effect large and how much of the differences in growth can be explained by trade? One advantage of the approach we have adopted is that underlying differences in productivity growth can be inferred from our estimated production function.

Figure 1 shows the relationship between openness and the rate of growth of GDP per capita. The figure shows deviations from country means purged of time effects (see figure notes for details on this procedure), so the figure exploits the time series variation in the data. The predicted line shown in the figure is the result of a regression which mirrors closely the result obtained by our more formal econometric techniques employed in the last section. The figure shows that a one percentage rise in openness is associated with an increase in the growth rate of income by .08 percent (recall all the data is in terms of five year periods). Any such permanent rise in openness has a permanent effect on the underlying growth of productivity.

From the summary statistics given in Table 1B we note that a move from one standard deviation below the means of the log of openness to one standard deviation above implies a rise in openness from 28 to 98 per cent. Our analysis suggests that such a rise would increase the underlying growth rate in the economy by 7 per cent per five year period. It will be noted that the average growth in income over the five year periods of our analysis is 9 per cent. Clearly a rise from 28 to 98 per cent in the trade share is large but, given that the effects can be interpreted as permanent effects on growth rates, the productivity gains available from increased openness to trade are substantial.

It is equally apparent from the data that, while potentially substantial, this trade effect cannot explain most of the variation in growth rates. If we consider the range of growth rates from one standard deviation below to one standard deviation above the sample mean, growth

rates vary from -6 to 24 per cent (per five year period), a range of 30 percentage points (see Table 1B). Clearly growth rates vary far more than can be explained by trade.

We turn now to the roles of physical and human capital in explaining growth performance. Figure 2 shows a plot of the growth rate of income per worker against that growth rate of physical capital per worker, expressed in deviations from country means purged of time effects. The slope of the regression line is 0.51 which is upward biased for reasons discussed in Section 4. Nevertheless, the figure confirms what we know from the regression analysis that the growth of physical capital is an important determinant of the growth of incomes. Figure 3 shows a similar plot for the growth rates of income per worker and human capital defined as the average years of education of the population aged over 15 years. Here the relationship between growth of income and the growth of human capital is much less clear.

The issue we now consider is the relative importance of trade, capital and underlying productivity growth in determining the differences in growth we observe in the data. As we have estimated a production function which allows for fixed effects we are in a position to measure the country specific differences in underlying productivity growth. Recall from the discussion in section 2 that part of the maintained hypothesis of those estimating the Solow model on cross-country data is that this is constant across countries. To investigate this issue Figure 4 shows the regional averages of the fixed effects from our growth equation reported in Table 3, column [5] (how these were obtained is explained in the notes to the figure). There are indeed significant differences in underlying time-invariant productivity growth and these differences are large. There is a twenty per cent (per five year period) gap between East Asia and the two worse performing regions which are Africa and the Middle-East. This finding is broadly consistent with the argument of Young (1995) that the underlying productivity growth in the NICs was 2 per cent per annum.

6 Summary and Conclusions

The question posed by this paper is whether either human capital or openness can be shown to cause productivity growth. We have posed this question by using a growth equation which can be derived directly from the production function and our assumptions as to the determinants of technical change. The advantage of such an approach is that it is possible to model the determinants of technical progress controlling for time invariant but country specific factors. We have used a panel to create the possibility of using past values of the variables as instruments for both physical and human capital and openness.

The use of panel data estimation techniques has proved problematic in previous studies. If differencing is used to remove fixed effects, and endogeneity is allowed for by instruments, a common finding has been that the resulting parameter estimates have large standard errors. The reasons for this are well understood. The importance of measurement error increases with differencing so there is no assurance that estimates that allow for fixed effects are an improvement on those that do not. We have used an estimator developed by Griliches and Hausman (1986) which addresses this issue by allowing information on different levels of differences to be combined. In the context of this paper, where we wish to distinguish between the roles of human capital and openness on both the growth and the level of income allowing for the possibility of fixed effects in underlying growth rates, this estimator has great appeal.

Proceeding by estimating a growth rate equation and allowing for both fixed effects and the endogeneity of the variables we find that greater openness causes faster rates of productivity growth. If the level of openness of an economy is doubled the underlying rate of technical progress will increase by 0.8 per cent per annum. As the level of openness varies from below 10 to above 400 per cent the estimates imply that substantial growth in underlying productivity is possible through changes in trade. We find no evidence, using these estimators, that human capital has any effect on productivity growth. Human capital has a small, and not statistically significant causal effect, on the level of output. Further, the results suggest that by exploiting the information in long differences we obtain large efficiency gains

and considerable reduction in the attenuation biases caused by measurement errors. We would therefore argue that the DCOMB estimator used in this paper is a useful empirical tool for researchers in this area.

By being explicit as to the differing roles of trade on the level of income and underlying growth rates we have also been able to investigate the respective roles of technical progress and factor accumulation in growth. The analysis implies that time invariant differences in productivity growth are an important factor in determining differences in growth rates across countries. Models such as many specifications of the Solow model which assume this rate to be constant cross countries may be misleading in any analysis of the determinants of growth.

Clearly the results leave open the question as to what determines the growth of physical capital. While we have allowed for its endogeneity in the growth process we may well be understating the role of either human capital or openness in so far as these variables affect investment in physical capital. We would argue that capturing the full effects of human capital and trade requires models of growth which allow for the importance of fixed effects in growth rate equations and do not ignore this important source of heterogeneity in cross country outcomes.

References

- Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies* 58, 277-297.
- Barro, R.J., 1991. Economic growth in a cross-section of countries. *Quarterly Journal of Economics* 106, 407-443.
- Barro, R.J., 1997. *Determinants of economic growth: A cross-country empirical study*. Cambridge Massachusetts: The MIT Press.
- Barro, R.J., Lee, J-W., 1993. International comparisons of educational attainment. *Journal of Monetary Economics* 32, 363-394.
- Barro, R.J., Lee, J-W., 2000. International data on educational attainment: Updates and implications. CID Working Paper no. 42.
- Beck, T., 2002. Financial development and international trade - Is there a link? *Journal of International Economics* 57, 107-131.
- Benhabib, J., Spiegel, M, 1994. The role of human capital in economic development: Evidence from aggregate cross-country data. *Journal of Monetary Economics* 34, 143-173.
- Bils, M., Klenow, P., 2000. Does schooling cause growth? *American Economic Review* 90, 1160-1183.
- Blundell R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics* 87, 115-143.
- Blundell R., Bond, S., 2000. GMM estimation with persistent panel data: an application to production functions. *Econometric Reviews* 19, 321-340.
- Bond, S., Hoeffler, A., Temple, J., 2001. GMM estimation of empirical growth models. CEPR Discussion Paper 3048. London: London School of Economics.
- Caselli, F., Esquivel, F., Lefort, F., 1996. Reopening the convergence debate: A new look at the cross-country growth empirics. *Journal of Economic Growth* 1, 363-389.

- Davidson, R., MacKinnon, J.G., 1993. Estimation and inference in Econometrics. New York, Oxford: Oxford University Press.
- Dollar, D., 1992. Outward-oriented developing countries really do grow more rapidly: evidence from 95 LDCs, 1976-1985. *Economic Development and Cultural Change* 40, 523-544.
- Durlauf, S.N., Quah, D.T., 1999. The new empirics of growth. Chapter 4 in J.B. Taylor and M. Woodford (ed.) *Handbook of Macroeconomics, Volume 1*, North-Holland.
- Easterly, W., Levine, R. 2002. It's not factor accumulation: stylised facts and growth models. In N. Loayza and R. Soto (ed.) *Economic growth: sources, trends and cycles*, Central Bank of Chile, Santiago, Chile. Mimeo.
- Edwards, S., 1998. Openness, productivity and growth: what do we really know? *Economic Journal* 108, 383-398.
- Feenstra, R., 2003. *Advanced International Trade: Theory and Evidence*. Forthcoming, Princeton University Press
- Frankel, J.A. Romer, D., 1999. Does trade cause growth? *American Economic Review* 89, 379-399.
- Greenaway, D., Morgan, W., Wright, P., 2002. Trade liberalisation and growth in developing countries. *Journal of Development Economics* 67, 229-244.
- Gemmell, N., 1996. Evaluating the impacts of human capital stocks and accumulation on economic growth: some new evidence. *Oxford Bulletin of Economics and Statistics* 58, 9-28.
- Griliches, A., Hausman, J.A., 1986. Errors in variables in panel data. *Journal of Econometrics* 31, 93-118.
- Griliches, Z., Mairesse, J., 1997. Production functions: the search for identification. In Strom, S. (ed.) *Essays in Honour of Ragner Frisch*, *Econometric Society Monograph Series*, Cambridge University Press.
- Grossman, G., Helpman, E., 1991. *Innovation and growth in the Global Economy*. Cambridge, Massachussets: The MIT Press.

- Hansen, L.P., 1982, Large sample properties of generalized method of moments estimators. *Econometrica* 50, 1029-1054.
- Harrison, A., 1996. Openness and growth: A time-series, cross-country analysis for developing countries. *Journal of Development Economics* 482, 419-47.
- Heston, A., Summers, R., Aten, B., 2002. Penn World Table Version 6.1, Center for International Comparisons at the University of Pennsylvania (CICUP).
- Hoeffler, A.E., 2002. The augmented Solow model and the African growth debate. *Oxford Bulletin of Economics and Statistics* 642, 135-158.
- Holtz-Eakin, D., Newey, W., Rosen, H., 1988. Estimating vector autoregressions with panel data. *Econometrica* 56, 1371-1395.
- Irwin, D.A., Terviö, M., 2002. Does trade raise income? Evidence from the twentieth century. *Journal of International Economics* 58, 1-18.
- Klenow, P.J. and Rodríguez-Clare, A., 1997. The neo-classical revival in growth economics: Has it gone too far? in Bernanke, B., Rotemberg, J., (ed.) *NBER Macroeconomics Annual*. Cambridge, Massachusetts: MIT Press.
- Krueger, A.B., Lundahl, M., 2001. Education and growth: Why and for whom? *Journal of Economic Literature* 39, 1101-1136.
- Krugman, P., 1987. The narrow moving bank, the Dutch disease and the competitive consequences of Mrs Thatcher: Notes on trade in the presence of dynamic scale economies. *Journal of Development Economics* 27, 41-55.
- Krugman, P., 1994. The myth of Asia's miracle. *Foreign Affairs* 73, 62-78.
- Levine, R., Renelt, D., 1992. A sensitivity analysis of cross-country growth regressions. *American Economic Review* 82, 942-963.
- Lucas, R.E. Jr. 1988. On the mechanics of economic development. *Journal of Monetary Economics* 22, 3-42.
- Mankiw, N.G., Romer, D., Weil, D.N., 1992. A contribution to the empirics of economic growth. *Quarterly Journal of Economics* 107, 407-437.

- Miller, S.M., Upadhyay, M.P., 2000. The effects of openness, trade orientation and human capital on total factor productivity. *Journal of Development Economics* 63, 399-423.
- Pritchett, L., 2001. Where Has All the Education Gone? *World Bank Economic Review* 15, 367-91.
- Rodriguez, F., Rodrik D., 1999. Trade policy and economic growth: A skeptic's guide to the cross-national evidence. NBER Working paper 7081. Cambridge, Massachusetts: National Bureau of Economic Research.
- Rodrik, D., 1988. Imperfect competition, scale economies and trade policy in developing countries. In Baldwin, R.E. (ed.) *Trade policy issues and empirical analysis*. Chicago: University of Chicago Press.
- Rodrik, D., 1991. Closing the technology gap: Does trade liberalization really help? In Helleiner, G. (ed.) *Trade policy, industrialization and development: New perspectives*. Oxford: Clarendon Press.
- Rodrik, D., 1995. Trade policy and industrial policy reform. In J. Behrman and J. Srinivasan (ed.) *Handbook of Development Economics, Vol. 3B*. Amsterdam: North-Holland.
- Romer, P.M., 1990. Endogenous technological change. *Journal of Political Economy* 98, S71-S102.
- Sachs, J., Warner, A., 1995. Economic reform and the process of global integration. *Brookings Papers on Economic Activity* 1, 1-118.
- Summers, R., Heston, A., 1991. The Penn World Table Mark 5: An expanded set of international comparisons, 1950-1988. *Quarterly Journal of Economics* 106, 327-368.
- Solow, R.M., 1956. A contribution to the theory of economic growth. *Quarterly Journal of Economics* 70, 65-94.
- Temple, J., 1999a. A positive effect of human capital on growth. *Economic Letters* 65, 131-134.
- Temple, J., 1999b. The new growth evidence. *Journal of Economic Literature* 37, 112-156.
- Temple, J., 2001. Generalizations that aren't? Evidence on education and growth. *European Economic Review* 45, 905-918.

Wooldridge, J. M., 2002. *Econometric analysis of cross Section and panel data*. Cambridge, Massachusetts: MIT Press.

Young, A., 1995. The tyranny of numbers: confronting the statistical realities of the East Asian growth experience. *Quarterly Journal of Economics* 110, 641-680.

TABLE 1A
SUMMARY STATISTICS:
OPENNESS, HUMAN CAPITAL, INCOME AND CAPITAL, 1970 AND 2000

	Openness (means)			Years of Education (means)		
	1970	2000	Growth Rate (a)	1970	2000	Growth Rate (a)
East Asia	93.3	143.6	7.2	5.51	8.87	7.93
Latin America	51.4	66.8	4.4	4.19	6.33	6.89
South Asia	23.0	48.9	12.6	1.91	4.16	12.95
South-East Asia	81.6	132.8	8.1	3.63	6.62	10.03
Middle East	43.1	78.4	10.0	2.34	6.00	15.73
Africa	53.8	72.0	4.9	1.91	3.59	10.52
Industrial	52.7	81.0	7.2	6.79	9.19	5.04
Australasia	58.0	58.7	0.2	8.48	11.33	4.83
Total	54.2	77.0	5.9	4.23	6.35	6.76
	Capital per Capita (b)			GDP per capita (b)		
	1970	2000	Growth Rate (a)	1970	2000	Growth Rate (a)
East Asia	5,439	33,673	30.4	3,666	11,668	19.3
Latin America	7,358	12,894	9.3	3,976	5,514	5.4
South Asia	1,221	3,361	16.9	1,073	2,095	11.2
South-East Asia	3,865	14,540	22.1	2,432	5,397	13.3
Middle East	2,919	8,694	18.2	2,676	4,572	8.9
Africa	1,880	2,567	5.2	1,436	1,632	2.1
Industrial	30,329	83,651	16.9	10,551	21,653	12.0
Australasia	26,837	84,973	19.2	8,859	21,930	15.1
Total	6,437	12,857	11.5	3,562	5,450	7.1

(a) The growth rate is the five year percentage average.

(b) Both Capital and GDP per capita are the exponential of the means of the logs of the variables.

TABLE 1B
SUMMARY STATISTICS FOR WHOLE SAMPLE

	$\Delta \text{Ln} (\text{Income per Capita})_t$	$\Delta \text{Ln} (\text{Capital per Capita})_t$	$\Delta \text{Human Capital}_t$	$\text{Ln} (\text{Trade Share})_{t-1}$	$\text{Human Capital}_{t-1}$
East Asia N=25	0.29 [0.10]	0.40 [0.12]	0.59 [0.50]	4.21 [0.92]	6.93 [1.77]
Latin America N=153	0.06 [0.14]	0.10 [0.12]	0.39 [0.58]	3.90 [0.60]	4.89 [1.65]
South Asia N=35	0.11 [0.08]	0.17 [0.09]	0.37 [0.36]	3.30 [0.65]	2.70 [1.77]
South-East Asia N=40	0.18 [0.15]	0.28 [0.18]	0.41 [0.28]	4.35 [0.78]	4.45 [1.72]
Middle East N=21	0.08 [0.22]	0.20 [0.16]	0.58 [0.18]	4.01 [0.57]	3.68 [1.47]
Africa N=179	0.03 [0.17]	0.07 [0.20]	0.31 [0.39]	4.01 [0.47]	2.44 [1.43]
Industrial N=153	0.13 [0.09]	0.18 [0.09]	0.41 [0.45]	3.96 [0.57]	7.62 [2.08]
Australasia N=20	0.09 [0.07]	0.10 [0.05]	0.33 [0.41]	3.99 [0.49]	9.34 [2.11]
Total N=626	0.09 [0.15]	0.14 [0.16]	0.38 [0.45]	3.96 [0.62]	4.89 [2.77]

Note: N is the number of observations, the figures in [] parentheses are standard deviations.

Definitions: The PWT measure of Openness is taken from the PENN World Tables (Mark 6.1) data, Heston et al. (2002) which is an update of their earlier data (Summers and Heston, 1991). It is the share of exports+imports in nominal GDP called OPENC.

The years of education figures are taken from the revised Barro and Lee (2000) data, which is an update of their earlier data set Barro and Lee (1993), and are a measure of the average years of schooling in the population aged over 15.

The figures for Income per worker are from the PENN World Tables 6.1. The figures for Capital per Capita have been constructed using the method proposed in Klenow and Rodríguez-Clare (1997) [see Appendix 2]. Both figures are expressed in 1996 international prices.

TABLE 2
TRADE, HUMAN CAPITAL AND INCOME: LEVELS RESULTS

	Cross-Section OLS: 1985		Pooled OLS: 1970-2000			
	[1]	[2]	[3]	[4]	[5]	[6]
Trade Share / 100	0.777 (3.34)**	0.022 (0.40)	0.577 (3.39)**	0.015 (0.30)		
Ln Population	0.097 (1.17)	-0.001 (0.04)	0.073 (0.94)	0.001 (0.07)	0.116 (1.35)	-0.006 (0.29)
Ln Capital/Labour		0.537 (9.59)**		0.544 (10.39)**		0.546 (10.58)**
Education		0.087 (2.93)**		0.085 (3.03)**		0.085 (3.04)**
Ln Trade Share					0.519 (2.70)**	-0.019 (0.38)
R-squared	0.08	0.91	0.06	0.90	0.06	0.90
Country effects (<i>p</i> -value) ⁽¹⁾			0.000	0.001	0.000	0.001
Observations	92	92	626	626	626	626
Countries	92	92	93	93	93	93

Note: The dependent variable is the log of per capita income. *t*-statistics based on standard errors robust to heteroskedasticity and, where applicable, autocorrelation are reported in parenthesis. Significance at the 1%, 5% and 10% level is indicated by *, ** and † respectively. All specification include a constant. Time dummies are included in the specifications reported in columns [3]-[6].

⁽¹⁾ Test for the presence of an unobserved country effect (Wooldridge, 2002; pp. 264-5). Under the null hypothesis that there are no unobserved effects, the test statistic is distributed asymptotically as standard normal.

TABLE 3
TRADE, HUMAN CAPITAL AND INCOME: GROWTH RESULTS

	[1] OLS	[2] Within	[3] DCOMB- GMM ⁽¹⁾	[4] DCOMB- GMM ⁽²⁾	[5] DCOMB- GMM ⁽¹⁾	[6] DCOMB- GMM ⁽²⁾
Δ Ln Trade Share	0.014 (0.58)	0.022 (0.82)	0.027 (1.09)	0.002 (0.06)	0.027 (1.09)	0.004 (0.11)
Ln Trade Share _{t-1}	0.009 (1.01)	0.051 (2.04)*	0.065 (3.01)**	0.066 (2.24)*	0.062 (2.89)**	0.064 (2.17)*
Δ Ln Population	-0.208 (1.03)	0.418 (0.85)	0.276 (0.67)	0.310 (0.75)	0.321 (0.81)	0.341 (0.86)
Δ Ln Capital/Labour	0.490 (8.98)**	0.496 (7.77)**	0.347 (4.70)**	0.381 (5.19)**	0.351 (4.73)**	0.384 (5.19)**
Δ Education	0.031 (2.83)**	0.010 (0.95)	0.008 (0.92)	-0.012 (0.72)	0.016 (1.72) ⁺	-0.009 (0.53)
Education _{t-1}	0.005 (1.31)	-0.012 (1.03)	-0.013 (1.33)	-0.008 (0.79)		
Fixed effects?	No	Yes	Yes	Yes	Yes	Yes
Capital/Labour endogenous?	No	No	Yes	Yes	Yes	Yes
Trade and Education endogenous?	No	No	No	Yes	No	Yes
Sargan/Hansen (<i>p</i> -value) ⁽³⁾			0.14	0.67	0.11	0.62
Country effects (<i>p</i> -value) ⁽⁴⁾	0.07	0.00				
Observations	626	626	626	626	626	626
Countries	93	93	93	93	93	93

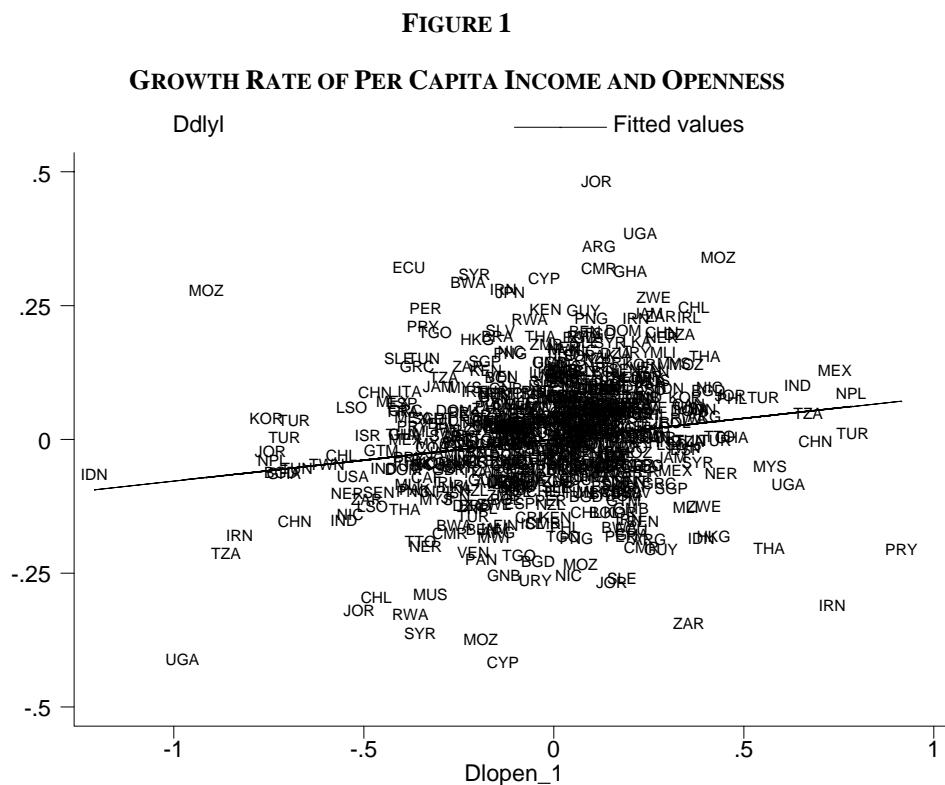
Note: The dependent variable is the five-year growth rate of the log of income per worker. *t*-statistics based on standard errors robust to heteroskedasticity and autocorrelation are reported in parenthesis. Significance at the 1%, 5% and 10% level is indicated by *, ** and ⁺ respectively. All regressions include time dummies and a constant.

⁽¹⁾ The instrument set consists of a constant and time dummies; the differenced log of the capital-labour ratio dated as follows: first differences, *t*-2; second differences, *t*-1, *t*-3; third differences, *t*-1, *t*-4; fourth, fifth and sixth differences, *t*-1; and contemporaneous values of the remaining explanatory variables in the model. The reported coefficients are one-step estimates.

⁽²⁾ The instrument set consists of the differenced log of the capital-labour ratio, the differenced log of population, the differenced log of the trade share, differenced education, dated as follows: first differences, *t*-2; second differences, *t*-1, *t*-3; third differences, *t*-1, *t*-4; fourth, fifth and sixth differences, *t*-1. A constant and time dummies are also included in the instrument set. The reported coefficients are one-step estimates.

⁽³⁾ Sargan/Hansen test for the validity of the overidentifying restrictions. Under the null hypothesis that the overidentifying restrictions are valid, the test statistic is distributed asymptotically as chi-squared with as many degrees of freedom as there are overidentifying restrictions.

⁽⁴⁾ See note (1) in Table 2.



Note: This is a scatter plot of the deviations from country means of per capita income growth [Ddlyl], purged of time effects, against the deviations from country means of the log of the PWT measure of openness lagged one period [Dlopen_1]. To purge the Ddlyl data of time effects we run a fixed effects (within) regression of per capita income growth on lagged openness and time dummies. We then calculate the residual and multiply the openness variable in deviations from country means by the associated coefficient. The sum of these two terms yields Ddlyl purged of time effects.

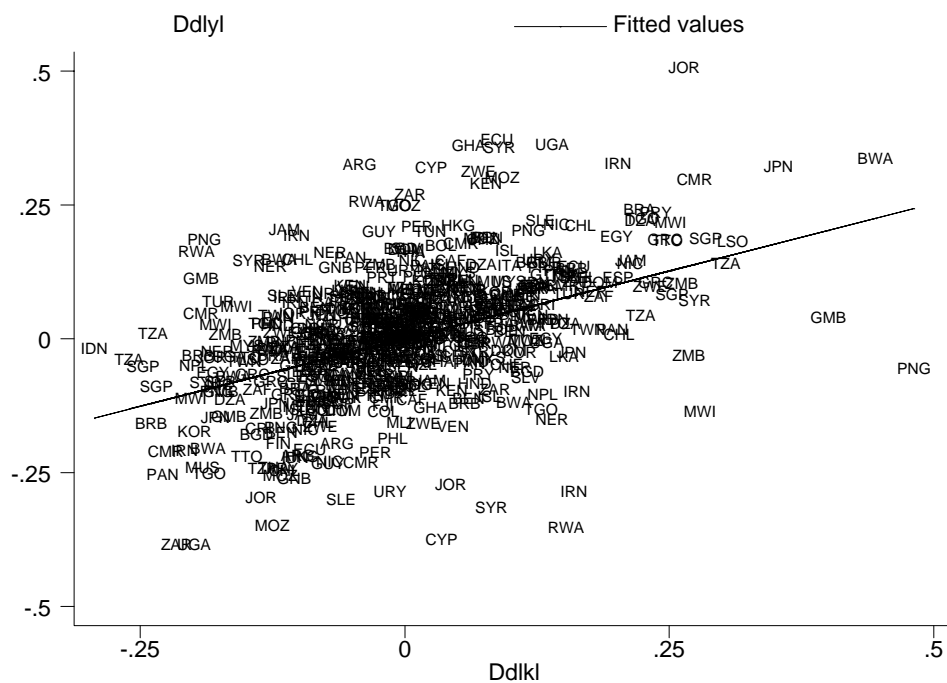
The fitted regression line shown is as follows:

$$[\text{Ddlyl}]_{it} = \quad 0.078 \text{ Dlopen}_{i,t-1} + \tau_i + \varepsilon_{it}$$

[3.46]

where the number in [] is a *t*-statistic.

FIGURE 2
GROWTH RATE OF INCOME PER WORKER AND GROWTH RATE OF
PHYSICAL CAPITAL PER WORKER



Note: This is a scatter plot of deviations from country means of per capita income growth [Ddlyl], purged of time effects (see notes to Figure 1), against the deviations from country means of the growth rates of the capital-labour ratio [Ddkl].

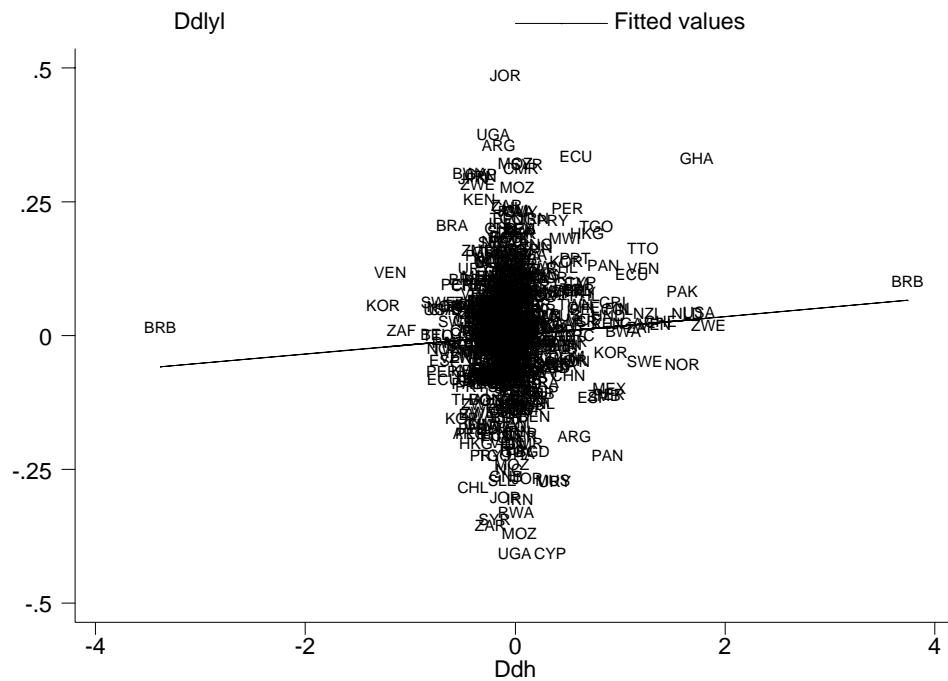
The fitted regression line shown is as follows:

$$[\text{Ddlyl}]_{it} = 0.51 [\text{Ddkl}]_{it} + \tau_i + \varepsilon_{it}$$

[10.3]

where the number in [] is a *t*-statistic.

FIGURE 3
GROWTH RATE OF INCOME PER WORKER AND GROWTH RATE OF HUMAN CAPITAL



Note: This is a scatter plot of the deviations from the means of per capita income growth [dev_dlyw], purged of time effects (see notes to Figure 1), against the deviations from the means of the log of capital per capita [dev_dh]. The underlying regression controls for time effects.

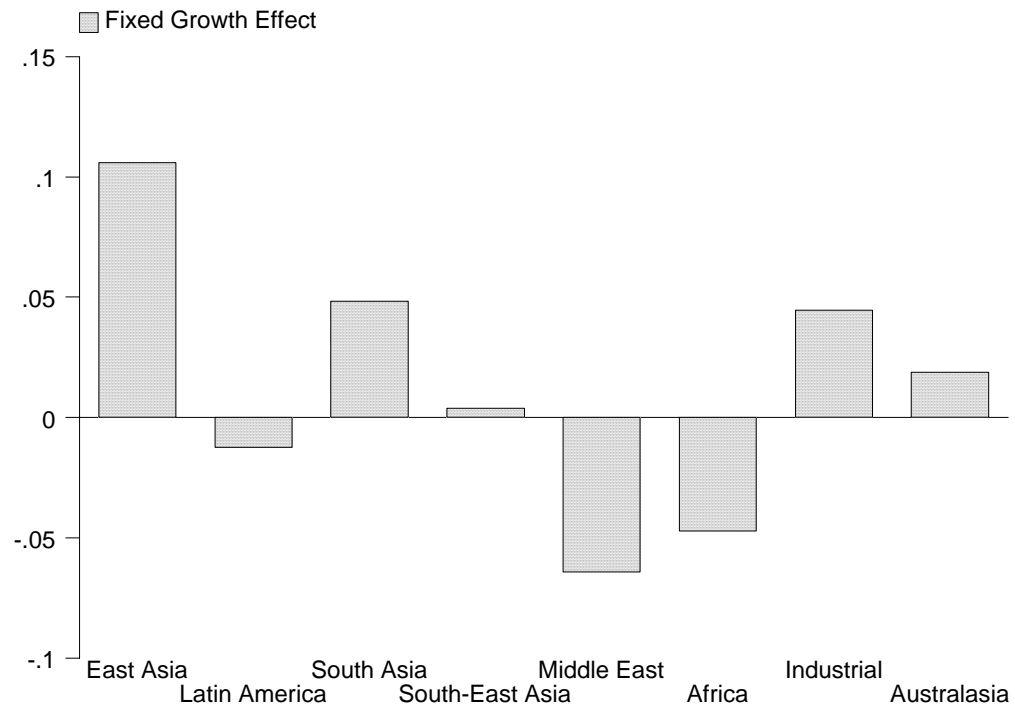
The fitted regression line shown is as follows:

$$[dev_dlyw]_{it} = 0.017Ddh$$

[1.45]

where the number in [] is a t -statistic. Removing the two extreme observations on BRB changes the coefficient on Ddh to 0.020 and the t -statistic to 1.46.

FIGURE 4
GROWTH RATE OF TECHNICAL PROGRESS BY REGION



Note: The figure shows the mean values by region of the estimated fixed growth effects based on the regression in Table 3, column [4]. The R-squared from a regression of the fixed growth effects on regional dummies is 0.30 and the coefficients on the regional dummies are jointly significant at the 1 per cent level.

Appendix 1: The Difference Combinations (DCOMB) GMM Estimator

This appendix provides a description of the difference combinations GMM estimator.

Consider

$$(A2.1) \quad y_{it} = x_{it}'\beta + \mu_i + v_{it}, \quad t = 1, 2, \dots, T,$$

where i and t are firm and time indices, y_{it} is the dependent variable, x_{it} is a row vector of order k of explanatory variables, β is a column vector of parameters of order k , μ_i is a fixed effect potentially correlated with x_{it} and v_{it} is a residual potentially correlated with x_{it} . The fixed effect is eliminated by taking differences:

$$(A2.2) \quad \Delta_s y_{it} = \Delta_s x_{it}'\beta + \Delta_s v_{it}, \quad s = 1, 2, \dots, (T-1).$$

If x_{it} is correlated with the residual v_{it} , OLS estimation of (A2.2) will yield biased and inconsistent results. Assume that a set of instruments is available that enable us to form a vector of moment conditions, expressed as

$$(A2.3) \quad E(\mathbf{z}_i' \mathbf{u}_i) = 0,$$

where \mathbf{u}_i is a n -dimensional column vector of stacked differenced residuals:

$$\mathbf{u}_i = [\Delta_1 v_{i2}, \Delta_1 v_{i3}, \dots, \Delta_1 v_{iT}, \Delta_2 v_{i3}, \Delta_2 v_{i4}, \dots, \Delta_{T-1} v_{iT}]'$$

and

$$\mathbf{z}_i = [\tilde{\mathbf{z}}_i \quad \bar{\mathbf{z}}_i]$$

is a $n \times q$ matrix of instruments. The instrument matrix consists of: $\tilde{\mathbf{z}}_i$, which is a block diagonal matrix with diagonal elements,

$$\tilde{\mathbf{z}}_i = \{z_{i2}^1, z_{i3}^1, \dots, z_{iT}^1, z_{i3}^2, z_{i4}^2, \dots, z_{iT}^{T-1}\},$$

where z_{it}^s is a row vector of instruments orthogonal to $\Delta_s v_{it}$; and $\bar{\mathbf{z}}_i$, which is a matrix of strictly exogenous variables included in the estimated equation. Provided $q \geq k$, we can obtain a consistent GMM estimator of β by minimising the quadratic

$$(A4) \quad J(\hat{\beta}) = \bar{\mathbf{g}}(\hat{\beta})' W_N^{-1} \bar{\mathbf{g}}(\hat{\beta}),$$

where $\bar{g}(\cdot)$ is the sample average of the moment conditions and W_N^{-1} is a weight matrix (Hansen, 1982). An efficient two-step GMM estimator, denoted $\hat{\beta}_2$, is based on

$$W_N(\hat{\beta}_1) = \text{Asy.Var}(\sqrt{N}\bar{g}(\hat{\beta}_1)),$$

where $\hat{\beta}_1$ is a consistent one-step GMM estimator for β based on some known weight matrix W_N . weight matrix that satisfies $p \lim_{N \rightarrow \infty} W_N = \Psi$, where $g_i(\hat{\beta}_1)$

A common procedure in instrumental variable estimation of panel data models is to use lags of x_{it} as instruments for contemporaneous differences (e.g. Holtz-Eakin et al., 1988; Arellano and Bond, 1992). If v_{it} is non-autocorrelated, values of x_{it} not dated t or $t-s$ will be orthogonal to $\Delta_s v_{it}$ and hence be valid instruments. Different instruments are available for different equations and the number of potential instruments, and hence q , grows rapidly with the time series dimension of the panel. It is well known from finite-sample theory and Monte Carlo results that if the number of instruments becomes ‘large’ instrumental variable estimators tend to become more and more biased, eventually approaching the OLS estimator as q approaches the total number of observations (Davidson and MacKinnon, 1993, p. 222). We therefore use only a sub-set of the available instruments, see notes to Table 3 for details.

Appendix 2: Constructing a measure of physical capital

The PWT6.1 data set contains no information on the stock of physical capital. Following Klenow and Rodríguez-Clare (1997) we construct such data using the capital accumulation equation

$$K_{it} = (1 - \delta)K_{i,t-1} + I_{it}, \quad t = 1966, 1967, \dots, 2000,$$

where I is investment in physical capital and t denotes year. This procedure requires data on investment, initial capital ($K_{i,1965}$) and the depreciation rate.

Investment: We obtain investment data by using the following formula:

$$I_{it} = ki_{it} \cdot rgdpl_{it} \cdot pop_{it} \cdot 1,000,$$

where $rgdpl$ is the PWT6.1 variable for real GDP per capita (Laspeyres); ki is the investment share of $rgdpl$; and pop is the population divided by 1,000.

Initial Capital: For each country we define the initial capital-output ratio as

$$\left(\frac{K}{Y}\right)_{1965} = \frac{i}{g + \delta + n},$$

where i , g and n are country averages of the investment to output ratio (ki), the growth rate of per capita income (based on the PWT6.1 variable $rgdpch$) and the population growth rate (based on pop), respectively, for all observations available in the 1950-1965 period. The depreciation rate is set as explained in the next paragraph. The above expression is the Solow equation for the capital-output ratio in the steady state. A similar procedure for estimating the initial capital-output ratio has been used by Klenow and Rodríguez-Clare (1997). We then obtain an estimate of the initial capital stock by multiplying the estimated $(K/Y)_{1965}$ by 1965 real GDP:

$$K_{1965} = (K/Y)_{1965} \cdot rgdpch_{1965} \cdot pop_{1965}.$$

Depreciation: Following Klenow and Rodríguez-Clare (1997) we set $\delta = 0.03$, but we have also experimented with higher depreciation rates. Using $\delta = 0.07$ tends to give slightly lower estimates of the coefficients on population and the capital-labour ratio, but only marginally different coefficients on openness and human capital.

