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Total Factor Productivity, Human Capital and Outward Orientation: Differences by Stage of Ddevelopment and Geographic Regions

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Abstract

Do openness and human capital accumulation promote economic growth? While intuition argues yes, the existing empirical evidence provides mixed support for such assertions. We examine Cobb-Douglas production function specifications for a 30-year panel of 83 countries representing all regions of the world and all income groups. We estimate and compare labor and capital elasticities of output per worker across each of several income and geographic groups, finding significant differences in production technology. Then we estimate the total factor productivity series for each classification. Using determinants of total factor productivity that include, among many others, human capital, openness, and distortion of domestic prices relative to world prices, we find significant differences in results between the overall sample and sub-samples of countries. In particular, a policy of outward orientation may or may not promote growth in specific country groups. even if geared to reducing price distortion and increasing openness. Human capital plays a smaller role in enhancing growth through total factor productivity.

Journal of Economic Literature Classification: F43, O47

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1. Introduction

Students of international trade commonly believe that international trade policies making a country more open to world trade and stimulating human capital accumulation promote a higher standard of living. That is, greater outward orientation increases efficiency in the use of resources, and encourages production specialization in some industries, in accordance with the principle of comparative advantage. The expansion of exports relaxes the foreign exchange constraint and accommodates larger imports of key inputs in the production process. Countries that pursue greater outward orientation, therefore, can experience faster economic growth. Among the external factors that affect growth, improvements in the terms of trade can exogenously increase output as well. In addition, the higher the human capital stock within a country, the better that country is at adopting the newer technology that promotes economic growth.

The macroeconomic growth literature identifies both factor accumulation and total factor productivity as principal determinants of growth. The relative influence of these broad causal factors provides a large area of research. In this paper, we separate the contribution of the basic inputs in production that directly affect output growth from factors that indirectly influence growth, that is, the factors that change the efficiency of those basic inputs. Put differently, those other factors in fact determine total factor productivity (TFP). We estimate a series of models, using a relatively large dataset, to calculate TFP and to examine a set of external as well as domestic factors that affect TFP.

Most cross-section and panel studies of economic growth put all countries into the same basket to estimate the elasticities of output with respect to capital and labor, or to calculate returns to scale. Those studies presume that all countries in the sample follow the same overall technology. A cursory examination of the wide disparities in per capita income and growth rates across countries, however, raises serious doubts on such a presumption. Countries that occupy different rungs of the development ladder probably also occupy different rungs of the technological ladder. Geographical and cultural differences can constrain the rate at which countries adopt modern technology.[1] Our paper examines whether countries in different income groups and geographical locations display similar output elasticities with respect to inputs, and/or similar returns to scale.

Expanded versions of the neo-classical growth model importantly assume that human capital directly enters the production function along with labor and physical capital (Mankiw, Romer, and Weil, 1992; Mankiw, 1005, and Miller and Upadhyay, 2000). Earlier attempts generally fail to uncover a significant contribution of human capital to output in large samples of countries, most likely due to severe measurement problems of human capital. In this paper, we calculate TFP employing only physical capital and labor in the production function and consider how human capital, along with variables capturing outward orientation, influences TFP.[2]

Our main findings include the following. For low-income countries, output responds much more to labor than to capital. That is, the output elasticity with respect to labor exceeds that with respect to capital. The total elasticity of output with respect to capital and labor for the low-income countries implies increasing returns to scale. That result, however, reverses itself for the middle- and high-income countries that display decreasing returns to scale. Thus, the returns to scale for different income groups or regions depends on the level of development.

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[1] Many studies emphasize the importance of such differences in growth. Culture plays a large role in the explanations provided, for instance, by Landes (1999) and Sachs (2000). Among other development constraints, differences in geography prove pivotal in Sachs (2001), who explores "the difficulty of applying temperate-zone technological advances in the tropical setting." (abstract).

When we classify countries by geographic regions instead, our previous results based on income categories extend only to Africa. African economies exhibit increasing returns to scale, while Asia, Europe, and Latin America show nearly constant returns to scale. That is, returns to scale for Asia, Europe, and Latin America all cluster around 1, indicating that constant returns may adequately approximate all regions except Africa.

We also find that countries in the middle-income group display elasticity characteristics closer to those for high-income countries than for low-income countries. Apart from relatively similar returns to scale estimate, the middle-income countries also possess a labor elasticity of output nearly equal to that for the high-income group. On the other hand, the elasticity of output with respect to capital is the highest in the middle-income countries, followed by low-income and high-income countries. If middle-income countries match high-income countries in the rate of technological progress, but accumulate capital more quickly, then their output should respond more rapidly to both those sources of growth. Our findings support such a story.

We find similar results for African and low-income countries despite the fact that 5 out of 19 countries in Africa do not belong to the low-income group, and 8 out of 22 countries in the low-income category do not belong to the African group.

Our assertion that all countries do not use the same technology also finds support from our estimates of total factor productivity. Our first set of total factor productivity estimates employs a panel-data fixed-effect regression for all countries with no control for regional or income differences. The second and third sets of total factor productivity estimates come from

[2] The argument relies on the vintage mix of capital and skill mix of labor, each with different levels of productivity, that are more naturally captured in terms of total factor productivity.

the composite series of TFP that use separate regressions for income groups and for geographic regions.

The results differ markedly. While middle- and high-income countries show small coefficients of variation in total factor productivity, around 7 percent of the mean, the corresponding coefficients for the low-income countries range from 55 percent to 125 percent. Similarly, regional regressions indicate that TFPs in Africa vary widely, up to 140 percent around the mean, whereas for all other regions such variation stays within 8 percent of the mean. Thus, including African and low-income countries with other countries in the world under the assumption that individual country intercepts summarize most of the nonrandom differences may grossly misrepresent reality.

The following section provides details of the production function estimates and a description of our calculated series for total factor productivity. Section 3 explains total factor productivity for each country group and geographic location and considers how important external and internal factors may influence the growth of total factor productivity around the world. Section 4 concludes.

2. Estimates of the Production Function and Total Factor Productivity

The Production Function

We estimate important parameters of production functions and calculate our series for total factor productivity from the Cobb-Douglas function specification on three sets of data---panel data for all countries, panel data separated by income category (low, middle and high), and panel data on geographic regions (Africa, Asia+, Europe+, and Latin America).

The Cobb-Douglas production function is written as follows:

(1) $$Y = A\,K^{\alpha} L^{\beta}, \qquad 0 < \alpha < 1 \text{ and } 0 < \beta < 1,$$

where Y equals real GDP, K equals the total physical capital stock, L equals the number of workers (labor force), and A equals an index of total factor productivity. We allow for the possibility of non-constant returns to scale by not restricting $(\alpha + \beta)$ to equal one.

Dividing equation (1) by the labor force (L) expresses output, and the physical capital stock on a per worker basis. That is,

$$y = A\, k^{\alpha} L^{\alpha+\beta-1}, \tag{2}$$

where y equals real GDP per worker, and k equals the per worker stock of physical capital. Those production functions display increasing, constant, or decreasing returns to scale as $\alpha+\beta$ is greater than, equal to, or less than one, respectively.

Rewriting equation (2) in natural logarithms yields the following:

$$lny = lnA + \alpha\, lnk + (\alpha + \beta - 1)\, lnL. \tag{3}$$

Thus, the tests for constant returns to scale involve whether the coefficient of lnL equals zero.

Including human capital as an input in the production function proves controversial. Mankiw, Romer, and Weil (1992) advocate such an approach on both theoretical and empirical grounds. In a model that is more comparable to our framework because of the use of panel data, however, Islam (1995) finds that human capital does not contribute significantly to explaining output in the Mankiw-Romer-Weil specification. Miller and Upadhyay (2000), however, do find a significant role for human capital in their estimations. In what follows, we include human capital in a second-stage model that studies total factor productivity.

Panel Data and Fixed-Effects Estimation

Our panel data cover the 1960 to 1989 time period (1959 to 1989 for any growth rate) for a sample of 83 countries in the full data set. The Data Appendix, Table A, lists the countries included in our sample. Our panel combines data in five-year blocks as follows: 1960-64, 1965-

69, 1970-74, 1975-79, 1980-84, and 1985-89. Usually, data series reflect averages of the information over five years in each block. Our data encompasses 498 observations (83 countries and 6 time blocks).[3] Our estimating equation emerges by adding a random error to equation (3). This error term incorporates the effects of omitted variables. Classical regression analysis assumes that the omitted variables are independent of the included right-hand-side variables and are independently, identically distributed.

When using panel data, however, we can further classify the omitted variables into three groups -- country-varying and time-invariant, time-varying and country-invariant, and country- and time-varying variables (see Hsiao, 1986 or Greene, 1997). The country-varying time-invariant variables differ across countries, but are constant within a country over time. The time-varying, country-invariant variables, such as technological shocks, differ over time but are constant at a point in time across countries. Finally, country- and time-varying variables differ across both countries and time.

The estimation of equation (3) without consideration of possible country-specific or time-specific effects can generate misleading results for ordinary-least-squares regressions. Problems emerge when either the unobservable country-specific or time-specific variables correlate with the included right-hand-side variables. Two alternative, but related, procedures exist for addressing these problems -- fixed-effect and random-effect models. We restrict our attention to fixed-effect estimation since the random-effects estimation requires that the omitted variables are uncorrelated with the included right-hand-side variables -- an unrealistic assumption in the context of our model.

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[3] For details of data, see Miller and Upadhyay (2000).

If the problem omits country-specific variables, we perform the regression after adjusting all variables by subtracting their respective means over time. Since the unobserved country-specific variables and the intercept do not change over time, such an adjustment drops these variables out of the regression equations. On the other hand, if the problem omits time-specific variables that correlate with the included right-hand-side variables, subtracting the mean over countries drops the intercept and the time-specific effects out of the regression. The revised regression equation in each case provides unbiased and consistent estimates.

Finally, when both country- and time-specific effects correlate with the included right-hand-side variables, we adjust for the means over countries and time. We adopt this last approach and consider fixed effects over countries and time. Our problem, however, has few elements in the time dimension. Thus, we directly include the six time-specific dummy variables, one for each period, and only adjust the data to avoid using 83 country dummy variables.

The estimating equation is as follows:

$$\text{(4)} \qquad \ln y = \ln A + \alpha \ln k + (\alpha + \beta - 1) \ln L, + \sum_{i=1}^{6} \theta_i \, time_i + \varepsilon,$$

where $time_i$ (i = 1, ..., 6) represent the time dummy variables and the variables for each country measure deviations from their country means over time. We then calculate the country-specific fixed effects of intercepts ($cint_j$) as follows:

$$\text{(5)} \qquad cint_j = \overline{\ln y}_j - \hat{\alpha}\, \overline{\ln k}_j - \hat{\delta}_1\, \overline{\ln L}_j \,,$$

where "-" over a variable implies the mean of that variable, "^" over a parameter means the estimate of that parameter, $\delta_1 = (\alpha + \beta - 1)$ in (4), and j = {1,2,3,...} is the index across countries. Note that the time-specific fixed effects appear directly as the respective coefficients of the time dummy variables.

Production Function Estimates: All Countries

The estimate of the Cobb-Douglas function (equation 4) for the full-panel data set yields the following results:

$$\text{(6)} \qquad ln\, y = 0.4756\; lnk - 0.0988\; lnL_{it} + \sum_{i=1}^{6} \theta_i\, time_i + \varepsilon_t\,.$$

$$(18.86) \qquad (-1.32)$$

$$R^2 = .7860 \qquad SEE = .1269 \qquad F(7{,}407) = 218.26 \qquad N = 498$$

The coefficient of *ln L* (i.e., -0.0988), although only significant at the 20-percent level, indicates that the production function exhibits slightly decreasing returns to scale. The coefficient of *ln k* assigns a value of 0.4756 to the elasticity of output with respect to the physical capital stock. These two coefficients combine to generate the implied elasticity of output with respect to the labor force of 0.4256. Thus, after accounting for country- and time-specific effects, the output elasticities with respect to labor and physical capital sum to a value of 0.9012, indicating a slightly decreasing returns to scale.[4]

Our dataset includes observations for 30 years for each country. Each data point, however, averages 5 yearly observations. Thus, we only have a short panel on the time dimension (six 5-year periods for each country), and hence autocorrelation is not of much concern. On the other hand, heterogeneity of countries in the panel along both the income and locational scales can cause the residual terms to be heteroscedastic. Using the Lagrange multiplier test for the Cobb-Douglas function, however, we find that the statistic equals only 0.021 with a high significance level of 0.88. Thus, the test fails to reject the null hypothesis of constant variances across countries.

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[4] The estimated $\theta_i s$, not reported, are available on request.

Production Function Estimates: Income Levels and Geographic Regions

Another way to test for possible differences in technology divides the sample into groups of countries in different ways. We use two methods to create sub-samples for more intensive study. First, we divide our sample into low-, middle-, and high-income countries based on real GDP per worker for two different periods: 1960-64, and 1970s. The categorization based on 1960-64 incomes allows one to study subsequent growth in originally similarly placed economies and convergence during the sample period. Technological differences among income groups for the entire 30-year period, however, can perhaps better discriminate, if we classify countries according to their income levels during the 1970s, the middle of the three decades in our sample. That is especially desirable if rapid growth elevates countries from low- to middle-income or from middle- to the high-income groups over our entire sample period.

The World Bank divides countries into low-, middle-, and high-income groups based on real GDP per capita. Using a number in the range of 2 to 2.5 to measure the ratio of population to labor force, we convert these ranges into ranges based on real GDP per worker. Thus, our classification based on 1960-64 incomes fixes $3,000 (in constant 1985 international prices) as the threshold GDP per worker between low- and middle-income countries and $10,000 per worker between middle- and high-income countries. For the classification based on incomes during the 1970s, an analogous exercise leads to $4,000 and $13,500 as the respective cutoffs for GDP per worker.[5]

Second, geography provides another important dimension along which to split our sample. Countries in Africa may use a level of technology that significantly differs from that used in Europe. Our regional sub-samples mostly follow continental divisions, except that we include Australia, Canada, New Zealand, and the U.S. in Europe+, and Fiji and Papua New Guinea in Asia+.

In sum, we divide the full-sample into three different subsamples. The first subsample segregates countries based on real GDP per capita – low-, medium-, and high-income -- using 1960-64 data. The second subsample also segregates based on real GDP per capita, but now using 1970s data. The third subsample segregates based on geography – Africa, Asia+, Europe+, and Latin America. Table 1 reports F-tests of the null-hypothesis that we can pool the data across income groups or geography, Those F-tests clearly reject the null-hypothesis, indicating that the subsample production function estimates differ significantly from each other.[6]

The results for the estimation of the Cobb-Douglas production functions appear in Table 1. Several noteworthy points emerge. Starting with income categories, we find that the elasticity of output with respect to capital in high-income countries falls substantially below that in other countries. This elasticity equals 0.17 for high-income countries when grouped by incomes for 1960-64, and rises to 0.31 for the same subset when we reclassify countries according to the 1970s' incomes. That increase traces to the movement of Japan and Ireland from the middle- to high-income group. We also find significantly decreasing returns to scale for high-income countries, as the output elasticities with respect to capital and labor sum to only about 0.5.

Second, we find a close similarity of results for middle- and low-income groups across our two income classifications. In particular, the middle-income group fairly well represents the entire sample in terms of key results. The returns to scale for the middle-income countries

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[5] We use the ratios of cutoff incomes and average incomes for 1960-64 in the previous procedure, and the average incomes for the 1970s,

[6] Similar F-tests where we consider whether one subsample (e.g., low-income countries) possesses production functions that differ significantly from a production function for the rest of the world (e.g., medium- and high-income countries) always imply that the production functions differ.

matches closely that for the whole set of countries. The combined elasticity of output with respect to capital and labor equals 0.82 for the middle-income group and equals 0.91 for all 83 countries. That comparability of the middle-income group with the world as a whole reflects a higher output elasticity with respect to capital (0.57 versus 0.48 for the entire sample) largely offset by a lower elasticity with respect to labor (0.25 versus 0.43).

The similarity of results, however, does not carry through to countries on either side of the income scale. Although the capital elasticity of output does not change that much (0.46 versus 0.48), the labor elasticity of output is much higher for the low-income countries (1.34 versus 0.43). Those values indicate that the production function exhibits significantly increasing returns to scale for low-income countries in sharp contrast, as discussed above, to the decreasing returns to scale for the high-income subset. That result, therefore, highlights the potential for convergence in income per worker between rich and poor countries. Focusing on our division of countries into income groups based on incomes for 1960-64, if low-income countries, on average, experience increasing returns to scale in production during the next 25-30 years, we expect incomes to converge and a number of countries in the sample possibly to move up the income distribution.[7]

Another way to explore for possible differences in technology separates countries into geographic regions (Frankel and Romer, 1999). The findings for our four regions show significant similarity in key parameters, except for Africa. The scale elasticity for Asia, Europe, and Latin America lies between 0.95 (Europe) and 1.08 (Latin America) whereas the elasticity for Africa equals 1.70, and closely follows the elasticity of 1.80 for low-income countries in our

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[7] We study convergence in income and total factor productivity among the same set of countries as in our current sample in an associated paper (Miller and Upadhyay, 2002). In that paper, we find, however, stronger evidence of absolute convergence in total factor productivity than in income.

earlier analysis. The elasticities of output with respect to capital alone are, however, more comparable for all groups since they range between 0.37 for Asia and 0.54 for Europe with the intermediate values assumed of 0.45 for Africa and 0.51 for Latin America.

In sum, we find evidence of increasing returns to scale for low-income and African countries, although these two sub-samples do not exactly overlap. Several Asian and Latin American countries appear in the low-income category, and several African countries appear in the middle-income category. Middle- and high-income countries display decreasing returns to scale whereas countries from Asia, Europe, and Latin America indicate a scale elasticity close to unity, ranging from slightly decreasing (0.95) for Europe to slightly increasing (1.08) for Latin America. Thus, we do find evidence of technological differences across groups of countries despite the fact that we limit our attention to a single Cobb-Douglas specification of the production function.[8]

As a final check, we calculate the correlation coefficient between the series for total factor productivity based on the pooled regression for the entire sample and the combined series for total factor productivity based on the separate estimates for income groups. The rank correlation coefficient between these two estimates of total factor productivity equals 0.74, which is far from perfect but not so low as to suggest no relationship.[9]

The findings from our sub-sample Cobb-Douglas production function regressions for the income and geographic groups raises at least two important questions that deserve further

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[8] Inclusion of human capital in an augmented production function is another approach to study growth and total factor productivity. For reasons and results discussed in a companion paper (Miller and Upadhyay, 2000), we do not pursue this approach here.

[9] If, instead, we omit the low income countries, either definition, or the African countries, and calculate TFP numbers from pooled regressions absent the low-income or African countries, then the correlation between the TFP numbers for the pooled versus the series for TFP gotten from the separate regressions equal 0.95, 0.96, and 0.99 for the omission of 1960-64 low income, 1970s low income, and African countries, respectively.

discussion.[10] First, if low-income and African countries exhibit increasing returns to scale, then why do we not observe the convergence of real GDP per capita? Several points relate to this question. The low-income and African countries did not experience the growth in their capital stocks that other country groups experienced. For example, capital stock per worker rose annually during 1960-64 - 1985-89 by only 2.6 percent per year (25 years) for Africa as compared to 2.9 percent for Latin America, 3.8 percent for Europe, and 4.3 percent for Asia. The slower growth rate is all the more unfortunate because of the small capital base that they started with in 1960. Thus, lack of convergence significantly relates to lack of capital accumulation along the production frontier. If low-income and African economies could accumulate capital faster, then the convergence process could start. In the 1990s, although not addressed in our paper, non-convergence between Africa and rest of the world was even more striking due to civil wars, lack of institution building, and limited foreign direct investment in many countries of our sample. In other words, we argue that the lack of growth of factors of production helped to retard progress in the low-income and African countries.

The negative movement in total factor productivity in many low-income and African countries for most periods also provided an important further drag on growth and convergence. On average, total factor productivity decreased monotonically over our sample period for low-income and African countries. Further, the previously mentioned propensity for civil wars and lack of institution building probably plays a dramatic role in total factor productivity movements. Thus, the slow growth of capital in Africa and negative total factor productivity movements did not allow those countries to exploit higher returns to scale in production and to induce convergence of per capita income.

[10] Editor Johnson first raised these questions after he read our initial submission to the journal.

Second, given that high-income countries exhibit decreasing returns to scale, how did those countries continue to increase real GDP per capita? Here, the conventional wisdom holds that the growth in total factor productivity provides a most important contribution to economic growth (e.g., Islam, 1995; Hall and Jones, 1999; Easterly and Levine, 2001). But, Young (1994) offers a contrarian view that factor accumulation and not total factor productivity growth explained economic growth in East-Asian countries.

3. Determinants of Total Factor Productivity

The basic characteristics of the different total factor productivity estimates from our model in the last section appear in Table 2. We find that for the low-income group, the mean of the natural logarithm of TFP per worker is negative and the coefficients of variation show a high degree of dispersion. In the regional classification, Africa displays similar characteristics, with a negative mean and high dispersion in the natural logarithm of TFP. For the middle- and high-income countries and those outside Africa, the natural logarithm of TFPs more closely cluster around their respective means.

The Basic Equation

In this section, we examine the role of both domestic and external variables in influencing total factor productivity. Our estimate proceeds with the following equation for total factor productivity:

$$\text{(7)} \quad \ln tfp = a_1 + a_2 \ln H + a_3 \ln open + a_4 \ln tot + a_5 \ln pd + a_6 \ln (1+\pi) + a_7 \ln \sigma_x + a_8 \ln \sigma_{tot} + a_9 \ln \sigma_{pd} + a_{10} \ln \sigma_\pi + \sum_{i=1}^{6} a_{10+i}\, time_i + \varepsilon,$$

where *open* equals the ratio of exports to GDP or total trade to GDP,[11] *tot* equals the terms of trade, *pd* equals local price deviation from purchasing power parity, π equals the inflation rate,[12] and σ_i equals the standard deviation of *i* (= *x, tot, pd,* and π) over the five-year sub-periods. Once again, we estimate equation (7) using the fixed-effects method.

Our main goal in this section considers how variables representing the performance of the external sector relate to total factor productivity, and how our results for countries in different income and locational groups compare with the results for the entire sample. We suppress the results for the time dummies from Tables 3, 4 and 5.

Table 3 reports the results of our estimates of equation (7) for the pooled sample and for countries at different levels of development based on the 1960-64 average incomes. The values for the TFP variable come from the Cobb-Douglas production function discussed in the last section. Starting with the external sector of the economy, the variables related to trade show a generally positive effect on total factor productivity. Openness exhibits a significant positive effect generally at the 1-percent level for all samples. Greater openness enhances growth of the economy through a larger total factor productivity.

The local price deviation from purchasing power parity displays a significant negative effect at the 5-percent level in the full sample. Here, larger deviations from purchasing power parity associate with lower total factor productivity. To the extent that local deviations from purchasing power parity imply a more-restricted, less-open domestic economy, the coefficient on this variable captures another aspect of the openness of the economy to trade, reinforcing our finding on the export-GDP ratio. The price deviation variable, however, loses its statistical

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[11] Although we considered both export-GDP ratio and total trade (imports plus exports) to GDP ratio as our measures of openness, the export-to-GDP measure of openness consistently performed better.

significance in income sub-samples and only retains its negative sign for the middle-income group.

The terms of trade possesses the expected positive effect in the full sample, but is only significant at the 20-percent level. So improvements in the terms of trade weakly associate with higher total factor productivity. Once again, however, this result seems driven solely by countries in the middle-income range. For other groups, the coefficients exhibit a statistically insignificant negative sign, even at the 20-percent level.

For the domestic variables, human capital exerts an insignificant, albeit positive, effect on TFP while inflation exerts a significant negative effect at the 1-percent level. Human capital turns significant for the middle-income group alone, and that too at the 10-percent level. We get greater consistency for the inflation effect, as most income classifications indicate a highly significant negative effects of inflation on total factor productivity. For the high-income countries, however, it loses its statistical significance and reverses sign. On average, the inflation rate for the high-income group falls well below the 20 percent or so beyond which, according to some studies, inflation begins impinging on growth (Bruno and Easterly, 1998 and Gylfason and Herbertsson, 2001). That finding that higher inflation associates with lower total factor productivity may explain the observed empirical regularity between higher inflation and lower economic growth.[13] That is, higher inflation leads to lower economic growth through its effect on total factor productivity.

The volatility variables (as measured by standard deviations) have, on average, much less significance in explaining total factor productivity. The one exception, the standard deviation of

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[12] We add 1 to actual inflation to avoid taking logs of negative inflation rates.

exports to GDP, exhibits a significant negative effect at the 1-percent level. That is, lower export instability associates with higher total factor productivity. This is true of the overall sample and of the low-, middle-, and high-income countries, although the coefficients are much less significant or insignificant for low-income countries. For the low-income group, the volatility coefficients are unexpectedly positive and statistically significant.

In sum, higher and more stable openness and a lower inflation rate associate with higher total factor productivity. The results for the whole sample do not in general extend to component income groups. In particular, the price deviation from purchasing power parity and the terms of trade do not behave in a predictable fashion across country classifications. This suggests that lumping countries at various levels of development together in an empirical growth study may not succeed in uncovering important policy implications.

Human Capital-Openness Interaction

Human capital effects do not emerge in our simple specification of the determinants of total factor productivity. Human capital may affect total factor productivity through its interaction with trade orientation.[14] Greater openness fosters competition, encourages the use of modern technology, increases the demand for high-skilled labor, and promotes learning by doing.

Countries Grouped by Income

Columns 2, 4, 6 and 8 in Table 3 add the interaction term between the human capital and openness variables. We find that markedly different results between two identical TFP regressions but for different TFP series---one estimated using a production function for the entire

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[13] While Levine and Renelt (1992) find that the effect of inflation on economic growth is fragile, they do find that it is consistently negative. Kormendi and Meguire (1985), Grier and Tullock (1989), and Miller and Russek (1997), among others, report evidence of a negative effect of inflation on economic growth.

sample of countries as in Miller and Upadhyay (2000, p.416) and the other based on a production function for each sub-sample as explained in the last section.

Human capital now exerts a significantly positive direct effect on total factor productivity at 10 percent level for middle- and high-income countries and a significantly negative direct effect for the low-income countries. In another major change, openness exhibits a significant negative effect on total factor productivity in low-income countries. Only the interaction term's coefficient is both positive and significant at the 1 percent level, indicating that low-income economies benefit from a concerted growth of human capital and openness but not necessarily from the development of one or the other in isolation. For middle-income countries, the direct effects of openness and human capital are positive but openness fails to interact with human capital to exert a positive influence on total factor productivity. For high-income countries, the direct effects of openness and human capital are positive and now openness interacts with human capital to reduce total factor productivity.

Other factors including the terms of trade, local price deviation, and domestic inflation do not discernibly change in the way they affect total factor productivity in the specification that includes the interaction term.

The findings for total factor productivity regressions classified by income during the 1970s yield no remarkable differences in results from those for countries grouped by 1960-64 income (see Table 4).

Countries Grouped by Geography:

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[14] Grossman and Helpman (1991) suggest that increased trade orientation may interact with human capital to produce higher output growth. Benhabib and Spiegel (1994) interact human capital with other variables including technological progress. Miller and Upadhyay (2000) employ a similar specification.

We do find interesting results when we consider total factor productivity regressions for geographical regions. The TFP series are based on a production function estimated separately for each region. The following paragraphs discuss the results for estimating equation (7) with and without the interaction between human capital and openness (see Table 5).

Similar findings emerge for African and low-income countries, because many countries appear in both sub-samples. But the results are by no means the same. For Africa, human capital does not affect total factor productivity, if we exclude the interaction term, whereas it displays a significantly negative effect if we include it. Openness, in turn, changes from having a significantly positive to a significantly negative effect on TFP for Africa when the interaction term appears. Much like low-income countries discussed in the preceding subsection, Africa experiences a significant (and larger) positive effect on its total factor productivity when human capital and openness interact with each other. The interaction term soaks away some of the direct positive effect of openness on total factor productivity.

Latin America displays similar characteristics in terms of the effects of human capital, openness, and the interaction between the two. In particular, the specification that includes the interaction term yields a negative coefficient for both human capital and openness.

For Asia, we do not find much evidence of a significant relation between any of these variables and total factor productivity. This is a bit surprising when we see many other studies indicating a close positive correlation between openness and growth in Asia, particularly East and Southeast Asia.[15] On the other hand, deviations of local prices from purchasing power parity exerts a significant negative effect on total factor productivity in Asia, but in no other region.

[15] See Pack and Page (1994), for example. Note, however, that Asia includes South Asia and other regions where the role of trade exhibits a less important role than in East Asia.

Interestingly, Asia is the sole region where PPP deviation and volatility in the terms of trade possess consistently negative effects.

Finally, domestic inflation does not significantly influence TFP in any region outside of Africa, although as noted in the last subsection, negative effects of inflation exist for the whole sample of countries as well as for the low- and middle-income groups.

Openness and Human Capital Effects with Interaction Terms

Columns 2, 4, 6, and 8 in Tables 3, 4, and 5 report the results after including the openness-human capital interaction term. The effects of openness and human capital on total factor productivity depend now on the values of human capital and openness, respectively. For example, the all-countries regression reports coefficients of –0.0961, 0.0925, and 0.0395, respectively. So the effect of human capital on total factor productivity depends on the value of openness and the effect of openness on total factor productivity depends on human capital. More formerly, the total coefficient on human capital equals (-0.0961 + 0.0395 *lnx*) and the total coefficient on openness equals (0.0925 + 0.0395 *lnH*). Now, as human capital increases, the effect of openness on total factor productivity remains positive and gets larger. As openness increases, on the other hand, the effect of human capital on total factor productivity gets less negative. In fact, the effect switches to a positive effect when exports exceed 11.4 percent of GDP. See Tables 6, 7, and 8.

Now consider the results for the low-income, African, and Latin American regressions that sing a similar song. More openness, ignoring the interaction term, associates with lower total factor productivity. The interaction term, however, shows that increasing human capital causes the negative effect to diminish in magnitude, and flips the overall sign positive when *ln* H exceeds 7.4, 7.0, 6.7, and 5.7 for the 1960-64 income, 1970s income, African, and Latin American regressions, respectively. For the low-income and African countries, those values fall within the actual sample range. But, for the Latin American countries, the sample range fully exceeds the switching value. That is, the combined effect of openness in Latin America always exceeds zero. Further, higher human capital, ignoring the interaction term, associates with lower total factor productivity. Now, more openness can reverse that negative relationship when exports exceed 6.2, 7.5, 9.7, and 57.4 percent of GDP for the 1960-64 income, 1970s income, African, and Latin American regressions, respectively. Although the openness thresholds lie within the openness ranges in each case, they fall much closer to the lower end of the range for the low-income and African countries and much nearer the high end of the range for the Latin American countries. Thus, low income and African countries more likely experience a negative correlation between human capital and total factor productivity while Latin American countries more likely face a positive correlation. Those results also appear in Tables 6, 7, and 8.

The middle-income and Asian regressions do not possess significant coefficients for openness, human capital, and their interaction term. Thus, no story exists concerning the effects of human capital and/or openness.

Finally, the high-income and European regressions also tell similar stories, but stories that reverse those of the low-income, African, and Latin American regressions. More openness, ignoring the interaction term, associates with higher total factor productivity. Then higher human capital reduces that positive linkage, and flips the overall sign negative when *ln* H exceeds 12.8, 13.0, and 10.2 for the 1960-64 income, 1970s income, and European regressions, respectively. In each case, the value of *ln H* that switches the overall coefficient negative lies within the sample range, although at the upper end of that range. That is, countries with high levels of human capital may experience a decrease in total factor productivity with an increase in openness. High human capital countries may reflect the technological innovators and more openness may lead to greater leakages of that technology to the rest of the world.[16] Further, higher human capital, ignoring the interaction term, associates with higher total factor productivity. Then more openness reduces that positive linkage, and reverses the sign when exports exceed 16.4, 15.8, and 36.1 percent of GDP for the 1960-64 income, the 1970s income, and the European regressions. Although the openness thresholds lie within the openness ranges, they fall nearer the lower end of the range for high-income countries and closer to the upper end of the range for European countries. Once again, refer to Tables 6, 7, and 8.

4. Conclusion

We study the effects of openness, trade orientation, and human capital on total factor productivity for a pooled cross-section, time-series panel data set of developed and developing countries. We first estimate multiple sets of total factor productivity based on Cobb-Douglas production function and the fixed-effect regression technique, involving output per worker, capital per worker, and the labor force. We classify countries along income and geography. Then, we search for the possible determinants of total factor productivity, with special emphasis on variables reflecting trade orientation and human capital.

Our results show that giving the economy a greater outward orientation benefits total factor productivity in general but not necessarily for specific classes of countries. We capture outward orientation through the export-GDP ratio, the terms of trade, and alignment of local prices with purchasing power parity. Among other variables, human capital expansion fails to have an independent positive effect on total factor productivity growth except for Europe.[17]

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[16] For the classifications based on income, only the U.S. and then Japan and the U.S. exceed the human-capital threshold level. For the European country classification, 15 of the 25 countries, including Japan and the U.S., exceed the human-capital threshold value.

[17] 'Europe' in this paper also includes Australia, Canada, Japan, New Zealand, and the U. S.

Even openness fails to elicit a significant positive effect on total factor productivity in all cases. That is, openness without the interaction term does contribute positively to total factor productivity for all country groups. But, including the interaction term causes the low-income, African, and Latin American countries to see a negative effect, excluding the positive effect of the interaction term. That positive effect of the interaction term can switch the overall sign to a positive value if the stock of human capital exceeds the threshold level. In addition, the interaction term for the high-income and European countries contributes negatively to the effect of openness and can switch the overall effect to a negative one if the openness value exceeds the threshold.

Similarly, the interaction between human capital and openness does not positively influence total factor productivity for several country groups. Absent the interaction term, human capital generally does not achieve significance, except for the positive effect in the middle-income countries. Including the interaction term causes the effect of human capital by itself to become negative in low-income, African, and Latin American countries, while positive for high-income countries. The interaction term can cause the overall effect to turn positive for the low-income, African, and Latin American countries if the openness exceeds the threshold level. Further, the interaction term's negative effect in high-income and European countries can reverse the positive effect of human capital by itself if the openness exceeds the threshold level.

Inflation, the other domestic variable, has a significant negative effect on total factor productivity in low-and medium-income countries, but not in high-income countries. In addition, that negative effect only occurs for Africa in the sub-samples based on geography.

Finally, even though a strong positive influence of outward orientation on growth through total factor productivity possesses obvious implications for policy, we conclude with a strong word of caution. Two sources of problems in our results and those in almost all empirical papers concern the following. While our dataset incorporates much digging into new and old sources and includes enormous cross-referencing, it still does not reflect the best possible quality. The policy implications, therefore, need further empirical investigation given better data. Second, the production function choice for a given country or group of countries is not yet fully resolved. In a companion paper, we consider outward orientation using translog and constant elasticity of substitution production function specifications. But, the enormous differences in results for country groups even within the Cobb-Douglas function as analyzed in this paper provide striking evidence. We, therefore, conclude that a large sample of countries included in a single panel model may yield incorrect policy implications for any given country about the effects of outward orientation, human capital, or inflation. Using a smaller sample of countries with strong similarity of characteristics probably holds much greater promise.

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Table 1: Production Function Estimates by Income Level and Region (Cobb-Douglas)

	Coef. of ln k	*Coef. of ln L*	*RTS*	$\overline{R}^2$
All Countries	0.4756* (18.86)	-0.0988‡‡ (-1.32)	*0.912: DRS*	0.786
Countries Grouped by 1960-64 Income Per Worker: **F(16, 391) = 9.45***				
High-Income	0.1683** (2.30)	–0.5114* (–5.43)	*0.489: DRS*	0.816
Middle-Income	0.5694* (12.72)	–0.1719‡‡ (–1.49)	*0.822: DRS*	0.827
Low-Income	0.4604* (13.68)	0.7953* (3.62)	*1.795: IRS*	0.779
Countries Grouped by 1970s Income Per Worker: **F(16, 391) = 4.52***				
High-Income	0.3096* (5.14)	–0.4824* (–5.12)	*0.518: DRS*	0.839
Middle-Income	0.6068* (13.48)	–0.1785‡‡ (–1.45)	*0.821: DRS*	0.830
Low-Income	0.4309* (12.56)	0.6548 (3.01)	*1.655: IRS*	0.748
Countries Grouped by Geographic Region: **F(24, 383) = 11.66***				
Africa	0.4452* (12.06)	0.7041* (2.52)	*1.7041: IRS*	0.763
Asia+	0.3657* (5.70)	0.0124 (0.05)	*1.0124: IRS*	0.783
Europe+	0.5408* (8.43)	–0.0486 (–0.33)	*0.951: DRS*	0.908
Latin America	0.5112* (7.93)	0.0807 (0.54)	*1.081: IRS*	0.916

Note: All regressions employ the fixed-effect technique for countries. The regressions explicitly include 6 time dummies to capture the fixed effects over time (not reported here). *RTS* indicates the returns to scale (constant, increasing, or decreasing). $\overline{R}^2$ equals the adjusted coefficient of determination. The F-test considers the null-hypothesis that each subgrouping possesses the same production function.

* means significant at the 1-percent level.
** means significant at the 5-percent level.
‡ means significant at the 10-percent level.
‡‡ means significant at the 20-percent level.

Table 2: Basic Statistics on Real GDP Per Worker and TFP Per Worker by Country Groups

Logarithm of Real GDP Per Worker					Logarithm of TFP Per Worker			
Countries Grouped by 1960-64 Income					*Countries Grouped by 1960-64 Income*			
	Mean	**Std. Dev.**	**Coef.Var.**			**Mean**	**Std. Dev.**	**Coeff.Var.**
Low	7.662	0.522	6.809		**Low**	-2.182	1.212	55.550
Middle	8.948	0.427	4.769		**Middle**	5.223	0.369	7.062
High	9.934	0.279	2.812		**High**	12.578	0.822	6.532
All	8.880	0.939	10.570		**All: Separate**[a]	5.298	5.497	103.743
					All: Pooled[b]	5.536	0.434	7.840

Countries Grouped by 1970s Income					*Countries Grouped by 1970s Income*			
	Mean	**Std. Dev.**	**Coeff.Var.**			**Mean**	**Std. Dev.**	**Coeff.Var.**
Low	7.645	0.482	6.303		**Low**	-0.789	0.988	125.183
Middle	8.928	0.406	4.545		**Middle**	4.946	0.369	7.454
High	9.899	0.310	3.135		**High**	10.882	0.778	7.145
All	8.880	0.939	10.570		**All: Separate**[a]	5.214	4.449	85.340
					All: Pooled[b]	5.536	0.434	7.840

Countries Grouped by Geographic Region					*Countries Grouped by Geographic Region*			
	Mean	**Std. Dev.**	**Coeff.Var.**			**Mean**	**Std. Dev.**	**Coeff.Var.**
Africa	7.826	0.756	9.661		**Africa**	-0.630	0.880	139.727
Asia+	8.692	0.711	8.180		**Asia+**	5.509	0.441	7.997
Europe+	9.732	0.506	5.198		**Europe+**	4.702	0.221	4.700
L. Amer.	8.969	0.578	6.448		**L. Amer.**	3.889	0.229	5.891
All	8.880	0.939	10.570		**All: Separate**[a]	3.431	2.336	68.079
					All: Pooled[b]	5.536	0.434	7.840

a Results for all countries are combined after performing regressions separately.
b Results for all countries are from the single pooled regression.

Table 3: **Total Factor Productivity Regressions**
(income categories based on 1960-64 average income)

	lntfp (all 83 countries)		*lntfp (22 low-income)*		*lntfp (38 middle-income)*		*lntfp (23 high-income)*	
lnH	0.0090	-0.0961‡‡	0.0452	-0.1041‡	0.0905‡	0.1246‡	0.0113	0.1805‡
	(0.29)	(-1.64)	(1.03)	(-1.98)	(1.83)	(1.86)	(0.20)	(1.93)
lnx	0.1237*	0.0925*	0.1040*	-0.4192*	0.0936**	0.2052‡‡	0.1923*	0.8285*
	(6.08)	(3.70)	(3.66)	(-3.45)	(2.44)	(1.34)	(3.50)	(2.87)
lnH lnx		0.0395**		0.0569*		-0.0133		-0.0645**
		(2.12)		(4.41)		(-0.75)		(-2.24)
lntot	0.0283‡‡	0.0286‡‡	-0.0163	-0.0325	0.0748*	0.0762*	0.0366	0.0369
	(1.38)	(1.40)	(-0.40)	(-0.87)	(2.69)	(2.73)	(0.78)	(0.81)
lnpd	-0.0703**	-0.0821**	0.0504	-0.0129	-0.0476	-0.0514	0.0183	-0.0090
	(-2.03)	(-2.35)	(0.87)	(-0.24)	(-0.72)	(-0.77)	(0.24)	(-0.12)
ln(1+π)	-0.1550*	-0.1560*	-0.1033**	-0.0972**	-0.2576**	-0.2498**	0.1506	0.0751
	(-3.78)	(-3.82)	(-2.02)	(-2.07)	(-2.45)	(-2.36)	(1.16)	(0.57)
σ_x	-0.0023*	-0.0028*	-0.0083‡‡	-0.0015	-0.0023*	-0.0023*	-0.0033**	-0.0037
	(-3.14)	(-3.65)	(-1.33)	(-0.25)	(-2.63)	(-2.70)	(-2.18)	(-2.48)**
σ_{tot}	0.00003	0.00004	0.0029**	0.0040*	-0.0001	-0.0001	-0.0017	-0.0009
	(0.23)	(0.30)	(2.29)	(3.31)	(-0.68)	(-0.68)	(-0.71)	(-0.38)
σ_{pd}	0.0006‡‡	0.0008‡	0.0008‡	0.0011*	-0.0002	-0.0003	-0.0027‡	-0.0025‡‡
	(1.60)	(1.94)	(1.76)	(2.63)	(-0.22)	(-0.24)	(-1.52)	(-1.43)
σ_{π}	0.0116‡‡	0.0117‡‡	-0.0029	-0.0063	0.0346‡	0.0331	-0.0399**	-0.0313‡
	(1.33)	(1.35)	(-0.16)	(-0.39)	(1.95)	(1.85)‡	(-2.16)	(-1.70)
$\bar{R}^2$	0.3040	0.3101	0.6880	0.7387	0.3444	0.3427	0.8505	0.8573
SEE	0.1166	0.1161	0.1131	0.1034	0.1139	0.1141	0.0922	0.0901

Note: The dependent variable, in each case, is the natural logarithm of total factor productivity. Other variables are defined as follows: *x* is the export-GDP ratio; *tot* is the terms of trade; *pd* is the local price deviation from purchasing power parity; π is the inflation rate; *d75* equals zero in 1960-64, 1965-69, and 1970-74 and equals one in 1975-79, 1080-84, and 1985-89; and σ_i equals the standard deviation of $i = x, tot, pd,$ and π over each 5-year sub-period. Moreover, just like the time dummy variables (results suppressed in this table), *d75* is not adjusted for its mean in the fixed-effect estimation.

* significant at the 1-percent level; ** significant at the 5-percent level.
‡ significant at the 10-percent level; ‡‡ significant at the 20-percent level.

Table 4: **Total Factor Productivity Regressions**
(income categories based on 1970s average income)

	lntfp (all 83 countries)		*lntfp (22 low-income)*		*lntfp (36 middle-income)*		*lntfp (25 high-income)*	
lnH	0.0090	-0.0961‡‡	0.0247	-0.1210**	0.0814‡‡	0.1239‡	0.0024	0.1550‡
	(0.29)	(-1.64)	(0.57)	(-2.29)	(1.61)	(1.75)	(0.05)	(0.07)
lnx	0.1237*	0.0925*	0.0942*	-0.4215*	0.0700**	0.1940‡‡	0.1771*	0.7266*
	(6.08)	(3.70)	(2.73)	(-3.35)	(2.22)	(1.31)	(3.53)	(2.84)
lnH lnx		0.0395**		0.0600*		-0.0135		-0.0561**
		(2.12)		(4.24)		(-0.86)		(-2.19)
lntot	0.0283‡‡	0.0286‡‡	-0.0151	-0.0372	0.0708**	0.0696**	0.0108	0.0063
	(1.38)	(1.40)	(-0.37)	(-0.98)	(2.52)	(2.47)	(0.25)	(0.15)
lnpd	-0.0703**	-0.0821**	-0.0084	-0.0300	-0.0460	-0.0359	0.0122	-0.0089
	(-2.03)	(-2.35)	(-0.14)	(-0.55)	(-0.65)	(-0.50)	(0.18)	(-0.13)
ln(1+π)	-0.1550*	-0.1560*	-0.1189**	-0.1014**	-0.2850**	-0.2743**	0.1057	0.0368
	(-3.78)	(-3.82)	(-2.31)	(-2.13)	(-2.60)	(-2.48)	(0.88)	(0.30)
σ_x	-0.0023*	-0.0028*	-0.0060	-0.0024	-0.0020**	-0.0022**	-0.0029**	-0.0032**
	(-3.14)	(-3.65)	(-0.96)	(-0.41)	(-2.39)	(-2.53)	(-2.07)	(-2.31)
σ_{tot}	0.00003	0.00004	0.0023‡	0.0030**	-0.0001	-0.0001	-0.0023	-0.0018
	(0.23)	(0.30)	(1.78)	(2.46)	(-0.60)	(-0.60)	(-1.05)	(-0.81)
σ_{pd}	0.0006‡‡	0.0008‡	0.0009**	0.0011**	-0.0001	-0.0002	-0.0028‡	-0.0027‡‡
	(1.60)	(1.94)	(2.00)	(2.58)	(-0.06)	(-0.16)	(-1.74)	(-1.70)
σ_π	0.0116‡‡	0.0117‡‡	-0.0021	-0.0048	0.0389**	0.0370**	-0.0353**	-0.0274‡
	(1.33)	(1.35)	(-0.12)	(-0.30)	(2.11)	(1.99)	(-2.05)	(-1.58)
$\bar{R}^2$	0.3040	0.3101	0.5789	0.6427	0.3076	0.3065	0.7703	0.7779
SEE	0.1166	0.1161	0.1136	0.1750	0.1400	0.1166	0.0864	0.0850

Note: The dependent variable, in each case, is the natural logarithm of total factor productivity. Other variables are defined as follows: *x* is the export-GDP ratio; *tot* is the terms of trade; *pd* is the local price deviation from purchasing power parity; π is the inflation rate; *d75* equals zero in 1960-64, 1965-69, and 1970-74 and equals one in 1975-79, 1080-84, and 1985-89; and σ_i equals the standard deviation of $i = x$, *tot, pd,* and π over each 5-year sub-period. Moreover, just like the time dummy variables (results suppressed in this table), *d75* is not adjusted for its mean in the fixed-effect estimation.

* significant at the 1-percent level; ** significant at the 5-percent level.
‡ significant at the 10-percent level; ‡‡ significant at the 20-percent level.

Table 5: **Total Factor Productivity Regressions**
(geographic regions)

	lntfp (Africa: 19 cntrs)		*lntfp (L. Amer: 22 cntrs)*		*lntfp (Asia: 17 cntrs)*		*lntfp (Erp+: 25 cntrs)*	
lnH	0.0058	-0.1160**	-0.0697	-0.1867**	0.0922	0.0097	0.0416	0.2535*
	(0.13)	(-2.15)	(-1.09)	(-2.20)	(1.10)	(0.08)	(0.68)	(3.75)
lnx	0.0827**	-0.3439*	0.1482*	-0.2646‡‡	0.0822‡‡	-0.1545	0.0725‡	0.7212*
	(2.43)	(-2.71)	(3.91)	(-1.30)	(1.32)	(-0.61)	(1.56)	(5.61)
lnH lnx		0.0510*		0.0461**		0.0254		-0.0707*
		(3.47)		(2.06)		(0.96)		(-5.33)
lntot	0.0086	0.0086	0.0218	0.0144	0.0070	0.0070	0.2621*	0.1690**
	(0.23)	(0.25)	(0.99)	(0.66)	(0.10)	(0.10)	(3.50)	(2.44)
lnpd	0.0820**	0.0456	0.0555	0.0518	-0.2600*	-0.2689*	-0.1038‡‡	-0.0844
	(1.24)	(0.72)	(0.82)	(0.78)	(-2.62)	(-2.70)	(-1.39)	(-1.26)
ln(1+π)	-0.1155**	-0.1083**	-0.0408	-0.0520	-0.0985	-0.0389	0.0308	0.0656
	(-2.27)	(-2.26)	(-0.53)	(-0.69)	(-0.27)	(-0.11)	(0.14)	(0.34)
σ_x	-0.0024	-0.0013	-0.0009	-0.0007	0.0048	0.0048	-0.0016**	-0.0025*
	(-0.44)	(-0.24)	(-0.27)	(-0.21)	(0.65)	(0.65)	(-2.38)	(-4.01)
σ_{tot}	0.0025**	0.0026	-0.00003	-0.00001	-0.0077*	-0.0071**	-0.0003	0.0007
	(1.96)	(2.14)	(-0.25)	(-0.11)	(-2.91)	(-2.58)	(-0.10)	(0.29)
σ_{pd}	0.0005	0.0008‡	0.0008‡	0.00004	0.0002	0.0008	-0.0029‡	-0.0025‡
	(1.15)	(1.73)	(0.09)	(0.05)	(0.05)	(0.14)	(-1.52)	(-1.49)
σ_π	-0.0048‡‡	-0.0055	-0.0353**	0.0039	-0.0301	-0.0421	-0.0546	-0.0535
	(-0.28)	(-0.34)	(-2.05)	(0.35)	(-0.08)	(-0.11)	(-1.00)	(-1.09)
$\bar{R}^2$	0.6867	0.7247	0.3578	0.3789	0.5207	0.5202	0.3849	0.5078
SEE	0.1098	0.1029	0.0785	0.0772	0.1452	0.1453	0.0769	0.0687

Note: The dependent variable, in each case, is the natural logarithm of total factor productivity. Other variables are defined as follows: *x* is the export-GDP ratio; *tot* is the terms of trade; *pd* is the local price deviation from purchasing power parity; π is the inflation rate; *d75* equals zero in 1960-64, 1965-69, and 1970-74 and equals one in 1975-79, 1080-84, and 1985-89; and σ_i equals the standard deviation of i = *x, tot, pd,* and π over each 5-year sub-period. Moreover, just like the time dummy variables (results suppressed in this table), *d75* is not adjusted for its mean in the fixed-effect estimation.

* significant at the 1-percent level; ** significant at the 5-percent level.
‡ significant at the 10-percent level; ‡‡ significant at the 20-percent level.

Table 6: Human Capital and Openness Interaction for Countries Classified by 1960-64 Income

	All Countries	**Low Income**	**Middle Income**	**High Income**
Ln H	–0.0961	–0.1041	0.1246	0.1805
Ln x	0.0925	–0.4192	0.2052	0.8285
Ln H ln x	0.0395	0.0569	ns	–0.0645
Openness Threshold (x)	11.4 (1.3, 141)	6.2 (1.3, 75.3)	-- (4.0, 141.2)	16.4 (3.8, 69.0)
Human-Capital Threshold (ln H)	-- (3.4, 14.2)	7.4 (3.4, 13.8)	-- (5.6, 13.4)	12.8 (6.0, 14.2)

Note: Coefficient estimates appear only if significant at the 20-percent level or better; ns means not significant; and – means not calculated. The openness threshold indicates the export to GDP percentage above which the coefficient on human capital changes sign. The numbers in parentheses give the range over which the export to GDP percentage varies for the respective sample. For example, the coefficient on human capital in the all-countries regression equals –0.0961. Once the ratio of exports to GDP exceeds 11.4 percent, then the positive coefficient on the human capital and export interaction term flips the combined sign on human capital to a positive value. The reverse story holds for the high-income regression. The human-capital threshold indicates the value of *ln H* above which the coefficient on openness (*ln x*) changes sign. The numbers in parentheses give the range over which *ln H* varies for the respective sample. (Recall that H equals the stock of human capital in the country, not human capital per worker.) For example, the coefficient on openness in the low-income country regression equals –0.4192. Once the *ln H* number exceeds 7.4, then the positive coefficient on *ln H* human capital openness interaction term flips the combined sign on openness to a positive value. And 7.4 falls within the range over which *ln H* varies (i.e., 3.4 to 13.8) for the low-income countries in the sample.

Table 7: Human Capital and Openness Interaction for Countries Classified by 1970s Income

	All Countries	Low Income	Middle Income	High Income
Ln H	–0.0961	–0.1210	0.1239	0.1550
Ln x	0.0925	–0.4215	0.1940	0.7266
Ln H ln x	0.0395	0.0600	ns	–0.0561
Openness Threshold (x)	11.4 (1.3, 141.2)	7.5 (1.3, 75.3)	-- (2.1, 141.2)	15.8 (3.8, 69.0)
Human-Capital Threshold (ln H)	-- (3.4, 14.2)	7.0 (3.4, 13.8)	-- (5.6, 12.1)	13.0 (6.0, 14.2)

Note: See Table 6.

Table 8: Human Capital and Openness Interaction for Countries Classified by Geographic Regions

	All (83 Countries)	Africa (19 Countries)	Latin American (22 Countries)	Asia (17 Countries)	Europe (25 Countries)
ln H	–0.0961	–0.1160	–0.1867	ns	0.2535
ln x	0.0925	–0.3439	–0.2646	ns	0.7212
ln H ln x	0.0395	0.0510	0.0461	ns	–0.0707
Openness Threshold (x)	11.4 (1.3, 141.2)	9.7 (1.3, 75.3)	57.4 (4.0, 69.0)	-- (2.1, 141.2)	36.1 (3.8, 100.1)
Human-Capital Threshold (ln H)	-- (3.4, 14.2)	6.7 (3.4, 11.0)	5.7 (6.2, 12.1)	-- (6.4, 13.8)	10.2 (6.0, 14.2)

Note: See Table 6.

Appendix:

Table 1A: Countries Classified by Income Per Worker in the Beginning and Middle of the Sample Period

Income Per Worker during 1960-64			Income Per Worker during 1970s		
22 Low:	**38 Middle:**	**23 High:**	**22 Low:**	**36 Middle:**	**25 High:**
Bangladesh	Algeria	Argentina	Bangladesh	Algeria	Argentina
Botswana	Barbados	Australia	Botswana	Barbados	Australia
Ghana	Bolivia	Austria	Ghana	Bolivia	Austria
Guinea-Bissau	Brazil	Belgium	Guinea-Bissau	Brazil	Belgium
Haiti	Chile	Canada	Haiti	Chile	Canada
India	Colombia	Denmark	India	Colombia	Denmark
Indonesia	Cyprus	Finland	Indonesia	Cyprus	Finland
Kenya	Dom. Republic	France	Kenya	Dom. Republic	France
Korea, Rep.	Ecuador	Germany, W.	Lesotho	Ecuador	Germany, W.
Lesotho	El Salvador	Iceland	Malawi	El Salvador	Iceland
Malawi	Fiji	Iran	Mozambique	Fiji	Iran
Mozambique	Greece	Israel	Niger	Greece	Ireland
Niger	Guatemala	Italy	P. New Guinea	Guatemala	Israel
P. New Guinea	Guyana	Mexico	Pakistan	Guyana	Italy
Pakistan	Honduras	Netherlands	Senegal	Honduras	Japan
Senegal	Hong Kong	New Zealand	Sri Lanka	Hong Kong	Mexico
Thailand	Ireland	Norway	Thailand	Jamaica	Netherlands
Togo	Jamaica	Spain	Togo	Jordan	New Zealand
Uganda	Japan	Sweden	Uganda	Korea, Rep.	Norway
Zaire	Jordan	Trinidad &Tob.	Zaire	Malaysia	Spain
Zambia	Malaysia	U.K.	Zambia	Malta	Sweden
Zimbabwe	Malta	U.S.A.	Zimbabwe	Mauritius	Trinidad &Tob.
	Mauritius	Venezuela		Nicaragua	U.K.
	Nicaragua			Panama	U.S.A.
	Panama			Paraguay	Venezuela
	Paraguay			Peru	
	Peru			Philippines	
	Philippines			Portugal	
	Portugal			Singapore	
	Singapore			South Africa	
	South Africa			Swaziland	
	Sri Lanka			Syria	
	Swaziland			Tunisia	
	Syria			Turkey	
	Tunisia			Uruguay	
	Turkey			Yugoslavia	
	Uruguay				
	Yugoslavia				

Note: Number of countries in *low-income* categories (union of 60-64 and 70s): 23, of which Sri Lanka is not in 60-64 classification, and S. Korea is not in the 70s classification. Number of countries in *middle-income* categories (union of 60-64 and 70s): 39, of which Korea is not in 60-64 classification, and Ireland, Japan and Sri Lanka are not in the 70s classification. Number of countries in *high-income* categories (union of 60-64 and 70s): 25, of which Ireland and Japan are not in 60-64 classification, but all countries appear in the 70s classification.

Table 2A: Countries Classified by Geographic Region

Africa: 19	Asia+: 17	Europe+: 25	L. America: 22
Algeria	Bangladesh	Canada	Barbados
Botswana	Hong Kong	U.S.A.	Dom. Republic
Ghana	India	Japan	El Salvador
Guinea-Bissau	Indonesia	Austria	Guatemala
Kenya	Iran	Belgium	Haiti
Lesotho	Israel	Cyprus	Honduras
Malawi	Jordan	Denmark	Jamaica
Mauritius	Korea, Rep.	Finland	Mexico
Mozambique	Malaysia	France	Nicaragua
Niger	Pakistan	Germany, W.	Panama
Senegal	Philippines	Greece	Trinidad &Tob.
South Africa	Singapore	Iceland	Argentina
Swaziland	Sri Lanka	Ireland	Bolivia
Togo	Syria	Italy	Brazil
Tunisia	Thailand	Malta	Chile
Uganda	Fiji	Netherlands	Colombia
Zaire	P. New Guinea	Norway	Ecuador
Zambia		Portugal	Guyana
Zimbabwe		Spain	Paraguay
		Sweden	Peru
		Turkey	Uruguay
		U.K.	Venezuela
		Yugoslavia	
		Australia	
		New Zealand	

Note: Except for Algeria and Tunisia, all the countries in Africa listed here are situated in sub-Saharan Africa. Fiji is located in the Pacific but included here in Asia+. Japan is categorized under Europe+. Five countries from outside of Europe have been included in Europe+: Canada, U.S., Japan, Australia, and New Zealand. Latin America includes Central America (including Mexico), the Caribbean, and South America.