Total Factor Productivity, Social Infrastructure, and Output per Worker: A Cross-Country Analysis[1]

First draft: September 22, 2006
This draft: June 26, 2008

Camelia Minoiu[2] and Emmanuel V. Pikoulakis[3]

Abstract. In this paper we develop and estimate a model of output per worker where total factor productivity is embedded into the model. Unlike previous research, we use the price of capital to proxy for capital intensity and the Economic Security Index developed by the ILO (2004) to capture social infrastructure. Using cross-sectional and panel regressions, we arrive at plausible and robust estimates of the key structural parameters of the model. Our results show that differences in capital intensity and educational attainment account for the bulk of cross-country variation in output per worker, leaving little residual variation. Total factor productivity accounts, at most, for a factor of 2.5 in explaining the 32−fold output gap between wealthy and poor nations.

Keywords: capital intensity, social infrastructure, economic security index, learning-by-doing, Lucas' external effect
JEL Classifications: O11, O39, O47, J24
Wordcount: ~ 9,500

---

[1] We are grateful to Alessandro Cigno, Michael Graff, A.G. (Tassos) Malliaris, Gianluigi Pelloni, Mahvash Qureshi, and Tomasz Wisniewski for helpful comments. We are indebted to Tomasz Wisniewski for his early contribution to this project.
[2] International Monetary Fund, African Department. Email: CMinoiu@imf.org; Tel. 202-623-9731. Fax 202-589-5318.
[3] The University of Hull. Email: EPikoulaki@aol.com

I. INTRODUCTION

It is widely recognized that the standard neoclassical growth model is ill-equipped to explain the large disparities in per capita income between the world's richest and poorest economies. Differences across countries in physical and human capital can only account for a fraction of the 32−fold observed gap in output per worker documented by Hall and Jones (1999). Specifically, if the capital elasticity of output were to equal the share of income from capital in the national accounts (usually taken to be ⅓), variations in capital per worker would only contribute a factor of 2 in explaining the observed output gap (Hall and Jones, 1999; Jones, 2001). Similarly, if the return to education were 10 percent, then differences in human capital alone would also contribute a factor of around 2 in explaining this gap (Jones, 2001). Thus, differences in physical and human capital combined would only explain ⅛th of the observed gap in incomes. The neoclassical theory of growth attributes the vast unexplained income disparities to differences in labor-augmenting technological progress or in total factor productivity (TFP). The major challenge, therefore, is to explain TFP, or, to quote Prescott (1998), "Needed: A Theory of Total Factory Productivity".

Two approaches have been adopted in modeling TFP. In one strand of the literature , technology is taken to be a public good, which implies that TFP cannot play a significant role in explaining cross-country differences in output per worker. An example of this approach is Mankiw, Romer, and Weil (1992), who take a country's TFP to be constant and cross-country differences in TFP to be part of the error term on the assumption that such differences are uncorrelated with the explanatory variables. This approach suffers from two limitations: it provides no insight into the factors that explain TFP and their relative importance, and the empirical analysis is subject to by omitted variable bias. Islam (1995) aims to address the latter by applying fixed effects panel methods to allow for country-specific, time-invariant heterogeneity. The result, however, is that in his empirical model most of country differences in output per worker end up being ascribed to unobserved individual heterogeneity. A second approach is that of modeling TFP in detail. For instance, Hall and Jones (1995) derive TFP residually and then model it separately using the quality of institutions as a proxy. These studies, however, fail to integrate their TFP model into a structural model of labor productivity. Such a model would shed light on the quantitative importance of TFP, on what determines differences in TFP across countries, and on what enables countries to take advantage of technological advances at the frontier of knowledge.

We develop and estimate a model of output per worker where TFP is embedded into a structural model of labor productivity. The aim is to arrive at plausible estimates of the key structural parameters of the model (elasticity of capital in production, returns to schooling) to shed some light on issues such as the mechanism through which technologies transfer among countries, and the role of social infrastructure in productivity. There are two elements of novelty to the study. First, we use the price of capital to proxy for capital intensity. Second, we use the Economic Security Index (*ESI*) developed by the ILO (2004) to capture social infrastructure. Our results are empirically robust and the parameters of our model suggest that differences in capital intensity and education account for the bulk of cross-country variation in output per worker, leaving little residual variation. TFP accounts, at most, for a factor of 2.5 in explaining the 32−fold gap in output per worker between wealthy and poor nations.

Several studies share the view that the standard neoclassical growth accounting understates the importance of physical capital accumulation in explaining cross-country income differences (Mankiw, Romer, and Weil, 1992; Barro and Sala-i-Martin, 1999; Howitt, 2000). Allowing differences in capital intensity to play a bigger role in explaining cross-country output differences enables us to introduce capital market behavior into the model in a rich and meaningful way. An early attempt to introduce the price of capital as a determinant in a model of growth is Jones (1994). The author establishes a negative relation between growth and the price of capital which he attributes to distortions that keep this price above its *equilibrium* level in poor economies. Parente *et al* (1999, 2000) argue that when distortions in the price of capital are introduced in a model with a household sector, implausible parameter values in production are no longer needed to explain the large disparities in incomes between poor and rich nations. Distortions in the price of capital not only inhibit capital accumulation but also divert resources from the market economy to the household sector. In an analysis of relative prices and wealth, Hsieh and Klenow (2007) demonstrate that the difference in investment rates between rich and poor economies are not the result of distortions. Instead, they reflect the relative inefficiency of poor economies in converting consumption goods into investment. Pikoulakis and Minoiu (2006) go one step further to introduce capital market equilibrium to explain empirically the relation between capital intensity, the price of capital, and the gap in output per worker between poor and wealthy nations.

In this study we use the price of capital to proxy for capital intensity and we distinguish between shocks that affect the demand and supply schedules for capital. Shifts in the supply schedule for capital arise from innovations in the technology of converting consumption goods into investment (installation costs technology) and by variations in tax rates—net of investment tax credits—on the purchase of investment goods. Shifts in the demand schedule arise from innovations that change the profitability of capital. By distinguishing between the two schedules we are able to control for shifts in both and are thus better placed to arrive at unbiased estimates of the elasticity of capital in production. In addition, this set-up allows us to explain how spillover effects and/or technical transfers take place. To illustrate, suppose—as in Coe and Helpman (1995)—that a country's TFP depends on its own research and development (R&D) as well as that of its trading partners so that an improvement in the technology of the trading partners improves the productivity of home capital. As a result, the demand schedule for capital in the home economy shifts outwards, raising the price of capital, and inducing a process of capital accumulation in line with the thinking behind Tobin's Q. Finally, our modeling of capital markets can—to some extent—address questions such as why capital does not flow from rich to poor countries (Romer, 1996) and why saving and investment rates are highly correlated in industrialized countries in the presence of a global capital markets (the Feldstein-Horioka puzzle, 1980).

As we use a broad definition of physical capital that emcompasses some form of intangible capital, our cross-country analysis shares features with the firm-level literature on organizational capital. For example, Black and Lynch (2004, 2005) define organizational capital to capture workforce training, employee voice, and work design, while Kruse and Blasi (1998) include employment security and selection systems among "high performance work practices". These studies demonstrate that workplace practices with a high component of organizational capital raise worker productivity and are likely to lead to an increase in overall firm productivity. Since the amount of organizational capital provided by firms would fall short of the social optimum in a decentralized economy, societies have adopted labor market institutions to protect and improve worker skills. The quality of these labor market institutions—viewed broadly as social infrastructure—serves as the ideal candidate for modeling intangible capital.

To capture the quality of institutions which govern workplace practices, we use the Economic Security Index (*ESI*) developed by the International Labor Organization (ILO, 2004). The index is based on the idea that as uncertainty increases, the modal citizen must spend more time on risk-control activities and less time on developmental, freedom-enhancing activities. The index encompasses seven concepts of security, but double weight is given to income security—essential for the freedom to make choices—and to representation security—essential to enable the vulnerable to retain income security (ILO, 2004). The highest-ranking five countries on the *ESI* ladder are Sweden, Finland, Norway, Denmark, and the Netherlands. The lowest-ranking five nations are Nepal, Sierra Leone, Bangladesh, Rwanda, and Burundi. Figure 1 illustrates how the *ESI* maps to output per worker across countries.

Although "the definition of social infrastructure as institutions and policies that promote production and investment over diversion and consumption is very broad" (Romer, 2001, p.148), we find that the *ESI* captures well the quality of country-level institutions and policies. Alternative institutional quality measures have been proposed in the literature to model intangible capital, including the rule of law, bureaucracy quality, corruption, risk of expropriation, government repudiation of contracts, and openness to international trade—all of which are suggestive of governments' commitment to fighting private diversion and limiting the scope of rent-seeking (Hall and Jones, 1999). Indices which more narrowly measure the quality of social infrastructure in labor markets have also been proposed in the literature (see Botero *et al*, 2004 for indices on employment contracts, collective relations, and social security; and Tang, 2008 for an analysis of worker skill acquisition in protective labor markets). While such measures are worthy alternatives, we focus on the index developed by Hall and Jones (1999) and show that the *ESI* fares well in terms of predictive power in a straightforward comparison with it.

Our approach to studying the central role of social infrastructure in economic growth differs from Hall and Jones (1999). For example, the authors estimate the effect of social infrastructure on output per worker through its distinct impact on physical capital, human capital, and TFP. In contrast, our approach to modeling social infrastructure in particular and output per worker in general follows a more conventional route. Keeping in line with the tradition, we estimate a structural model of output per worker whose key constituent parts are the intensity of physical capital, human capital, and TFP. We view social infrastructure as playing a central role in modeling TFP. In particular, we use the *ESI* to capture the direct effect of social infrastructure on labor productivity and we also interact it with schooling and the price of capital. The interaction of *ESI* with schooling is meant to capture the net result of a negative and a positive effect associated with schooling. The negative effect derives from a reduction in the average number of hours a representative worker supplies in the market to accommodate more schooling. The positive effect derives from an externality associated with schooling akin to Lucas' *external effect* (Lucas, 1988). The interaction between *ESI* and the price of capital is meant to capture adjustments in labor productivity deriving from innovations that affect the profitability of capital in general and that can account for spillover effects and/or technical transfers in particular. Nevertheless, it should be noted that externalities associated with human capital aimed at capturing Lucas' *external effect* can only be measured well if we can control for the *hours* each worker supplies, on average, for market activities. That is because the decision to work part time to attend additional schooling reduces output per worker. An analysis of this type, however, is limited by the fact that data on hours per worker is not available for most developing economies.

The remainder of the paper is organized as follows. Section II presents our benchmark model. In Section III we model, in detail, the three determinants of cross-country differences in output per worker (capital intensity, human capital, and TFP). Our empirical strategy and results are outlined in Section IV. Section V concludes the paper. All tables and figures are deferred to the appendix.

II. Our Benchmark Model

Our benchmark model is the version of the neoclassical model popularized by Hall and Jones (1999). Output is assumed to exhibit constant returns to scale in physical capital and in effective human capital. To describe this relationship, let the production function be:

$$(1)\ Y=(AH)^{1-\alpha}(K)^{\alpha}=(AH)\left(\frac{K}{AH}\right)^{\alpha}$$

where Y is output, A—the effectiveness of human capital, H—the stock of human capital, K—the stock of physical capital, and α is the elasticity of output with respect to physical capital. Country subscripts are omitted for simplicity.

It is convenient to define H as the product of the human capital embodied in the representative worker h and the number of workers currently employed L:

$$(2)\ H\equiv hL$$

Combining (1) with (2) we obtain the following expression for output per worker:

$$(3)\ \frac{Y}{L}\equiv y\equiv(Ah)\left(\frac{K}{AhL}\right)^{\alpha}=(Ah)\left(\frac{k}{Ah}\right)^{\alpha}$$

where $k\equiv\frac{K}{L}$. Using (1)−(3), we can confirm that

$$(4)\ \left(\frac{K}{AH}\right)^{\alpha}\equiv\left(\frac{k}{Ah}\right)^{\alpha}=\left(\frac{Y}{K}\right)^{\alpha/\alpha-1}$$

Substituting back into (3) yields

$$(5)\ y=(Ah)\left(\frac{Y}{K}\right)^{\alpha/\alpha-1}$$

Using subscript r for rich economies and subscript p for poor economies, the equation below reflects the relative importance of A, h and $\frac{K}{Y}$ in explaining the cross-country gap in output per worker:

$$(6)\ \ln\left(\frac{y_r}{y_p}\right)=\ln\left(\frac{A_r}{A_p}\right)+\ln\left(\frac{h_r}{h_p}\right)+\frac{\alpha}{1-\alpha}\ln\left(\frac{K_r}{Y_r}/\frac{K_p}{Y_p}\right)$$

How important is the contribution of each term in (6) in accounting for the large gap in output per worker between the richest and poorest economies? We proceed to provide an answer to this question by describing the building blocks of our model before taking it to the data.

III. The Building Blocks of the Benchmark Model

First, note that a stochastic, equilibrium, log-linear version of equation (5) can be described as follows:

$$(7)\ \ln y_{it}=\ln A_{it}+\ln h_{it}+\frac{\alpha}{\alpha-1}\ln\left(\frac{Y}{K}\right)_{it}+\gamma_t+c_i+\varepsilon_{it}$$

where t and i are the subscripts for time and cross-sectional units (years and countries, respectively), γ_t are intercepts allowing for year-specific shocks, c_i is a country-specific unobserved time-invariant fixed effect, and ε_{it} is white noise.

What follows describes the building blocks of our benchmark model, beginning with our modeling of the effectiveness of human capital.

A. Modeling the Effectiveness of Human Capital

Let us consider an identity that links the effectiveness of human capital in the *i*th country with the world frontier of technical progress:

$$(8)\ A_{it}\equiv\frac{A_{it}}{A_{wt}}A_{wt}=\frac{A_{it}}{A_{wt}}A_{w0}e^{gt}$$

where A_w represents the world frontier of the stock of usable knowledge assumed to grow at the rate g. To identify the main factors that enable countries to make better use of this stock of knowledge, let A_{it} be defined as follows

$$(9)\ \ln A_{it}=\beta_3\left(\ln ESI\right)_i+\beta_4\left(ESI\times\ln\left(\frac{Y}{K}\right)\right)_{it}+\beta_5(ESI\times\ln Sch)_{it}+\beta_6\left(Geo\right)_i+\ln\left(A_w\right)_0+gt+u_{it}$$

The first term in (9) is the *ESI* that measures the quality of labor market institutions. The second—an interaction between the *ESI* and the average product of capital—captures country-specific technology transfers and/or spillover effects. The third term interacts the *ESI* with schooling to control for the loss in output that results from a worker's decision to enter schooling and for any externalities attached to schooling. The fourth term accounts for the effects of climate and geography on productivity. The last three terms are the initial stock of world-wide usable knowledge (taken to be constant), trend growth, and a white noise error term.

Economic Security $\left(\ln(ESI)\right)$

At the firm level, worker productivity is positively related to firms' workplace practices which encourage workers to acquire and improve skills (Black and Lynch, 2001, 2004, 2005). At the societal level, a similar effect would be captured by the quality of institutions designed to protect and improve worker skills. Our measure of the quality of social infrastructure in the labor market captures the following types of security: (1) Labor Market Security; (2) Employment Security; (3) Job Security; (4) Work Security; (5) Skill Reproduction Security; (6) Income Security; and (7) Representation Security, each of which is represented by a sub-index. The seven sub-indices are weighed into the overall *ESI* estimated by the ILO for 90 countries.

To demonstrate the usefulness of the index as a measure of labor market institutional quality, we describe each of its components in turn. The Work Security index measures the extent to which the working environment affords workers safety against accidents or illness and the extent to which it puts limits on working time, unsociable hours, or night work for women. The Employment Security index measures protection against arbitrary dismissal, regulations on hiring and firing, imposition of costs on employers for failing to adhere to rules, etc. The Job Security index and the Skills Reproduction Security index capture, essentially, the extent to which workers can protect and improve upon their skills and career. The Labor Market Security index reflects the availability of employment opportunities through state-guaranteed employment. The Representation Security index measures the extent to which the state protects the collective voice of both workers and employers, expressed through independent trade unions and employers' associations. Finally, the Income Security index measures the extent to which the state protects a minimum income for workers to retain for the present and future, and pays attention to issues of income inequality through measures such as minimum wage laws, wage indexation rules, supplements to low income earners, and progressive taxation.

Technology Transfers and Spillover Effects $\left(ESI \times \ln\left(\frac{Y}{K}\right)\right)$

The interaction term between ESI and the average product of capital is aimed at capturing the fact that an economy with a high (low) quality of social infrastructure is better (less well) placed to benefit from a positive productivity shock or to neutralize the effects of a negative shock on income. To illustrate the economics behind this term, consider the effects of a labor-augmenting productivity shock on capital. The shock raises the effectiveness of human capital, thereby improving the productivity of existing physical capital. As a result, agents are willing to pay a higher price to hold the existing capital in their portfolios, setting in motion the process of capital accumulation associated with a rise in Tobin's Q. In other words, once we account for the effects of adjustment (installation) costs of capital, positive (negative) productivity shocks shift out (in) the demand schedule for capital, thus raising (reducing) the demand price of capital and setting in train the effects on capital accumulation associated with Tobin's Q.

This interpretation becomes more nuanced in our setting. Other things equal, we expect agents to be willing to pay a higher price to hold the existing capital in their portfolios when the quality of workplace laws and institutions is high and the productivity of capital is high. Therefore, variations in the interaction between ESI and the average product of capital will capture the extent to which each country is able to reap the benefits of technology shocks through technology transfers and/or spillover effects.

Economic Security and Schooling $\left(ESI \times \ln(Sch)\right)$

Other things equal, we would expect the interaction between ESI and schooling to mainly capture a positive externality effect similar to Lucas' *external effect*, which derives from a measure of the average level of accumulated human capital. However, in an economy where the agent can choose her number of work hours, she would be more inclined to choose part-time work when there are opportunities to acquire more schooling or participate in off-the-job training schemes. Assuming that most part-timers are attending some form of education or training, then the higher the average level of education in an economy, the higher the fraction of part-timers, the lower the average number of hours a worker supplies, and the lower her output. Moreover, the higher the level of economic security, the bigger the loss of output if agents choose to acquire more schooling. Therefore, once we control for economic security and average educational attainment, we expect the interaction term between the two to capture primarily the average number of hours of work supplied, leading to a negative coefficient estimate. If the product of this coefficient estimate with the sample average of the ESI is below unity (in absolute value), then schooling can be interpreted as conferring an externality effect similar to Lucas' *external effect.*

Geography $\left(Geo\right)$

In developing countries particularly, geography affects health and, thus, the quality of effort per hour and the number of hours for which a worker is employed (see Bloom, Sachs, Collier, and Udry, 1998; Sachs, 2000, 2003; Hausmann, 2001; Carstensen and Gundlach, 2006 on the relation between geography, disease vulnerability, and output per worker). To account for this effect, we include a geography variable which measures the percentage of a country's area that lies in the tropics and we expect the coefficient on geography to be negative. Notably, we do not include other health variables in the empirical model partly to preserve degrees of freedom, and partly because recent research suggests that standard variables such as life expectancy are only weakly correlated with subsequent economic performance over long time horizons (see Acemoglu and Johnson, 2007 for an analysis on a sample of developed nations).

B. Modeling Human Capital

If we interpret educational attainment as the time spent at school and if we assume the return to schooling to be constant, we can follow Jones (2001) to model human capital as follows:

(10) $h_{it} = e^{rs(Sch)_{it}}$

where rs is the marginal return to schooling. Since returns to schooling are diminishing in the years of schooling, we replace the schooling term by its logarithm. Thus, a linear version of (10) is given by

$$(11)\ \ln h_{it} = \beta_2 \ln(Sch)_{it}$$

The return to schooling for the *i*th country can be obtained by dividing the coefficient β_2 by the time average of schooling years for that country.

C. The Price of Capital, the Return on Capital, and the Equilibrium Capital Intensity

If capital-output ratios in rich economies are 3 to 5 times higher than those in poor economies, then the marginal product of capital (*mpk*) in poor economies must be 3 to 5 times higher than that in rich economies. This has led to the question of why capital does not flow from rich to poor economies. One explanation was offered by Romer (1996, p.135), according to whom "..tax policies, the possibility of expropriation, capital-market imperfections, and so on could cause capital not to flow to poor economies in the face of such differentials". While these reasons are clearly important, the data supports a simpler, yet compelling interpretation. As detailed in Pikoulakis and Minoiu (2006), there is little reason to believe that rates of return, or saving rates measured in current prices, vary considerably across countries in equilibrium. Therefore, if investment rates in international prices are low in poor countries, it is because the relative price of capital is much higher in poor economies—perhaps as much as 3 times higher (see also Hsieh and Klenow, 2007). This implies that variations in the relative (PPP) price of investment can proxy for variations in the average product of capital.

To fix ideas, consider the relation between the average product of capital and the rental price of capital in equilibrium:

$$(12)\ \ln\left(\frac{Y}{K}\right) \equiv \ln\left(\frac{mpk}{\alpha}\right) \equiv -(1-\alpha)\ln\left(\frac{k}{Ah}\right) = \ln\frac{rQ}{\alpha} = b + \ln Q$$

where $b \equiv \ln\frac{r}{\alpha}$ and r is the interest rate (gross of depreciation, taken to be constant along the steady-state path) and Q is the relative price of capital. Our hypothesis is that either b does not differ appreciably across countries or that these differences can be modeled to represent time invariant, country-specific unobserved heterogeneity. Accordingly, our hypothesis is that variations in the real price of capital can proxy for variations in capital intensity and that the elasticity of the (real) price of capital can measure the elasticity of output per worker with respect to capital intensity.

D. Interpreting the Parameters of the Model

Using (12) to substitute out the output-capital ratio in (7) and (9), our equilibrium, stochastic model of output per worker is given by

$$\begin{aligned}(13)\quad \ln y_{it} &= \beta_1 \ln Q_{it} + \beta_2 \ln Sch_{it} + \beta_3 \ln ESI_i + \beta_4 (ESI \times \ln Q)_{it} + \beta_5 (ESI \times \ln Sch)_{it} + \\ &+ \beta_6 (Geo)_i + \gamma_t + c_i + \varepsilon_{it}\end{aligned}$$

Equations (7), (10), and (11) confirm that the return to an extra year of schooling enjoyed by the representative worker in the *i*th country is found by dividing β_2 by the time average of schooling. Equations (7) and (10) imply that the absolute value of β_1 equals $\left(\alpha / 1-\alpha\right)$, which readily reveals the elasticity of capital in production.

Interestingly, the interaction of the *ESI* with the price of capital can also reveal the size of the elasticity of capital in production. This is because we expect the product of β_4 with the sample average of the *ESI* to equal $\left(\alpha / 1-\alpha\right)$. To see this, we combine (5) with (9) and (12) and we suppress subscripts, stochastic terms, constant terms, and the time trend, to write

$$\begin{aligned}(14)\quad \ln A &= \ln\left(\frac{y}{h}\right) + \frac{\alpha}{1-\alpha}\ln\left(\frac{Y}{K}\right) = \ln\left(\frac{y}{h}\right) + \frac{\alpha}{1-\alpha}\ln Q = \beta_3 \ln ESI + \beta_5 (ESI \times \ln Sch) + \beta_6 Geo + \\ &+ \frac{\alpha}{1-\alpha}\ln Q = \beta_3\left(\ln ESI\right) + \beta_4 (ESI \times \ln Q) + \beta_5 (ESI \times \ln Sch) + \beta_6\left(Geo\right)\end{aligned}$$

Thus, we have two sources to arrive at a measure of the elasticity of capital. What is of further interest is that both these measures are predicated on our hypothesis that capital market equilibrium—in a global setting—requires that rates of return on capital equalize across countries via adjustments in the price of capital. Accordingly, our model can shed light on the issue of whether technology transfers can be mediated through variation in asset prices. Moreover, if capital markets clear by adjustments in the rental price of capital, we should not be surprised to find a high correlation between saving rates and investment rates, thus mitigating the need for a country to lend or borrow abroad.

IV. Estimation

A. Sample of Countries

Our sample contains 33 countries which fulfilled the following three criteria during the period analyzed (1960−2000). First, they operated a market economy, and had high quality data on output per worker and the relative price of capital.[4] Second, they possessed full data on all other variables. Third, they yielded evidence that output per worker and the relative price of capital—the two variables that were found to be non-stationary—formed a co-integrating relationship, which is a property crucial to the analysis since our hypotheses are meant to apply to countries

[4] Data quality A−C in the PWT Mark 6.1 (Heston, Summers, and Aten, 2002).

exhibiting conditional convergence.[5]

Our cross-sectional dataset contains country-specific time-averages of each series (over 1960−2000) which have been cross-sectionally demeaned. In our panel dataset, all variables represent quinquennial averages between 1960−1964 and 1995−2000. Variable definitions, data sources, and summary statistics are included in the appendix (Tables 1−3).

B. Cross-sectional Results

Specification and Statistical Significance

The most comprehensive specification we estimate is cast in dynamic form since macroeconomic variables rarely adjust to their long-run equilibrium instantaneously. We consider the following cross-sectional specification:[6]

$$\begin{aligned} \ln y_i = {} & \beta_0 \Delta_T y_i + \beta_1 \ln Q_i + \beta_2 \ln Sch_i + \beta_3 \ln ESI_i + \beta_4 (ESI \times \ln Q)_{it} + \beta_5 (ESI \times \ln Sch)_{it} + \\ & + \beta_6 (Geo)_i + \varepsilon_i \end{aligned} \tag{15}$$

In writing (15) we have applied a Bewley-type linear transformation (Banerjee *et al*, 1993; Pesaran and Smith, 1995), which has the advantage that it readily yields long-run average coefficients and mean lag estimates together with their standard errors.[7] However, this leads the dynamic income term to be correlated with the error term. Moreover, schooling, the *ESI*, the price of capital, and the interaction terms are likely to be endogenous due to feedback from the dependent variable. To alleviate this problem, we employ an instrumental variables estimation strategy for all covariates other than the (strictly exogenous) geography term. Before discussing the cross-sectional results (shown in Table 4), we describe the instruments in more detail.

The instruments for schooling and the price of capital represent lagged values of each endogenous variable. That is, the two regressors are averaged over the period 1965−2000, while their instruments represent averages over 1960−1995. Clearly, these instruments are not exogenous (by construction and due to time correlation), but we rely on the Hansen-Sargan test of over-identification to determine whether there is sufficient evidence that the instruments taken together are valid. The dynamic term in income is instrumented with initial income.

In line with the literature, we instrument for economic security with ethnic fractionalization. This variable has been amply and successfully employed in empirical analyses of the determinants of cross-country income levels and growth (see Mauro, 1995; Easterly and Levine, 1997). We are confident that ethnic fractionalization captures a large amount of the exogenous variation in the *ESI* as reflected in the simple correlation between the two variables (Figure 2) and the high first-stage F-statistics. The Hansen-Sargan test comfortably fails to reject the null of instrument

---

[5] For a thorough treatment of cointegration in the context of cross-sectional and panel data (where *T* is not fixed), see Pesaran and Smith (1995) and Phillips and Moon (1999). A longer discussion of the issues involved in our specifications is also included in Pikoulakis and Minoiu (2006, pp. 11-12).

[6] In cross-sectional regressions, we do not include all regressors at once due to the few degrees of freedom available and the high degree of correlation between the interaction terms.

[7] $\Delta_T y_i = \dfrac{y_{iT} - y_{i0}}{T}$.

validity in 4 out of 6 regressions, and marginally in 2 out of 6 regressions. A remaining concern is whether the instrument satisfies the exclusion restriction. In their analysis, Hall and Jones (1999) find that ethnic fractionalization is insignificantly correlated with per capita income, a finding we replicate in our sample.[8] Similarly, the assumption in the literature is that ethnic fractionalization satisfies the exclusion restriction since it typically is used either as an instrument for institutional quality (Easterly, 2001) or as one of its fundamental determinants (Alesina *et al*, 2003). In cross-country analyses, it is institutional quality itself—as opposed to ethic fractionalization—which is considered to be a long-run determinant of income (Acemoglu, Johnson, and Robinson, 2005). We use this evidence to support the view that ethnic fractionalization does not have an impact on per capita income except through its effect on the quality of institutions—in our case, social infrastructure.

As anticipated, we find that economic security is strongly positively correlated with output per worker (Table 4). The interaction terms between *ESI* and schooling, and *ESI* and the price of capital are also significant and have the expected sign. This demonstrates that countries with high *ESI* are better placed to use more effectively the skills accumulated through schooling, and to exploit profitable opportunities in general and opportunities afforded by *learning-by-doing* in particular. The term on geography is also significant and enters with the expected sign indicating that climate plays an important role in explaining the productivity gap between rich and poor countries. While the term on schooling enters with the expected sign, this term has a statistically significant coefficient only when the regressions account, in addition to schooling, for the interaction of schooling with the *ESI*. In other words, at the aggregate level the contribution of schooling to output can be measured with precision when we control for the fact that the decision to acquire more schooling reduces the number of hours workers are able to supply in the market. The coefficient on the price of capital enters with the expected sign and in most cases is also statistically significant. However, to measure the elasticity of capital intensity in production, we must control for variations in the profitability of capital proxied by the interaction of the price of capital with the *ESI*. It is clear, therefore, that in principle a relatively comprehensive specification like (15) is preferable to a more parsimonious specification, although limitations such as small samples and multicollinearity often render feasible simpler specifications.

Economic Significance

The coefficients on the $\Delta_T y$ terms provide a measure of the mean lag, hence also a measure of the speed of adjustment to the balanced growth path. Given that our data consist of 5−year averages, these coefficients suggest a speed of adjustment ranging from 3.5 to 3.75 percent per year. Thus, the time it takes output per worker to reach halfway towards its balanced growth path—the *half-life*—ranges from 18.4 (=69/3.75) to 19.7 (=69/3.5) years.

In the four richest countries in our sample, a typical agent (over the age of 25) has attained, on average, 9.2 years of schooling. According to Table 4 regressions 3 and 4, this translates to a marginal return to schooling between 5.7 and 6.2 percent per year. Our data on schooling for the four poorest countries (India, Indonesia, Senegal, and Sri Lanka) suggests that a resident in these countries has attained, on average, 3.04 years of schooling, which translates to return on an extra year of schooling between 17.4 and 18.8 percent. These results are consistent with those arising

[8] The results are not shown, but are available from the authors upon request.

from Mincerian wage regressions (e.g., Psacharopoulos, 1994).

Having controlled for the direct effect of educational attainment on productivity, we turn to the net result of two indirect effects: (a) A negative effect deriving from a reduction in the average number of hours a representative worker supplies in the market to accommodate more schooling; (b) A positive externality effect akin to Luca's *external effect*. Given that the population average[9] for the *ESI* is 0.47, the interaction terms in regressions 3 and 4 suggest that a one percent reallocation of time from work to schooling reduces output per worker by 0.4 percentage points, leaving room for an *external effect*. It is worth mentioning that for a resident of a poor country who leaves employment to obtain an extra year of schooling, the "effective" opportunity cost is 7 percent (using the *ESI* average for the four poorest economies). It follows that the opportunity cost to pursue further schooling—once employed—is not particularly harsh in a poor country.

Regressions 5 and 6 can provide more precise estimates for the elasticity of capital intensity in production. Coefficient estimates range between 2.15 and 2.43 and translate to a value for α between 0.68 (=2.15/3.15) and 0.71 (=2.43/3.43). To arrive at these estimates, however, it is crucial to control for shifts in the demand schedule for capital to account for innovations in the productivity of capital. For instance, innovations at the world frontier of R&D raise the productivity of existing non-human (and human) capital in every economy through spillover and/or technical transfer effects and this sets in motion the process of net capital formation described above. Using the population average for *ESI* to evaluate the elasticity of output with respect to the demand price for capital, we obtain an elasticity of 1.4 ($=2.997\times0.47$) and 1.47 ($=3.133\times0.47$) in regressions 5 and 6, respectively. From equation (14) we learn that—given the stock of non-human and human capital—a one percentage point innovation in the effectiveness of labor requires an adjustment of $\left(\alpha/1-\alpha\right)$ percentage points in the price of capital for markets to clear. This implies an estimate for α between 0.58 and 0.6—one which is not significantly different from the estimates described above. This lends support to our modeling of the transfer of technologies among countries. More generally, it supports our use of the real price of capital as a proxy for variations in capital intensities and in the profitability of capital.

Applying an average treatment effect (ATE) on the *ESI* yields elasticity estimates that range between 1 and 1.27. This implies that differences in social infrastructure can account for a factor that can exceed a 3−fold contribution in explaining the (nearly) 10−fold difference in output per worker between the four richest and the four poorest economies in our sample (Belgium, Canada, the Netherlands, and the US vs. India, Indonesia, Senegal, and Sri Lanka). In panels 5 and 6 differences in human capital and in capital intensities combined explain a factor of a little more than 5 of the differential in output per worker referred to above. This means that the residual factor ascribed to multifactor productivity accounts for a little less than 2. Finally, the in-sample predictive power of regressions 3−6 is excellent. On average, the covariates explain more than 95 percent of the recorded in-sample difference in output per worker.

[9] By population average we mean the average of the *ESI* across the 90 countries for which the ILO constructed the index.

C. Panel Results

Our dynamic panel specifications—shown in Table 5—are autoregressive distributed lag versions of (12) estimated using the system GMM estimator proposed by Blundell and Bond (1998). The findings broadly confirm those from the cross-sectional setting.

The system GMM estimator is appropriate in this setting due to the dynamic nature and small time dimension of the panel (eight averages), and the likely high persistence in the dependent variable. The estimator combines orthogonality conditions from two equations (one in levels and another in differences) creating a large and powerful instrument set (representing past levels and past differences of the endogenous variables). The estimator has been shown to outperform alternative estimators which only use a subset of instruments from either equation (e.g., Arellano and Bover, 1995; Arellano and Bond, 1991). Together with our results, we present a battery of specification tests which confirm that the estimates are reliable. In particular, the Hansen statistic indicates that the instruments are valid while the Arellano-Bond residual autocorrelation statistics demonstrate that the instruments corresponding to the differenced equation are both valid and relevant. As before, we treat all explanatory variables other than geography as endogenous.

Notably, when (heterogeneous) random coefficients are present, dynamic panels (unlike dynamic cross sections) are vulnerable to biases difficult to eliminate by instrumental variables methods unless the explanatory variables exhibit no persistence (Pesaran and Smith, 1995). One way to address this issue—at least partially—is to also estimate a static panel and compare the results with those from the dynamic model. Accordingly, we apply the system GMM estimator to a static version of our model, in which the lagged dependent variable is omitted and the only reference to time is through a linear time trend (Table 6). After estimating a static and a dynamic version of a pooled regression on labor demand, Pesaran and Smith (1995) reported that "The most obvious feature of the results is the erratic performance of the dynamic pooled model, whose estimates are very sensitive to specification" (p.100). In our model, key parameter estimates such as the elasticity of schooling, the elasticity of capital intensity in production, and the coefficient on the interaction between *ESI* and the price of capital seem to exhibit more stability and precision in the static version.

As shown in Table 5, estimates of the speed of convergence to the balanced growth path range from 2.8 percent per year (panel 2) to 3.42 percent per year (panel 6), indicating a somewhat slower rate of convergence than in the cross-sectional case. Setting lagged output per worker equal to its current value we arrive at estimates of the long-run equilibrium multipliers. The last two panels are particularly useful in revealing precise estimates of the elasticity of capital intensity. Long-run equilibrium values range from 1.45 (panel 5) to 1.71 (panel 6), translating into an α value between 0.59 (=1.45/2.45) and 0.63 (=1.71/2.71). The coefficient on the interaction of the *ESI* with the real price of capital is measured with some precision in panel 6 and to a lesser extent in panel 5. Evaluating the elasticity associated with this interaction term at the population average for the *ESI* we obtain a long-run value of 1.39 which implies an α value of 0.58 (=1.39/2.39). To conclude, whether we use the supply price or the demand price of capital to capture variation in capital intensity, we obtain estimates for α which are not statistically significantly different.

The elasticity of schooling is measured with some precision in panels 3, 4, and 7. For a resident in a rich country these elasticities imply a return to schooling that ranges from 7 percent (panel 7) to between 7.34 and 7.9 percent (panels 3 and 4, respectively). For a resident in a poor country the range is 21 to 24 percent. Not surprisingly, panels 3, 4, and 7 are particularly useful in producing reasonably precise estimates for the coefficient on the interaction term between schooling and the *ESI*. Evaluated at the population average for the *ESI*, these panels suggest that a one percent reallocation of time from work to schooling reduces long-run output per worker between 0.49 and 0.53 percentage points (panels 7 and 4, respectively).

Having controlled for the contribution of human capital and of the intensity of physical capital, there remains a residual factor of about 2.7 which, by definition, measures the contribution of multifactor productivity. Finally, using panels 3, 4, and 6 to estimate an average treatment effect on the *ESI* yields elasticity estimates between 1.12 and 1.4—a range rather similar to that obtained in the cross-sectional analysis.

The coefficient estimates in Table 6 are the long-run equilibrium multipliers of the model, and the standard errors apply directly to them. In panels 5−8 we control for variations in capital intensity that arise from the supply side as well as the demand side of the model. Therefore, these panels are particularly useful as they deliver more precise estimates of one of the key parameters, specifically β_1. To begin with, elasticity estimates for capital intensity measured from the supply side of the model range from 1.66 to 1.91 (panels 7, 6). These estimates translate to a range for α values between 0.62 (=1.66/2.66) and 0.66 (=1.91/2.91). Evaluating the interaction between the *ESI* and the price of capital at the population average for the *ESI* we arrive at elasticity estimates of capital intensity measured from the demand side of the model that range from 1.04 ($=2.216\times0.47$) to 1.43 ($=3.051\times0.47$) and imply α values between 0.51 (=1.04/2.04) and 0.59 (=1.43/2.42). One can readily confirm that estimates of α derived from the supply side of the model are not statistically significantly different from estimates derived from the demand side.

It is reasonable to assume that estimates of the elasticity of schooling more accurately reflect the return to schooling when one accounts for the interaction of schooling with social infrastructure. Accordingly, panels 3, 4, 7, and 8 are deemed to deliver more precise estimates of a second key parameter, namely β_2. The elasticity of schooling that emerges from these regressions is between 0.39 and 0.43, implying an annual return to schooling between 4.2 and 4.7 percent for a resident of a rich country and between 12.8 and 14.1 percent for a resident of a poor country (in our sample). Our interpretation of the fact that the interaction of schooling with the *ESI* is statistically insignificant is that the positive externality associated with schooling just offsets the negative effect on productivity associated with the reduction in the supply of hours per worker to allow for extra schooling.

To get a measure of the combined direct and indirect effects of social infrastructure we propose to measure the average treatment effect of the *ESI*. The direct and indirect effects of the *ESI* combined average an elasticity of 1.03 of which a fraction of 1/5 accounts for the indirect effects of the *ESI*. On the basis of panel regressions 5−8—those that provide relatively precise estimates for the elasticities associated with the supply and demand price of capital—we conclude that inputs in production account for a factor of 4.8 of the gap in productivity per worker, leaving a factor just over 2 to account for total factor productivity. Finally, it is worth noting that geography does not seem to play a significant role in this static version of the model. Without further investigation on this issue, we may conclude that geography is an imperfect proxy.

In contrast to panels 5−8, the first four regressions can explain only a factor of 2.2 of the gap in output per worker between rich and poor nations, leaving a residual factor of 4.4. The key difference in these results is attributed to whether or not one controls for variations in capital intensity that arise from innovations in productivity. Only when we control for variations in the demand price for capital reflecting innovations in productivity can we measure with precision the role of physical capital in explaining disparities in incomes.

D. *ESI* and Other Measures of Social Infrastructure

In this section we determine how the *ESI* fares in explaining cross-country differences in output per worker relative to the index of government antidiversion policies of Hall and Jones (1999). This latter index equally weighs two variables: the first is the average of five *International Country Risk Guide* sub-indices—namely, law and order, bureaucratic quality, corruption, risk of expropriation, and government repudiation of contracts—and the second is the trade openness dummy variable of Sachs and Warner (1995).

We reconstruct the social infrastructure index of Hall and Jones (henceforth, '*GADP/Openness*') using the description provided by the authors (Hall and Jones, 1999, p. 97−98). Per worker output is then plotted against the *GADP/Openness* index and the *ESI*, respectively (Figures 3 and 4). Despite a simple correlation coefficient between the two indicators of 0.9, some differences emerge concerning how the two indices relate to output per worker. The *GADP/Opennes* index tends to cluster the richer economies at high values while the poorer nations have highly heterogeneous levels of social infrastructure: this leads to a clear pattern of heteroskedasticity. In contrast, the dispersion of output per worker is more evenly distributed along economic security values, with less clustering at the top end. However, the correlations from these scatterplots are not conditional on other covariates, so which of the two indices is better able to capture differences in incomes cannot straightforwardly be inferred.

We undertake non-nested hypothesis tests to discriminate between two competing models, each including one of two social infrastructure indexes (the *ESI* and *GADP/Opennes*) and the same set of covariates. The 2SLS regressions from Table 4 (with a climate control) were re-estimated including the *ESI* and *GADP/Opennes*, respectively, as alternative measures of social infrastructure. We report the results from two tests of non-nested hypotheses: the J test, proposed by Davidson and MacKinnon (1981), and the Cox test, designed by Cox (1961, 1962) and Pesaran (1974). The intuition behind the tests of non-nested hypotheses is as follows: the model with *ESI* is preferred to that with *GADP/Opennes* if it has more explanatory power. In that case, the fitted values from the *GADP/Opennes* model will not have a statistically significant coefficient if included as a regressor in the *ESI* model. While the J test uses simple t-statistics to discriminate between two models, the Cox-Pesaran test employs the likelihood ratio statistic.

According to both non-nested hypothesis tests, we cannot reject the null hypothesis that the *ESI* model is preferable (Table 7). Furthermore, the Cox test provides some evidence against the

GADP/Opennes model. Notwithstanding that such tests are not foolproof evidence of dominance of either social infrastructure indicator and should be interpreted with some caution due to the small sample size, the exercise lends further support to the conclusion that the *ESI* is a worthy proxy of the quality of labor institutions, and possesses substantial explanatory power for the variation in incomes across countries.

E. Robustness of Model Parameters

In this section we undertake a heuristic assessment of the robustness of our parameter estimates for β_1 and β_2 by applying them to diverse data sets to ascertain how well they explain these data. To set the stage, we begin with a summary of the key findings of our model. First, the four richest countries in our sample (Belgium, Canada, Netherlands, and the US) produce an output per worker which, on average, is nearly 10 times greater than the output per worker produced in the four poorest countries (Senegal, India, Sri Lanka, and Indonesia). Second, a representative agent in the richest four countries has, on average, attained a little more than 3 times the schooling attained by the representative agent in the four poorest economies. Third, capital intensity is slightly less than twice the capital intensity in the four poorest economies. Setting β_1 equal to 1.77 and β_2 equal to 0.40—the average values for β_1 and β_2 in panels 5-8 (Table 6)—we are able to explain a factor of 4.8 of the 9.7−fold differential in output per worker between the four richest and the four poorest economies; this implies that multifactor productivity accounts for a factor of just over 2.

In contrast, in the sample employed by Hall and Jones (1999), the gap in output per worker between the richest five and the poorest five economies (the US, Luxembourg, Canada, Switzerland, and Australia vs. Burundi, Malawi, Burkina Faso, Myanmar, and Niger) is 32−fold; capital intensity is 2.9 times larger in the richest economies than it is in the poorest economies; and average educational attainment is 8.1 times greater in the wealthiest economies. Applying the parameter values for β_1 and β_2 in panels 5−8 (Table 6) to the data used by Hall and Jones (1999), we find that differences in capital intensities and schooling years combined account for a factor of 15.2, leaving a residual factor of 2.1 to account for total factor productivity. Had we applied, instead, a parameter value for β_1 equal to 0.621—the average parameter value for β_1 in panels 1−4, we would have arrived at a residual factor equal to 7.0.

Finally, consider applying our parameter estimates to a data set that comprises direct estimates of capital, hence of capital intensity. Using data in the PWT Mark 5 (Summers and Heston, 1991) to construct capital stock per worker that includes residential construction and deriving capital intensities in 1985 international prices, we find that the average capital intensity in the US, Canada and Norway—the richest three countries[10]—is twice larger than the average capital intensity in India, Kenya and Zimbabwe—the three poorest economies with data on physical capital. Furthermore, education attainment is 2.5 times higher in the former than the latter countries, and there is a 13.45 fold output per worker gap between the two groups of economies. Assuming values of 1.77 and 0.40 for β_1 and β_2, we find that differences in human and physical capital combined account for a factor of 5.05, leaving a residual factor of 2.66. This confirms,

[10] Excluding Luxembourg.

once more, the robustness of the paremeter estimates for β_1 and β_2 in fitting the model to diverse data sets.

V. Concluding Remarks

In this paper we developed and tested a model of output per worker in which total factor productivity is embedded into the model. Our use of the relative price of capital to proxy for variations in capital intensity—a novel feature of our study—was found to be fruitful and the empirical results robust. To measure the elasticity of capital in production with precision, we distinguished between the demand and supply price of capital and controlled for variation in both of these prices. While variations in the supply price of capital are meant to reflect the cost of converting consumption goods into investment, variations in the demand price for capital are meant to capture innovations in productivity. As a result, variations in the demand price for capital can provide for a mechanism for spillover effects and/or technology transfers. We have also shown that our measure of the quality of social infrastructure—the Economic Security Index developed by the ILO—has substantive explanatory power in our cross-country model of output per worker. Moreover, the index fares well in a comparison with alternative measures of social infrastructure used in the literature such as the index developed by Hall and Jones (1999) to capture government antidiversion policies and opennes to trade.

Our findings suggest that there is an externality associated with the accumulation of physical capital, suggesting the workings of a *learning-by-doing* mechanism (Lucas, 1988; Stokey, 1988; Young, 1991), and an externality associated with human capital, suggesting the workings of Lucas' *external effect*. However, the magnitude associated with human capital can only be measured well if we can control for hours per worker spent on market activities. This is because the decision to work part-time to attend additional schooling reduces output per worker. Although data on hours per worker is currently unavailable for most developing countries, this could be a promising area for future research.

REFERENCES

Acemoglu, D. and Johson, S. (2007) "Disease and Development: The Effect of Life Expectancy on Economic Growth", *Journal of Political Economy*, Vol. 115, pp. 925−985.

__________, Johnson, S., and Robinson, J. (2005) "Institutions as the Fundamental cause of Long-Run Growth", in Aghion, P. and S. Durlauf (eds.) *Handbook of Economic Growth*, North Pole.

Alesina, A., Devleeschauwer, A., Easterly, W., Kurlat, S., and Wacziarg, R. (2003) "Fractionalization" *Journal of Economic Growth*, Vol. 8, pp. 155−194.

Arellano, M. and Bond, S.R. (1991) "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations", *Review of Economic Studies*, Vol. 58(2), pp. 277−297.

__________, and Bover, O. (1995) "Another Look at the Instrumental Variable Estimation of Error Correction Models", *Journal of Econometrics*, Vol. 68(1), pp. 29−45.

Banerjee, A., Dolado, J., Galbraith, J.W., and Hendry, D.F. (1993) "Cointegration, Error-Correction, and the Econometric Analysis of Non-Stationary Data (Advanced Texts in Econometrics)", *Oxford University Press*, USA.

Barro, R. J., and Lee, J. (2001) "International Comparisons of Educational Attainment: Updates and Implications", *Oxford Economic Papers*, Vol. 53(3), pp. 541−563.

__________,and Sala-i-Martin, X. (1999) *Economic Growth*, the MIT Press, Massachusetts Institute of Technology, Cambridge, MA.

Black, S.E. and Lynch, L.M. (2005) "Measuring Organizational Capital in the New Economy", Institute for the International Study of Labor (IZA), Discussion Paper No. 1524.

__________(2004) "What's Driving the New Economy: Understanding the Role of Workplace Practices", *Economic Journal*, Vol. 114(493), pp. 97−116.

__________(2001) "How to Compete: The Role of Workplace Practices and Information Technology on Productivity", *Review of Economics and Statistics*, Vol. 83(3), pp. 434−445.

Bloom, D.E., Sachs, J.D., Collier, P. and Udry, C. (1998) "Geography, Demography, and Economic Growth in Africa", *Brookings Papers on Economic Activity,* Vol. 1998(2), pp. 207−295.

Blundell, R.W., and Bond, S. (1998) "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models", *Journal of Econometrics,* Vol. 87(1), pp. 115−143.

Bosworth, B.P. and Collins, S.M. (2003) "The Empirics of Growth: An Update", *Brookings*

Papers on Economic Activity, Vol. 2003(2), pp. 113−206.

Botero, J., Djankov, S., La Porta, R., Lopez-de-Silanes, F. and Shleifer, A. (2004) “The Regulation of Labor”, *Quarterly Journal of Economics,* Vol. 119(4), pp. 1339−1382.

Carstensen, K. and Gundlach, E. (2006) “The Primacy of Institutions Reconsidered: Direct Income Effects of Malaria Prevalence”, *World Bank Economic Review*, Vol. 20(3), pp. 309−339.

Coe, D. and Helpman, E. (1995) “International R&D Spillovers”, *European Economic Review*, Vol. 39, pp. 859−887.

Cox, D. (1961) “Tests of Separate Families of Hypotheses”, Proceedings of the Fourth Berkely Symposium on Mathematical Statistics and Probability, Vol. 1. Berkley: University of California Press.

__________(1962) “Further Results on Tests of Separate Families of Hypotheses”, *Journal of Royal Statistical Society Series B*, Vol. 24, pp. 406−424.

Davidson, R. and MacKinnon, J.G. (1981) “Several Tests for Model Specification in the Presence of Alternative Hypotheses”, *Econometrica*, Vol. 49, Issue 3, pp. 781−793.

Easterly, W. (2001) “Can Institutions Resolve Ethnic Conflict?”, *Economic Development and Cultural Change*, Vol. 49, pp. 687−706.

__________, and Levine, R. (1997) “Africa’s Growth Tragedy: Policies and Ethnic Divisions”, *Quarterly Journal of Economics*. CXII (4), pp. 1203−1250.

Feldstein, M. and Horioka, C. (1980) “Domestic Saving and International Capital Flows”, *Economic Journal*, Vol. 90, pp. 314−329.

Hall, R.E., and Jones, C.I. (1999) “Why Do Some Countries Produce So Much More Output per Worker than Others?”, *Quarterly Journal of Economics,* Vol. 114(1), pp. 83−116.

Hausmann, R. (2001) “Prisoners of Geography”, *Foreign Policy*, No. 122, pp. 44−53.

Heston, A., Summers, R. and Atten, B. (2002) Penn World Table Version 6.1, Center for International Comparisons at the University of Pennsylvania (CICUP).

__________ (2006) Penn World Table Version 6.2, Center for International Comparisons at the University of Pennsylvania (CICUP).

Howitt, P. (2000) “Endogenous Growth and Cross-Country Income Differences”, *American Economic Review,* Vol. 90(4), pp. 829−846.

Hsieh, C.-T., and Klenow, S. (2007) “Relative Prices and Relative Prosperity”, *American Economic Review*, Vol. 97(3), pp. 526−585.

International Labor Organization (2004) *Economic Security for A Better World*. Programme on Socio-Economic Security, ILO Press.

Jones, C. (2001) *Introduction to Economic Growth*. Second Edition, W.W. Norton, New York-London.

__________(1994) "Economic Growth and the Relative Price of Capital", *Journal of Monetary Economics*, Vol. 34(3), pp. 359-382.

Knack, S. and Keefer, P. (1995) "Institutions and Economic Performance Cross-Country Tests Using Alternative Institutional Measures", *Economics and Politics*, VII, pp. 207−227.

Kruse, D and Blasi, J. (1998) "The New Employee/Employer Relationship", Rutgers Aspen Institute's Domestic Strategy Group, Aspen Colorado. Also in David Ellwood et al., *Working Nation: Workers, Work, and Government in the New Economy,* New York: Russell Sage Foundation, 2000.

Lucas, R.E. (1988) "On the Mechanics of Economic Development", *Journal of Monetary Economics,* Vol. 22(1), pp. 3−42.

Mankiw, N.G., Romer, D. and Weil, D.N. (1992) "A Contribution to the Empirics of Economic Growth", *Quarterly Journal of Economics,* 107, 407−437

Mauro, P. (1995) "Corruption and Growth", *Quarterly Journal of Economics,* CX, pp. 681−712.

Parente, S., Rogerson, L.R., and Wright, R. (2000) "Homework in Development Economics: Household Production and the Wealth of Nations", *Journal of Political Economy,* Vol. 108(4), pp. 680-687.

__________(1999) "Household Production and Development", *The Federal Reserve Bank of Cleveland Economic Review,* Vol. 35, pp. 21-36.

Pesaran, M.H. (1974) "On the General Problem of Model Selection", *The Review of Economic Studies*, Vol. 41, Issue 2, pp. 163−171

__________, and Smith, R. (1995) "Estimating Long -Run Relationships from Dynamic Heterogeneous Panels", *Journal of Econometrics,* Vol. 68(1), pp. 79−113.

Phillips, P.C.B. and Moon, H.R. (1999) "Linear Regression Limit Theory for Nonstationary Panel Data", *Econometrica,* Vol. 67(5), pp. 1057−1111.

Pikoulakis, E.V. and Minoiu, C. (2006) "Why do some countries produce so much more output than others: Some further results", Columbia University, Institute for Social and Economic Research and Policy Working Paper No. 2006−08.

Prescott, E.C. (1998) “Needed: A Theory of Total Factor Productivity”, *International Economic Review,* Vol. 39(3), pp. 525−551.

Psacharopoulos, G. (1994) “Returns to Investment in Education: A Global Update”, *World Development*, Vol. 22(9), pp. 1325−1343.

Romer, D. (2001) *Advanced Macroeconomics.* Second Edition, McGraw-Hill.

_________(1996) *Advanced Macroeconomics.* First Edition, McGraw-Hill.

Sachs, J.D. (2003) “Institutions Don’t Rule: Direct Effects of Geography on Per Capita Income”, NBER Working Paper No. 9490.

__________(2000) “Tropical Underdevelopment”, Center for International Development at Harvard University Working Paper No. 57.

__________, and Warner, A. (1995) “Economic Reform and the Process of Global Integration”, *Brookings Papers on Economic Activity*, Vol. 1995(1), pp. 1−95.

Stokey, N.L. (1988) “Learning by Doing and the Introduction of New Goods”, *Journal of Political Economy,* Vol. 96, pp. 701−717.

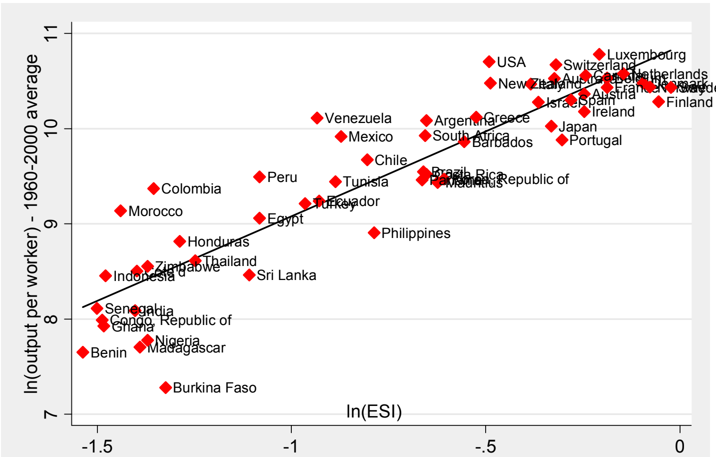
Summers, R. and Heston, A. (1991) “The Penn World Table (Mark 5): An Expanded Set of International Comparisons, 1950−1988”, *Quarterly Journal of Economics*, pp. 327−368.

Tang, H. (2008) “Labor Market Institutions, Firm-specific Skills, and Trade Patterns”, MIT Department of Economics, mimeo.

Young, A. (1991) “Learning by Doing and the Dynamic Effects of International Trade”, *Quarterly Journal of Economics*, Vol. 106, pp. 369−405.

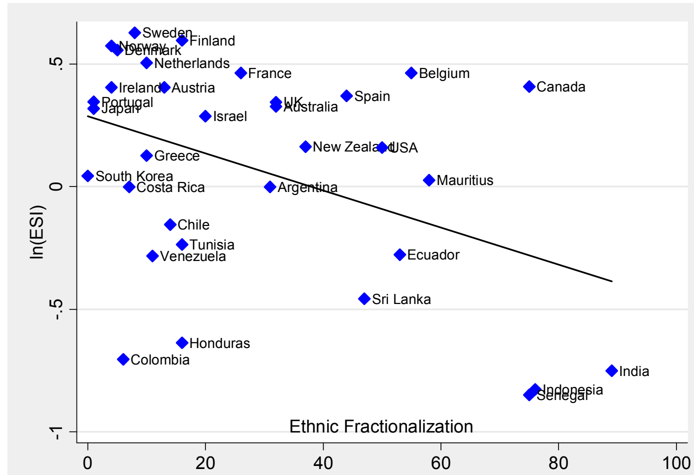
APPENDIX

Figure 1. Output per Worker and *ESI* (N=60)



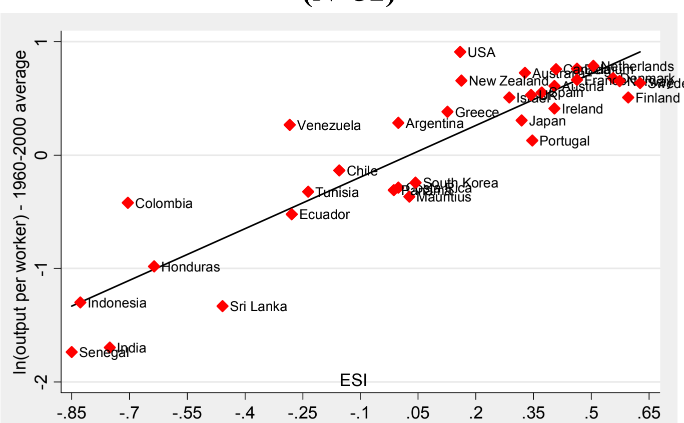
Largest common sample: 60 countries. Source: PWT, ILO.
Lowest ranking 5 countries are not shown.

Figure 2. *ESI* and Ethnic Fractionalization (first-stage, N=33)



Source: ILO, Sachs and Warner (1995).

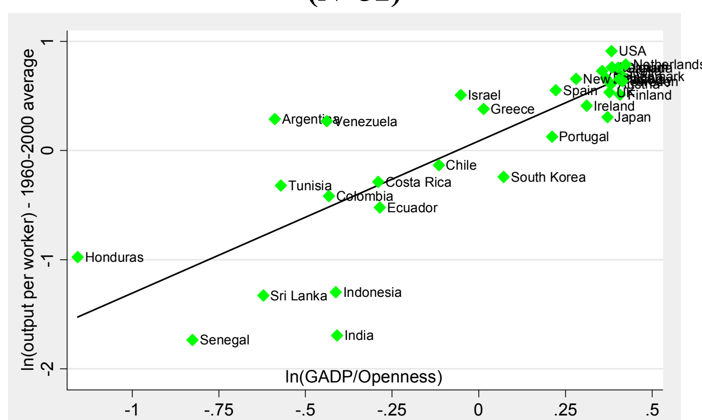
Figure 3. Output per worker and *ESI* (N=32)



Top 5 countries on ESI ladder: Sweden, Finland, Norway, Denmark, and the Netherlands
Bottom 5 countries on ESI ladder: Nepal (not shown), Sierra Leone, Bangladesh, Rwanda, and Burundi.

Source: PWT, ILO.

Figure 4. Output per worker and *GADP/Openness* (N=32)



Top 5 countries on GADP/Openness ladder: the Netherlands, Denmark, Sweden, Finland, and Norway.
Bottom 5 countries on GADP/Openness ladder: Honduras, Senegal, Sri Lanka, Argentina, and Tunisia.
Source: PWT, ICRG, Sachs and Warner (1995).

Table 1. Variable definitions, variable sources, and list of countries

Variable	Mnemonic	Source
Output per worker; relative price of capital, 1960-2000	Y, Q	PWT Mark 6.2
Educational attainment (average # years of education of the population 25 y.o. and above), 1960-2000	*Sch*	Barro and Lee (2001)
Economic Security Index, single observation taken on 1999 or closest year (1998 or 2000).	*ESI*	ILO (2004)
Geography (% area in tropics)	*Geo*	Bosworth and Collins (2003)
Ethnolinguistic fractionalization		Sachs and Warner (1995)
Hall and Jones (1999) government antidiversion policies index (constructed using the Institutional Country Risk Guide sub-indices)	*GADP*	Stephen Knack and Keefer, Philip (1995) IRIS-3: File of International Country Risk Guide (ICRG) data. College Park, Maryland: IRIS (producer). East Syracuse, New York: The PRS Group, Inc. (distributor)
Sachs-Warner trade openness dummy	*Openness*	Sachs and Warner (1995)
Hall and Jones (1999) index of social infrastructure	*GADP/Openness*	See *GADP* and *Openness* above.

List of countries in our sample

The following 33 countries were included in the cross-sectional and panel regressions: Argentina, Australia, Austria, Belgium, Canada, Chile, Colombia, Costa Rica, Denmark, Ecuador, Finland, France, Greece, Honduras, India, Indonesia, Ireland, Israel, Japan, Korea (Republic of), Mauritius (*), Netherlands, New Zealand, Norway, Panama, Portugal, Senegal, Spain, Sri Lanka, Sweden, Tunisia, United Kingdom, United States, and Venezuela.

* not used in non-nested hypotheses tests due to missing *GADP/Openness* data.

Table 2. Raw data and summary statistics in the cross-section (N=33)

No.	*Country*	*ln(Y)*	*ln(Q)*	*Sch*	*ESI*	*GADP/Openness*	*Geography (% tropics)*	*Ethnic Fractionalization*
1	Argentina	10.09	0.12	6.60	0.52	0.36	0.0	31
2	Australia	10.54	-0.05	9.96	0.72	0.92	0.1	32
3	Austria	10.42	-0.05	7.73	0.78	0.95	0.0	13
4	Belgium	10.57	-0.13	8.13	0.83	0.95	0.0	55
5	Canada	10.57	-0.07	9.82	0.79	0.97	0.0	75
6	Chile	9.70	0.24	6.07	0.45	0.58	0.1	14
7	Colombia	9.38	0.48	3.81	0.26	0.42	1.0	6
8	Costa Rica	9.52	0.41	4.74	0.52	0.48	1.0	7
9	Denmark	10.49	-0.13	9.31	0.91	0.98	0.0	5
10	Ecuador	9.28	0.00	4.75	0.40	0.49	1.0	53
11	Finland	10.33	-0.11	7.87	0.95	0.97	0.0	16
12	France	10.47	-0.13	6.77	0.83	0.93	0.0	26
13	Greece	10.17	-0.10	6.43	0.59	0.66	0.0	10
14	Honduras	8.82	0.47	2.70	0.28	0.20	1.0	16
15	India	8.15	0.50	2.78	0.25	0.43	0.5	89
16	Indonesia	8.57	0.42	2.88	0.23	0.43	1.0	76
17	Ireland	10.27	0.04	7.49	0.78	0.88	0.0	4
18	Israel	10.32	-0.24	8.35	0.70	0.61	0.0	20
19	Japan	10.12	-0.03	8.12	0.72	0.94	0.0	1
20	Mauritius	9.53	0.56	4.23	0.54	…	1.0	58
21	Netherlands	10.59	-0.09	7.83	0.87	0.99	0.0	10
22	New Zealand	10.48	0.03	10.73	0.61	0.86	0.0	37
23	Norway	10.47	-0.11	8.66	0.93	0.97	0.0	4
24	Portugal	9.49	0.14	5.81	0.52	0.80	0.0	1
25	Senegal	9.94	0.13	3.31	0.74	0.28	1.0	75
26	South Korea	8.11	0.55	1.77	0.22	0.69	0.0	0
27	Spain	10.35	-0.05	5.16	0.76	0.81	0.0	44
28	Sri Lanka	8.50	0.71	4.72	0.33	0.35	1.0	47
29	Sweden	10.45	-0.09	9.01	0.98	0.98	0.0	8
30	Tunisia	9.49	0.44	1.98	0.41	0.37	0.0	16
31	UK	10.73	-0.04	10.98	0.61	0.94	0.0	32
32	USA	10.35	-0.05	8.17	0.74	0.95	0.0	50
33	Venezuela	10.13	0.10	4.18	0.39	0.42	1.0	11
	Average	9.89	0.12	6.39	0.61	0.70	0.29	28.55
	Standard Deviation	0.75	0.26	2.63	0.23	0.26	0.45	25.63
	Minimum	8.11	-0.24	1.77	0.22	0.20	0.00	0.00
	Maximum	10.73	0.71	10.98	0.98	0.99	1.00	89.00

Table 3. Summary statistics in the panel (N=231)

Variable	Mean	Std. Dev.	Minimum	Maximum
ln(Y)	9.90	0.78	7.76	10.99
ln(Q)	0.12	0.29	-0.41	0.98
Sch	6.42	2.78	0.71	12.18
ESI	0.61	0.23	0.22	0.98
Ethnic Fractionalization	28.55	25.29	0.00	89.00
Geography (% area in tropics)	0.29	0.44	0.00	1.00

Table 4. Dynamic two-stage least squares (2SLS) cross-sectional regressions (N=33)

Dependent variable: Output per worker - ln(y)

Model →	[1]	[2]	[3]	[4]	[5]	[6]
$\Delta_T \ln(Y)$	-4.327***	-4.475***	-4.545***	-4.714***	-4.483***	-4.683***
	[0.992]	[0.969]	[1.020]	[0.952]	[1.023]	[0.915]
ln(Q)	-0.864*	-0.540	-0.943*	-0.654*	-2.430**	-2.150***
	[0.427]	[0.400]	[0.465]	[0.382]	[0.938]	[0.692]
ln(Sch)	0.182	0.221	0.525*	0.572**	0.168	0.210
	[0.272]	[0.214]	[0.284]	[0.263]	[0.240]	[0.181]
ln(ESI)	1.032***	0.820**	1.779***	1.614***	0.815**	0.574**
	[0.290]	[0.316]	[0.502]	[0.528]	[0.301]	[0.257]
ESI x ln(Sch)			-0.829**	-0.858**		
			[0.386]	[0.370]		
ESI x ln(Q)					2.997*	3.133**
					[1.521]	[1.419]
Geography		-0.445**		-0.402*		-0.485**
		[0.214]		[0.212]		[0.219]
DIAGNOSTICS						
First-stage F statistic						
Delta Y	13.03	21.55	13.03	21.55	13.03	21.55
ln(Q)	376.51	293.07	376.51	293.07	376.51	293.07
ln(Sch)	891.62	307.55	891.62	307.55	891.62	307.55
ln(ESI)	121.23	96.20	121.23	96.20	121.23	96.20
Interaction term			5324.94	3541.58	336.62	153.16
IV/Relevance test						
LR statistic	36.00	37.26	33.64	41.67	35.99	37.25
(p-value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Overidentification test						
J statistic	4.635	4.958	0.217	2.383	0.682	0.610
(p-value)	(0.0985)	(0.0838)	(0.6417)	(0.3037)	(0.4090)	(0.4348)

Note: Robust standard errors in brackets; * indicates significance at 10%; ** at 5%; *** at 1%. An intercept was estimated, but the coefficient is not shown. In the 2SLS regressions above, all independent variables are treated as endogenous, and the following instruments are used: lagged ln(Sch), lagged ln(Q), lagged ESI*ln(Sch), lagged ESI*ln(Q), Initial income, and Ethnic Fractionalization. LR statistic is for the Anderson canonical correlation likelihood-ratio test of the null hypothesis that the equation is underidentified. The J statistic is for the Hansen-Sargan test of joint null hypothesis that the instruments are uncorrelated with the error and correctly excluded from the estimated equation.

Table 5. Dynamic system GMM panel regressions (N=231). Dependent variable: Output per worker - ln(Y)

Model →	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
ln(Y) lagged	0.858***	0.860***	0.858***	0.860***	0.834***	0.829***	0.857***	0.853***
	[0.028]	[0.027]	[0.030]	[0.027]	[0.031]	[0.031]	[0.026]	[0.023]
ln(Q)	-0.069	-0.047	-0.115	-0.047	-0.240*	-0.292***	-0.113	-0.144
	[0.070]	[0.071]	[0.087]	[0.090]	[0.140]	[0.100]	[0.145]	[0.140]
ln(Sch)	-0.005	0.004	0.096*	0.102**	0.008	0.029	0.092*	0.084
	[0.035]	[0.031]	[0.050]	[0.045]	[0.038]	[0.030]	[0.054]	[0.053]
ln(ESI)	0.232***	0.179**	0.292***	0.254***	0.226***	0.141**	0.298***	0.228**
	[0.073]	[0.080]	[0.082]	[0.081]	[0.071]	[0.067]	[0.098]	[0.100]
ESI x ln(Sch)			-0.151**	-0.159**			-0.149*	-0.126
			[0.075]	[0.065]			[0.090]	[0.092]
ESI x ln(Q)					0.346	0.507**	-0.002	0.136
					[0.259]	[0.238]	[0.352]	[0.381]
Geography		-0.057*		-0.089***		-0.086***		-0.078***
		[0.030]		[0.023]		[0.026]		[0.023]
				DIAGNOSTICS				
Wald Chi-squared	9774.9	9964.9	13361.7	15578.9	12914.8	14607.2	13489.1	16893.5
m1 test p-value	0.013	0.011	0.009	0.007	0.017	0.015	0.005	0.005
m2 test p-value	0.920	0.923	0.828	0.889	0.978	0.993	0.840	0.881
Hansen test p-value	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Note: Robust standard errors in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%. An intercept and a full set of time dummies are included, but coefficients are not shown. In the system GMM regressions above, all independent variables are treated as endogenous, and their lags are used to construct the instrument set. In addition, the following strictly exogenous variables are used as instruments: ethnic fractionalization, % area in the tropics, and the time dummies. The statistics *m1* and *m2* represent the Arellano-Bond test of AR(1) in the differenced residuals. For the subset of instruments based on the orthogonality condition of the regressors in levels and their lagged differences to be valid and relevant, we wish to reject the null hypothesis of AR(1) in the first differenced residuals (validity), and fail to reject the null hypothesis of AR(2) in the first differenced residuals (relevance). The Wald Chi-squared is a measure of goodness of fit, and the Hansen test p-value is for the null hypothesis of over-identifying restrictions for the entire set of instruments (based on two sets of orthogonality conditions: between endogenous regressors in levels and their past differences, and between differenced regressors and their past levels). All available lags of data are used to construct the instrument set. Windmeijer's small sample correction has been applied to the standard errors.

27

Table 6. Static system GMM panel regressions (N=264). Dependent variable: Output per worker - ln(Y)

Model →	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
ln(Q)	-0.532**	-0.533**	-0.732***	-0.687**	-1.816***	-1.906***	-1.657***	-1.699***
	[0.207]	[0.261]	[0.156]	[0.259]	[0.606]	[0.544]	[0.496]	[0.469]
ln(ESI)	0.967***	0.971***	1.033***	1.001***	0.774**	0.617**	0.812**	0.698*
	[0.280]	[0.253]	[0.357]	[0.371]	[0.314]	[0.235]	[0.380]	[0.416]
ln(Sch)	0.339	0.339*	0.421*	0.429**	0.391*	0.423**	0.397**	0.390*
	[0.220]	[0.205]	[0.216]	[0.201]	[0.206]	[0.173]	[0.194]	[0.197]
ESI x ln(Sch)			-0.216	-0.228			-0.066	-0.044
			[0.361]	[0.351]			[0.329]	[0.342]
ESI x ln(Q)					2.777**	3.051***	2.216***	2.410***
					[1.081]	[0.946]	[0.827]	[0.827]
Geography		0.004		-0.071		-0.143		-0.129
		[0.298]		[0.266]		[0.270]		[0.257]
Time	0.082***	0.082***	0.089***	0.088***	0.087***	0.085***	0.090***	0.089***
	[0.020]	[0.019]	[0.016]	[0.015]	[0.018]	[0.016]	[0.017]	[0.016]
				DIAGNOSTICS				
Wald Chi-squared	2533.4	2527.4	2081.5	2151.6	1790.3	1736.9	2400.8	2420.3
m1 test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
m2 test p-value	0.485	0.489	0.527	0.529	0.579	0.629	0.581	0.581
Hansen test p-value	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Note: Robust standard errors in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%. An intercept is included, but coefficients are not shown. For other explanatory notes regarding the regressions, see Table 5.

28

Table 7. Non-nested hypothesis tests for competing models (N=32). Dependent variable: Output per worker - ln(Y)

	Index of Social Infrastructure:					
	Economic Security (*ESI*)			**Govt. Anti-Diversion Policies (*GADP/Openness*)**		
$\Delta_T \ln(Y)$	-4.685***	-4.692***	-4.629***	-5.061***	-4.870***	-5.615***
	[0.909]	[0.843]	[0.828]	[1.041]	[1.604]	[1.383]
ln(Q)	-0.889***	-0.857**	-2.040***	-1.111**	-1.179*	0.836
	[0.314]	[0.338]	[0.670]	[0.428]	[0.621]	[3.400]
ln(Sch)	0.214	0.529*	0.213	0.311	0.144	0.442
	[0.205]	[0.264]	[0.184]	[0.284]	[0.603]	[0.508]
ln(Social Infrastructure)	0.535*	1.333**	0.436*	0.024	-0.654	-0.263
	[0.275]	[0.496]	[0.234]	[0.415]	[2.744]	[0.921]
Social Infrastructure x ln(Sch)		-0.751**			0.438	
		[0.356]			[1.621]	
Social Infrastructure x ln(Q)			2.482*			-3.778
			[1.356]			[6.559]
Geography	-0.615***	-0.513**	-0.586***	-0.903***	-0.989*	-1.206
	[0.203]	[0.195]	[0.201]	[0.275]	[0.497]	[0.730]
	Ho: *ESI* model is preferable			Ho: *GADP/Openness* model is preferable		
J-test p-value	0.90951	0.80030	0.93811	0.24759	0.68950	0.00001
Cox test p-value	0.43173	0.25311	0.46336	0.00000	0.04403	0.00000

Note: Robust standard errors in brackets; * significant at 10%; ** significant at 5%; *** significant at 1%.
An intercept is included, but coefficients are not shown.

29