Cross Countries Economic Performances - SPF Approach[ǂ]

Walid Y. Alali[ǂǂ]

University of Oxford – Economic Department, Manor Road Building, OX1 3UQ
Oxford, United Kingdom

The differences in technical inefficiency (inefficient allocation of production inputs) explain the diverse cross-country economic performances, using estimating a "global" stochastic production frontier (SPF) model, and (Rodrik (2000)'s taxonomy of institutions), to compare the mean level of technical inefficiency for each country per period. Our model, consider three variables dimensions – human capital, openness, and institutions. Institutions are more fundamental to the sources of technical inefficiency. Specifically, the rule of law has a direct impact on improving technical efficiency. Democracy and sound money, do not have a direct impact on technical efficiency. However, their interactions with human capital are statistically significant. It points out the possibility that a minimum level of human capital matters for these two aspects of institutions to have any impact on technical efficiency. Regulation, on the other hand, shows a threshold effect. That said, after reaching a threshold level of regulation, excessive regulation leads to technical inefficiency.

Key Words: Economic Development, Institutions, Policy, Growth, Institutions Performance, Stochastic Production Frontier (SPF)

ǂ This series is composed of five papers (The new updated version of the papers was created in 2009 -2010), one is an overview and four empirical studies, which investigate the effects of institutions on cross-country economic development from different perspectives drawn from my MPhil thesis of "Essay on Institutions, Policies, and Economic Development". The first paper, entitled "Institutions, Policies, and Economic Growth Overview", reviews the relationship between institutions and policy regulation with economic development from the perspective of economic literature. The second paper, entitled "Impact of Institutions and Policy on Economic Growth: Empirical Evidence", empirical analysis to explore the interaction between the institution and economic development. The third paper, entitled "Role of Political Institutions on Economic Growth: Empirical Evidence", is an empirical analysis to explore the effect of political institutions on economic development. The fourth paper, entitled "Impact of Natural Environment, Regional Integration, and Policies on FDI", explores the effects of three determinants of bilateral FDI, including natural barriers, the "at-the-border" barrier (regional trade agreement), and the "behind-the-border" barrier (domestic regulatory environment). The fifth paper, entitled "Cross Countries Economic Performances - SPF Approach", explores the differences in technical inefficiency (inefficient allocation of production inputs) and explains the diverse cross-country economic performances, using estimating a "global" stochastic production frontier (SPF) mod.

ǂǂ Economist and Engineer with a PhD, researcher and advisor in different sustainable economic development areas.

1 Introduction

Previous paper of this series, entitled "Impact of Natural Environment, Regional Integration, and Policies on FDI", has attempted to provide some empirical evidence on the interrelationships between institutions and economic development from different dimensions (such as economic growth, economic reform and FDI). We essentially try to argue that institutions matter to different economic outcomes. This last paper in series, discusses the role of institutions in cross-country economic performances.

In second paper, entitled "Impact of Institutions and Policy on Economic Growth: Empirical Evidence", we investigated the effect of institutions on economic growth. The key research questions there are asking primarily asking to do and what institutions matter. Nevertheless, institutions are not production inputs. The mechanism of how they affect output is not demonstrated. The existing literature suggests that institutions may affect productivity, as measured by total factor productivity (TFP) obtained in the standard growth accounting framework. This strand of literature argues that cross-country economic performances are due to different rates of technical change. However, one should note that such TFP obtained as residual from growth accounting implicitly assumes that input allocations are efficient in all economies. This assumption is indeed fairly strong in cross-country analysis.

In this light, this paper proposes to measure technical efficiency instead of TFP growth. We propose that institutional differences affect input allocations, thereby resulting in diverse economic performances across countries. Earlier work by Olson (1996) succinctly points out that an institution is probably one of the most important factors to explain the consistent growth divergence among countries. He argues,

"… *Large differences in per capita income across countries cannot be explained by differences in access to the world's stock of productive knowledge or to its capital markets, by differences in the ratio of population to land or natural resources, or by differences in the quality of marketable human capital or personal culture*."

His empirical findings show that not all poor economies grow faster than rich ones as the theory of convergence has predicted. Even worse, the gap in per capita incomes between the relatively poor and relatively rich countries has increased over time. Prichett (1997) estimates that the proportional gap in GDP per capita between the richest and poorest countries has grown more than five-fold from 1870 to 1990. The proportional gap between the richest group of countries and the poorest grew from 3 in 1820 to 19 in 1998 (see Maddison (2001)).

North (1990) argues that all those determinants of growth – human capital, technological diffusion, and innovations as traditional growth theories suggested – shed no light on the source of growth because they are growing. North and Thomas (1973) note that,

"*We are left wondering: if all that is required for economic growth is investment and innovation, why have some societies missed this desirable outcome? ... The factors we have listed (innovation, economies of scale, education, capital accumulation, etc.) are not causes of growth; they are growth. … Growth will simply not occur unless the existing economic organization is efficient. Individuals must be lured by incentives to undertake the socially desirable activities. Some mechanism must be devised to bring social and private rates of return into closer parity.*"

A better understanding of the source of growth may be efficiency. Countries are "inefficient" in the sense that there is a considerable discrepancy between private benefit and social benefit whenever an economic transaction occurs[1]. Given an institutional arrangement, undertaking an economic activity may be socially profitable, but individuals rationally will not do it if the private cost exceeds the private benefit. Hence, the gains from the transaction cannot be realized. In other words, there actually exists a Pareto optimal (more efficient) outcome, but it cannot be achieved. It is, thus, interesting to investigate how much institutional rigidity could explain the disparity.

Against North's (1990)'s analytical framework aforementioned, estimating technical efficiency (TE) may help explain the diverse cross-country performances. Hultberg, Nadiri, and Sickles (1999), while measuring international TPF growth, also concur that technology diffusion and technical inefficiency are possibly caused by institutional rigidities. Unlike the previous work, on the methodology front, we propose to adopt the stochastic production frontier (SPF) model. This technique allows us to compare the level of technical inefficiency across countries vis-à-vis the global best practice. In addition, the model can also incorporate explanatory factors of technical inefficiency, namely, institutions in our case.

A similar "benchmarking" exercise is not new in cross-country analysis. The standard way is to assume the United States to be the best practice and be used for comparison. These studies then address how far the poor economies are falling behind the best practice. While the key focus of these studies is the comparative performances vis-à-vis the US, time-varying "best practice" is often neglected. In our study, we do not impose such a comparison. Instead, we estimate the world frontier without prior assumptions. In other words, we allow the global stochastic production frontier to shift over time. With regard to the source of technical inefficiency, we consider to test the effects of institutions, human capital and openness. The

[1] North and Thomas (1973) suggest that this discrepancy is caused and shaped by the institutional structure, especially when property rights are poorly defined.

literature survey we discussed in second paper, has set out the competing debate amongst these three parameters. In an alternative framework as we now propose, we will see if we can contribute some renewed empirical evidence to the debate – i.e. whether institutions, human capital, and/or openness explain cross-country economic performances, measured in terms of technical efficiency.

In short, there are three research objectives in this paper. Firstly, instead of using TFP measurement obtained from growth-accounting to understand the divergence of cross-country economic performances, we propose to use the stochastic production frontier model to measure technical efficiency. It does not assume away the inefficiency resulted from input misallocation. Yet, the technique allows us to construct a TFP index if we so wish. Subject to the model specification, the model can also capture any inter-temporal changes of both technological progress and technical efficiency.

Secondly, while understanding the fact that an institution is not a production input, we attempt to investigate exactly what role institutions play in the production process. Based on North's seminal work on institutions and economic development, we propose to measure the impact of institutions on cross-country technical efficiency, i.e. the efficiency of input allocations across economies.

Thirdly, we revisit the competing debate between the institutional view vis-à-vis the impacts of openness and human capital on economic development. From our empirical results, we will evaluate whether cross-country technical efficiency can be explained by any or all of these three factors.

This paper is organised as the following. First, we will survey the previous relevant literature of the effects of institution, openness, human capital on productivity in Section 2. We outline the fundamental concepts of stochastic production frontier in Section 3. The model we adopted for estimation is further elaborated in Section 4. Data used are discussed in Section 5. Section 6 presents the estimation results. We conclude in Section 7.

2 Literature Survey: Institutions, Openness, and Human Capital as Efficiency Sources

Productivity is the source of growth and deep determinants of cross-country economic development. Sources of TFP growth are considered to provide an opportunity for enhancing general welfare of the society. The large and growing literature consistently provides support to the claim that productivity, rather than factor accumulation, is the key explanation for international income disparities.

Productivity, frequently measured in terms of TFP, can be further segregated into technical progress and efficiency change. The former represents the country's knowledge as to how factors of production can best be combined. This can be the results of innovations or learning and imitation. Efficiency, on the other hand, represents how effective a country's factors are actually used. A distinct point between the two dimensions worth noting is that the presence of obsolete production techniques does not necessarily imply a technology gap. In fact, it may reflect a situation in which producers are discouraged from adopting best-practice techniques. The presence of suboptimal technologies may be a symptom of poor efficiency instead of resulting from unavailable technology.

Most of the existing empirical literature focuses on the source of TFP. From these empirical studies, nevertheless, we are unable to tell whether the differences in cross-country TFP growth are the results of technical change or efficiency change. In fact, there are views that technology is quite readily available, especially in this globalised era. The differences in economic performances across countries are believed to be the results of technical inefficiency.

Efficiency becomes more prominent in recent studies of economic development. Echoing the view of North on the role of efficiency differences as the source of diverge economic performances, Parente and Prescott (2005) lately also develop a theory to explain international income levels. From a historical perspective, they develop a relative efficiency theory of economic development to explain the evolution of international income levels in the last millennium.

The essence of their theory provides a sensible link between efficiency and institutions. They argue that a country starts to experience sustained increases in its living standard when production efficiency reaches a critical point. Countries reach this critical level of efficiency at different dates not because they have access to different stocks of knowledge, but rather because they differ in the amount of society-imposed constraints on the technology choices of their citizenry. Their theory argues that country-specific TFP, which they refer to as a theory of relative efficiency, is a consequence of policy differences. Their theory predicts that after a country reaches a critical point of efficiency, it begins to grow. Its income gap with the leader eventually stops increasing. Nevertheless, to reduce such a gap (i.e. to improve efficiency), the late starter has to use resources in the modern production function by making improvements in its policies and institutions. Growth miracles, as observed in Japan, South Korea, and Taiwan, are also the results of large increase in a late starter's relative efficiency. Parente and Prescott (2005) provide an essential theoretical foundation of our empirical investigation, even though technically speaking, we adopt a more refined measurement of cross-country technical efficiency instead of TFP, which we will discuss in the next section.

While efficiency is essential to close income gap, it is natural henceforth for us to explore the potential factors determining efficiency[2]. Sources of international technical efficiency are not frequently explored. Therefore, we will consider key factors previously examined in the productivity literature and see if they are applicable in our context. In our study, we consider three key dimensions: (i) human capital; (ii) openness, and (iii) institutions and macroeconomic policies. We will review the arguments and the empirical evidence put forth in the literature in turn.

2.1 Human Capital

Human capital enhances productivity in two possible ways. On one hand, it improves average labour productivity. On the other hand, it strengthens the innovation capacity and promotes technological progress. When summarising recent empirical work on the relationship between human capital and economic growth, Isaksson (2002) concludes that empirical results are diverse with respect to statistical significance (significant or not), magnitude (small or large), and sign (positive or negative) of the estimated parameter. Incorporating human capital or not in the production process produces mixed and somehow puzzling empirical results. For relatively rich countries, human capital is important, while its effect is negative for relatively poor ones.

In terms of empirical evidence, Benhabib and Spiegel (2005) refine their own established model in Benhabib and Spiegel (1994) by allowing for different functional forms for predicting TFP growth. Studying 84 countries between 1960 and 1995, they find a positive role for human capital as an engine of innovation, as well as a facilitator of TFP catch-up. The predictive capacity of the model seems very good because 22 of 27 countries that were forecast to fall behind did in fact do so.

Along the line of Acemoglu, Aghion, and Zilibotti (2006), Vandenbussche, Aghion, and Meghir (2006) specifically develops a theoretical model to understand the ambiguous effect of human capital on technological improvements. They argue that labour composition determines the form of technological improvements, either innovation or imitation, in an economy. Innovation requires relatively more skilled labour, whereas unskilled labour better endogenous labour allocations across these two activities. The authors opine that both the economy’s distance to the technological frontier and the composition of its human capital suit imitations.

[2] See Isaksson (2007a) for a comprehensive survey on the sources of productivity.

A country's level of technological development therefore depends on the determined economic development. Skilled labour (i.e. human capital) is growth-enhancing only when the country is proximate to the frontier.

2.2 Openness: FDI, Trade, and Financial Integration

Isaksson (2007a) reckons that knowledge is only created by a few leading technologically advanced developed economies. Elsewhere, technology is just being acquired. Identifying the channels through which technology can be transferred effectively is thus important. Amongst different forms of technology transfer, international trade, in particular imports, and FDI have a relatively high knowledge content embodied. Thus understandably openness is treated as the source of learning. It then presents indirect effects on productivity. Trade liberalisation may lead to increased competition and reduce a firm's X-inefficiency. Foreign competition may also lead domestic producers to expand or cease operations to improve overall efficiency. As Tybout (1992) recognises demand shifts accompanied by trade liberalisation, market flexibility (entry and exit), and the nature of competition may all affect the net effect of liberalisation on TFP.

FDI is also generally viewed as the key channel for the transfer of advanced technology from industrialised to developing economies. It is also believed to generate positive externalities in the form of knowledge spillovers to domestic firms. However, foreign capital may also crowd-out domestic investment, replace domestic production, and reduce competition. Hence, the net effect of technology transfer and efficiency gain as a result of openness is not definite.

Empirical studies of whether FDI spurs productivity is mostly micro-level in nature. Granér and Isaksson (2001) find that both mixed and pure foreign ownership is positively correlated with productivity growth. Keller (2004) uses case studies to show large positive FDI spillovers. On the contrary, Aitken and Harrison (1999) show a negative effect of FDI on productivity among Venezuelan plants, explaining that foreign firms recruit the most skilled workers and hence deprive domestic plants of their services. Cases in Hanson (2001) also show that spillovers from foreign capital are limited.

Also using SPF, Nourzad (2008) investigates the effect of FDI at macro-level technical inefficiency. His results suggest that increased FDI increases potential output in both developed and developing countries with the effect being more profound in the former. Furthermore, FDI reduces technical inefficiencies in developed economies, but not in those developing ones.

In a nutshell, these empirical results point to a general conclusion that FDI only has a positive impact on TFP growth in industrialised countries, while such positive results are harder to observe in developing countries. Isaksson (2007a) explains that it may be because technology transfer can be costly. Different absorptive capacities across countries may also help explain such a pattern.

This also suggests that openness and human capital may have to interact together to have any impact on productivity. Mayer (2001) attempts to interact technology transfer with human capital in a cross-country growth regression. The proxy of absorptive capacity is captured by an interaction term between human capital and imports of machinery and equipment (as percentage of GDP). During the studied period of 1970-1990 in 53 developing countries, the results show that the interaction term has a significant coefficient, meaning human capital is significant for technology adoption.

Separately, Isaksson (2001) uses data on 73 countries between 1960 and 1994 and shows that trade can be viewed as a significant carrier of knowledge or technology unless the recipient countries have the necessary level of human capital. Miller and Upadhyay (2000), covering 83 countries over the period 1960 and 1989, present a statistically significant impact of the interaction of exports and human capital on productivity. More specifically, they argue that the interactive term works differently in countries with different income levels. At low-income levels, human capital is negatively associated with TFP growth, while for middle- and high-income countries the effect is positive. Nevertheless, in the case of Harrison (1996), while analysing 51 countries between 1960 and 1987, shows that such interaction terms are seldom statistically significant.

In sum, empirical studies prevalently show that openness has positive effects for industrialised countries, while not necessarily for the case of developing countries. Again, this leads one to suspect that institutional quality may affect absorptive capacity, which in turn affects productivity growth. Although the trade channel could in principal facilitate technology transfer, the absorptive capacity of the recipient country, mainly depending on human capital and capital intensity, determines the magnitude of technology transfer.

Other than trade openness and FDI, financial openness also raises the issue of financing capital accumulation, which may have repercussions for productivity growth (Isaksson (2007a)). In economies where the financial system is well developed, investment opportunities can readily be seized, resources are more likely to be allocated optimally. Specialisation can thus be promoted. However, in developing countries with less sophisticated financial systems, firms may have to rely on retained earnings for investment or forego the opportunity. Financial constraints therefore may prevent poor countries from taking full advantage of technology transfer. Financial repression, often exemplified by negative or artificially low real interest rates, thwarts incentives to save. It also distorts the efficient allocation of savings into investment and hence brings negative effect on TFP growth.

The association between financial development and productivity growth receives great research interests lately. Fisman and Love (2004) study the relationship between industrial growth (covering 37 developed and developing industries with good growth opportunities in 42 countries between 1980 and 1990) and financial development. Based on Rajan and Zingales (1998)'s framework, they conclude that financial development spurs productivity growth. At the macro-level, Aghion, Howitt, and Mayer-Foulkes (2005) study 71 countries between 1960 and 1995. They find that financial development is a threshold variable, which affects convergence mainly through TFP growth rather than capital accumulation.

Recent studies also suggest that there are many channels through which financial openness can have a positive impact on productivity growth. For example, Kose, Prasad, and Terrones (2008) argue that financial openness could have a positive impact on TFP growth because they lead to more efficient resource allocation as Mishkin (2006) suggests. More specifically, the authors find that de jure capital account openness has a robust positive effect on TFP growth. The effect of de facto financial integration, measured by the stock of external liabilities to GDP, on TFP growth is less clear. FDI and portfolio equity liabilities boost TFP growth while external debt is actually negatively correlated with TFP growth. They explain that financial openness might affect the return to capital, thereby leading to changes in the entry and exit decisions of firms/plants. Aggregate factor productivity will increase because new plants are more productive than exiting plants. This reallocation from less productive to more productive plants would ultimately increase total factor productivity with no significant gains in employment. These productivity gains from both learning and selection effects may also have to spread over longer periods. It may turn out the net effect on TFP seems insignificant.

2.3 Institution and Macroeconomic Policies

The institution view argues that differences in efficiency across countries are the results of the underlying market-friendly institutions, including the set of formal and informal constraints that shape an individual's ability to act productively and cooperatively in the society. The role of institutions ensures efficient allocation of resources across sectors. On the other hand, policy instruments may also compensate for weak underlying institutions.

According to Isaksson (2007a)'s survey, the existing literature generally highlights three main institutional issues, namely, (i) enforcement of property rights (encourages investment), (ii) constraints on the actions of elitist, political and other groups with power (thus reduce risks of expropriation of incomes and others' investments), and (iii) equal opportunity for broad segments of society (e.g. enhanced investment in human capital and participation in productive activities). Theories argue that better security of property rights creates more incentives for savings and investment, leading to TFP growth. As defined in second paper of this series, we consider institutions as a measure composed of economic and political institutions, macroeconomic policies and regulations.

Openness, policy and institution are three typical deep determinants of productivity growth. Empirical studies frequently test their competing roles simultaneously. Alcalá and Ciccone (2004) claim that the way to measure trade matters to the empirical results. They use real openness (i.e. as predicted trade shares estimated based on gravity model), instead of trade share to GDP, and find a strong positive and statistically significant effect on productivity. Their results remain robust after controlling for geography and institutional quality. Nevertheless, Bosworth and Collins (2003), in respect of 84 countries during 1960-2000, show that trade renders insignificant effect in the presence of institutional quality. One possible explanation is that macro studies mask the heterogeneity bias. In reality, trade liberalisation might only benefit large firms. The removal of protective measures could be harmful for smaller enterprises. The net effect may therefore become insignificant.

Hall and Jones (1999), as previously discussed in second paper, strongly believe that the primary and fundamental determinant of a country's long-run economic performance (as measured by output per worker) is its social infrastructure. They argue that differences in social infrastructure cause large differences in capital accumulation, educational attainment and productivity, resulting in huge income disparities across countries. Nevertheless, Glaeser, et al. (2004) suggest that human capital may be more fundamental.

More specifically in terms of political regime, Przeworski and Limongi (1993) appear to favour dictatorships in terms of mobilising savings. However, the authors also recognise that methodological limitations, such as endogeneity problem of institutions and economic development, may hamper one to draw reliable conclusion. In the empirical work of Ulubasoglu and Doucouliagos (2004), their results support that both political and economic institutional variables are important to TFP. Their results show that higher levels of democracy have a positive and statistically significant effect on TFP and human capital. Using both economic and political freedom variables in the estimations, their results show that these two variables have positive effects on TFP.

Loko and Diouf (2009) consider altogether the effects of macroeconomic stability (in terms of inflation), FDI, trade openness and business environment on TFP in Maghreb countries in a dynamic panel data setting. They attempt to test the complementary effect of policies to trade openness following Chang, Kaltani, and Loayaza (2005). Their results demonstrate that macroeconomic stability, openness and the level of education are all important for productivity growth. In particular, higher inflation hampers productivity gains significantly, confirming the negative impact of macroeconomic instability. Notwithstanding, their three alternative measures of institutions – the degree of regulation of credit, labor, and business; law and order; and the economic freedom index – all point to the importance of institutions to high TFP growth.

On regulations, its effect on productivity appears to be straightforward. A less regulatory environment is conducive to a more competitive environment, thereby promoting productivity and efficiency growth. Stringent regulation is a hindrance to technology adoption and innovation, possibly because it reduces competitive pressures, technology spillovers and the entry of new high-tech firms. Crafts (2006) argues that regulation can be thought of as rules imposed by the State. Such rule can be used to correct market failures through acting to reduce the costs of negative externalities or imperfections of information by providing insurance or public goods. However, such action also typically imposes costs on the private sector. So there is a danger of excessive regulation where additional costs exceeded extra benefits. All in all, the effectiveness of regulation depends on enforcement as well as legislation.

One of the empirical studies investigating the effect of regulation and the institutional environment on productivity is Scarpetta, Hemmings, Tressel, et al. (2002). They note that, across OECD countries, growth paths have become increasingly disparate in the past decade. They suggest two possible reasons: (i) differences in productivity patterns of certain high-tech industries and (ii) differences in the adoption of information and communications technology (ICT). They find that stringent regulatory settings in the product market negatively affect TFP. In addition, labour market regulations that induce high hiring and firing costs also have a negative effect on TFP. In particular, such negative effects are worse for firms in countries which are far from the technological leader.

Based on the World Bank’s investment climate survey in five transition economies – the Kyrgyz Republic, Moldova, Poland, Tajikistan and Uzbekistan, Bastos and Nasir (2004) similarly conclude that productivity differences across countries can be explained largely by differences in the investment climate, e.g. policy, institutional and regulatory environment, in which businesses operate. In particular, competition seems to be the most important factor behind productivity performance, followed in the second place by infrastructure, while rent predation (e.g. corruption) occupies the third place. To sum up, we have reviewed some of the recent theoretical and mostly empirical literature, discussing the sources of productivity in this Section. The deep determinants of productivity include human capital, openness and institutions. Studies examining the effects of these factors alone do not bring conclusive evidence. Conflicting results are often found between developed and developing economies. The literature suggests that one would expect the determinants of productivity growth in technological leaders and recipients to be different (i.e. their relative positions in the global technology frontier matter). However, exactly how much the less developed economies are falling behind the technological leaders is not clear. By its very own nature, TFP per se does not allow us separately to understand how technical change and efficiency change take place. We fail to know if the economy does not "catch-up" because of the barriers of technological adoption or inefficient allocation of resources. In this regard, we consider an alternative measurement technique – i.e. stochastic production frontier – to estimate the efficiency change across countries.

3 Fundamentals of Stochastic Production Frontier (SPF)

To estimate the efficiency of production, Farrell (1957) suggests that the efficiency of an individual cross-section, say a firm, consists of two components: **(i)** technical efficiency, measuring the ability of a firm to obtain maximal output from a given set of inputs; **(ii)** allocative efficiency, measuring the ability of a firm to use the inputs in optimal proportions, given their respective prices. In a cross-country context, our primary research interests lie on the measurement of technical efficiency. In this section, we will discuss the basis of our estimation methodology, i.e. stochastic production frontier (SPF), and present a brief survey of some of its applications. Generally speaking, efficiency measurement relies on estimating a "global" production frontier of a number of cross-sections. Data envelopment analysis (DEA) and stochastic frontiers are two convention methods for such purpose. Coelli, Rao, and Battese (1998) compare the merits and characteristics between these two, which are summarised in Table 1 below:

Table 1: Comparison of Stochastic Production Frontier and Data Envelopment Analysis

Stochastic Production Frontier	Data Envelopment Analysis
(a) Estimation method	
Parametric	Non-parametric
(b) Account for stochastic disturbance	
Yes (more realistic)	No (yet conform with economic theory)
(c) Assume all inputs are efficiently used	
No	
(d) Data requirements	
Input and output quantities	
(e) Technical efficiency (TE) obtained	
Mean TE distribution	Exact Level of TE

Source: Coelli, et al. (1998)

As compared to DEA (also known as deterministic frontiers), although it ignores the stochastic effect on production frontier, they are more consistent with economic theory. DEA is also more advantageous in terms of obtaining the exact measure of technical inefficiency for each observation instead of its distribution. However, its chief disadvantage is that they are bound to be confounded by statistical ‘noise’, whereas stochastic frontiers are more realistic, at least in terms of econometrics. Moreover, due to its non-parametric approach, DEA is more sensitive to outliers. Since this study is primarily empirical in nature, the readiness of hypothesis tests developed for SPF provides an added advantage for us to choose SPF over DEA for our estimation.

3.1 Basic Framework

SPF is an estimation of a “global” production frontier of a number of cross-sections while incorporating stochastic assumptions. Based on this concept of productivity, we can measure the economic performance of each country relative to the world’s best possible output given the available resources and technology at each time period. This comparative measurement of economic performance against the world production frontier is regarded as technical efficiency.

SPF assumes a mixture of one-sided and two-sided (e.g. normal) errors. The error term is composed of two parts. The one-sided component captures the effects of inefficiency relative to the stochastic frontier. The two-sided component permits random variation of the frontier across cross-sections, and captures the effects of measurement error, other statistical ‘noise’, and random shocks outside the cross-sections’ control.

In a nutshell, the measurement attempts to capture that given the quantities of a list of inputs, there is a maximal possible output. However, this maximum level is random (to be precise, which is randomly distributed as a function) rather than exact. This assumes that some inputs or external effects have maximal possible effects, but others have potentially unbounded effects, e.g. weather. In general form, a production function can be specified as followed:

$$y_i = a_i\, f(\, x_i\, ;\, \beta\,) \qquad\qquad 0 < \; a_i \; \leq 1 \tag{1}$$

where *i* denotes the *i*-th cross-section. *y* denotes the unit of output. a measures the technology parameters. *x* is a (*1 x k*) vector of inputs of production and other explanatory variables and *β* is a vector of coefficients of inputs to be estimated. Rewriting eq. (1) in log-form gives:

$$\ln y_i \; = \ln f\; (\, x_i\, ;\, \beta\,) - \; u_i \tag{2}$$

Where $u_i \; = \ln a_i \; \geq 0$ represents technical inefficiency. Thus technical efficiency (TE) is given by $\exp(u_i)$ A Taylor-series expansion of $\exp(-u_i)$ around u = 0 yields $\exp(-u_i) = 1 - u + \frac{u^2}{2} - \frac{u^3}{3} + \cdots$. Hence for small values of u_i , $\exp(-u_i) \approx 1 - u_i$ as Cornwell and Schmidt (1996) suggest. Following Aigner, Lovell, and Schmidt (1977) and Meeusen and Broeck (1977), an SPF can thus be expressed as an error-component model:

$$y_i = f\ (x_i\ ;\ \beta\ ) \exp(v_i - u_i) \tag{3}$$

Assume $v \sim iid\ N\ (0\ ,\ \sigma^2)$ is a stochastic error independently distributed of u . It accounts for the measurement such as the effects of weather, strikes, luck etc on the value of the output variable together with the combined effects of unspecified input variables in the production function. Therefore it is simply treated as random disturbances.

u , on the other hand, is assumed to be a non-negative random variable associated with technical inefficiency of production and is again assumed to be independently distributed. Among the different cross-sectional SPF models, there are a number of specifications of u commonly proposed. For examples, Aigner, et al. (1977) and Meeusen and Broeck (1977) assume $u_i \sim iid\ N^+ + (0\ ,\ \sigma_v^2)$, Stevenson (1980) assumes $u_i \sim iid\ N^+ + (u\ ,\ \sigma_u^2)$ where as Greene (1990) assumes $u_i \sim iid\ gamma$ [3].

Since it is assumed that $u_i \geq 0$, it implies that, for each cross-section, its output must lie on or below its frontier $[\ f\ (x_i\ ;\ \beta\ )\ +\ v_i\ ]$. Any deviation technical implies and economic inefficiency. That said, the ratio of the output for the i-th firm relative to the maximum potential output, defined by the frontier function given the input vector x_i, can be used to obtain technical efficiency of the i-th firm:

$$TE_i = \exp(-u_i) = \frac{y_i}{f(x_i\ ,\beta)\ \exp(v_i)} \tag{4}$$

By definition, TE_i takes a value of zero to one.

Eq.(4) suggests that if $u_i = 0$, then ε_i [sum of 2-sided errors, u+v] is v_i, the error term is symmetric, and the data do not support a technical inefficiency story. However, if $u_i > 0$, then $\varepsilon_i = v_i - u_i$ is negatively skewed, and there is evidence of technical inefficiency in the data. In other words, the production process is subject to two random disturbances, namely u and v. The frontier is stochastic with random disturbance of $v_i \leq$ or ≥ 0. Technically speaking, we can estimate the variances of v_i and u_i for each cross-section.

[3] We do not aim at providing a survey on various SPF models for cross-sectional analysis since we will carry out panel data analysis. For further reference, Coelli, et al. (1998) and Kumbhakar and Lovell (2000) provide excellent surveys of different SPF models.

3.2 Some Applications of SPF

There are numerous studies using the stochastic frontier approach for various applications, mostly for firm-level and industry-level analyses. Models derived from different assumptions and techniques have been extensively employed. The technique was initially developed for applications at firm-level and industry-level studies, especially on agricultural economics (such as in Battese and Coelli (1992) and Battese and Coelli (1995)) concerning the measurement of inefficiency across different producers. Meeusen and Broeck (1977) were probably among the first to test their model on several manufacturing industries. After developing panel data stochastic frontier models[4], recent work like Paul, Johnson, and Frengley (2000), Bhattacharyya, Bhattacharyya, and Mitra (1997), Mahadevan (2002) and Kruger, Canter, and Hanusch (2000) deploy several variations of panel data SPF models for their micro-level studies.

Empirical applications of SPF have been reasonably extended to country-level data. Macro-level work mostly intends to estimate the efficiency levels across countries under different political environments and/or regime changes. In particular, the political changes that took place in Eastern Europe facilitate the comparison of efficiency levels in market-oriented vis-à-vis planned economies. For example, Koop, Osiewalski, and Steel (1999) initially focus their measurement exercise on 17 OECD countries. Koop, Osiewalski, and Steel (2000) extend further the measurement and make special reference to Poland and Yugoslavia in comparison to 20 Western economies.

Moroney and Lovell (1997) share a similar interest and measure the relative efficiencies of 7 transition economies in comparison to other Western economies. Klein and Luu (2003), on the other hand, use the indices of economic freedom and political constraints as independent variables for explaining inefficiencies in 39 countries from 1975 to 1990. Their results show that technical efficiency relates positively to policies supporting laissez-faire and political structures that promote policy stability. Adkins, et al. (2002) on the other hand investigate the impact of economic freedom on promoting efficiency.

However, SPF models are mostly applied to mere measurements of technical efficiency. The sources of technical inefficiencies are not considered and/or incorporated in these models. To incorporate exogenous variables to explain the sources of technical inefficiency, some of the

[4] Among others, more prevalently used panel data SPF models include Schmidt and Sickles (1984), Cornwell, Schmidt, and Sickles (1990) and Battese and Coelli (1992) and Battese and Coelli (1995). See Appendix Section A.3 for details.

researchers approach the problem using a 2-stage approach. In the first stage, they use the aforementioned SPF models to obtain the technical inefficiency measures, typically by maximum likelihood estimation (ML). In the second stage, the estimated technical inefficiency is treated as dependent variables to be regressed on a vector of explanatory variables in the form such as

$$E\ (v_i - u_i) = \mathrm{g}(z_i; y) + \varepsilon_i \tag{5}$$

where z_i is the vector of exogenous variables given $y = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$

In some cases, it is recognised that since the dependent variable u lies between 0 and 1, OLS estimates cannot be used. Instead, an estimation technique such as Tobit for limited dependent variable estimation is employed.

Amongst various studies of such kind, Liu, Liu, and Wei (2001) make special reference to trade openness in the case of India and China. They first employ a dynamic approach to the estimation of a production function and then in the second stage, technical efficiency is treated as a dependent variable. Their key results show the relationship of trade openness and their relative technical inefficiencies for the case of India and China.

Although it is fairly often that early literature associating technical inefficiency and its sources uses the aforementioned 2-stage approach, estimations of such kind are fundamentally problematic in terms of econometrics. As Battese and Coelli (1995), Coelli, et al. (1998) and Kumbhakar and Lovell (2000) argue, such an approach has at least 2 obvious flaws. Firstly, 2-stage estimations ignore the fact that SPF models in the first stage have assumed a particular distribution of the level of technical inefficiency, u. In other words, u is frequently assumed to be an independent random variable with particular distribution. This contradicts with the second stage, where the predicted mean efficiencies are assumed to have a functional form of z_i. It is thus statistically inconsistent to assume u again at the second stage with any form of specification.

Secondly, the 2-stage approach imposes a restricted assumptions that z_i are uncorrelated with x_i, the production inputs. Otherwise, the estimates obtained in the first stage are biased due to omitted variables. The biased estimates of technical inefficiency being used as dependent variables inevitably undermine the validity of results obtained in the second stage of estimation.

Since our primary research interest of this paper is to investigate whether institutions can explain the cross-country technical inefficiencies, SPF models that allow us to incorporate exogenous explanatory factors are essential. While recognising the inadequacies of using a 2-stage approach as in the current literature, we will employ an alternative approach to tackle the problem of such kind. The models we use will be discussed in more details in the next section (i.e. The fourth paper, entitled "Impact of Natural Environment, Regional Integration, and Policies on FDI",).

3.3 General Critics on SPF

We do not intend to argue that SPF models are strictly superior to DEA. Indeed, we fully recognise the limitations of this methodology. As Førsund, Lovell, and Schmidt (1980) point out, even though SPF captures a more realistic world, unfortunately there is no way of determining whether the observed performance of a particular observation compared with the deterministic kernel of the frontier is due to inefficiency or to random variation in the frontier. This constitutes the main weakness of the SPF model – i.e. it is not possible to decompose individual residuals into their two components, and so it is not possible to estimate technical inefficiency by observation. What we are estimating is simply the mean inefficiency over the sample, but not its "true" value.

Secondly, Coelli, et al. (1998) realise that when using the stochastic frontier approach, the specification of the functional form of the production function matters for the results. Monte Carlo simulation results from Giannakas, Tran, and Tzouvelekas (2003) indicate that the bias in the mean efficiency measures from stochastic frontier methods due to misspecification of functional form is sizeable. It can suggest a high level of inefficiency (10-30%) of output for the most efficient producers. As Ravallion (2003) also criticises; the approach using non-parametric methods is more preferable in some cases, especially when measuring social efficiency using social indicators. Parametric estimation, like SPF, is very sensitive to outliers and one must assume a continuous frontier. Likewise, the distribution of the inefficiency term also has to be specified.

The stability and reliability of the results are also concerns too. The measured efficiency is only relative to the best cross-section in the sample. Including extra cross-sections may alter the efficiency scores. Furthermore, measurement error and other noise may influence the slope and position of the frontier. Not surprisingly, measurement errors and outliers will likewise influence results significantly. In our estimations, we attempt to alleviate some of these problems by using a reliable source of data to minimize the measurement errors as far as possible.

4 Model Estimation and Specification

There are primarily four dimensions of SPF models developed and could be considered in our case. These include cross-sectional versus panel data models and with or without assuming time-varying technical efficiency. We will consider the most flexible forms of SPF models – i.e. panel data model with time-varying technical efficiency. The availability of panel data generally implies that there is a large degree of freedom for estimation. It also permits the simultaneous investigation of both technical change and technical efficiency change over time.

There is also one added advantage of using panel data SPF models. Specification of the error term and the inefficiency term is one of the major challenges of using stochastic production frontier estimation. However, Schmidt and Sickles (1984) show that when panel data are available, assumptions on the distribution of technical inefficiency could be relaxed since the parameters can be estimated using the traditional panel data methods of fixed-effects estimation or error-components estimation. Measuring the technical efficiencies of the sample can be rather straightforward hereafter as they can be obtained relative to the most efficient one(s). This view is also shared by Kumbhakar and Lovell (2000).

The basic framework of panel SPF model is generally similar to the cross-sectional one set out in Section 3.1. Appendix Section A.3 summarises some key panel time-varying SPF models, which are often used in the existing literature.

4.1 Battese and Coelli (1993) and (1995) Model

Our model of estimation is based on the Battese and Coelli (1993) and Battese and Coelli (1995) model. The key advantage of their model is that it allows incorporating the technical efficiency model in the stochastic production frontier estimation to perform a one-stage simultaneous estimation.

Following eq. (2), the stochastic production frontier in panel data form is defined as:

$$Y_{it} = x_{it}\beta + \mathrm{E}_{it} \tag{6}$$

Where $\mathrm{E}_{it} = V_{it} - U_{it}$ and $i = 1,\ldots,N$ and $t = 1,\ldots T$

Y_{it} is the logarithm of production output. V_{it} is assumed to be $iid \sim N(0\,,\ \sigma_v^2)$, independently distributed of the U_{it}, which are non-negative random errors associated with technical inefficiency of production. The technical efficiency model is specified as:

$$U_{it} = z_{it}\delta + W_{it} \tag{7}$$

where W_{it} is a random variable and is defined by the truncation of the normal distribution with zero mean and variance σ^2 and $W_{it} \geq -z_{it}\,\delta$. Technical inefficiency (U_{it}) is assumed to be independently distributed for all t and i and is obtained by truncation (at zero) of the normal distribution with mean $z_{it}\,\delta$ and variance vector of country specific institutional environment which may vary over time. δ is an (m x 1) vector of unknown coefficients. Technical efficiency of production can be defined as:

$$TE_{it} = \exp(-U_{it}) = \exp(-z_{it}\delta - W_{it}) \tag{8}$$

Therefore, the density functions for U_{it} and V_{it} are:

$$f(v) = \frac{\exp\left(-\frac{\frac{1}{2}v^2}{\sigma_v^2}\right)}{\sqrt{2\pi}\,\sigma_v} \quad -\infty < v < \infty \tag{9}$$

$$f_v(u) = \frac{\exp\left(-\frac{1}{2}(u-z\delta)^2\,/\sigma^2\right)}{\sqrt{2\pi}\,\sigma\Phi(\frac{z\delta}{\sigma})} \quad u \geq 0 \tag{10}$$

Where subscripts i and t are omitted for simplicity. Φ(·) represents the distribution function for the standard normal random variable. The joint density function for E = V – U and U is

$$f_{E,U}(\varepsilon,u) = \frac{\exp-\frac{1}{2}[\{(\varepsilon+u)^2/\sigma_V^2\}+\{(u-\frac{z\delta)^2}{\sigma^2}\}]}{2\pi\sigma\sigma_v\Phi(\frac{z\delta}{\sigma})}$$

$$= \frac{\exp-\frac{1}{2}[\{(u-u_\Phi)^2/\sigma_\Phi^2\}+(\varepsilon^2/\sigma_v^2)+(z\delta\,/\sigma)^2-(u_\Phi\,/\sigma_\Phi)^2]}{2\pi\sigma\sigma_v\Phi(\frac{z\delta}{\sigma})} \tag{11}$$

Alternatively,

$$f_{E,U}(\varepsilon,u) = \frac{\exp-\frac{1}{2}[\{(u-u_\Phi)^2/\sigma_\Phi^2\}+\{(\varepsilon+z\delta^2)/(\sigma_v^2+\sigma^2)\}]}{2\pi\sigma\sigma_v\Phi(\frac{z\delta}{\sigma})} \tag{12}$$

where $\mu_* = \dfrac{\sigma_v^2 z\delta - \sigma^2\varepsilon}{\sigma_v^2 + \sigma^2}$ and $\sigma_*^2 = \sigma^2\sigma_v^2 / (\sigma^2 + \sigma_v^2)$

Such that the density function for E = V – U is

$$f_E(\varepsilon) = \frac{\exp-\frac{1}{2}\left[(\varepsilon^2/\sigma_v^2)+(z\delta/\sigma)^2-(\mu_*/\sigma_*)^2\right]}{\sqrt{2\pi}\sigma_v\sigma\cdot\Phi(z\delta/\sigma)}\cdot\int_0^\infty \frac{\exp-\frac{1}{2}\left[(u-\mu_*)^2/\sigma_*^2\right]}{\sqrt{2\pi}}du$$

$$= \frac{\exp-\frac{1}{2}\left[(\varepsilon^2/\sigma_v^2)+(z\delta/\sigma)^2-(\mu_*/\sigma_*)^2\right]}{\sqrt{2\pi}(\sigma^2+\sigma_v^2)^{1/2}[\Phi(z\delta/\sigma)/\Phi(\mu_*/\sigma_*)]} \tag{13}$$

Alternatively,

$$f_E(\varepsilon) = \frac{\exp\{-\frac{1}{2}(\varepsilon - z\delta)^2/(\sigma_v^2 + \sigma^2)\}}{\sqrt{2\pi}\,(\sigma^2 + \sigma_v^2)^{\frac{1}{2}}\{\Phi(z\delta/\sigma)/\Phi(u_\Phi/\sigma_\Phi)\}} \tag{14}$$

The conditional density function for U given E = ε is thus

$$f_{U|E=\varepsilon}(u) = \frac{\exp-\frac{1}{2}\{(u - u_\Phi)^2/\sigma_\Phi^2\}}{\sqrt{2\pi}\sigma_\Phi \Phi(u_\Phi/\sigma_\Phi)} \tag{15}$$

Conditional expectation of ε -U given E = ε is

$$E\left(\varepsilon^{-U} \mid E = \varepsilon\right) = \left[\exp\left(-\mu_* + \frac{1}{2}\sigma_*^2\right)\right]\left\{\frac{\Phi[(\mu_*/\sigma_*) - \sigma_*]}{\Phi(\mu_*/\sigma_*)}\right\} \tag{16}$$

such that the density function for Y_{it} in eq.(6) can be derived from eq.(14):

$$f_{Y_{it}}(Y_{it}) = \frac{\exp-\frac{1}{2}\left\{\frac{(Y_{it} - x_{it}\beta + z_{it}\delta)^2}{\sigma_v^2 + \sigma^2}\right\}}{\sqrt{2\pi}(\sigma_v^2 + \sigma^2)^{\frac{1}{2}}\left[\Phi(d_{it})\big/\Phi(d_{it}^*)\right]} \tag{17}$$

Where $d_{it} = z_{it}\delta/\sigma, d_{it}^* = \mu_{it}^*/\sigma_*$ and $\mu_{it}^* = \left[\sigma_v^2 z_{it}\delta - \sigma^2(Y_{it} - x_{it}\beta)\right]\big/(\sigma_v^2 + \sigma^2)$

The logarithm of the likelihood function for the sample observations y is:

$$\begin{aligned} L^*(\theta^*; y) = &-\frac{1}{2}\left(\sum_{i=1}^{N} T_i\right)\left\{\ln 2\pi + \ln(\sigma^2 + \sigma_v^2)\right\} \\ &-\frac{1}{2}\sum_{i=1}^{N}\sum_{t=1}^{T_i}\left[(Y_{it} - x_{it}\beta + z_{it}\delta)^2/(\sigma_v^2 + \sigma^2)\right] \\ &-\sum_{i=1}^{N}\sum_{t=1}^{T_i}\left[\ln\Phi(d_{it}) - \ln\Phi(d_{it}^*)\right] \end{aligned} \tag{18}$$

where $\theta^* = (\beta', \delta', \sigma_v^2, \sigma^2)'$.

put $\sigma^2 = \sigma_v^2 + \sigma^2$ and $y = \sigma^2/\sigma_v^2$, eq. (18) can be expressed as

$$\begin{aligned} L^*(\theta^*; y) = &-\frac{1}{2}\left(\sum_{i=1}^{N} T_i\right)\left\{\ln 2\pi + \ln\sigma_s^2\right\} \\ &-\frac{1}{2}\sum_{i=1}^{N}\sum_{t=1}^{T_i}\left[(Y_{it} - x_{it}\beta + z_{it}\delta)^2/\sigma_s^2\right] \\ &-\sum_{i=1}^{N}\sum_{t=1}^{T_i}\left[\ln\Phi(d_{it}) - \ln\Phi(d_{it}^*)\right] \end{aligned} \tag{19}$$

where $d_{it} = z_{it}\delta \big/ \left(\gamma\sigma_s^2\right)^{1/2}$

$$d_{it}^* = \mu_{it}^* / \left[\gamma(1-\gamma)\sigma_s^2\right]^{1/2}$$

$$\mu_{it}^* = (1-\gamma)z_{it}\delta - \gamma(y_{it} - x_{it}\beta)$$

$$\sigma_* = \left[\gamma(1-\gamma)\sigma_s^2\right]^{1/2}$$

and $\theta = \left(\beta', \delta', \sigma_s^2, \gamma\right)'$.

The partial derivatives of eq. (18) with respect to β , δ ,σ 2 , γ are,

$$\frac{\partial L^*}{\partial \beta} = \sum_{i=1}^{N}\sum_{t=1}^{T_i}\left\{\frac{\left(Y_{it} - x_{it}\beta + z_{it}\delta\right)}{\sigma_s^2} + \frac{\phi\left(d_{it}^*\right)}{\Phi\left(d_{it}^*\right)}\cdot\frac{\gamma}{\sigma_*}\right\}\cdot x_{it}' \tag{20}$$

$$\frac{\partial L^*}{\partial \delta} = -\sum_{i=1}^{N}\sum_{t=1}^{T_i}\left\{\frac{Y_{it} - x_{it}\beta + z_{it}\delta}{\sigma_s^2} + \left[\frac{\phi(d_{it})}{\Phi(d_{it})}\cdot\frac{1}{\left(\gamma\sigma_s^2\right)^{1/2}}\cdot - \frac{\phi(d_{it})}{\Phi(d_{it})}\cdot\frac{1-\gamma}{\sigma_*}\right]\right\}\cdot z_{it}' \tag{21}$$

$$\frac{\partial L^*}{\partial \sigma_s^2} = -\frac{1}{2}\left(\frac{1}{\sigma_s^2}\right)\left\{\left(\sum_{i=1}^{N} T_i\right) - \sum_{i=1}^{N}\sum_{t=1}^{T_i}\left[\frac{\phi(d_{it})}{\Phi(d_{it})}d_{it} - \frac{\phi\left(d_{it}^*\right)}{\Phi\left(d_{it}^*\right)}d_{it}^*\right] - \sum_{i=1}^{N}\sum_{t=1}^{T_i}\frac{Y_{it} - x_{it}\beta + z_{it}\delta}{\sigma_s^2}\right\} \tag{22}$$

$$\frac{\partial L^*}{\partial \gamma} = \sum_{i=1}^{N}\sum_{t=1}^{T_i}\left\{\frac{\phi(d_{it})}{\Phi(d_{it})}\frac{d_{it}}{2\gamma} + \frac{\phi\left(d_{it}^*\right)}{\Phi\left(d_{it}^*\right)}\left[\frac{Y_{it} - x_{it}\beta + z_{it}\delta}{\sigma_*} + \frac{d_{it}^*(1-2\gamma)}{2\gamma(1-\gamma)\sigma_*^2}\right]\right\} \tag{23}$$

Where $\phi(\cdot)$ is the density function for the standard normal random variable. The necessary condition for maximizing the log-likelihood function is that these partial derivatives equal 0.

Estimation output can be obtained from the FRONTIER 4.1 program devised by Coelli (1996). The estimation follows a three-step procedure in estimating the maximum likelihood estimates of the parameters of a stochastic frontier production function. The three steps involve:

1) OLS estimates of the production function (including ß0 and σ_s^2 are obtained), such that all coefficients (except the intercept and σ_s^2) will be unbiased.

2) A two-phrase grid search of γ (between zero and one) is conducted. The OLS estimates of

σ_S^2 and β_0 are adjusted

$$\sigma_S^2 = \sigma_{OLS}^2[\pi(T-K)]/[T(\pi-2\hat{\gamma})] \quad \text{and} \quad \hat{\beta}_0 = \hat{\beta}_{0(OLS)} + \sqrt{\frac{2\hat{\gamma}\hat{\sigma}_S^2}{\pi}}$$

Respectively. The OLS estimates are used for the remaining parameters in ß.

3) The values selected in the grid search are used as starting values in an iterative procedure to obtain the final maximum likelihood estimates.

4.2 Post-estimation Test

The one-sided generalized likelihood-ratio test (hereafter called LR-Test) can be used for hypothesis testing. This aims at providing a statistical test of the goodness-of-fit between two models. In short, a relatively more complex model is compared to a simpler model to see if it fits a particular dataset significantly better. If so, the additional parameters of the more complex model are often used in subsequent analyses. The LR-Test is only valid if it is used to compare hierarchically nested models. That is, the more complex model must differ from the simple model only by the addition of one or more parameters. Further addition of parameters will always result in a higher likelihood score. However, there comes a point when adding additional parameters is no longer justified in terms of significant improvement in the goodness of fit for the model to a particular dataset. The LR-Test provides one objective criterion for selecting different possible models. This will also serve as the basis of our model selection among different specifications.

The LR-Test begins with a comparison of the likelihood scores of the two models. The likelihood-ratio test statistic is calculated as:

$$\lambda = -2[\log(likelihood(H_0)\log(likelihood(H_1) - A = \pi r^2 \qquad (24)$$

which has approximately chi-square distribution with degree of freedom equal to the number of parameters assumed to be equal to zero in the null hypothesis, H_0. Kodde and Palm (1986) design a Wald test to jointly test the equality of restrictions and provide the critical values for the LR-Test.

4.3 Model Specification

We specify our stochastic production frontier in the translog form as proposed by Christensen, Jorgenson, and Lau (1973):

$$lnY_{it} = \beta_0 + \beta_K lnK_{it+}\beta_L lnL_{it+}\beta_{KK}(lnK_{it})^2 + \beta_{LL}(lnK_{it})^2 + \beta_{KL}(lnK_{it}.lnL_{it})^2 + \beta_{Kt}(lnK_{it}.t) + \beta_{Lt}(lnL_{it}.t)^2 + \beta_t t + \beta_{tt}t^2 + v_{it} + u_{it} \qquad (25)$$

where $v_{it} \sim iid\ N(0,\sigma_v^2)$ is a random disturbance. u_{it} is the level of technical inefficiency of i-th cross-section at time t. β_0 is the constant term in the production function to capture the initial level of technology. The translog production function does not restrict the returns to scale of the production function and substitution possibilities. It is thus a more general and flexible form of specification in comparison to Cobb-Douglas production function for example.

As suggested by Coelli, et al. (1998), we also incorporate a time trend (t) to capture the potential shifts of the production frontier over time, which reflects the rate of technological change. In our specification, therefore, the coefficient β_t provides an estimate of the annual percentage change in output resulting from technological change. Since the translog specification is a second-order approximation, t_2 is also included. An estimate of the annual percentage change in output resulting from technological change is provided by the first partial derivative of eq. (25) with respect to t.

For the time-varying technical inefficiency model, our general form of specification is

$$u_{it} = \delta_i instit_{it} + \delta_H H + \delta_{iH} instit_{it}.H_{it} + \delta_{open} openness + \delta_t t + w_{it} \qquad (26)$$

where w_{it} is a random disturbance with a truncated normal distribution. *instit* is a set of variables measuring institutions. H measures human capital. The interaction term of human capital and institution allows us to see if the institution affects technical efficiency given the necessary level of human capital. Openness is a set of variables measures openness to trade, financial integration and capital account openness. δ is a vector of coefficients of the respective areas to be estimated. The final specification of the model will depend on the LR-Test results for different specifications.

All in all, our empirical investigation primarily concerns the sources of cross-country technical inefficiency. With regard to methodology, our work intends to contribute in three ways. Firstly, compared to the other growth-accounting (e.g. TFP growth measurement) literature, we extend the work to decompose the different sources of growth and attempt to seek the sources of cross-country divergence, in terms of technical change and efficiency change. Secondly, our study uses a one-stage approach to estimate the stochastic production frontier while incorporating the explanatory factors of technical inefficiency. Such design will avoid the inconsistent assumptions used when employing two-stage estimations. Finally, as we will discuss in the following, we use a relatively large number of economies comparing to other studies for a longer period of time. We are of the view that only employing a substantial amount of economies would bring the estimation of a "world frontier" more meaningful.

5 Data

We have a panel dataset for 108 cross-sections covering 24 OECD economies and 78 economies in East Asia and Pacific, Europe and Central Asia, Middle East and North Africa, Latin American and Caribbean, South Asia and Africa. Six high-income economies are also included but they are not classified by regions[5]. The full list of economies covered in our study is at Appendix Section A.2.

The study period starts from 1971 to 2000, signifying the beginning of globalization, free flow of information and capital. It also better reflects the uprising of emerging markets, in particular towards the latter periods of the studied period. The sample is nevertheless limited by the availability of institutional variables, which are only in place starting from 1970.

5.1 Output and Production Inputs

Output is measured as chain-weighted real GDP in constant 1996 prices, which is PPP-adjusted to facilitate cross-country comparison. We derive output (Y) data from the Penn World Table (PWT ver 6.1) (Heston, Summers, and Aten (2002)), where Y is obtained from real GDP per capita multiplied by population.

The labour force (L) is the number of workers from PWT, derived from real GDP per worker data. We understand that using employment data is a more accurate measure of production input than the total labour force. However, as far as we understand, only the OECD and Asia Development Bank (ADB) produce employment data. The International Labour Organisation (ILO) also collects cross-country unemployment rates, which could also be used to derive employment from labour force data. However, the sample size will be significantly reduced if these data sources are used.

Based on Isaksson (2007b), capital stock (K) can be calculated from real investment data. Total real investment is measured as real total output (Y) multiplied by the investment share of real GDP per capita in PWT. For missing values, we follow Isaksson (2009) to interpolate the series by taking the average of two years.

Our capital stock estimates are heavily based on Isaksson (2007b). As in King and Levine (1994), Benhabib and Spiegel (1997) and Limam and Miller (2004), amongst others, the

[5] Country classification by income groups and regions are based on World Bank Country

standard way is to use the perpetual inventory method with the steady-state initial capital stock. The 1960 capital stock is assumed to be the initial steady-state value for each country[11] and it is then incorporated with investment 098data to derive the capital stock for subsequent periods (till 2000). It is commonly assumed that the capital-output ratio is constant in the steady state. That said, physical capital and real output grow at the same rate. The depreciation rate δ is assumed to be 6% across countries over time.

Hence, the steady-state capital-output ratio for country i is derived as:

$$\kappa_i = i_i /(\delta + \lambda g_i + (1-\lambda) g_w) \tag{27}$$

i_t is the steady-state investment rate for country i, which is peroxide by average real investment rate for the first 10 years. $\lambda g_i + (1 - \lambda\ )$is the steady-state growth rate which is the weighted average of the country's growth rate and the world growth rate. λ is a measure of mean reversion of growth rates and equals to 0.25 as in Easterly, Kremer, Prichett, et al. (1993). g_i is the country's average growth rate over the period 1960 to 1969. g_w is the world growth rate and is approximated to be 4%. Initial capital stock in year 1960 (or earliest possible year in our sample) can thus be expressed as:

$$K_{i,60} = \kappa_i + Y_{i,60} \tag{28}$$

Where $Y_{i,60}$ is real GDP of country i in the year 1960.

The calculation of capital stock for the remaining years, using the perpetual inventory method, comes as the following:

$$K_{it+1} = I_{it} + (1+\delta)K_{it} \tag{29}$$

The series of capital stocks from 1960 to 2000 can thus be obtained.
We further take a non-overlapping 5-year average for all the variables to get rid of the business cycle effect. Islam (1995) also suggests that using a 5-year average series is less likely to be serially correlated. Our dataset therefore, collapsesods in total.

5.2 Explanatory Variables for TE Models

Descriptive statistics of our sample are at Appendix Section A.1. To recap, we consider three aspects of explanatory variables in the TE model, which include:

1. Human capital (H): average years of schooling of aged 15 or above from Barro and Lee (2001).

[11] Alternatively, we use data in the earliest possible year during the 60's subject to availability.

2. Institution: Our measures of different institutional variables primarily come from the Fraser Institute's Economic Freedom of the World Report of Gwartney, et al. (2008) and Polity IV project dataset of Marshall and Jaggers (2009). As in second paper, Rodrik (2000)'s taxonomy of institutions are again adopted. We will first use the composite quality of government index (QOG) from ICRG for testing the various specifications of the production function. In our key models, specifically, we use the Fraser's legal structure and security of property rights index (LEGAL) for "market-creating institutions". We use the composite index of regulation (REG) as a measure of "market-regulating institution". For "market-stabilising institutions", we consider the use of the access to sound money index (SM) to proxy the effectiveness of monetary policy. For "market-legitimising institutions", we use the institutionalised democracy index from Polity IV project (DEMOC).

3. Openness: We use four indicators **(i)** financial integration index from Lane and Milesi-Ferretti (2006) (FIN); **(ii)** capital account openness index from Chinn and Ito (2006) (KAOPEN), and **(iii)** total trade to GDP (TRADE), and; **(iv)** total FDI inflows to GDP (FDI). Both (iii) and (iv) are from World Development Indicators.

6 Estimation Results

6.1 Specification of Production Function

We first take a preliminary test of the specification of the production function as set out in eq. (25). For simplicity, we incorporate QOG, a composite index of the quality of government, as the only explanatory variable in the technical inefficiency model at this stage. The key aim of the results is to provide support to our specification of the production function. Test results are given in Table 2.

A Cobb-Douglas production function is specified in SPF Model (1), A Hicks-neutral translog production function is used for SPF Model (2) and a non-neutral translog production function is in SPF Model (3). As we explained earlier, the translog production function is a more flexible form of the Cobb-Douglas production function. Comparing SPF Models (2) and (3), the former model only accounts for Hicks-neutral technical change. That is, the production function shifts up and down but their slopes (e.g. marginal rate of technical substitution) do not alter. In SPF Model (3), non-neutral technical change is also accounted for by including terms involving the interactions of the other regressors and time. Non-neutral technical change is also referred to as biased technical change. That said, the movement of the production function will be biased in favour of certain inputs and against others.

All three SPF models show that the signs of elasticities of both capital and labour ($\beta_K\ and\ \beta_L$)

are positive as the theory predicted. Compared to the standard assumption of input shares of capital and labour to be one-third and two-third respectively, the parameters in SPF Model (1) show rather awkward results – β_K is around 0.6 whereas β_L is around 0.3. In SPF Models (2) and (3), the input elasticities are more sensible. The production functions in both models exhibit a decreasing return to scale, with β_K is around 0.25 and β_L is around 0.6.

Table 2: Maximum Likelihood Estimation of Stochastic Production Frontier Models

	SPF Model (1) Coeff. (std. error)	SPF Model (2) Coeff. (std. error)	SPF Model (3) Coeff. (std. error)
Dep var: *ln(Y)*			
β_0	1.6486 ***	3.0593 ***	2.8515 ***
	(0.1282)	(0.7104)	(0.7104)
β_K	0.6358 ***	0.2468 ***	0.2503 ***
	(0.0065)	(0.0686)	(0.0686)
β_L	0.3321 ***	0.5897 ***	0.6132 ***
	(0.0091)	(0.0909)	(0.0909)
β_{KK}	-	0.0254 ***	0.0219 ***
		(0.0036)	(0.0036)
β_{LL}	-	0.0101 *	0.0086
		(0.0061)	(0.0061)
β_{KL}	-	-0.0329 ***	-0.0284 ***
		(0.0086)	(0.0086)
β_t	-0.1790 ***	-0.1580 ***	-0.1579 ***
	(0.0340)	(0.0318)	(0.0318)
β_{tt}	0.0207 ***	0.0184 ***	0.0160 ***
	(0.0045)	(0.0043)	(0.0043)
β_{Kt}	-	-	0.0140 ***
			(1.6482)
β_{Lt}	-	-	-0.0152 ***
			(1.8987)
Dep. var: u_{it}			
δ_0	-3.4124	-3.5042 **	-3.3153 ***
	(2.8724)	(1.6482)	(0.4794)
δ_{QOG}	-6.2458	-5.9513 ***	-5.9151 ***
	(3.9504)	(1.8987)	(0.0091)
σ^2	1.4331	1.3565 ***	1.2926 ***
	(0.9350)	(0.4794)	(0.3263)
γ	0.9731 ***	0.9757 ***	0.9750 ***
	(0.0190)	(0.0091)	(0.0058)
Log(likelihood)	-141.5746	-106.6068	-100.2863

***, ** and * denote 1%, 5% and 10% statistical significance respectively.

We use the LR-test described in Section 4.2 as a basis for model selection. The test results are summarised in Table 3. The hypothesis test suggests that SPF Model (3) is supported. It will also form the baseline specification of our models.

Table 3: Hypothesis Testing for SPF Models (1) - (3)

	Null Hypotheses (H_0)	χ^2-stat	χ^2-critical[7]	Decision
(1)	$\beta_{KK} = \beta_{LL} = \beta_{KL} = \beta_{Kt} = \beta_{Lt} = 0$ (i.e. Model (1) vs. Model (3))	82.58	10.371	Reject H_0 (i.e. Accept Model (3))
(2)	$\beta_{Kt} = \beta_{Lt} = 0$ (i.e. Model (2) vs. Model (3))	12.64	5.138	Reject H_0 (i.e. Accept Model (3))

Since panel data are used, the SPF Model (3) also suggests that we can estimate the rate of technological change in our specification. The percentage change in output over periods resulting from technological change is provided by $\beta_t + 2t\beta_{tt}$, varying for different values of period t. Since β_{tt} is positive in our model, our results suggest that the rate of technological change increased over the measured periods. Moreover, it is also noted that β_{KL} and β_{Lt} are negative, implying a possible substitution effect between K and L over time and technical change is biased toward the use of capital.

The bottom panel of Table 4 is the technical inefficiency model. The parameter of β_{QOG} is negative at the 1% statistically significance level. Results of SPF Model (3) imply a negative relationship between QOG and technical inefficiency. γ, representing the percentage of variance of technical inefficiency to the total variance of the model, is around 98%. In other words, 98% of the variation of the model can be explained by the technical efficiency model. The figure is also statistically significant at 1% level, providing support to the technical inefficiency story.

6.2 Sources of Technical Inefficiency

Our main research interest is to investigate the sources of technical inefficiency. As specified in eq. (26), the estimation results of this full model (i.e. TE Model (1)) are in Table 4. The stochastic production function is specified in a way similar to SPF Model (3), i.e. a non-neutral translog production function. The technical inefficiency model incorporates δ_t, allowing technical inefficiency (u_{it}) to be time-varying.

7 Critical values of test statistics are obtained from Kodde and Palm (1986).

Table 4: Maximum Likelihood Estimation of Stochastic Production Frontier Model (TE Model (1))

	Coeff. (std. error)			Coeff. (std. error)	
Dep var: *ln(Y)*			**Dep. var: u_{it}**		
β_0	4.3784	***	δ_0	0.3074	**
	(0.7388)			(0.1449)	
β_K	0.0853		δ_{LEGAL}	-0.0543	*
	(0.0751)			(0.0324)	
β_L	0.6009	***	$\delta_{LEGAL*H}$	-0.0136	*
	(0.0906)			(0.0077)	
β_{KK}	0.0145	***	δ_{REG}	0.2730	***
	(0.0036)			(0.0690)	
β_{LL}	-0.0035		$\delta_{REG}{}^2$	-0.0589	***
	(0.0060)			(0.0119)	
β_{KL}	-0.0036		δ_{REG*H}	0.0379	***
	(0.0084)			(0.0119)	
β_t	0.0015		δ_H	-0.0624	
	(0.0620)			(0.0429)	
β_{tt}	0.0120	***	δ_{DEMOC}	0.0073	
	(0.0042)			(0.0165)	
β_{Kt}	0.0089	**	$\delta_{DEMOC*H}$	-0.0106	***
	(0.0045)			(0.0036)	
β_{Lt}	-0.0167	***	$\delta_{FINOPEN}$	-0.0115	*
	(0.0056)			(0.0059)	
			δ_{TRADE}	-0.0004	
				(0.0013)	
			δ_{KAOPEN}	0.0611	
				(0.0381)	
			δ_{FDI}	0.0220	***
				(0.0082)	
			δ_{SM}	0.0450	*
				(0.0240)	
			δ_{SM*H}	-0.0282	***
				(0.0073)	
			δ_t	0.0498	*
				(0.0296)	
σ^2	0.2612	***	Log(likelihood)	-43.9305	
	(0.0355)				
γ	0.9306	***			
	(0.0161)				

***, ** and * denote 1%, 5% and 10% statistical significance respectively.

First of all, on the effect of human capital (*H*) on technical inefficiency, the estimated parameter (δ_H) suggests negative association between the two. This implies that economies with more human capital tend to be more technically efficient, but the effect is not statistically significant.

In terms of institutions, the full model tests their direct impact on technical inefficiency as well as the interactive term of institutions with human capital, which attempts to measure the impact of institutions given a necessary level of human capital. Market-creating institution, *LEGAL* and its interactive term with H are both negative and statistically significant, albeit at 10% level only. In other words, economies with better secured property rights and legal system are less technically inefficient. $\delta_{LEGAL*H}$ is negative, signifying economies with more human capital are less technically inefficient even if their market-creating institutions are comparable.

Such a negative relationship is also found to be statistically significant for parameters of δ_{SM*H} and $\delta_{DEMOC*H}$. However, the direct impact of the market-stabilising institution, *SM*, and the market-legitimising institution, *DEMOC*, are found to be positive, although the former is only at 10% significance level and the latter is not statistically significant. These results are not in line with our hypothesis – better institutions tend to reduce technical inefficiency. This prompts us to test the validity of these parameters in the model.

On the impact of market-regulating institution – *REG*, the results are less straightforward. δ_{REG} is positive, suggesting that less regulation is more technically inefficient. It may first appear to be odd. However, this may also imply that there is a potential optimal level of regulation. As we argue earlier, market-regulating institution could be either market-promoting by rectifying monopoly and promoting competition or market-hampering by generating red-tape and bureaucratic delay. In this light, we incorporate a square term REG^2 to capture such an effect, which is statistically significant at 1% level. Taking both parameters together, our results suggest a U-shape relationship between technical inefficiency and the level of regulation. It implies that when the economy has a too low level of regulations, introducing more regulations can improve technical inefficiency. However, once the level of regulation reaches a critical point, more regulation will lead to worsening technical inefficiency.

For openness parameters, trade openness and capital account openness (δ_{TRADE} and δ_{KAOPEN}) do not have statistically significant impact on u_{it}. Financial openness has a positive impact on improving technical efficiency, although it is only statistically significant at 10% level. Unexpectedly, more FDI inflows associate with technical inefficiency. This is contrary to our expectation that more foreign capital leads to more foreign competition and more efficient use of production inputs. Our results, however, suggest that foreign firms (in the form of FDI) could possibly be more competitive and thus dominate the domestic markets. It thus crowds out the competition from domestic firms.

Against the estimation results of unexpected signs of some parameters obtained in TE Model (1), we deploy the formal LR-Test to test the validity of the coefficients more robustly. The test results are presented in Table 5 below.

Table 5: Hypothesis Testing for TE Model (1)

Null Hypotheses	Log(likelihood)	χ^2-stat	Decision
$\delta_{LEGAL}=0$	-45.79	3.72	Reject H_0
$\delta_{LEGAL*H}=0$	-45.20	2.54	Accept H_0
$\delta_{REG}=0$	-49.30	10.74	Reject H_0
$\delta_{REG}{}^2=0$	-53.34	18.82	Reject H_0
$\delta_{REG*H}=0$	-49.08	10.30	Reject H_0
$\delta_{H}=0$	-44.77	1.68	Accept H_0
$\delta_{DEMOC}=0$	-43.97	0.08	Accept H_0
$\delta_{DEMOC*H}=0$	-46.22	4.58	Reject H_0
$\delta_{FINOPEN}=0$	-45.13	2.40	Accept H_0
$\delta_{TRADE}=0$	-44.66	1.46	Accept H_0
$\delta_{KAOPEN}=0$	-45.44	3.02	Reject H_0
$\delta_{FDI}=0$	-46.11	4.36	Reject H_0
$\delta_{SM}=0$	-45.22	2.58	Accept H_0
$\delta_{SM*H}=0$	-49.05	10.24	Reject H_0

Note: The critical value of the log likelihood ratio test for degree of 1 is 2.706.

Table 5 points out that the LR-test rejects the validity and significance of some parameters in our full model – TE Model (1). This facilitates us to re-specify TE Model (1) into TE Model (2). In the latter model, we drop all parameters that can be accepted as zero in the LR-test. The estimation results of TE Model (2) are in Table 6.

Table 6: Maximum Likelihood Estimation of Stochastic Production Frontier Model (TE Model (2))

	Coeff. (std. error)			Coeff. (std. error)	
<u>Dep var: *ln(Y)*</u>			**<u>Dep. var: u_{it}</u>**		
β_0	4.1879	***	δ_0	0.3675	***
	(0.8048)			(0.1173)	
β_K	0.0760		δ_{LEGAL}	-0.0905	***
	(0.0800)			(0.0201)	
β_L	0.6322	***	δ_{REG}	0.3206	***
	(0.0904)			(0.0688)	
β_{KK}	0.0168	***	$\delta_{REG}{}^2$	-0.0524	***
	(0.0038)			(0.0111)	
β_{LL}	-0.0012		δ_{REG*H}	0.0055	
	(0.0061)			(0.0055)	
β_{KL}	-0.0087		$\delta_{DEMOC*H}$	-0.0096	***
	(0.0086)			(0.0027)	
β_t	0.0166		δ_{KAOPEN}	0.0577	*
	(0.0618)			(0.0342)	
β_{tt}	0.0112	***	δ_{FDI}	0.0180	***
	(0.0043)			(0.0075)	
β_{Kt}	0.0098	**	δ_{SM*H}	-0.0179	***
	(0.0045)			(0.0046)	
β_{Lt}	-0.0185	***	δ_t	0.0409	
	(0.0054)			(0.0281)	
σ^2	0.2329	***	Log(likelihood)	-49.4510	
	(0.0311)				
γ	0.9188	***			
	(0.0164)				

***, ** and * denote 1%, 5% and 10% statistical significance respectively.

The qualitative results remain. Comparing TE Model (1) and TE Model (2), the chi-square statistics of the LR-test is 11.041, which is below the critical value of chi-square with 6 degree of freedom (i.e. 11.911). In this case, we can argue that TE Model (2) indeed is a better model and fits better our data sample.

Similarly, we further test the nested model of TE Model (2) based on LR Test in Table 7. One point to note is that TE Model (2) suggests the absence of δ_0. We proceed to our final model specification – TE Model (3) – as the hypothesis tests suggest.

Table 7: Hypothesis Testing for TE Model (2)

Null Hypotheses	Log(likelihood)	χ^2-stat	Decision
$\delta_0 = 0$	-50.50	2.10	Accept H_0
$\delta_{REG*H} = 0$	-50.55	2.20	Accept H_0
$\delta_{KAOPEN} = 0$	-50.42	1.94	Accept H_0

Note: The critical value of the log likelihood ratio test for degree of 1 is 2.706.

Table 8: Maximum Likelihood Estimation of Stochastic Production Frontier Model (TE Model (3)) – Final Model

	Coeff. (std. error)			Coeff. (std. error)	
Dep var: *ln(Y)*			Dep. var: u_{it}		
β_0	3.8097	**	δ_{LEGAL}	-0.0914	***
	(0.8682)			(0.0223)	
β_K	0.1150		δ_{REG}	0.3363	***
	(0.0767)			(0.0618)	
β_L	0.6307	***	δ_{REG}^2	-0.0537	***
	(0.0967)			(0.0100)	
β_{KK}	0.0168	***	$\delta_{DEMOC*H}$	-0.0086	***
	(0.0036)			(0.0026)	
β_{LL}	-0.0008		δ_{SM*H}	-0.0153	***
	(0.0059)			(0.0034)	
β_{KL}	-0.0103		δ_t	0.0990	***
	(0.0082)			(0.0253)	
β_t	0.0156				
	(0.0621)				
β_{tt}	0.0111	***			
	(0.0044)				
β_{Kt}	0.0072				
	(0.0047)				
β_{Lt}	-0.0148	***			
	(0.0058)				
σ^2	0.2835	***	Log(likelihood)	-53.8462	
	(0.0301)				
γ	0.9326	***			
	(0.0155)				

***, ** and * denote 1%, 5% and 10% statistical significance respectively.

Estimation results of TE Model (3) are in Table 8 above. Comparing TE Models (2) without

δ_0 (with log-likelihood to be -50.5) and TE Model (3), we again carry out a LR-test in Table 9 to test jointly the openness parameters to be zero. The test results indicate that capital account openness and FDI are not statistically significant in explaining technical inefficiency. Henceforth, we will focus our discussion on the parameters obtained in TE Model (3).

Table 9: Hypothesis Testing for TE Model (2) vs. TE Model (3)

Null Hypotheses	Log(likelihood)	χ^2-stat	Decision
$\delta_{KAOPEN} = \delta_{FDI} = \delta_{REG*H} = 0$	-53.85	6.7	Accept H_0

Note: The critical value of the log likelihood ratio test for degree of 3 is 7.045

In the course of model selection through TE Models (1) to (3), generally speaking, only institutional factors survive in the final models. Other competing factors – human capital and openness – are not statistically significant in explaining the sources of cross-country technical inefficiencies. This provides empirical support to North's hypothesis – i.e. institutions are the determinant of the efficiency of production inputs, via which determine cross-country efficiency and hence economic performances. Although there are previous studies which conclude that human capital and openness in trade, foreign capital, capital account or financial integration may promote growth, we do not find such positive effects on technical efficiency. In other words, we argue that the level of technical efficiency is primarily driven by domestic market-friendly institutions rather than external forces like foreign competition brought forward by international trade or capital flow alike.

However, our final model – TE Model (3) – points out that not all clusters of institutions are directly associating with technical inefficiency. Market-creating institution, i.e. the security of property rights (LEGAL) and market-regulating institution (REG and REG_2) are directly associating with technical inefficiency. We obtain the negative relationship between these clusters of institutions and technical inefficiency as expected. Market-stabilising institution, i.e. sound monetary policy (SM), and market-legitimising institution, i.e. democratic institution (DEMOC), nonetheless have no direct and significant impact on technical inefficiency. Their interactions with human capital (H) are significantly negative at the 1% level. These results may suggest that these two clusters of institutions would only improve technical efficiency given that a necessary level of human capital. That said, a democratic economy is more efficient given a minimum level of human capital is reached. Likewise, the effectiveness of stabilising monetary policy to improve efficiency of production inputs also depends on human capital. These effects are believed to be determined by human capital, which are possibly due to the effectiveness of policy execution and governance. These market-friendly institutions in turn are believed to shape the incentive structures of the society and thus affect the efficiency of production inputs.

To sum up, our final model suggests that our dataset supports a technical inefficiency story (where γ is statistically significant at 1% level) when estimating a non-neutral translog stochastic production function. The time-varying technical inefficiency model tests three sets of explanatory factors of technical inefficiency – human capital, institutions and openness. Based on the test results of log-likelihood ratio tests, we find no direct effect of openness and human capital on technical inefficiency. However, human capital works with democracy and monetary stabilisation policy to improve technical inefficiency across countries. In contrast, better security of property rights and less regulatory environment associate with technical efficiency directly.

6.3 Measures of Technical Efficiency

Following Coelli, et al. (1998), since the SPF model can be defined as $\ln(y_{it}) = f(x_{it}, t, \beta) + v_{it} - u_{it}$, the measures of technical efficiency are essentially obtained from $TE_{it} = E(\exp(-u_{it}) \mid e_{it})$ where $e_{it} = v_{it} - u_{it}$. Technical efficiency (TE) can thus be calculated for each period and compared to the best practice. TE represents the mean value of technical efficiency given the amount of inputs. Since the production function is assumed to be stochastic in nature, the best possible TE lies somewhere below 1 due to stochastic disturbances. A summary table of average TE over the studied period is in Table 10. The complete measure of TE for each cross-section and time period is presented in Table 11.

Over the six measured periods, the USA topped the ranks of TE during 1971-75, 1976-80, 1986-90, and 1991-95. Trinidad and Tobago came first during 1981-85, possibly reflecting it as an oil-exporting economy. Ireland became the best practice in the last measured period, i.e. 1996-2000. The mean TE of the sample is quite stable (around 0.74-0.75) over the three decades. As one can expect, the industrialised economies are among the best practices. In contrast, the least technically efficient economies are mostly Sub-Saharan African countries.

Table 10: Average TE by Regions during 1971-2000

Period	71-75	76-80	81-85	86-90	91-95	96-00
High Income Group	0.8631	0.8707	0.8737	0.8933	0.8923	0.8895
Latin America and Caribbean	0.8204	0.8363	0.8083	0.7991	0.8090	0.8048
Sub-Saharan Africa	0.6006	0.6124	0.6079	0.6156	0.5928	0.5863
East Asia and Pacific	0.7154	0.7453	0.7474	0.7622	0.8095	0.7774
Middle East and North Africa	0.8317	0.8410	0.8371	0.8341	0.8442	0.8646
Europe and Central Asia	0.8572	0.8619	0.8865	0.9093	0.8808	0.8315
South Asia	0.5840	0.6204	0.6656	0.7141	0.7559	0.7573
All	***0.7393***	***0.7530***	***0.7493***	***0.7590***	***0.7586***	***0.7534***

Note: Average TE is calculated based on simple averages. High income group includes OECD economies and other high income groups. Regions are based on World Bank's Country Classification. Details of country coverage are at Appendix A.2.

Analysed by regions, there is a general upward trend of improvement in TE over the last three decades. Improvements are also found in the high income group even though they are amongst the best practices. However, sub-Saharan African countries indeed experienced a decline over the period. The most pronounced improvements are found in the East Asia and Pacific as well as South Asia regions, in particular starting from the 1990. Such improvements are also found in fast-growing countries like China and India during the same period.

Table 11: Cross-country Technical Efficiency during 1971-2000

Country	code	Period (71-75)	Rank	Period (76-80)	Rank	Period (81-85)	Rank	Period (86-90)	Rank	Period (91-95)	Rank	Period (96-00)	Rank
Algeria	DZA	0.8660	[37]	0.8547	[42]	0.8635	[40]	0.8396	[47]	0.7785	[65]	0.7791	[65]
Argentina	ARG	0.8586	[39]	0.8507	[44]	0.8147	[52]	0.8019	[59]	0.8991	[30]	0.9250	[20]
Australia	AUS	0.9120	[17]	0.9241	[10]	0.9288	[7]	0.9356	[9]	0.9379	[13]	0.9388	[10]
Austria	AUT	0.8718	[34]	0.8971	[29]	0.8905	[27]	0.9024	[29]	0.9082	[25]	0.8992	[32]
Bangladesh	BGD	0.4439	[97]	0.5310	[94]	0.6039	[85]	0.6618	[78]	0.7232	[70]	0.7304	[70]
Barbados	BRB	0.8059	[55]	0.8132	[58]	0.7837	[59]	0.8849	[36]	0.9000	[28]	0.9371	[12]
Belgium	BEL	0.9136	[16]	0.9230	[11]	0.9227	[14]	0.9328	[12]	0.9283	[16]	0.9256	[18]
Benin	BEN	0.6132	[83]	0.5587	[88]	0.5515	[89]	0.5726	[91]	0.5578	[89]	0.5896	[84]
Bolivia	BOL	0.7023	[73]	0.7713	[66]	0.7623	[65]	0.7563	[69]	0.8152	[59]	0.8012	[62]
Botswana	BWA	0.5668	[89]	0.7501	[72]	0.8599	[41]	0.8972	[31]	0.8945	[31]	0.9193	[24]
Brazil	BRA	0.8041	[56]	0.8116	[60]	0.7687	[61]	0.8208	[54]	0.8050	[62]	0.8422	[49]
Burki Faso	BFA	0.4292	[99]	0.4526	[99]	0.4925	[100]	0.4872	[101]	0.4746	[99]	0.4591	[98]
Burundi	BDI	0.6395	[81]	0.6542	[78]	0.5198	[94]	0.5117	[97]	0.4804	[98]	0.4002	[103]
Cameroon	CMR	0.7097	[71]	0.8101	[61]	0.8491	[44]	0.8202	[55]	0.6643	[77]	0.7151	[71]
Canada	CAN	0.9532	[4]	0.9560	[3]	0.9501	[3]	0.9500	[3]	0.9389	[12]	0.9373	[11]
Cape Verde	CPV	0.3956	[101]	0.4166	[102]	0.5269	[92]	0.5606	[94]	0.5368	[91]	0.5393	[87]
Central African Republic	CAF	0.6990	[74]	0.7617	[68]	0.7009	[75]	0.6833	[73]	0.5659	[88]	0.4924	[94]
Chad	TCD	0.3529	[103]	0.4474	[100]	0.3798	[104]	0.4244	[104]	0.4421	[102]	0.4440	[101]
Chile	CHL	0.8319	[46]	0.8769	[37]	0.8860	[31]	0.9148	[19]	0.9398	[11]	0.9301	[16]
China	CHN	0.4972	[92]	0.5030	[96]	0.6108	[84]	0.6459	[80]	0.7195	[72]	0.7435	[68]
Colombia	COL	0.8771	[30]	0.9017	[24]	0.8973	[24]	0.9082	[24]	0.9143	[22]	0.8901	[37]
Comoros	COM	0.6608	[78]	0.5579	[89]	0.5823	[86]	0.6010	[86]	0.5042	[94]	0.4502	[100]
Congo, Dem. Rep.	ZAR	0.6962	[75]	0.5648	[87]	0.5148	[95]	0.4881	[99]	0.3839	[103]	0.2183	[108]
Congo, Republic of	COG	0.2663	[106]	0.3140	[105]	0.4191	[103]	0.4879	[100]	0.4962	[95]	0.4909	[95]
Costa Rica	CRI	0.9239	[12]	0.9303	[7]	0.8775	[35]	0.8775	[39]	0.8537	[45]	0.8269	[53]
Cote d`Ivoire	CIV	0.7905	[60]	0.8132	[57]	0.7512	[68]	0.7813	[64]	0.8053	[61]	0.8199	[55]
Cyprus	CYP	0.6017	[84]	0.6337	[80]	0.7533	[66]	0.8534	[43]	0.8911	[36]	0.8972	[33]
Denmark	DNK	0.8967	[23]	0.8946	[30]	0.8953	[25]	0.9177	[18]	0.9209	[18]	0.9205	[23]
Dominican Republic	DOM	0.8727	[33]	0.8823	[35]	0.8831	[32]	0.8498	[44]	0.8510	[46]	0.9117	[27]
Ecuador	ECU	0.6660	[76]	0.7972	[62]	0.7513	[67]	0.7019	[70]	0.7230	[71]	0.6472	[79]
Egypt	EGY	0.9252	[10]	0.9043	[21]	0.9235	[13]	0.9350	[10]	0.9557	[3]	0.9630	[2]
El Salvador	SLV	0.9542	[3]	0.9530	[4]	0.9068	[19]	0.9069	[27]	0.9207	[19]	0.9208	[22]

Country	code	Period (71-75)	Rank	Period (76-80)	Rank	Period (81-85)	Rank	Period (86-90)	Rank	Period (91-95)	Rank	Period (96-00)	Rank
Equatorial Guinea	GNQ	0.9227	[13]	0.7299	[74]	0.6393	[81]	0.5860	[88]	0.4539	[101]	0.4557	[99]
Ethiopia	ETH	0.5783	[86]	0.6336	[81]	0.6793	[77]	0.6746	[77]	0.6458	[81]	0.6981	[74]
Fiji	FJI	0.7478	[66]	0.7767	[65]	0.7334	[69]	0.6996	[71]	0.8123	[60]	0.7985	[64]
Finland	FIN	0.8407	[44]	0.8443	[46]	0.8799	[33]	0.9048	[28]	0.8694	[42]	0.9052	[31]
France	FRA	0.8731	[32]	0.8876	[33]	0.8937	[26]	0.9071	[26]	0.8933	[35]	0.8939	[35]
Gabon	GAB	0.8907	[26]	0.8521	[43]	0.7284	[71]	0.7933	[61]	0.8723	[41]	0.8697	[42]
Gambia, The	GMB	0.7350	[68]	0.7277	[76]	0.6401	[80]	0.5838	[89]	0.4913	[96]	0.4439	[102]
Ghana	GHA	0.4626	[95]	0.4411	[101]	0.4833	[101]	0.5931	[87]	0.6688	[76]	0.6911	[75]
Greece	GRC	0.8108	[53]	0.8460	[45]	0.8208	[51]	0.8329	[51]	0.8328	[56]	0.8496	[47]
Guatemala	GTM	0.9188	[15]	0.9333	[6]	0.9224	[15]	0.9221	[16]	0.9277	[17]	0.9234	[21]
Guinea	GIN	0.4945	[94]	0.5455	[90]	0.5300	[90]	0.5698	[92]	0.6304	[83]	0.7043	[72]
Guinea-Bissau	GNB	0.1427	[108]	0.2198	[108]	0.2336	[107]	0.2172	[108]	0.2226	[107]	0.2409	[107]
Haiti	HTI	0.7753	[63]	0.7517	[71]	0.6818	[76]	0.5736	[90]	0.6577	[78]	0.9555	[4]
Honduras	HND	0.7063	[72]	0.7549	[70]	0.7823	[60]	0.7843	[63]	0.7002	[73]	0.5991	[82]
Hong Kong	HKG	0.8514	[42]	0.9099	[18]	0.9191	[16]	0.9370	[8]	0.9467	[7]	0.9169	[25]
Iceland	ISL	0.8018	[57]	0.8366	[49]	0.8442	[46]	0.8779	[38]	0.8498	[48]	0.8591	[45]
India	IND	0.5747	[88]	0.6428	[79]	0.7146	[72]	0.8056	[58]	0.8436	[53]	0.8869	[39]
Indonesia	IDN	0.8525	[41]	0.8737	[39]	0.8568	[43]	0.8446	[45]	0.8446	[52]	0.7663	[67]
Iran	IRN	0.9389	[7]	0.8408	[47]	0.7042	[74]	0.6806	[75]	0.7679	[67]	0.8607	[44]
Ireland	IRL	0.9246	[11]	0.9393	[5]	0.9356	[4]	0.9400	[7]	0.9554	[4]	0.9632	[1]
Israel	ISR	0.8824	[28]	0.8388	[48]	0.8665	[37]	0.8862	[34]	0.9134	[23]	0.8962	[34]
Italy	ITA	0.8272	[48]	0.8702	[40]	0.8872	[28]	0.9142	[20]	0.9085	[24]	0.9073	[29]
Jamaica	JAM	0.6010	[85]	0.5420	[92]	0.5248	[93]	0.6089	[85]	0.5923	[85]	0.5301	[88]
Japan	JPN	0.8223	[50]	0.8327	[51]	0.8410	[47]	0.8656	[41]	0.8466	[51]	0.7988	[63]
Jordan	JOR	0.8216	[51]	0.9287	[8]	0.9340	[5]	0.9076	[25]	0.8326	[57]	0.8353	[51]
Kenya	KEN	0.4321	[98]	0.4777	[98]	0.5290	[91]	0.6230	[83]	0.6419	[82]	0.6535	[78]
Korea, Republic of	KOR	0.7741	[64]	0.8117	[59]	0.7901	[55]	0.8620	[42]	0.8543	[44]	0.8176	[58]
Lesotho	LSO	0.6133	[82]	0.6033	[83]	0.5084	[97]	0.4919	[98]	0.3722	[105]	0.3078	[105]
Luxembourg	LUX	0.8964	[24]	0.8940	[31]	0.9011	[23]	0.9349	[11]	0.9445	[9]	0.9465	[9]
Madagascar	MDG	0.8097	[54]	0.7925	[63]	0.7898	[56]	0.7996	[60]	0.7719	[66]	0.7770	[66]
Malawi	MWI	0.2829	[105]	0.3053	[106]	0.3130	[106]	0.3359	[106]	0.3628	[106]	0.4698	[96]
Malaysia	MYS	0.8423	[43]	0.8894	[32]	0.8871	[29]	0.8797	[37]	0.9029	[27]	0.8658	[43]
Mali	MLI	0.4282	[100]	0.5429	[91]	0.4942	[99]	0.4537	[103]	0.4624	[100]	0.5280	[90]
Mauritania	MRT	0.8736	[31]	0.9019	[23]	0.7675	[62]	0.5510	[95]	0.5300	[93]	0.4956	[92]

Country	code	Period (71-75)	Rank	Period (76-80)	Rank	Period (81-85)	Rank	Period (86-90)	Rank	Period (91-95)	Rank	Period (96-00)	Rank
Mauritius	MUS	0.8844	[27]	0.9209	[12]	0.9279	[8]	0.9423	[5]	0.9501	[5]	0.9520	[6]
Mexico	MEX	0.8942	[25]	0.9163	[14]	0.9030	[21]	0.8850	[35]	0.8772	[39]	0.8562	[46]
Morocco	MAR	0.8197	[52]	0.7813	[64]	0.7627	[64]	0.8169	[56]	0.8166	[58]	0.8110	[59]
Mozambique	MOZ	0.9467	[5]	0.8975	[27]	0.8007	[53]	0.7678	[67]	0.7908	[64]	0.8073	[61]
Nepal	NPL	0.5782	[87]	0.5329	[93]	0.5111	[96]	0.5164	[96]	0.5340	[92]	0.5291	[89]
Netherlands	NLD	0.9022	[21]	0.9139	[15]	0.9060	[20]	0.9192	[17]	0.9284	[15]	0.9334	[13]
New Zealand	NZL	0.9398	[6]	0.9274	[9]	0.9279	[9]	0.9252	[14]	0.9353	[14]	0.9255	[19]
Nicaragua	NIC	0.9050	[20]	0.8747	[38]	0.7304	[70]	0.6159	[84]	0.5454	[90]	0.4932	[93]
Niger	NER	0.4958	[93]	0.4808	[97]	0.4258	[102]	0.4630	[102]	0.4813	[97]	0.5200	[91]
Nigeria	NGA	0.7773	[62]	0.6074	[82]	0.5629	[87]	0.6879	[72]	0.6693	[75]	0.5960	[83]
Norway	NOR	0.8004	[58]	0.8301	[52]	0.8483	[45]	0.8762	[40]	0.9000	[29]	0.9063	[30]
Pakistan	PAK	0.4993	[91]	0.5813	[85]	0.7088	[73]	0.8112	[57]	0.8401	[54]	0.8196	[56]
Panama	PAN	0.7241	[70]	0.7477	[73]	0.8582	[42]	0.8331	[50]	0.8474	[50]	0.7421	[69]
Papua New Guinea	PNG	0.6635	[77]	0.6721	[77]	0.6414	[79]	0.6767	[76]	0.7639	[68]	0.6752	[77]
Paraguay	PRY	0.8652	[38]	0.8994	[26]	0.8671	[36]	0.8421	[46]	0.8888	[37]	0.8487	[48]
Peru	PER	0.7290	[69]	0.7281	[75]	0.6735	[78]	0.6612	[79]	0.6529	[79]	0.7035	[73]
Philippines	PHL	0.7887	[61]	0.8170	[53]	0.7637	[63]	0.7687	[66]	0.7943	[63]	0.8081	[60]
Portugal	PRT	0.8369	[45]	0.8863	[34]	0.8662	[38]	0.9000	[30]	0.9042	[26]	0.8852	[40]
Rwanda	RWA	0.7676	[65]	0.8340	[50]	0.8368	[49]	0.7579	[68]	0.5966	[84]	0.6061	[81]
Senegal	SEN	0.5521	[90]	0.5780	[86]	0.6243	[83]	0.6811	[74]	0.6470	[80]	0.6847	[76]
Sierra Leone	SLE	0.9260	[9]	0.9061	[19]	0.9257	[10]	0.9129	[21]	0.7453	[69]	0.5730	[85]
Singapore	SGP	0.7393	[67]	0.7569	[69]	0.7855	[58]	0.7859	[62]	0.8490	[49]	0.8411	[50]
South Africa	ZAF	0.9215	[14]	0.9132	[16]	0.9250	[12]	0.9283	[13]	0.9411	[10]	0.9479	[7]
Spain	ESP	0.8682	[36]	0.8802	[36]	0.8647	[39]	0.8883	[32]	0.8937	[34]	0.8915	[36]
Sri Lanka	LKA	0.8239	[49]	0.8142	[55]	0.7897	[57]	0.7754	[65]	0.8387	[55]	0.8204	[54]
Sweden	SWE	0.8978	[22]	0.9056	[20]	0.9138	[17]	0.9232	[15]	0.9184	[20]	0.9258	[17]
Switzerland	CHE	0.9076	[18]	0.8975	[28]	0.9080	[18]	0.9120	[22]	0.8941	[33]	0.8717	[41]
Syrian Arab Republic	SYR	0.7934	[59]	0.8150	[54]	0.8791	[34]	0.8217	[53]	0.8944	[32]	0.9158	[26]
Taiwan	TWN	0.8781	[29]	0.9117	[17]	0.9250	[11]	0.9525	[2]	0.9576	[2]	0.9546	[5]
Tanzania	TZA	0.2239	[107]	0.2433	[107]	0.2316	[108]	0.2252	[107]	0.2213	[108]	0.2557	[106]
Thailand	THA	0.4527	[96]	0.5188	[95]	0.5606	[88]	0.6297	[82]	0.6810	[74]	0.6075	[80]
Togo	TGO	0.6452	[80]	0.5977	[84]	0.6389	[82]	0.6442	[81]	0.5869	[86]	0.4697	[97]
Trinidad and Tobago	TTO	0.9557	[2]	0.9605	[2]	0.9603	[1]	0.9415	[6]	0.9450	[8]	0.9327	[14]
Tunisia	TUN	0.6571	[79]	0.7621	[67]	0.7930	[54]	0.8376	[49]	0.8638	[43]	0.8870	[38]
Turkey	TUR	0.8572	[40]	0.8619	[41]	0.8865	[30]	0.9093	[23]	0.8808	[38]	0.8315	[52]
Uganda	UGA	0.8290	[47]	0.8142	[56]	0.9019	[22]	0.8391	[48]	0.8747	[40]	0.9107	[28]
United Kingdom	GBR	0.9059	[19]	0.9175	[13]	0.9305	[6]	0.9439	[4]	0.9476	[6]	0.9473	[8]
United States of America	USA	0.9571	[1]	0.9614	[1]	0.9572	[2]	0.9595	[1]	0.9600	[1]	0.9577	[3]
Uruguay	URY	0.8690	[35]	0.9034	[22]	0.8392	[48]	0.8869	[33]	0.9184	[21]	0.9306	[15]
Venezuela	VEN	0.9285	[8]	0.9004	[25]	0.8362	[50]	0.8304	[52]	0.8508	[47]	0.8185	[57]
Zambia	ZMB	0.3100	[104]	0.3326	[104]	0.3412	[105]	0.3585	[105]	0.3816	[104]	0.3915	[104]
Zimbabwe	ZWE	0.3787	[102]	0.3893	[103]	0.5046	[98]	0.5663	[93]	0.5685	[87]	0.5616	[86]

Our measured period is long enough to compare the experiences of economic development in different regions. Figure 1 clearly shows that China and India rapidly caught up with the USA. The catching-up was fairly persistent for India during the studied period. China only started picking up since the early 80s, echoing her "open-door" policy. In comparison to other emerging markets like Brazil, her TE improvements were relatively gentle. We can also compare these growth experiences with that of the "East Asian Tigers" as shown in Figure 2. The latter four economies also enjoyed fast growth during the last three decades. In conjunction, they showed rapid improvements in technical efficiency in the 70s and 80s.

Figure 1: TE of Brazil, China and India vis-à-vis USA

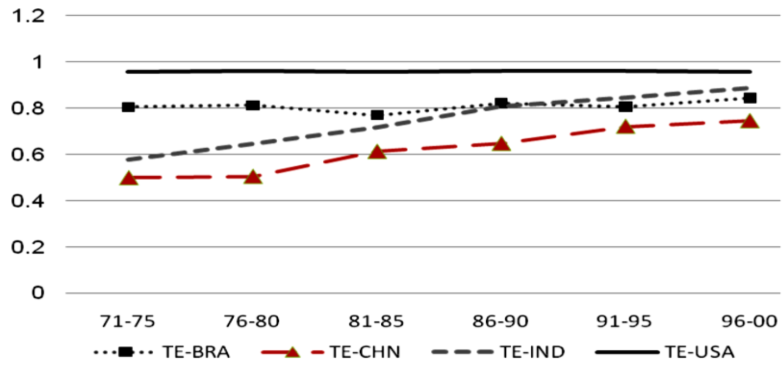
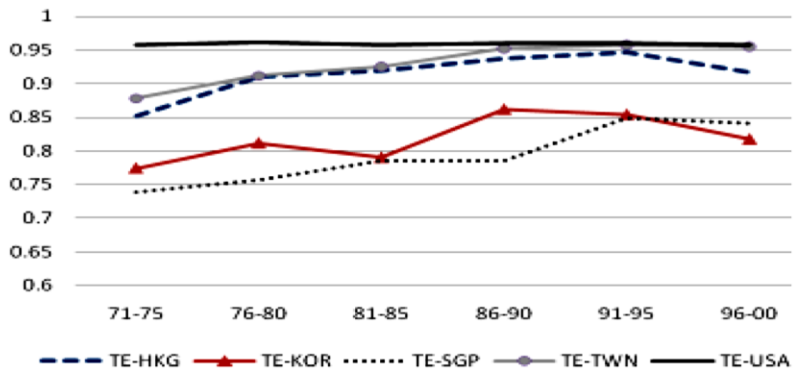


Figure 2: TE of Hong Kong, Republic of Korea, Singapore and Taiwan vis-à-vis USA



To calculate efficiency change (EC) over two periods, we can define EC as:

Efficiency change = $TE_{it}\ and\ TE_{is}$ from period s to period t (6-1)

Based on EC calculated, the four "Asian tigers" – Hong Kong, Singapore, South Korea and Taiwan – enjoyed an average efficiency gains of 1.5%, 2.7%, 1.2% and 1.7% respectively over the studied period. These figures represent above-average performances (around 0.85% for the full sample) on the global scale. This may be one underlying source of their impressive growth performances. Nevertheless, India and China show even more impressive improvements.

China registered an average 8.6% efficiency change whereas India showed an even more impressive 9.1% positive change. All these provide quantitative evidence that the rapid growth we found in these economies may not be a mere result of capital accumulation. Efficiency improvements may be their sources of growth. Figure 3-Figure 5 provide an overview of efficiency changes in other selected countries.

Figure 3: TE of Indonesia, Malaysia, Philippines and Thailand vis-à-vis USA

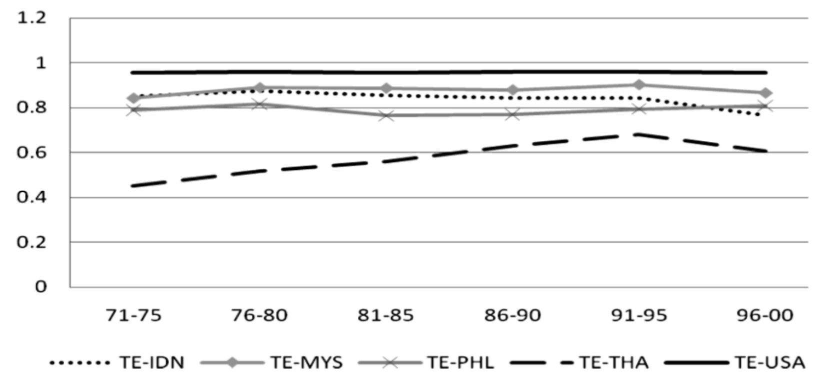
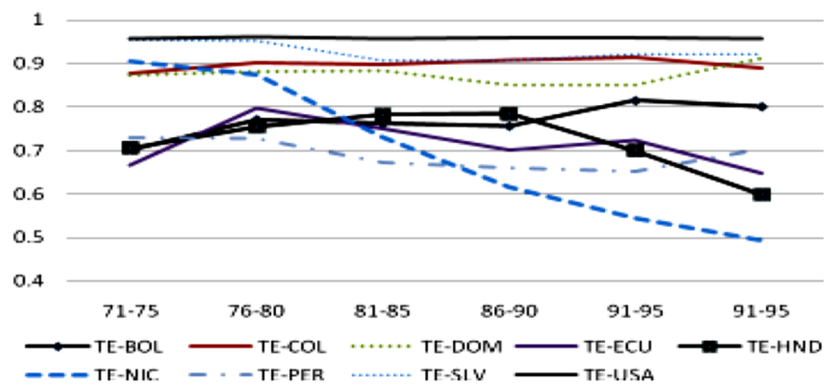
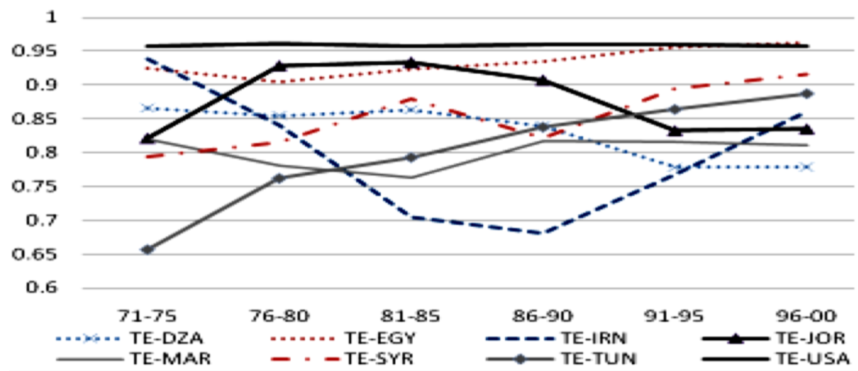


Figure 4: TE of Selected Lower Middle Income Countries in Latin America and Caribbean vis-à-vis USA



Note: Countries include Bolivia, Colombia, Dominican Republic, Ecuador, Honduras, Nicaragua, Peru and El Salvador.

Figure 5: TE of MENA Region vis-à-vis USA



Note: Countries cover Algeria, Egypt, Iran, Jordan, Morocco, Syrian Arab Republic and Tunisia.

To better illustrate that efficiency change is possibly the source of growth, we separate the sources of growth by capital accumulation, technical change and efficiency change. As mentioned earlier in our methodology, estimating a time-varying stochastic production frontier allows us to estimate technical change (TC) and TE. Technical change is calculated based on the first partial derivative of the stochastic production frontier with respect to time. According to Coelli, et al. (1998), a geometric mean can be used to estimate the technical change index between adjacent periods s and t as the following:

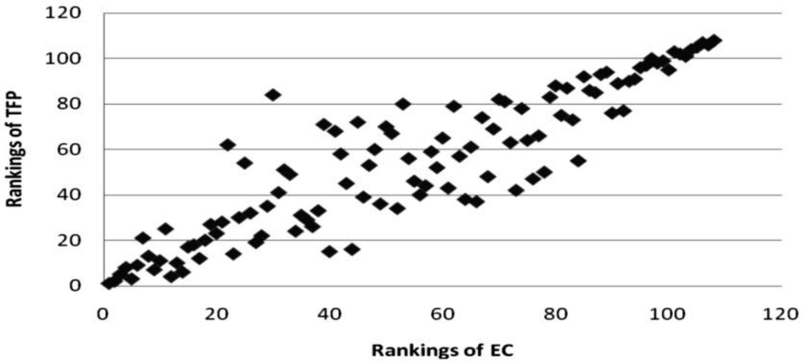
$$\left\{\left[1+\frac{\partial f(x_{is},s,\beta)}{\partial s}\right]\times\left[1+\frac{\partial f(x_{it},t,\beta)}{\partial t}\right]\right\}^{0.5}$$

Once we have decomposed growth, it also facilitates us to compare the sources of growth in developed countries as against that in developing countries. Rankings of efficiency change reveal that the sources of growth in developing countries primarily come from efficiency gains. Most of the economies topping the rankings of efficiency changes (i.e. with greatest efficiency gains in the sample) are low or lower middle income countries – for examples, Republic of Congo, Pakistan, Botswana, Bangladesh, India and China. In contrast, the sources of growth for high-income or developed countries come from technical changes (i.e. technological progress). For example, in terms of technical changes, Luxembourg, Iceland, Singapore, Norway and New Zealand are amongst those showing most distinct technical changes. This points out that the development strategy for developing countries mainly aims at "catching-up", whereas that of the developed countries is by means of innovations.

Since our sample is dominated by developing countries, we naturally find a strong correlation of TFP and EC. For demonstration purpose, Figure 6 shows a simple correlation plot between the rankings of TFP as against that of EC and TC of the 108 economies being studied in our sample.

The most important lesson of decomposing the sources of growth after all is not the comparison of rankings. The main point to note is that when we compare cross-country TFP growth using a standard Solow-growth accounting framework (i.e. by assuming that all factors of production are efficiently used), the results obtained may only reveal a partial picture of the sources of growth. Through estimating a stochastic production frontier, we are able to segregate the two sources conceptually. More importantly, we could identify the sources of technical inefficiency which is helpful in implying policy implications.

Figure 6: Ranking s of EC, TC as against TFP of 108 Economies



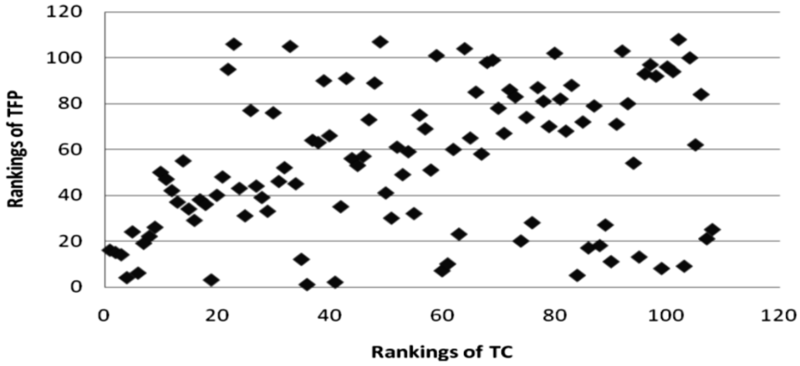


Table 12: Sources of Economic Growth (rate of change in %) for the Sample Countries (1971-2000)

Country	Y	K	L	EC	Rank[EC]	TC	Rank[TC]	TFP	Rank[TFP]
Algeria	4.195	5.634	3.743	-2.047	91	-0.066	48	-2.113	89
Argentina	2.689	2.904	1.635	1.656	33	-0.256	53	1.400	49
Australia	3.289	3.449	1.916	0.583	59	0.643	32	1.226	52
Austria	2.77	3.536	0.59	0.630	56	1.240	20	1.871	40
Bangladesh	4.335	3.452	2.324	10.644	6	-3.417	103	7.227	9
Barbados	4.266	2.084	1.649	3.204	23	3.123	3	6.328	14
Belgium	2.449	2.864	0.534	0.263	68	1.189	21	1.452	48
Benin	3.372	5.893	2.597	-0.645	82	-1.381	77	-2.026	87
Bolivia	2.855	2.492	2.389	2.788	26	-0.331	55	2.457	32
Botswana	10.736	11.891	3.278	10.759	5	1.325	19	12.084	3
Brazil	4.992	5.719	2.975	1.025	45	-1.700	85	-0.675	72
Burkina Faso	3.818	6.78	1.991	1.470	39	-2.062	91	-0.593	71
Burundi	0.523	5.457	1.463	-8.525	101	-2.087	92	-10.612	103
Cameroon	4.188	6.03	2.303	0.842	50	-1.428	79	-0.586	70
Canada	3.544	4.935	2.102	-0.334	77	0.127	40	-0.207	66
Cape Verde	5.584	6.315	2.145	6.876	14	2.043	6	8.920	6
Central African Republic	-0.275	0.564	1.562	-6.338	99	-0.892	69	-7.230	99
Chad	2.649	0.332	2.486	5.605	18	-1.121	74	4.484	20
Chile	4.395	4.695	2.525	2.279	29	0.010	42	2.289	35
China	6.759	8.673	1.954	8.618	11	-5.134	108	3.483	25
Colombia	4.73	5.718	3.302	0.311	67	-1.233	75	-0.923	74
Comoros	2.158	3.929	3.063	-6.963	100	1.183	22	-5.781	95
Congo, Dem. Rep.	-3.256	2.151	2.488	-19.478	108	-3.319	102	-22.797	108
Congo, Republic of	5.905	3.184	2.733	13.692	1	0.283	36	13.975	1
Costa Rica	3.879	5.607	3.522	-2.166	92	1.021	26	-1.145	77

Country	Y	K	L	EC	Rank[EC]	TC	Rank[TC]	TFP	Rank[TFP]
Cote d`Ivoire	3.506	3.638	3.49	0.827	51	-1.059	71	-0.231	67
Cyprus	5.414	4.519	1.224	8.517	12	2.575	4	11.092	4
Denmark	2.003	2.394	0.715	0.530	64	1.398	17	1.928	38
Dominican Republic	5.719	7.184	2.983	0.939	47	-0.018	45	0.920	53
Ecuador	4.257	4.08	3.271	-0.021	72	0.200	38	0.179	63
Egypt	5.188	6.261	2.77	0.816	53	-2.135	93	-1.318	80
El Salvador	2.145	3.82	2.701	-0.686	83	-0.041	47	-0.727	73
Equatorial Guinea	4.22	8.686	1.648	-12.757	107	1.178	23	-11.578	106
Ethiopia	2.988	2.579	2.329	3.982	22	-3.749	105	0.233	62
Fiji	3.255	3.086	2.586	1.621	34	2.238	5	3.859	24
Finland	2.934	3.047	0.565	1.534	36	1.456	16	2.991	29
France	2.532	3.412	0.725	0.479	65	-0.238	52	0.241	61
Gabon	4.265	5.67	2.226	-0.056	73	1.732	12	1.677	42
Gambia, The	3.936	9.021	3.414	-9.466	103	-0.437	59	-9.903	101
Ghana	3.728	1.527	2.887	8.748	10	-1.915	90	6.833	11
Greece	2.695	3.122	1.135	0.969	46	0.958	28	1.928	39
Guatemala	3.899	4.571	3.174	0.103	69	-0.415	57	-0.311	69
Guinea	3.877	2.336	2.686	7.468	13	-0.501	61	6.967	10
Guinea-Bissau	6.235	2.643	2.168	12.794	2	0.076	41	12.870	2
Haiti	5.175	5.589	0.847	6.345	16	-1.732	88	4.614	18
Honduras	3.216	4.793	3.251	-2.877	94	-0.009	43	-2.886	91
Hong Kong	7.139	8.016	2.872	1.543	35	1.056	25	2.600	31
Iceland	4.034	3.747	1.971	1.428	40	3.711	2	5.140	15
India	4.876	5.253	1.998	9.121	7	-4.650	107	4.471	21
Indonesia	6.357	10.9	2.854	-2.030	89	-3.215	101	-5.245	94
Iran	3.698	5.588	3.157	-1.027	87	-0.732	66	-1.760	85
Ireland	5.473	5.863	1.197	0.823	52	1.511	15	2.335	34

Country	Y	K	L	EC	Rank[EC]	TC	Rank[TC]	TFP	Rank[TFP]
Israel	4.593	5.027	2.885	0.365	66	1.644	13	2.009	37
Italy	2.779	3.061	0.637	1.889	31	-0.164	50	1.726	41
Jamaica	0.897	1.116	1.929	-2.036	90	0.895	30	-1.140	76
Japan	3.45	5.691	0.834	-0.532	79	-1.087	73	-1.619	83
Jordan	6.567	8.299	4.645	0.568	61	1.081	24	1.649	43
Kenya	5.572	4.209	3.573	8.780	8	-2.201	95	6.579	13
Korea, Republic of	7.509	10.461	2.511	1.222	42	-0.796	67	0.426	58
Lesotho	4.262	12.226	1.723	-12.447	106	-0.113	49	-12.560	107
Luxembourg	4.525	3.602	1.141	1.104	44	3.745	1	4.849	16
Madagascar	1.42	1.924	2.625	-0.805	85	-2.608	98	-3.412	92
Malawi	5.187	3.272	2.728	11.054	3	-1.679	84	9.375	5
Malaysia	6.775	8.829	3.052	0.606	58	-0.273	54	0.333	59
Mali	3.196	2.761	1.959	5.142	19	-1.912	89	3.230	27
Mauritania	1.752	6.186	1.984	-10.033	104	-0.672	64	-10.705	104
Mauritius	5.599	5.882	2.408	1.492	37	1.801	9	3.293	26
Mexico	4.064	4.905	3.444	-0.849	86	-1.076	72	-1.926	86
Morocco	3.931	5.764	2.741	-0.135	74	-1.019	70	-1.155	78
Mozambique	1.121	2.963	1.95	-3.003	95	-2.989	100	-5.992	96
Nepal	4.671	9.062	2.098	-1.680	88	-2.232	96	-3.912	93
Netherlands	3.003	3.168	1.438	0.687	55	0.806	31	1.493	46
New Zealand	2.291	2.954	1.85	-0.302	76	1.763	11	1.460	47
Nicaragua	0.27	2.714	3.539	-11.306	105	0.443	33	-10.863	105
Niger	1.715	1.48	2.75	1.251	41	-1.537	82	-0.286	68
Nigeria	2.113	6.944	2.753	-4.128	97	-3.483	104	-7.610	100
Norway	3.633	3.698	1.249	2.522	28	1.815	8	4.337	22
Pakistan	4.943	4.097	2.57	10.786	4	-2.812	99	7.975	8
Panama	3.776	5.23	2.849	0.882	49	1.340	18	2.222	36

Country	Y	K	L	EC	Rank[EC]	TC	Rank[TC]	TFP	Rank[TFP]
Papua New Guinea	3.037	3.41	2.409	0.702	54	-0.010	44	0.692	56
Paraguay	4.905	7.849	3.01	-0.298	75	0.218	37	-0.080	64
Peru	2.829	2.758	3.205	-0.589	81	-0.334	56	-0.924	75
Philippines	3.733	4.741	2.81	0.557	62	-1.720	87	-1.163	79
Portugal	4.449	5.806	1.437	1.180	43	0.430	34	1.610	45
Rwanda	3.491	6.401	2.499	-4.025	96	-2.272	97	-6.298	97
Senegal	3.131	2.965	2.526	4.524	21	-1.334	76	3.190	28
Sierra Leone	-0.104	4.476	1.832	-8.567	102	-1.487	80	-10.055	102
Singapore	7.947	9.424	3.575	2.664	27	1.892	7	4.555	19
South Africa	2.583	2.356	2.551	0.570	60	-0.673	65	-0.103	65
Spain	3.311	4.238	1.145	0.543	63	-0.028	46	0.515	57
Sri Lanka	4.658	7.801	2.161	-0.003	71	-1.392	78	-1.395	81
Sweden	2.05	2.308	0.841	0.619	57	0.999	27	1.618	44
Switzerland	1.261	1.938	0.915	-0.793	84	1.537	14	0.744	55
Syrian Arab Republic	6.954	6.073	3.604	3.058	24	-0.177	51	2.882	30
Taiwan	8.275	10.624	1.936	1.698	32	-0.435	58	1.263	51
Tanzania	2.985	2.481	2.888	2.979	25	-2.168	94	0.811	54
Thailand	6.282	7.637	2.365	6.468	15	-1.706	86	4.762	17
Togo	2.197	5.849	3.043	-5.702	98	-0.880	68	-6.582	98
Trinidad and Tobago	2.697	4.431	1.553	-0.481	78	1.797	10	1.316	50
Tunisia	5.621	3.813	3.16	6.295	17	0.348	35	6.643	12
Turkey	4.26	6.599	2.233	-0.551	80	-1.550	83	-2.101	88
Uganda	4.701	6.819	2.697	2.077	30	-3.792	106	-1.715	84
United Kingdom	2.332	2.655	0.514	0.900	48	-0.611	62	0.288	60
United States of America	3.44	4.79	1.638	0.013	70	-1.537	81	-1.524	82
Uruguay	2.617	3.24	0.992	1.482	38	0.954	29	2.436	33
Venezuela	1.031	2.626	3.742	-2.436	93	0.175	39	-2.261	90
Zambia	1.582	0.088	2.59	4.798	20	-0.642	63	4.156	23
Zimbabwe	3.871	2.656	2.587	8.765	9	-0.441	60	8.324	7

7 Concluding Remarks

In this paper, we point out that conventional growth empirics are not sufficient to understand diverse economic performances. Measuring technical efficiency may be more in line with the theoretical foundation of explaining cross-country economic performances. Compared to TFP measurement, using an SPF approach may help us understand the sources of growth better as this methodology also allows us to disentangle technical change and technical efficiency change. In addition, the model allows us to incorporate explanatory factors of technical inefficiency.

In terms of investigating the sources of technical efficiency, we identify three key competing views on potential sources, firstly human capital, secondly openness and last but not least institutions. In the existing literature, there is no conclusive empirical evidence showing which factors are more prominent. Effects of these deep determinants also depend on the level of economic development.

We apply the Battese and Coelli (1993) model to estimate technical efficiency and incorporate its determining factors in a single model. Using a translog stochastic production function specification, we cannot find empirical evidence to show that human capital, trade openness, financial integration and capital account openness have direct impacts on explaining cross-country technical inefficiency. In terms of institution, we find that the rule of law has a direct impact on decreasing technical inefficiency. Regulation, nevertheless, shows an optimal level. That said, only after reaching a threshold of a minimum amount of regulation, does too much regulation leads to technical inefficiency. Democracy and stability of monetary policy have no direct impact on technical inefficiency as our empirical results show. However, their interactions with human capital in turn are statistically significant. It implies that these two aspects of institutions only work with a given level of human capital to improve technical efficiency. Our findings seem to support the view of North and Parente and Prescott's theory that to reduce the income gap between developed economies and developing economies, the late starters have to use resources by making improvements in their institutional quality.

Our model also shows that technical efficiency is time-varying. Based on our estimated stochastic production frontier, we can proceed with deriving cross-country efficiency changes and technical changes. As expected, the industrialised economies are among the best-practice. Comparing the performances across regions, we find that emerging markets like China and

India experienced drastic improvements in technical efficiency. Sub-Saharan African countries stayed well below the frontier over our studied period, although the performances of individual countries are quite diverse. When we further segregate the sources of growth into efficiency changes and technical changes, we find that the main source of growth in developing countries is through the channel of efficiency change. In developed economies, in contrast, the source of growth primarily comes from technical change (i.e. technological progress).

Our research helps our understanding of the economic importance of institutions. Also, it attempts to quantify to what extent market-sustaining institutions could hamper economic performances. Our quantifiable indicator is the estimated mean level of technical efficiency, as compared to that of the best practice. One of our major findings is that income disparities across countries may result from the way production inputs are allocated, rather than factor accumulation.

This study provides empirical support to demonstrate what the likely and potential benefits of structural reform are that help strengthen market-sustaining institutions. In particular for developing countries, as we find, the main source of growth comes from efficiency change, which in turn relies on institutions and their interaction with human capital.

APPENDICES

A.1 Descriptive Statistics and Correlation Matrices

Descriptive Statistics of Institutional Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Key Variables					
GDPPC_gr	1101	0.0163	0.0458	-0.4288	0.3237
DEMOC	986	3.9782	4.1208	0	10
LEGAL	664	5.3639	1.9251	1.1500	9.3340
IPOLITY2	1189	5.3734	3.4537	0	10
QOG	625	0.5488	0.2351	0.0556	1.0000
XCONST	1006	0.1601	14.2511	-88.0000	7.0000
REG	699	5.4414	1.1096	2.4700	8.7600
SM	800	6.5251	2.2143	0.0000	9.8633
SCHOOLING	715	4.7890	2.9261	0.0420	12.2470
Control Variables					
fdi_gdp	956	0.0303	0.1276	-0.0528	3.5772
pop_gr	1375	0.0181	0.0165	-0.1605	0.1773
fin_open	865	1.7679	6.5469	0.1195	179.2779
ca_open	1037	-0.0657	1.4480	-1.8081	2.5408
lliab_gdp	840	0.4439	0.3376	0.0084	3.0226
gcon_gdp	1143	23.5662	11.3795	2.5525	79.5660
ln(trade_gdp)	1075	4.1823	0.6104	0.8215	5.9644
ln(invest_gdp)	1143	2.4376	0.6801	-0.0657	4.5148

Correlation Matrix of Institutional Variables

	GDPPC_gr	*DEMOC*	*LEGAL*	*IPOLITY2*	*QOG*	*XCONST*	*REG*	*SM*	*SCHOOLING*	*Lagged ln(GDPPC)*
GDPPC_gr	1									
DEMOC	0.0627	1								
LEGAL	0.2585	0.5181	1							
IPOLITY2	0.0713	0.9717	0.5463	1						
QOG	0.2014	0.5742	0.8768	0.5767	1					
XCONST	0.1616	0.2917	0.3219	0.2609	0.367	1				
REG	0.2321	0.3741	0.4496	0.4165	0.4159	0.1684	1			
SM	0.1725	0.2457	0.4578	0.2541	0.4351	0.1707	0.4611	1		
SCHOOLING	0.1479	0.6487	0.7006	0.6767	0.7633	0.2917	0.4132	0.3771	1	
Lagged ln(GDPPC)	0.0507	0.5626	0.6907	0.5373	0.7403	0.2505	0.436	0.4232	0.8356	1

A.2 List of Economies

List of Panel Units - Country Coverage

	Economy	*Code*	*Income group*
	Industrial Economies		
1	Australia	AUS	High income
2	Austria	AUT	High income
3	Belgium	BEL	High income
4	Canada	CAN	High income
5	Denmark	DNK	High income
6	Finland	FIN	High income
7	France	FRA	High income
8	Germany	DEU	High income
9	Greece	GRC	High income
10	Iceland	ISL	High income
11	Ireland	IRL	High income
12	Italy	ITA	High income
13	Japan	JPN	High income
14	Luxembourg	LUX	High income
15	Netherlands	NLD	High income
16	New Zealand	NZL	High income
17	Norway	NOR	High income
18	Portugal	PRT	High income
19	Spain	ESP	High income
20	Sweden	SWE	High income
21	Switzerland	CHE	High income
22	United Kingdom	GBR	High income
23	United States	USA	High income
	East Asia and Pacific		
1	China	CHN	Lower middle income
2	Hong Kong, China	HKG	High income: nonOECD
3	Indonesia	IDN	Lower middle income
4	Korea, Rep.	KOR	High income: OECD
5	Malaysia	MYS	Upper middle income
6	Philippines	PHL	Lower middle income
7	Singapore	SGP	High income: nonOECD
8	Thailand	THA	Lower middle income
	Europe and Central Asia		
1	Hungary	HUN	Upper middle income
2	Turkey	TUR	Lower middle income
	Middle East and North Africa		
1	Egypt, Arab Rep.	EGY	Lower middle income
2	Iran, Islamic Rep.	IRN	Lower middle income
3	Israel	ISR	High income: nonOECD
4	Jordan	JOR	Lower middle income
5	Morocco	MAR	Lower middle income

	Economy	*Code*	*Income group*
6	Tunisia	TUN	Lower middle income
	Latin America & Caribbean		
1	Argentina	ARG	Upper middle income
2	Belize	BLZ	Upper middle income
3	Bolivia	BOL	Lower middle income
4	Brazil	BRA	Lower middle income
5	Chile	CHL	Upper middle income
6	Colombia	COL	Lower middle income
7	Costa Rica	CRI	Upper middle income
8	Dominican Republic	DOM	Lower middle income
9	Ecuador	ECU	Lower middle income
10	El Salvador	SLV	Lower middle income
11	Guatemala	GTM	Lower middle income
12	Honduras	HND	Lower middle income
13	Jamaica	JAM	Lower middle income
14	Mexico	MEX	Upper middle income
15	Panama	PAN	Upper middle income
16	Paraguay	PRY	Lower middle income
17	Peru	PER	Lower middle income
18	Trinidad and Tobago	TTO	Upper middle income
19	Uruguay	URY	Upper middle income
20	Venezuela, RB	VEN	Upper middle income
	South Asia		
1	Bangladesh	BGD	Low income
2	India	IND	Low income
3	Pakistan	PAK	Low income
4	Sri Lanka	LKA	Lower middle income
	Sub-Saharan Africa		
1	Cameroon	CMR	Low income
2	Côte d'Ivoire	CIV	Low income
3	Gabon	GAB	Upper middle income
4	Ghana	GHA	Low income
5	Kenya	KEN	Low income
6	Madagascar	MDG	Low income
7	Malawi	MWI	Low income
8	Mali	MLI	Low income
9	Mauritius	MUS	Upper middle income
10	Niger	NER	Low income
11	Nigeria	NGA	Low income
12	Rwanda	RWA	Low income
13	Senegal	SEN	Low income
14	South Africa	ZAF	Lower middle income
15	Togo	TGO	Low income
16	Zambia	ZMB	Low income
17	Zimbabwe	ZWE	Low income

Note ^ : Country code and income group classifications are based on World Bank Country Classification.

A.3 Summary Table of Time-Varying Technical Efficiency Models

General Form : $y_{it} = \alpha_t + x'_{it}\beta + v_{it} - u_{it}$				
Model	**Time Trend and TE Specification**	**Additional Parameters**	**Error Form Assumptions**	**Estimation Technique**
Cornwell, *et al.* (1990)	$\alpha_{it} = \delta_{i1} + \delta_{i2}t + \delta_{i3}t^2$ $\hat{\alpha}_t = \max_i \{\hat{\alpha}_{it}\}$ $\hat{u}_{it} = (\hat{\alpha}_t - \hat{\alpha}_{it})$	*I x 3*	$u_{it} \sim iid\ N^+(0, \sigma_u^2)$ $v_{it} \sim iid\ N(0, \delta_v^2)$	FE RE EIV
Kumbhakar (1990)	$u_{it} = \beta(t)u_i$ $\beta(t) = [1 + \exp\{\gamma t + \delta t^2\}]^{-1}$	*2*	$u_i \sim iid\ N^+(0, \sigma_u^2)$ $v_{it} \sim iid\ N(0, \sigma_v^2)$	ML
Battese and Coelli (1992)	$u_{it} = \beta(t)u_i$ $\beta(t) = \exp\{-\gamma(t - T)\}$	*1*	$u_i \sim iid\ N^+(0, \sigma_u^2)$ $v_{it} \sim iid\ N(0, \sigma_v^2)$	ML
Kumbhakar and Hjalmarsson (1993)	$u_{it} = \tau_i^* + \xi_{it}$	*I*	$\xi_{it} \sim iid\ N^+(0, \sigma_\xi^2)$ $v_{it} \sim iid\ N(0, \sigma_v^2)$	1st stage: FE/RE 2nd stage: Conditional Maximum Likelihood
Lee and Schmidt (1993)	$\alpha_{it} = \lambda_t \delta_i^*$ $u_{it} = \max_i \{\hat{\beta}_t \hat{u}_i\} - (\hat{\beta}_t \hat{u}_i)$	*T – 1*	$u_i \sim iid\ N^+(0, \sigma_u^2)$ $v_{it} \sim iid\ N(0, \sigma_v^2)$	FE RE
Chan Ahn and Lee (1994)	$\alpha_{it} = \lambda_t \delta_i^*$ $u_{it} = \max_i \{\hat{\beta}_t \hat{u}_i\} - (\hat{\beta}_t \hat{u}_i)$	*T - 1*	$u_i \sim iid\ N^+(0, \sigma_u^2)$ $v_{it} \sim iid\ N(0, \sigma_v^2)$	GMM

BIBLIOGRAPHY

Acemoglu, D. and S. Johnson (2003). "Unbundling Institutions." NBER Working Paper # 9934.

Aigner, D., C. A. K. Lovell, et al. (1977). "Formulation and Estimation of Stochastic Frontier Production Function Models." Journal of Econometrics 6: 21-37.

Alesina, A. and R. Perotti (1996). "Income Distribution, Political Instability, and Investment." European Economic Review 40: 1203-1228.

Barro, R. J. (1990). "Government Spending in a Simple Model of Endogeneous Growth." The Journal of Political Economy 98(5(2)): S103-125.

Barro, R. J. (1991). "Economic Growth in a Cross Section of Countries." The Quarterly Journal of Economics 106(2): 406-443.

Barro, R. J. (1994). "Democracy and Growth." NBER Working Paper No. 4909. Barro, R. J. and X. Sala-i-Martin (1997). Economic Growth. Cambridge, Mass, MIT.

Benhabib, J. and M. M. Spiegel (1997). "Cross-Country Growth Regressions." Economics Research Reports, New York University: New York, NY.

Bertrand, M. and F. Kramarz (2002). "Does Entry Regulation Hinder Job Creation? Evidence from the French Retail Industry." The Quarterly Journal of Economics 117: 1369-1413.

Capita Income." NBER Working Paper # 9490.

Claessens, S. and L. Laeven (2002). "Financial Development, Property Rights, and Growth." World Bank Policy Research Department Working Paper 2924.

Coelli, T. (1996). "A Guide to FRONTIER Version 4.1: A Computer Program for Stochastic Frontier Production and Cost Function Estimation." Centre for Efficiency and Productivity Analysis (CEPA), University of New England Working Paper 96/07.

Coelli, T., D. S. P. Rao, et al. (1998). An introduction to efficiency and productivity analysis. Boston, Kluwer Academic Publishers.

Easterly, W. and R. Levine (2001). "It's Not Factor Accumulation: Stylized Facts and Growth Models." mimeo.

Easterly, W., M. Kremer, et al. (1993). "Good Policy or Good Luck? Country Growth Performance and Temporary Shocks." Journal of Monetary Economics 32: 459-84.

Edwards, S. (1998). "Openness, Productivity and Growth: What do we really know?" Economic Journal 108(447): 383-398.

Fare, R., S. Grosskopf, et al. (1994). "Productivity Growth, Technical Progress, and Efficiency

Change in Industrialized Countries." American Economic Review 84(1): 66-83.

Fisman, R. and V. Sarria-Allende (2004). "Regulation of Entry and the Distortion of Industrial Organization." NBER Working Paper No. 10929.

Freedom House (2004). Freedom in the World 2004 -- The Annual Survey of Political Rights and Civil Rights.

Greenaway, D., W. Morgan, et al. (2002). "Trade Liberalization and Growth in Developing Countries." Journal of Development Economics 67(1): 229-244.

Greene, W. H. (1990). "A Gamma-Distributed Stochastic Frontier Model." Journal of Econometrics 46(1/2): 141-64.

Gwartnet, J. D., R. Lawson, et al. (2002). Economic Freedom of the World 2002: 2002 Annual Report. Vancouver, The Fraser Institute.

Hall, R. E. and C. I. Jones (1999). "Why Do Some Countries Produce so Much More Output Per Worker Than Others?" The Quarterly Journal of Economics 114(1): 83-116.

Harrison, A. (1995). "Openness and Growth: A Time-series, Cross-country Analysis for Developing Countries." NBER Working Paper No. 5221.

Hernando, D. S. (1993). The Missing Ingredient: What poor countries will need to make their markets work. The Economist. 328: SS8-SS12.

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

Islam, N. (1995). "Growth Empirics: A Panel Data Approach." The Quarterly Journal of Economics: 1127-1170.

Islam, R. (2004). "What are the Right Institutions in a Globalizing World -- And ... can we keep them if we've found them?" World Bank Policy Research Department Working Paper No. 3448.

King, R. J. and R. Levine (1994). "Capital Fundamentalism Economic Development and Economic Growth." Carneige-Rochester Conference Series on Public Policy 40(Jun): 259-292.

Kirzer, I. M. (1979). "The Perils of Regulation: A Market-Process Approach." Occassional Paper of the Law and Economics Centre, University of Miami School of Law.

Knack, S. and P. Keefer (1995). "Institutions and Economic Performance: Cross- Country Tests Using Alternative Institutional Measures." Economics & Politics 7(3): 207-27.

Knack, S. and P. Keefer (1997). "Why Don't Poor Countries Catch Up? A Cross- National Test of an Institutional Explanation." Economic Inquiry 35: 590-602.

Landau, D. (1986). "Government and Economic Growth in the Less Developed Countries: An Empirical Study for 1960-1980." Economic Development & Cultural Change 35(1): 35-75.

Limam, Y. R. and S. M. Miller (2004). "Explaining Economic Growth: Factor Accumulation, Total Factor Productivity Growth and Production Efficiency Improvement." University of Connecticut Department of Economics Working Paper No. 2004-20.

Lucas, R. E., Jr (1988). "On the Mechanics of Economic Development." Journal of Monetary Economics 22(1): 3-42.

Maddison, A. (2001). The World Economy: A Millennial Perspective. Paris, OECD. Marshall, M. G., K. Jaggers, et al. (2003).

Meeusen, W. and J. v. d. Broeck (1977). "Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error." International Economic Review 18: 435-444.

Myers, S. C. and N. Majluf (1984). "Corporate Investment and Financing Decisions When Firms Have Information That Investors Do Not Have." Journal of Financial Economics 13: 187-222.

North, D. C. and R. P. Thomas (1973). The Rise of the Western World -- A New Economic History. Cambridge, Cambridge University Press.

Olson, M. J. (1993). The Political Economy of Comparative Growth Rates. The Political Economy of Growth. D. C. Mueller. New Haven, Conn, Yale University Press.

Olson, M. J. (1996). "Distinguished Lecture on Economics in Government: Big Bills Left on the Sidewalk: Why Some Nations are Rich, and Others Poor." The Journal of Economic Perspectives 10(2): 3-24.

Persson, T. (2001). "Political Institutions Shape Economic Policy." NBER Working Paper # 8214.

Polity IV Project:Political Regime Characteristics and Transitions, 1800-2003.

Prichett, L. (1997). "Divergence, Big-Time." Journal of Economic Perspectives 11: 3-17. Quarterly Journal of Economics 70: 65-94.

Romer, P. M. (1986). "Increasing Returns and Long-Run Growth." Journal of Political Economy 94: 1002-1036.

Romer, P. M. (1990). "Endogenous Technological Change." Journal of Political Economy 98(5): S71-102 Part 2.

Sachs, J. D. (2003). "Institutions Don't Rule: Direct Effects of Geography on Per

Scarpetta, S., P. Hemmings, et al. (2002). "The Role of Policy and Institutions for Productivity and Firm Dynamics: Evidence from Micro and Industry Data." OECD Economics Department Working Paper No. 329.

Schumpeter, J. A. (1911). The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle. Oxford, Oxford University Press.

Scully, G. W. (1988). "The Institutional Framework and Economic Development." Journal of Political Economy 96: 652-662.

Solow, R. (1956). "A Contribution to the Theory of Economic Growth." The

Stevenson, R. E. (1980). "Likelihood Functions for Generalized Stochastic Frontier Estimation." Journal of Econometrics 13(1): 57-66.

Stiglitz, J. E. and A. Weiss (1981). "Credit Rationing in Markets with Imperfect Information." American Economic Review 71: 393-410.

Temple, J. (1999). "The New Growth Evidence." Journal of Economic Literature 37(1): 112-156.

World Bank Group (2002). World Development Indicators CD-ROM, World Bank Group.

Young, A. (1992). "A Tale of Two Cities: Factor Accumulation and Technical Change in Hong Kong and Singapore." NBER Macroeconomics Annual: 13-54.