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ECONOMIC GROWTH AND FDI INFLOWS: A STOCHASTIC FRONTIER ANALYSIS

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ABSTRACT

Despite plausible theoretical grounds for presuming a positive relationship between foreign direct investment inflows (FDI) and economic growth, existing empirical evidence on this nexus is inconclusive. In an effort to add to the empirical literature, this paper estimates the relationship between FDI and the rate of growth of GDP using a stochastic frontier model and employing panel data covering 45 countries over the period 1997 to 2004. We find that FDI inflows exert a positive impact on economic growth only in the presence of a highly skilled labour; corruption has a negative impact on economic growth; and trade openness increases economic growth by means of efficiency gains.

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INTRODUCTION

In general, economists agree that foreign direct investment inflows (FDI) lead to an increased rate of economic growth (see, for example, Blonigen, 2005). A major growth-enhancing characteristic of FDI is the advanced technology that often accompanies foreign capital investment. In addition, domestic investors can also adopt this advanced technology. In other words, FDI generates positive externalities through technology spillovers. At the same time, increased foreign capital can help to narrow the savings gap (i.e. the gap between the domestic savings ratio and the desired level of investment ratio). In short, FDI should exert positive effects on economic growth, particularly in developing countries which suffer from low productivity and capital stock deficiencies (see, for instance, Johnson, 2006).

Despite these plausible theoretical grounds for anticipating a positive relationship between GDP and FDI, available empirical evidence is mixed. For example, De Mello (1999) found that whether FDI contributes to the economic growth depends on primarily host country characteristics, especially the quantum of skilled labour. Borensztein et al. (1998) also established that although FDI has a positive impact on

GDP, the magnitude of this effect depends on the level of human capital. Using both cross section and panel data analysis, Johnson (2006) demonstrated that FDI inflows boosted economic growth in developing countries, but not in advanced nations. Alfaro (2003) conducted a cross-country analysis and found that total FDI exerted an ambiguous effect on host country economic growth; FDI inflows into the primary sector tended to have a negative effect on growth. Numerous other empirical studies have also provided mixed evidence on the link between economic growth and FDI (Wijeweera et. al. 2007; Zhang 2001; Johnson 2006). The relationship between FDI and the rate economic growth is critically important for policy making in the real-world. The past two decades have witnessed a massive surge in FDI inflows. Indeed, according to UNCTAD (2005), global FDI inflows increased from approximately U$55 billion in 1980 to around U$1,400 billion in 2000. This unprecedented growth in FDI inflows has prompted academic economists and policy makers alike to devote much more effort to understanding the empirical relationships between GDP growth and FDI inflows in host countries.

The present paper seeks to contribute to the empirical literature on the relationship between economic growth and FDI flows in host nations. Theoretical foundation for our study rests squarely on the well-known endogenous growth model (Romer, 1990). According to the endogenous growth models, output is a function of the standard factors of production plus human capital. We employ a stochastic frontier model (SFM) to estimate the model. The SFM model contains factor inputs variables and inefficiency variables. We use capital, labour and human capital as factor inputs as well as several variables as inefficiency variables. We also include a proxy for the level of infrastructure and a proxy for the level of corruption in the host economies. The major focus of the paper is the role of FDI inflows in economic growth. Accordingly, FDI inflows are included as an inefficiency variable. In essence, we investigate whether FDI enhances economic efficiency and increases real GDP in a host economy.

It is appropriate to consider briefly how the present study contributes to the empirical literature on FDI and economic growth. Although a numerous studies have examined how FDI inflows and GDP interrelate with each other, a large majority of this work includes GDP merely as an explanatory variable in the FDI determinant function. In other words, only a subset of studies has focused mainly on the effects of FDI inflows on the economic growth in the host economy.

While most of the available literature in this area has employed the least-squares method to examine the relationship between FDI and economic growth, our study employs a stochastic frontier production function approach. This approach allows us to distinguish the effects of FDI on economic growth via technical and efficiency change and quantify the effects of FDI, along with other variables, on efficiency levels. Only a limited number of macroeconomic empirical studies using the stochastic frontier have been undertaken. For example, Iyer et al. (2004) used this approach to examine the spillover effects of FDI inflows for 20 OECD countries. Nourzad (2008) employed a stochastic translog production frontier to estimate technical inefficiency indices whose conditional mean is specified as a function of FDI and its interaction with openness in the economy. In the same vein, we chose the stochastic frontier approach to examine whether FDI inflows enhance economic growth via efficiency gains and to estimate technical efficiency for the countries selected. In essence, the stochastic frontier method constructs an efficient frontier by imposing the same technology across all countries in the sample.

Deviations from the frontier are divided into inefficiency and noise components. We make use of Battese and Coelli (1993, 1995) in accordance with the original models of Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977).

In this paper, we specifically use only theoretically relevant variables in our estimation procedures. For instance, we control for the host country infrastructure to determine whether it has any impact on the overall FDI spillover effects on the host economy. We also use a corruption index provided by Transparency International (2006) to control for any institutional inefficiency. This latter innovation is introduced to test our intuition that positive technology spillovers from FDI inflows are underestimated if we do not control for the institutional inefficiency in the host country. In addition to these features, we employ a more updated data panel for the estimations. Our data panel covers 45 countries over the period 1997 to 2004. Unlike many existing studies, this data panel includes both developed countries and developing countries. We also apply Chow tests in order to see if estimates are different between two groups. By contrast, as we have seen, a majority of empirical work on economic growth and FDI has focused exclusively on industrialised countries mainly due to data availability. Instead, our panel covers more than 80 percent of total worldwide FDI inflows during the period in question. Our 45 country sample also incorporates the largest FDI recipient countries such as the United States, China, Britain and Canada.

Our paper is divided into four main parts. Section 2 provides a brief synoptic review of the empirical literature and seeks to situate the present study within this work. Section 3 outlines the methodology and data sources employed in the paper. Section 4 discusses the results that emerge from the estimations performed on our model. The paper ends with some brief concluding remarks in section 5.

EMPIRICAL APPROACHES TO FDI AND ECONOMIC GROWTH

How we should best estimate the relationship between FDI and GDP has been an issue amongst empirical economists for some time. The question arises due to the unconvincing results on which way causation runs between these two variables. Some commentators have argued that that GDP growth induces FDI while other observers believe this logic is reversed. To date, Granger causality test results have been inconclusive. By way of illustration, using time series data for 11 developing countries, Zhang (2001) conducted a Granger causality test to examine the direction of the relationship between FDI and GDP. He found plausible feedback effects from economic growth to FDI inflows. In addition, Choe (2003) also demonstrated that FDI granger causes economic growth and *vice versa*.

In other work, some studies used FDI as the dependent variable and GDP was included to control for the market size hypothesis, which states that multinational companies will always evaluate the size of the host country's market when considering the location of its FDI (Moosa, 2002). This market hypothesis has been tested in many empirical papers (see, for example, Chakraboty and Basu, 2002; Billington, 1999; and Wijeweera and Clark, 2006). A second set of studies has used GDP as the dependent variable and FDI as an explanatory variable. This work has estimated growth models to in an effort to understand the relationship between GDP and FBI. The present paper falls squarely within this tradition. Accordingly, we now briefly review some of the more important previous empirical work in this category.

Balasubramanyam et al. (1996) used cross-section data for 46 developing countries over the period 1970 to 1985 and employed the OLS method to estimate the relationship between economic growth and FDI inflows. They found that FDI has positive spillover effects on economic growth, but that its effects are limited to host countries that adopt export promoting policies. In contrast, positive effects were weaker for import substituting economics. In a similar vein, Borenztein et al. (1998) used cross-section data for 69 developing countries during the period 1970 to 1989, but then employed seemingly unrelated regression methods for their estimations. Their main finding was that FDI has a positive effect on economic growth, but the magnitude of the relationship depends on the quality of the human capital of the host country. They observed that chief reason for the positive effects seems to be technology diffusion.

In other work, Olofsodotter (1998) applied the standard OLS method to cross-section data for 50 developing and developed countries over 1980 to1990. He found that, due to technology spillovers, the FDI stock has a positive effect on the economic growth rate. De Mello (1999) used panel fixed-effects estimation to identify the relationship, using data for 32 developed and developing nations. He established that FDI can lead to better technology and improved management in the host country. However, the evidence was rather weak on whether FDI actually creates economic growth. Using time-series data for 11 developing countries, Zhang (2001) found evidence of growth enhancement from FDI. However, the magnitude again appeared to depend on host country conditions. By contrast, Carkovic and Levine (2002) employed both panel and cross-section data for 72 developing and developed countries over the time period 1960-1995 period to investigate the issue, using both OLS and Generalized Method of Moments (GMM) methods of estimation. They established that FDI inflows do not exert a robust influence on economic growth. With the aid of panel data for 80 developed and developing countries, Choe (2003) conducted a Granger causality test for GDP and FDI. He found that FDI Granger-caused economic growth and *vice versa*, but the effects are more apparent from growth to FDI. Bengoa and Sanchez-Robles (2003) used panel data for 18 Latin American countries applying random and fixed-effects techniques for its estimation. They established a positive effect on economic growth and the magnitude seemed to depend on host country conditions.

Johnson (2006) employed a panel of 90 countries and hypothesized that FDI should have a positive effect on economic growth as a result of technology spillovers and physical capital inflows. Performing both panel and cross-section analysis, he found that FDI inflows enhance economic growth in developing economies, but not in developed economies. In addition, Johnson (2006) also provides an excellent review of the existing empirical literature on FDI and economic growth that invokes macroeconomic data. Finally, Alfaro (2003) used cross-country data for the period 1981 to 1999 and examined the impact of FDI on growth in the primary, manufacturing and services sectors. The author suggested that the benefits of FDI vary greatly across sectors. Thus, FDI in the primary sector tended to have a negative effect on growth, this relationship was positive for the manufacturing sector, and ambiguous in the service sector.

METHOD OF ANALYSIS

The Basic Model

A stochastic frontier production function is applied to panel data to examine whether FDI inflows enhances economic growth via efficiency gains and to estimate technical efficiency for the selected countries. The stochastic frontier method constructs an efficient frontier by imposing the same technology across all countries in the sample. Deviations from the frontier are divided into inefficiency and noise components. The model of Battese and Coelli (1993, 1995) is used in accordance with the original models of Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). It has the general form:

$$Y_{it} = f(X_{it}, \alpha)\exp(\varepsilon_{it}) \tag{1}$$

where Y_{it} is the output of country i (i = 1, 2, …, N) in year t (t = 1, 2, …, T); X_{it} is the corresponding matrix of explanatory variables; α is the vector of parameters to be estimated; and ε_{it} is the error term that is composed of two independent elements, V_{it} and U_{it}, such that $\varepsilon_{it} \equiv V_{it} - U_{it}$. The V_{it}s are assumed to be symmetric identically and independently distributed errors that represent random variations in output and are assumed to be normally distributed with mean zero and variance, σ_V^2.

Following Battese and Coelli (1995), the U_{it}s are assumed non-negative random variables that represent the stochastic shortfall of outputs from the most efficient production. It is assumed that U_{it} is defined by truncation of the normal distribution with mean,

$$\mu_{it} = \delta_0 + \sum_{j=1}^{J} \delta_j Z_{jit} \tag{2}$$

and variance, σ^2, where Z_{jit} is value of the j-th explanatory variable associated with the technical inefficiency effect of country i in year t; and δ_0 and δ_j are unknown parameters to be estimated.

The parameters of both the stochastic frontier model and the inefficiency effects model can be consistently estimated by the maximum-likelihood method. The variance parameters of the likelihood function are estimated in terms of $\sigma_S^2 \equiv \sigma_V^2 + \sigma^2$ and $\gamma \equiv \sigma^2 / \sigma_S^2$.

Given the specification in (1) and (2), the technical efficiency of production for the i-th country in the t-th year is defined by

$$TE_{it} = \exp(-U_{it}) \quad (3)$$

The prediction of the technical efficiencies is based on its conditional expectation, given the observable value of (V_{it}-U_{it}) (Jondrow et al. 1982; Battese and Coelli 1988). The technical efficiency index is equal to one if the farm has an inefficiency effect equal to zero and it is less than one otherwise

Empirical Model and Data

One of the key steps of the SFM is to choose the appropriate production function for the analysis. In this paper, we opt to use the translog function (Christensen, Jorgenson and Lau, 1973) in lieu of the more popular Cobb-Douglas production function. The functional form of the translog production technology specified in (4).

$$\ln Y_{it} = \alpha_0 + \sum_{j=1}^{4} \alpha_j \ln X_{jit} + 0.5 \sum_{j \le}^{4} \sum_{k}^{4} \alpha_{jk} \ln X_{jit} \ln X_{kit} + \omega_1 t + \omega_1 t^2 + V_{it} - U_{it} \quad (4)$$

All of the variables are as defined before except for t and t^2, which controls for the linear and quadratic time trends, respectively. The translog function has become more prevalent because the Cobb-Douglas functional form imposes severe restrictions on the technology by restricting the production elasticities to be constant and the elasticities of input substitution to be unity. We tested the Cobb-Douglas against the translog function to determine whether it was an adequate representation of the data, and found conclusive evidence that it was not. We have therefore excluded the Cobb-Douglas specification from further consideration.

The dependent variable in this model is the real GDP in terms of millions of USD. In our stochastic frontier model, there are two types of variables; factor inputs and inefficiency variables. Standard factors of production such as labour (in thousands), capital (gross capital formation in constant 2000 USD millions), and human capital (percentage of government spending on education) are included in the factor inputs section. We also include a proxy for the infrastructure (telephone main lines per 1000 people), various interaction terms of explanatory variables, a linear and non-linear time trend terms are also included in the inputs section. We expect positive sign for all of factor inputs variables.

Our focus of this analysis is to find whether FDI enhances efficiency in the host economy. According to Iyer et al (2004), FDI inflows increase efficiency in a host country via several ways: direct transfer of technology, domestic firms learn by watching foreign firms or demonstration effect, domestic firms enhance efficiency by competing with foreign firms or demonstration effect, and workers that a retrained in FDI firms relocate to domestic firms by transferring the knowledge or labour mobility. Hence FDI (in USD millions) inflows is considered as the main inefficiency variable. In addition, several more variables are included in our inefficiency model. CPI varies from 0 (highly corrupt) to 10 (highly clean). The host country's trade with the rest of the world (Openness) is represented by the sum of exports and imports in USD millions. The Corruption Perceptions Index (CPI) obtained from the Transparency International is used to control for institutional inefficiency. In order to control for the interaction between FDI and education we have included a cross term along with an interaction term for time trend and FDI in the inefficiency model. A significantly negative coefficient in the inefficiency model suggests an increase in efficiency or increase in the growth rate.

Before we estimate the model, two important factors need to be taken into account. First, it can be argued that relationship between GDP and FDI follows a two-way causality resulting in the simultaneity problem in the estimation. As we indicated earlier in the literature review, in fact some studies have used FDI as the dependent variable (see, for instance, Wijeweera et. al 2007); other work, like Iyer et al. (2004) has used GDP as the dependent variable. In order to tackle this issue, we conducted a Granger Causality Test for FDI and Real GDP. The Granger Causality Test results shown in Table 1 confirm the suitability of our choice of GDP as the dependent variable because there is a strong one-way causality from real GDP to FDI. Simultaneity is thus not a serious problem in our approach.

TABLE 1. GRANGER CAUSALITY TEST RESULTS

Null Hypothesis:	F-Statistic	Prob
LGDP does not Granger Cause LFDI	1.25	0.29
LFDI does not Granger Cause LGDP	2.96	0.02

Note: Lag 4 is used in the test.

Second, it is standard practice in the contemporary empirical literature to test for the stationarity of the variables in the model before they are used in estimation and inference. Accordingly, we conducted an Im, Pesaran, and Shin panel unit root test to evaluate the stationarity properties of the variables. This test allows for individual unit root processes to be assessed. Our test results suggest that all of the variables contain a unit root in levels, implying they are nonstationary. The results are shown in Table 2. Nonetheless, we opted not to use differenced data because Johansen test suggests that there is at least one cointegration relationship among the variables. Another advantage of using the data in levels is that compared to differenced data, level data keep long-run properties intact.

The stochastic frontier production functions, defined by equation (4), and the technical inefficiency models, defined by equation (2), are jointly estimated by the maximum-likelihood method using FRONTIER 4.1 (Coelli 1996) **. All values are mean-corrected to zero; hence the first order estimates of the translog model are the corresponding elasticity estimates.

TABLE 2. IM, PESARN AND SHIN UNIT ROOT TEST RESULTS

Variable	Statistic	Prob.**
Real GDP	3.11255	0.9991
Capital	0.1638	0.5651
Corruption	-1.5678	0.0585
Labor Force	2.70127	0.9965
Infrastructure	1.59313	0.9444
FDI Inflows	-0.9613	0.1682
Openness	-1.18238	0.1185
Education	1.67541	0.23451

Various tests of null hypotheses for the parameters in the frontier production functions and in the inefficiency models are performed using the generalised likelihood-ratio test statistic defined by:

$$\lambda = -2 \{\log [L(H_0) - \log [L(H_1)]\}. \qquad (6)$$

where $L(H_0)$ and $L(H_1)$ denote the values of the likelihood function under the null (H_0) and alternative (H_1) hypotheses, respectively. If the null hypothesis is true, the test statistic has approximately a chi-square or a mixed chi-square distribution with degrees of freedom equal to the difference between the parameters involved in the null and alternative hypotheses. If the inefficiency effects are absent from the model, as specified by the null hypothesis, H_0: $\gamma=\delta_0=\delta_1=\delta_2=\ldots\delta_{11}=0$, then λ is approximately distributed according to a mixed chi-square distribution with 13 degrees of freedom. In this case, critical values for the generalised likelihood-ratio test are obtained from Table 1 of Kodde and Palm (1986).

DISCUSSION OF RESULTS

We estimated six different models including various cross products, inefficiency variables and trend terms. However, the best specification is determined by the expected outcomes and other diagnostic tests. The results are reported only for the best specification with intercept and without intercept for the inefficiency effects model. Table 3 shows the stochastic frontier results with no intercept, while the Table 4 presents the results for the same specification, but with the intercept. Our findings may be summarized as follows:

TABLE 3. RESULTS WITHOUT INTERCEPT

	Coefficients	Standard Error	T-Ratios
Frontier Model			
Constant	0.2998	0.0463	6.4736
Capital	0.7795	0.0427	18.2525
Labour	0.2376	0.0509	4.6672
Infrastructure	0.0343	0.0582	0.5903
Education	0.1079	0.0281	3.8414
$Capital^2$	0.0917	0.0568	1.6146
Capital × Labour	-0.0649	0.0579	-1.1205
Capital × Infrastructure	-0.0325	0.0600	-0.5411
Capital × Education	-0.0262	0.0170	-1.5406
$Labour^2$	0.0553	0.0637	0.8673
Labour × Infrastructure	0.0041	0.0609	0.0674
Labour × Education	0.0507	0.0199	2.5456
$Infratructure^2$	-0.1317	0.0752	-1.7509
Infrastructure × Education	0.0655	0.0203	3.2271
$Education^2$	-0.0052	0.0105	-0.4927
Year	0.0204	0.0103	1.9700
$Year^2$	0.0109	0.0067	1.6176
Inefficiency Effects Model			
Intercept			
FDI Inflows	1.8E-05	6.2E-06	2.9274
Openness	-3.1E-08	1.2E-07	-0.2665
Corruption	-0.0966	0.0199	-4.8606
Education	0.0622	0.0225	2.7617
Trend	0.0775	0.0170	4.5500
FDI * Trend	2.9E-07	5.5E-07	0.5257
FDI * Educ	-4.0E-06	1.4E-06	-2.8375
Variance Parameters			
Sigma-squared	0.0494	0.0054	9.1109
Gamma	0.8065	0.0671	12.0116
Log-likelihood	106.13		
LR-Test (1)	59.79		

TABLE 4. MODEL 2 WITH INTERCEPT

	Coefficients	Standard Error	T-Ratios
Frontier Model			
Constant	0.5269	0.0384	13.7306
Capital	0.7251	0.0406	17.8666
Labour	0.2816	0.0488	5.7657
Infrastructure	0.0457	0.0582	0.7852
Education	-0.0387	0.0228	-1.6981
Capital2	-0.0619	0.0592	-1.0457
Capital × Labour	0.0811	0.0614	1.3208
Capital × Infrastructure	0.0747	0.0642	1.1632
Capital × Education	-0.0083	0.0170	-0.4895
Labour2	-0.0914	0.0678	-1.3468
Labour × Infrastructure	-0.0882	0.0656	-1.3449
Labour × Education	0.0210	0.0193	1.0893
Infratructure2	-0.1991	0.0798	-2.4956
Infrastructure × Education	0.0658	0.0205	3.2188
Education2	0.0218	0.0098	2.2396
Year	-0.0018	0.0091	-0.1949
Year2	0.0123	0.0062	1.9902
Inefficiency Effects Model			
Intercept	1.545	0.185	8.357
FDI Inflows	1.4E-05	4.0E-06	3.488
Openness	-3.4E-07	9.0E-08	-3.739
Corruption	-0.091	0.014	-6.649
Education	-0.147	0.032	-4.599
Trend	0.019	0.017	1.117
FDI * Trend	8.1E-07	3.1E-07	2.642
FDI * Educ	-3.6E-06	6.0E-07	-5.992
Variance Parameters			
Sigma-squared	0.0488	0.0041	11.9517
Gamma	0.9931	0.0147	67.5328
Log-likelihood	132.74		
LR-Test (1)	113.02		

(a) A majority of the factors of production are significant. Furthermore, cross products have t values close to one or more than one. This suggests that there are some interactions amongst the variables. Thus translog model specification is more appropriate than the familiar Cobb-Douglas model specification.
(b) The coefficients of capital, labour and human capital have expected signs and they are statistically significant at conventional levels.
(c) Capital comes as the single most important factor of production with an elasticity of 0.7795, followed by labour at 0.2376, and human capital at 0.1079. Infrastructure has the expected sign, but it is not statistically significant.
(d) The interaction term between education and labour is positive and statistically significant at 5 percent level. This suggests that although that the magnitude of the separate human capital elasticity is smaller compared with other major inputs, the overall impacts of education on the growth will be much higher. This proposition is further confirmed by the positive and significant coefficient of the infrastructure and the education variable.
(e) We have included sufficient trend terms to capture the time trend that appears in the growth variable. Both linear and quadratic trend coefficients are positive although they are just significant at conventional levels.

The gamma parameter is 0.81, which means that 81 per cent of the disturbance term is due to inefficiency. An examination of the results of a likelihood ratio test using a mixed chi-squared distribution confirms the presence of technical inefficiency. We thus conclude that the technical inefficiency term is a significant addition to the model. It is important to stress that in this particular model, these variables are included as inefficiency variables. Therefore a negative coefficient means an increase in efficiency and a positive effect on growth. Our results do not provide convincing evidence regarding the impact of FDI inflows on economic growth. In model 1, FDI inflows has the expected negative sign (i.e. a positive impact on growth), but it is statistically insignificant. In model 2, we have a statistically significant coefficient, but with an unexpected sign.

A positive sign for FDI as an inefficiency variable is counterintuitive. In general, FDI inflows should enhance economic growth by bringing in new technology as well as influencing domestic productivity through technological spillovers. One possible explanation for this anomaly has been advanced by Hanson (2001), he argued that multinational firms could confine domestic firms to less profitable ventures creating productivity losses. If these losses are greater than the corresponding productivity gains created by multinational investment, then we can expect an aggregate negative impact on economic growth. In addition, if FDI crowds out domestic investment, it could have harmful effects on domestic economic growth. Moreover, some commentators have argued that although some countries favour FDI over domestic investment, and grant tax concessions and other incentives, this serves only to underline market failure.

However, our results do not necessary suggest that FDI inflows have a detrimental effect on the economic growth. For example, it is interesting to observe that the coefficient of the interaction term of FDI and Education is negative and significant. Since a negative sign on the coefficient of an explanatory variable shows an increase in efficiency in our model, FDI inflows along with high quality educated labour would therefore increase both efficiency and growth. This is an important finding, especially for developing countries with unskilled labour. These nations cannot thus rationally anticipate high economic growth by simply attracting FDI without increasing the level of education of the economically active population.

In our results, openness has positive effect on economic growth, confirmed by both models. This is not surprising. Casual empirical observation amply illustrates the obvious fact shows that countries that have chosen to open their economies over the last two decades have achieved considerably higher growth compared to countries that remained comparatively closed. The coefficient of corruption has to be interpreted more carefully. Corruption is indexed such that the higher value refers to cleaner administration. Accordingly, a negative sign indicates that less corruption has positive impact on the economic growth. Both model 1 and model 2 indicate that less corruption in the host country would increase growth in GDP. This may be due to various factors. One avenue through which corruption can depress economic activity lies in its potentially inhibitory impact on foreign direct investment (FDI). Although economic theory is ambiguous on the ultimate effects of corruption on FDI, it does propose several different mechanisms that can discourage FDI, including corrupt institutions acting as a tax on investment and heightened insecurity and uncertainty (see, for instance, Hakkala, Norback and Svaleryd 2005 and Wei 2000).

Finally, the technical efficiency (TE) index shows how far a country is from its best possible production frontier. The TE index is equal to one if the nation is fully efficient and zero if it is completely inefficient. TE statistics provided in Table 5 are based on model 2. Table 5 suggests that Britain and Canada are closest to the production frontier. In our sample, Thailand is the least efficient country as far as average technical efficiency is concerned.

TABLE 5. TECHNICAL EFFICIENCY

Country	**Technical Efficiency**
Argentina	0.94
Australia	0.90
Belgium	0.93
Bolivia	0.71
Canada	0.96
Chile	0.82
China	0.61
Colombia	0.78
Czech Republic	0.59
Denmark	0.91
Dominican Republic	0.72
Ecuador	0.64
Finland	0.92
France	0.91
Germany	0.94
Greece	0.83
Guatemala	0.85
Honduras	0.64
Hong Kong	0.86
Hungary	0.60
Iceland	0.90
India	0.72
Israel	0.87
Italy	0.73
Japan	0.90
Mexico	0.77
Netherlands	0.94
New Zealand	0.86
Paraguay	0.62
Peru	0.82
Poland	0.66
Russian	0.72
South Africa	0.85
Spain	0.84
Sweden	0.94
Switzerland	0.93
Thailand	0.58
UK	0.96
Uruguay	0.94
USA	0.95
Venezuela	0.79

CONCLUDING REMARKS

This paper has attempted to make a contribution to the empirical literature on the relationship between FDI and the rate of growth of GDP using a stochastic frontier model and employing panel data covering 45 countries over the period 1997 to 2004. Four main inferences can be drawn from our analysis: Firstly, FDI inflows exert a positive impact on economic growth in the presence of a highly skilled labour. But FDI by itself does not induce efficiency gains. Secondly, by merely increasing FDI inflows a country cannot improve its efficiency. Put differently, a given nation cannot absorb the advanced technology accompanying FDI unless there is well-trained skilled labour force.

Thirdly, corruption has a negative impact on economic growth. Finally, trade openness increases economic growth by means of efficiency gains. From the perspective of policy makers in developing countries, what are the chief implications of our findings? In a nutshell, poor nations can increase their economic growth rate by taking steps to (a) curb the level of corruption; (b) improve the level of education; and then (c) strongly encourage direct foreign investment.

ENDNOTES

* The authors would like to thank an anonymous referee for helpful comments to an earlier draft.
** The FRONTIER software uses a three-step estimation method to obtain the final maximum-likelihood estimates. First, estimates of the α-parameters are obtained by OLS. A two-phase grid search for γ is conducted in the second step with α-estimates set to the OLS values and other parameters set to zero. The third step involves an iterative procedure, using the Davidson-Fletcher-Powell Quasi-Newton method to obtain final maximum-likelihood estimates with the values selected in the grid search as starting values.

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