Article

Stochastic Frontier Analysis of 40 Countries Using Panel Data: Measuring Technical Efficiency and Productivity Growth*

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Abstract

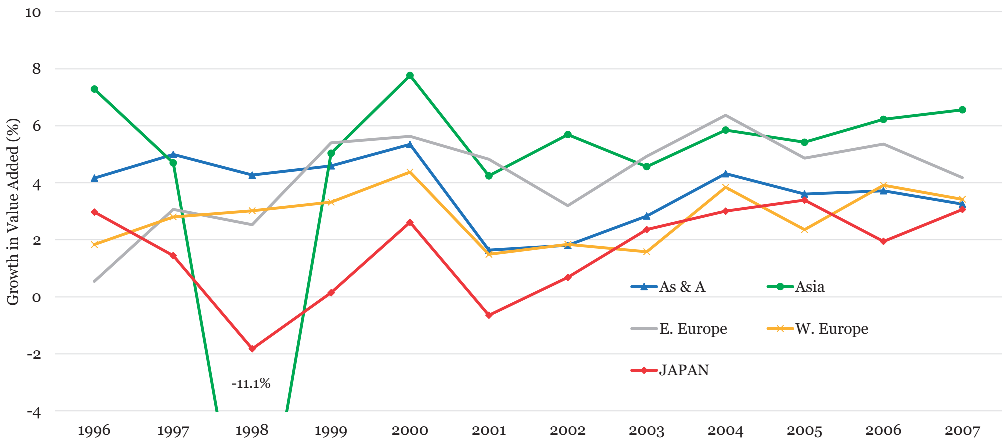
This study builds and estimates stochastic frontier analysis (SFA) models to obtain technical efficiencies for 40 countries over the course of 1995-2007 using the World Input-Output Database (WIOD). Moreover, based on these technical efficiency estimates, total factor productivity (TFP) growth is calculated. Estimating an SFA model that takes fixed effects and environmental factors into account, technical change and scale effect are also measured in addition to technical efficiencies. By including environmental factors, results reveal that economies with higher capital-labor ratios tend to be more efficient in production than otherwise. Using the three variables: technical change, scale effect change and technical efficiency change, TFP growth is measured and ranked among the 40 countries in this present study. Results show that productivity-wise, Asia actually does not fare so well. The reasoning behind this could be the existing gap within the region for TFP growth, between South Korea and China in particular. China's growth in technical efficiency marks the highest whereas its growth in TFP is the lowest in this study's sample. The highly negative growth in its scale effect contributes to this extreme result. Japan's scale effect growth has also been declining relative to its technical efficiency growth. However, with a relatively higher technical change and non-negative scale effect change, Japan's TFP growth has been higher than the averages of other regions in this study. Increasing growth in scale effects may have the most potential to help boost Japan's staggering growth in value added.

JEL: C33, F43, F69, O30, O57
Keywords: stochastic frontier analysis (SFA), fixed effects, total factor productivity (TFP), technical change, technical inefficiency, scale effect, production function

1. Introduction

How much value added an economy adds to their production in both goods and services deems important in an increasingly globalized world. Figure 1 shows the growth in value added over the years by region. Although Asia's value added dropped gravely in 1998 due to the Asian financial crisis, it has shown strong recovery and ranks the highest compared to other regions in this study. In contrast, Japan shows its stagnating growth in value added throughout the years. In fact, regions consisting mainly of developed economies such as the Americas and Australia as well as Western Europe also seem to be struggling with growth in value added.

Figure 1: Growth in Value Added Over the Years by Region (1995-2007)



Source: Author's calculations based on WIOD SEA.

Quantitatively capturing what makes an economy productive and efficient is very crucial when enacting policies aiming to increase the economic pie. This paper further extends Yane (2021) and measures stochastic frontier analysis (SFA) models to obtain technical efficiency estimates for 40 countries over the course of 1995-2007. Moreover, based on these technical efficiency estimates, total factor productivity (TFP) is calculated.

Estimating an SFA model that takes fixed effects and environmental factors into account, technical change and scale effect are also measured in addition to technical efficiencies. By including environmental factors, results reveal that economies with higher capital-labor ratios tend to be more efficient in production than otherwise.

Using the three variables: technical change, scale effect change and technical efficiency change, TFP growth is measured and ranked among the 40 countries in this present study. Results show that productivity-wise, Asia actually does not fare so well. The reasoning behind this could be the existing gap within the region for TFP growth, between South Korea and China in particular. China's growth in technical efficiency marks the highest whereas its growth in TFP is the lowest in this study's sample. The highly negative growth in its scale effect contributes to this extreme result.

Japan's scale effect growth has also been declining relative to its technical efficiency growth. However, with a relatively higher technical change and non-negative scale effect change, Japan's TFP growth has been higher than the averages of other regions in this study. Increasing growth in scale effects may have the most potential to help boost Japan's staggering growth in value added.

The remainder of this paper is organized as follows. Section 2 presents an overview of SFA and TFP decomposition. Section 3 describes the data used in this study. Section 4 explains the SFA estimation adopted in this current study. TFP calculation results are discussed in Section 5. Section 6 concludes.

2. SFA Models and Decomposition of TFP

This paper adopts the SFA approach developed in the literature on technical efficiency and productivity, more specifically in the statistical and parametric branches of this literature. The focus of SFA is to obtain an estimator for one of the components of TFP, which is the degree of technical efficiency. In addition, another component of TFP, technical change, is captured by a time trend and interactions of the regressors with time. The model used here is essentially that developed by Aigner et al. (1977) and by Meeusen and van den Broeck (1977). Their formulation was extended by Pitt and Lee (1981) and Schmidt and Sickles (1984) for the panel data case. Since these two last mentioned studies, a number of enhancements have been suggested, such as that of Battese and Coelli (1992), in which the technical inefficiency is modeled so as to be time variant. A thorough compilation of this literature can be found in Kumbhakar and Lovell (2000).

The general stochastic production frontier model is described by the equations below, where ***y*** is the vector for the quantities produced by the various countries, ***x*** is the vector for production factors used, and ***β*** is the vector for the parameters defining the production technology:

$$y = f(t, x, \beta) \cdot \exp(v) \cdot \exp(-u), \;\; u \geq 0. \tag{1}$$

The ***v*** and ***u*** terms (vectors) represent different error components. ***v*** refers to the random part of the error, while ***u*** is a downward deviation from the production frontier. Thus, $f(t,x,\beta) \cdot exp(v)$ represents the stochastic frontier of production and ***v*** has a symmetrical distribution to capture the random effects of measuring errors and exogenous shocks that cause the position of the deterministic nucleus of the frontier, $f(t,x,\beta)$, to vary from country to country. The level of technical efficiency (TE), that is, the ratio of observed output to potential output (given by the frontier) is captured by the component $exp(-u)$ (note that $TE_{it} = y_{it}/exp(x_{it}\beta) = exp(x_{it}\beta - u_{it})/\exp(x_{it}\beta) = \exp(-u_{it})$ and, therefore, 0<TE<1). For each country i and each time period t, we have:

$$y_{it} = f(t, x_{it}, \beta) \cdot exp(v_{it}) \cdot exp(-u_{it}); \;\; i = 1, \ldots, N, t = 1, \ldots, T. \tag{2}$$

It is assumed that $v \sim i.\ i.\ d\ N(0, \sigma_v^2)$ and $u \sim N^{+}(\mu, \sigma_u^2)$, that is, ***u*** has a truncated normal distribution (with a nonnull average $\boldsymbol{\mu}$), and the two error components are independent of each other and $\boldsymbol{x}$ is supposed exogenous, the model can be estimated by maximum-likelihood (ML) techniques and the restriction of a half-normal distribution (μ = 0) can be tested. Given these conditions, the traditional asymptotic properties of the ML estimators hold.

Assuming a translog production technology with two production factors, namely, capital (K) and labor (L), the model can be expressed in the following way:

$$\begin{aligned}\ln y_{it} = \beta_0 + \beta_t \cdot t + \beta_K \ln K_{it} + \beta_L \ln L_{it} + 0.5 \cdot \beta_{KK}(\ln K_{it})^2 + 0.5 \cdot \beta_{LL}(\ln L_{it})^2 \\ + \beta_{KL}(\ln K_{it}) \cdot (\ln L_{it}) + v_{it} - u_{it}.\end{aligned} \tag{3}$$

The output elasticities with respect to K and L can be obtained from equation (3), working out the derivatives. Due to the use of a translog technology, these elasticities are country and time specific. The technical change measure is also specific for each country and period of time and can be obtained by partial differentiation of the deterministic part of equation (3) with respect to time.

Bauer (1990) and Kumbhakar (2000) suggested a quite ingenious, yet simple, type of productivity decomposition which goes beyond the division of productivity changes into a catchup effect and a technical innovation effect. Such framework also accounts for scale effects and inefficient allocation of productive factors. To perform this decomposition, we must first estimate the model depicted by equation (3). Then, it is possible to “compose” the rate of TFP change from the results. In the expressions that follows, dots over variables indicate time derivatives, g_{TFP} denotes the rate of TFP growth, s_K and s_L are the shares of capital and labor in aggregate income, and ε_K and ε_L are output elasticities with respect to the factors of production.

The TFP measure can be computed from the observed data without any estimation. The resulting measure is called the Divisia index of TFP growth. It gives us information about output growth that is not explained by the growth of the factor inputs used in production. Thus, the components of productivity change can be identified from algebraic manipulations from the deterministic part of the production frontier depicted in equation (2) combined with the usual expression for the TFP growth Divisia index:

$$g_{TFP} = \frac{\dot{y}}{y} - s_K \frac{\dot{K}}{K} - s_L \frac{\dot{L}}{L} \quad . \tag{4}$$

From the deterministic part of equation (2), we have

$$\frac{\dot{y}}{y} = \frac{\partial \ln f(t, K, L, \beta)}{\partial t} + \varepsilon_K \frac{\dot{K}}{K} - \varepsilon_L \frac{\dot{L}}{L} - \frac{\partial u}{\partial t} \quad . \tag{5}$$

In the expressions that follow, RTS denotes returns to scale with $RTS = \varepsilon_K + \varepsilon_L$, g_K is the growth rate of capital ($\dot{K}/K$) and g_L is the growth rate of labor ($\dot{L}/L$). $\lambda_K = \varepsilon_K/RTS$ and $\lambda_L = \varepsilon_L/RTS$ are defined as normalized shares of capital and labor in income. Combining equations (4) and (5), we have:

$$g_{TFP} = TC - \dot{u} + (RTS - 1) \cdot [\lambda_K \cdot g_K + \lambda_L \cdot g_L]$$
$$+ [(\lambda_K - s_K) \cdot g_K + (\lambda_L - s_L) \cdot g_L]. \tag{6}$$

That is, TFP growth can be split into four elements:
(i) technical change, measured by $TC = \partial \ln f(t, K, L, \beta) / \partial t$;
(ii) change in technical efficiency, denoted by $-\dot{u}$;
(iii) change in scale effects, given by $(RTS\text{-}1) \cdot [\lambda_K \cdot g_K + \lambda_L \cdot g_L]$;
(iv) change in allocative efficiency, measured by $[(\lambda_K\text{-}s_K) \cdot g_K + (\lambda_L\text{-}s_L) \cdot g_L]$[1].

We can now study the impact of each of the components of TFP. If the technology is immutable, it does not contribute to productivity gains. The same happens with technical inefficiency. If it does not vary in time, it also does not have any impact on the rate of change of productivity.

The contribution of economies of scale depends both on technology as well as on factor accumulation. The presence of constant returns to scale (RTS = 1) cancels out the third component on the right of equation (6). In the case of increasing returns to scale (RTS > 1) and an increase in the number of productive factors, we have a higher rate of productivity growth. If the amounts of production factors diminish, then we would have a reduction in the rate of productivity growth. An inverse analogous reasoning can be made for decreasing returns and reduction (increase) in the number of productive factors.

3. Data

This study uses data from the Socio-Economic Accounts (SEAs) from the World Input-Output Database (WIOD)[2], which was released for the general public in April 2012, and later updated in 2016. The international supply and use table covers annual time-series data from 1995 to 2014 for 40 countries. Table 1 lists the country coverage.

Table 1: Country Coverage by Region

Americas and Australia		Eastern Europe		Western Europe	
Australia	AUS	Austria	AUT	Belgium	BEL
Brazil	BRA	Bulgaria	BGR	Germany	DEU
Canada	CAN	Cyprus	CYP	Denmark	DNK
Mexico	MEX	Czech Republic	CZE	Finland	FIN
United States	USA	Estonia	EST	France	FRA
Asia		Greece	GRC	United Kingdom	GBR
China	CHN	Hungary	HUN	Ireland	IRL
Indonesia	IDN	Lithuania	LTU	Italy	ITA
India	IND	Latvia	LVA	Luxembourg	LUX
Japan	JPN	Poland	POL	Malta	MLT
South Korea	KOR	Romania	ROU	Netherlands	NLD
Taiwan	TWN	Russia	RUS	Spain	ESP
		Slovak Republic	SVK	Portugal	PRT
		Slovenia	SVN	Sweden	SWE
		Turkey	TUR		

The SEAs contain annual data from 1995 to 2009 on industry output and value added, capital stock and investment, and wages and employment.[3] The variables used in this study are gross value added at current basic prices, nominal gross fixed capital formation, and total hours worked by persons engaged. Unfortunately, data on nominal gross capital formation is available only until 2007, so observations for years 2008 and 2009 are dropped from this study. All values are adjusted to real values using 1995 prices.

Thus, the real sectoral output (value-added output) is the dependent variable and gross fixed capital formation and labor hours are the independent variables or inputs in this study. Following Coelli et al. (2005), logarithmic mean-scaled quantities are used.[4] In other words, all variables are mean-scaled, and converted into logarithm values. The descriptive statistics are shown in Table 2.

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
lmY	520	−4.692	3.2457	−10.95	2.9026
lmK	520	−4.697	3.2386	−11.83	2.9377
lmL	520	−1.826	1.9294	−5.957	2.7622
mYear	520	0	3.7453	−6	6

4. Estimation of Technical Efficiency

4.1 Z Variables

This paper is concerned with specification and estimation of technical efficiency as well as technical change in order to measure TFP in Section 5. Here we argue that technical efficiency is likely to be governed by some exogenous variables. Therefore, it is important to account for environmental factors and other characteristics (Z variables) that can have an impact on technical efficiency.

In the stochastic frontier model proposed by Battese and Coelli (1995), the efficiency level may be affected by these additional explanatory variables. That is, the inefficiency term $\boldsymbol{u}$ follows a positive truncated normal distribution with constant scale parameter σ_u^2 and a location parameter $\boldsymbol{\mu}$ that depends on the additional variables:

$$u \sim N^+(\mu, \sigma_u^2) \quad \text{with} \quad \mu = \delta z \ , \tag{7}$$

where δ is an additional parameter (vector) to be estimated. These δs are called "efficiency effects frontiers." The Z variables in this present empirical model are capital-labor ratio and regional factor dummies:

$$u_{it} \ \sim \ N^+\left[\mu_{it} = \delta_1 \left(\frac{K}{L}\right)_{it} + \delta_2 region_i, \sigma_u^2 \right]. \tag{8}$$

These shift variables help us estimate the contribution of the Z variables to technical efficiency.

4.2 Fixed Effects

The frontier production technology can be estimated by many different specifications of the stochastic frontier model. This study adopts a model that incorporates individual fixed effects in the production technology frontier by including country-specific fixed effects. The estimation results are shown in Table 3.

Table 3: SFA Estimation Results

	Fixed Effects Model
(Intercept)	−3.068***
	(0.089)
lmK	0.246***
	(0.026)
lmL	0.049
	(0.050)
I(0.5 * lmK^2)	−0.010*
	(0.004)
I(0.5 * lmL^2)	−0.097***
	(0.018)
I(lmK * lmL)	0.021***
	(0.006)
mYear	0.017***
	(0.001)
Z_KL	−0.023***
	(0.002)
Z_factor(region2)As & A	−0.076*
	(0.035)
Z_factor(region2)Asia	0.956***
	(0.054)
Z_factor(region2)E. Europe	0.266***
	(0.014)
Z_factor(region2)W. Europe	−0.009
	(0.013)
sigmaSq	0.005***
	(0.000)
gamma	1.000***
	(0.000)
Fixed Effects	Yes
Log Likelihood	843.364
n	520

Notes: Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A likelihood ratio test against the corresponding OLS model indicates that the fit of this SFA model is significantly better than the fit of the corresponding OLS model. The estimation algorithm re-parametrizes the variance parameter of the noise term σ_v^2 and the scale parameter of the efficiency term σ_u^2 and instead estimates the parameters $\sigma^2=\sigma_v^2+\sigma_u^2$ and $\gamma=\sigma_u^2/\sigma^2$. The parameter γ lies between zero and one and indicates the importance of the inefficiency term. If γ is zero, the inefficiency term $\boldsymbol{u}$ is irrelevant and the results should be equal to OLS estimation results. In contrast, if γ is one, the noise term $\boldsymbol{v}$ is irrelevant and all deviations from the frontier are explained by technical inefficiency. The results show that the estimate of γ is one.

Further, the estimation results reveal that an annual rate of technical change is approximately 1.7%, statistically significant at the 0.1% level. The coefficient of capital-labor ratio is negative and significantly significant at the 0.1% level. This means that users of higher capital-labor ratio have a significantly smaller inefficiency term $\boldsymbol{u}$. In other words, they are significantly more efficient.

4.3 Alternative Estimations

In order to reach the specification that better fits our model, various specifications have been tested in this study.[5)] First of all, the production technology frontier could be a Cobb-Douglas or Translog functional form. Therefore, likelihood ratio tests need to be conducted to determine which specification is superior to the other. For all models, the Cobb-Douglas functional form was rejected in favor of the Translog specification.

Another major specification contrast is whether individual efficiencies are time-invariant or time-variant. Time-variant individual efficiencies mean that each country has an individual efficiency and the inefficiency terms $\boldsymbol{u_{it}}$ of all countries can fluctuate over time as indicated by an additional coefficient $\boldsymbol{\eta}$. For more details on this model specification, see Battese and Coelli (1992). In this study, the t-test for the coefficient $\boldsymbol{\eta}$ and a likelihood ratio test indicate that the effect of time on the efficiencies is not statistically significant, i.e., the efficiencies do not change over time.

Furthermore, a model with Translog production frontier with non-constant and non-neutral technical change was estimated, however, failed to converge. Therefore, the model in this present study is that of Translog production frontier with constant and neutral technical change.

5. Measuring TFP

As explained in Section 2, the three measures that affect a country's TFP is:

(i) the current state of technology, which might change due to technical change (TC);
(ii) technical efficiency (TE), which might change if the country's distance to the current frontier changes; and
(iii) scale effect (SE), which might change is an economy's size relative to the optimal economy size changes.

Hence, change of an economy's TFP (ΔTFP) can be decomposed into technical changes (ΔTC), technical efficiency changes (ΔTE) and scale effect changes (ΔSE):

$$\Delta TFP \approx \Delta TC + \Delta TE + \Delta SE \quad . \tag{9}$$

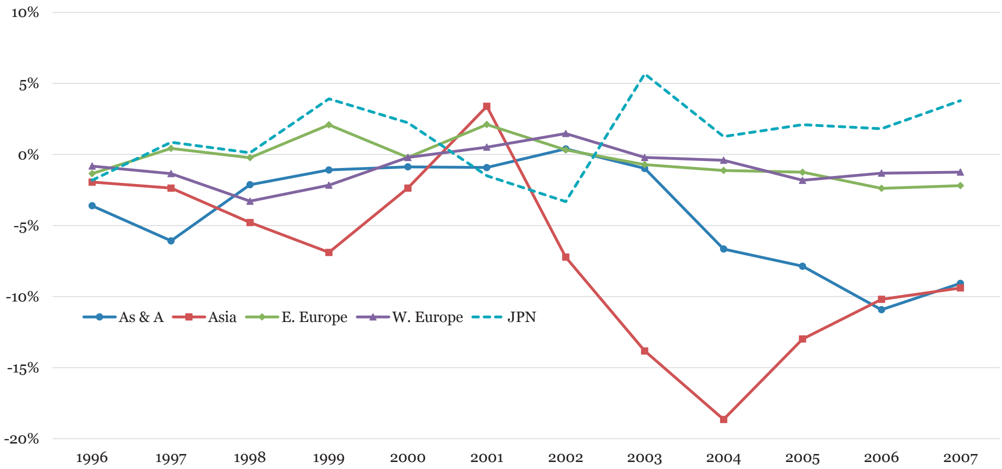
First, the ranking of the average annual TFP change for all 40 countries is listed in Table 4. South Korea ranks top, followed by Slovakia, Taiwan, Indonesia and Estonia. China ranked the lowest, followed by India, Brazil, USA and Bulgaria, with negative productivity growths. All countries' changes in scale effects are negative. What is striking is that China has the highest growth in technical efficiency. However, with the most negative change in scale effect, China ranked the lowest in this study for TFP growth.

Table 4: Average Annual Percentage Change: 1995-2007

		ΔTFP	ΔSE	ΔTE
1	KOR	0.035	−0.012	0.030
2	SVK	0.024	−0.017	0.024
3	TWN	0.023	−0.009	0.015
4	IDN	0.019	−0.008	0.010
5	EST	0.018	−0.028	0.028
6	SWE	0.013	−0.016	0.012
7	JPN	0.013	−0.002	−0.002
8	MLT	0.012	−0.007	0.001
9	CYP	0.011	−0.013	0.007
10	CZE	0.010	−0.015	0.008
11	SVN	0.009	−0.018	0.010
12	FIN	0.007	−0.019	0.009
13	LVA	0.004	−0.031	0.018
14	HUN	0.004	−0.022	0.008
15	AUT	0.003	−0.013	−0.001
16	LTU	0.001	−0.032	0.016
17	BEL	0.000	−0.012	−0.005
18	LUX	−0.001	−0.019	0.001
19	CAN	−0.003	−0.024	0.004
20	DEU	−0.004	−0.016	−0.006
21	FRA	−0.005	−0.020	−0.002
22	GRC	−0.009	−0.027	0.001
23	NLD	−0.010	−0.023	−0.004
24	POL	−0.011	−0.038	0.010
25	TUR	−0.012	−0.051	0.021
26	PRT	−0.013	−0.023	−0.008
27	MEX	−0.016	−0.041	0.008
28	RUS	−0.016	−0.044	0.010
29	DNK	−0.021	−0.022	−0.016
30	ITA	−0.022	−0.025	−0.015
31	IRL	−0.023	−0.045	0.005
32	ESP	−0.028	−0.042	−0.003
33	GBR	−0.031	−0.043	−0.005
34	ROU	−0.042	−0.049	−0.010
35	AUS	−0.042	−0.048	−0.011
36	BGR	−0.049	−0.046	−0.021
37	USA	−0.067	−0.082	−0.002
38	BRA	−0.080	−0.088	−0.009
39	IND	−0.183	−0.226	0.026
40	CHN	−0.258	−0.325	0.050

Next, the visualized calculations of TFP growth over time by region are shown in Figure 2. At the start of our sample period, all economies saw negative TFP growth. Many regions peaked in 2001 and 2002. By 2007, all regions marked negative TFP growth again. Focusing on Japan, however, reveals that Japan has been experiencing relatively positive TFP growth.

Figure 2: TFP Growth by Region

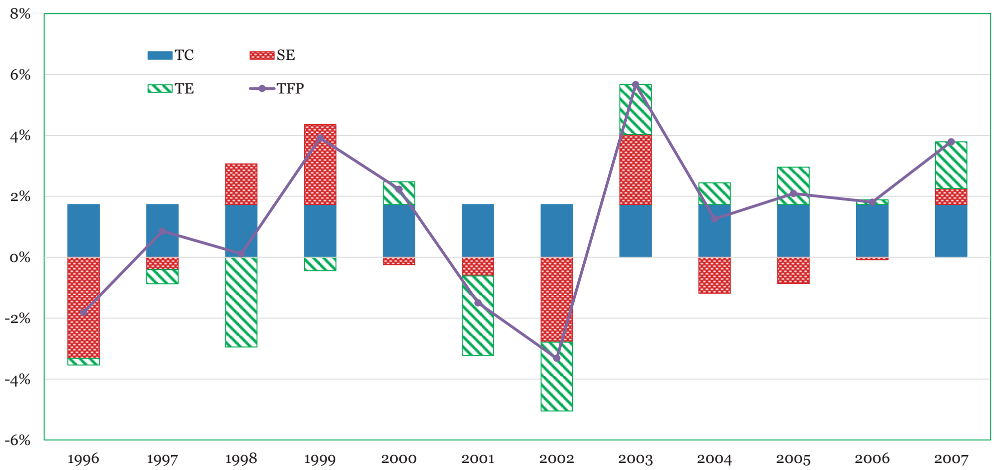


Source: Author's calculations.

5.1 Decomposing Japan's TFP Growth

Finally, Figure 3 depicts the decomposition TFP growth over the years of Japan in particular. Since 2003, Japan's scale effect growth has been declining relative to technical efficiency growth. In 2007, change in technical change (1.7%) contributed the most to its positive growth in TFP, followed by growth in technical efficiency (1.5%). Growth in scale effect was merely 0.5%.

Figure 3: Decomposition of Japan's TFP Growth



Source: Author's calculations.

6. Conclusion

This study builds and estimates SFA models to obtain technical efficiencies for 40 countries over the course of 1995-2007 using WIOD's SEAs. Moreover, based on these technical efficiency estimates, TFP growth is calculated.

Estimating an SFA model that takes fixed effects and environmental factors into account, technical change and scale effect are also calculated in addition to technical efficiencies. By including environmental factors, results reveal that economies with higher capital-labor ratios tend to be more efficient in production than otherwise.

Using the three variables: technical change, scale effect change and technical efficiency change, TFP growth is measured and ranked among the 40 countries in this present study. Results show that productivity-wise, Asia actually does not fare so well. The reasoning behind this could be the existing gap within the region for TFP growth, between South Korea and China in particular. China's growth in technical efficiency marks the highest whereas its growth in TFP is the lowest in this study's sample. The highly negative growth in its scale effect contributes to this extreme result.

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Policy implications for this study are mainly a note of precaution: it is important to accurately measure and capture TFP growth and its components, as well as distinguishing them. Only then will we be able to enact cost effective and efficient policies that accurately target the factors that need more support.

There is still much to do in this field of study. First, the method to measure TFP has been inconsistent depending on the study referenced. It is important to standardize the measurement of TFP growth and its decomposition in order to be able to compare across studies.

That being said, possible future research includes investigating further by dividing countries into groups based on income. This will be beneficial since there may be effects depending on different levels of income of an economy.

Furthermore, refining the measurement of technical change will be an important step to be able to make the decomposition of TFP growth more meaningful and informative. In addition, obtaining information on prices so efficiency can be decomposed into technical efficiency and allocative efficiency will be fruitful for further research as well.

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Notes

1) Since we do not have information on price in our dataset, this part regarding the price effects is omitted from this current analysis.
2) This database is available at http://www.wiod.org/home. The core of the database is a set of harmonized national supply and use tables, linked together with bilateral trade data in goods

and services. These two sets of data are then integrated into a world input-output table. See Timmer (2012) for the detailed framework and calculations.

3) Further details on the SEA database can be found in Erumban et al. (2012).

4) This study uses the mean-scaled input quantities to enable interpreting the first-order coefficients of the logarithmic input quantities as output elasticities at the sample mean.

5) The estimation results for alternative models can be obtained by email on request.

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パネルデータを用いた40ヵ国の確率的フロンティア分析 —技術効率性と生産性の計測—*

本論文では、World Input-Output Database（WIOD）をもとに、確率的フロンティア分析（SFA）モデルを用いて1995年から2007年までの40ヵ国の技術効率性を推計している。この技術効率性とさらに技術変化と規模の効果も推計することにより、全要素生産性（TFP）を計算する。固定効果を考慮したモデルの下で効率性効果モデルを用いることで環境変数zを考慮した結果、資本・労働比率が高い国のほうがより効率性が高くなることが分かった。TFPの成長率を計算した結果、地域でみるとアジアのTFPはさほど高くなく、アジア内で起こっているTFP成長率の格差が顕著に出ていることが分かった。主に韓国と中国との差が大きい。これは、中国の技術効率性の成長率は高い一方で、規模の効果の成長率がマイナスで大きいことに起因する。日本でも技術変化と技術効率性の成長率は比較的高く、その結果としてTFP成長率も高いものの、規模の効果の成長率は低いという結果が得られた。

JEL: C33, F43, F69, O30, O57
キーワード : 確率的フロンティア分析（SFA）、固定効果、全要素生産性（TFP）、技術変化、技術非効率性、規模の効果、生産関数

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