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## Abstract

Based on Cuesta (2000), this paper develops a stochastic frontier production model that allows for different groups of firms to have different patterns of technical efficiency over time. The authors apply the model to the Malaysian manufacturing sector to decompose total factor productivity growth into technical efficiency change and technical progress for different firm sizes—e.g., large and small—in seven industries during 2000–2004. The empirical results indicate that technical efficiency has worsened across all industries and firm sizes. In contrast, evidence of substantial technical progress was found in all industries. In fact, technical progress has been larger than technical efficiency deterioration in most industries and firm sizes, leading to total factor productivity growth. The analysis identifies the industries and firm sizes that lag the most in productivity, and thus have the greatest scope for policies that facilitate productivity growth.

# I. Introduction

Malaysia has been hit hard by the global financial and economic crisis, with its gross domestic product (GDP) growth slowing down sharply from an average of 6% in 2003–2007 to 4.6% in 2008, and an outright contraction of 3.1% is projected for 2009. A successful small open economy with exceptionally high levels of openness and integration into the world economy, Malaysia has borne the full brunt of the recession in the industrialized countries, in particular the United States (US). Although Malaysia's financial system was largely unscathed by the global financial crisis, the collapse of demand for imports in the US had a pronounced negative impact on Malaysia's exports and growth. Trade rather than financial contagion has been the primary mechanism that transmitted the crisis from the industrialized countries to Malaysia. The economy is expected to recover in 2010, with a projected GDP growth of 4.2%. Nevertheless, the global crisis has been a sobering experience for Malaysian policy makers, highlighting the vulnerability of their economy to the global business cycle.

Malaysia is thus currently grappling with the short-term task of achieving a secure recovery from the slowdown. However, well before the onset of the global crisis, the country was already confronted with a number of structural issues that threatened to slow down its long-run trend growth. For one, the investment rate, or the ratio of aggregate investment to GDP, has declined noticeably since the Asian financial crisis of 1997/1998. Partly as a result, GDP growth has also fallen since the Asian crisis. The balance of evidence suggests that the investment drop-off largely reflects a return to more optimal investment rates rather than suboptimal underinvestment. That is, it is more likely that Malaysia suffered from over-investment in the pre-crisis period than under-investment in the post-crisis period. At a broader level, as a high-flying second-generation newly industrialized economy (NIE), Malaysia has reached income levels where output growth would have to rely more on productivity growth and less on accumulation of capital and labor. While the high-savings, high-investment paradigm has propelled Malaysia's rapid growth in the past, future growth will have to be driven by higher total factor productivity.

Although from a macroeconomic perspective an economy can use capital and labor more efficiently to boost economic growth, productivity is more accurately a microeconomic concept that refers to how firms use their factors of production efficiently. Intuitively, total factor productivity is likely to differ for different groups of firms even within the same industry. For example, there are big structural differences between large multinational companies (MNCs) employing hundreds of employees and domestic small-and-medium enterprises (SMEs) with only a dozen employees. Even if it is assumed that both groups of firms have access to the same production technology—i.e., same potential production frontier—they may differ a lot with respect to their technical efficiency—i.e., the gap between potential output and actual output. There is also no obvious a priori reason why productivity growth should be identical for different groups of firms over time. For example, in response to the gradual introduction of restrictive labor market regulations, larger firms may suffer greater productivity losses than smaller firms that typically rely more on part-time workers. Or, a chronic shortage of skilled workers may have a bigger effect on the productivity of smaller firms since larger firms tend to be better at attracting and retaining skilled workers.

Productivity differences across different groups of firms can affect the productivity of an industry and the economy as a whole. In particular, in some countries there are concerns that the productivity of domestic SMEs may lag substantially behind the productivity of larger companies, many of which are foreign-owned. If the productivity of the SMEs is in fact significantly lower than that of other firms in the same industry, this can drag down the productivity of the industry. Replicated on an economy-wide basis, low SME productivity can drag down the productivity of the entire economy. These kinds of concerns are highly relevant for the Malaysian manufacturing sector where SMEs account for about 90% of total firms, 30.7% of output, and 31.6% of employment. In recognition of the significance of SMEs in the economy, the Government of Malaysia has recently started to look to SMEs as a potential source of growth. The rebalancing of growth toward domestic sources in the aftermath of the global crisis will give further impetus to this renewed interest in the SMEs, which are typically geared more toward domestic demand than larger firms. In the Ninth Malaysian Plan, for 2006–2010, the government has identified as a key strategic priority the development of competitive and resilient SMEs that are equipped with strong technical and innovation capacity as well as managerial and business skills. The plan recommended that SMEs in the manufacturing sector upgrade themselves into higher value added activities.

The difference in productivity and productivity growth across different groups of firms is of more than passing interest for policy makers. In particular, information about the productivity of each group of firms in an industry is more useful for policy makers than information about the productivity for the industry as a whole. For example, if an industry's poor productivity performance is due to the low and stagnant productivity of a particular group of firms—e.g., SMEs—enhancing the group's productivity will be the key to enhancing the industry's productivity. Different groups of firms are subject to different types of structural impediments and policy distortions that impede their productivity growth. SMEs typically face higher cost of and more difficult access to bank credit and other external financing than large firms. For example, although developing Asia did not suffer the severe credit crunch that gripped the US and the European Union during the global financial crisis, the flow of credit to SMEs was disrupted to some extent. Another example of a production constraint that is more binding for SMEs than larger firms is shortage of skilled workers. Although a chronic shortage of skilled and professional workers is an economy-wide problem that is hindering Malaysia's transition to higher value added, more knowledge-based industries and activities, SMEs are suffering disproportionately from the skills crunch.

The central objective of this paper is to empirically examine recent trends in total factor productivity and its two components—technical efficiency change and technical progress—for different groups of firms in several Malaysian manufacturing industries during 2000–2004. The firms are grouped by size, which, in turn, is determined by the number of employees. To pursue the objective, the authors develop a stochastic frontier production model that allows for group-specific temporal variation in technical inefficiency. The model is based on Cuesta (2000), which specifies a production model with firm-specific temporal variation in technical efficiency. The production model is useful when different groups of firms have different productivity trends. The model occupies an intermediate position between the model in Battese and Coelli (1992), which imposes a common temporal pattern in technical efficiency on all sample firms, and the model in Cuesta (2000), which assumes a unique temporal pattern for every firm. In addition to allowing for different temporal patterns of productivity growth across different groups of firms, the model also solves the "incidental parameters problem" in Cuesta's model, which results from the number of parameters increasing with sample size. To perform the empirical analysis, the authors apply the model to the Malaysian manufacturing sector.

This paper is organized as follows. Section 2 presents a stochastic frontier production model with group-specific temporal variation in technical inefficiency and gives the functional form of the estimation model. Section 3 discusses the data and reports the main empirical results, and Section 4 presents some concluding observations.

# II. A Model with Group-Specific Time-Varying Technical Inefficiency

A stochastic frontier production function is defined by

$$y_{it} = f\left(x_{it}, \beta\right) + v_{it} - u_{it}\ , \tag{1}$$

where $y_{it}$ is the output of the $i^{th}$ firm ($i$ = 1, .., N) in the $t^{th}$ time period ($t$ = 1, ..., T), $f(\cdot)$ is the production frontier, $x$ is an input vector, $\beta$ is a $k \times 1$ vector of parameters to be estimated. The efficiency error, $u$, represents production loss due to company-specific technical inefficiency; thus, it is always greater than or equal to zero ($u \geq 0$), and it is assumed to be independent of the statistical error, $v$, which is assumed to be independently and identically distributed as $N\left(0,\sigma_v^2\right)$. Note that technical inefficiency in (1) varies over time.

Cornwell, Schmidt, and Sickles (1990) introduced firm-specific time-varying technical inefficiency in the stochastic frontier approach by modeling technical inefficiency through the intercept of the production frontier in panel data model.[1] In this model, stochastic frontier can be rewritten as:

$$y_{it} = \alpha_{it} + f\left(x_{it}, \beta\right) + v_{it} \text{ where } \alpha_{it} = \theta_{i1} + \theta_{i2}t + \theta_{i3}t^2. \tag{2}$$

Thus, every firm has its own temporal pattern of technical inefficiency specified by a quadratic function. This model requires only three parameters to capture the time path of individual efficiency change and is suitable for a short cross-section and long time-series panel dataset.

Lee and Schmidt (1993) suggested an alternative time-varying generalization by specifying that technical inefficiency is time-varying and subject to an arbitrary temporal pattern of technical efficiency. In this model, the technical inefficiency effects are defined as the product of individual firm effect and arbitrary time effects:

$$\alpha_{it} = \theta_t \alpha_i, \tag{3}$$

where $\theta_t$ is a parameter to be estimated. Therefore, this model is flexible in estimating the temporal pattern of technical inefficiency because it does not restrict the time path to a specific functional form. Recently, Kim and Lee (2006) generalized the Lee and Schmidt (1993) model to allow for different temporal patterns across different groups of firms by relaxing the unrealistic restriction that the temporal pattern be the same for all firms. Kim and Lee (2006) modified technical inefficiency (3) as:

$$\alpha_{it} = \theta_{gt} \alpha_i, \tag{4}$$

where the subscript g represents the group. Kim and Lee (2006) showed that the model is very useful in identifying and estimating the unique temporal patterns of productivity changes in East Asian countries, which is distinct from those of the other group of countries.

The above models utilized panel data model in specifying the time-varying technical inefficiency captured by the intercept of fixed effects model. Panel data are also utilized in random effect models in which technical inefficiency is identified through an error component. In this approach, Kumbhakar (1990) proposed technical efficiency as a function of time as:

1 The panel data model in the stochastic frontier approach was developed by Pitt and Lee (1981), Schmidt and Sickles (1984), Kumbhakar (1987), and Battese and Coelli (1988).

$$u_{it} = u_i \eta_t = u_i [1 + \exp\left(bt + ct^2\right)^{-1}] , \tag{5}$$

where $b$ and $c$ are parameters to be estimated and $u_1$ one-sided frontier error with truncated normal distribution. Battese and Coelli (1992) adjusted the model to deal with unbalanced panel data by using a different function of time for each firm. This model specifies time-varying technical inefficiency as:

$$u_{it} = u_i \eta_t = u_i \exp\left(-\eta\left[t - T\right]\right), \tag{6}$$

where the distribution of $u_1$ is taken to be the non-negative truncation of the normal distribution, $N\left(\mu, \sigma_u^2\right)$, and $\eta$ is a parameter that represents the rate of change in technical inefficiency. A positive value ($\eta > 0$) is associated with an improvement in the technical efficiency of a firm over time. Under this specification, the temporal pattern of technical inefficiency is monotonous and common to all firms, as every firm shares the same $\eta$ that determines the time path of technical inefficiency.

Cuesta (2000) generalized (6) by allowing for firm-specific pattern of temporal change of the technical inefficiency term—i.e., every firm has its own unique time path of technical inefficiency. In this case, technical inefficiency can be rewritten as:

$$u_{it} = u_i \eta_{it} = u_i \exp\left(-\eta_i\left[t - T\right]\right), \tag{7}$$

where $\eta_i$ is firm-specific parameters that capture the different patterns of temporal variation among firms. Cuesta (2000) suggested this model as a stochastic frontier counterpart of the Cornwell, Schmidt, and Sickles (1990) and Lee and Schmidt (1993) model that proposed a time varying pattern of temporal change in the fixed-effect panel model. Thus, in principle, Cuesta's model is desirable because it can use the information that technical inefficiency is one-sided. At the same time, the model has the advantage of not imposing a common pattern of inefficiency change to all sample firms, unlike earlier models. However, the model has to assume independence between inputs and technical efficiency. Moreover, the model suffers from "incidental parameters problem" as the number of parameters increases with the sample size. This means that the maximum likelihood estimator could be inconsistent.[2]

To address the incidental parameters problem, the authors propose to modify Cuesta's model so that group-specific parameters for groups of firms are estimated instead of firm-specific parameters. Thus, the model modifies technical inefficiency (5) as:

$$u_{it} = u_i \eta_{gt} = u_i \exp\left(-\eta_g\left[t - T\right]\right), \tag{8}$$

2 See Cuesta (2000) for detailed discussion.

where the subscript g represents the group of firms (g=1,…,G). By modifying Cuesta (2000) in a straightforward manner, the log-likelihood function of the production frontier model (1) and (6) becomes:

$$
\begin{aligned}
\ln\left(\Omega^{*};y\right) = & -0.5\left(\sum T_i\right)\ln(2\pi) - 0.5\left(\sum T_i - 1\right)\ln\left(\sigma_v^2\right) \\
& -0.5\left(\sum \ln\left(\sigma_v^2\right) + \left[\exp\left\{-\eta_g\left(t-T\right)\right\}\right]^{'}\left[\exp\left\{-\eta_g\left(t-T\right)\right\}\right]\sigma_u^2\right) \\
& -N\ln\left[1-F\left(-\left(\mu/\sigma_u\right)\right)\right] + \sum \ln[1-F\left(-\left(\mu^{*}/\sigma^{*}\right)\right)] \\
& -0.5\sum[\left(Y_i - f\left(X_i;\beta\right)\right)^{'}\left(Y_i - f\left(X_i;\beta\right)/\sigma_v^2\right)] \\
& -0.5N\left(\mu/\sigma\right)^2 - 0.5\sum\left(\mu_i^{*}/\sigma_i^{*}\right)^2
\end{aligned}
\tag{9}
$$

where $\Omega^{*} = \left(\beta^{'},\sigma_v^2,\sigma_u^2,\mu,\eta_g\right)^{'}$, *f*(.) and *F*(.) represent the probability density function and cumulative probability density function, respectively and:

$$
\begin{aligned}
\mu_i^{*} &= \left\{\mu\sigma_v^2 - \exp\left[-\eta_g\left(t-T\right)\right]\varepsilon_i\sigma_u^2\right\} \Big/ \left\{\sigma_v^2 + \left\{\exp\left[-\eta_g\left(t-T\right)\right]\right\}^{'}\left\{\exp\left[-\eta_g\left(t-T\right)\right]\right\}\sigma_u^2\right\} \\
\sigma_i^{*} &= \sigma_u^2\sigma_v^2 \Big/ \left\{\sigma_v^2 + \left\{\exp\left[-\eta_g\left(t-T\right)\right]\right\}^{'}\left\{\exp\left[-\eta_g\left(t-T\right)\right]\right\}\sigma_u^2\right\}.
\end{aligned}
\tag{10}
$$

Maximum-likelihood estimates can be applied for the parameters of the stochastic frontier model, defined by (1) and (8), in which the variance parameters are expressed in terms of $\gamma = \sigma_u^2/\sigma_s^2$ and $\sigma_s^2 = \sigma_u^2 + \sigma_v^2$.

The model is a counterpart of Kim and Lee (2006) in the sense that it allows for different temporal patterns across different groups of firms. While the Cuesta (2000) model is useful for estimating firm-specific technical inefficiency, measuring such efficiency often becomes impossible if the sample size becomes large, to more than several hundred, due to lack of convergence. In this case, the model could provide a practical alternative if grouping firms makes economic sense. Now the model will be applied to Malaysian manufacturing industries to consider the impact of firm size on technical efficiency and productivity growth.

For estimation purposes, the production frontier can be specified in translog form as

$$
\begin{aligned}
\ln y_{it} = & \alpha_0 + \sum_j \alpha_j \ln x_{jit} + \alpha_T t + 0.5\sum_j \sum_l \beta_{jl}\ln x_{lit}\ln x_{jit} \\
& + 0.5\beta_{TT}t^2 + \sum_j \beta_{Tj} t \ln x_{jit} + v_{it} - u_{it} \quad ,j,\ l = L,\ K,
\end{aligned}
\tag{11}
$$

where $y_{it}$ is the observed output, *t* is the time variable and the *x* variables are inputs. Subscripts *j* and *l* indicate inputs (*j*, *l* = *L*, *K*), and the efficiency error, *u*, is specified by (8).

The technical efficiency level of firm $i$ at time $t$ ($TE_{it}$) is defined as the ratio of the actual output to the potential output as follows:

$$TE_{it} = \exp\left(-u_{it}\right). \tag{12}$$

The rate of technical progress (TP) is defined by the following:

$$TP = \partial \ln f\left(x,t\right)/\partial t = \alpha_T + \beta_{TT} t + \sum_j \beta_{Tj} \ln x_j \text{ , } j = L,\ K. \tag{13}$$

The growth rate of total factor productivity (TFP), which is the sum of technical progress (TP) and technical efficiency change (TEC), can be derived from equations (12) and (13) as follows:

$$TFP = TP - \left(du/dt\right). \tag{14}$$

TFP depends not only on technical progress but also changes in technical inefficiency. TP is positive (negative) if exogenous technical changes shift the production frontier outward (inward). If *du/dt* is negative (positive), then technical efficiency improves (deteriorates) over time, and *–du/dt* can be interpreted as the rate at which an inefficient producer inside the production frontier moves toward the production frontier, or, equivalently, reduces the gap between potential and actual output.

# III. Data and Empirical Results

In this section, the data and variables used in the empirical analysis are discussed, and main findings reported.

## A. Data and Variables

The data used in this paper are from a balanced panel consisting of annual time-series observations for 1,965 Malaysian manufacturing firms during 2000–2004, yielding a total of 9,825 observations. The sample covers all the companies within the seven main manufacturing industries listed in the *Annual Survey of Manufacturing Industries* published by the Department of Statistics, Malaysia. The survey provides a unique firm identification number for every participating firm and this number was used to transform the annual survey into a panel data set. Since the data set is a balanced panel, every firm in the sample has data for all five sampling years. Therefore, no firms have been dropped from the data set, even though the survey questionnaire does not identify mergers and acquisitions. The seven sample industries are electrical and electronics (E&E), textiles and apparel (textiles), transport equipment, chemical, rubber, machinery and food industries. According to the 2004 survey, these industries account for about 64.8% of total Malaysian manufacturing output, 55.6% of total employment, and 63.1% of total capital stock. Of the seven industries, the E&E industry is the largest in terms of output and capital, followed by the chemical, and transport equipment industries.

Capital stock (*K*) is defined as the actual quantity of tangible fixed assets, and the survey provides the market value of a firm's net fixed asset.[3] Labor input (*L*) was represented by the total number of workers engaged in production, including paid part-time and full-time employees and working proprietors and unpaid family members. Real value-added (*VA*) is measured as total revenue minus bought-in materials, and services represented output.

For purposes of estimation, value-added (capital stock) figures were deflated into 2000 constant prices by using the GDP deflator (the gross domestic fixed capital formation deflator) obtained from the *National Accounts* compiled by the Department of Statistics, Malaysia. Labor compensation was deflated by the consumer price index published by the Bank of Malaysia. All other nominal variables were also deflated into constant prices. Table 1 presents sample means and standard deviations.

**Table 1: Summary Statistics for Variables in the Stochastic Frontier Production Functions for Malaysian Manufacturing Industries**

| | E & E | Transport | Rubber | Textiles | Chemical | Food | Machinery |
|---|---|---|---|---|---|---|---|
| *log V* | 16.1214 | 14.7794 | 14.7866 | 13.7320 | 15.3303 | 13.6017 | 14.3577 |
| | (1.9602) | (2.0374) | (1.8262) | (1.9149) | (1.7417) | (1.6951) | (1.3774) |
| *log K* | 15.4320 | 13.7627 | 14.3742 | 12.3020 | 14.8797 | 12.9418 | 13.1910 |
| | (2.4801) | (2.7366) | (2.3023) | (3.2202) | (2.1999) | (2.1963) | (2.1373) |
| *log L* | 5.6164 | 4.4489 | 4.8092 | 4.0273 | 4.3323 | 3.7922 | 3.8186 |
| | (1.5303) | (1.4793) | (1.4536) | (1.6254) | (1.0870) | (1.0964) | (1.0055) |
| No. of Firms | 317 | 169 | 142 | 351 | 262 | 587 | 137 |

E & E = electrical and electronics industry.
Notes: Standard deviations are in parentheses.
Source: Authors' calculations.

To apply the group-specific technical inefficiency model, sample firms are classified into ultra-small-sized firms (5–15 employees), small-sized firms (16–50 employees), medium-sized firms (51–150 employees), large-sized firms (151–300 employees), and ultra-large-sized firms (300+ employees).

## B. Decomposition of Total Factor Productivity

Table 2 presents the maximum-likelihood estimates of the parameters in the translog stochastic frontier production function with group-specific technical inefficiency effects, as defined by equations (7) and (11). The estimates of $\gamma$ are statistically significant at

[3] Capital stock denotes an average book value of firm's fixed assets including transport equipment, computer, machinery and equipment, and furniture and fittings.

the 1% level for every industry. All of the coefficient estimates of η are negative except for the transport equipment industry, and those are statistically significant for all size groups in the rubber, textiles, and food industries, for three small- to large-size groups in the chemical and machinery industries, and for two larger-size groups in the E&E and transport industries. A significant γ, along with a negative and significant η, implies that technical inefficiency exists and increases over time.[4]

**Table 2: Maximum-Likelihood Estimates for Parameters of the Stochastic Frontier Model with Group-Specific Time-Varying Technical Inefficiency for Malaysian Manufacturing Industries**

| | E & E | Transport | Rubber | Textiles | Chemical | Food | Machinery |
|---|---|---|---|---|---|---|---|
| *Const.* | 12.328** | 12.250** | 12.247** | 9.547** | 12.480** | 9.809** | 9.933** |
| | (0.767) | (0.712) | (1.012) | (0.261) | (0.968) | (0.382) | (0.827) |
| *Log K* | –0.199 | –0.214 | –0.399** | –0.127** | –0.290* | –0.154** | –0.036 |
| | (0.117) | (0.112) | (0.112) | (0.022) | (0.145) | (0.041) | (0.074) |
| *Log L* | 0.597** | 0.916** | 0.734** | 1.139** | 1.267** | 0.960** | 1.304** |
| | (0.167) | (0.200) | (0.276) | (0.083) | (0.271) | (0.128) | (0.207) |
| *T* | 0.072 | –0.176 | 0.082 | 0.103* | 0.076 | 0.363** | –0.020 |
| | (0.083) | (0.094) | (0.162) | (0.047) | (0.101) | (0.065) | (0.106) |
| *log L* | –0.013 | –0.042 | –0.024 | –0.036** | –0.115** | –0.025* | –0.038 |
| **log K* | (0.019) | (0.023) | (0.024) | (0.008) | (0.022) | (0.011) | (0.022) |
| *t*log K* | –0.003 | –0.000 | 0.016 | –0.006 | –0.000 | –0.007 | –0.011 |
| | (0.006) | (0.006) | (0.014) | (0.003) | (0.006) | (0.005) | (0.008) |
| *t*log L* | –0.002 | 0.031 | –0.025 | –0.003 | 0.015 | –0.005 | 0.041* |
| | (0.011) | (0.016) | (0.024) | (0.007) | (0.018) | (0.012) | (0.020) |
| $(\log K)^2$ | 0.019** | 0.024** | 0.030** | 0.021** | 0.035** | 0.024** | 0.018** |
| | (0.006) | (0.006) | (0.005) | (0.001) | (0.006) | (0.001) | (0.002) |
| $(\log L)^2$ | 0.027 | 0.032 | 0.020 | 0.007 | 0.128** | 0.004 | –0.035 |
| | (0.018) | (0.026) | (0.031) | (0.011) | (0.028) | (0.020) | (0.029) |
| $t^2$ | 0.012* | 0.021* | –0.016 | 0.012* | 0.007 | –0.023** | 0.027** |
| | (0.006) | (0.008) | (0.014) | (0.005) | (0.008) | (0.006) | (0.008) |
| $\sigma_s^2$ | 0.496** | 0.683** | 1.386** | 0.625** | 1.096** | 0.962** | 0.526** |
| | (0.049) | (0.124) | (0.412) | (0.139) | (0.099) | (0.063) | (0.067) |
| $\gamma$ | 0.680** | 0.789** | 0.811** | 0.772** | 0.803** | 0.749** | 0.764** |
| | (0.021) | (0.019) | (0.054) | (0.048) | (0.011) | (0.011) | (0.022) |
| $\mu$ | 1.162** | 1.469** | 1.236* | 0.699* | 1.877** | 1.698** | 1.268** |
| | (0.093) | (0.197) | (0.532) | (0.296) | (0.131) | (0.100) | (0.111) |
| $\eta_{us}$ | –0.035 | 0.017 | –0.151** | –0.093** | –0.026 | –0.137** | –0.053 |
| | (0.035) | (0.025) | (0.051) | (0.022) | (0.024) | (0.017) | (0.037) |
| $\eta_s$ | –0.036 | 0.002 | –0.245** | –0.112** | –0.057** | –0.151** | –0.060* |
| | (0.028) | (0.020) | (0.049) | (0.023) | (0.019) | (0.014) | (0.023) |
| $\eta_m$ | –0.030 | –0.038 | –0.360** | –0.115** | –0.084** | –0.179** | –0.115** |
| | (0.024) | (0.021) | (0.049) | (0.025) | (0.018) | (0.017) | (0.031) |
| $\eta_l$ | –0.044* | –0.090* | –0.389** | –0.188** | –0.097** | –0.157** | –0.177** |
| | (0.021) | (0.037) | (0.073) | (0.032) | (0.023) | (0.030) | (0.053) |
| $\eta_{ul}$ | –0.078** | –0.132** | –0.329** | –0.101** | –0.049 | –0.149** | –0.680 |
| | (0.020) | (0.041) | (0.048) | (0.030) | (0.042) | (0.041) | (0.412) |
| *LLR* | –1163.342 | –620.498 | –667.415 | –1133.834 | –1225.825 | –2699.206 | –420.636 |

E & E = electrical and electronics industry.

Notes: Asymptotic standard errors are in parentheses. *(**) The coefficients are statistically significant at the 5(1)% level. Subscripts US, S, M, L, and UL, represent ultra-small firms (5–15 employees), small firms (16–50),medium firms (51–150), large firms (151-300), and ultra-large firms (300+), respectively.

Source: Authors' calculations.

[4] The estimates of η is insignificant for some firm size groups in some industries, implying technical efficiency might be time-invariant. However, η is mostly insignificantly negative, so the authors used the time-varying model.

Table 3 presents the test results for group-specific efficiency parameters of the stochastic frontier model. The null hypothesis of the existence of group-specific technical inefficiency is tested against the alternative hypothesis of the same temporal technical inefficiency pattern ($H_A \eta_{us} = \eta_s = \eta_m = \eta_l = \eta_{ul}$ ) for all firm sizes. The null hypotheses are tested using likelihood ratio tests. The likelihood-ratio test statistic is $\lambda = -2[L(H_0) - L(H_1)]$, where $L(H_0)$ and $L(H_1)$ are the values of the log-likelihood function under the specifications of the null and alternative hypotheses, $H_0$ and $H_A$, respectively. If the null hypothesis is true, then $\lambda$ has approximately a Chi-square distribution with degrees of freedom equal to the number of restrictions. The null hypothesis of group-specific technical inefficiency is supported in every industry, except the E&E and chemical industries. Thus, the group-specific technical inefficiency model is an appropriate specification for the Malaysian manufacturing sector, except the two industries.[5]

**Table 3: Hypotheses Test for Efficiency Parameters of the Stochastic Frontier Model with Group-Specific Time-Varying Technical Inefficiency for Malaysian Manufacturing Industries (Alternative Hypothesis,** $H_a$: $\eta_{us} = \eta_s = \eta_m = \eta_l = \eta_{ul}$)

| | E & E | Transport | Rubber | Textiles | Chemical | Food | Machinery |
|---|---|---|---|---|---|---|---|
| Test statistics | 5.833 | 14.429 | 10.681 | 10.880 | 0.137 | 13.820 | 10.081 |
| P-value | 0.211 | 0.006 | 0.030 | 0.027 | 0.997 | 0.007 | 0.039 |
| Decision | Accept $H_a$ | Reject $H_a$ | Reject $H_a$ | Reject $H_a$ | Accept $H_a$ | Reject $H_a$ | Reject $H_a$ |

E & E = electrical and electronics industry.

Notes: Test statistics are log-likelihood ratio test statistics ($\lambda$), and $\eta_{us}, \eta_s, \eta_m, \eta_l, \eta_{ul}$ represents group $\eta$ of ultra-small sized firms (5-15), small sized firms (16-50), medium sized firms (51–150), large sized firms (151-300), and ultra-large sized firms (300+), respectively.

Source: Authors' calculations.

Table 4 represents average TEC by industry and firm size groups. TEC is estimated as log-difference of TE ($TEC_t = \ln TE_t - \ln TE_{t-1} \cong (TE_t - TE_{t-i})/TE_{t-1}$).[6] Average TEC was –0.119 for the entire sample period, implying an 11.9% decrease in output due to technical inefficiency. Average TEC was –0.097 in 2001–2002, and –0.140 in 2003–2004.

[5] The authors used the group-specific technical inefficiency model for every industry in order to estimate group-specific TEC and TFP estimates. However, coefficient estimates of Battese and Coelli (1992) in which $\eta$ is the same for all firm size groups are available from the authors upon request.

[6] Notice that $lnTE_t - lnTE_{t-1} = -(u_t - u_{t-1}) = -du/dt$.

**Table 4: Average Annual Rates of Technical Efficiency Change (TEC) of Malaysian Manufacturing Industries**

| Size | Period | E & E | Transport | Rubber | Textiles | Chemical | Food | Machinery | Total |
|---|---|---|---|---|---|---|---|---|---|
| US | 2001–02 | –0.0458 | 0.0327 | –0.1524 | –0.0655 | –0.0547 | –0.1673 | –0.0658 | –0.0741 |
| | 2003–04 | –0.0491 | 0.0316 | –0.2041 | –0.0785 | –0.0576 | –0.2186 | –0.0732 | –0.0928 |
| | 2001–04 | –0.0475 | 0.0322 | –0.1783 | –0.0720 | –0.0562 | –0.1930 | –0.0695 | –0.0835 |
| S | 2001–02 | –0.0400 | 0.0041 | –0.1609 | –0.0678 | –0.1069 | –0.1773 | –0.0689 | –0.0882 |
| | 2003–04 | –0.0430 | 0.0040 | –0.2576 | –0.0842 | –0.1198 | –0.2379 | –0.0776 | –0.1166 |
| | 2001–04 | –0.0415 | 0.0041 | –0.2093 | –0.0760 | –0.1134 | –0.2076 | –0.0733 | –0.1024 |
| M | 2001–02 | –0.0330 | –0.0528 | –0.1795 | –0.0776 | –0.1254 | –0.1760 | –0.1088 | –0.1076 |
| | 2003–04 | –0.0350 | –0.0570 | –0.3586 | –0.0971 | –0.1479 | –0.2493 | –0.1365 | –0.1545 |
| | 2001–04 | –0.0340 | –0.0549 | –0.2691 | –0.0874 | –0.1367 | –0.2127 | –0.1227 | –0.1310 |
| L | 2001–02 | –0.0493 | –0.0878 | –0.1725 | –0.0954 | –0.1373 | –0.1481 | –0.1219 | –0.1160 |
| | 2003–04 | –0.0537 | –0.1049 | –0.3631 | –0.1373 | –0.1664 | –0.2008 | –0.1724 | –0.1712 |
| | 2001–04 | –0.0515 | –0.0964 | –0.2678 | –0.1164 | –0.1519 | –0.1745 | –0.1472 | –0.1436 |
| UL | 2001–02 | –0.0696 | –0.1237 | –0.1809 | –0.0567 | –0.0595 | –0.1460 | –0.0720 | –0.1012 |
| | 2003–04 | –0.0810 | –0.1602 | –0.3399 | –0.0689 | –0.0655 | –0.1948 | –0.2685 | –0.1684 |
| | 2001–04 | –0.0753 | –0.1420 | –0.2604 | –0.0628 | –0.0625 | –0.1704 | –0.1703 | –0.1348 |
| Total | 2001–02 | –0.0475 | –0.0455 | –0.1692 | –0.0726 | –0.0968 | –0.1629 | –0.0875 | –0.0974 |
| | 2003–04 | –0.0524 | –0.0573 | –0.3047 | –0.0932 | –0.1114 | –0.2203 | –0.1456 | –0.1407 |
| | 2001–04 | –0.0500 | –0.0514 | –0.2370 | –0.0829 | –0.1041 | –0.1916 | –0.1166 | –0.1191 |

E & E = electrical and electronics industry.

Notes: Firm size group of US, S, M, L, and UL represent ultra-small sized firms (5—15 employees), small-sized firms (16—50), medium-sized firms (51—150), large-sized firms (151—300), and ultra-large-sized firms (300+), respectively.

Source: Authors' calculations.

TEC is negative, which implies that TE is deteriorating for every industry and every firm size, except the smallest two firm sizes in the transport industry. The deterioration of TE is fastest in the rubber industry at –0.237, followed by the food, machinery, and chemical industries. The deterioration of TE is slowest in the E&E industry at –0.050, followed by the transport and textiles industries. TEC varies across firm sizes within each industry. The deterioration of TE is slowest in the ultra-small firm-size group at –0.083 and the fastest in large firm-size group at –0.143.[7] The other groups have estimates that range from –0.134 to –0.102. The TEC difference between each firm-size group is especially conspicuous in the transport industry. The deterioration of TE has gathered speed from the sub-period of 2001–2002 to the sub-period of 2003–2004. The distribution of TEC among the firm-size groups within industry is more or less stable between the two sub-periods, as is the overall TEC rankings of the industries. The one noticeable exception is the decline of TEC in ultra-large firms in the machinery industry.

Overall, the TEC estimates indicate that technical inefficiency is a big obstacle to higher productivity in the Malaysian manufacturing sector. Technical efficiency has worsened for almost every firm-size group in every industry. This implies that firms are moving further away from, rather than closer toward the production frontier. According to the results, the TE of larger firms deteriorated more sharply than the TE of smaller firms. This suggests

[7] However, TE increases as firm size increases, since TE is highest for the largest firm size at 0.458 and lowest for the smallest firm size at 0.288. Estimates of TE are available from the authors upon request.

that the TE slowdown in the Malaysian manufacturing sector during the sample period was driven by the growing inefficiencies of larger firms. One possible explanation is that larger firms were less flexible and adaptable than smaller firms to the economic downturn of 2003–2004. For example, smaller firms typically rely more on part-time and informal workers, and this gives them more leeway to adjust their workforce during recessions. Specific groups of firms that lag in terms of TE include ultra-large firms in the transport, E&E, and rubber industries and large firms in the textile and chemical industries.

Table 5 reports the average TP for each firm size in each industry. TP is estimated for every observation according to equation (13). Average TP was 0.124 for the entire sample period, implying a 12.4% gain in output due to technical progress. Average TP was 0.112 in 2001–2002 and 0.137 in 2003–2004. TP is positive for every industry for the sample period as a whole and both sub-periods. Therefore, in contrast to technical efficiency change, which was a source of lower productivity and output growth, TP is a source of higher productivity and growth.

**Table 5: Average Annual Rates of Technical Progress (TP) of Malaysian Manufacturing Industries**

| Size | Period | E & E | Transport | Rubber | Textiles | Chemical | Food | Machinery | Total |
|---|---|---|---|---|---|---|---|---|---|
| US | 2001–02 | 0.0953 | –0.0050 | 0.1289 | 0.1013 | 0.1489 | 0.1522 | 0.1014 | 0.1033 |
| | 2003–04 | 0.1450 | 0.0936 | 0.0563 | 0.1516 | 0.1819 | 0.0612 | 0.2170 | 0.1295 |
| | 2001–04 | 0.1202 | 0.0443 | 0.0926 | 0.1265 | 0.1654 | 0.1067 | 0.1592 | 0.1164 |
| S | 2001–02 | 0.0861 | 0.0437 | 0.1188 | 0.0812 | 0.1705 | 0.1364 | 0.1173 | 0.1077 |
| | 2003–04 | 0.1354 | 0.1355 | 0.0425 | 0.1315 | 0.2023 | 0.0462 | 0.2290 | 0.1318 |
| | 2001–04 | 0.1108 | 0.0896 | 0.0807 | 0.1064 | 0.1864 | 0.0913 | 0.1732 | 0.1197 |
| M | 2001–02 | 0.0778 | 0.0722 | 0.1239 | 0.0654 | 0.1823 | 0.1176 | 0.1328 | 0.1103 |
| | 2003–04 | 0.1275 | 0.1637 | 0.0461 | 0.1163 | 0.2148 | 0.0266 | 0.2438 | 0.1341 |
| | 2001–04 | 0.1027 | 0.1180 | 0.0850 | 0.0909 | 0.1986 | 0.0721 | 0.1883 | 0.1222 |
| L | 2001–02 | 0.0720 | 0.1029 | 0.1226 | 0.0553 | 0.1953 | 0.1072 | 0.1603 | 0.1165 |
| | 2003–04 | 0.1224 | 0.1938 | 0.0505 | 0.1068 | 0.2268 | 0.0173 | 0.2713 | 0.1413 |
| | 2001–04 | 0.0972 | 0.1484 | 0.0866 | 0.0811 | 0.2111 | 0.0623 | 0.2158 | 0.1289 |
| UL | 2001–02 | 0.0633 | 0.1367 | 0.1164 | 0.0438 | 0.2072 | 0.0936 | 0.2070 | 0.1240 |
| | 2003–04 | 0.1141 | 0.2238 | 0.0409 | 0.0961 | 0.2367 | 0.0033 | 0.3271 | 0.1489 |
| | 2001–04 | 0.0887 | 0.1803 | 0.0787 | 0.0700 | 0.2220 | 0.0485 | 0.2671 | 0.1364 |
| Total | 2001–02 | 0.0789 | 0.0701 | 0.1221 | 0.0694 | 0.1808 | 0.1214 | 0.1438 | 0.1124 |
| | 2003–04 | 0.1289 | 0.1621 | 0.0473 | 0.1205 | 0.2125 | 0.0309 | 0.2576 | 0.1371 |
| | 2001–04 | 0.1039 | 0.1161 | 0.0847 | 0.0949 | 0.1967 | 0.0762 | 0.2007 | 0.1247 |

E & E = electrical and electronics industry, L = large-sized firm, M = medium-sized firm, S = small-sized firm, UL = ultra-large-sized firm, US = ultra-small-sized firm.

Note: Refer to notes to Table 4.

Source: Authors' calculations.

TP was the slowest in the food industry at 0.076 and the fastest in the machinery industry at 0.200. Estimated TP of the other industries ranged from 0.084 to 0.196. For the total sample, TP increased from 0.112 in the first sub-period of 2001–2002 to 0.137 in the second sub-period of 2003–2004. However, TP dropped greatly in the rubber and food industries between these two periods. TP was led by the chemical industry in the first sub-period, and by the machinery industry in the second sub-period. In terms of TP by firm size, TP is the fastest in the largest firm-size group at 0.136 and the slowest in the smallest firm–size group at 0.116. TP for the other size groups ranges from 0.119 to 0.128. However, TP varies widely across the firm sizes within each industry—TP increases as firm size increases in the chemical, machinery, and transport industries, but decreases in the other industries. This implies that the shifting-up of the production frontier of the manufacturing sector is not always led by larger firms, contrary to the popular perception that TP is driven by larger firms that typically invest more in research and development activities.

In fact, in the Malaysian manufacturing sector, TP was the fastest among the smallest firms in the food, rubber, textiles, and E&E industries. Other than the E&E industry, these industries are mature and declining, and unlikely to have much room for major breakthrough in production technology. Instead, TP is often brought about by incremental improvements in production techniques or adoption of existing technology by smaller firms. Furthermore, larger firms are slow to invest in mature and declining industries. In the E&E industry, both large and small firms have avenues for TP. In this fast-growing industry, technological innovation is often led by small venture firms and labs, but large foreign multinational companies that have operations in Malaysia tend to be early adopters of new technologies.

Table 6 reports the average total factor productivity growth (TFPG) for each firm size and industry. TFPG is the sum of TP and TEC as in equation (14). For the entire sample period, average TFPG was 0.005, implying a 0.5% increase in output due to total factor productivity growth. Average TFPG was 0.015 in 2001–2002, and –0.003 in 2003–2004. Therefore, TFP improved during the sample period as a whole and the first sub-period but deteriorated during the second sub-period.

**Table 6: Average Annual Rates of Total Factor Productivity Growth (TFPG) of Malaysian Manufacturing Industries**

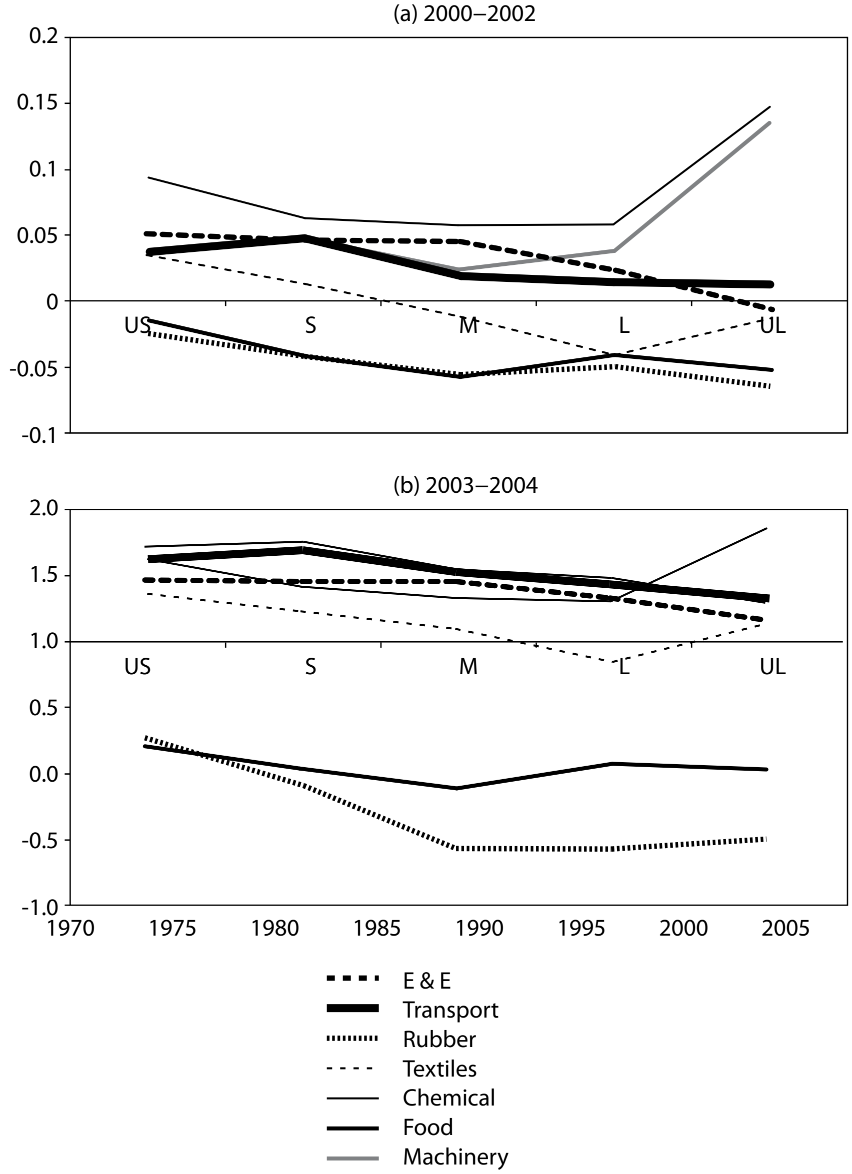
| Size | Period | E & E | Transport | Rubber | Textiles | Chemical | Food | Machinery | Total |
|---|---|---|---|---|---|---|---|---|---|
| US | 2001–02 | 0.0495 | 0.0377 | –0.0234 | 0.0358 | 0.0941 | –0.0150 | 0.0355 | 0.0306 |
| | 2003–04 | 0.0959 | 0.1252 | –0.1477 | 0.0730 | 0.1242 | –0.1573 | 0.1438 | 0.0367 |
| | 2001–04 | 0.0727 | 0.0815 | –0.0856 | 0.0544 | 0.1092 | –0.0862 | 0.0897 | 0.0337 |
| S | 2001–02 | 0.0460 | 0.0478 | –0.0421 | 0.0134 | 0.0635 | –0.0409 | 0.0483 | 0.0194 |
| | 2003–04 | 0.0924 | 0.1396 | –0.2151 | 0.0472 | 0.0825 | –0.1916 | 0.1514 | 0.0152 |
| | 2001–04 | 0.0692 | 0.0937 | –0.1286 | 0.0303 | 0.0730 | –0.1163 | 0.0999 | 0.0173 |
| M | 2001–02 | 0.0448 | 0.0193 | –0.0556 | –0.0122 | 0.0569 | –0.0584 | 0.0240 | 0.0027 |
| | 2003–04 | 0.0925 | 0.1066 | –0.3124 | 0.0191 | 0.0668 | –0.2226 | 0.1072 | –0.0204 |
| | 2001–04 | 0.0687 | 0.0630 | –0.1840 | 0.0035 | 0.0619 | –0.1405 | 0.0656 | –0.0089 |
| L | 2001–02 | 0.0227 | 0.0151 | –0.0498 | –0.0401 | 0.0580 | –0.0408 | 0.0383 | 0.0005 |
| | 2003–04 | 0.0687 | 0.0889 | –0.3126 | –0.0305 | 0.0603 | –0.1834 | 0.0988 | –0.0300 |
| | 2001–04 | 0.0457 | 0.0520 | –0.1812 | –0.0353 | 0.0592 | –0.1121 | 0.0686 | –0.0147 |
| UL | 2001–02 | –0.0062 | 0.0129 | –0.0645 | –0.0128 | 0.1476 | –0.0523 | 0.1349 | 0.0228 |
| | 2003–04 | 0.0330 | 0.0635 | –0.2989 | 0.0271 | 0.1711 | –0.1914 | 0.0586 | –0.0196 |
| | 2001–04 | 0.0134 | 0.0382 | –0.1817 | 0.0072 | 0.1594 | –0.1219 | 0.0968 | 0.0016 |
| Total | 2001–02 | 0.0314 | 0.0266 | –0.0471 | –0.0032 | 0.0840 | –0.0415 | 0.0562 | 0.0152 |
| | 2003–04 | 0.0765 | 0.1048 | –0.2573 | 0.0272 | 0.1010 | –0.1893 | 0.1120 | –0.0036 |
| | 2001–04 | 0.0539 | 0.0657 | –0.1522 | 0.0120 | 0.0925 | –0.1154 | 0.0841 | 0.0058 |

E & E = electrical and electronics industry, L = large-sized firm, M = medium-sized firm, S = small-sized firm, UL = ultra-large-sized firm, US = ultra-small-sized firm.
Note: Refer to notes to Table 4.
Source: Authors' calculations.

During 2001–2002, TFPG was the fastest in the chemical industry at 0.084, followed by the machinery industry at 0.056, and the E&E industry at 0.031. During 2003–2004, TFPG grew most rapidly in the machinery industry at 0.112, followed by the transport industry at 0.104, and the chemical industry at 0.101 in 2003–2004. TFP growth is the slowest in the rubber industry at –0.152 for the entire sample period, followed by the food industry at –0.115. For these two industries, TFP deteriorated throughout the sample period whereas TFP grew in all the other industries, with growth ranging from 0.012 to 0.092.[8] TFPG was led by the largest firms in the chemical and machinery industries but by ultra-small firms in all the other industries, except that in the transport industry. TFP grew the fastest among small firms (Figure 1). For the entire sample of firms, the estimated TFPG was highest among the smallest firms at 0.034 and lowest among large firms at –0.015. The estimates for the other firm sizes range from –0.008 to 0.017.

[8] Previous studies based on the growth accounting method find a wide range of TFP estimates for the Malaysian manufacturing sector—e.g., Maisom et al. (1994): 8.13% during 1974–1989; Okamoto (1994): 0.3% during 1986–1990; the National Productivity Corporation of Malaysia (1999): 2.79% during 1980–1998, and 1.60% during 1990–1996; Tham (1996, 1997): 0.1 during 1986–1993, and 0.3% during 1986–1991; the World Bank (1989): 3.8% during 1975–1979, and –1.9% during 1981–1984. In a study adopting the stochastic frontier approach, Kim and Shafii (2009) reported the growth rate of TFP ranges from –11.2% to 16.5% during 2000–2004.

**Figure 1: Average Rates of Total Factor Productivity Growth (TFPG) of Malaysian Manufacturing Industries by Firm Size, 2001–2002 and 2003–2004**




E & E = electrical and electronics industry, L = large-sized firm, M = medium-sized firm, S = small-sized firm, UL = ultra-large-sized firm, US = ultra-small-sized firm.

(Overall, the estimated TFPG was positive in every industry during 2001–2004 except the in the rubber and food industries. This indicates that the substantial negative impact of technical inefficiencies on the productivity of the Malaysian manufacturing sector is generally more than offset by robust technical progress. As a result, the Malaysian manufacturing sector as a whole has become more productive even though productivity improvement significantly varies across industries. Of particular concern are the food and rubber industries, where TFPG has declined for all firm size groups. For all the other industries, not only is TFPG positive for 2001–2004, but it has also improved from 2001 to 2002 and from 2003 to 2004. This provides further grounds for optimism about the productivity of the Malaysian manufacturing sector.

# IV. Concluding Observations

Malaysia is an upper middle-income country that is now reaching a development stage where productivity growth will be more important to economic growth than accumulation of capital and labor. TFP growth refers to the increase in output that cannot be accounted for by an increase in inputs. A more accurate measurement of productivity and productivity growth calls for using firm-level or industry-level data. Such analysis is also more useful for policy makers since it enables them to identify industries and groups of firms that are lagging in productivity, and thus to effectively target productivity-enhancing policies. Dividing Malaysian firms on the basis of size is especially meaningful because there are big structural differences between SMEs and larger firms in the Malaysian manufacturing sector. Many larger manufacturers are foreign multinational companies that use state-of-the-art technology to produce for the global markets while SMEs tend to use older technology and are more geared toward domestic demand.

To measure TFP growth and its two main components—TEC and TP—for five different firm sizes in seven Malaysian manufacturing industries during 2000–2004, the authors develop a stochastic frontier production model that allows for TEC, TP and TFP growth to vary across the different groups. The empirical results indicate that technical inefficiency is a serious impediment to higher productivity and hence output growth in the Malaysian manufacturing sector. Technical inefficiency grew in almost every firm size in every industry although it is more pronounced for larger firms. On the other hand, the authors find that technical progress has boosted productivity and output growth in every industry. The authors also find that larger firms generally experienced stronger TP but in some industries, smaller firms also experienced substantial TP. TP was larger than the loss of technical efficiency and hence led to positive TFP growth in five out of seven industries. Therefore, by and large the Malaysian manufacturing sector has become more productive during the sample period.

In terms of policy implications, the findings imply that technical efficiency change may be at least as important as technical progress in lifting up the TFP of the Malaysian manufacturing sector. As such, policies that enable firms to reduce the gap between their actual and potential output—e.g., more flexible markets that allow firms to use labor more efficiently—may do as much to improve productivity as policies that shift out their production frontier—e.g., subsidies for research and development. Evidence thus reconfirms the often overlooked fact that productivity is often the result of mundane incremental improvements in using inputs more efficiently rather than quantum leaps in production technology or techniques. Interestingly, evidence indicates that the need for improving technical efficiency is greater for larger firms than smaller firms. More generally, the findings identify the industries and firm sizes that lag the most in productivity growth and thus require the most attention from policy makers. However, it is important to note that promoting productivity often calls for governments to do less rather than more. More specifically, policy distortions that provide explicit or implicit subsidies to particular industries or groups of firms are often a serious impediment to productivity growth. Removing such distortions will not only raise productivity at the firm- and industry-level but, at a broader level, facilitate the economy-wide reallocation of resources toward high-productivity industries and activities.

The stochastic frontier production model and its application to the Malaysian manufacturing sector suggest a number of useful topics for future research. Most immediately, the model can be applied to other countries and the services sector. East Asian countries are in various stages of transiting from growth driven by factor accumulation to growth that relies more on productivity growth, and empirical analysis that yields productivity estimates for different industries and groups of firms should help policy makers facilitate the transition. More generally, the model allows productivity growth of different groups of firms to be estimated and compared—there is no reason why structurally different groups of firms should experience the same pattern of productivity growth. It is possible to group firms on the basis of other firm characteristics such as foreign versus domestic ownership. Finally, the production model can also be applied to different groups of countries to compare their productivity growth patterns.

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## About the Paper

Using a stochastic frontier production model, Sangho Kim, Donghyun Park and Jong-Ho Park examine the recent evolution of technical efficiency change, technical progress, and total factor productivity growth across five firm sizes and seven industries in the Malaysian manufacturing sector during 2000–2004. They find that while technical efficiency has generally worsened, substantial technical progress has more than offset it, resulting in positive total factor productivity growth. The study identifies the industries and firm sizes that lag the most in productivity, and thus have the greatest scope for productivity-enhancing policies.

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