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EFFICIENCY PERFORMANCE IN MALAYSIAN MANUFACTURING INDUSTRIES

Mansor H. IBRAHIM*

The present analysis measures and evaluates the efficiency performance of Malaysian manufacturing industries based on panel estimation methods of a stochastic frontier production function. Our findings suggest that the Malaysian manufacturing industries are relatively efficient, having the average technical efficiency levels of more than 70 per cent. Still some industries have been identified to have low levels of technical efficiency. These include Leather and Leather Products, Iron and Steel, Paper and Paper Products, Non-Ferrous Metals, and Food. In addition, we also find that several industries have a reduction in the efficiency levels over time. Among them are Leather and Leather Products, Paper and Paper Products, Non-Ferrous Metals, other Chemical Products, and Electrical Machinery. Accordingly, to survive the upcoming liberalized markets, adjustments to boost efficiency levels in these industries need to be made.

I. Introduction

Since the Pioneer Industries Ordinance of 1958 and the later emphasis on industrialization during the New Economic Policy (1970-1990), the Malaysian manufacturing sector has assumed an increasingly important role in the nation's development process. In 1960, when the Malaysian economy was fundamentally agriculture-based, the manufacturing share of the gross domestic products was only under 9 per cent. With an average annual growth of 10 per cent in the manufacturing production over the period 1960-1990, its share in the GDP has increased tremendously. It now accounts for more than 30 per cent of the country's gross domestic product, exceeding that of the once dominant agricultural sector. Furthermore, it contributes more than 50 per cent of the nation's total exports and 17 per cent of the total employment. The rapid transformation of the sector makes industrialization a focal policy objective of the Malaysian government, which is manifested in the Malaysia's attempt to be fully industrialized by the year 2020.

* Assistant Professor at the Department of Economics, International Islamic University, Malaysia. The helpful suggestions of the anonymous referees are greatly acknowledged. The usual disclaimer applies.

However, in the face of upcoming global competition through various liberalization programs such as the ASEAN Free Trade Area (AFTA), performance evaluation of the sector seems needed. Particularly, in line with the national policy emphasis on "productivity-driven growth" as recently tabled in the Seventh Malaysian Plan, the technical efficiency performance of the manufacturing sector deserves scrutiny. Essentially, the technical efficiency (henceforth, TE) quantifies the extent to which the industries achieve the maximum attainable output as specified by the technological frontier function. Since the technical efficiency improvement leads to an increase in the production at given levels of inputs, it is an important ingredients of total factor productivity growth. Besides, the industry-level efficiency estimates provide useful information. The identification of the industries with low levels of efficiency calls for corrective measures from the related industries or even direct technical assistance from the government. This is highly important, as it would help the industries to survive competition in the liberalized markets. Also, if high inefficiency exists, technological progress or transfer may not be an affective source of productivity growth.[1] The knowledge of the industries' efficiency levels would, thus, be an important starting point in carving specific policy directions of the related industries.

Accordingly, the main purpose of this paper is to measure and evaluate the efficiency performance of Malaysian manufacturing industries. The measurement is based on a stochastic frontier production function, first suggested by Aigner et al., (1977) and Meeusen and Van den Broeck (1977). In the analysis, we utilize an industry-level panel data set covering the period 1983-1991. The organization of the paper is as follows. In Section 2, we discuss the specific methodology used, which takes into consideration the panel structure of the data sample. Section 3 describes the data set and the variables in the model. The estimates of TE are presented in Section 4. Exploratory analysis of the temporal efficiency levels is also made in the same section. Finally, Section 5 consists of our concluding remarks.

II. Methodology

The methodology used is based on the estimation of a production frontier function. Since the pioneer work of Farrell (1957), the efficiency frontier analysis has undergone several extensions. In 1977, Aigner et al., and Meeusen and Van den Broeck independently suggested a stochastic frontier framework. That is, the frontier representing the best practice in the utilization of the available resources and technology is viewed as stochastic. The formulation improves upon the earlier

[1] Graphically, it means that shifting up the technological frontier through the adoption of new technology may have little effect on the output growth if no effort is made to move the point of the production toward the frontier, i.e., reducing inefficiency.

deterministic frontier in that the efficiency measurement is not confounded by measurement errors or exogenous shocks to the production process. Another extension of the model is the application of the frontier to a panel data set. This includes the work by Pitt and Lee (1981), Schmidt and Sickles (1984), Cornwell et al., (1990), and Simar (1991). The extension makes possible the measurement of time-varying efficiency performance.

Essentially, the production frontier relates the available inputs to the maximum obtainable output. The extent to which the industries achieve (or falls short of) this maximum is referred as technical efficiency (or inefficiency). To begin, the technological frontier function, relating factor inputs to output, is assumed to have a Cobb-Douglas representation. Although the specification is restrictive, it has been found to be applicable for the manufacturing production in developing countries.[2] Thus, we have

$$Y_{it} = \alpha + X_{it}\beta + \varepsilon_{it} \tag{1}$$

$$\varepsilon_{it} = -v_{it} + u_{it} \tag{2}$$

where Y_{it} is a measure of output level of industry i in period t, X_{it} is a vector of factor inputs used by industry i in period t, (α, β) is a vector of the model's parameters to be estimated; and ε_{it} is the error term of the model. In the specification, the error term is composed of two components: a stochastic component (u_{it}), and an inefficiency component (v_{it}). The term u_{it} is assumed to be independently and identically distributed $N(0, \sigma^2_u)$. It represents the standard classical error term absorbing the effects of all other variables excluded from the model. These include those factors that are beyond the industry's control. Thus, it accounts for stochastic variations in the industry's frontier. The second error term (v_{it}) is assumed to be non-negative, distributed asymmetrically, with variance σ^2_v and independent of u_{it}. It represents the degree of inefficiency that exists in a given industry.

The model may be simply rewritten in a standard panel form as:

$$Y_{it} = \alpha + X_{it}\beta - v_{it} + u_{it} \tag{3}$$

To estimate the degree of technical efficiency, specification of the inefficiency component of the error terms needs to be made. Schmidt and Sickles (1984) consider

[2] See, for instance, Wu (1995) and Jia (1991). In particular, Jia (1991) compares three models of the production function and concludes that the Cobb-Douglas production function is an appropriate representation of Chinese industrial production. Although there is an argument that the use of the same production function that underlies the inter-industry production may not be appropriate, we follow the empirical convention to assume that there exists an inter-industry production function. Moreover, we believe that the employment of panel estimations (fixed and random effects models) may take into account the inter-industry differences in production.

a variant of (3) where they assume $v_{it} = v_i$, a time-invariant firm effect characterizing inefficiency. This assumption leads to a standard fixed effects model, the estimation of which may be made using standard methods such as "within", GLS, or the Hausman and Taylor instrumental variable estimation methods. Then, the efficiency measures may be constructed based on the estimated fixed effects. However, as has been argued by Cornwell et al., (1990), that the assumption that the firm effects are time-invariant is a very strong assumption. The specification also fails to take into consideration the panel structure of the data in a sense that time varying efficiency measures may be estimated. Also, as Simar (1991) noted, there may exist random elements that stochastically affect efficiency itself. Thus, both the stochastic and efficiency components of the error terms should be viewed as random.

To account for the possible time-varying and stochastic efficiency, we employ a random-effects model. The v_{it} could be then viewed as a one-sided random deviation from the frontier, representing inefficiency of production. In the analysis, the GLS estimation method is used to estimate the production frontier function. In particular, t he GLS estimators of (3) can be obtained using the following steps. First, the OLS estimation of (3) is made and its residuals are saved. The variances of the two random components are then consistently estimated using the standard decomposition of the variance of the OLS residuals (see Simar, 1991 for details). The second step of the estimation is to perform a quasi-transformation of the variables in the model using the estimated values of the two variances. That is,

$$\tilde{Z}_{it} = Z_{it} - c\bar{Z}_i \tag{4}$$

$$c = 1 - \sqrt{\frac{\sigma^2_u}{\sigma^2_{u} + T\sigma^2_v}} \tag{5}$$

where Z is the variable under consideration. Lastly, the GLS estimators of β are obtained based on the simple OLS estimation of the quasi-transformed model as:

$$\tilde{Y}_{it} = \alpha(1-c) + \tilde{X}_{it}\beta + \varepsilon_{it} \tag{6}$$

To measure efficiency, the estimated values of the inefficiency component of the error terms are needed. Particularly, based on the GLS estimators, we need to compute ε_{it}. This can be obtained easily from the following relation:

$$\varepsilon_{it} = \tilde{\varepsilon}_{it} + \frac{c}{1 - c}\,\bar{\tilde{\varepsilon}}_i \tag{7}$$

Given (7), we use two approaches to obtain the estimated measures of time-varying efficiency. The first approach is based on a "max" transformation of ε_{it}, that is, $v_{it} = \max \varepsilon_{it} - \varepsilon_{it}$ [Simar, (1991)]. This translation is made to be consistent with the concept of frontier and efficiency. The second approach follows the suggestion by Cornwell et al., (1990) which specifies the efficiency component to be a function of time. According to this approach, the residuals obtained from (7) are regressed on time and time-square variables independently for each industry. Then, the predicted values from the regressions are subject to the same "max" translation and, consequently, are taken to be the measures of the efficiency components. In the upcoming analysis, the former approach is referred as MT while the latter as CSS.[3]

Subsequently, the degree of TE of industry i in period t may be measured by the ratio of the observed output Y_{it} to the maximum attainable output, y_{it}. That is, we have:

$$TE_{it} = \frac{Y_{it}}{y_{it}} \exp(-v_{it}) \tag{8}$$

where y_{it} corresponds to the case where inefficiency is non-existent, or $v_{it} = 0$. Measured in this way, the efficiency performance index will be between zero and one. The most efficient production representing the best practice will take the value of one. The closer the index to one, the more efficient is the industry relative to the best practice.

It should be noted here that, although the random-effects model improves upon the shortcoming of the fixed-effects model, it has its own drawbacks. Particularly, for the GLS estimators to be more efficient than those of the LSDV (i.e., fixed-effect models), the regressors have to be uncorrelated with the random effects. The LSDV method, however, does not require the same assumption to hold. Rather than testing for the correlatedness between them directly using, for example, Hausman test, we re-estimate the production function using the fixed-effects model (FE). In this case, the estimated inefficiency component, which is time-invariant, is based on the "max" transformation of the fixed-effects coefficients [see, Schmidt and Sickles, (1984)]. Then, equation (8) is applied to obtain TE measures. We believe that this is a sensible way to follow as we are interested in the relative efficiency across industries and not in the method which may be the most appropriate. The computed TE would, furthermore, provide a robustness check of our efficiency measures based on the random effect estimation.

For the purpose of estimation, we use the gross values of output (GVO) as a measure of production. The input vector includes labor (L), capital (K), and material (M) inputs. All the variables mentioned are expressed in the natural logarithmic terms. We also include a time trend (T) as an additional regressor to allow for the possibility of technological progress over the time period considered.

3 For a detailed formulation of the latter approach, see, Cornwell et al., (1990). It has been recently applied in several empirical works employing panel data. See, for instance, Fecher and Pestieau (1993), Liu (1993) and Wu (1995).

As noted by Moomaw and Williams (1991), the GVO is preferable to its alternative, the value added (VA), as a measure of output. In particular, the omission of the material input in the value added specification may not accurately capture the contribution of all inputs to the productivity measure [Sudit and Finger, (1981)]. In addition, for the value added function to be valid, the production function must possess weak separability property between the material input and other primary inputs. However, the use of the GVO also has its own shortcoming. As argued by Wu (1993), (1995), there exists the possibility of double counting in the GVO specification. And if this is the case, the efficiency measures may be overstated. This stems from the fact that the production function would have a better fit, resulting in small variations in the disburbance terms. In addition, simultaneity bias may exist if the production and the quantity of material inputs to be used are decided concurrently. These points need to be taken into consideration when interpreting our results.

III. Data and Variables

The main data on manufacturing output and input quantities are from *Industrial Surveys* (various issues) published by the Dept. of Statistics (DOS), Government of Malaysia. The data set consists of 28 industries covering the period 1983-1991. It is quite comprehensive in that it covers more than 80 per cent of the output and 70 per cent of the total employment in the manufacturing sector in the reference year 1988 [Yokoyama, (1992)]. The producer price index obtained from Annual Economic Reports is used to deflate all the variables expressed in current prices.

The gross value of output (GVO) is expressed in thousands of Malaysian Ringgit at 1980 constant price. The preferred measure of labor input would have been the total number of workers' hours used in production. This measure is not available from the Malaysian manufacturing data set. Accordingly, we define labor input (L) as the total number of employees engaged in the production during the month of December or the last pay period of a given year.[4] To measure capital input (K), we use the value of fixed assets as on 31st December of a given year expressed in 1980 constant prices, as a proxy. Thus, it is assumed here that the flow of capital services to the production is closely related to the size of fixed assets. The material inputs (M) are the costs of materials at 1980 constant prices.

Table 1 provides the mean values and average annual growth rates of the variables used. During the time period under consideration, the size of the manufacturing sector has expanded tremendously. The annual average growth rate of output for all industries

[4] One major weakness in the use of the total number of employees is that it does not reflect the skill mix of the labor force. Accordingly, the results obtained may be biased. However, due to the unavailability of reasonable proxies for skill mix such as education profile and years of experience, we proceed to estimate the production function using the total number of employees. We believe that the use of employment costs, as suggested by a referee, will not solve the problem due to the imperfect nature of Malaysian labor markets and the widely accepted view that the increase in labor wages are not tied to labor productivity.

is 12.33 per cent. The overall average growth rates of the factor inputs are 7.84 per cent, 12.72 per cent and 13.07 per cent for L, K, and M respectively. Looking at individual industries, we observe that the majority of the industries experience impressive growth rates of output, exceeding 10 per cent. Only two industries, Tobacco and Non-Ferrous Metal, have negative growth rates of 1.87 per cent and 2.38 per cent respectively. Inspection of the table also reveals that both material inputs and real capital, as measured by the real values of fixed assets, have a very high growth of above 10 per cent for most of the industries. They seem to be important contributing factors to high production growth of the manufacturing sector.[5] Given diminishing marginal returns of the factor inputs and increasingly tight factor markets, continuing dependence on the factor growth may not be indefinitely feasible. Instead, the efficiency of the production processes, which economizes on the uses of the available resources, needs to be improved. In the ensuing section, we turn to the estimation of TE as a starting point to identify the most and the least efficient industries, the knowledge of which may be helpful for policy purposes.

IV. The Estimates of Technical Efficiency

Table 2 presents the estimation results of the frontier function using the two-step GLS method. The following points may be observed. First, the performance of the estimation is satisfactory. The adjusted R^2 is very high (0.9943) and all coefficients have the expected signs. Second, with respect to individual coefficients, the coefficients of all inputs are positive and significant at the one per cent level. The estimated output elasticities with respect to labor, capital, and material inputs are 0.04, 0.13, and 0.80 respectively. This shows the dominant impact of materials input on the growth rate of manufacturing production.[6] With regard to the coefficient of the time trend capturing the rate of technological progress, we find it to be insignificant. Lastly, the production process of the Malaysian manufacturing sector may be characterized by constant returns to scale. The summation of the inputs' coefficients equals 0.9784, which is not statistically different from one.

The distribution and descriptive statistics of TEs based on the three approaches and their simple correlation coefficients are reported in Table 3.[7] Column 1, table 3(a) summarizes the estimated TEs using MT method. According to this method, the

5 Note that while the growth rates of material and capital inputs are high, the growth rates of labor inputs are relatively low. The unmatched increases in the use of labor may explain the low output growth as compared to material input or capital growth in some industries. Viewed from a different angle, the Malaysian industries may be inefficient in the input mix.

6 Empirically, the high coefficient of the material inputs is not surprising, as it has normally been found elsewhere, see, for instance, Liu (1993). In the Malaysian context, it may possibly reflect the nature of Malaysian production processes, that is, the low value-added coefficients may capture the fact that the Malaysian industries are involved mainly with sub-processes or assembly processes in the production of output for exports.

7 The estimates of time-varying TE for all industries and over the time period 1983-1991 using MT and CSS approaches are not reported here. They are available upon request from the author.

TABLE 1

Mean Values and Average Annual Growth Rates of Variables

(1980-1993)

Industry	No. of Establishment	Real GVO	Real Capital	Real Materials	No. of Employees
OVERALL	219.00	1,749.80	699.09	1,311.30	22,156.00
	(4.02)	(12.33)	(13.07)	(13.07)	(7.84)
Food	1284	10,254.00	2,363.70	9,186.20	68,935
	(0.90)	(5.14)	(2.97)	(5.18)	(3.10)
Beverages	63	527.58	297.39	264.44	5,168.20
	(-0.59)	(5.31)	(2.41)	(6.95)	(-2.57)
Tobacco	23	758.96	196.02	434.76	4,630.60
	(3.01)	(-1.87)	(-1.81)	(-1.37)	(-1.10)
Textiles	208	1,458.90	597.09	1,022.90	32,974.00
	(3.13)	(10.69)	(11.46)	(9.97)	(3.87)
Wearing Apparel	239	1,038.00	207.91	705.66	44,516.00
	(6.35)	(18.53)	(14.23)	(19.28)	(11.64)
Leather and Leather Products	23	27.91	11.38	20.01	1,067.90
	(5.07)	(19.85)	(18.97)	(21.64)	(21.14)
Footwear	10	22.63	8.14	13.85	1,136.10
	(0.93)	(6.16)	(9.42)	(6.10)	(1.61)
Wood and Cork Products	678	2,498.30	975.51	1,715.40	68,147.00
	(0.75)	(8.96)	(8.80)	(9.06)	(5.26)
Furniture and Fixtures	329	266.57	132.26	166.78	12,030.00
	(2.40)	(16.72)	(20.88)	(17.20)	(12.69)
Paper and Paper Products	116	571.98	763.74	385.59	9,761.90
	(4.10)	(17.37)	(26.60)	(17.64)	(11.14)
Printing and Publishing	248	856.45	355.79	446.05	20,937.00
	(6.42)	(2.60)	(-7.93)	(0.05)	(5.99)
Industrial Chemicals	88	2,888.40	3,163.90	1,604.10	7,659.70
	(4.73)	(13.51)	(4.96)	(12.69)	(9.51)
Other Chemical Products	142	962.56	309.92	593.76	10,531.00
	(1.48)	(9.59)	(8.92)	(10.47)	(3.54)

contd.

TABLE 1
(continued)

Industry	No. of Establishment	Real GVO	Real Capitals	Real Materials	No. of Employment
Petroleum Refineries	10	2,707.70	642.90	2,413.10	1,216.90
	(2.79)	(1.57)	(7.61)	(0.82)	(3.60)
Miscellaneous of	24	110.55	31.32	69.82	915.22
Petroleum & Coals	(7.80)	(17.89)	(13.37)	(18.13)	(4.17)
Rubber Products	296	3,318.50	1,036.70	2,528.40	42,439.00
	(6.02)	(7.56)	(12.19)	(7.32)	(9.66)
Plastic Products	272	884.25	420.28	587.27	23,347.00
	(5.37)	(17.63)	(17.91)	(17.54)	(13.86)
Pottery, China	26	84.60	78.50	38.66	4,420.40
& Earthenware	(9.91)	(15.69)	(13.59)	(16.42)	(17.60)
Glass and	21	188.55	254.85	103.48	2,743.60
Glass Products	(6.87)	(11.42)	(12.48)	(9.05)	(5.79)
Non-Metallic	347	1,383.30	1,615.40	724.58	21,961.00
Mineral Products	(0.63)	(9.15)	(11.36)	(9.08)	(3.31)
Iron and Steel	129	1,780.80	1,390.90	1,400.00	11,436.00
	(1.08)	(15.05)	(17.96)	(16.35)	(5.52)
Non-Ferrous Metal	21	855.43	215.84	765.56	3,566.30
	(11.29)	(-2.38)	(14.56)	(-3.29)	(7.95)
Fabricated Products	494	1,453.00	616.84	1,029.80	25,248.00
	(2.38)	(12.36)	(13.96)	(12.91)	(7.46)
Machinery	388	1,290.10	473.26	879.81	18,521.00
	(-0.20)	(19.39)	(20.77)	(20.22)	(10.78)
Electrical Machinery	283	10,204.00	2,399.20	7,846.70	135,780.00
	(10.82)	(20.36)	(22.30)	(21.45)	(13.78)
Transport Equipment	228	1,875.20	780.49	1,296.70	20,419.00
	(2.28)	(17.09)	(9.83)	(18.44)	(5.16)
Scientific, Measuring	19	383.37	145.45	260.72	8,829.70
& Controlling	(6.99)	(25.45)	(29.73)	(28.14)	(15.17)
Other Manufacturing	132	343.10	89.79	212.33	12,041.00
Industries	(6.60)	(20.01)	(10.94)	(21.35)	(13.08)

Note: Numbers in parantheses are the average annual growth rates.

TABLE 2

Results of the Estimated Production Frontier Model
(Two-step GLS Method)

Variables	Parameter Estimates	Standard Errors
Constant	0.4674	0.0529*
ln(L)	0.0427	0.0080*
ln(K)	0.1319	0.0114*
ln(M)	0.8038	0.0029*
T	0.0027	0.0029
σ^2_u	0.0038	
σ^2_v	0.0007	
No. of observations	252	
Adjusted R^2	0.9943	

Note: *Significant at 1 per cent level of significance.

TABLE 3

Results of the Estimated TE Using Three Alternative Approaches

(a) Distribution of Technical Efficiency

Efficiency Level	Estimation Approaches MT	CSS	FE
0.90 - 1.000	0	3	2
0.80 - 0.899	6	4	4
0.70 - 0.799	10	16	7
0.60 - 0.699	12	5	13
0.50 - 0.599	0	0	2
Below 0.50	0	0	0
Mean	0.7268	0.7656	0.7283
Min	0.6040	0.6365	0.5358
Max	0.8876	0.9349	1.0000

(b) Correlation Coefficients

	MT	CSS	FE
MT	1.000		
CSS	0.999	1.000	
FE	0.834	0.834	1.000

production of the Malaysian manufacturing sector is quite near to the frontier shaped by the Malaysian industries. Or alternatively, we may state that, relative to the best practice of the industries, the Malaysian manufacturing sector is quite efficient. The panel sample mean TE is 73 per cent. The distribution of the measured TE is as follows. Six of the 28 industries can be considered as highly efficient relative to the performance of all industries, having measures of TE exceeding 80 per cent. These include Tobacco (88.7 per cent); Beverage (88.1 per cent); Printing and Publishing (86.3 per cent); Industrial Chemicals (82.6 per cent); Pottery, China and Earthenware (80.7 per cent); and other Chemical Products (80.1 per cent). There are ten industries attaining moderate levels of efficiency between 70 per cent and 80 per cent. Lastly, 12 of the 28 industries have the calculated TE less than 70 per cent. The least efficient industries are Leather and Leather Products (60.4 per cent); Iron and Steel (61.6 per cent); Paper and Paper Products (62.7 per cent); Non-Ferrous Metal (63.4 per cent); and Food (66.4 per cent).

The CSS approach rates all industries more favorably in terms of their efficiency performance when compared to the MT method, the summarized results of which are given in Column 2, Table 3(a). According to this method, the sample mean of the TE is 76 per cent. Seven of the industries attain the efficiency levels higher than 80 per cent, with three of them being more than 90 per cent efficient. Majority of the industries (16 out of 28) falls within the intermediate case, having the TE index between 70 per cent to 80 per cent. Only five industries have the efficiency levels below 70 per cent. Yet the relative ranking of the MT and CSS approaches are highly similar. The simple correlation coefficient between the two indices is extremely high 0.99 (panel b). In only one case the ranking is reversed, that is between Miscellaneous of Petròleum and Coals and other Manufacturing Industries.

Lastly, for comparison purpose, the last column of table 3(a) provides the distribution and descriptive statistics of the TEs based on the FE approach. Notably, the estimated TEs are more dispersed compared to the previous two alternative measures. Yet, the three alternative measures seem to be comparable, where all of them have mean efficiency levels of over 70 per cent. The simple correlation coefficients of the fixed effect index and the previous two measures esceed 0.80 (panel b), indicating that their relative rankings in the industries are quite similar. Indeed, the three measures consistently rank seven of the industries amongst the ten most efficient industries. Four of them are always rated in the five most efficient industries. These include Beverage, Tobacco, Printing and Publishing and Industrial Chemicals. Meanwhile, eight of the industries are consistently grouped in the ten least efficient ones. Two of the industries, Leather and Leather Products and Non-Ferrous Metals are always ranked in the five least efficient industries. Accordingly, the approaches we employ seem to be robust in grouping the industries in most, moderate and least efficient groups. The correlatedness assumption does not seem to make much difference in relative efficiency rankings of industries.

To this point, our discussion is limited to the identification of average efficiency performance as well as efficiency comparisons across industries and estimation methods. Since the constructed TE, using MT and CSS approaches, are time varying, it may be of interest to examine the efficiency performance of the industries over time. Table 4 summarizes the temporal efficiency performance of the 28 industries. Generally, there seems to be no significant improvement or decline in the levels of TEs [see Table 4(a)]. For most industries, the annual average rates of the efficiency changes over the years 1983 to 1991 are between -1.0 per cent to 1.0 per cent. Only three industries are identified to have improved by more than 1.0 per cent by at least one of the two efficiency measures. These include Glass and Glass Products, Miscellaneous of Petroleum and Coals and Industrial Chemicals. According to both measures, Non-Ferrous Metal and Scientific, Measuring and Controlling Industries have an important decline in efficiency performance by more than 1.0 per cent annually. The MT approach, furthermore, adds Leather and Leather Products to this list. Lastly, two more industries (Paper and Paper Products and Publishing) are noted to have experienced a negative rate of efficiency change as measured by the CSS method. Recall that the first four industries of the declining TEs are also grouped as least

TABLE 4

Temporal Technical Efficiency Performance

(a) Rate of Technical Efficiency Change, 1983-1991

Percentage Change	Number of Industries according to MT	CSS
Below 1.0%	3	4
-1.0% - 0.0%	14	10
0.0% - 1.0%	8	12
Above 1.0%	3	2

(b) Test of Equality the Mean Efficiency Levels, 1983-1986 and 1987-1991

Test of Equity	Number of Industries according to MT	CSS	Either
Significantly increase	3	7	8
Significantly decrease	7	9	9
Not significant	18	12	11

Note: Significance used is 10 per cent level of significance (two-tailed test).

efficient industries. The discouraging efficiency performance of these industries over time should be a cause of concern. In addition, the Non-Ferrous Metals has been noted earlier to have a negative growth rate in the real gross values of output. It might be that the decline in its efficiency may partially account for the reduction in its production process.

We also compare whether the average efficiency levels of all industries for two sub-periods, 1983-1986 and 1987-1991, are statistically significantly different using a standard t-test for equality between two means. The results are summarized in Table 4(b). They conform the previous finding that most of the industries have no significant change in the efficiency levels between the two sub-periods. Yet, adding to the list of the industries we have noted earlier, more industries are identified to have significant changes (increase and decrease) in the TEs. To our surprise, the Electrical Machinery Industry is included in the group of industries that is loosing ground on its efficiency performance. Attention needs to be given to the industry as it is considered to play a pivotal role in the industrial sector of the Malaysian economy.

It is perhaps useful to compare our efficiency estimates with the estimates of productivity growth from other studies. The insignificant changes of efficiency measures obtained in the present study seem consistent with existing findings that the Malaysian total factor productivity growth (TFPG) estimated roughly over the sample period is negligible. For instance, Kawai (1994) estimated the Malaysian TFPG to be only 0.7 per cent during 1980-1990, although he found that the TFPG was 2.5 per cent during 1970-1990. Similarly, using the growth accounting approach, Tham (1995) noted that the growth in manufacturing TFP was rather dismal averaging just only 0.3 per cent annually over the period 1986-1991.[8] The rather low efficiency changes and productivity growth are probably a reflection of productivity slowdown over the years under investigation, as the country became dependent on inputs rather than productivity to promote growth.

Indeed, this pattern seems to conform to the experience of other fast-growing Asian economies. Over the years 1989-1990, the manufacturing TFPG for Singapore was -1.1 per cent [Young, (1995)]. Although many studies have documented high manufacturing productivity growth in the case of South Korea using data that date back to 1963 [see, for instance, Dollar and Sokoloff, (1990); Moon et al., (1991); and Young, (1995)], the estimate for recent years, i.e., 1985-1990, by Young (1995) is only 0.8 per cent. The only exception to this pattern is Taiwan, which experienced high productivity growth of 2.8 per cent over the period 1980-1990 as compared to 1.7 per cent over 1966-1990. These findings thus seem to confirm the belief that the growth in the fast-growing Southeast Asian and Far East Asian countries is input-driven rather than productivity-driven.

8 See, Tham (1995), Table 1A, Appendix II for a summary of several past studies. They generally suggested low TFPG during the years covered in our study.

To summarize our foregoing discussion, Table 5 presents the classification of the industries according to the groupings (least, moderate and most efficient) and to temporal performance (no significant change, increasing and decreasing) based on the MT and CSS indices. The differences in the TE levels across industries call for different policy orientation. The most efficient industries may aim at improving or shifting the frontier through, for example, the adoption of new technology. However, recommending the same policy for the least efficient industries may not be fruitful. Instead, the improvement in the efficiency levels needs to be made first. In addition,

TABLE 5

Classification of Industries according to their Efficiency Performance

Efficiency	Temporal Efficiency Performance		
Rankings	Increasing	Decreasing	No Change
Ten Most Efficient	Beverages, Industrial Chemicals, Miscellaneous of Petroleum and Coals, Other Manufacturing Industries.	Printing & Publishing, Other Chemical Products, Electrical Machinery.	Tobacco, Pottery, China and Earthenware, Non-Metallic Mineral Products
Eight Moderately Efficient	Wearing Apparel, Wood and Cork Products, Glass and Glass Products.	Scientific, Measuring and Controlling Rubber Products	Petroleum Refineries, Machinery, and Transport Equipment.
Ten Least Efficient	Plastic Products.	Furniture and Fixtures, Non-Ferrous Metal, Paper and Paper Products, Leather and Leather Products.	Fabricated Products, Textiles, Footwear, Food, Iron and Steel.

*The Temporal efficiency performance in based on the results of Table 4(b), last column.

the declining industries in terms of their respective efficiency performance also need an efficiency boost. Although theory does not clearly specify the factors that may improve the efficient levels, non-price factors such as ownership and organizational structure, work effort, capital intensity and competition have been suggested as policy alternatives and may affect TE.

V. Conclusion

This paper measures the efficiency performance of the Malaysian manufacturing industries. The panel model approaches are adopted to estimate the stochastic frontier function and subsequently obtain the indices of technical efficiency. Based on the analysis, several industries have been identified to have low TE levels relative to industries as a whole. Most notably, these include, Leather and Leather Products, Iron and Steel, Paper and Paper Products, Non-Ferrous Metals and Food. In addition, some of the industries are noted to have experienced a reduction in their efficiency levels over time. The most notable among them are Leather and Leather Products, Furniture and Fixtures, Paper and Paper Products, Non-Ferrous Metals, Scientific, Measuring and Controlling, Printing and Publishing, other Chemical Products, and Electrical Machinery. The first five industries are also the least efficient industries. However, the last three industries are the high performance industries, deterioration of their efficiency performance should therefore be a cause of concern. As the present analysis does not address the question of efficiency differentials across industries further research in this areas might be on identifying the determinants that affect the performance of industries. This would prove fruitful for formulating specific policy recommendations to upgrade the efficiency performance of Malaysian industries.

International Islamic University
Malaysia

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