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## Abstract

We study the link between plant turnover and productivity using Indonesian plant-level data for the period of 1990-95. First, we compare productivity differentials among incumbents, entrants, and exiting plants by constructing the Farrell technical efficiency index using data envelopment analysis. We test the significance of these differentials using Simar and Wilson (1998) bootstrap algorithm and Li's (1996) nonparametric test of closeness between unknown distributions. We find that the incumbent plants are on average the most productive group in every year of the estimation period. Also, the new plants are relatively less productive than the exiting plants in the early years. However, they are more productive than the exiting plants in the later years. Second, and more importantly, we estimate the productivity change during the study period using the Malmquist productivity change index and decompose the change to see if the differences in measured productivity change among the three groups of plants come from differences in the efficiency change or the technical change. Since the existing literature rarely distinguishes between these two different components, little is known whether exiting plants are less productive because of their inability to catch up to the current frontier or to adopt a better technology. Similarly, not much known whether entrants' ability to survive come from their being equipped with a 'better' technology or being able to catch up to the current frontier. Our findings indicate that although new plants enter with relatively lower productivity levels, they exhibit the highest productivity change during the early years. In addition, we find entrants' high productivity growth in the early period is due to a movement toward the frontier, while in the later period is due to an upward shift of the technology frontier. Exiting plants, on the other hand, exhibit the lowest productivity change during the early years when entrants experience high productivity change.



Keyword(s): Productivity dynamics, bootstrap, nonparametric test, data envelopment analysis, plant level, manufacturing.

JEL Code(s): D24, L63

## 1. Introduction

In this paper, we study the link between plant turnover and changes in productivity using Indonesian plant-level data for the period of 1990-95. Unlike in some of the earlier empirical studies such as those surveyed by Caves (1998), Bartelsman and Doms (2000), and Tybout (2000) based on similar micro-level data from developed and developing countries, our focus is on the distinction between technological catch-up and technological change as related to the productivity differentials between entering, exiting, and surviving firms.[1] More specifically, borrowing from the productivity frontier literature, we investigate how these three groups of firms differ in terms of their productivity movements across time with respect to the estimated productivity frontiers. In particular, we seek to answer the questions such as which group moves away from or toward the frontier and which of them shifts the frontier.

Surprisingly, such distinction has been largely ignored in the productivity and firm turnover literature. For example, the literature is relatively silent on the question of whether exiting firms are less productive due to their failure in becoming more efficient (that is moving toward the frontier) or in adopting a better technology (that is shifting out their frontier). Similarly, the literature is relatively silent on the possible reasons that entrants are more efficient than “exiters” due to the entrants being closer to the frontier or due to their ability to enter with a better technology. If entrants are more productive than the dying firms as a result of the entrants' better technology, for example, then there is an argument for providing more incentives or access to the dying firms to acquire new technology. Otherwise, the more logical incentives to provide to the dying firms would be those which lead to their improvement in efficiency, such as better utilisation of their existing capacity, rather than their purchasing of new machineries.

[1] See, for example, Kumar and Russell (2002) for a recent use of such distinction.

In addition to our primary objective, we also seek to extend Liu and Tybout (1996) by comparing two additional measures of productivity: the multilateral total factor productivity (TFP) index as used in Aw, Chung, and Roberts (2000) and the Farrell technical efficiency index first proposed by Farrell (1957). In their study, Liu and Tybout (1996) tested Hopenhayn (1992)'s prediction that exiting firms tended to be the least productive group and the surviving firms would stochastically dominate new entrants in terms of productivity using plant level panel data from two developing countries: Chile and Colombia.[2] Their findings confirmed that new plants were typically more productive than dying plants, but they were less productive than the industry-wide average. More importantly, however, they also found that the two different measures of productivity they used, namely the divisia index and a `technical efficiency' index,[3] might lead to two different productivity patterns. Thus, they suggested the need for investigating other measures of productivity in terms of the relationship between turnover patterns and productivity. We aim to contribute to the understanding of this issue by utilising two other highly popular non-parametric measures of productivity mentioned above.

We estimate and decompose productivity change into technical change (technological change) and efficiency change (technological catch-up) by computing the Malmquist index of productivity change as used in Färe, Grosskopf, Norris and Zhang (1994). We compute both the Farrell technical efficiency index and the Malmquist productivity change index nonparametrically using a linear programming activity analysis approach also known as Data Envelopment Analysis (DEA).[4] Based on the computed indices, we conduct formal statistical tests of productivity differences using Simar and Wilson's (1998) bootstrap algorithm and Li's

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[2] See also Jovanovic (1982), Lambson (1991), and Ericson and Pakes (1995) for more theoretical discussions on this topic.

[3] Both indices are measured as the ratios of output and an index of factor inputs. For the divisia index, the factor input index is simply cost-share weighted sum of log inputs. For the technical efficiency index, the factor input index is output-elasticity weighted sum of log inputs. The output elasticity is obtained from econometric estimation of a Cobb-Douglas production function. We refer to the original paper for further detail.

[4] This term was originally coined by Charnes, Cooper and Rhodes (1978).

(1996) test of closeness between two unknown distribution functions.[5] Due to the significant increase in complexity of the linear programming problem as the size of the sample study increases, we restrict our estimation only on the Indonesian electronics manufacturing plants. Interestingly, however, this subsector was one of those which exhibited the most rapid change during the study period, since the period coincided with the beginning of an export-oriented industrialisation strategy adopted by the country and the sector was one of those receiving a large inflow of foreign investments.

Our results indicate that the two different measures, namely the multilateral productivity index and the Farrell efficiency index computed based on pooled-observations, provide essentially similar patterns of productivity. More specifically, we find that, on average, survivors are the most efficient group in every period regardless of the two different measures. We also find that, at the early period, entrants are relatively less efficient than the exiting plants ("exiters"). However, at the later period, entrants are relatively more efficient than the other group. Our bootstrap analysis suggests that the differences in mean productivity of these three groups are statistically significant. This result is further supported by the result of Li's test which rejects the null hypothesis of distribution closeness between survivors and exiters and between entrants and exiters. However, the productivity distributions of survivors and entrants are not found to be statistically significantly difference. Finally, the decomposition of the Malmquist index shows that entrants seem to enter with a low efficiency level. This is probably due to a high financial cost or a steep learning curve in the adoption of a newer technology that faced by the entrants. Plausibly, as time goes by, they would catch up to the new frontier and become more efficient.

[5] See, for example, Kumar and Russel (2002) for a similar application of such test.

The rest of this paper is organized as follows. Section 2 discusses the specification of the DEA models and the multilateral productivity index. Section 3 describes the data and the firm turnover classification. Section 4 discusses the results. Section 5 concludes.

## 2. Empirical Methodology

*Farrell technical efficiency*

For the measurement of technical efficiency, we use Farrell (1957) input-oriented efficiency measure defined as

$$F_i(x, y) = \min\{\lambda : \lambda x \in L(y)\} \tag{1}$$

where $y \in \Re^M$ is output, $x \in \Re^N$ is input, and $L(y) = \{x : x \text{ can produce } y\}$ is the associated input requirements set. Thus, $F_i(x, y)$ measures how much a firm can reduce its inputs to produce the same amount of output. Assuming constant returns to scale (C) and strong disposability of both inputs and outputs (S), the value of $F_i(x^{k'}, y^{k'})$ for any firm $k'$ can be computed in the static activity analysis or DEA framework as the solution to the following linear programming problem:

$$\begin{aligned} & F_i\left(x^{k'}, y^{k'} \mid C, S\right) = \min \lambda \\ & s.t. \\ & \textstyle\sum_{k=1}^{K} z_k y_{km} \geq y_{k'm},\ m = 1, \ldots, M \\ & \textstyle\sum_{k=1}^{K} z_k x_{kn} \leq \lambda x_{k'n},\ n = 1, \ldots, N \\ & z_k \geq 0,\ k = 1, \ldots, K \end{aligned} \tag{2}$$

where $K$ is the total number of firms in that period.

*Multilateral TFP Index*

For comparison purposes, we also compute a multilateral index commonly used to measure total factor productivity (TFP). The particular measure we use is originally due to

Caves, Christensen and Diewert (1982) and extended by Good, Nadiri and Sickles (1996). In this approach, the log value of TFP for any firm *k* at period *t* is defined as

$$\begin{aligned}\ln TFP_{kt} = \; & \left(\ln y_{kt} - \overline{\ln y_t}\right) + \sum\nolimits_{s=2}^{t}\left(\overline{\ln y_s} - \overline{\ln y_{s-1}}\right) - \\ & \left[\sum\nolimits_{n=1}^{N} \tfrac{1}{2}\left(S_{nkt} + \overline{S_{nt}}\right)\left(\ln x_{nkt} - \overline{\ln x_{nt}}\right) + \right. \\ & \left.\sum\nolimits_{s=2}^{t}\sum\nolimits_{n=1}^{N}\left(\overline{S_{ns}} + \overline{S_{ns-1}}\right)\left(\overline{\ln x_{ns}} - \overline{\ln x_{ns-1}}\right)\right]\end{aligned} \qquad (3)$$

where $S_n$ denotes cost share of input $x_n$ and $\ln y_t$, for example, denotes the corresponding value of output of a hypothetical reference firm constructed from the industry average.

The basic idea of this TFP measure is that it measures the proportional difference in total factor productivity for firm *k* in period *t* relative to the hypothetical plant in the base year.[6] The formula given in equation (3) is composed of two parts: output less inputs. The first component of the output part expresses firm *k*'s output as deviation from the output of the reference plant. The second component sums the changes in output of the reference plant across time. Therefore, the first component captures the cross-sectional distribution of output; whereas, the second component capture the shifts in the distribution of output over time. Finally, the input part can be described in essentially the same way.

*Malmquist index of productivity change*

For the measurement and decomposition of productivity change, we use the input-oriented Malmquist index as follows:[7]

[6] For our purpose, we select 1990 as our base year.
[7]The *t*-period Malmquist index is due to Caves, Christensen and Diewert (1982). The geometric mean version and its decomposition is due to F¨are, Grosskopf, Lindgren and Roos (1994).

$$
\begin{aligned}
&M_i\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \left(\frac{D_i^t\left(y^{t+1}, x^{t+1}\right)}{D_i^t\left(y^t, x^t\right)} \times \frac{D_i^{t+1}\left(y^{t+1}, x^{t+1}\right)}{D_i^{t+1}\left(y^t, x^t\right)}\right)^{\frac{1}{2}} \\
&EFCH\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \frac{D_i^{t+1}\left(y^{t+1}, x^{t+1}\right)}{D_i^t\left(y^t, x^t\right)} \\
&TECH\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \left(\frac{D_i^t\left(y^{t+1}, x^{t+1}\right)}{D_i^{t+1}\left(y^{t+1}, x^{t+1}\right)} \times \frac{D_i^t\left(y^t, x^t\right)}{D_i^{t+1}\left(y^t, x^t\right)}\right)^{\frac{1}{2}} \\
&M_i\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = EFCH \times TECH
\end{aligned}
\tag{4}
$$

where $D_i^t\left(y^t, x^t\right) = \sup\left\{\lambda : x/\lambda \in L(y)\right\}$ is the *t*-period based input-oriented distance function[8] for activity in period *t*. Since $D_i$ and $F_i$ are reciprocal to each other (that is, $D_i^t\left(y^t, x^t\right) = 1/F_i\left(y^t, x^t\right)$ under our technology assumptions), then each distance function in equation (4), and thus $M_i$, can be calculated as the solution of a linear programming problem similar to that presented in equation (2). We then decompose $M_i$ into efficiency change (*EFCH*) and technical change (*TECH*) as shown in equation (4) above.

*Bootstrap and test of productivity differences*

Despite the deterministic nature of the DEA method, the resulting efficiency scores should still be considered as estimates because they are measured based on an estimate of the true unobserved production frontier (Simar and Wilson, 1998). Due to the likely sampling variations in the estimated frontier, we assess the variability of the efficiency estimates using a bootstrap method proposed by Simar and Wilson (1998) as follows:[9]

(1). For any firm *k*, compute $\hat{F}_k = \hat{F}_i\left(y^{k'}, x^{k'}\right)$ using the sample *K* observations of plant inputs and output vector $\left(y^{k'}, x^{k'}\right)$ following equation (2),

[8]The concept of input distance function is originally from Shephard (1953).
[9]We refer to the original paper for more details.

(2). Using the empirical distribution of $\hat{F}_k$, $k = 1 \ldots K$ and the reflection method of Silverman (1986), pick a random draw of efficiency scores ( $F^*_{k,b}$ ) for each plant *k*,

(3). Compute the bootstrapped value of plant inputs ( $x^k_b$ ) corresponding to the randomly drawn efficiency score such that $x^k_b = \frac{\hat{F}_k}{F^*_{k,b}} x^k$ ,

(4). Using equation (2) and $\left(x^k_b, y^k\right)$, compute the bootstrapped values of efficiency scores $\hat{F}^b_k = \hat{F}_i\left(y^{k'}, x^{k'}_b\right)$,

(5). Repeat (1)-(4) for at least 1000 replications, to obtain the bootstrapped sampling distribution of $\hat{F}_k$.

The bootstrapped sampling distribution of the efficiency estimates provide a straight-forward way of testing productivity differences in the sampling mean. However, recent nonparametric test literature also allows us to test the differences in the distribution of the efficiency scores more directly. One particular method is Li's (1996) test of the closeness of two distributions using sample distributions of unequal size based on the kernel density method.

More specifically, define *g*(*x*) and *h*(*x*) as the population densities of the efficiency scores of surviving and entering plants, respectively. Let $\left\{F^s\right\}$ and $\left\{F^e\right\}$ denote $K_1$ and $K_2$ random samples of efficiency scores for surviving (incumbent) and entering firms, respectively. Then, to test the null hypothesis *Ho* : *g*(*x*) = *h*(*x*), Li (1996) shows that under *Ho,* $h \to 0$, $K_1 h \to \infty$, and $K_2 h \to \infty$:

$$J = K_1 h^{\frac{1}{2}} \frac{\tilde{I}}{\hat{\sigma}} \sim N(0,1) \tag{5}$$

where

$$\tilde{I} = \frac{1}{h}\sum_{i=1}^{K_1}\sum_{j=1}^{K_2}\left[\mathrm{K}\left(\frac{F_i^s - F_j^s}{h}\right) + \mathrm{K}\left(\frac{F_i^e - F_j^e}{h}\right) - \mathrm{K}\left(\frac{F_i^s - F_j^e}{h}\right) - \mathrm{K}\left(\frac{F_i^e - F_j^s}{h}\right)\right]$$

and

$$\hat{\sigma}^2 = \frac{1}{\sqrt{\pi}}\left[\frac{1}{K_1^2}\sum_{i=1}^{K_1}\sum_{j=1}^{K_1}\mathrm{K}\left(\frac{F_i^s - F_j^s}{h}\right) + \frac{K_1}{K_1^2}\mathrm{K}\left(\frac{F_i^e - F_j^e}{h}\right) + \frac{K_1}{K_1^2}\sum_{i=1}^{K_2}\sum_{j=1}^{K_2}\mathrm{K}\left(\frac{F_i^e - F_j^e}{h}\right) \frac{1}{K_2^2}\sum_{i=1}^{K_1}\sum_{j=1}^{K_2}\mathrm{K}\left(\frac{F_i^s - F_j^e}{h}\right) + \frac{1}{K_2^2}\sum_{i=1}^{K_2}\sum_{j=1}^{K_1}\mathrm{K}\left(\frac{F_i^e - F_j^s}{h}\right)\right]$$

for a given Gaussian kernel function $\mathrm{K}(\bullet)$.

## 3. Data and Plants Classification

Our data set is constructed from a series of annual plant level surveys of Indonesian manufacturing establishments conducted in 1990–1995. Despite its formal name, the survey covers all manufacturing plants with at least 20 workers.[10] This data set provides detailed information on each plant's output, input, and other characteristics. For our purpose, we measure the plants output using their constant price value of total output. On the input side, Labour input is the total number of paid production and non-production workers. Material input is computed as the deflated value of raw materials plus energy. Finally, we use the deflated book value of total assets for a measure of capital input.[11]

The (unbalanced) panel structure of the data set enables us to identify plant turnovers through out the period. At the same time, the unbalance nature requires us to "fill up" the panel to make it balance in order to use linear programming to measure $M_i$ and its decomposition. In this paper, we propose to fill up the panel by a convex combination of

[10] In practice, due to non-responses and other technical problems, it is estimated that the survey coverage is slightly higher than 90 per cent of the plants population.
[11] The output deflator is producer price index for at least for 3 digit SIC level whenever available.

existing plants in each period, so that the 'actual' reference technology would not be affected by the artificial data. In this approach, we then ignore any measured $M_i$ associated with the artificial observations.

Using the firms' identification numbers, we classify them into groups of entrants, exits, and survivors. For our purpose, we set 1990 and 1995 as the defining periods for entry and exit classification. In particular, we classify all plants which do not make it until the end period, 1995, as exiters.[12] Similarly, we classify all plants which are not observed in beginning period, 1990, as entrants. However, the exit classification takes precedence over the entry classification. For example, Plant 4 in Table (1) is classified as an exiter rather than an entrant. Finally, all plants observed at both the beginning, 1990, and the ending, 1995, are considered as survivors.

Table (1) also provides other examples of plant turnover classification. In particular, it shows that a complication in determining turnover status may arise. For example, we have to decide whether or not Plant 4 is an entrant or an exit. One way to solve this problem is to simply delete this plant from our sample. However, we choose not to follow this suggestion because we think it would waste a valuable observation and, more importantly, it may bias our construction of technology. Thus, we decide to treat such a plant as an exiting plant. In a similar spirit, we treat Plant 7, for another example, as a surviving plant. Fortunately, in our empirical analysis, all but one survivor continues to exist in every period.[13]

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[12] Thus, our exiters should be treated merely as proxy for the unknown "true" exits. However, given the census nature of the surveys and the way they are conducted, the likelihood for an establishment's disappearance from the sample is to represent a true exit is very high.
[13] Furthermore, the number of cases such as plants 4 and 6 in Table (1) is very small in our sample.

**Table 1: Examples of plant turnover classification**

| | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 | Status |
|---|---|---|---|---|---|---|---|
| Plant 1 | ✔ | ✔ | ✔ | ✔ | ✔ | ✔ | Survivor |
| Plant 2 | ✔ | ✔ | | | | | Exit |
| Plant 3 | | | | | ✔ | ✔ | Entrant |
| Plant 4 | | | | ✔ | | | Exit |
| Plant 5 | | | | | | ✔ | Entrant |
| Plant 6 | | ✔ | | ✔ | | ✔ | Entrant |
| Plant 7 | ✔ | | | | | ✔ | Survivor |
| . | . | . | . | . | . | . | . |
| . | . | . | . | . | . | . | . |
| Plant K | . | . | . | . | . | . | . |

Finally, the classification method is dependent on the sample period and any missing values. For example, a firm observed in 1990-1994 but not in 1995 may not necessarily exit. It is possible that our failure to observe the plant is due to its failure in responding to the survey questionnaire in time and not due to its exiting the industry. In addition, our classification is sensitive to changes in industry classification of the firms which may happen when a firm switch its main output. The first problem may be more serious and more likely to happen than the second one. However, we have no way to avoid this and, to some extent, this problem is limited by the high coverage of the survey. The second problem is less likely if we use a more general level of industry classification. For example, our sample industry is based on a 3-digit SIC level which is quite general and independent of any possible entry-exit pattern across the 4 or 5 digit levels. The use of more general SIC is not without cost. An obvious cost is with a more general SIC we introduce more heterogeneity in, for example, product characteristics.

## 4. Results

*Efficiency comparisons*

The empirical results are summarized in Tables (2)–(4). To help in the discussion of the results, we also provide charts to visualize these tables and give us a clearer pattern of the results. We start with a basic description of plants distribution according to their transition groups and their total market shares. Based on our classification method, there are 70 plants classified as survivors, 43 plants as exiting plants, and no entrants in 1990.[14] In the same period, the survivors control around 76% of the market in terms of sales value, while the exiting plants have 24% share. By 1995, the compositions change dramatically. The number of entrants increases from 0 in 1990 to 160 in 1995. In terms of market share, by 1995 the entering plants control as much as 51% while survivors' share drops to 49%. Therefore, overall, the electrical equipment and electronics industry grows rapidly, especially beginning in mid 1990s.

**Table 2: Number of Plants and Market Share**

| | Number of Plants | | | Market Share | | |
|---|---|---|---|---|---|---|
| Year | Entrant | Exiter | Survivor | Entrant | Exiter | Survivor |
| 1990 | - | 43 | 70 | - | .24 | .76 |
| 1991 | 22 | 30 | 69 | .08 | .17 | .75 |
| 1992 | 41 | 33 | 69 | .21 | .13 | .67 |
| 1993 | 55 | 14 | 69 | .24 | .06 | .70 |
| 1994 | 96 | 12 | 70 | .45 | .01 | .54 |
| 1995 | 160 | - | 70 | .51 | - | .49 |

Table (3) and Figure (1) provides a summary of average[15] efficiency/productivity as measured by three different approaches: Farrell input oriented index, multilateral TFP index, and Average Labour Productivity. These indices provide some evidence that on average survivors are more efficient than entrants, which are, in turn, more efficient than exiters.

[14] This lack of entrant in 1990 is merely a consequence of our using 1990 as the 'entry gate.' Similarly, we will observe no exit in 1995 simply because we use 1995 as the 'exit gate.'
[15]For the Farrell index we use a geometric average. For ln $TFP$ and Labour productivity we use their arithmetic averages.

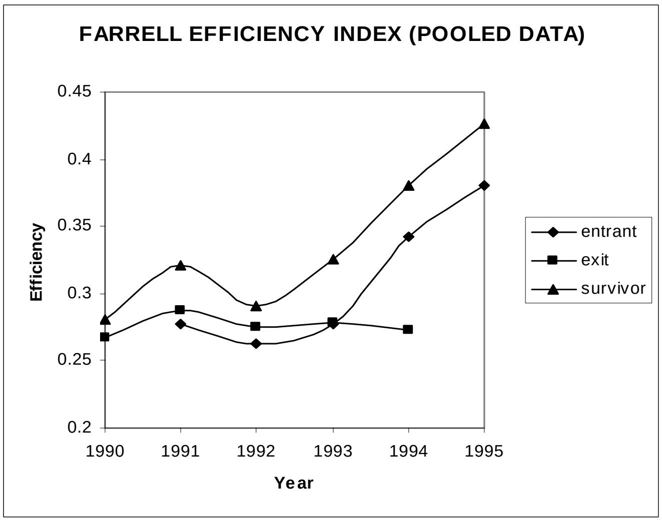
There is some similarity in the patterns shown by the Farrell and multilateral indices. On the other hand, the pattern shown by the average labour productivity measure is quite dissimilar. This should provide a warning in interpreting any result in similar studies which uses only average labour productivity. Furthermore, both the Farrell and multilateral indices indicate survivors and entrants improve their efficiency over time. However, this should be interpreted more carefully, since the improvement in productivity we observe may come from improvement in technology (innovative effect) as opposed to improvement in efficiency (catching up effect) or both.

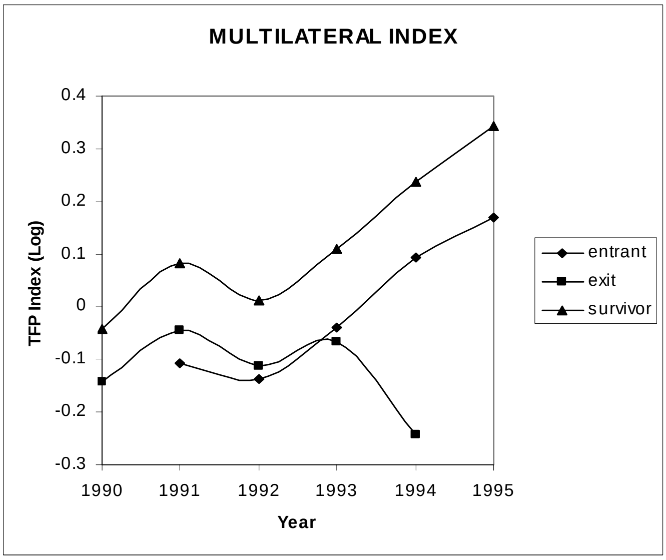
**Table 3: Plant average productivity/efficiency**

| | Farrell efficiency | | | Multilateral index of TFP | | | Labour productivity | | |
|---|---|---|---|---|---|---|---|---|---|
| Year | Entrant | Exit | Survivor | Entrant | Exit | Survivor | Entrant | Exit | Survivor |
| 1990 | - | .268 | .280 | - | -.422 | -.042 | - | -.398 | .245 |
| 1991 | .278 | .287 | .321 | -.107 | -.044 | .083 | -.078 | .039 | .308 |
| 1992 | .263 | .275 | .291 | -.138 | -.114 | .012 | .293 | .091 | .368 |
| 1993 | .278 | .278 | .326 | -.039 | -.066 | .111 | .119 | -.009 | .409 |
| 1994 | .342 | .273 | .380 | .093 | -.244 | .238 | .258 | -.214 | .453 |
| 1995 | .380 | - | .426 | .169 | - | .342 | .364 | - | .589 |

We can verify the significance of the differences in average Farrell efficiency scores among plant groups shown by the left-most chart in Figure (1) by studying the box plots of group average bootstrap values shown in Figure (2) below. In that box diagram, S, X, and N denotes survivors, exiters, and entrants, respectively. It is clear that survivors are significantly more efficient than the other two groups. Also, entrants are more efficient than exiters only at the later period. In terms of time trend, exiters do not seem to perform worse over time. It is possible, however, for the least efficient to exit earlier so that, for example, X90 seems to be significantly lower than X91-X93.

**Figure 1: Average productivity across all establishments using three different measures, 1990-1996**



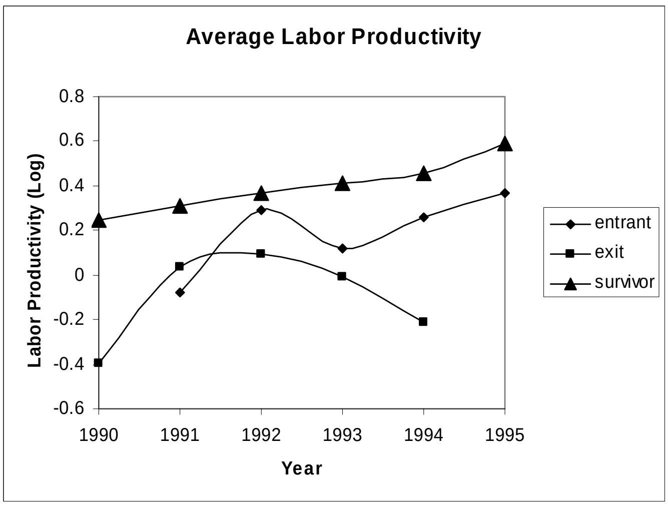
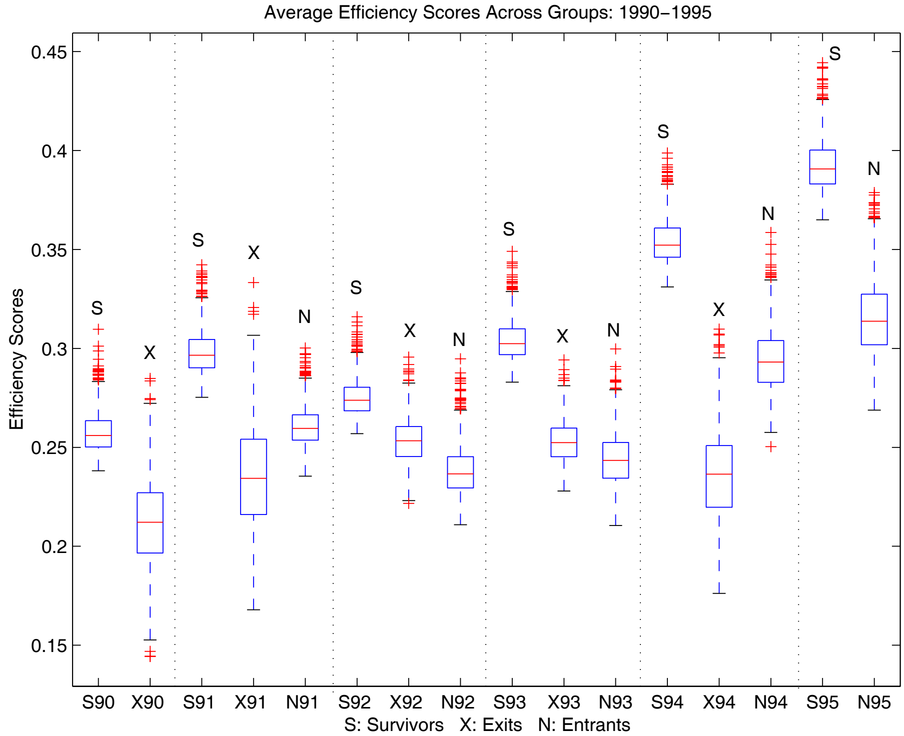



**Figure 2: Average Efficiency Scores based on bootstrap replications.**




Finally, to formally test whether or not each these groups of plants has a different distribution of efficiency, we conduct Li's (1996) test. The null hypotheses and the results of the tests are summarized in Table (4). As can be seen from the table, the test results confirm the statistical significance of efficiency differences across groups as shown by the line plots of the average efficiency and the box plots of the average bootstrap values. Figure (4) compares the empirical density and cumulative distribution of efficiency scores (theta) for each group of plants.

### 4.2 Productivity growth comparison

Figure (4) provides further evidence of the similarity between our distance-function based measures and the multilateral indices. In this figure, the pattern of productivity growth as

**Table 4: Test Results of the Closeness of Productivity Distribution**

| Null hypotheses | z-test statistics | P-value | Conclusion |
|---|---|---|---|
| Ho: $f\left(\theta^{S}_{90-95}\right)=g\left(\theta^{X}_{90-94}\right)$ | 3.898 | 0.000 | Reject Ho |
| Ho: $f\left(\theta^{S}_{90-95}\right)=g\left(\theta^{N}_{91-95}\right)$ | 0.148 | 0.441 | Fail to reject Ho |
| Ho: $f\left(\theta^{X}_{90-94}\right)=g\left(\theta^{N}_{91-95}\right)$ | 3.969 | 0.000 | Reject Ho |

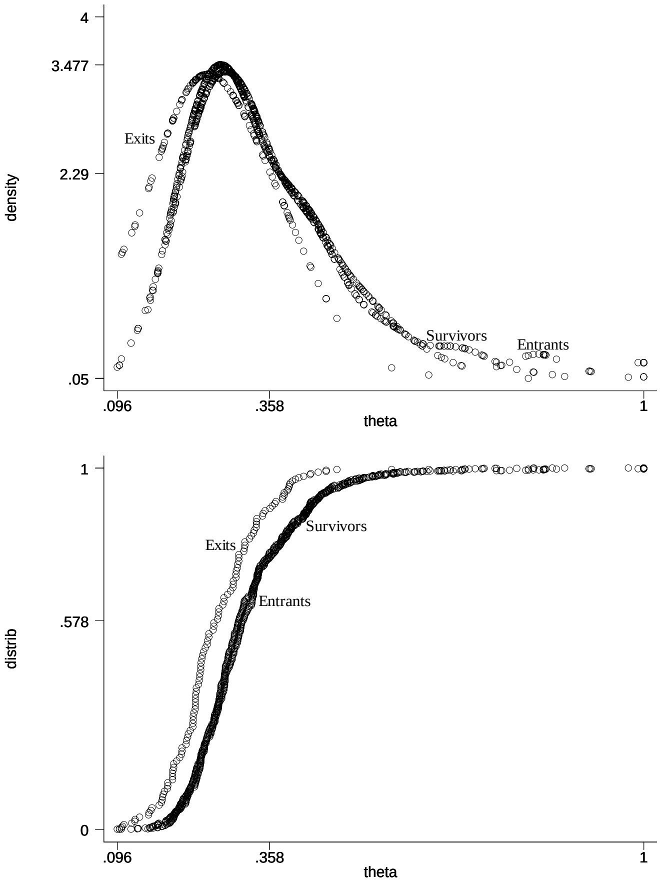
$f(\cdot)$ and $g(\cdot)$ are unknown probability density function
$z \sim N(0,1)$
$\theta$ denotes Farrell efficiency scores based on pooled data;
S, X, and N indexes survivors, exiters, and entrants respectively.

measured by the Malmquist index and by the change in the multilateral index is quite similar.[16] This similarity is significant in the sense that our computation of the Malmquist index is based only on paired-period, while the computation of the multilateral index based on the whole sample period. From this figure, we can see that entrants seem to have higher productivity growth than survivor. Also exiting plants tend to slow down in their productivity.

Finally, Figure (5) and Table (5) provide a decomposition of the productivity change.[17] From the decomposition we see a similar pattern exhibited by the entrants and the survivors. Notice that both groups tend to deteriorate in terms of efficiency in the second half of the sample period, while, at the same time, they tend to gain in terms of technology. This provides us with an evidence of improvement in the reference technology. In particular, the improvement is so much that leads to an average entrant/survivor to fall behind in terms of efficiency. For the exiters, their technology shrinks while they gain efficiency. The gain in efficiency among the remaining exiters may indicate a self-selection process where the least

[16] Period 1 refers to 1990–1, period 2 refers to 1991–2, and so on.
[17] The multilateral approach does not allow us to compute a similar decomposition. As a result, studies based only on such measure would not utilize such information and should be interpreted with caution.

**Figure 3: Empirical probability density and cumulative distribution of Farrell efficiency scores by turnover classification.**




productive among them exited in earlier period. The shrinkage in their technology indicates their inability to switch to the better technology relative to the new and the surviving plants.

**Figure 4: Average plant productivity change, 1990-1995.**

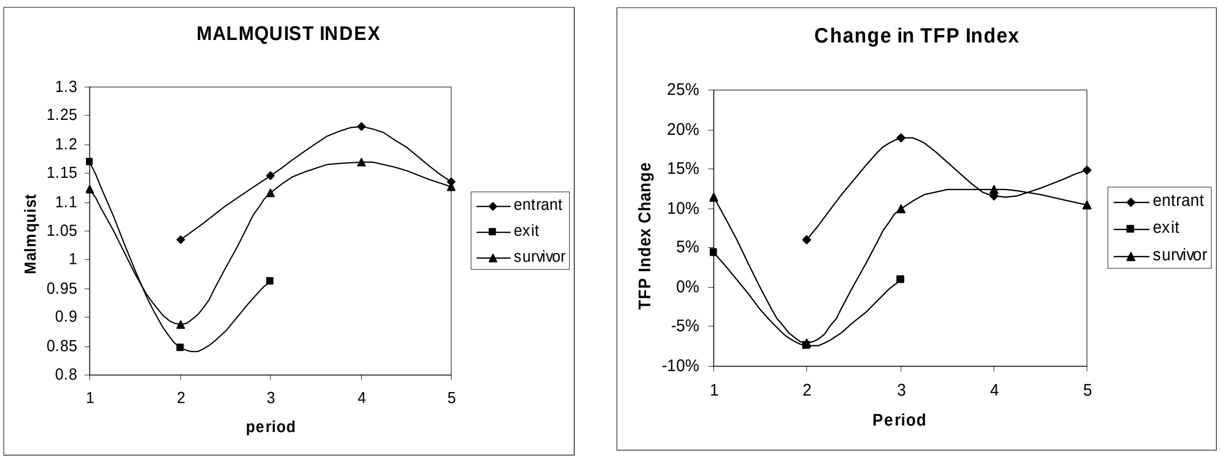


**Figure 5: Decomposition of Productivity Change**

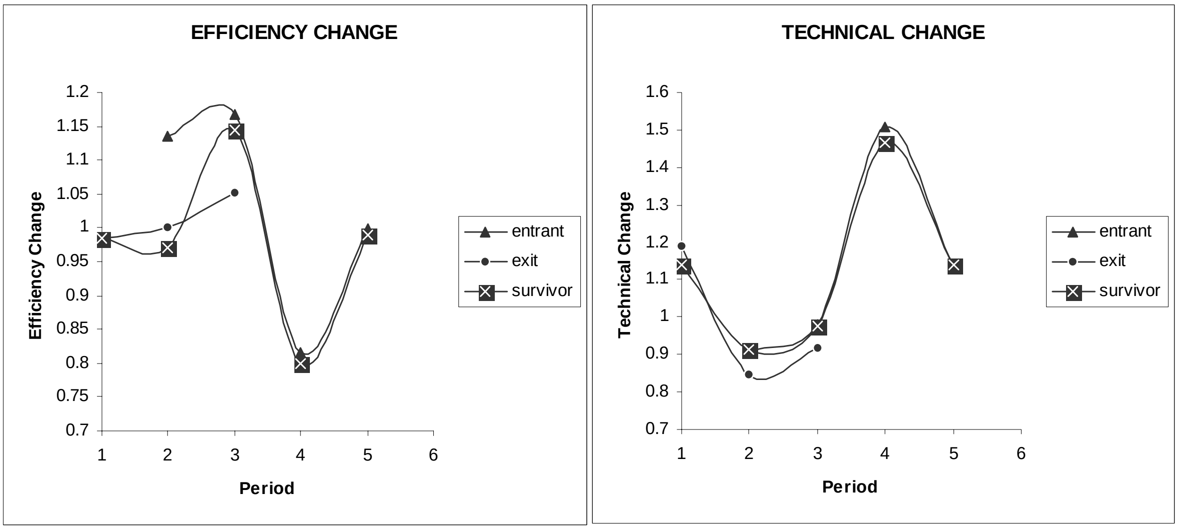



**Table 5: Malmquist Index and Its Decomposition**

| | Malmquist Index | | | Efficiency Change | | | Technical Change | | |
|---|---|---|---|---|---|---|---|---|---|
| Period | Entrant | Exit | Survivor | Entrant | Exit | Survivor | Entrant | Exit | Survivor |
| 1990–1 | - | 1.170 | 1.122 | - | .985 | .986 | - | 1.190 | 1.139 |
| 1991–2 | 1.036 | .847 | .888 | 1.135 | 1.001 | .971 | 0.910 | 0.848 | .914 |
| 1992–3 | 1.146 | .963 | 1.117 | 1.168 | 1.051 | 1.144 | 0.981 | .917 | .977 |
| 1993–4 | 1.233 | - | 1.170 | 0.817 | - | .799 | 1.508 | - | 1.464 |
| 1994–5 | 1.135 | - | 1.126 | .999 | - | .990 | 1.136 | - | 1.138 |

## 5. Conclusion

In this paper, we have reported three different measures of efficiency/productivity: Farrell input oriented efficiency index, multilateral TFP index and average Labour productivity. In addition, we have also reported a measure productivity change based on the Malmquist productivity change index and compare that to a measure based on the multilateral index. All these measures are based on a rich plant-level data set of Indonesian electrical equipment and electronics manufacturing establishments.

We highlight three important findings. First, we find that the multilateral and the Farrell efficiency computed based on pooled-observations provide essentially similar patterns of productivity. Hence, we can conclude, at least for our case, the multilateral TFP index seems to measure efficiency in terms of proportional distance from an ‘industry level’ production frontier. As a result, any change in this measure would be a mixture of the movement toward the frontier (the catching up effect) and the shift of the frontier (the innovative effect). For example, we would not be able to find out which effect underlies the increasing efficiency patterns observed from both entrants and survivors.

Second, the above mixed-effect problem is avoided if we use Malmquist productivity index. The Malmquist index decomposes into mutually exclusive efficiency change and technical change. Thus, we can have more insights regarding the trend of productivity for each turnover groups. For example, we find entrants tend to catch up early and adopt ‘better’ technology at later period. In other words, they start with positive efficiency change, continue with lower efficiency due to their adoption of better technology, and end with catching up to the new frontier. Surviving plants a similar pattern.

Third, we find evidence in support of Hopenhayn’s prediction in the sense that survivors are the most efficient of all plants. These results are statistically significant based on bootstrap analysis and Li’s nonparametric test of the closeness of distributions. Furthermore, entrants are significantly more efficient than exiters at the later period after entry, mostly due to their ability to move their production frontier and increase their efficiency. The difference between survivors and entrants at the later period appear to be insignificant.

We believe our results might be explained in terms of two important developments in the Indonesian manufacturing industry during the sample period. First, starting in mid 1980s, Indonesia launched a sequence of major deregulation of its manufacturing sector. These deregulation resulted in large inflows of foreign direct investment and market reorientation, from domestic to international (Pangestu, 1994 and Hill, 1996). The market reorientation may bring increased pressures from international competition on plants for improving their efficiency. At the same time, deregulation in bureaucracy and tariff structure would facilitate such efforts toward greater efficiency, which may explain the increasing efficiency early on. Second, the timing for opening the economy for foreign investment coincided with the industrial relocation from the East Asian economies, namely Japan, South Korea, Taiwan and Hong Kong (Jomo, 1997). Faced with increasing costs, in particular Labour costs, plants from these economies came to Indonesia and invested in the forms of either joint-ventures with existing local plants or new plants. This second development may explain the similar patterns of technical change between survivors and entrants above.

Finally, it would be interesting to see how the findings would vary across different subsectors of the Indonesian manufacturing industry. We leave this for our future research.

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