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# Sources of Productivity Growth in the Indonesian Manufacturing Industries

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## ABSTRACT

Generating output growth by adding more inputs into the production process may not be sustainable in the long run for any economy, given the limited resources. On the other hand, if productivity growth dominates the production process, it will generate more output without excessive increase in input use. Hence, this paper examines whether the output growth in Indonesia's manufacturing sector is excessive inputs driven or productivity driven. Productivity driven growth is measured by Total Factor Productivity (TFP) growth, which is decomposed into its major components of technological progress and technical efficiency within the framework of varying coefficients stochastic frontier analysis (VSFA) using Indonesia's annual Large and Medium Manufacturing Industries Survey data over the period 2002–2014. The measurement of the components of TFP growth not only provides more insights and better understanding of the dynamic nature of the production processes, but also has important policy implications. The mean TFP growth during the period 2002-2014 was estimated to be 4.3 per cent and was mostly contributed by technological progress experienced by firms. The policy implication is that technical efficiency could still be improved for the selected technology to reap the full benefit of increasing output from the chosen technology.

## KEYWORDS

Total factor productivity growth; Varying coefficients stochastic frontier analysis; Technological progress; Technical efficiency Indonesia

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## 1. Introduction

Indonesia is the fourth most populous country with 280 million people in 2023 in the world and the world's largest island group (archipelago) with more than 17,000 islands. These islands are diverse from each other, with different cultures and geographical features. The economy of Indonesia is the largest in Southeast Asia and is one of the emerging market economies. As a middle-income country and the member of the G20, Indonesia is classified as a newly industrialized country. Indonesia's economic structure has changed significantly in the recent decades. Before the 1980s, Indonesia depended heavily on the agricultural sector. During the 1950s and 1960s, the Indonesian government focused on promoting agricultural self-sufficiency programs by implementing several policies. However, with the declining oil price in the 1980s, the Indonesian government diversified its exports from exporting oil toward exporting manufacturing goods. Since that decade, manufacturing has contributed 27 per cent on average to the Indonesia's GDP from 2000 to 2015. In terms of the size of the industry, large- and medium-sized firms have contributed most to manufacturing's value-added, which is 40 per cent of the total manufacturing GDP. By contrast, small- and micro-scale industries in the same period contributed less than 10 per cent on average[1]. Despite the importance of large- and medium-scale industries to Indonesia's economy, these industries have experienced unstable and low output growth in the recent decades, which is an alarming concern for the Indonesian policymakers. It is in this context, the objective of this study is to identify the major causes for the low output growth of the large- and medium- scale manufacturing industries in Indonesia.

Output growth can be achieved through growth in productivity and/or excessive use of inputs. However, it is not sustainable in the long-run to increase output by excessive use of inputs, given the limited resources. Productivity growth is the most important factor at firm level or industry level since it allows the firm or industry to compete with other sectors of the economy for limited resources and even improve its competitiveness in the marketplace. The benefits of productivity growth can be distributed in several ways, such as through better wages and conditions for labour, lower prices for consumers and increased tax payments to the government, which can be used to fund social and economic programs (Parham, 2011). Hence, it is crucial from the policy perspective to examine whether output growth is due to excessive inputs use or productivity driven.

In this study, productivity driven output growth is measured by total factor productivity (TFP) growth. TFP recognises that all inputs are scarce and productivity driven growth of output comes from all combined inputs, not just one input. To analyse the sources of productivity driven growth, TFP in this study is decomposed into its two major components, technological progress and technical efficiency change. Technological progress, which comes from technological inventions and innovations (Hulten et al., 2001) resulting in increased output, causes a shift in the production function. However, technological progress cannot be the only source of TFP as long as firms are not operating on the production possibility frontier of the chosen technology that shows the maximum potential output (Kalirajan et al., 1996). A firm's capability and willingness to produce the maximum potential output by following the 'best practice' techniques of the chosen technology is defined as technical efficiency (TE) in the literature. Consequently, technical inefficiency is 'a gap that normally exists between a firm's actual and potential maximum possible levels of output' (Kalirajan et al., 1996).

The theoretical implication of the above argument is that the different methods of application of inputs by different firms deviating from the 'best practice' techniques recommended by the technology will not yield the potential maximum possible output for those firms. In other words, the contribution of inputs to output growth, which is measured through the sign and size of the input response (slope) coefficient, will vary across firms. Now, the interesting question is about why all firms are not following the 'best practice' techniques of the chosen

[1] Additionally, the data for micro and small-scale industries are not available for 5-digit ISIC (more detailed classification) as in the case of the medium- and large-scale industries.

technology. It is argued in the literature that different methods of application of inputs across firms is influenced by the existing institutional and organisational factors and shifts in social attitudes (Hulten et al., 2001). Then, it is imperative to include the above aspect of firms' decision-making behaviour with respect to inputs application in the modeling of the output growth, which is followed in this paper by estimating the stochastic varying input response coefficients frontier production function. Further, it is logical to argue that high rates of technological progress can co-exist with deteriorating technical efficiency performance and relatively low rates of technological progress can also co-exist with an improving technical efficiency performance. Therefore, specifically focused policy actions are required to improve the performances of the two components of the TFP growth.

The research questions that are empirically examined in this paper are the following:

- Whether Indonesia's medium- and large-scale manufacturing firms' output growth is excessive inputs driven or productivity driven?
- Whether high rates of technical progress co-exist with deteriorating or improving technical efficiency performance in the Indonesian medium- and large-scale manufacturing firms?

The rest of the paper is organised as follows. Section 2 summarises the literature review on Indonesian manufacturing industries performance. The theoretical framework of the varying coefficients stochastic frontier analysis is discussed in Section 3. After describing the data, the empirical model used in the study is explained in Section 4. The empirical results and discussion are presented in Section 5. Section 6 concludes the paper with policy implications and suggestions.

## 2. A brief review of the Indonesian manufacturing analysis

Several studies have analysed Indonesian manufacturing productivity in the past. Pitt and Lee (1981) introduced variance component models to estimate the production frontier function in the Indonesian case. They used firm-level data from the Indonesian weaving industry. By implementing a time-invariant efficiency component with the Cobb-Douglas functional form, it was found that the weaving industry gained between 60 and 70 per cent in average technical efficiency. Another study about Indonesian manufacturing performance was conducted by Hill and Kalirajan (1993). Using the conventional constant coefficient stochastic frontier production function approach (SFA), they examined firms' technical efficiency using the Indonesian textile industry from the Indonesian Small Industry Census in 1986. From a sample size of 2250 firms, the authors concluded that inter-firm disparities in inefficiency are substantial. Furthermore, their findings also suggested that the level of labour -to- capital substitution was substantially high in the textile industry.

Timmer (1999) studied firm performance in large-and medium- scale manufacturing in Indonesia from 1975 to 1995. In his paper, he estimated total factor productivity growth, by applying the growth accounting method and estimated that manufacturing output grew at the rate of 60 per cent per year over the years observed. He argued that this output growth was decomposed by 18 per cent due to labour input and 22 per cent due to TFP growth, whose annual growth was 3 per cent. Timmer also found that there was no significant evidence of factor input shifting from less efficient to more efficient firms. However, policy changes in the manufacturing sector were found to be beneficial in boosting industries' performance. From the perspective of global competitiveness, it has been argued that with the actual level of TFP achieved, the Indonesian manufacturing sector faces challenges to catch-up with the world frontier.

By utilising firm-level data in some sectors in manufacturing, Margono and Sharma (2006) investigated the level of technical efficiency and TFP growth in the food, textile, chemical and metal products industries from 1990 to 2003 by implementing the stochastic frontier model and decomposing TFP into three components of technological progress, a scale component, and technical efficiency change. In terms of TFP growth, only the chemical sector gained positive TFP growth at the level of 0.5 per cent, while other sectors faced negative levels of

TFP growth. The authors argued that TFP growth was driven positively by technical efficiency change, but negatively by technological progress. Their results showed that the metal product sector achieved the highest mean technical efficiency of 68.9 per cent, while the food, garment, and chemical industries obtained 50.8 per cent, 47.9 per cent and 68.7 per cent technical efficiency respectively.

Mohamad Ikhsan (2007) applied a similar methodology as Margono and Sharma (2006) to analyse TFP growth in medium and large-scale manufacturing firms from 1988 to 2000. He estimated that average technical efficiency generally decreased by 1.47 per cent per year with significant inter-industry variation as some particular sub-sectors had improved their level of efficiency. Moreover, he also argued that the Asian financial crisis in 1998 impacted differently on a firm's performance in each subsector industry. Regarding TFP growth, Mohamd Ihksan calculated that TFP grew at the rate of 2.8 per cent annually, contributed mainly by technical efficiency with the share of TFP contribution being 3.98 per cent. On the other hand, technological progress and scale component contributed 1.47 per cent and 1.28 per cent respectively towards TFP growth. His study argued that arranging and retaining technological infrastructure is crucial to increasing productivity growth since the learning-by-doing effect in technology adoption was found to be highly significant in the estimation. Furthermore, since technological progress had been decreasing, the component that may help to increase TFP growth is technical efficiency. Therefore, an increase in firm efficiency is crucial in the Indonesian manufacturing sector.

Unlike others who applied individual firm-level data, Margono et al. (2011) analysed technical efficiency and TFP growth in Indonesia using provincial-level data between 1993 and 2000. The authors who implemented SFA and TFP decomposition in their research found that TFP decreased gradually by 7.5 per cent annually across provinces because of low levels of technical efficiency. They argued that output growth was determined by the accumulation of input growth. Using a different data set, the Indonesia Stock Exchange data set, Prabowo and Cabanda (2011) investigated firm technical efficiency during 2000-2005 in 121 firms. Based on their estimation, the mean technical efficiency of the sample was 71 per cent.

Particular focus on the effect of FDI on domestic firm performance has also been analysed by Suyanto et al, (2009) . They examined the effect of foreign direct investment (FDI) on productivity growth in Indonesian chemical and pharmaceutical plants by implementing stochastic frontier analysis and the Malmquist output-oriented index to decompose productivity growth. From their estimation, they argued that FDI provided positive spillovers for productivity growth in particular, boosting only technological progress, not technical efficiency. Suyanto and Salim (2013) investigated the effects of FDI spillovers on the technical efficiency of Indonesian pharmaceutical firms from 1990-1995. The authors compared two approaches, SFA and data envelopment analysis (DEA), to estimate how FDI affects domestic firms' efficiency. From the estimation, they argued that the two approaches demonstrated similar results. It has been concluded that foreign-owned firms gained higher technical efficiency than domestically owned firms. Similarly, it had been found that firm productivity of foreign-owned firms was higher than that of locally owned firms. However, when the degree of foreign ownership increased, productivity would decrease, but technical efficiency would increase.

After focusing on only one sector in the industry, Suyanto et al., (2014) investigated the effects of FDI on firms' efficiency in all manufacturing sectors between 1988 and 2000. Their results show that FDI had positive effects on efficiency improvement. However, when the estimation is divided into two different samples; low and high efficiency, the results were different. In the low-efficiency group, FDI boosted efficiency. In contrast, FDI brought negative impacts on the firm's efficiency among high-efficiency firms. Moreover, when FDI was classified into different spillovers such as horizontal, backward, forward, the effects of spillovers varied. Horizontal spillovers were found to have positive effects on productivity and technical efficiency. Backward spillovers contributed positively to efficiency but negatively to productivity. On the other hand, forward spillovers have an opposite direction where they have positive effects on productivity but negative effects on efficiency. Another spillover that was captured in

Suyanto and Bloch's research is technology spillovers from FDI (Sari et al., 2016).

Most of those above studies also estimated TFP growth by decomposing into technological progress and technical efficiency. Those studies assumed that all firms applied the 'best practice' techniques of the chosen technology and hence would have the same input response coefficients to output. Hence, those studies assumed that the difference between a firm's actual and potential maximum outputs solely results from the difference in intercept coefficients, which is questionable. As discussed above, it is logical to argue that the slope coefficients would also vary across firms due to the heterogeneity in the method of application of inputs, which may vary from the 'best practice' application of inputs dictated by the technology. Those studies implicitly assumed that there were not any significant differences in the method of application of inputs from the recommended 'best practice' techniques across firms and hence all firms had the same production slope coefficients. This would result in a misspecification bias when time-varying unobservable factors may exist leading to differences in slope coefficients. To address this limitation, drawing on Kalirajan and Obwona (1994), this paper applies a stochastic varying coefficients frontier production function analysis (VSFA) framework, which assumes variation in the method of application of inputs from the 'best practice' methods across firms. This approach enables us to predict the frontier production function to estimate not only firm-specific slope coefficients, but also firm-specific TE.

## 3. Theoretical framework of the stochastic varying coefficients frontier production function analysis and firm-specific technical efficiency[2]

### 3.1. Theoretical Modelling

Theoretically the potential maximum output is defined as the output that is obtained by following the 'best practice' methods of application of inputs recommended by the technology. In other words, potential maximum output is achieved through realizing full technical efficiency. It is logical to argue that not all firms would follow the 'best practice' methods of application of inputs due to their firm-specific production environments. Hence, heterogeneity in the method of application of inputs, which may vary from the 'best practice' application of inputs dictated by the technology, would lead to variations in the inputs response or slope coefficients across firms. Therefore, contrary to the conventional stochastic frontier production function, which assumes a constant slope across firms, it becomes necessary to assume a varying slope across firms. In turn, such variations would lead to differences in the level of firm-specific technical efficiency. Therefore, it is important from the policy perspective to take into account of the fact of variations in the method of application of inputs across firms, which is carried out in this study.

To address the limitation of the conventional constant-slope stochastic frontier analysis that overlooks to show variation in the firm's methods of applying inputs, drawing on the random coefficient regression model (RCRM) popularised by Swamy (1970), Kalirajan and Obwona (1994) developed the varying coefficients stochastic frontier analysis. The RCRM allows for estimating heterogeneity in functional relations between dependent and independent variables. Consider the model:

$$y_i = x_i\beta_i + u_i \tag{1}$$

where $y_i = (y_{i1}, y_{i2}, \dots, y_{in})$ is an observation's n x 1 sized-vector on the left-hand side variable; xi is an observations' matrix with sized of n x K matrix of observations on the right-hand side variables, where K is the number of ranks. In terms of panel data, this matrix will be represented as $x_{itk}\ (t = 1,2,\dots,T; k = 0,1,\dots,K-1)$; $\beta_{ji}$ is a coefficients' K x n-vector which is turned into $\beta_{itk}\ (t = 1,2,\dots,T; k = 0,1,\dots,K-1)$ for panel data

[2] Similar discussion on the varying coefficients estimation but not in the context of stochastic frontier production function has been done by Ackerberg et al. (2015).

estimation; and $u_i \equiv (u_{i1}, u_{i2}, \dots u_{in})$ is an unobserved random error vector. There are T observations on each of the n individual units.

The above model follows the assumptions given below:

- The sample sizes (n and T) have to be larger than the number of ranks (K).
- The left-hand side variables are non-stochastic (Xi-), and are fixed in repeated samples on yi.
- The unobserved random error vector (ui is independently distributed with an expected mean of zero (E(ui) = 0) and a variance-covariance matrix of ui is σiiIT.
- The coefficient vectors $\beta_{ji}(j = 1,2, \dots k)$ and $(i = 1,2, \dots, n)$ are independent and identically distributed (iid) with $E(\beta_{ji}) = \bar{\beta}_j$ and $E[(\beta_{iji} - \bar{\beta}_j)(\beta_{iji} - \bar{\beta}_j)'] = \Delta$, which is non-singular.
- The vectors ui and βj are independent for every $i = 1,2, \dots, n$.

Assumption 3 implies that the disturbance is both contemporaneously and serially uncorrelated. Assumption 4 suggests that the vectors of estimated coefficients $(\beta_{ji})$ are random drawings from the same non-singular multivariate distribution with mean $\bar{\beta}_j$ and variance-covariance matrix Δ.

The coefficients to be estimated are $\bar{\beta}, \Delta$ , and $\sigma_{ii}$. These parameters can be predicted by assuming

$$B_{ji} = \bar{\beta}_j + \delta_{ji}(j = 1,2,..k) \; and \; (i = 1, 2, \dots, n) \tag{2}$$

where $\delta_{ji}$ is a random element's $K \; x1$ vector. Drawing from assumption 4, random elements are iid with zero mean and variance-covariance matrix Δ. Now, Equations 1 and 2 can be written as follows:

$$\begin{bmatrix} y_1 \\ y_2 \\ . \\ . \\ . \\ y_n \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \\ . \\ . \\ . \\ x_n \end{bmatrix} \bar{\beta} + \begin{bmatrix} x_1 & 0 & \dots & 0 \\ 0 & x_2 & \dots & 0 \\ . & . & \cdots & . \\ . & . & \cdots & . \\ . & . & \cdots & . \\ 0 & 0 & \dots & x_n \end{bmatrix} \begin{bmatrix} \delta_1 \\ \delta_2 \\ . \\ . \\ . \\ \delta_n \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ . \\ . \\ . \\ u_n \end{bmatrix} \tag{3}$$

or more compactly as,

$$y = X\bar{\beta} + D(X)\delta + u \tag{4}$$

where $y \equiv [y'_1, y'_2, \dots, y'_n]', X \equiv [X'_1, X'_2, \dots, X'_n]', \delta \equiv [\delta'_1, \delta'_2, \dots, \delta'_n]', u \equiv [u'_1, u'_2, \dots, u'_n]'$.

To estimate $\bar{\beta}$, Aitken' generalized least square is applied. Thus the best linear unbiased estimators for $\bar{\beta}$ is

$$\bar{b}(\theta) = (X'H(\theta)^{-1}X)^{-1}X'H(\theta)^{-1}y = \left[\sum_{j=1}^{n} X_j'\{X_j \Delta X'_j + \sigma_{jj} I_T\}^{-1} X_j\right]^{-1} . \left[\sum_{i=1}^{n} X_i'\{X_i \Delta X'_i + \sigma_{ii} I_T\}^{-1} y_i\right]^{-1}$$

$$= \sum_{i=1}^{n} W_i(\theta) b_i \tag{5}$$

where

$$W_i(\theta) = \left[\sum_{j=1}^{n} \{\Delta + \sigma_{jj}(X'_j X_j)^{-1}\}^{-1}\right]^{-1} . \left[\sum_{i=1}^{n} \{\Delta + \sigma_{ii}(X'_i X_i)^{-1}\}^{-1}\right]^{-1}, \; bi = (X'_i X'_i)^{-1} . X'_i y_i \tag{6}$$

For the panel data, the variance of estimated parameters $(bi)$ and the variance of disturbance error are different among individual observations because $X_i$ varies across the individuals. After estimating $\Delta$ and obtaining the estimates of the mean response coefficients in (5), predictions of the individual response coefficients $B_{ij}$; $s$ are obtained following the methods suggested by Lee and Griffiths (1979).

In order to calculate the technical efficiency of each firm, the estimation of potential output is the first thing that should be generated. The estimation of the potential output is based on the estimates of $\beta_{ij}$ ; $j = 0, 1,2, \ldots k, and\ i = 1,2,..n$, which are parameter estimates of each firm's output response from specific inputs. From among these parameter estimates, the production responses that follow the 'best practice' method can be inferred from the size of the parameter estimates. It is logical to argue that the input response coefficients would be the largest for those firms that follow the 'best practice' methods of applying the inputs. Hence, the largest estimates of the input response coefficients are selected from among the firm-specific estimates of the input response coefficients, which are different across individuals at the specific time period, as follows:

$$\beta_j^* = \max_i\{\beta_{ij}\}, \qquad j = 0,1,2, \ldots, K, and\ i = 1,2, \ldots n \tag{7}$$

There are two different arguments about the best response coefficients ($\beta_j^*$). First, it is reasonably assumed that not every firm applies all its inputs efficiently by following the 'best practice' methods. Hence, production response coefficients are not required to be the same for all firms and also all production coefficients may not come from any single firm. To illustrate, assuming there are 100 observations, the best response of labour input maybe from the fifth observation, but the best response for capital may come from the twentieth observation. Another argument about the best response coefficients is that the possibility of getting the best response coefficient from one observation cannot be totally ruled out. "The human capital theory literature argues that a firm which uses some inputs efficiently may also use all inputs efficiently" (Kalirajan and Obwona, p. 90, 1994). Firm-specific potential maximum output is calculated by multiplying the best input response coefficients shown in equation (7) with the corresponding actually used firm-specific input levels and by adding them up.

The frontier production function that shows the potential output and as a benchmark for each of the sample firm ($y_i^*$) is calculated by:

$$ln\, y_i^* = \beta *_0 + \sum_{k=1}^{K} \beta *_k\, lnx_{ik} + \alpha_{it} t, i = 1,2, \ldots .n\ and\ t = 1,2 \ldots .T$$

The ratio of the firm-specific actual output to the calculated potential maximum output shows the firm-specific technical efficiency for that particular year.

Therefore, a firm's specific TE will be: $\frac{\text{actual output}}{\text{potential output}}$.

### 3.2. Total Factor Productivity Growth: Measurements and Decomposition

Thus, drawing on the above discussions, it is rational to argue that three core components determining output growth are input growth, technological progress, and technical efficiency change. Assume that a firm faces two periods, periods 1 and 2, and hence, the firm will operate on two production frontiers, $F1$ for period 1 and $F2$ for period 2 as shown in Figure 1. Technological progress shows the improvement of potential outputs from period 1 to period 2 at the certain level of inputs used. This improvement is measured by the distance from $F2$ to $F1$, that is, ($y2^{*\prime\prime} - y2^*$) by utilising $X2$ input levels or ($y1^{*\prime\prime} - y1^*$) by applying $X1$ input levels. Technological progress or technical change involves the development of technology that can be represented by shifting the production frontier. To illustrate, the installation of more developed equipment for coal-fired power plants extends a firm's potential productivity beyond previous limits. Another component of TFP is technical efficiency. A firm is identified as technically inefficient if it does not work on its frontier production function, such as operating at $Y1$ or $Y2$. Therefore, technical inefficiency ($TI$) can be calculated by measuring the vertical distance between the potential output reflected on frontier output ($y1^*$ $or$ $y2^{*''}$) and the actual output produced by the firm ($Y1$ $or$ $Y2$) at a certain level of input ($X1$ $or$ $X2$). It can be seen that technical inefficiency is $TI1$ in period 1 and $TI2$ in period 2. Moreover, technical efficiency improvement can be measured by calculating the difference between $TIl$ and $TI2$ ($TI1 - TI2$). If the difference is positive, it shows that there has been technical efficiency improvement in the production process. On the other hand, if the value is less than zero, it indicates that technical inefficiency increases over time (Kalirajan et al., 1996). From Figure 1, it can be seen that the decomposition of output growth is $Output\ growth = Y2 - Y1$,

$$\begin{aligned} D &= A + B + C \\ &= [Y1* - Y1] + [Y1*'' - Y1*] + [Y2 - Y1*''] \\ &= [Y1* - Y1] + [Y1*'' - Y1*] + [Y2 - Y1*''] + [Y2*'' - Y2*''] \\ &= [Y1* - Y1] + [Y1*'' - Y1*] - [Y2*' - Y2] + [Y2*'' - Y1*''] \\ &= \{[Y1* - Y1] - [Y2*' - Y2]\} + [Y1*'' - Y1*] + [Y2*'' - Y1*''] \\ &= \{TI1 - TI2\} + TC + \Delta Yx \end{aligned} \tag{8}$$

= Technical inefficiency change + Technological progress + input growth.

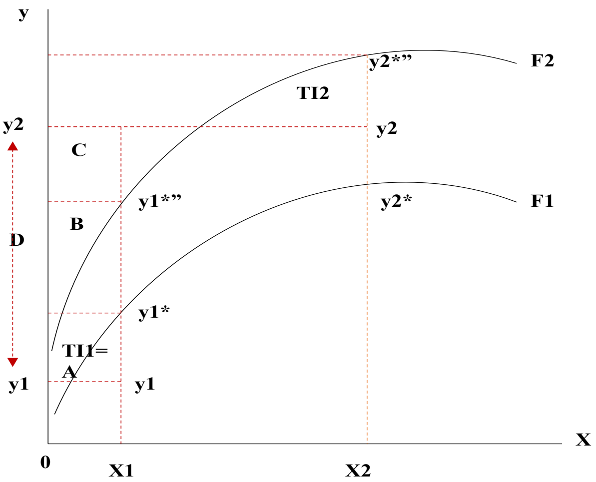


**Figure 1.** Output growth decomposition.

*Source: Kalirajan et al. (1996).*

Since the TFP growth (TFPG) is defined as output growth that is not defined by input growth, TFPG is calculated as:

$$TFPG = Technical\ inefficiency\ change + Technological\ progress = (TI1 - TI2) + TC \tag{9}$$

Then, TFP growth in equation 9 between consecutive period (t-1) and t for the ith firm can be calculated as:

$$\Delta TFPG = ln\left(\frac{TFPG_{i,t}}{TFPG_{i,t-1}}\right) \tag{10}$$

## 4. Data and empirical model

### *4.1. Data description*

This research utilises firm-level data of the Indonesian large and medium manufacturing industries annual survey undertaken between 2002 and 2014. The whole period of analysis is divided into two periods; one the period before the Global Financial Crisis (2002-2008) and the other the period after the Global Financial Crisis (2009-2014). Total factor productivity growth is calculated between the above two periods for further analysis. The survey is conducted by the Indonesian Central Agency on Statistics (BPS)[3]. Moreover, this research uses balanced panel data to measure technical efficiency and TFP because balanced panel data enables us to observe all existing firms without worrying about the exit firms and new entrants during certain periods. All the firms4 are classified under the 5-digit International Standard Classification (ISIC) Rev 4. Moreover, Baltagi (2009) also argues that using balanced data will avoid the problem of inflating error terms resulting from unbalanced panel data estimation. Since there are more than one-year periods, to consider the monetary effect, all the monetary variables are deflated using the wholesale price index (WPI) at 2005 as a base year.

The variables used in the production function are given in Table 1 below.

**Table 1.** Definition of variables.

| Variables | Definitions |
|---|---|
| $Y$ | The total output produced by a firm (thousand IDR) that is deflated by the wholesale price index (WPI) for five-digit ISIC industries at a constant price of 2005 |
| $C$ | Total value of fixed asset owned by firms, such as buildings, machinery, transportation, livestock and other capital goods, which contribute to the continuity of a production process (thousand IDR) deflated by WPI at a constant price of 2005 |
| $L$ | Total number of workers (males and females) in one year (person) |
| $E$ | Total expenditure on gasoline, diesel fuel, kerosene, public gas, lubricant and electricity deflated by WPI at a constant price of 2005 |
| $M$ | Total values of raw materials are (goods are processed into another form) and other items used in the processing of raw materials. It is in thousand IDR and deflated by WPI at a constant price of 2005 |
| $t$ | Time trend |

### *4.2. Empirical Model*

The empirical model estimated in this study is as follows:

$$lny_{it} = \beta_{0t} + \beta_{i1t} lncap_{it} + \beta_{i2t} lnlab_{it} + \beta_{i3t} lnengy_{it} + \beta_{i4t} lnraw\ matl_{it} + \beta_{i5t}\, t + u_{it}$$

Where, y refers to output and rest of the variables are self-explanatory. u refers to the statistical error term and i = 1 to 390 and t = 1 to 13.

## 5. Results and discussion of components of TFP and TFP growth

[3] The panel data used in this study is drawn from the 'secondary' data only. The Annual Survey of large and medium Industries covers all large and medium scale firms (complete enumeration) in the territory of Indonesia collected by the Indonesian Central Agency on Statistics (BPS). As these surveys are the only major surveys covering the entire medium and large-scale manufacturing firms in Indonesia, these are used by researchers in Indonesia and overseas. Large-scale firms are processing industrial manufacturing firms with a total workforce of 100 people or more. While medium scale firms are manufacturing industrial firms with a workforce of 20 - 99 workers.
The method used to record information in data collection is a combination of direct and indirect interviews (self-enumeration) by BPS. Direct interviews are usually for questions that can be answered directly by the person in charge of the firm. While the indirect interview concerns leaving the questionnaire at the firm by providing a technical explanation of how to fill it out, the questionnaire is left for the firm to fill out. If the questionnaire has been completely filled out by the firm, it can be returned via the survey officer, sent via post, sent via e-mail to BPS, and sent via facsimile to BPS. The accuracy of the data has not been doubted in the literature.

[4] No information is given in the survey whether a firm is an incorporated entity or production entity as there is no information about the detailed goods produced by the firm.

## *5.1. Components of TFP: Technical efficiency*

**Table 2.** Descriptive statistics of the output and input in the analysis.

| Period | | Mean | Min | Max | Number of firms | Observations |
|---|---|---|---|---|---|---|
| 2002 - 2008 | Output | 4.94e+07 | 26,727.3 | 2.79e+09 | 390 | 2,730 |
| | Capital | 5,079,993 | 12,021.7 | 1.79e+08 | 390 | 2,730 |
| | Labour | 206.9 | 20 | 7,716 | 390 | 2,730 |
| | Energy | 1,341,638 | 104.2 | 2.90e+08 | 390 | 2,730 |
| | Raw material | 3.71e+07 | 14,472.6 | 4.34e+09 | 390 | 2,730 |
| 2009 - 2014 | Output | 6.17e+07 | 24,430 | 3.74e+09 | 390 | 2,340 |
| | Capital | 6,084,576 | 11,252.22 | 3.27e+08 | 390 | 2,340 |
| | Labour | 201.4 | 20 | 7,616 | 390 | 2,340 |
| | Energy | 1,089,352 | 111.9 | 1.39e+08 | 390 | 2,340 |
| | Raw material | 4.47e+07 | 13,266.2 | 2.54e+09 | 390 | 2,340 |

Table 3 presents the range of estimates of the response coefficients of inputs for an individual firm during the tth period of analysis resulting from the stochastic varying coefficients frontier production function Analysis (VSFA) for the periods 2002-2008 and 2009-2014. It can be seen that the variations in the input response coefficient are quite substantial under the VSFA approach. This suggests that the application methods to use different inputs vary among firms. This means that each input contributes to output differently across the sample. Therefore, it can be argued that applying the varying-slope to estimate production frontiers is more appropriate than the conventional constant-slope approach.

**Table 3.** Range of estimates resulting from VSFA.

| Period | Inputs | Range of parameters | Mean of parameters |
|---|---|---|---|
| 2002-2008 (earlier period) | Constant | -0.047 – 0.056 | 0.03** |
| | | (0.013 - 0.022) | (0.02) |
| | Capital | -1.035 – 1.2 | 1.05*** |
| | | (0.16 - 0.48) | (0.09) |
| | Labour | -0.29 – 0.13 | 0.024*** |
| | | (0.01 - 0.01) | (0.0085) |
| | Energy | -0.22 - 0.092 | 0.04** |
| | | (0.039 - 0.088) | (0.027) |
| | Raw material | -0.095 – 0.28 | 0.12*** |
| | | (0.038 - 0.11) | (0.05) |
| | Time | -0.16 – 0.016 | 0.002*** |
| | | (0.006 - 0.064) | (0.0009) |
| 2009-2014 (later period) | Constant | -0.05 – 0.037 | 0.025** |
| | | (0.015 - 0.02) | (0.014) |
| | Capital | 0.88 – 1.36 | 1.09*** |
| | | (0.35 - 0.54) | (0.09) |
| | Labour | -0.32 – 0.168 | 0.028*** |
| | | (0.03 - 0.05) | (0.0069) |
| | Energy | -0.2 – 0.052 | 0.07*** |
| | | (0.02 - 0.08) | (0.024) |
| | Raw material | -0.23 – 0.13 | 0.06*** |
| | | (0.052 - 0.09) | (0.02) |
| | Time | -0.016 – 0.039 | 0.006** |
| | | (0.002 - 0.006) | (0.003) |

*Notes: Figures in brackets are standard errors of estimates. ** refers to significant at the 5% level. *** refers to significant at the 1% level.*
*Source: Authors' estimations.*

The mean technical efficiency during the period of 2000–2008 worked out to be 49 per cent (Figure 2). This means that firms could increase their output by about 51 per cent with the same levels of inputs, but by following the 'best practice' methods of application of inputs at the firm-level. The range of TE is between 27 per cent and 100 per cent with a standard deviation of 0.17.

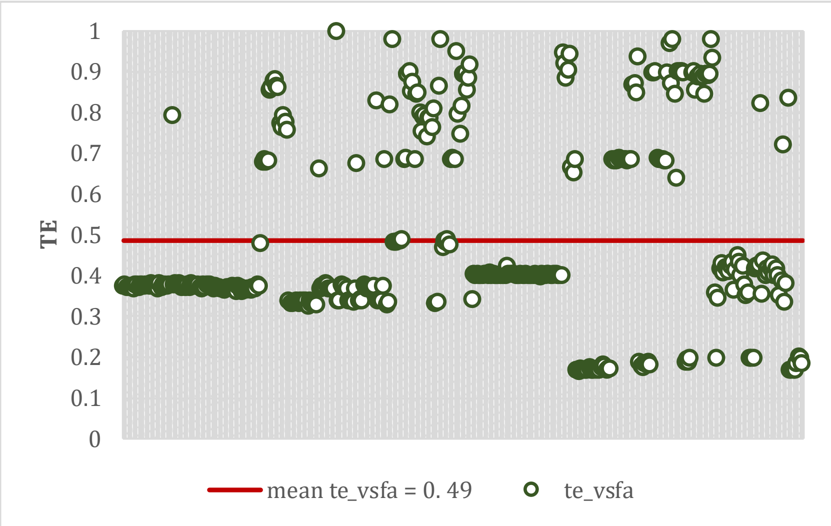


**Figure 2.** Distribution of technical efficiency by firms, 2002-2008.

*Source: Authors' estimations.*

In the latter period, between 2009 and 2014, there is a different pattern of technical efficiency (Figure 3). In this period, the mean of TE worked out to be 51 per cent. In other words, firms could increase their output by about 49 per cent with the same amounts of inputs, but following the 'best practice' application of inputs.

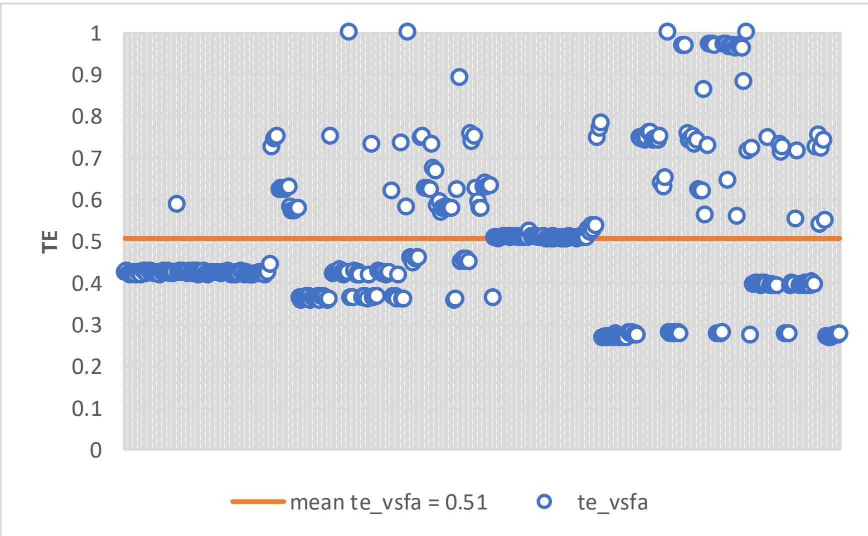


**Figure 3.** Distribution of technical efficiency by firms, 2009-2014.

*Source: Authors' estimations.*

## *5.2. Components of TFP: Technological progress*

Another important determinant of the TFP is technical change or technological progress that measures how frontier production shifts due to technological improvement. Moreover, shifts over time of production frontiers (that is, technological progress), are assumed to be neutral in the constant intercept stochastic frontier production function approach. The procedure proposed and empirically demonstrated in this paper relaxes the restrictive assumption of neutral technological progress. In this paper the assumption is that frontier production functions themselves shift non-neutrally over time.

The average technological progress in the years 2009-2014 relative to 2002-2008 was 4.3 per cent with a range from -18.9 to 31.2 per cent. This condition reflects that technological progress in the manufacturing sector varies among individual firms. This is because the degree of technological upgrading across the firms in Indonesian manufacturing is disparate. There are many factors contributing to the divergent pattern of technological development across the firms. For example, FDI, as the main source of technological progress, has remained heavily dominated by capital and resource-intensive manufacturing firms (Frankema & Linblad, 2006). Another reason is that research and development expenditure in the manufacturing sector is still relatively low compared to other countries such as South Korea and Taiwan. The value of technological change is presented in Figure 4.

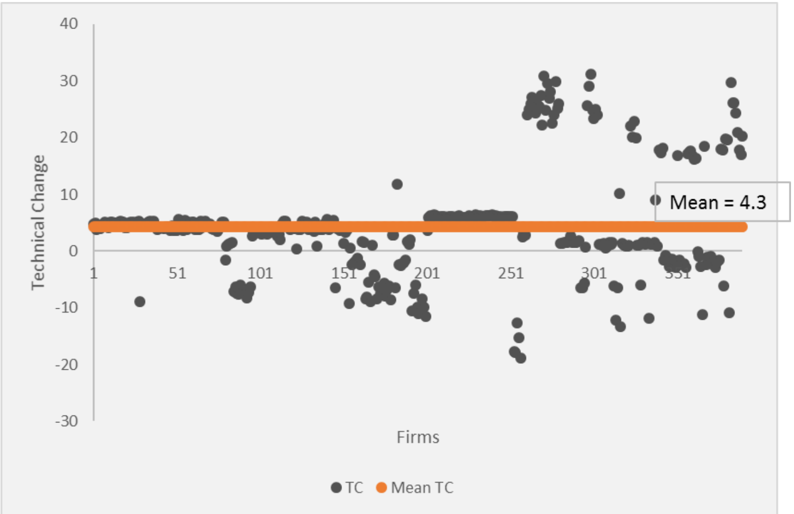


**Figure 4.** Technological change by firms.

*Source: Authors' estimations.*

## *5.3. Total Factor Productivity Growth*

The first component of decomposing TFP is technical inefficiency change. This is measured by changes in the years 2009-2014 compared to 2002-2008. The mean of technical inefficiency change is –0.023, which means that there is 2.3 per cent of the average increase in firm's technical efficiency improvement in 2009-2014 compared to 2002-2008. The inefficiency changes range from -3.8 per cent to 4.2 per cent. Nevertheless, 23 per cent of the samples experienced a decrease in technical efficiency in the later period. Technical inefficiency change is presented in Figure 5.

Figure 6 shows that the average TFP growth in Indonesian manufacturing during the period 2002-2014 was 4.3 per cent. This result is relatively consistent with previous studies. Timmer (1999) found that the food industry's TFP grew at a rate of 5.7 per cent between 1991 and 1995. Meanwhile, the textile industry experienced TFP growth at a rate of 3.6 per cent. Aswicahyono and Hill (2002), using data on 28 industries, found that Indonesian manufacturing's TFP growth from 1981 to 1993 was 4.9 per cent on average. However, the findings of this study are not directly comparable with those previous studies because the methodological approach taken is different. The previous studies assume a neutral shift in the production frontier instead of a non-neutral shift, as assumed in this study.

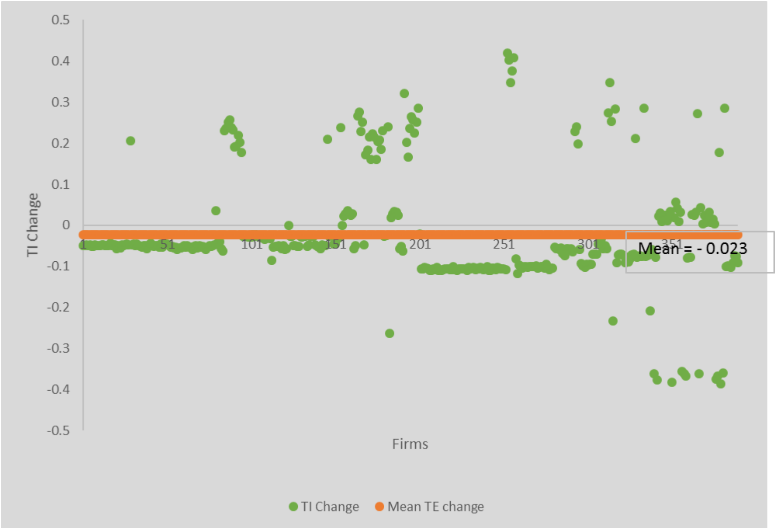


**Figure 5.** Technical inefficiency change by firms.

*Source: Authors' estimations.*

Considering the mean and the variance in TFP growth, it is inferred that the TFP growth in the sample is dominated by the value of technological progress. Regarding the general performance of the firms, 42 per cent of the sample gained higher TFP growth than the sample mean TFPG. On the other hand, 24 per cent of the sample experienced negative TFP growth. From the above discussions, with respect to the first research question, the answer is that generally in Indonesian manufacturing, output growth was contributed by the TFP growth due to technological progress more relative to technical efficiency improvement during the study period. In other words, the output growth in Indonesian medium- and large-scale manufacturing firms was productivity driven. In addition, the answer to the second research question is that the above empirical results indicate that high rates of technical progress co-existed with improving technical efficiency performance in the Indonesian medium- and large-scale manufacturing firms.

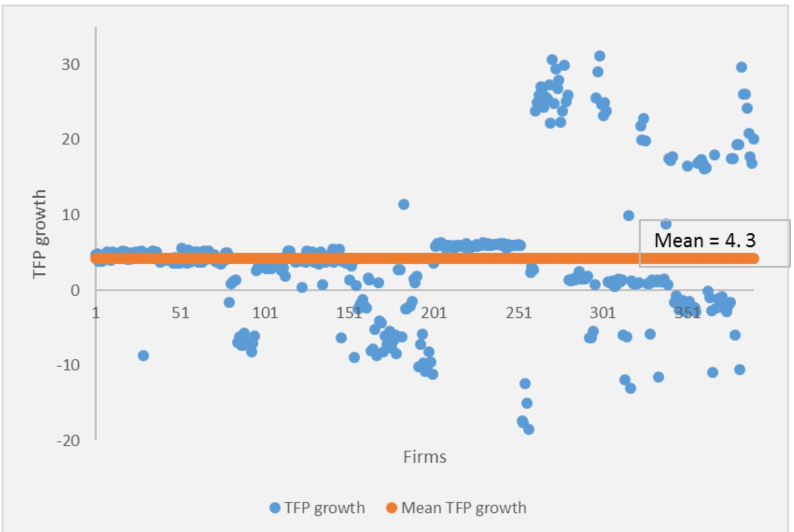


**Figure 6.** Total Factor Productivity (TFP) growth by firms.

*Source: Authors' estimations.*

## 6. Conclusion and Policy Suggestions

This study examined why the large- and medium-scale industries, which are crucial to the Indonesia's economic growth, have experienced unstable and low output growth in the recent decades. It is in this context, using the panel data covering the years 2002-2024 the objective of this study is to identify the major causes for the low output growth of the large- and medium- scale manufacturing industries in Indonesia. Specifically the research questions examined are: whether the output growth in the Indonesian manufacturing industries is excessive inputs driven or productivity driven; and whether there is technological progress along with technical efficiency improvement or technical efficiency deterioration during the study period.

The productivity driven growth is evaluated by measuring the total factor productivity (TFP) growth by decomposing it into technical efficiency and technological progress by using the varying coefficients stochastic frontier production function (VSFA) approach. By arguing, that TE measured through VSFA considers firm's heterogeneity in decision-making and application of inputs more accurately; total factor productivity growth in this study is measured drawing on this approach. The measurement of the components of the TFP growth provides a means of measuring the phenomenon of catching up (with the frontier) and also of innovation (shifts in the frontiers). VSFA reveals that TFP growth during 2002 – 2014 in Indonesia's large- and medium-scale industries was 4.3 per cent, which is larger than the technical efficiency improvement of 2.3 per cent over the study period. This fact implies that the output growth in the Indonesian medium- and large-scale manufacturing industries was productivity driven and also there was technological progress along with technical efficiency improvement between the years 2002 and 2014.

Finally, the measures of distinct TFP growth components not only provide more insights and better understanding of the dynamic nature of the production processes, but also have important policy implications. For example, the empirical analysis revealed that TFP growth was contributed mostly by technological progress and to a lesser amount by technical efficiency improvement during the study period. The implication is that simply by pursuing equal opportunity for industrial technology development to boosting productivity in the Indonesian manufacturing sector will not be sufficient. The empirical results showed that technical efficiency could further be improved significantly. Hence, besides technological progress it is equally important to disseminate the 'best practice' method of application of inputs directed by the chosen technology across the manufacturing firms. In the absence of such effective dissemination of the 'best practice' method across the manufacturing firms, the policy actions intended to improve the rate of total factor productivity growth would be misdirected. The policy implication is that the private sector and the Indonesian Government need to intensify the technology diffusion programs to emphasize the importance of following the 'best practice techniques' of the chosen technologies to improve their TFP growth further.

This study contributes to the existing literature on the Indonesian manufacturing productivity analysis in the following way. To the best of the authors' knowledge, studies applying the stochastic varying inputs response coefficients frontier in measuring technical efficiency and total factor productivity growth are scarce. Focusing on the Indonesian manufacturing sector, most previous studies on efficiency performance in the Indonesian case have followed the assumption that all firms have constant inputs response from inputs across firms implying that there is no heterogeneity in decision-making and application of inputs. Thus, this limitation has been overcome in this study by applying the stochastic varying inputs response coefficients frontier to consider firm-specific heterogeneity in estimating technical efficiency and total factor productivity growth. Nevertheless, other type of methodological limitations cannot be overlooked. For example, in the dynamic, diversified world, the modes of economic governance and policies to increase productivity driven output growth have been rapidly changing from increasing incentives to improving competition. Hence, the output growth patterns have been shifting throughout history and, without doubts, will shift in the future. Thus, more unique avenues and expansion of the horizon for impending research and study on sub-national, national, and international macroeconomics would emerge that would make current methodologies of the output growth analysis outdated.

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## Declaration of Competing Interest

The authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

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