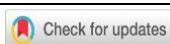


# The Impact of Technology Improvement on Indonesia Manufacturing Industry Productivity

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## ABSTRACT

**Objective:** The technology is main component in innovation, especially on industry manufacturing to increases production capability. The aim of this study is to examine the total factor productivity growth (TFPg) and its component in Indonesian industry manufacturing based on technology improvement. **Method:** The stochastic frontier analyses are used to calculate (TFPg). This study attempts to analyses the variation in the TFPg across year, and technology adaption. **Results:** The first is the analysis of year-wise comparison, show that experiences negative TFP growth or the average TFP score of current period degrades down from average score in the prior period. Second is the analysis based on technology adaption, show that the degression of productivities are mainly driven by technological regress indicating that the majority firms need innovation in technology utilized in the production process. The medium-high technology on industry manufacturing has highest score of TFP, means technology improvement support on firm productivity. **Novelty:** The lack of analysis regarding TFPg using a technology adaptation approach makes it a challenge to dig deeper.

## INTRODUCTION

The productivity of manufacturing firms has significant implications for improving technology innovation. Advanced manufacturing technology and lean-agile manufacturing have been linked to business excellence, indicating the potential for improved performance through technological advancements (Ghobakhloo & Azar, 2018). Additionally, international trade and R&D spillovers have been found to impact the productivity of manufacturing firms, highlighting the interconnectedness of global trade and innovation (Parameswaran, 2009). Efficient inventory management has been identified as a competitive advantage for contemporary manufacturing firms, emphasizing the importance of effective resource utilization (Sule & Oshi, 2022). Moreover, the involvement of venture capital has been explored for its potential impact on the total factor productivity growth of Chinese manufacturing firms, indicating the role of external funding in driving productivity improvements (Yang & Wang, 2016).

Determinants of productivity in manufacturing firms are influenced by a variety of factors that can be grouped into several key categories. One of component productivity is technical efficiency in manufacturing firms, such as those observed in Ghana, provide insights into the factors influencing operational effectiveness and resource utilization (Faruq & Yi, 2010). Furthermore, the accumulation of technology and its impact on total factor productivity in the Indian manufacturing sector underscores the significance of technology adoption for enhancing productivity at the firm level (Kaur & Mehta, 2023). Additionally, the application of quality function deployment in laser metal processing

demonstrates the integration of open innovation for product quality planning, emphasizing the role of innovation in enhancing product quality and efficiency (Syreyshchikova et al., 2021). The impact of firms' external search strategies on exploratory and exploitative innovation further underscores the relationship between openness and innovation outcomes, indicating the potential for open innovation to drive diverse forms of innovation within manufacturing firms (Tang et al., 2019). Moreover, technology for production scheduling in the context of open innovation and sustainability highlights the evolving nature of manufacturing processes and the integration of sustainability considerations into production planning (Shim & Park, 2016).

The efficiency and productivity of Indonesian manufacturing industries had been the subject of extensive research. Studies have examined the potential spillovers from foreign direct investment (FDI) on Indonesian manufacturing, indicating that FDI has introduced proprietary technology and innovative management, resulting in efficiency enhancements Sari (2019). Furthermore, there is evidence of productivity growth in Indonesia's manufacturing industry, with studies investigating whether this growth signifies re-industrialization or de-industrialization (Sugiharti et al., 2019). Moreover, technical inefficiency in Indonesian manufacturing firms has been analyzed using stochastic frontier analysis, reflecting the industry's role in improving the efficiency and productivity of firms (Astanto et al., 2022). The optimization of tool path strategy for the master ceramic jewelry mold pattern using advanced software and CNC technology demonstrates the industry's commitment to enhancing production processes (Ratnanta et al., 2021). Additionally, research has employed stochastic frontier approaches to examine total factor productivity growth in Indonesian manufacturing, shedding light on the industry's productivity dynamics (Ikhsan, 2007). The export orientation of Indonesia's manufacturing industry has also been investigated, highlighting the industry's role in optimizing the potential of the export market (Basri et al., 2020). Overall, these studies collectively provide valuable insights into the efficiency and productivity of Indonesia's manufacturing industry, reflecting its significance in the country's economic landscape.

The impact of technology improvement on the manufacturing industry in Indonesia is a topic of significant interest due to the potential benefits it offers to the sector. The adoption of technology in Indonesian manufacturing has been noted to enhance production effectiveness (Putri et al., 2023). Specifically, the use of technology has led to faster production processes, enabling companies to maintain competitiveness and increase productivity, as observed in the garment industry (Ariyani et al., 2021). However, despite these advancements, challenges persist in increasing the productivity of workers in the industrial sector (Wahyuni et al., 2022). However, despite the evident benefits of technology adoption, the manufacturing sector in Indonesia has historically lagged behind other countries in the Asia Pacific region in terms of technology contribution to growth (Malini et al., 2021).

The rest of the section explains the data, methodology, and econometric specification of SFA approach to estimate technical efficiency and the calculation of TFP growth (Section 2). Section 3 presents the findings of this study and offers further discussion. Finally, the conclusion is provided in Section 4.

## RESEARCH METHOD

### Data

The data collected from annual survey of medium and large manufacturing firm conducted by Statistic Indonesia (BPS). The medium and large manufacturing classified by number of employ at least 20 workers annually. The Industrial Statistics Guidelines (UNINDO, 2010) classified industry by technology used on research and development (R&D) expenditure incurred in the production of manufactured group. The manufacturing industries at the 2-digit level ISIC Rev 4 based on technology used, show at Table 1.

**Table 1. Industrial Classification 2-digit ISIC**

Medium-high and High Technology		Medium Technology	Low Technology
Code/Subsector		Code/Subsector	Code/Subsector
20 Chemicals and Chemical Product	22 Rubber and plastics product	10 Food product	
21 Pharmaceuticals	23 Other non-metallic mineral product	11 Beverages	
26 Computer, Electronic and Optical Product	24 Basic metals	12 Tobacco product	
27 Electrical Equipment	32 Other manufacturing except medical and dental instrument	13 Textiles	
28 Machinery and Equipment	33 Repair and installation of machinery and equipment	14 Wearing apparel	
29 Motor Vehicles, trailers, and semi-trailers		15 Leather and related products	
30 Other transport equipment except ships and boats		16 Wood and products and wood and cork	
		17 Paper and paper products	
		18 Printing and reproduction of recorded media	
		19 Coke and refined petroleum products	
		25 Fabricated metal products except weapons and ammunition	
		31 Furniture	

Source: UINDO (2010).

The production function consists of output and inputs variables. The output variable is measured by total value output produced by a firm in a given year. The inputs are capital, labor, material, and energy. The capital is proxy by the replacement value of fixed assets, which are lands and buildings, vehicles, machinery, and other capital goods. Due to the unavailability of the data, the labor is defined as the number of employees worked

in the firm. Material input is calculated using the total cost of materials required in the production process both domestically or imported sourced. The energy is expenditure of each firm on gasoline, diesel fuel, kerosene, public gas, lubricant, and electricity. In regard to the output and capital, material, and energy variable, which are measured in monetary values and mandatory to be deflated. The deflation procedure uses a wholesale price index (WPI) published by at a constant price of 2010. The descriptive statistics of the output and inputs variables are listed in the Table 2.

**Tale 2.** Descriptive Statistic

Variable	Unit		2010	2011	2012	2013	2014
Output (Y)	Billion	Mean	106549.90	113223.20	124086.70	122395.20	1229.48
	Rupiah	Std. Dev	1023990.00	734686.80	1020495.00	920943.10	9522.56
Capital (K)	Billion	Mean	2226.95	2385.92	2844.19	29111.67	2084.93
	Rupiah	Std. Dev	21302.71	20586.17	32360.72	842892.90	89987.77
Labor (L)	Workers	Mean	198.09	208.92	211.20	211.20	200.39
		Std. Dev	701.40	771.35	847.01	855.36	834.86
Material (M)	Billion	Mean	64679.98	4391.76	68975.71	65088.54	561.13
	Rupiah	Std. Dev	763939.00	38646.87	610433.60	435760.20	3989.92
Energy (E)	Billion	Mean	4392.15	67667.64	4918.51	4797.33	8438.74
	Rupiah	Std. Dev	58012.80	439940.20	40063.75	43563.53	144224.10

Note: The mean is referred to the arithmetic mean while Std. Dev stands for the standard deviation

## Methodology

This study uses stochastic frontier analysis (SFA), which has been widely used to estimate technical efficiency. SFA was proposed by Aigner et al. (1977) and Meeusen & Broeck (1977). The parametric forms and assumptions of stochastic frontier model have been developed by many researchers. For instance, Kumbhakar (1987), Pitt & Lee (1981), and Schmidt & Sickles (1984) models treated the inefficiency as time invariant. In these models, there would be difficult to know whether heterogeneity or inefficiency is more likely to represent the systematic time invariant differences in the firm output. Battese & Coelli (1992) and Kumbhakar (1990) models defined the inefficiency as a product of a function of time and an individual specific effect. The variants allow inefficiency to change over time without firm effects. The time-variant inefficiency of each firm is the same in these models and leaving inefficiency and the individual heterogeneity inseparable. Battese and Coelli (1995) model allows the inefficiency to rely on exogenous variables such that researcher could estimate the determinants of inefficiency.

The conventional panel stochastic models are not designed to distinguish between unobserved individual heterogeneity and inefficiency. In this regard, the models inadvertently add the time-invariant heterogeneity into the estimated inefficiency (Wang & Ho, 2009). Therefore, it might possess potential to create bias in the measurement of inefficiency. Greene (2005a) proposes a true fixed effect stochastic model to address this problem. The model is as follow:

$$y_{it}^* = \alpha + \beta' x_{it} + \tau' z_i + v_{it} \quad (1)$$

Where  $y_{it}^*$  is the output of firm  $i$  at year  $t$ ,  $x_{it}$  refers to the vector of inputs.  $z_i$  indicates a vector of firm specific characteristic.  $\alpha$  and  $\beta$  are the parameters to be estimated while

$v_{it}$  denotes the random error. This model includes the time invariant term,  $\tau'z_i$ , in  $\beta'x_{it}$  and the model becomes

$$y_{it} = \alpha + \beta'x_{it} + v_{it} - u_{it} \tag{2}$$

Where  $u_{it}$  is the inefficiency term. The efficiency estimation by using this framework begins by estimating the technology parameters ( $\alpha, \beta, \sigma_u$  and  $\sigma_v$ ). By means of estimating these parameters one can measure the composed deviation which formulates as follow:

$$\varepsilon_{it} = v_{it} - u_{it} = y_{it} - \alpha - \beta'x_{it} \tag{3}$$

However, the purposes of the studies are mainly to estimate inefficiency term ( $u_{it}$ ) and not the firm-specific heterogeneity ( $\varepsilon_{it}$ ). The measurement of inefficiency in this study applies the measurement inefficiency done by Jondrow et al. (1982) (JLMS) formulated as follow:

$$E[u_{it}|\varepsilon_{it}] = \frac{\sigma\lambda}{1+\lambda^2} \left[ \frac{\phi(a_{it})}{1-\Phi(a_{it})} - a_{it} \right] \tag{4}$$

Where  $\sigma = [\sigma_{v^2} + \sigma_{u^2}]/2$ ,  $\lambda = \sigma_u/\sigma_v$ ,  $a_{it} = \pm(\varepsilon_{it}\lambda)/\sigma$ , and  $\phi(a_{it})$  implies the standard normal density.  $\Phi(a_{it})$  infers to the cumulative distribution function (CDF) evaluated at ( $a_{it}$ ).

Stochastic frontier analysis requires the selection of the best fitted production function model. Therefore, the flexible functional form of production function namely Translog model will be tested against the sub-translog models. By means of using the Translog production function, the risk of error in terms of model specification could be reduced. The translog production function model is adapted from equation 2 and formulated as follow:

$$y_{it} = \alpha + \sum_{n=1}^N \beta'_n x_{nit} + \frac{1}{2} \sum_{n=1}^N \sum_{m=1}^N \beta'_{nm} x_{nit} x_{mit} + \sum_{n=1}^N \beta'_{nt} x_{nit} t + \beta'_t t + \frac{1}{2} \beta'_{tt} t^2 + v_{it} - u_{it} \tag{5}$$

Where  $y$  is the total output and  $xn$  and  $xm$  indicate the inputs used in production process such as capital, labor, material, and energy.  $v_{it}$  represents the random error while  $u_{it}$  is the technical inefficiency. The subscript  $i$  and  $t$  denote the  $i$ -th firm and  $t$ -th year respectively. The  $\beta$  implies the estimated coefficient. In this study, the output and input variables are transformed into natural logarithm and calculated the deviation of each observation from the geometric mean. For instance, the geometric mean of capital ( $K_{it}$ ) is  $\bar{K}$  which will be transformed into natural logarithm ( $\ln(\bar{K})$ ). Each observation in capital variable will be transformed into natural logarithm  $\ln(K_{it})$  before subtracted from the geometric mean. The formula is as follow:

$$k_{it} = \ln(K_{it}) - \ln(\bar{K}) \tag{6}$$

Generally, the sub-translog production function models consist of Hicks-neutral, no technological progress, and Cobb Douglas model. Each of these models will be tested and the best fitted model will be used as production function model in this analysis. At first, the hypothesis testing is done by the test between Hicks-neutral ( $H_0$ ) and translog ( $H_1$ ). Hicks-neutral model is defined through dismissed the parameter interaction of input and time ( $\beta_{nt} = 0$ ) in the equation 5. The next is the test between the no technological progress ( $H_0$ ) and translog ( $H_1$ ). The no technological model assumes that the time

coefficients are excluded ( $\beta_t = \beta_{tt} = \beta_{nt} = 0$ ) from the translog model. The third test is is Cobb-Douglas ( $H_0$ ) against translog ( $H_1$ ) production function. The null hypothesis consists of the parameter of inputs ( $\beta_{nm} = \beta_{nt} = \beta_t = \beta_{tt} = 0$ ). These hypotheses testing are consistently estimated using generalized likelihood ratio statistic by measuring the following formula:

$$\lambda = -2[l(H_0) - l(H_1)] \quad (7)$$

The  $l(H_0)$  represents the log-likelihood estimated value of the restricted frontier model while  $l(H_1)$  implies the log-likelihood estimated value of the translog model. When the  $\lambda$  calculation is less than the critical value of  $\chi^2$  distribution, the null hypothesis is not rejected.

The estimation results of inputs in the production function from equation 5 are calculated into elasticity output with respect to each input. The calculation of the elasticity is as follow:

$$\varepsilon_{nit} = \partial y_{it} / \partial x_{nit} = \beta'_n + \frac{1}{2} \sum_{n=1}^4 \sum_{m=1}^4 \beta'_{nm} x_{m_{it}} + \beta'_{nt} t \quad (8)$$

The elasticity output with respect to each input at a given year will be summed up and accounted into total elasticity. The total elasticity is formulated as follows:

$$\varepsilon_{Tit} = \sum_{n=1}^N \varepsilon_{nit} \quad (9)$$

This study provides analysis about total factor productivity (TFP). Comin (2010) defines TFP as the proportion of output not explained by the inputs used in the production but it is expressed by the efficient and intensity inputs usage in the production process. TFP is calculated by summing up its components which consist of technical efficiency change (TEC), scale efficiency change (SEC), and technological change (TC). The formula of TFP growth is as follow:

$$TFP g_{it,t-1} = TEC_{it,t-1} + SEC_{it,t-1} + TC_{it,t-1} \quad (10)$$

Where:

$$TEC_{it,t-1} = \ln \left( \frac{TE_{it}}{TE_{it,t-1}} \right) \times 100 \quad (11)$$

$$SEC_{it,t-1} = \frac{1}{2} \sum_{n=1}^N \left[ \left( \frac{\varepsilon_{Tit-1}}{\varepsilon_{Tit}} \varepsilon_{nit} + \frac{\varepsilon_{Tit-1-1}}{\varepsilon_{Tit-1}} \varepsilon_{nit-1} \right) (x_{nit} - x_{nit-1}) \right] \times 100 \quad (12)$$

$$TC_{it,t-1} = 0.5 \left[ \left( \frac{\partial y_{it-1}}{\partial t} \right) + \left( \frac{\partial y_{it}}{\partial t} \right) \right] \times 100 \quad (13)$$

$TE_{it}$  is technical efficiency and  $\varepsilon_{Tit}$  is the total elasticity of output with respect of inputs.  $\varepsilon_{nit}$  implies the elasticity of output with respect to each input.  $y_{it}$  is the output and  $x_{nit}$  is the input used in the production function. The subscript of i and t are the index of firm and time respectively. TEC denotes the managerial improvement. SEC reflects the movement towards the most optimum production scale while TC exhibits the shift of production frontier because of the usage of sophisticated technology (Arora & Lohani, 2017).

## RESULTS AND DISCUSSION

The analysis is embarked by selecting the most suitable production function. Although this study relies on the utilization of Translog production function, the test remains essential to identify whether Translog is the most suitable one. The selection is conducted

using Loglikelihood Ratio test based on formula in Eq (7). The results are reported in Table 3. According to the Table 3, Translog is the most suitable function as it reveals that  $\lambda > \chi^2$

**Table 3.** Likelihood Ratio Test

	HN (df=4)	NTP (df=6)	CD (df=16)	Decision
<b>Translog (Baseline)</b>	15824.181	60885.013	68778.687	TL
$\chi^2$	13.277	16.812	32.000	

Note: HN is Hicks-neutral; NTP is no technological progress, and CD is Cobb Douglas.

Table 4 reports the result of estimation using Stochastic Frontier Analysis from four different production function. According to Table 3, the coefficients across production function tend to show similar magnitude and sign. In this regard, the estimation using Translog production function is robust. In terms of coefficient's magnitude, variable of raw material reveals the largest magnitude, supporting prior studies discussing Indonesian manufacturing industry (Esquivias & Harianto, 2020; Sari, 2019; Suyanto et al., 2012; Yasin, 2021).

**Table 4.** Estimation using Stochastic Frontier Analysis

Variables	Coefficient	Model 1	Model 2	Model 3	Model 4
<i>Constant</i>	$\beta_0$	0.510* (0.003)	0.530* (0.004)	0.242* (0.004)	0,304* (0,004)
<i>k</i>	$\beta_k$	0.176* (0.001)	0.209* (0.001)	0.058* (0.001)	0,078 (0,001)
<i>l</i>	$\beta_l$	0.164* (0.002)	0.163* (0.002)	0.108* (0.002)	0,122* (0,002)
<i>m</i>	$\beta_m$	0.588* (0.001)	0.609* (0.002)	0892* (0.001)	0,848* (0,001)
<i>e</i>	$\beta_e$	0.135* (0.001)	0.085* (0.001)	-0.016* (0.001)	0,001 (0,001)
<i>k<sup>2</sup></i>	$\beta_{kk}$	0.030* (0.001)	0.031* (0.001)	0.021* (0.001)	
<i>l<sup>2</sup></i>	$\beta_{ll}$	0.043* (0.002)	0.053* (0.001)	0.046* (0.003)	
<i>m<sup>2</sup></i>	$\beta_{mm}$	0.033* (0.001)	0.013* (0.001)	0.045* (0.001)	
<i>e<sup>2</sup></i>	$\beta_{ee}$	0.080* (0.001)	0.020* (0.001)	0.004* (0.001)	
<i>kl</i>	$\beta_{kl}$	0.013* (0.001)	-0.006* (0.001)	0.009* (0.001)	
<i>km</i>	$\beta_{km}$	-0.029* (0.001)	-0.002* (0.001)	-0.024* (0.001)	
<i>ke</i>	$\beta_{ke}$	0.001*** (0.001)	-0.014* (0.001)	-0.015* (0.001)	
<i>lm</i>	$\beta_{lm}$	-0.045* (0.001)	-0.029* (0.001)	-0.005* (0.001)	
<i>le</i>	$\beta_{le}$	-0.009* (0.001)	-0.015* (0.001)		

Variables	Coefficient	Model 1	Model 2	Model 3	Model 4
$me$	$\beta_{me}$	(0.001) -0.030*	(0.001) 0.002*		
$t$	$\beta_t$	(0.001) -0.235	(0.000) -0.248*		
$t^2$	$\beta_{tt}$	(0.001) -0.127	(0.001) -0.235*		
$kt$	$\beta_{kt}$	(0.001) -0.036			
$lt$	$\beta_{lt}$	(0.001) -0.024			
$mt$	$\beta_{mt}$	(0.001) 0.109			
$et$	$\beta_{et}$	(0.001) -0.061			
Sigma-squared	$\delta_0$	(0.001) 0.179*	(0.001) 0.197*	(0.003) 0.343*	(0.003) 0.342
Gamma	$\Gamma$	(0.006) 0.314*	(0.006) 0.314*	(0.006) 0.459*	(0.006) 0.405
Log-likelihood function		-49214.294	-57126.382	-79656.798	-83603.636
LR test of the one sided error		4275.93	3588.71	6592.75	5061.06

Note: Standard errors are in parentheses. \*, \*\*, and \*\*\* denote significance at alpha 1%, 5%, and 10% respectively.

The following analysis is to calculate TFP growth with its three decompositions: technical efficiency change (TEC), technical progress/technical change (TC), and scale efficiency change (SEC). The decomposition reveals to what extent each component contributes to the TFP growth magnitude. In this study, the analyzes of TFPg and its components are classified based on the year, and technology improvement.

**Table 5.** Year-wise Comparison of TFPg and Its Components

Year	TFPg	TEC	TC	SEC
2010-2011	1.310	-0.001	1.315	-0.004
2011-2012	-0.025	0.001	-0.030	0.004
2012-2013	-2.675	0.001	-2.655	-0.022
2013-2014	-6.295	-0.002	-6.499	0.206
<b>2010-2014</b>	<b>-1.921</b>	<b>0.000</b>	<b>-1.967</b>	<b>0.046</b>

**Note:** TFPg, TEC, TC, SEC represent average in percentage

Table 5 denotes the calculation of total factor productivity growth and the decompositions annually. The industry manufacture experiences negative TFP growth or the average TFP score of current period degrades down from average score in the prior period. The TFP growth for average years of 2010-2014 is -1.921% with the largest adverse impact from negative technical change by -1.967%. The negative TC implies that industry manufacture performs technological regress for over years of 2010-2014. Likewise, other components (TEC and SEC) also experience negative magnitude although those do not exceed than 1%. These results are in accordance with Sari et al. (2021) who suggest the

improvement of technological progress and optimization of production scale in Indonesian manufacturing industry. The year of 2010-2011 or TFP growth in 2011 is the only period which the score experience positive, contributed mostly from the solid magnitude of technical change (TC) by 1.315%. This period, TEC and SEC remain negative, strengthening arguments that industry manufacturing faces do not managerial improvement and not production in optimum scale.

Table 6 informs the average of total factor productivity change and the decomposition by technology adaption. Among these deteriorated firms, the degression of productivities are mainly driven by technological regress indicating that the majority firms need innovation in technology utilized in the production process. The medium-high technology on industry manufacturing has highest score of TFP, means technology improvement support on firm productivity. This suggests that firms operating within these sectors are more efficient in utilizing inputs to generate outputs compared to those in low-tech or medium-low tech industries (Camino, 2022). Otherwise, low technology on industry manufacturing has average lowest score in TFP, means it had to improve the technology used for production. The lowest score of TFP industries classified as low technology, such as food processing, textiles, and furniture manufacturing, consistently show lower TFP scores compared to medium and high-tech sectors. This reflects inefficiencies in converting inputs into outputs, which can be attributed to outdated technologies and production method (Rostiana et al., 2020). The other components of TFP such as technical efficiency change also exhibits negative scores while the scale efficiency change on average has improved. The efficient scale of operation might not be achieved because of the regulation affecting the productivity of firms and influencing the ability of firms to adjust the economic and technological condition (Rasmussen, 2010).

**Table 6.** Technology Adaption Comparison of TFPg and Its Components

Code	TFP	TEC	TC	SEC
Medium-high and High Technology				
20	-1.950	0.000	-1.994	0.041
21	-1.587	0.000	-1.637	0.047
26	-1.921	0.000	-1.972	0.036
27	-1.943	0.000	-1.987	0.037
18	-1.894	0.001	-1.942	0.053
29	-1.937	0.000	-1.984	0.038
30	-1.819	0.000	-1.864	0.045
Medium Technology				
22	-1.904	0.000	-1.952	0.041
33	-1.890	0.000	-1.940	0.054
24	-2.039	0.000	-2.081	0.032
32	-1.777	0.000	-1.828	0.051
33	-1.912	0.000	-1.960	0.049
Low Technology				
10	-1.958	-0.001	-2.001	0.045
11	-1.994	0.001	-2.042	0.050
12	-1.996	0.000	-2.040	0.046
13	-1.937	-0.001	-1.984	0.046
14	-1.938	0.000	-1.983	0.049

Code	TFP	TEC	TC	SEC
15	-1.920	0.000	-1.966	0.048
16	-1.901	0.000	-1.945	0.050
17	-1.867	-0.001	-1.910	0.036
18	-1.951	-0.001	-2.001	0.051
19	-1.987	0.000	-2.032	0.041
25	-1.899	0.000	-1.947	0.046
31	-1.863	0.000	-1.907	0.049
Average	-1.901	0.000	-1.948	0.045

## CONCLUSION

This study examines the total factor productivity growth and its decompositions of crude palm oil industry through stochastic frontier analysis (SFA). The data is sourced from the annual survey of medium and large manufacturing establishments conducted by the Statistics Indonesia from 2010 to 2014. **Fundamental Finding:** the calculation result of elasticity of output for all years is mainly contributed from raw materials. The total elasticity reveals that the magnitude is less than unity, indicating decreasing return to scale of the productivity in the crude palm oil industry. This study yields into two analyses of productivity growths which are yearly based, and technology based. **The implication:** the first is the analysis of year-wise comparison, show that experiences negative TFP growth or the average TFP score of current period degrades down from average score in the prior period. Second is the analysis based on technology adaption, show that the degression of productivities are mainly driven by technological regress indicating that the majority firms need innovation in technology utilized in the production process. The medium-high technology on industry manufacturing has highest score of TFP, means technology improvement support on firm productivity. **Limitation:** the latest data used in this study was 2014. **Future Research:** hopefully there will be manufacturing industry data that uses company codes, so that this research can use the latest data.

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