

TECHNICAL EFFICIENCY OF THE INDONESIAN TEXTILE AND TEXTILE PRODUCT INDUSTRY

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ABSTRACT

This study investigates the determinants of the Indonesian textile and textile product (TPT) industry's technical efficiency. Employing the rich balanced panel data of 3,365 firms over 2007-2013 with a non-parametric approach to the Data Envelopment Analysis (DEA) Bootstrapping and Tobit regression, this study discovers that the production operations are inefficient, especially the companies upstream. The improvement of technical efficiency is driven by firm size, market concentration, foreign ownership, and exports. An intriguing finding is that the capital-labour ratio negatively impacts efficiency, implying higher capital for production will make the production even more inefficient. The machines in most TPT firms are old, so larger capital may not help. This study recommends the government design policies that support the machinery restructuring so that capital can support production efficiency.

Keywords: Efficiency, Textile and Textile Product, Bootstrapping, Tobit

JEL: L60; D24

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Introduction

The manufacturing industry contributes significantly to many economies, including Indonesia. One group in this sector, i.e., Textile and The Textile Product (TPT,) is one of the largest contributors amongst other non-oil manufacturing subsectors. The Central Bureau of Statistics (2013) recorded that the average contribution to the non-oil manufacturing subsector in 2013 was 11%, which was higher than other subsectors, e.g., paper and printed goods at 5%, cement and non-metal mining products at 3%, iron base metals and steel at 2%, and other goods at 1%. Production in the TPT industry requires high technology, capital, and highly skilled workers. Therefore, the TPT industry is prioritised in the National Industrial Development Master Plan for the 2015-2035 period.

Identifying the critical success factors of the TPT industry's performance is important to technically evaluate the production optimality. The analysis often involves technical efficiency with a parametric method such as Stochastic Frontier Analysis (SFA) or a non-paramet-

ric method such as Data Envelopment Analysis (DEA) (Setiawan et al., 2012; Sari et al., 2016; Joshi and Sigh, 2012; Rezitis and Kalantzi, 2016; Amornkitvikai and Harvie, 2010; Yasin, 2020). However, none of these studies has investigated the Indonesian TPT industry of Indonesia from 2010 onwards using a combined method, e.g., DEA Bootstrapping and Tobit regression. Indonesian firms' characteristics are heterogeneous and spread across 20 provinces, making it an intriguing case. This study aims to investigate the determinants of efficiency from the firm's external and internal factors. The company's external factors include the Herfindahl Hirschman Index (HHI), which represents TPT's competitiveness in the market (Setiawan et al., 2012), export intensity (Gumbau-Albert and Maudos, 2002), and foreign ownership (Amornkitvikai and Harvie, 2010). Meanwhile, internal factors include company size (Rezitis and Kalantzi, 2016), absorptive capacity (Sari et al., 2016), and capital-labour ratio (Josho and Sigh, 2012).

This study contributes to the literature in two ways. First, it combines DEA Bootstrapping and Tobit regression to examine the determinants of technical efficiency of Indonesian TPT companies. The technical efficiency estimate is improved from previous studies, which uses conventional DEA without further investigation of its determinants. Second, this study employs Indonesia's rich panel firm-level dataset from 2007 to 2013 to investigate the impact of external and internal factors on the TPT industry. This estimate allows the production frontier to be well-captured instead of pooling all subsectors into a single production frontier, e.g., Yasin (2021), Sari et al. (2016), Sari (2019).

The rest of the sections are constructed as follows: Section 2 is the literature review that discusses the theory of efficiency and its possible determinants. Section 3 explains the data and employed methodology. Section 4 presents the results and discussion, followed by the conclusion and policy recommendation in Section 5.

Literature Review

Production theories associated with efficiency were first introduced by Farrell (1957), following the model developed by Debreu (1951). This efficiency measurement accommodates multiple inputs. The concept consists of technical efficiency and scale efficiency (Coelli et al., 2005). Technical efficiency is achieved by minimising inputs used to produce the predetermined output level or maximising output using the available inputs. Efficiency scores range from 0 to 1, with the value of 1 implying that a company operates under the most optimal efficiency level.

Conventional literature suggests that parametric and non-parametric approaches can measure technical efficiency. The parametric approach uses the Stochastic Frontier Analysis (SFA), enabling the reference limit to be defined in non-deterministic efficiency estimates (Purwono et al., 2018). Meanwhile, the non-parametric approach employed in this study was Data Envelopment Analysis (DEA), based on a linear form of programming that calculates the ratio of input and output and measures the relative efficiency of all comparable production units (Tipi et al., 2009). There are two alternatives for measuring technical efficiency. The first is the input orientation, which measures the level of technical efficiency of a company that uses minimum inputs to produce a certain level of output. Meanwhile, the output orientation aims to measure the level of technical efficiency of a company that produces maximum output by utilizing a certain amount of input.

One of the determinants of efficiency is company size, which represents the scale of production of each company. The greater the size of the company, the larger the production scale. A large production scale needs more labour, raw materials, and advanced technology

(Amornkitvikai and Harvie, 2010). Big companies generally have greater technical efficiency because they have better production management (Wooldridge, 2016).

The Herfindahl-Hirschman Index (HHI) is one technique to measure market concentration. The value ranges from zero to one. The closer it is to one, the more concentrated the market is. A large HHI shows a higher concentration of sales from only a few producers. High concentration only in certain companies can drive other less productive companies out of the market. This will reduce the companies' performance and technical efficiency (Setiawan et al., 2012). Companies with higher market power (higher HHI) lack control over prices, reducing technical efficiency (Al-Muharrami and Matthews, 2009). In addition, high HHI lowers competition between companies, lowering the incentives to maximise efficiency (Setiawan et al. 2012).

Another determinant of efficiency is the ownership of the company, whether it is foreign or domestic. According to Law Number 6 the Year 1968 concerning Domestic Investment, if more than 75 % of the capital is domestically owned, the company is classified as a domestic company. Meanwhile, if less than 75 % of the capital is domestically owned, then the company is classified as a foreign company. Capital ownership could be closely linked to technical efficiency. Firms with foreign capital might provide high-quality standards for local producers in the downstream markets (Sari, 2019) because there is usually technology transfer. With advanced technology, companies can optimise their resources and improve their competitiveness, hence their technical efficiency (Amornkitvikai and Harvie, 2010).

The intensity of exports shows the companies' total output. The greater the ratio of output to exports, the higher the intensity of exports. According to Trofimenko (2008), higher export intensity indicates good performance. Good performance indicates and supports efficiency (Wooldridge, 2016). Companies with high export intensity are expected to increase efficiency so that their products are competitive (Gumbau-Albert and Maudos, 2002).

An absorptive capacity represents the ratio of costs incurred per labour, which includes salaries, benefits, and training costs. A high absorptive capacity indicates greater costs incurred by a company for labour, which means that the company employs less workforce. The role of absorptive capacity in technical efficiency is different. More training costs incurred for workers are associated with an increased absorptive capacity. Improving workers' skills by sending them to training can affect a company's technical efficiency (Le and Pomfret, 2011). A high absorptive capacity indicates that the human resources can absorb existing technology and improve technical efficiency. The higher the technology adoption, the higher the technical efficiency is (Henry et al., 2009).

A capital-labour ratio shows the comparison between capital used in a company and the number of workers. A high capital-labour ratio means the use of capital is greater than the workforce. As indicated by advanced technology, high efficiency makes the capital-labour ratio high (Rezitis and Kalantzi, 2016). Likewise, a capital-labour ratio can also show a negative relationship with technical efficiency when the capital used in a company, i.e., machinery, is underutilised or decreases the production capacity (Joshi and Sigh, 2012).

Data and Research Methods

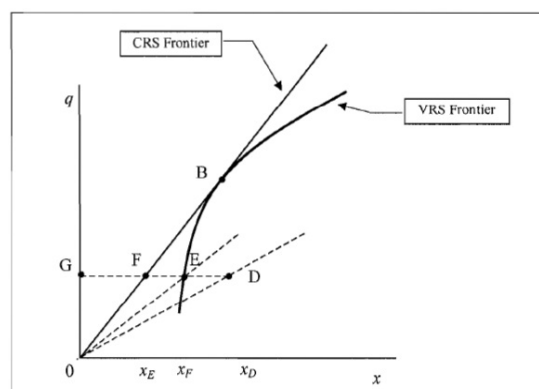
This study employs the 3,365 balanced firm-level data of the TPT industry collected by the Central Bureau of Statistics of Indonesia (BPS Indonesia) from 2007 to 2013. The variables are divided into three parts: output, input, and the determinants of efficiency. The output is taken from the total production of each company through the production process valued in

the Indonesian Rupiah (IDR). Input variables consist of labour, capital, energy, and raw material. The capital (K) is proxied by each company's total fixed capital used in IDR for production activities consisting of land, buildings, vehicles, machinery and equipment, and others. The energy variable is taken from the amount of electrical energy used in the production process in IDR by each company through the production process. The raw material is taken from the production raw material for both import and domestic market. To avoid biased values, all nominal output and input variables are deflated by the Wholesale Price Index (IHPB), with 2010 as the base year.

The determinants of efficiency consist of six variables: export, capital-labour ratio, firm size, market concentration (HHI), ownership, and absorptive capacity. The export value is measured from the percentage of output exported in per cent. The capital-labour ratio is measured by the amount of capital and the number of workers in the production process. The firm size is calculated from the output value of a company in a particular year divided by the total output value in the same industry group in the same year to generate a ratio. Although BPS Indonesia defines large and medium firms according to the number of workers, this study uses output-based following previous studies (see. Sari et al., 2016; Yasin, 2021; Esquivias and Harianto, 2020). The HHI measures the market concentration, valued between 0 and 1. Ownership is a dummy variable representing the capital owned by companies, with the value of 1 for foreign companies and 0 for otherwise. The absorptive capacity is measured from the costs incurred for each worker because data on the labour quality was not available (Sari et al., 2016). The labour costs consist of wages, overtime wages, gifts or bonuses, benefits, and training costs.

This study uses Data Envelopment Analysis (DEA) Bootstrapping to measure technical efficiency. DEA model was discovered by Charnes et al. (1981), who is also known for Charnes-Cooper-Rhodes (CCR) model or the constant return to scale (CRS) model. This model introduces a measurement of efficiency for each decision-making unit (DMU). The maximum ratio is estimated by comparing weighted output and weighted input. The ratio for each DMU must have a value of less than or equal to one.

Meanwhile, a Banker-Charnes-Cooper (BCC) model (Banker et al., 1984) or DEA model assumes a variable return to scale (VRS). In this model, units produce changes at various output levels. Each DMU is considered to operate in varying returns to scale. Each DMU does not operate at an optimal scale as the proportions of additional input and output are not always the same, so if there is an additional input by n times, the output does not necessarily increase n times. This mechanism implies that output can be more or less than n times (Sunarto, 2010).



Source: Coelli et al. (2005)

Figure 1: Efficiency

The technical efficiency of company D with VRS assumption is as follows:

$$TE_{VRS} = \frac{GE}{GD} \tag{1}$$

The value of the efficiency scale ranges from 0 to 1, where a value of 1 indicates that the company has operated on the utmost efficient scale (Coelli et al., 2006). Point B is when the company is at the optimum condition because the company is working at a constant return to scale (CRS), operating under variable return to scale (VRS).

The DEA method is a non-parametric analysis method that aims to measure the level of relative technical efficiency compared to other production units with the same purpose. This study employs VRS (1) with the following specification.

$$\begin{aligned} &Max_{\Phi, \lambda} \Phi \\ &s.t. - \Phi y_i + Q\lambda \geq 0 \\ &xi - X\lambda \geq 0 \\ &11'\lambda \geq 0 \\ &\lambda \geq 0 \end{aligned} \tag{2}$$

where Φ is the efficiency score; λ is the $I \times 1$ constant vector or constraint vector; y_i output vector i ; x_i is the input vector i ; Q is the overall output matrix i ; X is the overall input matrix i .

However, the DEA approach also has weaknesses. It does not consider noise or random errors in the use of linear programming to estimate frontier, so it cannot determine the accuracy of the resulting efficiency values. Given the limitations, Simar and Wilson (1988) estimated the standard error (bias) of the DEA scores using the bootstrapping technique. The purpose of this technique is: a) to estimate the standard error and confident intervals of each efficiency value generated by the DEA, and b) to make inferences that are consistent with the determinants of efficiency. Bootstrapping can also reduce serial correlation problems between the value of efficiency produced by each company (Selim and Bursalioğlu, 2015).

The procedure to bootstrap DEA, according to Simar and Wilson (1998), starts with calculating the DEA efficiency value using the VRS assumption. Second, efficiency values are produced $\theta_i^*, i = 1, \dots, n$ in a form of $\theta_1^*, \dots, \theta_n^*$, adjusted into $(\theta_{1b}^*, \theta_{2b}^*, \dots, \theta_{nb}^*)$, where b is a number of iterations of bootstrap. The fourth step is calculating the number of bootstrap inputs with the formula $x_{ib}^* = \left(\frac{\theta_i^*}{\theta_{ib}^*}\right)x_i$. The fifth step is to use bootstrap input to estimate the DEA bootstrap value θ_{ib}^* . After that, iteration b is repeated to make a set of estimates $\{\theta_{ib}^*, b = 1, \dots, B\}$. The average bootstrap estimator can be used as a DEA estimator by considering a bias and a confidence interval (Assaf and Matawie, 2010).

The final result of the bootstrapping method is obtained bias-corrected efficiency scores. The resulting bias value is used for the accuracy of efficiency calculations with a mathematical model as follows:

$$\hat{\delta}(x, y) = \delta(x, y) - bias_B[\delta(x, y)] = 2\delta(x, y) - B^{-1} \sum_{b=1}^B \delta_b^*(x, y) \tag{3}$$

with the following sample variance conditions.

$$\delta_b^*(x, y) < \frac{1}{3}(bias[\delta(x, y)])^2 \tag{4}$$

where the DEA efficiency values obtained from the estimated DEA are reduced by the bias generated from the bootstrap.

The main difference between general DEA and bootstrapped DEA lies in the results of the technical efficiency values. The engineering efficiency values are reduced by the bias value generated from the estimation. The efficiency value from the DEA bootstrapping can be tested for significance or accuracy by using confident intervals (Tziogkidis, 2012).

The linear regression method used in this study is the Tobit method because the variable data are dependent, namely technical efficiency with the assumption of VRS being censored. According to Greene (2012), censored data is limited to a certain range with a uniform value at a particular value and must be estimated using the Tobit method. The TPT industry is still distorted, so it is more appropriate to use the VRS assumption than the CRS assumption (Setiawan et al., 2012). In general, the Tobit method used to estimate determinants of technical efficiency can be written as follows (Haryanto et al., 2015).

$$\begin{aligned}
 TE_i^* &= \beta' z_i + u_i \\
 TE_i^* &= L_{1i} \text{ if } TE_i^* \leq L_{1i} \\
 TE_i^* &\text{ if } L_{1i} \leq TE_i^* \leq L_{2i} \\
 L_{2i} &\text{ if } TE_i^* \leq 1
 \end{aligned} \tag{5}$$

where TE_i^* is the latent variable or VRS assumption of technical efficiency score, TE_i is the observed dependent variable, z_i is a vector of independent variables namely Firm Size, HHI, Absorptive Capacity, Capital-output Ratio, Capital Ownership, and Export, β is vector of the estimated parameter, and u_i remaining models and TE_i with distribution of $N(0, \sigma^2)$.

The basic assumptions of Tobit regression are normality and heteroscedasticity (Greene, 2012). When these two important assumptions are violated, the maximum likelihood estimator will be inconsistent again. Estimating the parameters of the Tobit model is conducted by looking at the marginal effect of each independent variable on the conditional expected value function. There are four functions of conditional expectation value that can be used to interpret the coefficient of estimated regression of Tobit. However, this study only employs two conditional expectations:

- The marginal effect on latent variable:

$$\frac{\partial E(y | x)}{\partial X_k} = \beta_k \tag{6}$$

- The marginal effect on the actual variable:

$$\frac{\partial E(y | x)}{\partial X_k} = \beta_k \Phi\left(\frac{x\beta}{\sigma}\right) \tag{7}$$

Wooldridge (2016) explains some of the stages required in the Tobit model. The first is to test the model specifications and Tobit assumption. This step aims to determine whether the specification in this study is suitable for Tobit estimation—whether or not the assumption of homoscedasticity and the distribution of normal errors (normality) are satisfied. The two assumptions need to be met, otherwise, the guesswork or parameter is inefficient and inconsistent (Greene, 2012). The model specifications and Tobit assumptions are tested using Lagrange Multiplier (LM). The null hypothesis (H0) is not rejected if the LM statistic is larger than any critical values at alpha 1%, 5%, and 10%. If this is the case, the specification in this

study is homoscedastic and has errors with normal distribution. Otherwise, if the LM statistic is less than the critical values, the alternative hypothesis (H1) is not rejected. In this case, the specification is heteroscedastic and does not have errors with normal distribution.

The second step is to test parameters to reveal the robustness of the estimated specification using the partial test, i.e., the Wald test and the simultaneous test, i.e., the Likelihood Ratio (LR) test. The Wald test is a statistical test used to determine the level of significance of an independent variable in partially influencing a dependent variable. The H0 is if the independent variables do not partially affect the dependent variable. The H1 is if the independent variables affect the dependent variable. The decision considers the t-table.

The hypothesis of the LR test is set from H0 if $\beta_1 = \beta_2 = \dots = \beta_n = 0$, which means there is no joint effect of the independent variables simultaneously on the dependent variable and H1 if at least one of the parameters is not equal to zero. This means that there is an influence of the independent variables on the dependent variable simultaneously. If the calculated F value is greater than then the null hypothesis (H0) is rejected. This means that variations from the regression model can explain the variation of independent variables and vice versa.

Finding and Discussion

The Data Envelopment Analysis (DEA) bootstrapping found that the average value of technical efficiency in the TPT industry from 2007 to 2013 was 0.2475. The overall technical efficiency is illustrated in Figure 2.

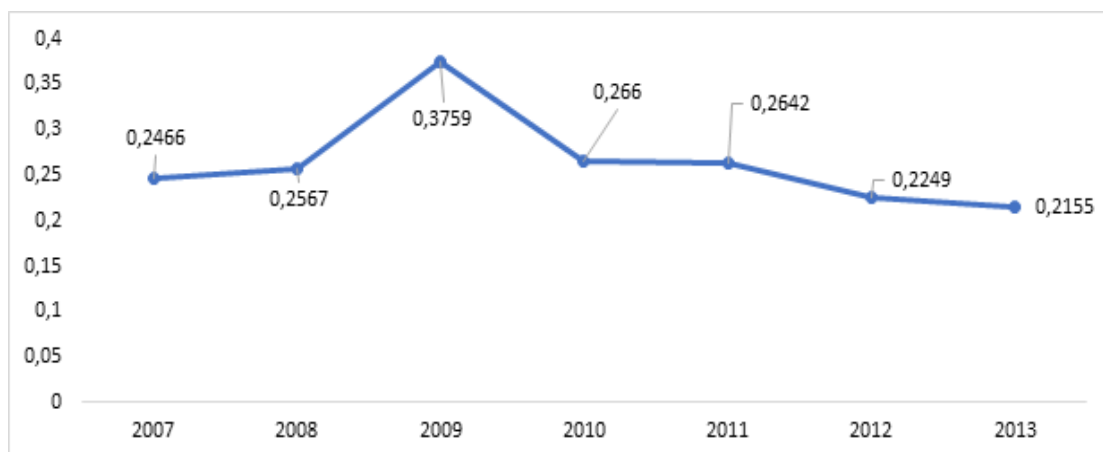


Figure 2: Technical Efficiency Scores Over Time

The efficiency value shows that companies in the TPT industry operate in far from efficient conditions. Moreover, the values fluctuate, indicating the inability of production management to optimise the existing human resources and the potential output generated from the fixed inputs.

This study groups the TPT industry based on the technical efficiency of larger than 0.5 and lower than 0.5 and the upstream and downstream activities. The upstream industry frequently produces fibre that is subsequently spun into yarn products, while the downstream industry is the garment manufacturing industry. This division is illustrated in Figure 3.

Figure 3 shows that the upstream companies in the TPT industry are less efficient than the downstream industry. The downstream industry is mostly at 57% efficiency in the TE>0.5 group, whereas in the group of TE<0.5 the efficiency is at 47%. Conversely, the firms in the upstream industry are largely at less than 0.5% of efficiency in the group of TE<0.5 and less

dominant in the group of $TE > 0.5$. This finding implies a gap between the upstream and downstream companies in the TPT industry. The upstream companies face low competitiveness caused by high production costs, so they cannot compete with imported products. Meanwhile, the downstream companies prefer to use imported raw materials rather than raw materials produced by the upstream companies. The government has stipulated the policy to deal with this issue; for instance, the Ease of Importing Export Purpose (KITE) aims to provide greater opportunities for downstream businesses to import raw materials for export purposes.

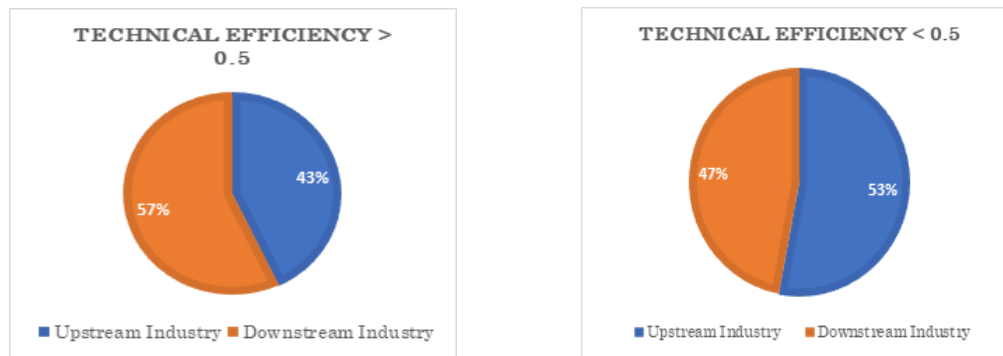


Figure 3: The proportion of Upstream and Downstream Textile and Textile Products Industries Based on the TE classification > 0.5 and < 0.5

Table 1 provides the information on the Tobit regression on the latent variable. The results show five significant variables in the Wald test, five significant variables at a 1 % level. One variable is not significant: the absorptive capacity. The Chi-Square test results show that the model is significant, with an error rate of almost close to 0 %. Table 1 shows that the coefficient of company size (Fsize) to the value of the company's technical efficiency is 0.3450. A positive coefficient indicates that the greater the company's size, the higher the latent variable, i.e., the technical efficiency will be. The marginal effect on this variable shows a coefficient of 0.2348. A positive coefficient indicates that, on average, an increase in company size will increase the value of the company's technical efficiency.

Table 1: The Tobit Regression of the Latent Variable

Variable	Coefficient	Standard Error
Fsize	0.3450***	0.000
HHI	-0.0499***	0.000
Abs	-0.0004	0.504
KLratio	-0.0264***	0.000
Ownership	0.0233***	0.000
Export	0.0506***	0.000
Constanta	0.4050***	0.000
Number of Observation	23,555	
Prob > Chi-Square	0.000	
Left Censored Observations: 299		
Right Censored Observations: 12		
No Censored Observations: 23244		
Note: *** Significant at $\alpha=1\%$		

Source: Own Calculation

The HHI index coefficient of the company's technical efficiency is -0.0499. The greater the value of the HHI, the lower the latent variable, i.e., the company's technical efficiency. The marginal effect on this variable shows a coefficient of -0.0340. A negative coefficient indicates that an increase in the HHI will decrease the company's technical efficiency.

The coefficient of the capital-labour ratio to the value of the company's technical efficiency is -0.0264. A 1 % increase in the capital-labour ratio will reduce the latent variable, i.e., the company's technical efficiency value by 0.0002 (0.0264×0.01). The marginal effect on this variable shows a coefficient of -0.0180, which means that an increase in the capital-labour ratio of 1 % will reduce the value of the company's technical efficiency by 0.0001 (0.0180×0.01).

The coefficient of the ownership to the value of technical efficiency is 0.0233. This means that a foreign-owned company has a latent variable value, i.e., a technical efficiency value higher than 0.0233 compared to a domestically-owned company. The marginal effect on the type of company shows a coefficient of 0.0153. This means that, on average, companies with foreign ownership have a technical efficiency value of 0.0153, higher than the value of technical efficiency with domestically-owned companies.

The coefficient of export (Exp) to the value of technical efficiency is 0.0506. This can be interpreted that increasing the average export by 1 % will increase the value of the latent variable in the form of a technical efficiency value by 0.0506. The marginal effect on this variable shows a coefficient of 0.0344. This means that, on average, an increase in exports of 1 % will increase the value of the company's technical efficiency by 0.0344.

Table 2 shows the result of the actual variable's Tobit regression. Four variables were significant at a 1 % level, and one variable was not significant: the absorptive capacity.

Table 2: The Tobit Regression of the Actual Variable

Variable	Coefficient	Standard Error
Fsize	0.2348***	0.000
HHI	-0.0340***	0.000
Abs	-0.0002	0.504
KLratio	-0.0180***	0.000
Ownership	0.0153***	0.000
Export	0.0344***	0.000

Note: * Significant at $\alpha=1\%$**

Source: Own Calculation

The following test is the Lagrange Multiplier (LM) test. Based on the results of the Lagrange Multiplier (LM) test on the determinant model of technical efficiency, the statistic was 3.10957. The critical value at α 1% is 6.97759, at α 5% is 3.84401, and at α 10% is 2.84760. Because the LM test statistic is less than any critical values (at 1% and 5%), then H_0 is not rejected. It can be concluded that the model is fitted with the Tobit regression method, which means that the distribution of errors is normal and homoscedasticity. Therefore, the expected results of Tobit parameters are consistent and efficient.

The following test is the Wald test, carried out to determine the level of significance of the independent variable in partially influencing the dependent variable. In the technical efficiency determinant model, company size, HHI, capital-labour ratio, company type dummy, and exports significantly influence the value of technical efficiency. Variable company size, capital-labour ratio, company type dummy, HHI, and export have a probability value of 0.000,

meaning less than $\alpha = 1\%$. Meanwhile, the partial absorptive capacity variable was not proven to affect the value of technical efficiency, as indicated by a probability value of 0.504.

Likelihood Ratio (LR) test results on the determinant model of technical efficiency show that the Chi-Square probability value is 0,000 or close to 0 %. This value indicates that the value of the Chi-Square probability is less than the significance level $\alpha = 1\%$, so H_0 is rejected. This can be interpreted that all the variables in the determinant model of technical efficiency, namely company size, HHI, absorptive capacity, capital-labour ratio, ownership, and exports, simultaneously have a significant effect on the dependent variable in the form of technical efficiency.

Tables 1 and 2 show that the coefficient of firm size variables has a positive relationship with the company's technical efficiency value. This means that, on average, a larger company size will increase the value of the company's technical efficiency. This is because large companies have more human resources in quantity and quality. Large companies usually have a robust system to recruit workers, choosing the highly skilled only. They can improve a company's managerial ability, which improves technical efficiency.

The finding is supported by [Usman et al. \(2014\)](#) and [Amornkitvikai and Harvie \(2010\)](#), arguing that larger companies generally have higher technical efficiency than those medium or small-sized companies. Moreover, larger companies have a larger production scale. The greater production scale certainly requires labour, raw materials, and more expertise in technology. This allows a larger company to increase the value of the company's technical efficiency than a small- or medium-sized company.

Empirically, [Ciani et al. \(2020\)](#) found that a foreign and large company in Indonesia generates 25 per cent higher productivity than a domestic and smaller company. It is because foreign-owned and large companies' performance is enhanced by access to sophisticated technology, advanced managerial know-how, and access to foreign demand. In this regard, the government may provide incentives for industries by offering loans with low-interest rates so that the industry can develop its business. Through loans with low-interest rates, companies can purchase sophisticated technology to enlarge the production scale. Consequently, human resource capacity should also be developed to utilise sophisticated technology fully.

The Tobit estimate shows that the coefficient of the market concentration variable has a negative relationship with the value of the company's technical efficiency. This means that companies with a higher market concentration averagely can reduce the value of the company's technical efficiency. The negative relationship is because companies with a higher market concentration have greater market power than other companies. Market power shows a higher market share. Companies with higher market shares tend to have low incentives to improve their production management capabilities and focus more on increasing the quantity of output to be produced. A high quantity of output produced can lead to mismanagement in company operations ([Usman et al., 2014](#)). This finding is supported by [Setiawan et al. \(2012\)](#), arguing higher concentration may push other less-productive companies out of the market so that the company's performance decreases and impacts decreasing the company's technical efficiency.

The estimation shows that companies with foreign ownership have a positive relationship with technical efficiency. This means that companies with foreign ownership types have higher technical efficiency values than those with domestic ownership. This is because companies with foreign ownership are companies with advanced technology which can optimise output with specific inputs. In addition, companies with foreign ownership can provide effi-

ciency spillovers to companies at the same firm level. As previously discussed, companies with a high foreign ownership type have a value of the technical efficiency above 0.5, more than companies with domestic ownership type whose dominant technical efficiency value is below 0.5 (TE value <0.5).

These results are in line with research by [Svedin and Stage \(2016\)](#). Capital ownership by foreign or domestic companies becomes a factor in the efficiency of a company. Ownership of capital from foreign companies can improve efficiency because foreign capital is associated with technology transfer compared to companies that get capital from domestic. With the existence of this technology, a company can optimise the use of its resources and increase competitiveness.

The capital-labour ratio has a negative relationship with technical efficiency. This means that a greater capital-labour ratio reduces the company's technical efficiency value. The capital-labour ratio represents the use of machines in the production process compared to labour. The higher the capital-labour ratio, the higher the use of machines in the production process. This study found it in contrast to the prior theories. However, [Sari et al. \(2016\)](#) argued that this negative impact may be attributed to the old machinery utilised by TPT firms, reducing technical efficiency. Another study (e.g., [Joshi and Sigh 2012](#)) discovered a similar result and argued that the negative capital-labour ratio is caused by underutilised or decreased production capacity. Under these conditions, the Indonesian government has issued a policy related to machine restructuring, which began to be implemented in 2007. The machine restructuring policy program targeted companies with machines or equipment older than 10 years. The condition of the machine requires revitalisation or restructuring. This machine restructuring policy is in the form of subsidies or lower prices of new machines at certain levels and conditions.

Export has a positive relationship with technical efficiency. This means that a higher export intensity will increase technical efficiency. High export agencies show that the output of these companies has high competitiveness so that they can compete in the global market. High competitiveness is characterized, among others, by low prices. Companies with higher export intensity will strive to improve their production management capabilities to produce highly competitive output. Increased production management capabilities can increase the company's technical efficiency value. Companies with high export intensity have a good performance, which increases the efficiency rate. They are forced to compete with such a high standard in the global market ([Gumbau-Albert and Maudos, 2002](#); [Trofimenko, 2008](#); [Usman et al., 2014](#)).

Conclusion

This study investigates the determinants of technical efficiency of textile and textile products (TPT) in Indonesia using the DEA bootstrapping approach and Tobit regression. Based on the calculation of DEA bootstrapping, the value of overall technical efficiency in the TPT industries from 2007 to 2013 was 0.2475 or 24.75 %. The efficiency value indicates that companies in the industry operate in an inefficient condition where the TE value less is than 1. To achieve efficient conditions, the textile and textile product industries have the potential to increase their output by 75.25 %. The highest and lowest technical efficiency values based on the ISIC 5-digit group are in the sewing and nonwoven industries. Each has technical efficiency values of 0.4386 or 43.86 % and 0.2111 or 21.11 %. Based on the Tobit regression results, it was found that firm size, HHI, absorptive capacity, capital-labour ratios, firm type dummy, and exports simultaneously and significantly influenced the value of the company's technical efficiency. Conversely, partial absorptive capacity does not significantly affect the technical efficiency value of the TPT industry companies in Indonesia.

This study suggests some policies based on the results. First, the government's policy needs to increase the company's managerial capabilities through a more strategic training program. The government should also provide incentives to workers as a reward or relief from income tax. Secondly, in terms of production equipment, the government can provide financing by lowering lending rates so that companies in the TPT industry can purchase machines with more advanced technology. Thirdly, the government could re-intensify the electricity energy subsidy program to stabilise the cost of production as electricity is the largest component of production costs in this industry. Fourth, the government can attract foreign investors through policies such as tax holidays and by maintaining a stable macroeconomy. Industries with foreign capital ownership are vulnerable to volatility in exchange rates, so the government should maintain a stable exchange rate both internally and externally. Fifth, the machine restructuring program could be targeted more effectively. Sixth, an export indicator can be improved by increasing product competitiveness through standardisation by Indonesian National Standard (SNI), providing incentives for export duties, improving infrastructure specifically for the flow of goods and services, and anti-dumping customs policies. In this case, domestic firms can reap benefits from the export channel.

This study has some limitations that can be improved in further studies. For instance, this study does not embrace endogeneity issues that might occur between the independent variables. Future studies will benefit from accommodating this issue by creating more rigorous and robust models.

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