

Technical Efficiency of Indonesia's Sugar Manufacturing Industry: Based on DEA-Bootstrap Approach

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Abstract

This study aims to measure the technical efficiency of companies in the sugar industry in Indonesia and determine the factors that influence the technical efficiency scores of these companies. The data was used in the form of time series for 2010-2014 with observations of 340 companies. The Bootstrap data envelopment method with the assumption of a return to scale variables and input orientation is used to measure the company's technical efficiency score. The results will be analyzed further as the dependent variable with Tobit regression for the technical efficiency determinant analysis stage. Based on the analysis results, the average score of the technical efficiency of the sugar industry is 0.67. Based on Tobit's estimation, the location factor is significant to the technical efficiency score, while the export, import, company ownership, market concentration, and firm size are not significant

Keywords: Data Envelopment Analysis Bootstrap; Sugar Industry; Technical Efficiency, Tobit Regression

JEL Classification: O14, L66

INTRODUCTION

The plantation-based industry plays a leading sector in economic growth, employment and encourages an even distribution income. The existence of the sugar industry acts as an economic asset and social capital (Marpaung et al., 2011). The sugar industry is one of Indonesia's oldest and most crucial plantation subsector manufacturing industries. History shows that Indonesia experienced the heyday of the sugar industry around 1930 with the number of operating sugar factories being 179 sugar factories, the productivity of around 14.8 percent and yields reaching 11-13.8 percent and peak production getting approximately 3 million tons, sugar exports had reached about 2.4 million tons. This is supported by the ease of obtaining fertile land, cheap labor, irrigation priorities, and discipline in applying technology (Susila & Sinaga, 2005).

Every year the demand for sugar continues to increase in line with population growth, increasing people's purchasing power and the development of industries that use sugar as their raw material. Although there is an increase in national sugar production, the production figure has not met household consumption of sugar. To meet the national sugar demand, Indonesia must import



sugar. According to BPS (2016), based on the development of Indonesian sugar production, consumption, and imports (Figure 1), there is a gap between national sugar production and consumption, from 2005-2012, where national sugar production fluctuated with small variations, this is not comparable to consumption and imports which tend to increase throughout the year. In 2010 it reached 2.29 million tons and decreased by 1.95 percent in 2011 to 2.24 million tons. In 2012 production it was increased by 15.87 percent to 2.60 million tons.

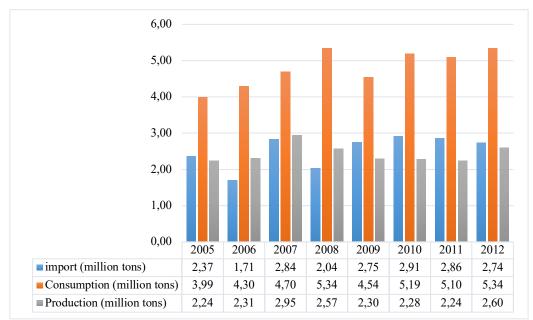


Figure 1. Development of Indonesian sugar production, consumption, and imports during 2005-2012

Source: BPS (2021)

The data on sugar production in Indonesia shows that the sugar production sector faces challenges example, the area of plantations decreased to less than 420,000 hectares (ha) in 2020. Similarly, production had fallen from 29.5 million tons (MT) in 2018 to 27 MT in 2020. In addition to the aging factory, challenges come from reduced cultivated land, lack of varieties, agricultural inefficiency, technological change, and lack of product diversification. Low productivity and technical inefficiency are often associated with a lack of adequate research and development support (Win et al., 2021). In the face of increasingly high competition, every company must always improve its efficiency. Efficiency is part of productivity which is defined as the ability of a production unit to obtain maximum output by using a certain number of inputs. Higher efficiency can increase the company's ability to generate company profits, both in terms of sales and the capital used to generate these profits. Therefore, that efficiency must be taken into account in industrial development efforts because it can provide an overview of the industry's performance.

Karimov et al. (2014) conducted a study on the Production and scale efficiency of maize farming households in South-Western Nigeria. The output variable is the total output of corn, and the input variable is labor, fertilizer, agricultural equipment, seeds, soil, and agricultural chemicals. The research method is DEA bootstrapping. The results indicate that there is an opportunity to



increase efficiency with the use of technology, several socio-economic variables such as employment outside agriculture, education, extension services, and credit, have a positive impact on the technical efficiency of farmer households, the government can use efficiency indicators to evaluate the efficiency of resource use. In crop production, increasing efficiency will increase domestic corn production, which will reduce social unrest and food insecurity.

A prior study by Wang et al. (2013) conducted a study on rural household apple production's technical and cost-efficiency. The output variable is the total production of apples, and the input variable is land, labor (wage workers and apple farmers), fertilizers, and pesticides, the dependent variable is the value of technical efficiency and the value of cost efficiency, while the independent variable is the level of education, technical training, density crop, apple planted area, apple yield per unit, cultivation area ratio, temperature, and rainfall. The research method is DEA and Tobit. The results showed that TE and CE were quite low in Shaanxi. Two aspects mainly caused the inefficient production of apple farmers. One of them is the inefficient operation of apple orchards by farmers and unfavorable environmental conditions, which greatly affect the growth of apples, different determinants identified by Tobit regression indicate that environmental factors such as temperature and uncontrolled rainfall have a strong influence on Apple farming TE and advice on the formation of integrated government training associations (i.e., agricultural cooperatives) based on apple production technology.

Ru and Si (2015) conducted a study on Total-factor energy efficiency in China's sugar manufacturing industry. The output variable is total sugar production, the input variables being capital, labor, raw materials, and energy consumption. The dependent variable is the value of technical efficiency. In contrast, the independent variables are foreign ownership, private ownership, land area, recovery rate, safe productivity, material, creativity. The research method is DEA bootstrapping, Probit and Tobit. The results showed that during the harvest season, the average TFEE was 0.57, there were spatial differences in TFEE in the Guangxi sugar industry, the highest in the southern region, the TFEE of foreign-owned sugar factories was larger than that of private and state-owned sugar factories, the larger the size of the sugar mills. The higher the TFEE, private ownership, land area, raw materials, safe productivity, total recovery rate, and technical progress, the higher the TFEE, private ownership, land area, and technical progress.

Based on the previous description, the sugar industry is exciting to study, especially regarding its declining productivity. High productivity must be supported by efficiency in the production process to grow rapidly, making it possible to produce more optimally and increase competitiveness. The main obstacles faced by sugar factories today are the low quality of raw materials, low factory efficiency, high quantity of imports, high stopping hours, and production costs (Dewan Gula Indonesia, 2010). Therefore, research on the efficiency of the sugar industry in Indonesia is an interesting study to determine the level of efficiency in the sugar industry in Indonesia in 2010-2014. This study identifies the level of technical efficiency and the determinants of technical efficiency to analyze the influence between the determinants of technical efficiency and the level of technical efficiency of the sugar industry, in contrast to research by Lei Ru and Wei Si (2015) measuring efficiency by considering TFEE, while in this technical efficiency is



calculated based on the output of the sugar industry by considering inputs in the form of labor, capital, material, and energy

METHOD

Data

The data used in this study is secondary data which is firm-level data. This data is the result of the annual survey report of manufacturing industry companies for five years, from 2010 to 2014, published by the Indonesian Central Statistics Agency in the form of raw data. The data used is sugar industry data in the form of unbalanced panel data, a combination of cross-section data and time-series data. The cross-section data in this study are all companies included in the sugar industry based on the Indonesian Standard Classification of Business Fields (KBLI) in 2009 5-digit ISIC code, while the time series data are sugar industry data from 2010 to 2014. The total observations in the study are 340 DMU (ISIC 10721).

Table 1. Definition of Operational Variable

Data	ion of Operational Variable Definition of Operational Variable	Data
(Variable)	•	Source
Output (Y)	Output is the total value of goods produced by each company in the sugar industry during the year of production (Thousands of Rupiah)	BPS
Capital (K)	Capital is all fixed assets such as land, buildings, machinery, equipment, vehicles, and others used for production activities (Thousands of Rupiah)	BPS
Labor (L)	The labor variable used in this study is the number of male and female workers/employees, both paid and unpaid workers (Number of people)	BPS
Material (M)	Raw materials are the main inputs used in sugar production activities (Thousands of Rupiah)	BPS
Energy (E)	Energy variable is the value or cost of various types of energy such as electricity, fuel, and lubricants used for the production process by each company (Thousands of Rupiah)	BPS
Technical Efficiency	The value of technical efficiency from the results of data processing using DEA Bootstrapping. (Ratio)	BPS
Dummy Locations	The dummy locations of the companies in this study are companies located in the Province of Sumatra and Java (Ratio)	BPS
Company ownership (Foreign)	Company ownership is the percentage of foreign capital ownership in each company in the sugar industry (Percentage)	BPS
Market concentration	Market concentration can be measured using HHI based on the sum of the squares of the market shares of all firms in the industry (Index)	BPS
Dummy Export	The export in question is the output exported by each company in the sugar industry (Ratio)	BPS
Dummy Import	Imports are raw materials imported by each company in the sugar processing industry (Ratio)	BPS



Model

Technical Efficiency

The researcher uses the DEA method, which is a non-parametric method, assuming that the sugar industry tries to minimize inputs to get a certain output (input-oriented) with a VRS measurement scale and a bootstrapping approach. The model can be written as follows:

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\begin{aligned} & \text{Min } _{\theta, \lambda} \theta, \\ & \text{st} & -q_i + Q \lambda \geq 0, \\ & \theta x_i - X \lambda \geq 0, \\ & \text{I1'} \lambda = 1 \\ & \lambda \geq 0. \end{aligned} \tag{1}
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 θ is an efficiency score that has a value between 0-1. A value of 1 indicates that the DMU is on the frontier or technically efficient, and a value of less than 1 indicates that the DMU is not working technically efficiently to reduce its input without affecting its output. λ is the constant vector Ix1, xi is the input vector I, and qi is the output vector i. X is the overall input matrix, Q is the entire output matrix i. I1' λ is the convexity constraint that ensures that inefficient firms are compared to firms of the same size/scale (Coelli, 2005).

Bootstrapping

DEA is a linear programming model assuming that there is no random error used to measure the technique's efficiency (Vincová, 2005). Ignoring statistical noise in the estimation can lead to biased DEA estimates and inaccurate results because all deviations from the frontier are considered inefficient (Dao, 2013). Simar and Wilson (1998) introduced a method to implement the bootstrap DEA technique, which is used to correct bias and set a confidence interval for each efficiency value generated by DEA.

Simar and Wilson (2000) calculated Bootstrap using the following biascorrected estimator:

$$\hat{\delta}(x,y) = \delta(x,y) - bias_B[\delta(x,y)] = 2\delta(x,y) - B^{-1} \sum_{b=1}^B \delta_b^*(x,y) \dots (2)$$
Condition of sample variance:

$$\delta_b^*(x,y)\frac{1}{3}(bias_B[\delta(x,y)])^2....(3)$$

Where $\delta(x,y)$ is the original efficiency score dan $\delta(x,y)$ and the corrected bias efficiency score. Meanwhile, $\delta_b^*(x,y)$ is the bootstrap estimate of the efficiency score on the b-the order of the B bootstrap repetition. The DEA model with the bootstrap approach in this study uses the R software and the FEAR package developed by Wilson (2010) to test the efficiency of the input-oriented technique with the VRS scale.

2.2.3. Tobit

Tobin J (1958) developed the Tobit regression model designed to estimate a linear relationship between variables when the dependent variable is limited by a minimum value or a maximum value (or both). Tobit regression using Stata 13 software.

TE_{it}=
$$\beta_1$$
DSumatera_{it}+ β_2 DJawa_{it}+ β_3 Asing+ β_4 HHI+ β_5 Exspor_{it}+ β_6 Import_{it}+e_{it}... (4) $TE_{it} = 0$ if $TE_{it}^* \le 0$: left sensor; $TE_{it} = TE_{it}^*$ if $0 < TE_{it}^* < 1$: uncensored;



 $TE_{it} = 1$ if $TE_{it}^* \ge 1$: right sensor

RESULTS AND DISCUSSION

The efficiency score of this research technique was obtained using the DEA Bootstrap method. The variable return-to-scale (VRS) assumption used in this study means that each company is assumed to operate at a scale that is not yet optimal. The range of technical efficiency scores obtained is 0-1, where a company with an efficiency score of 0 is the least efficient company, and an efficiency score of 1 is the most efficient company. The Bootstrap procedure in this study uses the Farrell (1957) efficiency measure, which is a reciprocal function of the Shepard efficiency measure. This procedure is asymptotic so the efficiency score produced in this study did not reach a score equal to 1. Companies that operate efficiently have used all of their inputs, namely capital, labor, raw materials, and energy, optimally. Meanwhile, companies that do not work efficiently have not used the available inputs optimally to change the combination of inputs still to produce output. The average score of technical efficiency in the sugar industry from 2010-2014 is 0.674 or about 67 percent so that there is still 33 percent of inputs that can be optimized so that the sugar industry can be technically efficient, assuming the company does not operate at an optimal scale due to existing constraints.

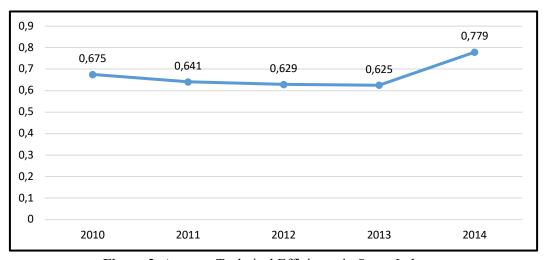


Figure 2. Average Technical Efficiency in Sugar Industry Source: Data Envelopment Analysis

In 2010 the average efficiency value was 0.675. In 2011 there was a slight decline of around 0.641, then in 2012 and 2013, it decreased again by 0.629 and 0.625. The average technical efficiency score in 2014 was the highest average in the sugar industry during the 2010-2014 period, which was 0.779. The highest efficiency score was achieved by PSID 10982 by obtaining a score of 0.959 in 2010, indicating that the inefficiency in production activities was 0.041. Overall, the specified output can be achieved if the company can reduce input by 4.1%, and the lowest efficiency score is achieved by PSID 18584 in 2010, with a score of 0.213 in 2010, indicating the inefficiency in production activities is 0.959. Overall, the specified output can be achieved if the company can reduce input by 95.9%. Fluctuations in average technical efficiency in 2010-2014 can be caused by several



factors in this research focusing on Locations Company ownership, Market concentration (HHI), Export and Import factors.

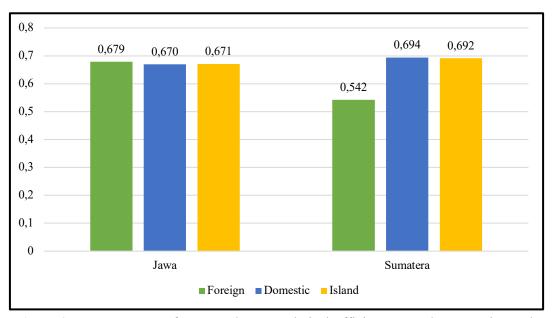


Figure 3. Average Score of Sugar Industry Technical Efficiency Based on Location and Company Ownership in 2010-2014
Source: Data Envelopment Analysis

Figure 3 illustrates the average technical efficiency score in the sugar industry by location, foreign ownership, and domestic from 2010 to 2014. The average technical efficiency score in Sumatra is higher than in Java. Sumatra Island with an average technical efficiency of 0.69 with a total of 42 companies, while the sugar industry in Java Island has an average technical efficiency of 0.671 with a total of 281 companies, although the number of companies on the island of Java is more than that on the island of Sumatra. However, the average technical efficiency on the island of Sumatra is higher, and this is because the sugar factories in Sumatra are generally new, designed with capacities that meet efficient economies of scale, while sugar factories in Java were generally built during the colonial period. Also, most (53%) sugar mills in Java are dominated by factories with small milling capacity (<3,000 TCD), 44 percent with a milling capacity of 3,000-6,000 TCD, and only 3.0 percent with a milling capacity of over 6,000 TCD. Approximately 68 percent of the existing sugar factories are more than 75 years old (generally small scale) and do not receive adequate maintenance. This condition causes a lowefficiency level (as seen from the unit cost/kg sugar produced).

The cost of producing sugar per ton in a small-scale sugar factory is much higher than that in a large-scale sugar factory or with relatively new machines (Sawit et al., 2004). The yield of sugarcane received by farmers on the island of Java is generally lower than that of farmers in Java. However, sugarcane farmers in Java use fertilizers and incur higher labor costs. The low yield is related to the sugar factory's dependence on raw materials from sugar cane traders because they control sugar cane from small farmers whose number is estimated at 60 percent. Mixing and setting the same milling time between sugarcane farmers and sugarcane traders has reduced the yield of sugarcane received by farmers. This factor is the cause of



the poor relationship between farmers and sugar factories because sugar factories are not willing to apply individual yields (Mardianto et al., 2005). After all, they control sugar cane from small farmers whose number is estimated at 60 percent. Mixing and setting the same milling time between sugarcane farmers and sugarcane traders has reduced the yield of sugarcane received by farmers.

This factor is the cause of the poor relationship between farmers and sugar factories because sugar factories are not willing to apply individual yields (Mardianto et al., 2005). They control sugar cane from small farmers whose number is estimated at 60 percent. Mixing and setting the same milling time between sugarcane farmers and sugarcane traders has reduced the yield of sugarcane received by farmers. This factor is the cause of the poor relationship between farmers and sugar factories because sugar factories are not willing to apply individual yields (Mardianto et al., 2005).

The average score of the technical efficiency of companies owned by foreign and domestic companies in Java shows a significant difference. The number of sugar companies on the island of Java is 272 domestic and 38 foreign companies, whilst on the island of Sumatra, there are 43 domestic companies and four foreign companies. The average technical efficiency score of foreign companies located in Java is 0.679, while the average technical efficiency score of domestic companies located in Java is 0.670. The average technical efficiency score of foreign and domestic companies located on Sumatra Island have significant differences. Significant foreign companies have an average technical efficiency of 0.542, and domestic companies have an average technical efficiency score of 0.694.

The allocation of productive assets in the form of capital ownership by foreigners has become an important theory in maximizing company performance, and this is because foreign ownership of capital affects investors' incentives to apply their resources as inputs to the company. Ownership of capital affects the cost of capital, investment level, technology transfer rate, and the sharing of profits from foreign investment. In addition, foreign ownership determines the extent to which a foreign company can control its subsidiaries and protect its assets.

Domestic owned companies on Java have an average score of technical efficiency slightly lower than the average score of technical efficiency of foreign companies. This could be because privately managed, and foreign-funded companies can improve technical efficiency due to technology transfer and building distribution networks. According to Sahoo and Nauriyal (2014), in general, the ownership of foreign companies tends to be more efficient than domestic companies. Foreign companies have better access to financial resources and intangible assets, such as more sophisticated technology, skills, and superior management practices. Stephanie et al. (2018); Shahverdi et al. (2015) that foreign ownership/FDI significantly increases technical efficiency scores. Companies managed by foreign parties, in general, can take advantage of technology that is not yet known by companies managed by local parties so that foreign companies have the advantage of producing palm oil with a more efficient combination of inputs. In addition, large foreign investor funding can be used to conduct more sophisticated research and development with higher quality inputs for more efficient production activities.

Domestic owned companies on the island of Sumatra have an average score of technical efficiency slightly higher than the average score of technical efficiency



of foreign companies, and this can occur due to problems with technology transfer constraints, company management, and high learning costs about different market conditions (Faruq, 2008). Foreign companies have quite high standards regarding raw materials. When the sugarcane harvest from the community is not good, foreign companies experience a decrease in the supply of raw materials, which affects the company's output which in turn affects the technical efficiency of the company.

Foreign ownership determines the extent to which a foreign company can control its subsidiaries and protect the company's assets. Previous studies have built a theory on how companies consider the ownership structure for overseas affiliates to maximize their performance. Will it allocate all of its own, or will it have to share ownership with local partners? If they choose joint ownership, how big is the share to maximize performance for foreign companies or local partners or equilibrium conditions (Priyanto & Qibthiyyah, 2020). According to Tybout (1992), trade liberalization increases technical efficiency by causing less efficient factories to exit the market. Theoretically, trade openness should increase technical efficiency through economies of scale; exports increase the potential for productive capacity and imports, thereby encouraging domestic companies to become more efficient to remain competitive.

Girma et al. (2008); Hsieh and Klenow (2009) state that domestic firms know the domestic market, legal and political environment; while foreign companies bring in capital, modern technology, better corporate governance, as well as managerial skills and international networks. Therefore, wholly foreign-owned companies will not achieve higher performance than joint venture companies due to more limited knowledge of the domestic market, laws, regulations, and bureaucratic environment; and workers' attitudes towards incentives, as well as a lack of political connections with local government, are often considered key determinants of performance.

Table 2 shows the results of the estimation of technical efficiency determinants using Tobit regression. Two variables included in the company location dummy, namely the Sumatra and Java Island dummy, were significant at the 1 percent level, but the Export Dummy, Import Dummy, Company ownership, market concentration, and firm size variables were not statistically significant. Six dummy variables of company location, dummy import, company ownership, market concentration, and firm size have a positive effect on technical efficiency. Meanwhile, the export dummy variable hurts technical efficiency. Simultaneous test results show that the chi-square probability value is 0.0000. The chi-square probability value is less than the 1% or 0.01 significance level, so H0 is rejected, and H1 is accepted.

Sumatra Province (DSumatera) on technical efficiency obtained a coefficient of 0.5630. The positive sign of the coefficient can be interpreted that, on average, companies located in the Province of Sumatra have a technical efficiency score of 0.5630 higher than companies located in other Provinces. The marginal effect of Java Province (Java) on technical efficiency obtained a coefficient of 0.5789. This means that, on average, companies located in Java province have a technical efficiency score of 0.5789 higher than companies located in other provinces. The results of this study are by research conducted by Stephanie et al. (2018) that differences in location cause differences in the technical efficiency scores of an industry. Geographically, these areas are suitable as plantation



locations, especially sugar cane plantations, because of the support of soil type and structure as well as climate. Sugar factories are also generally located close to their input sources: sugarcane plantations. This is provided to reduce transportation costs if the factory is located far from the source. The existence of an agreement with the local government can facilitate production activities.

Table 2. Tobit Regression Estimation Results

Variable	Coefficient
Company	0.563071
Sumatra	(0.000)
Java	0.578985
Java	(0.000)
Exmont	-0.006479
Export	(0.959)
Imported	0.039272
Imported	(0.343)
Company ownership (Foreign)	0.000297
Company ownership (Foreign)	(0.491)
Market concentration	0.140190
warket concentration	(0.565)
Firm Size	0.734972
riiii Size	(0.104)
Total obs	340
Prob > chi2	0.0000

Export dummy is not significant and has a negative efficiency. Exports are not significant because Indonesia's sugar production is mostly consumed domestically, and only a small portion is exported to foreign countries. The market share for sugar products has reached various countries in Asia, Africa, and negative export results can occur because the company has not been able to increase production capabilities to achieve better efficiency through exporting (learning by exporting), and this often happens in developing countries (Lemi & Wright, 2018).

Dummy Imports do not significantly affect technical efficiency because higher import growth than exports cause a trade deficit. Sugar commodity is one of the biggest contributors to Indonesia's trade balance deficit in the January-October 2020 period. Along with the increase in import volume in January-September 2020, the value of sugar imports rose 63.8 percent on an annual basis from US\$1.0 billion to US\$1.7 billion. This increase was higher than the growth in import volume, which reached 58 percent annually. Company ownership does not significantly affect technical efficiency. The results of this study are the same as the research conducted by Liu and Sathye (2016) that foreign ownership hurts technical hurts that this negative relationship occurred because the professionalism and expertise brought by foreign investors had not yet had a significant effect on the company; for example, most of the trade was still local.

Market concentration does not significantly affect technical efficiency. This means that companies operating in a more concentrated market will have lower technical efficiency scores, similar to Harianto (2020) results, which remarked that industrial concentration due to import competition can reduce the company's



efficiency level. This is because the large number of imported goods entering the domestic market causes the domestic market to become less competitive and efficient. Alam and Morrison (2000) describe that companies with a high industrial concentration level will reduce efficiency. The logic of this inverse relationship is that the less concentrated an industry is, the competition between companies will increase, forcing companies to be more competitive and will lead to better efficiency. On the other hand, high concentration will reduce competition between companies, thereby reducing incentives for companies to maximize their efficiency level.

Firm Size does not significantly affect technical efficiency because firm size increases management complexity and costs. Detailed supervision in large-scale companies is possible more than in small-scale companies. In addition, large-scale firms with low technical efficiency are better able to stay in the market even if they have economic problems than small-scale firms in competitive markets. Therefore, small-scale companies that survive the competition in the market on average show a higher level of technical efficiency than large-scale companies.

CONCLUSION

Based on the introduction, problem formulation, and discussion in this study, several conclusions were obtained, namely, in the efficiency analysis with bootstrap data envelopment analysis assuming a return to scale and input-oriented variable, it was found that the average technical efficiency score of 340 sugar industry companies in Indonesia in 2010-2014 was 0.67. The efficiency score shows that the average sugar industry company has not worked efficiently. It has a score of less than 100%. Overall, due to the inefficiency of 0.33, the input must be reduced by 33% to achieve efficient production. In the Tobit regression results, the factors that significantly affect the technical efficiency score are the company location factors, namely Java and Sumatra, while exports, imports, company ownership, market concentration, and firm size have no significant effect. All factors have a positive influence except for exports. The limitations of this study are that the latest data is not available, it does not research allocative efficiency and economic efficiency. Further research is expected to add variables that can reflect the determinants of efficiency, for example, the age of the company the average education of workers can also use other efficiency analysis methods, for instance, free disposal hull and stochastic frontier analysis.

REFERENCES

- Alam, I. M. S., & Morrison, A. R. (2000). Trade reform dynamics and technical efficiency: the Peruvian experience. *The World Bank Economic Review*, 14(2), 309-330
- BPS. (2016). Distribusi Perdagangan Komoditas Gula Pasir Indonesia. Badan Pusat Statistik, Jakarta.
- Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). An introduction to efficiency and productivity analysis. United States: *Springer Science & Business Media*.
- Dao, G. T. N. (2013). An analysis of the technical efficiency of crop farms in the Northern Region of Vietnam. Australia: University of Canberra.



- Dewan Gula Indonesia. (2010). *Laporan Gula Indonesia 2010*. Laporan Intern: 17-23
- Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society: Series A (General)*, 120(3), 253-281
- Faruq, H. (2008) "Survival in the export market of Sub-Saharan African Firms," *The Empirical Economics Letters*, 7(12), 1213–1220.
- Girma, S., Y. Gong., & H. Görg. (2008). Foreign direct investment, access to finance, and innovation activity in China. *World Bank Economic Review*, 22(2), 367–82.
- Harianto, S. K. (2020). Kompetisi, penanaman modal asing, dan efisiensi teknis: studi kasus industri manufaktur Indonesia. Doctoral Dissertation. Universitas Airlangga.
- Hsieh, C. T., & P. Klenow. (2009). Misallocation and manufacturing TFP in China and India. *Quarterly Journal of Economics*, 124(4), 1403–48.
- Karimov, A., Awotide, B. A., & Amos, T. T. (2014). Production and scale efficiency of maize farming households in South-Western Nigeria. *International Journal of social economics*.
- Lemi, A., & Wright, I. (2018). Exports, foreign ownership, and firm-level efficiency in Ethiopia and Kenya: an application of the stochastic frontier model. *Empirical Economics*, 1-30.
- Liu, L. X., & Sathye, M. (2016). The impact of foreign ownership and offshore investing on technical efficiency: Evidence from the Chinese managed funds industry. *The Journal of Wealth Management*, 18(4), 138-151.
- Mardianto, S., Simatupang, P., Hadi, P. U., Malian, H., & Susmiadi, A. (2005). Peta jalan (road map) dan kebijakan pengembangan industri gula nasional.
- Marpaung, Y. T. F., Hutagaol, P., Limbong, W. H., & Kusnadi, N. (2011). Perkembangan industri gula Indonesia dan urgensi swasembada gula nasional. *IJAE (Jurnal Ilmu Ekonomi Pertanian Indonesia*), 2(1), 1-14.
- Priyanto, E. A., & Qibthiyyah, R. M. (2020). Pengaruh Kepemilikan Asing Terhadap Kinerja Perusahaan Manufaktur Di Indonesia. *Jurnal Kebijakan Ekonomi*, 15(2), 3.
- Ru, L., & Si, W. (2015). Total-factor energy efficiency in China's sugar manufacturing industry. *China Agricultural Economic Review*, 7(3), 360-373. https://doi.org/10.1108/CAER-11-2014-0131
- Sahoo, B. K., & Nauriyal, D. K. (2014). Trends in and determinants of technical efficiency of software companies in India. *Journal of Policy Modeling*, 36(3), 539-561.
- Sari, D. W., Khalifah, N. A., & Suyanto, S. (2016). The spillover effects of foreign direct investment on the firms' productivity performances. *Journal of Productivity Analysis*, 46(2-3), 199-233
- Sawit, M., Erwidodo, H., Kuntohartono, T., & Siregar, H. (2004). Penyelamatan dan penyehatan industri gula nasional. Kajian Akademis. Jakarta: Sekretariat Dewan Ketahanan Pangan.
- Shahverdi, Z., & Hj Abd Jalil, S. (2015). The inefficiency of Malaysian palm oil refineries and the impact of different factors on its inefficiency. *International Journal of Organizational Leadership*, 4, 342-355.



- Simar, L., & Wilson, P. W. (2000). A General Methodology for Bootstrapping in Non-Parametric Frontier Models. *Journal of Applied Statistics*, 27(6), 779-802.
- Stephanie, H., Tinaprilla, N., & Rifin, A. (2018). Efisiensi pabrik kelapa sawit di Indonesia. *Jurnal Agribisnis Indonesia*, 6(1), 13-22.
- Susila, W. R., & Sinaga, B. M. (2005). Analisis kebijakan industri gula Indonesia. *Jurnal Agro Ekonomi*, 23(1), 30-53.
- Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica: Journal of the Econometric Society*, 24-36.
- Tybout, J. R. (1992). Linking trade and productivity: New research directions. *The World Bank Economic Review*, 6(2), 189-211.
- Vincová, K. (2005). Using DEA models to measure efficiency. *Biatec*, 13(8), 24-28.
- Wang, L., Huo, X., & Kabir, S. (2013). Technical and cost efficiency of rural household apple production. *China Agricultural Economic Review*.
- Wilson, P. W. (2010). FEAR 1.15 user's guide. South Carolina: Clemson University
- Win, T., Haryanto, T., & Sari, D. W. (2021). Analysis of energy efficiency of Indonesia's sugar industry. *International Energy Journal*, 21(2), 245-255.