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SWEET SUCCESS OR SOUR STRUGGLES? EFFICIENCY OF THE EAST JAVA SUGAR INDUSTRY

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ABSTRACT

East Java is one of the major sugar-producing provinces in Indonesia, home to sugar firms that have been operating for more than a century. However, the annual increase in sugar consumption has not been matched by a corresponding increase in production. Therefore, this study examines the efficiency of the sugar industry in East Java using an output-oriented approach, which separates persistent and transient inefficiencies, as well as an input-oriented approach that examines the use of machinery and energy, along with the determinants of inefficiency. This study applies the Stochastic Frontier Analysis (SFA) method, utilizing microdata from Statistik Industri (SI). The results reveal a trend of decreasing returns to scale in the sugar industry in East Java. Inefficiency in the sugar industry is primarily driven by persistent inefficiency, indicating the presence of structural problems. Furthermore, production inefficiency was found to be higher than inefficiency related to the use of machinery and energy. Export intensity has been shown to reduce inefficiencies in production, machinery use, and energy use. Additionally, greater reliance on imported materials contributes to lower energy inefficiency, while increased market concentration tends to exacerbate production inefficiency.

Keywords: *Sugar Industry, Efficiency, Production, Energy, Machinery*

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ABSTRAK

Jawa Timur merupakan provinsi penghasil gula utama di Indonesia dengan pabrik-pabrik gula yang telah beroperasi selama lebih dari satu abad. Namun, peningkatan konsumsi gula setiap tahunnya tidak diikuti oleh peningkatan produksi yang sebanding. Oleh karena itu, penelitian ini meneliti efisiensi industri gula di Jawa Timur dengan pendekatan orientasi output, yang memisahkan inefisiensi persisten dan transien, serta orientasi input yang mencakup penggunaan mesin dan energi, serta faktor-faktor determinan inefisiensi. enelitian ini menggunakan metode Stochastic Frontier Analysis (SFA) dengan memanfaatkan data mikro Statistik Industri (SI). Hasil penelitian menunjukkan adanya kecenderungan decreasing return to scale pada industri gula di Jawa Timur. Inefisiensi pada industri gula didominasi oleh inefisiensi persisten, yang mengindikasikan adanya permasalahan struktural. Selain itu, inefisiensi produksi tercatat lebih tinggi dibandingkan inefisiensi penggunaan mesin dan energi. Intensitas ekspor

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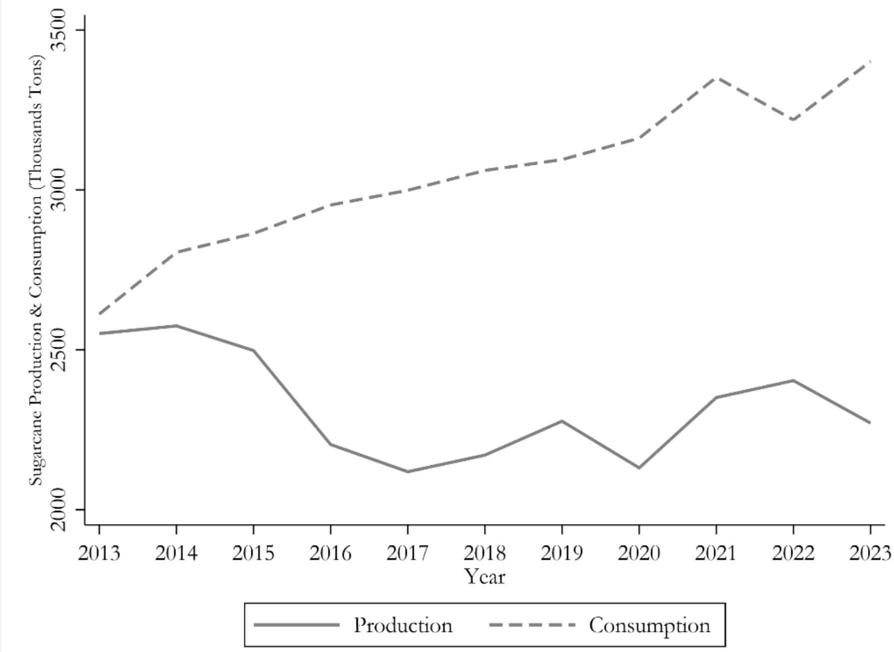
terbukti mampu menurunkan inefisiensi produksi, penggunaan mesin, dan energi. Sebaliknya, intensitas penggunaan material impor mampu menurunkan inefisiensi energi, sementara tingginya konsentrasi pasar cenderung memperburuk inefisiensi produksi.

Kata Kunci: *Industri Gula, Efisiensi, Produksi, Energi, Mesin*
JEL: D24, L66

Introduction

Sugar is one of the staple food commodities with a strategic function in Indonesian society (Sulaiman et al., 2023). Almost every food consumed daily by the public contains sugar, leading to an increasing demand for sugar in society. This indicates that sugar holds significant economic value, both for the sugarcane industry and sugar producers themselves.

Figure 1 illustrates national sugarcane production and consumption trends from 2013 to 2023, revealing a widening gap between the two. Sugarcane consumption exhibits a steady upward trend, particularly after 2018, indicating growing demand. In contrast, production has generally declined since 2013. Despite slight increases, production remains significantly lower than consumption, highlighting a persistent supply deficit. This widening gap suggests that domestic sugarcane production is insufficient to meet national demand, likely leading to increased reliance on imports. Several factors contribute to this disparity, including declining land area and productivity, inefficiencies in sugar processing, and the low yield of the national sugar industry (Bernardo et al., 2019).



Source: (National Sugar Summit, 2023)

Figure 1: National Sugarcane Production and Consumption, 2013-2023

The slow growth in national sugarcane production is also attributed to issues both in the plantation sector (on-farm) and the non-plantation sector (off-farm) (Marin *et al.*, 2019). Issues in the plantation sector (on-farm) that influence the low or high productivity of sugarcane include soil fertility, the availability of skilled labor capable of applying proper sugarcane cultivation techniques, irrigation systems, and the adoption of technology, all of which play a crucial role in determining the productivity of sugarcane plantations (Chohan, 2019). Moreover, the low productivity of sugarcane is also caused by various factors such as weather conditions and climate change (Murali & Puthira, 2017); the weak oversight of agricultural subsidies and fertilizer distribution; as well as poor infrastructure access between farmland and sugar mills (Guo et al., 2021).

Meanwhile, in the non-plantation (off-farm) sector, several factors influencing the low or high productivity of sugarcane include sugarcane quality, the required harvesting time, and the quality of sugar mill machinery management, all of which play a crucial role in determining the extraction yield of sugar mills in Indonesia (Win et al., 2021). The low extraction yield of sugar mills in Indonesia depends on the technology used in sugar milling machinery. Compared to other ASEAN countries, Indonesia has a lower extraction yield, recorded at 7.50% in 2018 (USDA, 2018). This is lower than the Philippines (9.20%) and Thailand (10.70%).

To boost the extraction yield of sugar mills and enhance the productivity of sugar factories in Indonesia, the government, through the Ministry of Industry, issued Minister of Industry Regulation (*Permenperin*) No. 50/M-IND/PER/3/2012 on the Sugar Industry Revitalization Program through the Restructuring of Sugar Mill Machinery and/or Equipment. This regulation was introduced to accelerate the Sugar Industry Revitalization Program, considering that most sugar mills in Indonesia are over 100 years old (USDA, 2018). However, sugar mill owners have not optimally utilized financial support for machinery revitalization as mandated by Permenperin 50/2012. The revitalization of sugar mill machinery can take 5 to 8 months to repair and upgrade the equipment, which would temporarily halt their sugar production (Soewardi & Wulandari, 2019). Additionally, several findings indicate that sugar mill revitalization has negative impacts, such as disruptions to workflow and business processes in the sugar industry (Lin et al., 2008); uncertainty regarding profit projections and cash flow (Rezende & Richardson, 2015); and the cessation of factory operations, as observed in several sugar firms following revitalization in Poland (Smutka et al., 2018).

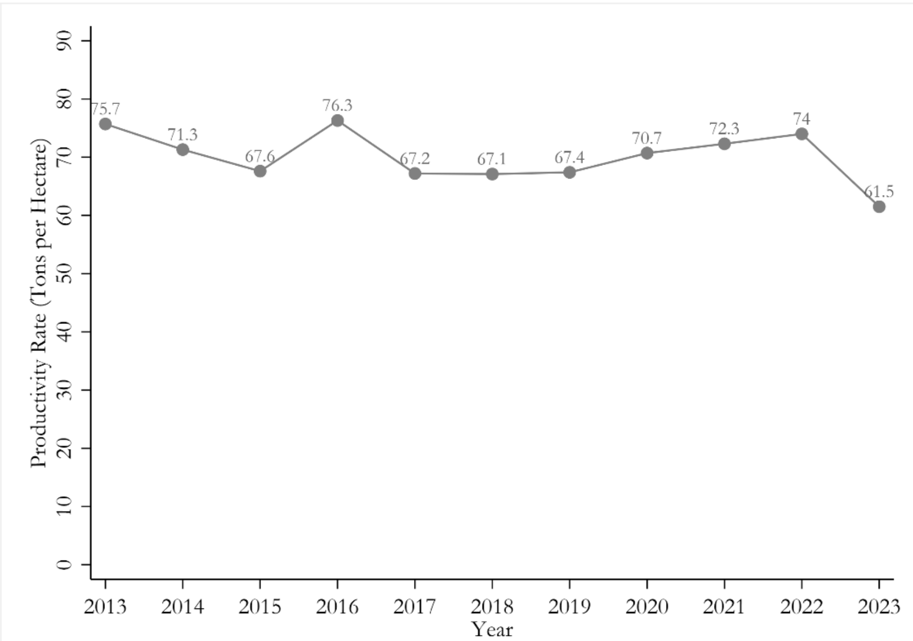


Figure 2: Indonesia Sugar Productivity Rate, 2013-2023

Source: (National Sugar Summit, 2023)

These issues affect national sugar productivity. Problems such as outdated machinery, low extraction yields, and challenges in the sugarcane plantation sector contribute to consistently low sugar productivity each year (Win et al., 2021). Over the past decade, Indonesia reached its highest sugar productivity in 2016, recording 76.3 tons per hectare. However, by 2023, Indonesia's sugar productivity had declined to 61.5 tons per hectare. This figure marks the lowest national sugar productivity level in the past ten years.

To support national sugar production, Indonesia has 58 operational sugar mills, 37 of which are state-owned enterprises, while the remaining 21 are privately owned and distributed across 12 provinces. One of the key provinces contributing to national sugar production is East Java, which serves as the country's primary sugar-producing region. Approximately 41% of Indonesia's total sugar production, or 74% of the total sugar production on Java Island, originates from East Java (Wulandari et al., 2024). In addition, East Java is the largest sugarcane-producing province in Indonesia, with a plantation area of 238,002 hectares and a production volume of 1,145,588 tons in 2022. There are 24 state-owned sugar factories and five privately-owned sugar factories spread throughout East Java *(Direktorat Jenderal Perkebunan Kementerian Pertanian Republik Indonesia*, 2024)

East Java's role as the largest sugarcane-producing province in Indonesia is closely linked to the sugar economy during the Dutch colonial era. In addition to hosting numerous sugar mills, East Java was home to the world's first private sugarcane research facility, Proefstation Oost-Java (East Java Research Station), which was established by a sugar company in the city of Pasoeroean (Pasuruan) (Tegegn & Dhont, 2023). From this research center, various highly productive and disease-resistant sugarcane varieties were developed, leading to what became known as the "varietal revolution" (Galloway, 2005). The reason why East Java was chosen as the center of sugar cane processing during the Dutch colonial era was the massive development in East Java (van Zanden & Marks, 2013), as well as due to East Java's more adaptable dry-season climate for sugarcane cultivation (Tegegn & Dhont, 2023). As a result, during the Dutch colonial era, East Java became the world's largest sugar producer and the second-largest sugar exporter after Cuba from 1870 to 1930. In 1930–1931, sugar exports from East Java accounted for 18% of total global sugar exports, amounting to 2,222,000–2,969,000 tons out of the 12,330,000–13,969,000 tons of total global sugar exports.

Although 47% of sugar mills are located in East Java, according to the (USDA, 2018) report, the productivity of the sugar industry in East Java is lower than that of Lampung Province, which accounts for only 32% of Indonesia's sugar mills. Seven sugar mills are located in Lampung, one of which is a state-owned enterprise (*BUMN*), while the remaining six are privately owned. This contrasts with East Java, which has 24 state-owned sugar mills and five private sugar mills. The large number of state-owned sugar mills in East Java is a result of the nationalization of Dutch firms carried out in the 1950s, following Indonesia's independence (Tegegn & Dhont, 2023). The nationalization of firms was not accompanied by machinery upgrades, resulting in low sugar mill efficiency and decreased productivity. As a consequence, the productivity of nationalized sugar mills is lower than that of privately owned sugar mills. Technological and managerial advancements have been key factors behind the higher productivity of privately owned sugar mills compared to state-owned sugar mills.

Most sugar mills in East Java are aging facilities resulting from nationalization, necessitating in-depth research on their sustainability by analyzing output elasticity, production efficiency, energy and machinery efficiency, and the determinants of inefficiency. This study contributes to the literature in two key aspects by addressing gaps in previous research. First, it is the first study to analyze the production efficiency of Indonesia's sugar industry by distinguishing between persistent efficiency and transient efficiency, whereas prior research has only focused on overall efficiency without differentiating these components. Second, this study enriches the literature on efficiency in the manufacturing sector, particularly in the sugar industry, by simultaneously assessing production efficiency, machinery utilization, energy efficiency, and their determinants. This research gap highlights the lack of attention to studies on the sugar industry, particularly in East Java, Indonesia's largest sugar-producing province.

Literature Review

Research on production efficiency, especially in the sugar industry, has been conducted in several countries using the stochastic frontier analysis (SFA) method, and different results have been found. Gicheru et al. (2007) found that the sugar industry in Kenya operates efficiently and has increased efficiency over time. Privatization of firms from public firms and the application of appropriate technology is one of the factors that can improve technical efficiency. In contrast to previous research, Sabur & Sina (2018) found a decrease in technical efficiency over time in the sugar industry in Bangladesh. Furthermore, Onour (2022) found that the main sources of inefficiency in the sugar industry were a decrease in labor productivity, a decrease in the scale of output, and no optimal utilization of capital in producing sugar.

In Indonesia, research on the efficiency of the sugar industry is still limited. Research by Marta & Erza (2017) and Taufiqo et al., (2021) analyzed the efficiency of the sugar industry using the data envelopment analysis (DEA) method which found that the sugar industry in Indonesia operates inefficiently, however, both studies used different input variables. Taufiqo et al., (2021) added energy variables into the production function as well as location, ownership, export, and import variables into the inefficiency function, while Marta & Erza (2017) only used variables of the amount of sugarcane milled, area, and milling capacity as inputs to measure production efficiency without further analyzing inefficiency factors. In a smaller scope, research on the efficiency of the sugar industry in East Java is also still limited to sugar factories owned by PT Perkebunan Nusantara XI. Gama et al. (2019) found that of the 15 sugar factories observed, only 40% operated efficiently. Meanwhile, Murdianti & Hanoum (2020) found that only 38% of sugar firms reached the optimal efficiency level. In addition, these two studies did not attempt to analyze more deeply the aspects of efficiency from the input side and the determinants of inefficiency.

The sugar industry in East Java has been the focus of many studies, as the province is a major sugar producer in Indonesia. Masyhuri et al. (2020) identified that land area, organic fertilizer use, and labor are the main factors in sugarcane production, while Yunitasari & Priyono, (2021) highlighted the close economic link between the sugar industry and the sugarcane farming sector as the main material. In terms of technology, Cavalcante & de Albuquerque (2015) emphasize the importance of standardizing production equipment, while Hindasgeri et al. (2022) underline the role of automation in improving operational efficiency. In terms of energy efficiency, Rafik et al. (2015) found that the use of membrane technology can significantly reduce energy consumption, while Riajaya et al. (2024) highlighted the utilization of optimizing water and energy use. In addition, other factors such as the even distribution of materials in the rainfall mapping for East Java (Mardhiana et al., 2021), and government policy support (Kulsum & Suciati, 2023) also contribute to improving the efficiency of the sugar industry in East Java.

Methodology

Data

The data used in this study is a firm-level panel dataset sourced from *Statistik Industri,* obtained through a survey conducted by the Central Bureau of Statistics (*Badan Pusat Statistik*/ BPS). The survey collects information by distributing questionnaires to all medium and large firms listed in the firm directory compiled by BPS. The dataset covers all manufacturing firms that employ at least 20 workers annually. Large firms are defined as those with more than 99 workers, while medium-sized firms are those with 20 to 99 workers.

This study uses panel data from 2011 to 2015, covering a total of 150 firms. Although *Statistik Industri* (SI) survey data is available for the period 2017 to 2019, it was excluded due to changes in firm identification codes introduced by BPS in 2017, with no concordance table available to match the new codes with the old ones. Additionally, the 2017 data lacks provincial information, further limiting its usability. Therefore, data from 2011 to 2015 was selected to ensure consistency and accuracy.

The production function and disaggregated input distance function include both output and input variables. The output variable is measured by the total value of sugar production produced by each firm in a given year. The input variables consist of capital (K), labor (L), materials (M), and energy (E). Capital is proxied by the estimated value of fixed assets, which is further divided into two components: machinery (K1) and non-machinery capital (K2), which includes land, buildings, vehicles, and other capital goods. Labor is defined as the number of workers employed. Materials are measured as the total cost of materials used during the production process, including both domestic and imported materials. Energy is defined as the total expenditure on gasoline, diesel, fuel, kerosene, public gas, lubricants, and electricity. The output, capital, materials, and energy variables are all measured in constant monetary terms, adjusted using the 2010 Wholesale Price Index (WPI).

The inefficiency function includes several exogenous variables: export intensity, imported material intensity, firm size, and market concentration. Export intensity is defined as the ratio of a firm's exported output to its total output, while imported material intensity is the ratio of imported materials to total materials used. Firm size is represented as a dummy variable, where firms employing more than 99 workers are classified as large firms (coded as 1), and firms with 20 to 99 workers are classified as medium firms (coded as 0). Market concentration is proxied using the Herfindahl-Hirschman Index (HHI), where a higher HHI indicates greater output concentration among firms, signaling reduced competition. Table 1 provides the variable measurement of the output, input, and exogenous variables.

Table 1: Variable Measurements

Variable	Proxy
Output (Y)	Total gross output value, capturing each firm's production, excluding semi-finished and unprocessed goods.
Capital (K)	Value of fixed assets, incorporating buildings, machinery, vehicles, and other capital goods.
Machinery Capital (K1)	Value of machinery capital goods.
Non-machinery capital (K2)	Value of fixed assets, including buildings, vehicles, and other capital goods.
Labor (L)	Number of workers engaged in production activities.
Material (M)	Total expenditure on domestic and imported materials.
Energy (E)	Total expenditure of the firm on gasoline, diesel, kerosene, coal, coal briquettes, gas, and other fuels.
Export Intensity (Exp)	Proportion of exported output relative to the total output produced.
Import Material Intensity (Imp)	Proportion of imported materials relative to total materials used.
Firm Size (FSize)	Firm size dummy variable, coded as 1 for firms with more than 99 workers (large firms).
Market Concentration (HHI)	Measured using the Herfindahl-Hirschman Index (HHI) approach.

Empirical Models

Stochastic frontier analysis (SFA), a parametric approach, and data envelopment analysis (DEA), a nonparametric approach, are the two primary methods for calculating technical efficiency. However, the DEA method has several limitations, including treating all deviations from the production frontier as inefficiency, assuming the absence of stochastic errors, and being highly sensitive to outliers. In contrast, the SFA method offers several advantages over DEA. SFA can simultaneously measure efficiency and identify its underlying determinants within a single stage of analysis, whereas DEA requires a two-stage process. Moreover, SFA is capable of distinguishing between inefficiency and stochastic variations in the production frontier, thereby improving the robustness of efficiency estimates (Lai & Kumbhakar, 2018). This advantage stems from SFA's assumption that deviations from the production frontier arise not only from inefficiency but also from random noise. As a result, factors beyond the firm's control can be explicitly incorporated into the measurement of technical efficiency (Kumbhakar & Tsionas, 2021). Therefore, this study adopts the parametric SFA method as the more appropriate approach, while the nonparametric DEA method is not employed.

Mathematically, the basic equation for a stochastic production function can be expressed as:

$$Y_{it} = (X_{it}; \beta) \tag{1}$$

Whereas Y_{it} is the output produced by firm i at time t, and X_{it} is the input variables of firm i at time t used in the production process.

The stochastic translog production function following Battese & Coelli (1995) is given as follows:

$$\begin{aligned} y_{it} = \beta_0 + \beta_1 k_{it} + \beta_2 l + \beta_3 m_{it} + \beta_4 \ln E_{it} + \tfrac{1}{2}\beta_5 (k_{it})^2 + \tfrac{1}{2}\beta_6 (l_{it})^2 + \tfrac{1}{2}\beta_7 (m)^2 + \\ \tfrac{1}{2}\beta_8 (e_{it})^2 + \beta_9 (k_{it} l_{it}) + \beta_{10}(k_{it} m_{it}) + \beta_{11}(k_{it} e_{it}) + \beta_{12}(l_{it} m_{it}) + \beta_{13}(l_{it} e_{it}) + \\ \beta_{14}(m_{it} e_{it}) + \beta_{15} t + \tfrac{1}{2}\beta_{16}(t^2) + \beta_{17}(k_{it} t) + \beta_{18}(l_{it} t) + \beta_{19}(e_{it} t) + v1_{it} - u1_{it} \end{aligned} \tag{2}$$

Where y_{it} represents the output produced by firm i at time t, and the input factors used in the production process by firm i at time t consist of capital (k), labor (l), materials (m), and energy (e). All output and input variables are expressed in natural logarithms and are measured as deviations from their geometric mean. The parameter β denotes the estimated coefficients. The term $v1_{it}$ represents the statistical noise for firm i at time t, assumed to follow an independent and identically distributed normal distribution: $v1_{it}$ ~iid.N(0, σ^2_{vit}). Meanwhile, $u1_{it}$ represents the production inefficiency term for firm i at time t, assumed to follow a non-negative truncated normal distribution: $u1_{it}$ ~iid.N+(μ, σ^2_{uit}).

A firm's production is considered technically efficient if its potential output (Y^*_{it}) equals its actual output (Y_{it}). Consequently, the value of technical efficiency ranges between 0 and 1, which can be expressed as follows:

$$u1_{it} = \frac{Y_{it}}{Y^*_{it}} \tag{3}$$

The exogenous variables that allegedly affect production efficiency are export intensity (Exp), import intensity (Imp), firm size (FSize), and market concentration (HHI). This can be expressed in equation (4).

$$u1_{it} = \delta_0 + \delta_1 Exp_{it} + \delta_2 Imp_{it} + \delta_3 FSize_{it} + \delta_4 HHI_{it} + w1_{it} \tag{4}$$

Where $w1_{it}$ represents the error term for firm i at time t in the inefficiency function.

The parameters of the production function (Equation 2) and technical inefficiency (Equation 4) are estimated simultaneously using the maximum likelihood method, assuming appropriate distributions for both error components, $v1_{it}$ and $u1_{it}$. The likelihood function is expressed in terms of the variance parameters: $\sigma^2_s \equiv \sigma^2_v + \sigma^2_u$ and $\gamma \equiv \sigma^2_u / \sigma^2_s$, where γ ranges between 0 and 1. A γ value close to zero indicates that the ordinary least squares (OLS) model provides a better fit, suggesting that inefficiency is negligible. Conversely, a γ value close to one indicates that the stochastic frontier model is more appropriate, as inefficiency plays a significant role in explaining deviations from the production frontier.

The estimated coefficients of the production function in Equation (2) cannot be directly interpreted in economic terms. However, they can be used to derive the output elasticity with respect to each input (Adli & Sari, 2024; Sari et al., 2016; Yasin, 2023). The output elasticity for each input can be calculated using the following formula:

$$\varepsilon_{nit} = \frac{\partial y_{it}}{\partial x n_{it}} = \beta_n + \frac{1}{2}\sum_{n=1}^{4}\sum_{m=1}^{4}\beta_{nm} x m_{it} + \beta_{nt} t \tag{5}$$

Furthermore, following Kumbhakar et al. (2014), who employed the translog production function, the overall inefficiency can be decomposed into persistent inefficiency and transient inefficiency, as expressed in the following formulation:

$$\begin{aligned} y_{it} = {} & \beta_0 + \beta_1 k_{it} + \beta_2 l + \beta_3 m_{it} + \beta_4 \ln E_{it} + \tfrac{1}{2}\beta_5 (k_{it})^2 + \tfrac{1}{2}\beta_6 (l_{it})^2 + \tfrac{1}{2}\beta_7 (m)^2 + \\ & \tfrac{1}{2}\beta_8 (e_{it})^2 + \beta_9 (k_{it} l_{it}) + \beta_{10} (k_{it} m_{it}) + \beta_{11} (k_{it} e_{it}) + \beta_{12} (l_{it} m_{it}) + \beta_{13} (l_{it} e_{it}) + \\ & \beta_{14} (m_{it} e_{it}) + \beta_{15} t + \tfrac{1}{2}\beta_{16} (t^2) + \beta_{17} (k_{it} t) + \beta_{18} (l_{it} t) + \beta_{19} (m_{it} t) + \beta_{19} (e_{it} t) + \\ & v2_{it} + \mu_i - \eta_i - u2_{it} \end{aligned} \tag{6}$$

The term $v2_{it}$ represents the random error for firm i at time t, while μ_i denotes firm-specific effects that capture unobserved, time-invariant factors influencing production. The overall inefficiency is decomposed into two distinct components: η_i, which captures persistent (time-invariant) inefficiency, and $u2_{it}$, which captures transient (time-variant) inefficiency. By distinguishing between these two sources of inefficiency, along with firm-specific effects, this approach allows for the assumption that firms can reduce inefficiency by addressing short-term operational constraints (transient inefficiency), while other inefficiency factors—often structural or systemic in nature—tend to persist over time (persistent inefficiency) (Yasin et al., 2025).

The Shephard sub-vector input distance function approach is applied to measure the efficiency levels associated with the use of disaggregated inputs (Boyd & Lee, 2019; Dolšak et al., 2022; Liu et al., 2024). In its general form, the disaggregate input distance function can be defined as follows:

$$D_X = (X_{it}; Y_{it}) = (K_{it}, L_{it}, M_{it}, E_{it}, Y_{it}) = (K1_{it}, K2_{it}, L_{it}, M_{it}, E_{it}, Y_{it}) \tag{7}$$

Where $K1_{it}$ represents the input variable for machinery used by firm i at time t, while $K2_{it}$ denotes the capital input variable other than machinery for firm i at time t. The stochastic disaggregate input distance function for machinery usage, formulated using the translog model, is presented in the following equation:

$$\ln D_{K1it}(K1_{it}, K2_{it}, L_{it}, M_{it}, E_{it}, Y_{it}) = \ln K1_{it} + \ln D_{K1it}(1, K2_{it}, L_{it}, M_{it}, E_{it}, Y_{it}) \tag{8}$$

$$\begin{aligned} -k1_{it} = {} & \beta_0 + \beta_1 k2_{it} + \beta_2 l_{it} + \beta_3 m_{it} + \beta_4 e_{it} + \beta_5 y_{it} + \tfrac{1}{2}\beta_6 (k2_{it})^2 + \tfrac{1}{2}\beta_7 (l_{it})^2 + \tfrac{1}{2}\beta_8 (m_{it})^2 + \\ & \tfrac{1}{2}\beta_9 (e_{it})^2 + \beta_{10} (y_{it})^2 + \beta_{11} (k2_{it} l_{it}) + \beta_{12} (k2_{it} m_{it}) + \beta_{13} (k2_{it} e_{it}) + \beta_{14} (k2_{it} y_{it}) + \\ & \beta_{15} (l_{it} m_{it}) + \beta_{16} (l_{it} e_{it}) + \beta_{17} (l_{it} y_{it}) + \beta_{18} (m_{it} e_{it}) + \beta_{19} (m_{it} y_{it}) + \beta_{20} (e_{it} y_{it}) + \beta_{21} t + \\ & \tfrac{1}{2}\beta_{22} (t^2) + \beta_{23} (k2_{it} t) + \beta_{24} (l_{it} t) + \beta_{25} (m_{it} t) + \beta_{26} (e_{it} t) + \beta_{27} (y_{it} t) + v3_{it} - \\ & D_{k1it}(k1_{it}, k2_{it}, l_{it}, m_{it}, e_{it}, y_{it}) \end{aligned} \tag{9}$$

$$\begin{aligned} \ln\left(\tfrac{1}{K1_{it}}\right) = {} & \beta_0 + \beta_1 k2_{it} + \beta_2 l_{it} + \beta_3 m_{it} + \beta_4 e_{it} + \beta_5 y_{it} + \tfrac{1}{2}\beta_6 (k2_{it})^2 + \tfrac{1}{2}\beta_7 (l_{it})^2 + \\ & \tfrac{1}{2}\beta_8 (m_{it})^2 + \tfrac{1}{2}\beta_9 (e_{it})^2 + \beta_{10} (y_{it})^2 + \beta_{11} (k2_{it} l_{it}) + \beta_{12} (k2_{it} m_{it}) + \beta_{13} (k2_{it} e_{it}) + \\ & \beta_{14} (k2_{it} y_{it}) + \beta_{15} (l_{it} m_{it}) + \beta_{16} (l_{it} e_{it}) + \beta_{17} (l_{it} y_{it}) + \beta_{18} (m_{it} e_{it}) + \beta_{19} (m_{it} y_{it}) + \\ & \beta_{20} (e_{it} y_{it}) + \beta_{21} t + \tfrac{1}{2}\beta_{22} (t^2) + \beta_{23} (k2_{it} t) + \beta_{24} (l_{it} t) + \beta_{25} (m_{it} t) + \beta_{26} (e_{it} t) + \\ & \beta_{27} (y_{it} t) + v3_{it} - u3_{it} \end{aligned} \tag{10}$$

Subsequently, the stochastic disaggregate input distance function for energy usage, formulated using the translog model, can be expressed in the following equation.

$$\ln D_{Eit}(K_{it}, L_{it}, M_{it}, E_{it}, Y_{it}) = \ln E_{it} + \ln D_{K1it}(K_{it}, L_{it}, M_{it}, 1; Y_{it}) \quad (11)$$

$$\begin{aligned} -e_{it} = {} & \beta_0 + \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 m_{it} + \beta_4 y_{it} + \tfrac{1}{2}\beta_5 (k_{it})^2 + \tfrac{1}{2}\beta_6 (l_{it})^2 + \tfrac{1}{2}\beta_7 (m_{it})^2 + \\ & \tfrac{1}{2}\beta_8 (y_{it})^2 + \beta_9 (k_{it} l_{it}) + \beta_{10} (k2_{it} m_{it}) + \beta_{11} (k_{it} y_{it}) + \beta_{12} (l_{it} m_{it}) + \beta_{13} (l_{it} y_{it}) + \\ & \beta_{14} (m_{it} y_{it}) + \beta_{15} t + \tfrac{1}{2}\beta_{16} (t^2) + \beta_{17} (k_{it} t) + \beta_{18} (l_{it} t) + \beta_{19} (m_{it} t) + \beta_{20} (y_{it} t) + \\ & v4_{it} - D_{k1it}(k_{it}, l_{it}, m_{it}, e_{it}; y_{it}) \end{aligned} \quad (12)$$

$$\begin{aligned} \ln\left(\frac{1}{E_{it}}\right) = {} & \beta_0 + \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 m_{it} + \beta_4 y_{it} + \tfrac{1}{2}\beta_5 (k_{it})^2 + \tfrac{1}{2}\beta_6 (l_{it})^2 + \tfrac{1}{2}\beta_7 (m_{it})^2 + \\ & \tfrac{1}{2}\beta_8 (y_{it})^2 + \beta_9 (k_{it} l_{it}) + \beta_{10} (k2_{it} m_{it}) + \beta_{11} (k_{it} y_{it}) + \beta_{12} (l_{it} m_{it}) + \beta_{13} (l_{it} y_{it}) + \\ & \beta_{14} (m_{it} y_{it}) + \beta_{15} t + \tfrac{1}{2}\beta_{16} (t^2) + \beta_{17} (k_{it} t) + \beta_{18} (l_{it} t) + \beta_{19} (m_{it} t) + \beta_{20} (y_{it} t) + \\ & v4_{it} - u4_{it} \end{aligned} \quad (13)$$

Where $v3_{it}$ and $v4_{it}$ represent the error terms for firm ii at time tt from the disaggregate input distance functions for machinery usage and energy usage, respectively. Furthermore, $u3_{it}$ denotes the machinery usage efficiency of firm i at time t, while $u4_{it}$ denotes the energy usage efficiency of firm i at time t.

Disaggregate input usage is considered efficient when the reciprocal of the input distance function equals the actual input usage. Consequently, the efficiency value for disaggregate input usage ranges between zero and one. The efficiency of machinery usage and energy usage can be represented by Equations (14) and (15), respectively.

$$u3_{it} = \frac{K1/D_{K1}(K1_{it}, K2_{it}, L_{it}, M_{it}, E_{it}; Y_{it})}{K1} = \frac{1}{D_{K1}(K1_{it}, K2_{it}, L_{it}, M_{it}, E_{it}; Y_{it})} \quad (14)$$

$$u4_{it} = \frac{E/D_E(K_{it}, L_{it}, M_{it}, E_{it}; Y_{it})}{E} = \frac{1}{D_E(K_{it}, L_{it}, M_{it}, E_{it}; Y_{it})} \quad (15)$$

The exogenous variables are assumed to affect efficiency of machine and energy use. Both functions are expressed in equations (16) and (17).

$$u3_{it} = \delta_0 + \delta_1 Exp_{it} + \delta_2 Imp_{it} + \delta_3 FSize_{it} + \delta_4 HHI_{it} + w2_{it} \quad (16)$$

$$u4_{it} = \delta_0 + \delta_1 Exp_{it} + \delta_2 Imp_{it} + \delta_3 FSize_{it} + \delta_4 HHI_{it} + w3_{it} \quad (17)$$

Where $w2_{it}$ and $w3_{it}$ are the error terms of firm i at time t from the input usage efficiency function.

The production function selection test was conducted using the translog production subfunction as the null hypothesis (H_0) and the transcendental logarithmic (translog) production function as the alternative hypothesis (H_1). According to studies by Kumbhakar et al. (2012) and Wang et al. (2021), a Hicks-neutral technological progress production function is present when there is no interaction between input and time $(\beta_{nt} = 0)$. Second, the absence of technological progress occurs when the time coefficients are zero $(\beta_t = \beta_{tt} = \beta_{nt} = 0)$. Third, the Cobb-Douglas production function applies when all coefficients other than those associated with inputs are zero $(\beta_t = \beta_{tt} = \beta_{nt} = \beta_{nm} = 0)$. The selection of the appropriate functional form is performed using the generalized likelihood-ratio (LR) test, calculated using the following equation:

$$\lambda = -2[l(H_0) - l(H_1)] \quad (18)$$

Where $l(H_0)$ represents the log-likelihood value of the translog production subfunction (covering Hicks-neutral technological progress, no technological progress, and Cobb-Douglas cases), and $l(H_1)$ represents the log-likelihood value of the translog maximum likelihood estimation (MLE). Hypothesis testing for this production function selection is conducted by rejecting H_0 if the LR test statistic (λ) exceeds the critical value from the $\chi2$ distribution table, with the degrees of freedom equal to the number of restricted parameters. If H_0, is rejected, it can be concluded that the appropriate production function model is the transcendental logarithmic (translog) function.

Results and Discussion

The sugar industry in East Java demonstrates intriguing dynamics. As shown in Table 2, the average firm output reaches IDR 449,000 million, with substantial variation between large and small firms. Capital investment, particularly in machinery (K1), plays a crucial role in the industry. Most of the capital is allocated to machinery, while investment in non-machinery assets, such as buildings and vehicles, is relatively modest. Additionally, materials (M) and energy (E) serve as the primary inputs in the production process, with firms spending an average of IDR 192,000 million on materials and IDR 25,900 million on energy. The considerable energy expenditure highlights the high energy demands associated with sugar production.

The majority of output from the sugar industry is exported, with export intensity reaching 92.42%, highlighting the industry's strong dependence on the global market. In terms of competition, the relatively low Herfindahl-Hirschman Index (HHI) of 0.0695 suggests a competitive market, with no single firm—or small group of firms—dominating the industry. Additionally, the sector is dominated by large firms, which make up 98% of all firms. Furthermore, with a low reliance on imported materials, most firms source their inputs locally, further integrating them into the domestic supply chain.

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std. Dev	Min	Max
Y	150	449,000	513,000	2,190	3,200,000
K	150	330,000	15,800,00	370	16,500,000
K1	150	267,000	1,330,000	150	13,000,000
K2	150	63,100	301,000	355	3,510,000
L	150	814	449	20	2,217
M	150	192,000	250,000	119	1,720,000
E	150	25,900	98,300	34	817,000
Exp	150	0.9242	0.2341	0	1
Imp	150	0.0059	0.0275	0	0.2424
FSize	150	0.9800	0.1405	0	1
HHI	150	0.0695	0.0072	0.0636	0.0836

Notes: Obs is the number of observations, Mean refers to the arithmetic mean, Std. Dev is the standard deviation, Min is the minimum value, and Max is the maximum value.

Table 3 presents the generalized log-likelihood test results from each analysis, which were used to determine the appropriate production function for this study. Referring to a significance level of α = 1 percent in the $\chi2$ test (Sari, 2019; Sari et al., 2016; Sugiharti et al., 2022; Suyanto et al., 2014; Yasin & Sari, 2022), the results show that λ exceeds $\chi2$ in both the production efficiency and energy use analyses. This confirms that the translog production function is the most appropriate choice for these analyses. In contrast, the analysis of machine usage indicates that the Hicks-Neutral production function provides a better fit.

Table 3: Generalized Likelihood Ratio Test

	Model	Hicks-Neutral (df = 4)	No-Technological Progress (df = 6)	Cobb-Douglas (df = 16)	Decision
Production	Translog (Baseline)	108.85	208.39	70.47	Translog
	χ^2	13.28	16.81	3.,00	
Machinery	Translog (Baseline)	-3.68	226.64	188.45	Hicks-Neutral
	χ^2	15.08	18.48	40.29	
Energy	Translog (Baseline)	23.91	29.72	53.26	Translog
	χ^2	13.28	16.81	32.00	

Table 4: Maximum-Likelihood Estimation

Production			Input Distance Functions					
			Machinery			Energy		
Variable	Coeff.	S.E	Variable	Coeff.	S.E	Variable	Coeff.	S.E
constant	0.4080***	3.6192	constant	0.3851***	0.7237	constant	-0.7661***	0.3221
k	0.0654	0.3975	$k2$	0.0675	0.5040	k	-0.0342	0.0778
l	-0.1280	2.3467	l	-0.1712	0.8849	l	-0.8812***	0.2022
m	0.5886**	0.4092	m	0.3192**	0.5960	m	0.1194*	0.1316
e	0.1584*	0.2240	e	-0.0312	0.5205	y	-0.2242*	0.1696
k^2	0.0632	0.1791	y	-0.1230	0.6853	k^2	0.0146	0.0627
l^2	0.0401**	3.3286	k^2	-0.1827**	0.2093	l^2	-1.0201***	0.3047
m^2	0.1733***	0.0722	l^2	-0.1330	0.8433	m^2	0.0312	0.0884
e^2	-0.0741	0.3049	m^2	0.1001	0.3941	y^2	-0.0061	0.1021
$k\,x\,l$	0.2531	0.7616	e^2	-0.0505	0.2176	$k\,x\,l$	0.1063*	0.0983
$k\,x\,e$	-0.1634*	0.0431	y^2	-0.0250	0.8083	$k\,x\,m$	-0.0621	0.0725
$k\,x\,m$	-0.1634	0.0431	$k2\,x\,l$	-0.1806	0.7858	$k\,x\,y$	0.0581	0.0734
$l\,x\,m$	-0.0031**	0.6501	$k2\,x\,e$	0.1316	0.3469	$l\,x\,m$	0.4224***	0.1377
$l\,x\,e$	-0.0860	0.4441	$k2\,x\,m$	0.2112**	0.3095	$l\,x\,y$	-0.1640*	0.1357
$m\,x\,e$	-0.0021	0.3027	$k2\,x\,y$	-0.1187	0.4849	$m\,x\,y$	0.0078*	0.0720
t	0.0264*	0.4097	$l\,x\,m$	-0.1127	0.694.	t	-0.0735	0.0834
t^2	-0.0972	0.5249	$l\,x\,e$	0.0866	0.4981	t^2	0.0763*	0.1230
$k\,x\,t$	0.0170	0.1010	$l\,x\,y$	0.1609**	0.6831	$k\,x\,t$	-0.0446	0.0459
$l\,x\,t$	0.2155*	0.7357	$m\,x\,e$	-0.0638	0.2043	$l\,x\,t$	0.2487**	0.1080
$m\,x\,t$	-0.0169*	0.3334	$m\,x\,y$	-0.0921	0.3995	$m\,x\,t$	-0.0809*	0.0598
$e\,x\,t$	-0.1028	0.0409	$e\,x\,y$	0.0451	0.3086	$y\,x\,t$	-0.0179	0.0575
			t	0.2046	0.4187			
			t^2	0.4200*	0.5398			
σ^2	0.8415***	0.0837	σ^2	1.2778***	1.3503	σ^2	1.4942***	0.1560
γ	0.9404***	0.2060	γ	0.9363***	0.0029	γ	0.9436***	0.0555

Notes: *significant at α = 10%, ** significant at α = 5%, *** significant at α = 1%.

Table 4 presents the estimated coefficients of the production function. Due to space constraints, only selected estimation results are provided for each efficiency analysis (production, machinery, and energy). The coefficients shown in Table 4 cannot be directly interpreted in economic terms. Therefore, it is necessary to calculate output elasticities to obtain meaningful economic insights (see Table 5).

Table 5: Output Elasticity

Input	Elasticity
ε_k	0.0721
ε_l	0.0429
ε_e	0.1178
ε_m	0.5820
ε_{total}	0.8147

Notes: ε_k refers to capital elasticity, ε_l refers to labor elasticity, ε_e refers to energy elasticity, ε_m refers to material elasticity, and ε_{total} refers to total elasticity

Table 5 presents the contribution of each input — capital, labor, material, and energy — to the output of the sugar industry in East Java. Among these inputs, the elasticity of material (ε_m) is the highest, at 0.5820, indicating that material inputs play the largest role in determining output. This suggests that a 1% increase in material input leads to a 0.582% increase in output, highlighting the industry's strong dependence on both the quantity and quality of materials. This reliance is further supported by East Java's position as the largest sugarcane-producing province in 2023, with a production volume of 1.12 million tons, accounting for 49.34% of total national production (BPS, 2024). Consequently, ensuring both the availability and quality of sugarcane — the primary raw material — is essential for increasing production levels. Energy ranks as the next most important factor, with an elasticity value of 0.1178, highlighting the energy-intensive nature of sugar processing. Sugar production involves multiple stages — extraction, refining, and crystallization — all of which demand substantial energy inputs.

The capital elasticity, at 0.0721, is higher than that of labor but remains relatively lower than the elasticities of materials and energy. This low capital elasticity can be attributed to the widespread use of outdated machinery (Win et al., 2021). Many firms continue to operate with machines that were installed decades ago, which tend to function inefficiently and contribute to lower overall productivity. This situation highlights the urgent need for modernization. By adopting newer, more efficient machinery, the sugar industry in East Java could enhance productivity, reduce downtime, and lower maintenance costs, ultimately improving capital elasticity.

Labor elasticity is the lowest, at 0.0429, indicating that increases in labor input contribute the least to output. Specifically, a 1% increase in labor input results in only a 0.0429% increase in output. This low value suggests that the industry may have reached a point of labor saturation, where adding more workers does not significantly boost production. Several factors could contribute to this, including the skill level of the workforce. This finding highlights that simply expanding the labor force is not an effective strategy for increasing production. Instead, efforts to enhance labor productivity — through training programs and improved management practices — would likely yield better results

The total elasticity value of 0.8147 indicates that the sugar industry in East Java operates under decreasing returns to scale (DRS), suggesting that the current production process is not yet optimized for scalability. This condition is largely driven by the low elasticity of both capital and labor, which limits the industry's ability to efficiently scale up production.

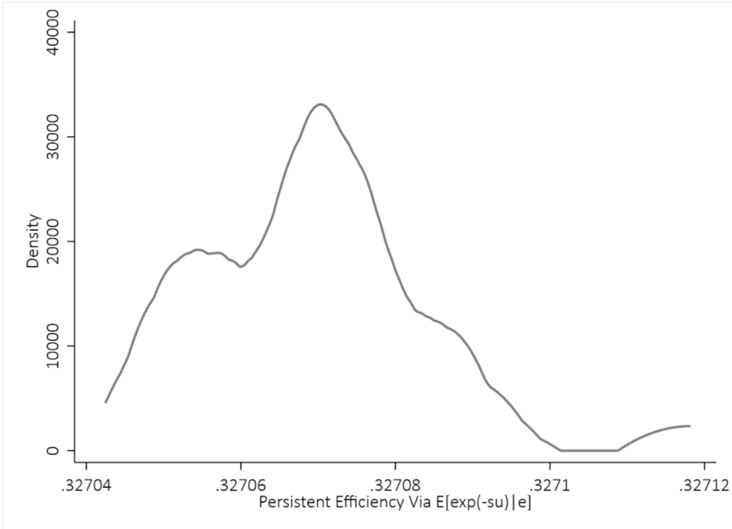


Figure 3: Persistent Efficiency Distribution

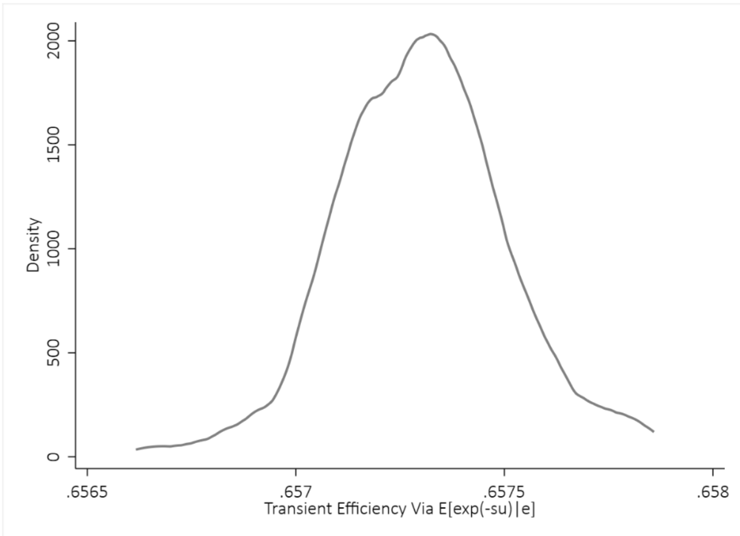


Figure 4: Transient Efficiency Distribution

Figure 3 presents the distribution of persistent efficiency, while Figure 4 shows the distribution of transient efficiency in the sugar industry in East Java. Both persistent and transient efficiency levels are relatively homogeneous. However, persistent efficiency tends to be significantly lower, with levels around 32%, compared to transient efficiency, which reaches approximately 65%. This indicates that the industry experiences substantially higher levels of persistent inefficiency than transient inefficiency. Persistent inefficiency is characterized by its time-invariant nature and is typically caused by structural problems or systematic managerial weaknesses (Chen et al., 2021; Yasin et al., 2025). In contrast, transient inefficiency is time-variant, reflecting conditions where producers have the potential to improve technical efficiency over time to meet the benchmark. These inefficiencies arise from unsystematic management issues and can generally be addressed in the short term (Badunenko & Kumbhakar, 2016).

A major structural challenge facing the sugar industry is aging infrastructure. Over 65% of Indonesia's sugar mills — particularly in East Java — have been operating for more than a century, with some exceeding 100 years of service (Win et al., 2021). These older mills have high specific energy consumption (SEC), especially in their heating systems, making them far less efficient than modern facilities. The continued use of outdated machinery also requires more frequent maintenance, which increases operating costs and reduces overall efficiency.

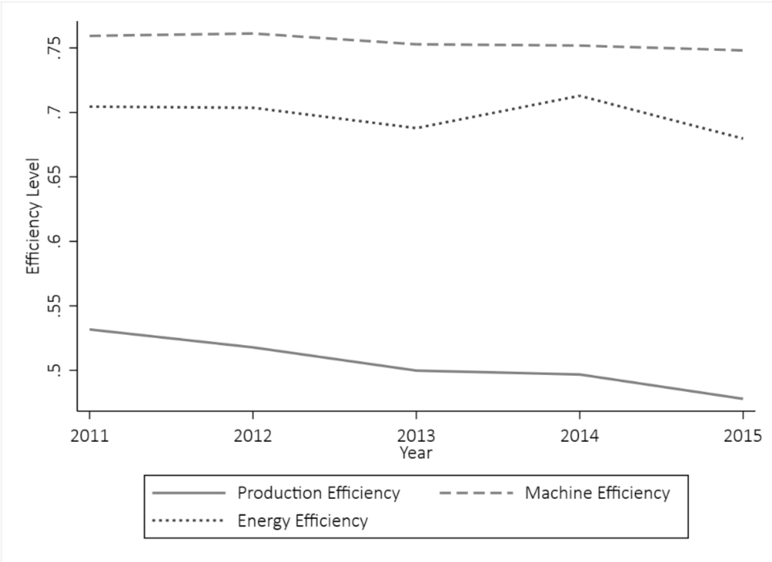


Figure 5: Trends in Production, Machinery, and Energy Efficiency Levels

Figure 5 illustrates the efficiency level for production, machinery use and energy use in the East Java sugar industry from 2011 to 2015. During this period, production efficiency consistently decreased from 0.5317 in 2011 to 0.4779 in 2015. This decline was caused by various factors, mainly the impact of El Niño and outdated infrastructure.

The El Niño phenomena in 2012 and 2015 were marked by reduced rainfall and extended dry seasons (Cash & Burls, 2019). These drought conditions lowered soil moisture levels and disrupted sugarcane growth during the critical vegetative phase, negatively impacting sugarcane cultivation in East Java. As a result, lower yields reduced production efficiency, as the crops were unable to reach optimal growth. Beyond climatic influences, aging infrastructure and machinery further contribute to the decline in production efficiency. Many sugar mills in East Java continue to depend on machinery that has been in operation for decades. These aging machines are often inefficient, more susceptible to breakdowns, and require extensive maintenance. This dependence on outdated equipment drives up maintenance costs and causes frequent operational disruptions, ultimately lowering the overall efficiency of the sugar industry.

Machine usage efficiency has remained relatively stagnant over the past five years, with only slight fluctuations. It started at 0.7593 in 2011 and declined slightly to 0.7481 in 2015. This stagnation suggests that while machines are consistently utilized, their efficiency has not improved. The gradual decline may indicate increasing inefficiencies due to wear and tear, inadequate maintenance, or outdated technology. These findings align with previous analyses highlighting the issue of antiquated machinery in the industry (Sulaiman et al., 2023; Toharisman & Triantarti, 2016; Win et al., 2021). To address this, the East Java sugar industry could benefit from investing in equipment modernization and implementing regular maintenance schedules to maximize machine efficiency.

Beyond aging infrastructure, the technology gap between older and newer sugar mills also impacts energy efficiency. Upgrading heating systems and adopting energy-saving practices can significantly enhance overall efficiency. In sugar manufacturing, heating systems play a crucial role in juice extraction, water evaporation, crystallization, refining, and drying—processes essential for producing high-quality sugar. However, financial constraints and limited access to capital have hindered the widespread adoption of modern technologies. The industry's high specific energy consumption is also driven by reliance on traditional energy sources like coal and petroleum, which are less efficient than modern alternatives such as biomass or renewable energy. Additionally, differences in managerial expertise and operational practices contribute to variations in energy efficiency, with well-managed factories making more effective use of energy resources. Addressing these challenges requires substantial investments in machinery modernization, the adoption of energy-efficient technologies, and improvements in managerial expertise to optimize energy use across the industry.

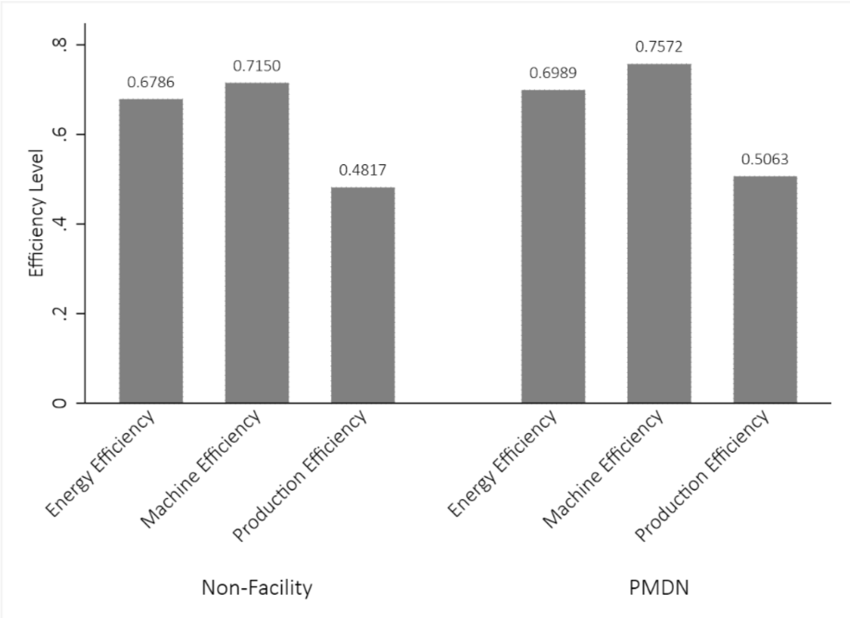


Figure 6: Production, Machinery, and Energy Efficiency Scores by Capital Ownership

Figure 6 shows that firms with capital ownership sourced from Domestic Investment (PMDN) achieve higher average efficiency scores in production, machinery utilization, and energy use compared to firms with non-facility capital. This is largely due to the fact that firms with PMDN capital must meet several criteria to qualify for business expansion and new investment facilities, as outlined in *Pasal 77 UU Cipta Kerja*. These criteria include absorbing a large workforce, being classified as a high-priority sector, contributing to infrastructure development, facilitating technology transfer, engaging in pioneering industries, operating in 3T areas (underdeveloped, remote, and outermost regions) or other designated areas, promoting environmental sustainability, conducting research, development, and innovation activities, partnering with MSMEs or cooperatives, using domestically produced capital goods, machinery, or equipment, and contributing to tourism business development. These facilities, including fiscal incentives, make PMDN-funded firms more attractive to investors, which in turn drives output growth. This finding aligns with Nurilmih et al. (2023), who concluded that PMDN positively influences the manufacturing industry. Increased domestic investment optimizes production factors and enhances resource efficiency.

The finding that there is no significant difference in efficiency scores between sugar firms located inside and outside industrial estates in East Java (see Figure 7) can be explained by several key factors. One of these is the uniformity of technology and production processes in the sugar industry. Firms in this sector generally use similar machinery and operational systems, ensuring a relatively consistent level of production efficiency regardless of location

(Cavalcante & de Albuquerque, 2015). This technological standardization means that a firm's location is not a significant factor in its efficiency performance. Additionally, equal access to raw materials also contributes to this similarity in efficiency. The sugar industry heavily relies on sugarcane as its primary raw material, which is fairly evenly distributed across different regions of East Java (Mardhiana et al., 2021; Masyhuri et al., 2020). Since firms both inside and outside industrial estates have comparable access to this resource, there are no substantial logistical advantages that would significantly enhance efficiency for one group over the other.

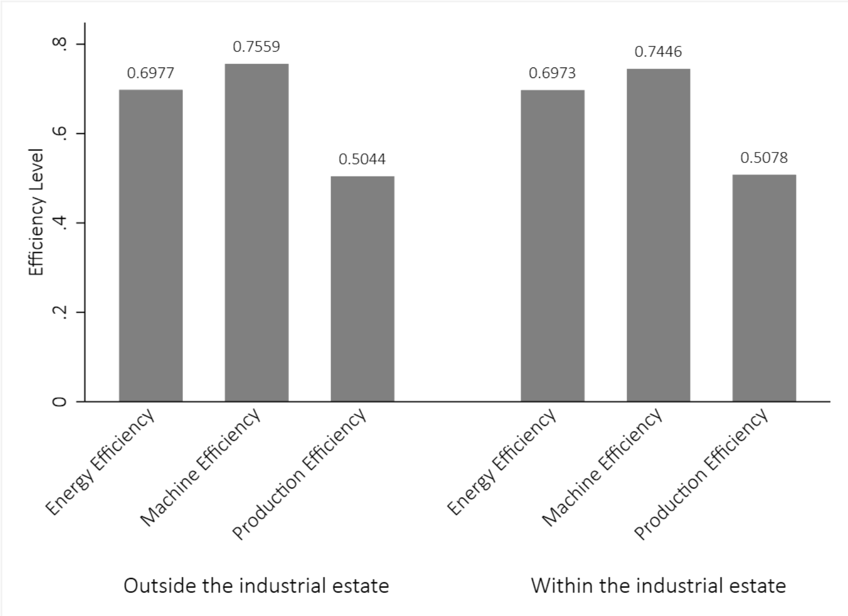


Figure 7: Production, Machinery, and Energy Efficiency Scores by Firm Location

The results of the analysis as listed in figures 10, 11, and 12 show that Tulungagung Regency is consistently the region with the highest level of efficiency in terms of production, machinery, and energy. Machine efficiency in sugar factories in Tulungagung Regency and Bondowoso Regency occurs due to technological improvements made in sugar factories in these areas. Technological improvements in sugar factories in Tulungagung Regency use sulfitation technology to produce premium sugar (Antara, 2013) In addition to the use of sulfitation technology, technological improvements in sugar factories in Tulungagung Regency are carried out by adding a "juice smoothing" tool that functions to purify sap and increase the efficiency of sugar refining.

Although Tulungagung Regency has the highest efficiency level compared to other regions in East Java, it has the smallest actual output and potential output. This compares to Sidoarjo and Malang Regency, which have the highest actual output compared to other regions in East Java. This is because the area of sugarcane plantations and sugar production in Sidoarjo and Malang are larger than those in Tulungagung and Bondowoso. On average, the area of sugarcane plantations in Malang Regency and Sidoarjo Regency is larger at 41 thousand hectares and 4 thousand hectares respectively, compared to the area of sugarcane plantations in Tulungagung Regency and Bondowoso Regency, which both have 5 thousand hectares each. In addition, sugar production in Malang and Sidoarjo districts is greater than that of Tulungagung and Bondowoso Regency at 243 thousand tons and 27 thousand tons, respectively, while sugar production in Tulungagung and Bondowoso Regency is only 30 thousand tons each. Although the output produced by Sidoarjo Regency and Malang Regency is higher than that of Tulungagung Regency. However, Sidoarjo Regency has lower production, machinery and energy efficiency.

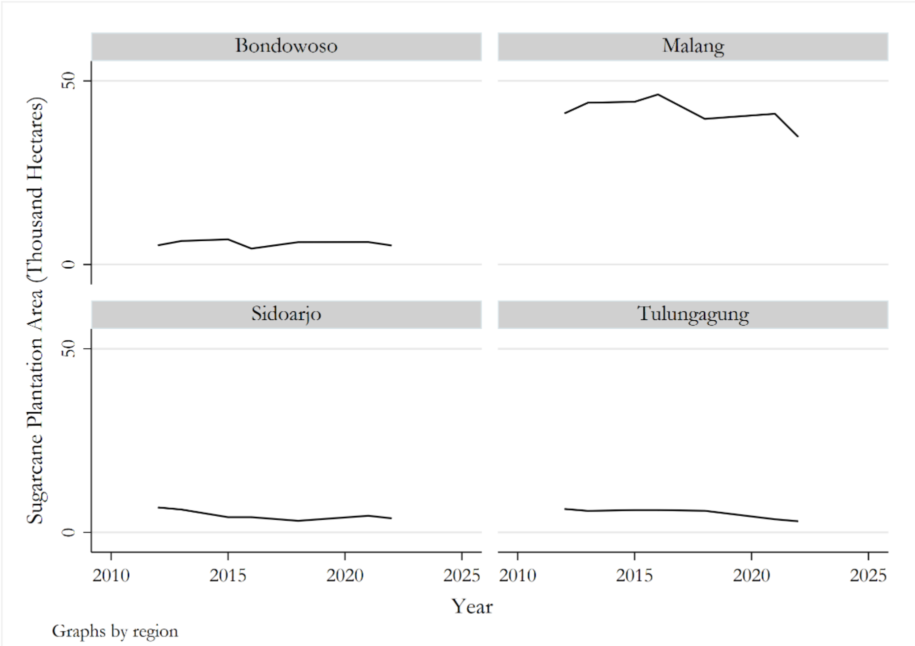


Figure 8: Sugarcane Plantation Area

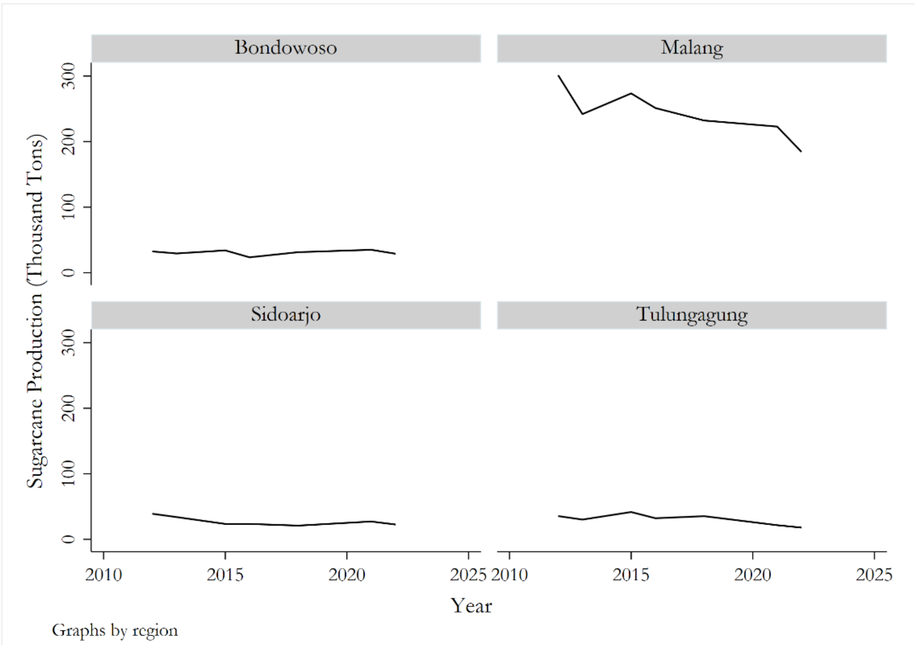


Figure 9: Sugarcane Production

First, on the aspect of production efficiency, several previous studies have mentioned that sugar mills in Sidoarjo Regency have a low level of efficiency (Anastasya et al., 2020; Purnama., 2023). Production efficiency in sugar factories in Sidoarjo Regency occurs because sugar factories do not maximize the use of standard milling capacity as set by the company (Anastasya et al., 2020). In addition, low production efficiency is also caused by two factors, namely material and human resources (Purnama., 2023). Material factors are caused by the unavailability of materials and the quality of materials that do not meet company standards. While the human resource factor is the low morale and fatigue experienced by workers, thus reducing worker productivity.

Second, in the aspect of machine efficiency, sugar factories in Malang Regency have a low Overall Equipment Effectiveness (OEE) value (Maknunah et al., 2017). OEE measures how effectively machines are used in the production process through three main components: availability, performance and quality. The findings show that the OEE value of the sugar factory machinery is in the range of 70.52%-78.81% and has not yet reached the ideal OEE value of 85%. Not achieving the ideal OEE value is influenced by the low level of one of the components, namely the reduced speed loss factor.

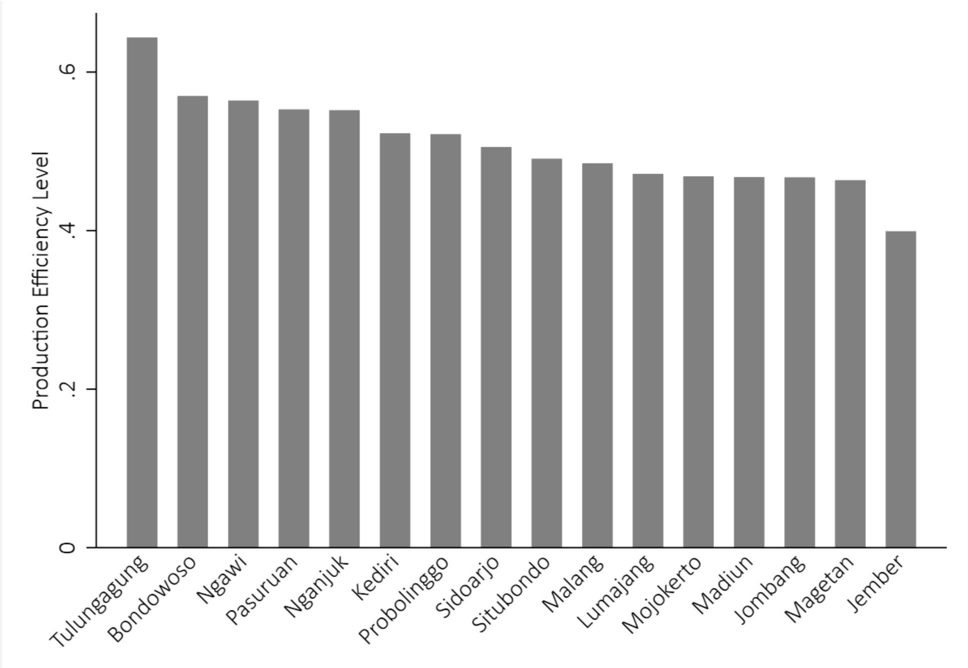


Figure 10: Production Efficiency by Region

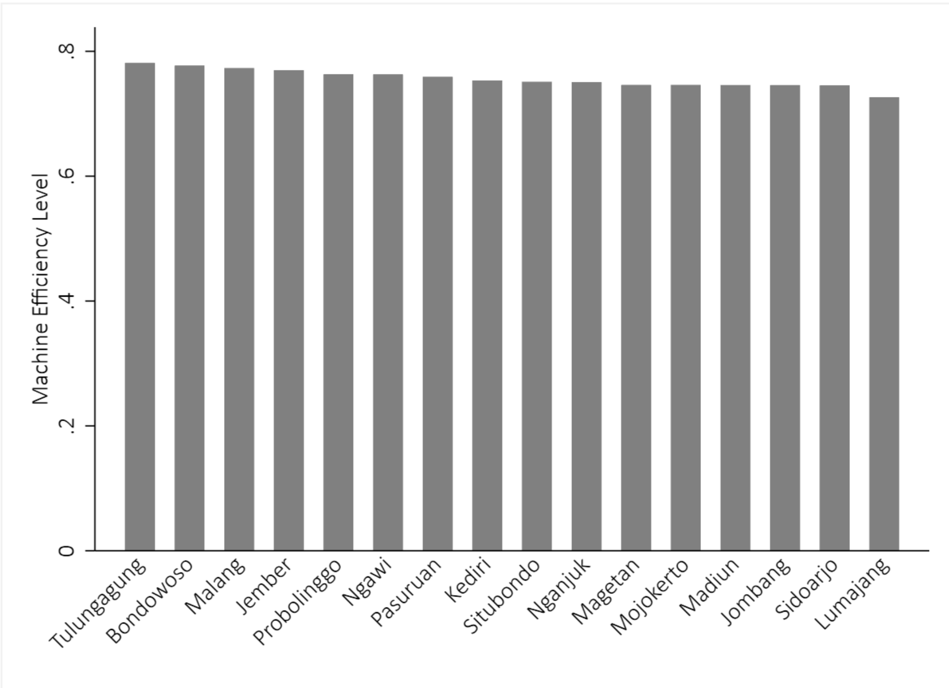


Figure 11: Machinery Efficiency by Region

Third, in the aspect of energy efficiency, one of the driving factors for increasing energy efficiency is managerial factors (Soepardi et al., 2018). Research conducted by Hanani et al. (2023) shows that Malang Regency has a managerial gap in sugarcane management compared to other areas such as Kediri and Mojokerto. Sugarcane farmers in Malang Regency have lower managerial skills to make decisions and have lower production technology when compared to the two regions.

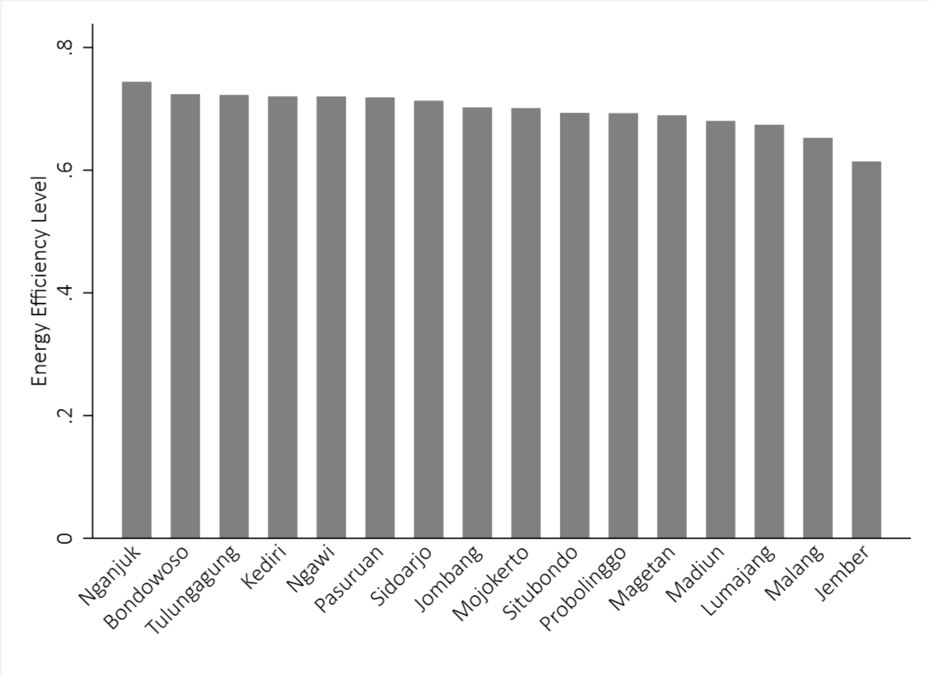


Figure 12: Energy Efficiency by Region

Table 6: Determinants of Production, Machinery, and Energy Inefficiency

Production			**Input Distance Functions**					
			Machinery			**Energy**		
Variabel	**Coeff.**	**S.E**	**Variabel**	**Coeff.**	**S.E**	**Variabel**	**Coeff.**	**S.E**
Constant	-0.5768***	4.9971	Constant	-0.1855***	1.0562	Constant	0.4093***	0.7830
Exp	-2.4171**	1.0090	Exp	-0.2245***	0.8816	Exp	-0.9047**	0.3186
Imp	1.2238	1.9305	Imp	-0.1104	1.0366	Imp	-0.0366*	0.1084
FSize	-1.0945	1.9117	FSize	-0.2482	0.8952	FSize	-0.7689	1.3327
HHI	0.2542	0.6470	HHI	0.0939	1.1456	HHI	-0.2686	0.1657
σ^2	0.8415***	0.0837	σ^2	1.2778***	1.3503	σ^2	1.4942***	0.1560
γ	0.9404***	0.2060	γ	0.9363***	0.0029	γ	0.9436***	0.0555

Notes: *significant at α = 10%, ** significant at α = 5%, *** significant at α = 1%.

Table 6 presents the estimation results of the determinants of production inefficiency, machinery use, and energy. Export intensity can reduce production inefficiency in the East Java sugar industry due to several main factors. Involvement in exports exposes firms to intense competition in the international market. This competitive pressure forces firms to optimize their production processes, reduce waste, and improve efficiency in order to survive in the global market. Moreover, exporting encourages firms to participate in international networks, bringing them closer to the frontier of the global economy. This argument supports previous research on 'learning by exporting' which suggests that exposure to international competition and practices positively affects firms' economic performance and innovation capacity. (Adli & Sari, 2024; Golovko et al., 2023; Liang et al., 2024; Yasin & Esquivias, 2023). By learning and adapting to global best practices, exporting firms can improve their production efficiency and competitiveness.

Market concentration proxied by HHI will increase the level of production inefficiency. A high HHI value reflects a low level of competition. Without competitive pressure to continuously improve and innovate, firms are reluctant to optimize their operations, which can lead to a decrease in production efficiency (Zheng & Khan, 2021). In addition, high market concentration can hinder innovation as firms facing low levels of competition have lower incentives to invest in research and development activities (Sun et al., 2022; Zhong et al., 2020). Low innovation can result in outdated production processes and technologies leading to higher levels of inefficiency.

Export intensity was found to reduce inefficiencies in the use of machinery and energy which supports the research by Goldar & Goldar (2023), Maskun et al. (2021), and Roy & Yasar (2015). Incentives for export-oriented industries play a very important role. The Ministry of Industry of the Republic of Indonesia has proposed incentivizing energy costs for export-oriented industries to improve their competitiveness by reducing production costs. This initiative, known as energy refund, provides firms with a rebate for electricity costs incurred to produce export goods. By receiving such incentives, firms can reduce their energy costs which can be reallocated to improve machinery and energy efficiency. This policy aims to encourage competition between domestic industries and competitors in other countries, thereby improving the efficiency and competitiveness of export-oriented firms.

The intensity of imported materials can reduce the level of inefficiency in energy use in the East Java sugar industry due to the higher quality of materials compared to local materials. Imported materials often come from regions with advanced agricultural and processing techniques (Yinguo et al., 2022). In contrast, locally sourced materials vary in quality, requiring additional energy to sort, process and refine them to achieve the desired product standard (Bribián et al., 2011).

Conclusion

This study employs a parametric approach, specifically Stochastic Frontier Analysis (SFA), to measure production, machinery, and energy efficiency in East Java's sugar industry. The findings reveal a tendency toward Decreasing Returns to Scale (DRS) in East Java's sugar industry, indicating the need for innovation or new technology to optimize the production process. Additionally, the average production efficiency has consistently declined significantly over time. This decline is attributed to several factors, including the impact of El Niño-induced climate change and the use of outdated industrial infrastructure.

From the input perspective, the average efficiency of machinery utilization has remained relatively stagnant, with a slight decline over time. This stagnation indicates that while the machinery is routinely used, it is not operating at a higher level of efficiency. On the other hand, average energy efficiency has also shown a declining trend. The technology gap between older and newer sugar mills significantly impacts energy efficiency. Traditional energy sources, such as coal and petroleum, used in older machinery tend to be less efficient compared to modern alternatives like biomass or renewable energy.

This study also found that there is a dominance of persistent inefficiency compared to transient inefficiency in the sugar industry in East Java. This indicates the existence of structural problems or systematic managerial incompetence in the production process of the sugar industry in East Java. The key sources of these structural problems include the use of outdated infrastructure, low-skilled labor, and limited capital availability.

Based on the district/city-level analysis, the most efficient sugar mills are located in Tulungagung and Bondowoso. Consistent with their high production efficiency rankings, these two districts also exhibit relatively higher machinery and energy efficiency compared to other regions. However, in terms of output volume, Tulungagung and Bondowoso have the lowest actual and potential output among all districts. Conversely, Sidoarjo and Malang, which generate the highest output, have lower efficiency scores. This suggests the presence of input misallocation inefficiencies in Sidoarjo and Malang's sugar mills.

The determinants of production inefficiency in East Java's sugar mills are significantly influenced by export intensity and market concentration. An increase in export intensity reduces production inefficiency, whereas higher market concentration leads to greater inefficiency. From the input perspective, higher export intensity also reduces machinery and energy inefficiency. Meanwhile, an increase in the intensity of imported materials only contributes to reducing energy inefficiency.

Based on the findings above, several steps are needed to address persistent inefficiency in East Java's sugar industry. First, capital modernization. Investing in advanced machinery and technology can transform the production process, making it more efficient. This is crucial for competing in a global market that prioritizes efficiency.

Second, enhancing the competitiveness of East Java's sugar products in the global market. This step is essential not only to improve the competitiveness of East Java's sugar industry but also to reduce inefficiency levels. To achieve this, incentives for the sugar industry are necessary, such as tax reductions, similar to those implemented by the Brazilian government, or subsidies for transportation and export logistics, as practiced in India and Thailand.

Third, conducting research on the development of high-quality sugarcane varieties by involving key stakeholders such as the National Research and Innovation Agency (BRIN), the Ministry of Agriculture (*Kementerian Pertanian*), and academics. This is crucial due to industry's dependence on raw materials, highlighting the importance of a stable and high-quality domestic sugarcane supply. Enhancing sugarcane quality in East Java would lead to higher production standards and lower production costs.

Fourth, implementing a minimum price policy by the government. Setting a minimum price can help stabilize sugar prices and increase farmers' income. This policy ensures stable prices for farmers' harvests, reducing the risk of market price fluctuations that could negatively impact their earnings. As a result, farmers would have greater financial security and be more motivated to maintain optimal production levels, without the fear of sudden price drops.

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