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THE EFFECT OF COVID-19 PANDEMIC ON THE TECHNICAL EFFICIENCY OF MANUFACTURING INDUSTRY IN INDONESIA

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Abstrak

Penelitian ini bertujuan mengkaji tingkat efisiensi teknis dan menganalisis pengaruh pandemi COVID-19 terhadap efisiensi teknis industri manufaktur Indonesia. Penelitian menggunakan data tingkat subsektor manufaktur selama periode 2017–2022 dengan metode *Stochastic Frontier Analysis* (SFA) dan fungsi produksi *transcendental logarithmic* (translog). Hasil penelitian menunjukkan bahwa efisiensi teknis industri manufaktur Indonesia meningkat selama pandemi, dengan skor rata-rata tertinggi pada 2020 sebesar 0,869, diikuti 2021 sebesar 0,865. Efisiensi teknis cenderung lebih tinggi pada industri berukuran lebih besar, memiliki tingkat konsentrasi pasar lebih tinggi, rasio modal terhadap output lebih rendah, serta proporsi kepemilikan negara lebih kecil. Temuan ini mengindikasikan bahwa peningkatan efisiensi selama pandemi mencerminkan penyesuaian operasional dalam menghadapi tekanan krisis, bukan kondisi produksi yang ideal. Penelitian ini memberikan bukti empiris mengenai efisiensi dan ketahanan industri manufaktur Indonesia dalam menghadapi disrupsi pandemi. Implikasi kebijakannya mencakup penguatan kapasitas adaptasi industri melalui diversifikasi rantai pasokan, pengembangan industri hulu domestik, dan penyediaan infrastruktur logistik yang tangguh. Selain itu, konsolidasi usaha, investasi berbasis inovasi, dan reformasi tata kelola BUMN perlu diarahkan untuk mendukung efisiensi berkelanjutan dengan tetap menjaga persaingan yang sehat serta ruang bagi pelaku usaha kecil.

Abstract

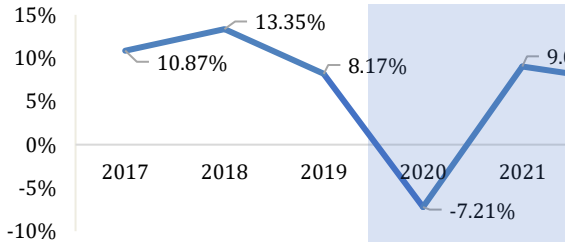
This study examines technical efficiency and the influence of the COVID-19 pandemic on Indonesia's manufacturing industry. Using manufacturing subsector-level data for 2017–2022, the study employs Stochastic Frontier Analysis (SFA) with a transcendental logarithmic (translog) production function. The results show that technical efficiency increased during the pandemic, with the highest average score recorded in 2020 at 0.869, followed by 2021 at 0.865. Technical efficiency tends to be higher in industries characterized by larger size, greater market concentration, lower capital-to-output ratios, and smaller shares of state ownership. These findings suggest that efficiency gains during the pandemic reflected operational adjustments under crisis conditions rather than ideal production conditions. The study provides empirical evidence on the efficiency and resilience of Indonesia's manufacturing industry in responding to pandemic-related disruptions. Policy implications include strengthening industrial adaptive capacity through supply chain diversification, domestic upstream industry development, and resilient logistics infrastructure. Business consolidation, innovation-driven investment, and governance reforms in state-owned enterprises should also support sustained efficiency while maintaining fair competition and opportunities for small businesses.

Introduction

The COVID-19 pandemic, which began in late 2019, not only triggered a global health crisis that claimed millions of lives but also crippled global economic stability (Gautam et al., 2022). To curb the rate of transmission, governments in various countries implemented strict social restriction policies that directly led to a decline in mobility and a drastic weakening of public purchasing power(Zhang & Zheng, 2022). As a result, the global economy—including Indonesia's—was dragged into a deep recession marked by a significant contraction in Gross Domestic Product (GDP) growth (BPS, 2024). In Indonesia itself, the tangible impact of this crisis is evident in the sharp decline in GDP growth in 2020, which plunged to a negative rate of -2.07%.

This weakening of the national economy is inextricably linked to the severe blow suffered by the manufacturing sector, which is, in fact, the largest contributor to Indonesia's GDP. This strategic sector, which is crucial for job creation, experienced severe operational disruptions due to supply chain disruptions and a decline in market demand (Ciravegna et al., 2023). Data from BPS (2022) show that the pandemic caused total production output in the large and medium-sized manufacturing industries to contract by -7.21% in 2020. Nevertheless, the manufacturing sector began to demonstrate resilience in 2021 with a growth rebound of 9.03%, signaling the start of the national economic recovery.

Graphic 1. Growth Rate of Output in Indonesia's Large and Medium-Sized Manufacturing Industries, 2017-2022 (% yoy)



Source: BPS (2022)

Apart from the scale of output, a crucial performance metric for the manufacturing industry is technical efficiency, which reflects the ability of a business unit to utilize its resources optimally to generate output as effectively as possible (Farrell, 1957). Enhancing technical efficiency serves as both a primary parameter and a fundamental strategy for industries to build resilience and make informed decisions amidst external shocks Unfortunately, the majority of empirical studies on the impact of the COVID-19 pandemic on the global manufacturing industry still focus on financial indicators such as profitability (Athira et al., 2024; Zhang & Zheng, 2022). Meanwhile, literature that specifically employs technical efficiency as the primary proxy for performance during a crisis remains relatively scarce, particularly within the national context.

In the domestic context, several studies in Indonesia show varied results; some record a decline in performance(Candrawati & Purwanti, 2024), while others detect an increase in profitability or efficiency in specific subsectors, such as the Fast-Moving Consumer Goods (FMCG) industry (Meiryani et al., 2022; Uluwiyah et al., 2024). Aside from the health crisis factor, the level of technical efficiency is also heavily influenced by internal industry characteristics, such as firm size, market competition levels, capital-to-output ratios, and state-ownership status (Esquivias & Harianto, 2020; Setiawan & Sule, 2020), To accurately measure these levels of technical efficiency and inefficiency, this study applies the Stochastic Frontier Analysis (SFA) method based on the approach by Battese & Coelli (1995). The parametric SFA method is chosen because it can simultaneously estimate the production function frontier and analyze the determinants of technical inefficiency in one-stage.

Literature Review

Theory of Production

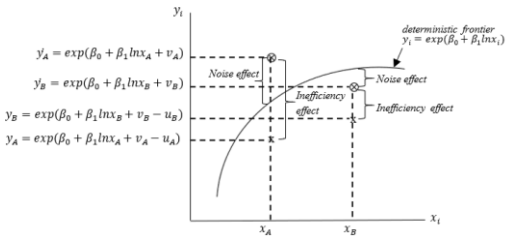
Production is a fundamental activity that combines and transforms various input factors into useful outputs in the form of goods or services, and it also encompasses all supporting activities, such as the procurement of raw materials, the recruitment of labor, and quality control (Pindyck & Rubinfeld, 2013; Salvatore, 2001). The technical relationship between the maximum combination of inputs used and the resulting output is described by a production function, which is mathematically simplified as $q = f(K, L)$, where q represent output, K

represent capital, and L represent labor. This function is determined by the level of technology, which reflects the technical feasibility of a business unit operating efficiently by utilizing inputs as effectively as possible (Pindyck & Rubinfeld, 2013).

Theory of Technical Efficiency

In economics, efficiency refers to the selection of the optimal combination of inputs to maximize surplus without wasting resources (Pindyck & Rubinfeld, 2013). Farrell (1957) divides the productive efficiency of a business unit into two main components: allocative efficiency, which is based on price structure, and technical efficiency, which reflects the business unit's capacity to produce maximum output from a given set of inputs along the production frontier. Technical efficiency is measured by estimating the production frontier to determine the maximum output that can be achieved using a specific combination of inputs (Battese & Coelli, 1992) . To map this production frontier, the empirical literature offers two main approaches: deterministic non-parametric methods such as Data Envelopment Analysis (DEA), and stochastic econometric-based parametric methods such as Stochastic Frontier Analysis (SFA) (Coelli et al., 2005). Unlike DEA, which assumes that all deviations from the frontier line represent inefficiency, the SFA method specifically decomposes the error term into two main components. The first component is two-sided random statistical noise v_i, which captures factors beyond the control of the business unit, such as measurement errors and random shocks, while the second component is one-sided technical inefficiency u_i, which reflects the business unit's operational inability to achieve optimal output.

Graphic 2. Stochastic Production Frontier



Source: Coelli et al. (2005)

Graphically and mathematically, the basic stochastic production frontier model is formulated using the log-linear production function $Y_i = f(x_i;\beta)\exp(v_i - u_i)$. Based on this formulation, the technical efficiency (TE) is calculated as the ratio of the observed actual output to the ideal frontier output, which is simplified to $TE = \exp(-u_i)$. A production unit is considered perfectly efficient if $u_i = 0$, meaning its efficiency level is one $TE = 1$; conversely, the larger the value u_i, the farther the production unit's position lies below the production frontier. Given that this model involves two error components with strict distribution assumptions—such as normally distributed statistical noise $v_i \sim N(0, \sigma_v^2)$ and inefficiency that is generally assumed to follow a half-normal or truncated-normal distribution u_i— the use of the Ordinary Least Squares (OLS) method is inadequate because it produces biased estimates. Therefore, the Maximum Likelihood Estimation (MLE) approach is applied as the best estimation method because it is capable of producing parameters consistent with the characteristics of the frontier model (Coelli et al., 2005).

Therefore, the Maximum Likelihood Estimation (MLE) approach was applied as the best estimation method because it is capable of producing parameters consistent with the characteristics of the frontier model(Coelli et al., 2005). In its development, the use of panel data structures (Pitt & Lee, 1981) has been deemed far superior to cross-section data because it allows for the observation of long-term changes in production structure, improves the accuracy of separating noise and inefficiency effects, and serves as an alternative to rigid distribution assumptions (Widodo et al., 2014). Furthermore, instead of using the traditional two-stage approach—which violates error distribution assumptions—this study adopts the one-stage approach pioneered by Coelli et al. (2005). Through a system of simultaneous equations based on MLE, the stochastic production function $y_{it} = \beta_{0t} + x_{it}\beta + v_{it} - u_{it}$ and the technical inefficiency effect model $u_{it} = z_{it}\delta + w_{it}$ are estimated simultaneously. This integrated approach not only maps technical efficiency levels—ranging from 0 to 1—across industrial subsectors but also consistently tests the direct effects of industry-specific factors and external explanatory variables (z_{it}) on variations in these technical efficiency levels.

Data and Research Methods

Data

This article uses data on medium- and large-scale manufacturing industries from 2017 to 2022 provided by the Central Statistics Agency (BPS) at the subsector level. The final dataset to be estimated is organized as a balanced panel dataset. The panel data is synchronized based on the 4-digit ISIC classification. All variables used in the production frontier function are expressed in Indonesian Rupiah (IDR), except for labor, which is represented by the total number of employees. Since the variables capital (K), raw materials (M), energy (E), and output (Y) are expressed in market values, the wholesale price index (WPI) for the manufacturing industry at the 4-digit ISIC level is used to deflate these variables. After performing data cleaning, we finally obtained a balanced panel dataset with 145 subsectors per year and a total of 870 observations.

The variables used in the technical inefficiency function are measured as follows. The COVID-19 pandemic is measured using a year dummy variable (COVID) set to 1 for the years 2020 and 2021; firm size (SIZE) is measured based on the number of employees; industry concentration (CR4) is measured based on the market share of the four largest firms at the 4-digit ISIC level; capital-output intensity (COR) is measured by the ratio of capital to output; and the proportion of state ownership (SOE) is measured by the ratio of state-owned enterprises in each subsector. In addition, Table 1 presents the descriptive statistics of the variables.

Table 1. Summary Statistic of Variables

Variable	Mean	Std. Dev.	Min	Max	Unit
Y (Output)	70,225.28	156,031.00	35.09	2,431,180	Billion Rupiah
K (Capital)	269,117.50	2,237,807.00	36.56	53,527,820	Million Rupiah
L (Labor)	41,919.83	76,431.19	186	734,188	People
M (Material)	33,222.63	93,365.58	2.52	1,608.718	Billion Rupiah
E (Energy)	1,604.81	3,579.60	0.58	40,121.88	Billion Rupiah
COVID (1=2020&2021)	0.33	0.47	0	1	*Dummy*
SIZE	41,919.83	76,431.19	186	734,188	People
CR4	48.37	20.67	6	100	Percentage
COR	0,48	1,67	0,00056	30,03	Ratio
SOE	1,44	4,06	)	14,44	Ratio

Research Methods Section

Following the seminal work of Farrell (1957) and the pioneering work of Aigner et al. (1977) technical efficiency can be derived from stochastic production frontier which can be written as:

$$Y_i = f(x_i;\beta)\exp(v_i - u_i) \quad (1)$$

where v_i is a random error with a mean of zero, associated with random factors beyond the industry's control, while u_i is associated with the industry's technical inefficiency. Technical efficiency (TE) is defined as the ratio of observed output (Y_i) to the maximum possible output (Y_i^*) of i^{th} industry, that is:

$$TE_i = Y_i/Y_i^*$$

$$= f(x_i;t,\beta)\exp(v_i - u_i)/f(x_i;t,\beta)\exp(v_i)$$

$$= \exp(-u_i) \qquad (2)$$

Technical efficiency in the stochastic frontier framework is expressed as exp $(-u_i)$, which represents a random variable bounded between zero and one. To examine the influence of COVID-19 pandemic on subsector-level efficiency, this study employs the one-stage stochastic frontier model developed by Battese & Coelli (1995). Within this approach, the parameters of the frontier are estimated using a specified functional form that captures the relationship between inputs and outputs.

$$lny_{it} = \beta_0 + \sum_n \beta_n lnx_{nit} + \beta_t t + \frac{1}{2}\sum_n\sum_k \beta_{nk} lnx_{nit} lnx_{kit} + \frac{1}{2}\beta_{tt}t^2 + \sum_n \beta_{nt} lnx_{nit} t + v_{it} - u_{it} \quad (3)$$

where y s output and x is inputs of production consisting of L (labor), K (capital), M (material) and E (energy), t is time, i is industry, $\beta's$ are parameters to be estimated, ln denotes natural logarithm, v_{it} is the stochastic error term, and u_{it} is technical inefficiency. In this model, the technical inefficiency effect is a function of COVID-19 pandemic. Following Huang & Shen (2024) the pandemic is operationalized using a dummy variable. The COVID dummy variable is assigned a value of 1 for 2020 and 2021—the years during which the pandemic occurred—and

0 for all other years. Variables of industrial structure and characteristics included in the model are industrial size (SIZE), industrial concentration ratio (CR4), capital output ratio (COR), and state-ownership (SOE). The technical inefficiency function can be expressed as:

$$u_{it} = \delta_0 + \delta_1 COVID_{it} + \delta_2 lnSIZE_{it} + \delta_3 CR4_{it} + \delta_4 COR_{it} + \delta_5 SOE_{it} + w_{it} \quad (4)$$

where w_{it} is an error term. The stochastic production frontier in Equation (3) and the technical inefficiency function in Equation (4) can be estimated simultaneously in one-stage by using the Maximum Likelihood Estimation (MLE) method in RStudio with the "frontier" package developed by Coelli & Henningsen (2013), which provides the same features as FRONTIER 4.1.

Result and Discussion

The reliability of empirical findings largely depends on selecting an appropriate functional form in applied research. While the Cobb–Douglas specification has been widely adopted in stochastic frontier analysis due to its simplicity and ability to handle data imperfections, it is constrained by restrictive assumptions such as constant technological change. In contrast, the Translog production function offers greater flexibility but often faces estimation challenges, particularly multicollinearity among explanatory variables. To address these issues, both Cobb–Douglas and Translog specifications are sequentially tested using the generalized likelihood ratio (LR) test, which serves as a critical tool when theoretical considerations do not clearly indicate the suitable functional form. The statistical evidence in this study supports the use of the flexible Translog specification, as presented in Equation (3).

Table 2. Log-Likelihood Tests for Model Specification of the Stochastic Production Frontier

Restrictions	λ	***Critical Value*** (α = 1%)	
Cobb-Douglas			
($\beta_{KK} = \beta_{KL} = \beta_{KM} = \beta_{KE} = \beta_{LL} = \beta_{LM} = \beta_{LE} = \beta_{MM} = \beta_{ME} = \beta_{EE} = \beta_{TT} = \beta_{KT} = \beta_{LT} = \beta_{MT} = \beta_{ET} = 0$)	120,732	30,578	H_0 reject

Note: The Log-likelihood ratio statistics are calculated from the equation for the translog-production frontier, based on the restricted and unrestricted models. The critical values are based on the Chi-squared distribution

The results of the stochastic production function estimation using the Maximum Likelihood Estimation (MLE) method are presented in Table 3. The results show that all production inputs have a significant effect on the output of large and medium-sized manufacturing industries (IBS) in Indonesia during the 2017–2022 period. The labor (L) and energy (E) variables were found to make positive contributions, where a 1% increase in each input was associated with a 1.44% increase in output ($\boldsymbol{\alpha = 1}$%) and 0.37% ($\boldsymbol{\alpha = 10}$%), which is consistent with the findings of Widodo et al. (2015). Conversely, the capital variable (K) and material variable (M) exhibit significant negative coefficients of -0.2906 and -0.743, respectively, indicating the presence of dislocations or inefficiencies in input allocation, such that an increase in these production factors actually reduces output **(Tovar & Wall, 2024)**. Meanwhile, the time trend variable (*t*) has a significant positive value (0,264), confirming the positive impact of technological progress, which consistently shifts the production frontier toward greater productivity during the observation period.

In the simultaneous estimation of the technical inefficiency function, the value of the gamma parameter ($\boldsymbol{\gamma}$) was found to be statistically significant at the 1% level, confirming that variations in deviations from the frontier are still influenced by the technical inefficiency component, even though its proportion is relatively small. Interestingly, the COVID-19 pandemic dummy variable showed a significant negative coefficient of 0,0364 at the 1% level. This negative coefficient in the inefficiency model indicates that during the pandemic (2020–2021), the level of inefficiency actually decreased—in other words, the technical efficiency of the manufacturing industry improved significantly. This phenomenon of "forced adjustment" was driven by survival pressures resulting from operational and supply chain disruptions, which compelled business units to eliminate idle capacity, reorganize

working hours, and accelerate the digitization of business processes in order to operate closer to the optimal production frontier **(Candrawati & Purwanti, 2024; Hiong & Ab-Rahim, 2025)**.

Table 3. Result of the Stochastic Production Frontier

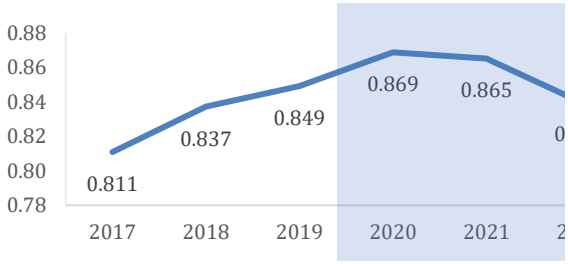
	coefficient	*standard-error*	*t-ratio*	
Production Function				
Constanta	20,44800	1,99500	10,2493	***
lnK	-0,29060	0,17497	-1,6609	*
lnL	1,44430	0,30066	4,8040	***
lnM	-0,74267	0,28830	-3,5563	***
lnE	0,36869	0,20376	1,8094	*
½(lnK2)	0,04177	0,00917	4,5529	***
½(lnL^2)	0,07973	0,03004	2,6541	***
½(lnM^2)	0,10637	0,01499	7,0925	***
½(lnE^2)	0,03320	0,01373	2,4169	**
½(lnKlnL)	-0,02836	0,02538	-1,1174	
½(lnKlnM)	-0,03287	0,01947	-1,6879	*
½(lnKlnE)	-0,00501	0,01683	0,0297	
½(lnLlnM)	-0,08872	0,03589	-2,4717	**
½(lnLlnE)	-0,03375	0,03242	-1,0409	
½(lnMlnE)	-0,06855	0,01868	-3,6687	***
T	0,26469	0,13596	1,9467	*
T2	-0,01815	0,00937	-1,9365	*
(lnK)T	-0,00054	0,00546	-0,0997	
(lnL)T	0,00078	0,00954	0,0816	
(lnM)T	-0,01018	0,00719	-1,4055	
(lnE)T	0,00431	0,00694	0,621	
Inefficiency Function				
Constanta	1,22020	0,14203	8,5910	***
COVID	-0,03635	0,00642	-5,6593	***
lnSIZE	-0,07852	0,00975	-8,0530	***
CR4	-0,00625	0,00068	-9,1151	***
COR	0,05359	0,01057	5,0683	***
SOE	0,00567	0,00165	3,4162	***
SigmaSq	0,09329	0,00474	19,6772	***
Gamma	1,00e-08	2,34e-09	4,2608	***

Note: ***, **, and * is significant at the 1%, 5%, and 10%

Internal industry characteristics also play a crucial role in significantly influencing the level of technical inefficiency in the national manufacturing sector by 1%. The variables of industry size (SIZE) and market concentration (CR4) have negative coefficients (of -0.03635 and -0.00625, respectively), which means that larger industry scale (economies of scale) and a concentrated (oligopolistic) tend to reduce inefficiencies and strengthen operational resilience (Esquivias & Harianto, 2020; Huang & Shen, 2024). Conversely, the capital-output ratio (COR) and state-ownership (SOE) variables yield positive coefficients (of 0.0535 and 0.00536, respectively). These findings indicate that an excessively high capital-output ratio reflects low capital investment productivity, while an increase in the proportion of state ownership tends to trigger technical inefficiencies due to the dual burden on state-owned enterprises (SOEs) of carrying out the government's social and policy missions in addition to the company's commercial objectives (Abramov et al., 2017; Septiani & Setiawan, 2023).

The COVID-19 pandemic in early 2020 dealt a severe blow to Indonesia's large and medium-sized manufacturing sector (IBS). This extreme market pressure forced many business units to incur losses and eventually cease operations; data from the Statistic Indonesia recorded a decline of 709 companies, a 7.2% contraction in output (equivalent to 526 trillion rupiah), and the layoff of 338,000 workers (a 5.4% decrease). Despite experiencing a massive contraction in capacity, empirical estimates reveal an intriguing anomaly: the average technical efficiency score of Indonesia's manufacturing industry actually increased significantly and peaked during the pandemic, reaching 0.869 in 2020 and 0.865 in 2021. This increase in efficiency amid the crisis indicates the adaptability and resilience of business units in rigorously restructuring production factors, reducing idle capacity, and eliminating operational inefficiencies to ensure survival (Demsetz, 1973), which states that only efficient production units are capable of surviving in the market.

Table 4. Technical Efficiency in Indonesia's Manufacturing Industry



The acceleration in technical efficiency during this crisis period is also closely tied to the foundation of digital transformation established through the Making Indonesia 4.0 roadmap, which has been implemented since 2018 (Bappenas, 2021). These automation- and system-integration-based modernization policies provided momentum for manufacturing companies to accelerate the adoption of technology in response to mobility restrictions, thereby ensuring that capital productivity remained optimally maintained. However, entering the post-pandemic phase in 2022, average technical efficiency declined again to 0.840. This decline reflects a new adjustment pattern resulting from the normalization of production capacity and shifts in demand, exacerbated by external pressures such as disruptions in global supply chains and surging energy prices caused by the outbreak of the Russia-Ukraine conflict (DJKN, 2022). Thus, these dynamics underscore that while crises can trigger high short-term efficiency, sustaining efficiency in the post-pandemic era requires greater industrial flexibility in the face of new structural cost volatility.

Conclusion and Policy Implications

Conclusion

This study investigates the technical efficiency of Indonesia's manufacturing industry during 2017–2022 using the Stochastic Frontier Analysis (SFA) with a translog production function. The findings reveal that the COVID-19 pandemic significantly increased efficiency, with average values peaking in 2020 (0.869) and 2021 (0.865). These findings suggest that most manufacturing subsectors sustained operations and demonstrated resilience during the crisis. E . Efficiency improvements were concentrated in subsectors producing essential goods, supported by stable demand, adaptive capacity, and fiscal policy interventions, while declines occurred in subsectors reliant on disrupted global supply chains and weakened foreign demand. Driven by severe survival pressures, business units engaged in "forced adjustments" by restructuring production factors, cutting idle capacity, and expanding digitization under the *Making Indonesia 4.0* framework. This adaptive resilience allowed efficient industry to operate closer to the optimal frontier, validating Demsetz's efficiency hypothesis. Moreover, industry characteristics played a decisive role: larger firms with higher market concentration tended to be more efficient, whereas higher capital-output ratios and greater state ownership reduced efficiency.

Policy Implications

The observed increase in technical efficiency during the COVID-19 pandemic should be interpreted as a result of forced adaptation rather than ideal conditions. Policymakers can draw lessons from these adaptive mechanisms to design strategies for normal periods. Key priorities include promoting supply chain diversification, strengthening upstream industries, and developing resilient logistics infrastructure to reduce vulnerability to external shocks. Efficiency gains should also be supported through innovation-oriented investment, fiscal incentives for R&D, and digital integration, rather than relying solely on physical capital expansion. At the same time, governance reforms in state-owned enterprises are essential to enhance operational efficiency while maintaining their social functions. Finally, since larger firms and concentrated markets tend to be more efficient, policies should encourage scale consolidation while ensuring balanced competition. This requires adaptive competition policies that prevent monopolistic practices, safeguard consumer welfare, and facilitate market access for small and medium enterprises, thereby maintaining a healthy competitive environment without sacrificing inclusivity.

Declaration

Authors' Contributions

D. S.: Conceptualization, Methodology, Investigation, Data Curation, Formal Analysis, Writing –Original Draft, Writing –Review & Editing. W. W.: Supervision, Methodology, Validation, Writing – Review & Editing. The research was initiated by D. S. as an Undergraduate's student. All stages of the research were conducted under consultation and

supervision of W. W.. Both authors have read and approved the final version of the manuscript.

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Informed Consent Statement

Not applicable.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Availability of Data and Materials

This study uses secondary data obtained from public sources. The data can be accessed through the official website of the Statistics Indonesia at [https://www.bps.go.id]. The data used was taken from publications on the Manufacturing Industrial Statistics and Manufacturing Industrial Indicator.

Use of Artificial Intelligence (AI)

The author hereby states that in writing this article, artificial intelligence (AI) was used, specifically Microsoft Copilot and Deepl, which were utilized during the research process to develop the manuscript outline and translate the content. All intellectual content, including ideas, analysis, data interpretation, and conclusions, is the sole responsibility of the author and was not automatically generated by AI tools. The authors also affirm that every section of the manuscript assisted by AI has undergone a careful review and verification process and has been adapted to meet the principles of high scientific integrity, accuracy, and originality.

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