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Technical Efficiency and Downstreaming in Indonesia's Basic Metal Industry: A Stochastic Frontier Analysis Approach

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ABSTRACT
This study measures technical efficiency and identifies the determinants of technical inefficiency in Indonesia's basic metal industry during 2017 to 2019 by using a translog stochastic frontier model. The analysis employs firm-level data from the annual manufacturing large and medium industry survey (IBS) of Bureau Statistics Indonesia, comprising a balanced panel of a 420 firms with 1,260 observations, and is estimated following the Battese Coelli (1995) with one-step-approach. The results reveal that the basic metal industry is on average 90.58% technically efficient, leaving an aggregate output gap of approximately 11.6%. it is noted that downstreaming depth contributed most strongly to reducing technical inefficiency, followed by import intensity, and export orientation, whereas firm size contributed to higher inefficiency, meanwhile foreign ownership and research and development were found to be insignificant. The estimates of input elasticities indicate that material is the dominant input, and the industry operates under slightly increasing returns to scale. Suggesting that capacity expansion through smelter development remains economically efficient. These findings provide firm-level quantitative evidence that the mineral downstreaming policy is associated not only with higher aggregate value added but also with improved production efficiency.

INTRODUCTION

The basic metal manufacturing industry plays a strategic role in the Indonesian economy as one of the country's leading industrial sectors, particularly within the context of the mineral resource downstreaming policy. The ban on the export of raw mineral ores was first introduced under Law No. 4 of 2009 on Mineral and Coal Mining, which was subsequently revised through Law No. 3 of 2020 to strengthen the regulatory framework and promote the structural transformation of the sector from a raw material exporter into a producer of high value-added processed products. According to data from Statistics Indonesia (BPS), the Gross Domestic Product (GDP) growth rate of the basic metal industry reached 10.37% in 2017, peaked at 12.64% in 2018, and then moderated to 4.25% in 2019. This

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growth pattern indicates the substantial impact of the downstreaming policy, which stimulated the expansion of smelting and refining capacities during the 2017–2018 period (Badan Pusat Statistik, 2019).

Despite the rapid growth of the basic metal manufacturing industry between 2017 and 2019, the sector continues to face structural challenges rooted in the historical development of Indonesia's metal mining industry. Suseno (2019) reported that during the 2000–2015 period, the metal mining sector contributed an average of 1.41% to Indonesia's Gross Domestic Product. Historically, however, the sector experienced relatively modest annual growth of approximately 3.02%, largely due to its dependence on exporting raw materials with low value-added. To reduce this dependence, Indonesia has promoted the development of domestic processing and refining (*smelter*) industries capable of transforming raw mineral ores into higher value-added products. This necessity became the foundation of Indonesia's mineral downstreaming policy, which has been reinforced through regulations encouraging the construction of domestic smelters while restricting exports of unprocessed mineral ores (Suparji & Mizi, 2019). These policies encourage metal companies to integrate downstream processing activities into their production supply chains. As a result, Indonesia has experienced a significant increase in metal processing capacity, particularly in the nickel industry, where the number of smelters increased from 17 units in 2019 to 48 units in 2023 (Guberman et al., 2024; Rivota & Wardhana, 2026).

However, the expansion of production capacity also introduces efficiency challenges within firms' internal production processes, including technological readiness, the availability of skilled human resources, and the management of raw material and energy supply chains. The basic metal industry is characterized as both capital-intensive and energy-intensive, requiring substantial capital investment and energy consumption (Guberman et al., 2024; Margono & Sharma, 2006). Consequently, the efficient utilization of production inputs has become a critical determinant of industrial competitiveness in both domestic and international markets. Therefore, measuring technical efficiency is essential for evaluating the extent to which firms have optimally utilized their production potential and for assessing the effectiveness of government support policies.

Numerous studies have examined the technical efficiency of Indonesia's manufacturing sector across various subsectors. However, empirical studies specifically investigating the basic metal industry (ISIC/KBLI Division 24) using firm-level data and the Stochastic Frontier Analysis (SFA) approach remain limited. This study addresses this research gap through three primary contributions. First, it measures the technical efficiency of Indonesia's basic metal manufacturing industry using a firm-level SFA model. Second, it introduces downstreaming depth as a determinant of technical inefficiency. Third, it estimates firm-level efficiency scores by calculating potential output and examining firm characteristics through the identification of returns to scale.

Based on this background, this study addresses three research questions: (1) What is the average level of technical efficiency of Indonesia's basic metal manufacturing industry during the 2017–2019 period? (2) Which factors significantly influence firms' technical inefficiency? (3) What are the implications of these findings for Indonesia's mineral downstreaming policy?

RESEARCH METHOD

This study employs firm-level data obtained from the Annual Survey of Large and Medium Manufacturing Industries conducted by Statistics Indonesia (BPS). The analysis focuses on the basic metal manufacturing industry classified under the two-digit Indonesian Standard Industrial Classification (KBLI 24) for the 2017–2019 period. The original dataset consisted of 566 firms per year. Data cleaning was subsequently performed based on several criteria, including positive values for output, labor, total inputs, total energy consumption, and value-added ratios used to identify the downstreaming characteristics of firms in the basic metal industry. These criteria were selected because the Translog stochastic frontier production function requires all input and output variables to be strictly positive.

The study utilizes a balanced panel dataset comprising firms that consistently appeared throughout the observation period. After data cleaning, the final sample consists of 420 firms observed over three years, resulting in a total of 1,260 firm-year observations. The use of a balanced panel ensures estimation stability by maintaining a consistent composition of observational units, thereby minimizing instability caused by changes in sample composition and preserving data coherence. The model parameters were estimated using the Maximum Likelihood Estimation (MLE) method (Baltagi, 2013; Greene, 2005). Because the analysis is conducted at the two-digit industrial classification level (KBLI 24), the available data do not permit identification of specific metal product categories. Consequently, the findings should be interpreted as representing the basic metal manufacturing industry as a whole, complemented by descriptive analyses comparing foreign-owned and domestically owned firms.

This study applies Stochastic Frontier Analysis (SFA) with a panel data framework using the one-step approach, in which the stochastic frontier production function and the technical inefficiency model are estimated simultaneously through Maximum Likelihood Estimation (MLE) using Frontier 4.1 software (Coelli, 1996). A key parameter examined in the model is $\gamma = \sigma^2_u / (\sigma^2_u + \sigma^2_v)$ where a value of γ approaching 1 indicates that the variation in output is predominantly explained by technical inefficiency rather than random statistical noise. The Translog Stochastic Frontier Analysis (SFA) model with three production inputs is specified following Battese and Coelli (1995):

$$\begin{aligned}\ln(Y_{it}) = \beta_0 + \beta_1 ln(L_{it}) + \beta_2 ln(M_{it}) + \beta_3 ln(E_{it}) + \beta_4 [{}^1/_2 ln(L_{it})^2 + \beta_5 [{}^1/_2 ln(M_{it})^2 \\ + \beta_6 [{}^1/_2 ln(E_{it})^2 + \beta_7 [ln(L_{it}) \times \ln(M_{it})] + \beta_8 [ln(L_{it}) \times \ln(E_{it})] \\ + \beta_9 [ln(M_{it}) \times \ln(E_{it})] + v_{it} - u_{it}\end{aligned}$$

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Where Y denotes total output, L represents labor, M refers to raw materials, and E denotes energy input. All variables are expressed in natural logarithms and are mean-centered by subtracting their respective geometric means. The subscripts i and t represent the firm and the year of observation, respectively. The term $v_{it} \sim N(0, \sigma_v^2)$ denotes the random error, which is assumed to follow a normal distribution, i_{it}, while u_{it} represents technical inefficiency, which is assumed to be independently distributed and statistically independent of v_{it}. The technical inefficiency model is specified as follows:

$$u_{it} = \delta_0 + \delta_1 EXP + \delta_2 OWN + \delta_3 RND + \delta_4 \ln(FIRM) + \delta_5 DOWN + \delta_6 IMP +$$

Where EXP, OWN, and RND are dummy variables representing export orientation, foreign ownership, and research and development (R&D) activities, respectively. FIRM denotes firm size, DOWN represents downstreaming depth (measured as the ratio of value added to output), and IMP refers to imported raw material intensity. The capital stock variable is excluded from the stochastic frontier specification because approximately 57–65% of the firms in the sample reported zero fixed capital assets throughout the observation period. The issue of measurement error in capital stock data collected from manufacturing surveys in developing countries has been discussed by Collard-Wexler and De Loecker (2016), and specifically in the context of a similar research focus by Margono and Sharma (2006).

Furthermore, in determining the characteristics of the company, it is done by measuring the elasticity of potential output to input which is calculated as a partial derivative of the frontier approach, by evaluating the average value based on: $\varepsilon L = \beta_1 + \beta_4 lnL + \beta_7 lnM + \beta_8 lnE$, with analogous formulations for M and E. The results of the return to scale measurement are obtained from $RTS = \varepsilon_L + \varepsilon_M + \varepsilon_E$. Potential output is calculated as $Y^* = {}^{Y}\!/_{TE}$, and output gap = $Y^* - Y$, to translate the determinants of inefficiency into potential output increases that can be carried out by companies in the basic metal industry.

RESULT AND DISCUSSION

Table 1. Estimation of Frontier Production Function and Determinants of Inefficiency

Parameter	Variable	Coefficient	*t*-ratio
Production Function			
β□	Constant	2.986***	10.667
β□	ln L	0.932***	10.758
β□	ln M	0.098	1.358
β□	ln E	0.205***	4.209
β□	½ (ln L)²	0.221***	10.025
β□	½ (ln M)²	0.154***	17.597
β□	½ (ln E)²	0.025***	3.283
β□	ln L × ln M	−0.161***	−101.058
β□	ln L × ln E	0.007	0.597
β□	ln M × ln E	−0.035***	−7.943

Inefficiency Determinants			
δ□	Constant	0.2342***	9.840
δ□	Export Orientation	−0.1942***	−5.073
δ□	Foreign Direct Investment	0.0074	0.635
δ□	R&D Activity	−0.1703	−0.904
δ□	Firm Size	0.0300***	5.668
δ□	Downstreaming	−0.4062***	−54.626
δ□	Import Intensity	−0.2484***	−18.986
σ^2	Sigma	0.1925***	30.782
γ	Gamma	0.0000	0.003
Observations	—	1,260	—
Mean Technical Efficiency		0.9058	—

Note: * significance at the 10% level, ** significance at the 5% level, *** significance at the 1% level.

The estimation results in Table 1 show that the translog-shaped stochastic production function represents the production process in the base metals industry in Indonesia. Among the production input variables, labor has the largest coefficient and is significant at the 1% level, followed by energy, while raw materials have no significant effect. These results indicate that, on average, the output of the base metals industry is more responsive to changes in labor use than to changes in raw materials. This is due to the labor-intensive and energy-intensive nature of the base metals industry. Furthermore, the interaction terms between the input variables labor and raw materials (−0.161) and raw materials and energy (−0.035) are negative and significant, indicating a substitution relationship between the inputs.

In the inefficiency model, downstreaming yielded the largest determinant effect in reducing technical inefficiency by -0.4062, followed by import intensity at -0.2484 and export orientation at -0.1942. These results indicate that companies with a higher value-added-to-output ratio, greater intensity of imported raw material use, and a stronger export orientation tend to operate more technically efficiently. Conversely, foreign direct investment and R&D activity did not significantly influence technical inefficiency, thus the contribution of base metal processing from 2017 to 2019 did not indicate technical efficiency in company productivity. Meanwhile, firm size had a positive and significant effect on increasing company technical inefficiency. Overall, the average technical efficiency score for the base metal industry during the 2017–2019 period reached 0.9058, meaning the average company operated at approximately 90.6% of its potential output, leaving approximately 9.4% room for inefficiency.

Table 2. Results of the Production Function Selection Test and the Test for the Existence of Inefficiency Effects

Hypothesis	LR Test	Degrees of Freedom (df)	χ^2 (1%)	Decision
H□: Cobb–Douglas vs. H□: Translog	229.52	6	16.07	Reject H□
H□: Half-Normal vs. H□: Truncated-Normal	−0.01	1	5.41	Fail to Reject H□
Test for the Presence of Inefficiency Effects				
H□: $\delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = 0$	133.80	6	16.07	Reject H□

Table 2 presents the results of the likelihood-ratio test to determine the most appropriate model specification. First, the functional form test rejects the null hypothesis of Cobb-Douglas against translog with an LR value of 229.52 at df = 6, so that the form of the translog production function is statistically more appropriate to describe the production technology of the basic metal industry than Cobb-Douglas. Second, the distribution test of the inefficiency components cannot reject the null hypothesis of half-normal against truncated-normal with an LR value of −0.01 at df = 1, which means that the assumption of a half-normal distribution ($\mu = 0$) is sufficient for the production function so that the model does not require additional parameters and the half-normal translog is set as the selected specification in this test. Third, the test for the existence of an inefficiency effect rejects the null hypothesis of no inefficiency effect with an LR value of 133.80 at df = 6, so that the use of the stochastic frontier approach is proven to be more appropriate than the Ordinary Least Squares (OLS) estimation and the inefficiency determinant variables together have a significant effect. The results of these three tests confirm that the translog model with a half-normal distribution and the inefficiency effects model of Battese & Coelli (1995) are valid specifications for the base metals industry data.

Table 3. Average Technical Efficiency at the Industry Scale

Year	Large-Scale Industry	Medium-Scale Industry
2017	0.944	0.946
2018	0.866	0.886
2019	0.905	0.889

Note:
Medium-Scale Industry: Annual output of IDR 50–100 billion.
Large-Scale Industry: Annual output of IDR 100 billion or more.

Based on the description in Table 3, the average technical efficiency by industry scale is shown. During 2017-2019, medium-scale base metal industries recorded a slightly higher average efficiency of 0.907 compared to large-scale industries, which averaged 0.905. Both groups exhibited a similar pattern, with efficiency declining in 2018 for large-scale base metal industries to 0.866 and for medium-scale industries to 0.886, before companies' performance improved again in 2019. The fluctuation pattern in 2018 aligns with a period of rapid metal processing capacity expansion, during which new capacity additions were not fully utilized.

Table 4. Average Technical Efficiency by Capital Status

Year	Domestic Investment (PMDN)	Foreign Direct Investment (PMA)	Non-Facility Firms
2017	0.937	0.945	0.956
2018	0.874	0.880	0.875
2019	0.903	0.884	0.895

Note:
PMDN (Domestic Investment): Capital investment originating from domestic investors or the domestic government.
PMA (Foreign Direct Investment): Capital investment originating from foreign investors.
Non-Facility Firms: Firms operating without investment facilities or incentives provided by either the government or foreign investors.

Table 4 presents the average technical efficiency by capitalization status. Domestic Investment (PMDN) companies had the highest average efficiency (0.908), followed by Foreign Investment (PMA) companies at 0.904 and non-facility companies at 0.903. The differences between the three capitalization groups were relatively small. Table 1 shows that foreign ownership had no significant effect on technical efficiency, and that firm size across all three groups experienced a decline in efficiency in 2018 and improved again in 2019. This indicates that other factors influence the performance of all companies, regardless of their capital source. Consequently, the introduction of new, suboptimal smelter capacity suppresses average efficiency in the short term before eventually reaching optimal operational efficiency due to adjustment costs incurred by the companies involved during capacity expansion that year (Eisner & Strotz, 1963; Stefanou, 2009).

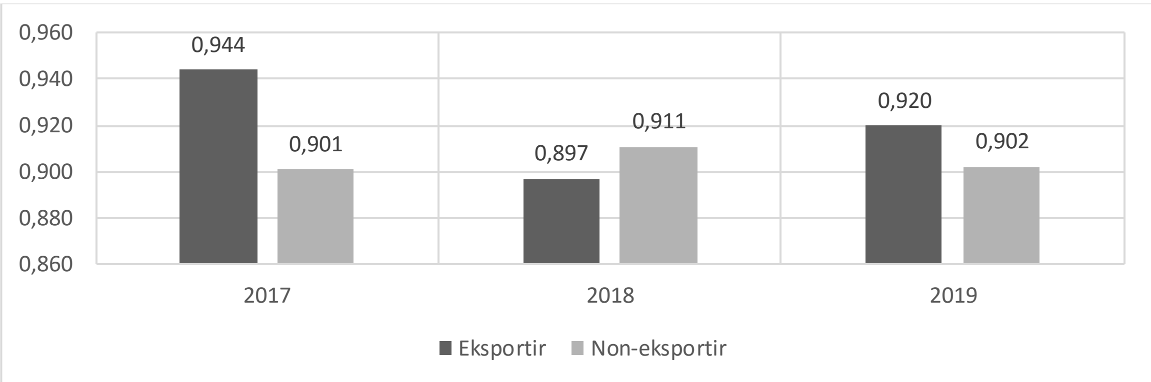

Figure 1. Average Growth of Technical Efficiency by Export and Non-Export 2017-2019

Figure 1 shows that exporting companies consistently have higher efficiency in 2019, an average value of 0.920, compared to non-exporters. These results are consistent with the export orientation coefficient which is significant at the 1% level. Meanwhile in 2017-2018 there were quite contrasting changes in the export activities of basic metal companies, before finally in 2019 the export orientation returned to relatively stable. These results are a basis for validation of the learning by exporting phenomenon which occurs based on global competition standards which force companies to adopt the best production and management efficiency of manufacturing companies (Sari et al., 2016; Yasin, 2021). This is also in line with the argument from Yasin (2021) that connectivity with international markets encourages the transfer of technology and knowledge which improves company performance. Even though downstreaming increases the added value of production, Östensson (2019) believes that the existence of a coercive downstream policy based on export bans will actually result in a greater risk of reducing production performance in the short term due to unpreparedness of domestic processing capacity and this has been experienced by Indonesia in the 2014-2016 period.

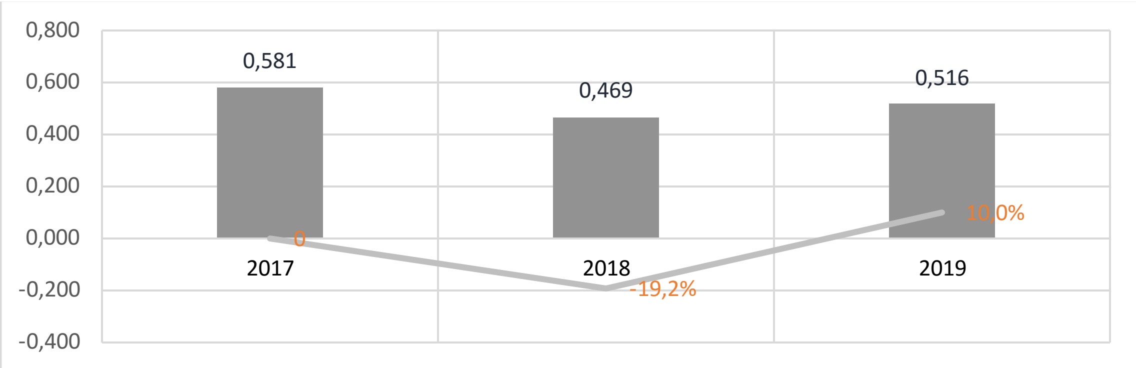

Figure 2. Average Growth According to Industry Downstreaming 2017-2019

Figure 2 shows that the average downstreaming ratio decreased by 19.2% from 0.581 in 2017, fluctuating in 2018 to 0.469, before rising again in 2019. The fluctuation in 2018 was attributed to the expansion of smelting capacity, which temporarily depressed the value-added ratio. This significantly impacted downstreaming, which was the highest inefficiency variable, with a coefficient of -0.4062. This pattern also explains the decline in technical efficiency that occurred in the same year from export-import activities. This also contributes to the downstreaming policy of the base metal industry, which has been quantitatively proven to increase production efficiency, with companies having higher added value in production inputs and base metal processing capacity, as well as more modern technology (Farawansa & Ratnawati, 2024; Östensson, 2019; Rivota & Wardhana, 2026; Suseno, 2019).

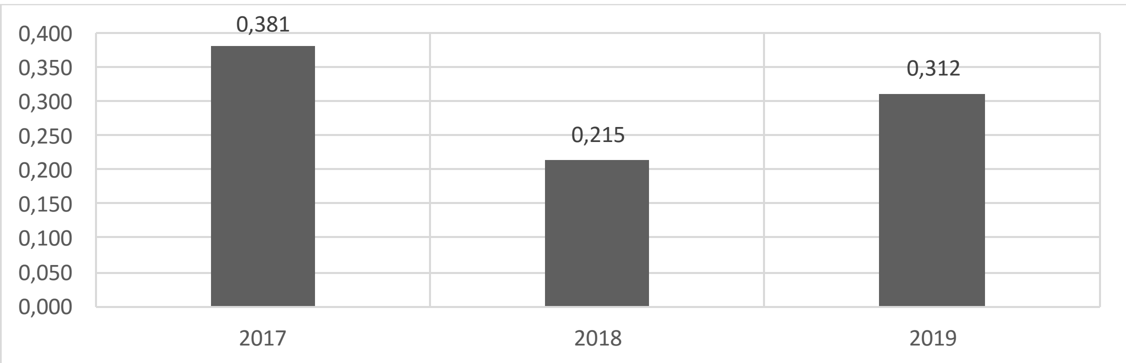

Figure 3. Average Growth of Technical Efficiency by Import Intensity in 2017-2019

Figure 3 shows the trend of imported raw material intensity, with the average import intensity reaching its lowest point in 2017 from 0.381 to 0.215 in 2018, then experiencing a significant increase of 0.312 in 2019. This condition is one of the variables with the largest fluctuations among the three determinants. Weakening access to imported raw materials in 2018 is associated with declining efficiency in the same year, consistent with the import intensity coefficient which reduces technical inefficiency with a coefficient of -0.2484 significant at the 1% level. These estimation results confirm the dual role of imports as found in Yasin (2021), although in general import intensity can suppress productivity, access to quality imported raw materials and capital goods to a certain extent can actually support more efficient production practices. This is also confirmed by Amiti & Konings (2005) and M. Wang & Wong (2012), who stated that import activities carried out by basic mineral companies are used for technology transfer and more efficient input provision for manufacturing industries in developing countries.

Table 5. Potential Output of the Base Metals Industry

Indicator	Large-Scale			Medium-Scale		
	Industry (PMDN)	Industry (PMA)	Industry (Non-Facility)	Industry (PMDN)	Industry (PMA)	Industry (Non-Facility)
Actual Output	906,478	1,389,878	761,413	41,135	38,986	32,339
Potential Output	1,004,131	1,528,960	842,627	45,121	43,366	35,667
Potential Output Increase	97,653	139,083	81,214	3,986	4,380	3,329

Note: in billions of rupiah

Table 5 shows the change in the potential output value of the base metals industry, based on inefficiency scores, into potential output increases, according to business scale and capitalization status. Overall, the difference between potential and actual output ranges from 9–11% across all groups, in line with the average technical inefficiency of around 9.4% in Table 1. Within large-scale industries, the largest nominal potential output increase is found in foreign-invested companies (PMA) at 139,083 billion rupiah, followed by domestic-invested companies (PMDN) at 97,653 billion rupiah, and non-facility companies at 81,214 billion rupiah. These companies, based on their production scale, have significantly higher output values than medium-sized industries, which have potential increases ranging from 3,329 billion to 4,380 billion rupiah. The PMA group at both scales shows a slightly higher proportional potential output increase of around 10–11%, indicating that foreign-invested companies still have room for efficiency improvements that has not been fully utilized.

The utilization rate of potential output in the base metals industry, with companies operating at an average of approximately 90% of their potential output, is a novel finding and represents a significantly higher output value than that of Margono & Sharma (2006), who reported that the Indonesian manufacturing industry generally operates at only 55.87% of its potential output, with the metal products sector operating at 68.91%. This difference reflects the improvement in efficiency of the base metals sector following the strengthening of downstreaming policies, as well as differences in the periods and levels of data aggregation between studies. The large total output gap indicates that there is still substantial room to increase output without additional inputs, particularly through strengthening the depth of downstreaming and the efficiency of raw material and energy supply chains.

To optimize the potential of the base metals industry, several policy implications are needed. First, accelerating the target for metal processing (smelters) is necessary to deepen the downstreaming structure of companies, as each increase in the ratio of value added to output has empirically significantly reduced technical inefficiency. Second, strengthening the absorption capacity of technical human resources, which is part of technology transfer through foreign investment and R&D activities, can significantly contribute to company efficiency. Third, synchronizing the supply chain for domestic raw materials needs to be strengthened by ensuring supply stability between mining companies and metal and mineral raw material smelters.

CONCLUSION

This study estimates the technical efficiency of the Indonesian base metals industry using a translog production function with a stochastic frontier analysis (SFA) approach, incorporating the Battese and Coelli (1995) inefficiency effects model. The results of the estimation show that the average technical efficiency of the Indonesian base metals industry is 0.906%, meaning the average company operates at 90.6% of its maximum potential output. This value is relatively high and indicates an efficiency increase of approximately 9.4%. Factors influencing inefficiency in the base metals industry include export orientation, downstreaming, R&D intensity, firm size, and import intensity, which significantly reduce technical inefficiency. Meanwhile, foreign ownership does not significantly impact inefficiency. On the other hand, exporting firms are consistently more efficient, indicating a crucial role for the base metals industry in fostering international market openness.

These findings confirm that the translog half-normal specification with the inefficiency effects model is an adequate approach through maximum likelihood estimation (MLE). However, this study is limited by its lack of more detailed company capital data. Therefore, further research recommends incorporating capital variables to obtain more measurable efficiency estimates, particularly in the production efficiency of the base metals industry. Furthermore, to comprehensively encourage sustainable increases in the production efficiency of Indonesia's base metals industry, policies are needed that support the strengthening of downstreaming and the value of domestic raw material supplies, expand access to quality imported raw materials, and update export-import regulations that are adaptive to the global economy.

REFERENCES

Aigner, D., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, *6*(1), 21–37. https://doi.org/https://doi.org/10.1016/0304-4076(77)90052-5

Amiti, M., & Konings, J. (2005). Trade Liberalization, Intermediate Inputs and Productivity: Evidence from Indonesia. *American Economic Review*, *97*(5). https://doi.org/10.1257/aer.97.5.1611

Badan Pusat Statistik. (2019). *Pendapatan Nasional Indonesia 2015-2019*. https://www.bps.go.id/id/publication/2025/06/20/63d723755172c429560055db/pendapatan-nasional-indonesia-2020-2024.html

Battese, G. E., & Coelli, T. J. (1992). Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India. *Journal of Productivity Analysis*, *3*(1–2), 153–169.

Collard-Wexler, A., & De Loecker, J. (2016). Production Function Estimation with Measurement Error in Inputs. *NBER Working Paper*. http://www.nber.org/papers/w22437

Farawansa, S. M., & Ratnawati, E. (2024). Diagnosis Of Nickel Industry Downstreaming Policy In Export Restriction Towards Increasing Economic Added Value In Indonesia. *Jurnal Legalitas*, *17*(1), 1–16. https://doi.org/10.33756/jelta.v16i1.xxxx

Farrell, M. J. (1957). The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society*, *120*(3), 253–290. https://doi.org/10.1002/0471667196.ess7018

Guberman, D., Shreiber, S., & Perry, A. (2024). Export Restrictions on Minerals and Metals: Indonesia's Export Ban of Nickel . In *Office of Economics, U.S. International Trade Commission* (Vol. 2, Issue 1). https://www.usitc.gov/publications/332/working_papers/ermm_indonesia_export_ban_of_nickel.pdf

Kumbhakar, S. C., & Lovell, C. A. K. (2000). *Stochastic Frontier Analysis*. Cambridge University Press. https://doi.org/DOI: 10.1017/CBO9781139174411

Margono, H., & Sharma, S. C. (2006). Efficiency and Productivity Analyses of Indonesian Manufacturing Industries. *Journal of Asian Economics*, *17*(6), 979–995. https://doi.org/10.1016/j.asieco.2006.09.004

Meeusen, W., & van Den Broeck, J. (1977). Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. *International Economic Review*, *18*(2), 435–444. https://doi.org/10.2307/2525757

Muslikhati, M. (2025). Imports of Raw Materials, Spillover of Foreign Investment and Technical Efficiency of Indonesia's Manufacturing Industry Exports. *E-Journal Ekonomi Bisnis Dan Akuntansi, Vol. 12 No. 2 (2025): e-JEBA Volume 12 Number 2 Year 2025*, 150–164.

Östensson, O. (2019). Promoting downstream processing: resource nationalism or industrial policy? *Mineral Economics*, *32*(2), 205–212. https://doi.org/10.1007/s13563-019-00170-x

Prasethea, K. F., Suyanto, S., & Sundari, M. S. (2020). Determinants of Technical Efficiency in Indonesian Manufacturing: The Case of Motor-Vehicle Firms. *Jurnal Ekonomi Pembangunan: Kajian Masalah Ekonomi Dan Pembangunan; Vol 21, No 2 (2020): JEP 2020*. https://doi.org/10.23917/jep.v21i2.10634

Rivota, D. R., & Wardhana, A. R. (2026). *Navigating the Complexities of Indonesia ' s Journey to Develop a Downstream Nickel Industry*. Springer Nature Switzerland. https://doi.org/10.1007/978-3-032-06139-3

Sari, D. W., Khalifah, N. A., & Suyanto, S. (2016). The spillover effects of foreign direct investment on the firms' productivity performances. *Journal of Productivity Analysis*, *46*(2–3), 199–233. https://doi.org/10.1007/s11123-016-0484-0

Setiawan, M., Emvalomatis, G., & Oude Lansink, A. (2012). The relationship between technical efficiency and industrial concentration: Evidence from the Indonesian food and beverages industry. *Journal of Asian Economics*, *23*(4), 466–475. https://doi.org/https://doi.org/10.1016/j.asieco.2012.01.002

Suseno, T. (2019). Analisis dampak sektor pertambangan mineral logam terhadap produk domestik bruto. *Jurnal Teknologi Mineral Dan Batubara*, *15*(2), 133–144. https://doi.org/10.30556/jtmb.vol15.no2.2019.688

Suyanto, S., Astanto, T. J., Santoso, H. W., & Salim, R. (2022). Technical Inefficiency in Nine Clusters of Indonesian Manufacturing Firms And its Determinants: Stochastic Frontier Analysis. *Jurnal Ekonomi Pembangunan: Kajian Masalah Ekonomi Dan Pembangunan*, *23*(2), 241–253. https://doi.org/10.23917/jep.v23i2.18113

Suyanto, Salim, R., & Bloch, H. (2014). Which firms benefit from foreign direct investment? Empirical evidence from Indonesian manufacturing. *Journal of Asian Economics*, *33*, 16–29. https://doi.org/https://doi.org/10.1016/j.asieco.2014.05.003

Wang, H. J., & Schmidt, P. (2002). One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. *Journal of Productivity Analysis*, *18*(2), 129–144. https://doi.org/10.1023/A:1016565719882

Wang, M., & Wong, M. C. S. (2012). International R & D Transfer and Technical Efficiency: Evidence from Panel Study Using Stochastic Frontier Analysis. *World Development*, *40*(10), 1982–1998. https://doi.org/oi.org/10.1016/j.worlddev.2012.05.001

Yasin, M. Z. (2021). Measuring the Productivity of the Foods and Beverages Industries in Indonesia : What Factors Matter? *Economics and Finance in Indonesia*, *67*(1), 132–146.