Does R&D Stimulate Firm's Efficiency in the Indonesian Manufacturing Sector?

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Abstract

The impact of research and development (R&D) spending has been shown significantly in promoting country's economic growth and productivity. Hence, we examine the research question by employing Indonesian manufacturing firm-level dataset in the years of 2017–2019 and by using Stochastic Frontier Analysis (SFA) to reveal whether heterogeneous firm's R&D spending contributes to the efficiency performance of the company. The finding reveals the robust positive effect of R&D spending to the efficiency performance, which implies that firms allocating more R&D spending will perform better efficiency due to, for example, managerial expertise improvements. An interesting finding is shown by the interaction model for which larger R&D allocated by foreign firm will boost better efficiency than that allocated by domestic firms, supporting prior arguments that foreign firm can be the driver of innovation as they are more likely to be closer to the world technology frontier. Several policy implications are suggested such as in-house R&D program to encourage human capital development and tax incentive to avoid market rivalry with foreign firms.

Keywords: R&D; technical efficiency; Indonesian manufacturing industry
JEL Classification: O31; O32; O33; O38

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1. Introduction

The impact of research and development (R&D) spending has been shown significantly in promoting country's economic growth and productivity, as in Juhro et al. (2022) and Männasoo et al. (2018). The mechanism occurred through the innovation processes boosting technological progress postulated by Schumpeterian model (Aghion & Howitt, 1992). Prior studies adopted this seminal theory in various evidences such as developed countries (Edquist & Henrekson, 2017; Yazgan & Yalçinkaya, 2018), developing countries (Erdal & Göçer, 2015; Shen et al., 2019), and middle-income countries (Kim & Park, 2018). However, although the indicator of productivity has been postulated to capture the degree to which technological progress in a country, as in Solow (1957), the effect of R&D in affecting to what extent the country maintain an equal level of efficiency in their use of factor of production because of different economies of scale remains leaving research gap amongst current studies. Hence, we aim to answer this research question by scrutinizing the degree to which R&D spending encourage technical efficiency.

Our hypothesis is motivated by theoretical argument of Aghion & Howitt (1992) postulating that the process of innovation causes the products' quality improvements. Furthermore, how fast the innovation is invented depends on the integration of research activities and human capital contributing to the acceleration of absorptive capacity for new knowledge creation as well as mimic of others (Cohen & Levinthal, 1990; Männasoo et al., 2018). This process of knowledge creation and innovation is then used for firms to improve not only technological progress but also the managerial skills and technical knowledges, which are captured by technical efficiency indicator (Erena et al., 2021), and altogether improving country's productivity, as suggested by Farrell (1957) (see Figure 1 for the framework illustration). In this sense, the standard classical assumption that neglects the possible slack of production due to different managerial competencies is no longer pertinent.

Figure 1: Framework of R&D to the Productivity Improvements

We examine the research question by employing Indonesian manufacturing firm-level dataset in the years of 2017–2019 and by using Stochastic Frontier Analysis (SFA) to reveal whether heterogeneous firm's R&D spending contributes to the efficiency performance of the company. The utilization of SFA under Maximum Likelihood Estimator (MLE) is more reliable as it estimates simultaneously through the inefficiency equation and production function, than that the standard production function using Ordinary Least Square (OLS) estimator. Moreover, the evidence of Indonesian manufacturing industry deserves more attention due several reasons. First, Indonesian manufacturing sector is greatly connected with many large economies through export activities such as China (22.9%), United States (11.91%), and Japan (5.85%) (Ministry of Industry of Republic Indonesia, 2023). In this regard, examining the R&D behaviour to the firm's efficiency performance will also imply to export decision to the international partners that impose stringent standards of outputs and productions.

Secondly, Indonesia has experienced dynamic performance due to global economic fluctuations in the last two decades. It was embarked in 1999 when the manufacturing sector contribution dropped by almost a half than it obtained before the crisis period (Yasin, 2022). Although it successfully caught up for the following 2 years, another crisis of 2008 hit Indonesian export markets causing demand drops (Basri & Rahardja, 2010). Interestingly, along this cycle, manufacturing sector has been becoming the largest contributor of the Indonesian economy by averagely more than 20% (Yasin, 2021). Hence, the survival behaviour of manufacturing sector as the largest contributor to the GDP through the process of innovation needs more investigation.

Lastly, the most intriguing attention, is the presence of inward foreign direct investment (FDI) in a form of multinational companies (MNCs) in Indonesia and South-East Asian Countries that causes significant knowledge transfer for the last two decades. Suyanto et al. (2021) argued that the growth of inward FDI in Indonesia from mid-1980-s to 2019 has multiplied by about 90 times reaching 25 billion USD in 2019. Likewise, South-East Asian economies also surge from 1.3% in 2000 to 13.02% in 2018, contributed mainly from large countries such as Japan (14.46%), China (9.52%), and South Korea (6.08%) (The ASEAN Secretariat, 2017; Yasin, 2023). As superior technology owned by MNCs affiliated to their parent's company in advanced countries is closer to the global technology frontier, the spending for their R&D may also stimulate the managerial skill and technical knowledge for efficiency improvements, not only for their internal performance but also the domestic company's response.

Our study contributes to the literatures in three ways. First, we address the firm-level R&D spending in affecting firms' technical efficiency. Theoretically, the perspective of technical efficiency will not capture the general macroeconomic indicator such as economic growth that may involve longer and complicated transmission through which R&D spending influences economy (see. Banelienė & Melnikas, 2020; Inekwe, 2014; Liu, 2016), but it will instead capture the proportional measurement of inputs in producing outputs. Hence, this perspective is suitable to be examined along with R&D spending as the essential factor for firms' performance.

Our second contribution stems from the utilization of R&D dataset. Not many studies of R&D discussed Indonesian evidence due to lack of reliable R&D datasets, notably for the firm-level data. Several studies tackle it by employing macro level and weighting strategies (Juhro et al., 2022; Kuswardana et al., 2021). Recently, the data of BPS statistics in 2017–2019 has provided the variable of R&D

activities spending which is intriguing for further investigation, notably its effect to the efficiency.

Our third contribution is by emphasizing the behaviour of R&D spending. Although some limited studies of Indonesian evidence have shown the effect of R&D spending to the economic performance, not many of them reveal the behaviour of R&D spending interacted with firm and sectoral heterogeneous characteristics. Therefore, we propose the interaction model in which the R&D not only stimulates technical efficiency alone but also simultaneously promote it with capital-ownership specific, technology-intensity specific, as well as firm-level specific indicators. This strategy enables the R&D to be captured together in affecting economic performance. The remaining sections deliver the data, empirical strategy, and econometric specifications to identify export spillover. Section 3 presents the findings of this study and explain further discussion. Finally, the conclusion and policy implications are provided in Section 4.

2. Methodology

2.1. Data

We use the annual firm-level data spanning from 2017 to 2019 of Statistik Industri (SI). The Statistik Industri represents the Large and Medium Manufacturing firms by 74% of the population and categorizes firms by size: a firm as a large firm if it has more than 99 workers; while a medium-size firm is when the firm possesses labour between 20–99. We cover an unbalanced panel dataset. This span of these periods is selected due to absence of SI data in 2016. Moreover, the SI data has switched the firm identification between the year of 2015 and 2017. In this sense, we cannot panel the year of 2015 and 2017. Finally, the year of 2019 is the latest dataset available provided by BPS Statistics.

There are several data adjustments and cleaning processes to deal with the dynamic of manufacturing firms' data in 2017–2019. First, the change of firm's subsector classification over the periods is solved by selecting the mode of the subsector as the two-digit classification. Second, all monetary-value variables are deflated using the Wholesale Price Indices of Indonesia of 2010 as the base year. Third, several firms do not reveal their R&D spending, but we do not exclude them from the analysis and recognize it as omitted value. Finally, we obtain the number of observations by 44,039.

There are several variables employed in our analysis, classified into two groups. The first group is the variables for production function components which are mainly in monetary measurements in Rupiah: total outputs (annual total final production), capital (total fixed assets such as building and vehicles), labour (number of total workers employed), energy (the total spending for energy consumption), and raw materials (the total utilization of raw materials for production). The second group of variables is the determinants of technical efficiency consisting of the spending for R&D activities (in Rupiah) referred to Tebourbi et al. (2020), dummy of importer, dummy of exporter, wages level, dummy for large company, dummy for capital ownership (either foreign or domestic with the threshold by 10%), and the technology-intensity classification. The descriptive statistics of these variables are summarized in Table 1.

Table 1: Descriptive Statistics

Variable	Obs	Unit	Mean	Std. dev.	Min	Max
Total Outputs	44,039	Billion Rupiah	85.78289	607.1638	0.000594	42664.2
Capital	44,039	Billion Rupiah	126.5815	2538.164	0.000125	227217
Labour	44,039	Workers	196.6175	831.1213	20	55252
Energy	44,039	Billion Rupiah	1.597014	43.24632	0.000101	7258.05
R&D Spending	44,039	Million Rupiah	66.35513	3028.831	0	395295
Wages	44,039	Million Rupiah	21.11996	36.54441	0.032151	5535.03
Foreign Firm	44,039	Dummy	0.109585	0.312375	0	1
Large Firms	44,039	Dummy	0.311519	0.46312	0	1
Importer	44,039	Dummy	0.365699	0.481631	0	1
Exporter	44,039	Dummy	0.088989	0.284732	0	1

2.2. Empirical Strategy and Technical Analysis

The basic theory of how technical efficiency is generated is from the production function under the slack space. Our basic production function as stated as follows.

$$Y = f(K, L, E, M) \tag{1}$$

Where Y is the total output as the function of K (capital), L (labour), E (energy), and M (materials). The Equation (1) is arranged in the stochastic panel model under Cobb-Douglas specification as:

$$y_{it} = \beta_0 + \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 e_{it} + \beta_4 m_{it} + \epsilon_{it} \tag{2}$$

Where $y_{it}, k_{it}, l_{it}, e_{it}, m_{it}$ are variables in the log form for total outputs, capital, labour, energy, and raw materials. ϵ_{it} is the error terms. The coefficient in Equation (2) may be estimated with standard Ordinary Least Square (OLS) if we assume standard production function. However, since we assume the presence of technical efficiency, we should use Stochastic Frontier Analysis (SFA) under Maximum Likelihood Estimator (MLE). The stochastic frontier model for panel data is specified as follows:

$$y_i = \beta_0 + \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 e_{it} + \beta_4 m_{it} + v_{it} - u_{it} \tag{3a}$$

$$u_{it} = \delta_0 + z_{it}\delta + \omega_{it} \tag{3b}$$

Where v_{it} is the error terms under $iid.N(0, \sigma_v^2)$ assumption and it independent from u_{it} which is non-negative random variable capturing technical inefficiency and assumed as $N^+(z_{it}\delta, \sigma_u^2)$. Meanwhile, ω_{it} is the random variable under truncation of the normal distribution with zero mean and variance σ^2 and point of truncation by $z_{it}\delta$ i.e. $\omega_{it} \geq -z_{it}\delta$ (see Sari et al., 2016). The estimation of technical efficiency is measured from the conditional expectation given the assumption in (3a) and (3b) as follows.

$$TE_{it} = \frac{y_{it}}{\hat{y}_{it}} \tag{4a}$$

$$TE_{it} = \frac{f(k_{it}, l_{it}, e_{it}, m_{it}; \beta).exp(v_{it} - u_{it})}{f(k_{it}, l_{it}, e_{it}, m_{it}; \beta).exp(v_{it})} \tag{4b}$$

$$TE_{it} = exp(-u_{it}) \tag{4c}$$

$$TE_{it} = exp(-z_{it}\delta - \omega_{it}) \tag{4d}$$

Where y_{it} is the realized outputs under the existence of inefficient condition while $\hat{y}_{it}$ is the potential maximum outputs under which inefficiency does not exist. In this regard, TE scores range between 0 and 1 as the closer y_{it} to the $\hat{y}_{it}$ indicates that the inefficiency score is smaller (i.e. larger technical efficiency).

The estimation of production function and inefficiency effects are estimated simultaneously using maximum-likelihood method with likelihood function as stated in variance parameters $\sigma_s^2 \equiv \sigma_v^2 + \sigma^2$ and $\gamma \equiv \frac{\sigma^2}{\sigma_s^2}$ which lies between 0 and 1. Several studies considered γ parameter to decide whether the frontier model is appropriate (see. Sari, 2019; Yasin, 2022) in which larger γ implies that frontier model is preferred than the standard OLS estimation assuming the absence of inefficiency, however Kumbhakar et al. (2015) suggested the utilization of generalized log-likelihood test with relevant null hypotheses by calculation likelihood ratio statistic $\lambda = -2[l(H_0) - l(H_1)]$ where $l(H_0)$ is the log-likelihood value of restricted model, i.e. standard production function without inefficiency, and $l(H_1)$ is the log-likelihood value of frontier model. We reject null hypothesis if $\lambda > \chi^2$ distribution with degrees of freedom equal to the number of parameters involved in the restriction. In this regard, we use the latest approach to decide suitability of the frontier model.

We apply a flexible functional form of production function namely Translog (transcendental logarithmic) instead of Cobb-Douglas production function. This strategy enables the production behaviour to capture more flexible substitution elasticity and impose less constrains (Christensen et al., 1973). Our specification refers to the SFA model of Battese & Coelli (1995) under which inefficiency function is affected by exogeneous factors, as follows.

$$\begin{aligned} y_{it} \quad = \quad & \beta_0 + \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 e_{it} + \beta_4 m_{it} + \frac{1}{2}(\beta_5 k_{it}^2 + \beta_6 l_{it}^2 + \beta_7 e_{it}^2 + \beta_8 m_{it}^2) \\ & + \beta_9 (k_{it} \times l_{it}) + \beta_{10}(k_{it} \times e_{it}) + \beta_{11}(k_{it} \times m_{it}) + \beta_{12}(l_{it} \times e_{it}) + \beta_{13}(l_{it} \times m_{it}) \\ & + \beta_{14}(e_{it} \times m_{it}) + \beta_{15} t + \beta_{16}(k_{it} \times t) + \beta_{17}(l_{it} \times t) + \beta_{18}(e_{it} \times t) + \beta_{19}(m_{it} \times t) \\ & + \frac{1}{2}\beta_{20} t^2 + \beta_d D_i + v_{it} - u_{it}(4a) \end{aligned} \tag{5a}$$

$$u_{it} = \delta_0 + \delta_1 R\&D_{it} + \delta_z Z_{it} + \omega_{it} \tag{5b}$$

Where $y_{it}, k_{it}, l_{it}, e_{it}, m_{it}$ are variables in the log form for total outputs, capital, labour, energy, and raw materials. v_{it} is the error terms under $iid.N(0, \sigma_v^2)$ assumption and it independent from u_{it} which is non-negative random variable capturing technical inefficiency and assumed as $N^+(z_{it}\delta, \sigma_u^2)$. Meanwhile, ω_{it} is the random variable under truncation of the normal distribution with zero mean and variance σ^2 and point of truncation by $z_{it}\delta$ i.e. $\omega_{it} \geq -z_{it}\delta$. $R\&D_{it}$ is the research and development (R&D) spending in log-form and Z_{it} contains control variables namely dummy of importer, dummy of exporter, wages level, dummy for large company, dummy for capital ownership (either foreign or domestic with the threshold by 10%), and the technology-intensity classification. We also apply for log-likelihood test to examine suitability of Translog production function other Cobb-Douglas ($\beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = \beta_{16} = \beta_{17} = \beta_{18} = \beta_{19} = \beta_{20} = 0$).

3. Result and Analysis

The analysis is embarked by overviewing the ratio of R&D spending to total outputs in our datasets. We illustrate it in Figures 2 and 3.

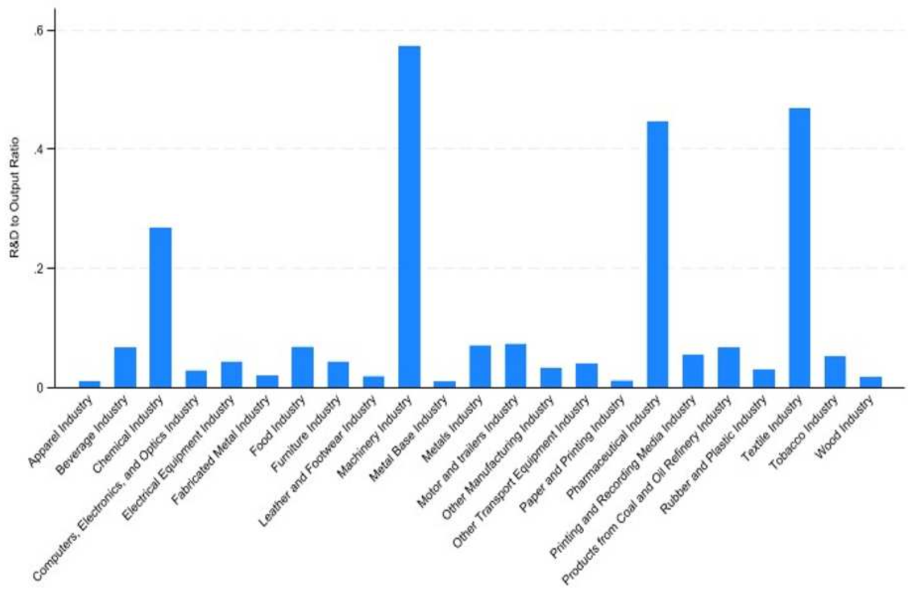

Figure 2: R&S to Output Ratio Across Subsectors

According to Figure 2, the largest R&D to output ratio is achieved by the subsector Machinery Industry by approximately 57%. The next three largest subsectors with R&D to output ratio are Textile Industry (46%), Pharmaceutical

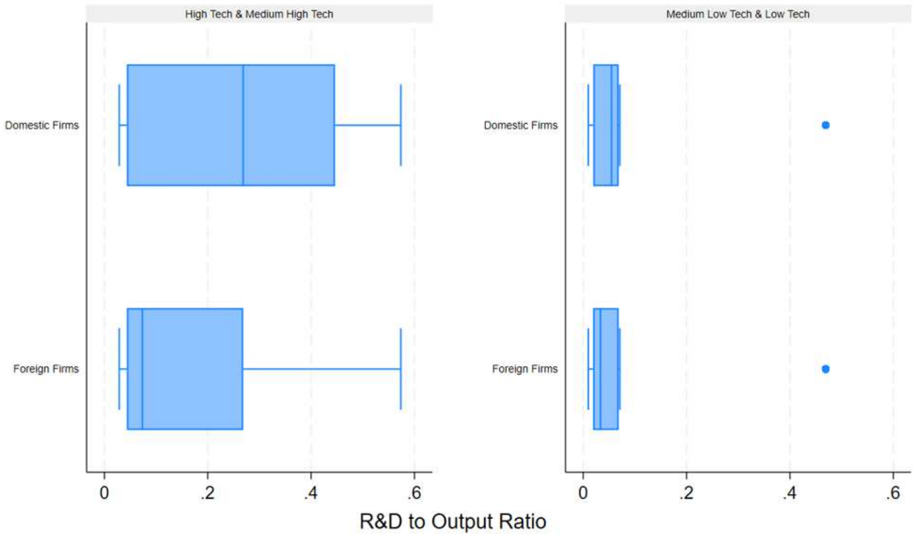

Figure 3: R&D to Output Ratio Across Technology Intensity Group and Capital

Industry (44%), and Chemical Industry (26%), while the rest of subsector reveals the magnitude by less than 20%. Meanwhile, Figure 3 depicts the R&D to Output Ratio across to the technology group classification based on OECD (2011) as well as the capital ownership (domestic vs foreign). The data shows that the domestic high-tech and medium high-tech firms have the highest average R&D to output ratio as well as variability amongst others by about greater than 20%. Meanwhile, foreign high-tech and medium high-tech firms, although reveal lower average, the upper quartile is relatively the same with the domestic high-tech and medium high-tech. In contrast, both domestic and foreign medium low-tech and low-tech shows similarly distribution with the average by less than 20% and one outlier for each of them.

The following analysis is to look at the regression result using Stochastic Frontier Analysis (SFA) reported in Table 2.

The first part that is essential to examine is the suitability of maximum likelihood estimation from SFA rather than standard Ordinary Least Square (OLS). This test is undertaken through the log-likelihood ratio test (LL test) for Model 1, Model 2, Model 3, and Model 4 for both OLS and MLE. The result shows that the likelihood function for OLS in these four models are, respectively, -35626.127, -35626.127, -35626.127, and -35626.127. Hence, we obtain the LLR test by 6133.694, 6132.574, 6143.994, and 6142.614 which are much greater than the critical value from χ^2-table and concludes than the utilization of SFA is suitable.

According to Table 2, the coefficient for production function is mainly statistically significant with robust effects. However, the coefficient from the Translog

Table 2: Regression Results Using SFA

Variable	Model 1		Model 2		Model 3		Model 4	
	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
Production Function								
Constant	0.348***	0.027	0.326***	0.022	0.350***	0.026	0.354***	0.026
k	0.030***	0.004	0.030***	0.004	0.030***	0.004	0.030***	0.004
l	0.400***	0.009	0.397***	0.009	0.401***	0.010	0.400***	0.010
e	0.060***	0.005	0.061***	0.005	0.060***	0.005	0.060***	0.005
m	0.553***	0.005	0.552***	0.005	0.553***	0.005	0.553***	0.005
k^2	0.007***	0.001	0.006***	0.001	0.007***	0.001	0.007***	0.001
l^2	0.109***	0.005	0.110***	0.005	0.110***	0.005	0.109***	0.005
e^2	0.024***	0.001	0.024***	0.001	0.024***	0.001	0.024***	0.001
m^2	0.137***	0.001	0.137***	0.001	0.137***	0.001	0.137***	0.001
$k \times l$	0.015***	0.002	0.015***	0.002	0.015***	0.002	0.015***	0.002
$k \times e$	0.003***	0.001	0.003***	0.001	0.003***	0.001	0.003***	0.001
$k \times m$	-0.016***	0.001	-0.017***	0.001	-0.017***	0.001	-0.017***	0.001
$l \times e$	0.006***	0.002	0.006***	0.002	0.006***	0.002	0.006***	0.002
$l \times m$	-0.122***	0.002	-0.122***	0.002	-0.121***	0.002	-0.121***	0.002
$e \times m$	-0.026***	0.001	-0.026***	0.001	-0.026***	0.001	-0.026***	0.001
t	-0.040*	0.023	-0.043**	0.022	-0.042*	0.022	-0.042*	0.023
$t \times k$	0.006	0.011	0.007	0.011	0.007	0.011	0.007	0.011
$t \times l$	-0.003	0.002	-0.003	0.002	-0.003	0.002	-0.003	0.002
$t \times e$	-0.040***	0.004	-0.041***	0.004	-0.040***	0.004	-0.039***	0.004
$t \times m$	0.006***	0.002	0.006***	0.002	0.006***	0.002	0.007***	0.002
t^2	0.027***	0.002	0.027***	0.002	0.027***	0.002	0.026***	0.002
Inefficiency Effects								
Contant	6.485***	0.121	6.411***	0.099	6.507***	0.120	6.488***	0.128
R&D	-0.007***	0.001	-0.006***	0.001	-0.008***	0.001	-0.009***	0.001
Wages	-0.368***	0.008	-0.365***	0.006	-0.370***	0.008	-0.368***	0.008
Foreign Firm	-0.077***	0.017	-0.092***	0.017	-0.073***	0.018	-0.074***	0.018
High-Tech Firm	0.378***	0.039	0.302***	0.019	0.422***	0.030	0.403***	0.027
R&D × Foreign Firm			-0.009***	0.001				
R&D × High-Tech Firm					0.004**	0.002		
R&D × Wages							0.002*	0.001
Import	-0.119***	0.011	-0.126***	0.008	-0.121***	0.012	-0.120***	0.012
Export	-0.005	0.013	-0.024***	0.007	-0.004	0.012	-0.005	0.015
Large Firm	0.011	0.012	0.006	0.012	0.012	0.012	0.010	0.013
σ^2	0.263***	0.002	0.259***	0.002	0.264***	0.002	0.264***	0.002
γ	0.093***	0.010	0.053***	0.004	0.104***	0.007	0.105***	0.007
Log-likelihood Ratio	-32559.28		-32559.84		-32554.13		-32554.82	
Dummy Subsector-Specific in Production Function	YES		YES		YES		YES	
Number of Observation	44039		44039		44039		44039	

Note: ***, **, *: Significant at alpha 1%, 5%, 10%.

The negative coefficient of inefficiency effects denotes positive effect to the technical efficiency as $TE_{it} = exp(-u_{it})$.

production function cannot be directly interpret and requires the calculation of elasticity to ensure monotonicity condition. Figure 3 reports the elasticity distribution across factors of production in our datasets from Model 1.

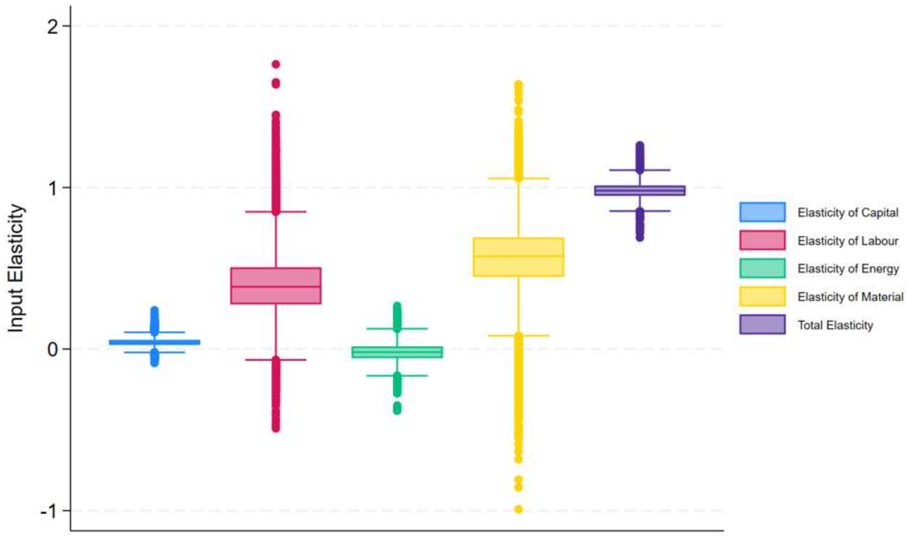

Figure 4: Input Elasticity

According to Figure 4, all the inputs reveal mainly positive elasticity, indicating the monotonicity condition of production function with constant return to scale.

We then interpret the results from the inefficiency effects in which the determinants of technical efficiency are shown. According to Table 2, R&D spending is consistent for all model in negatively affecting inefficiency. This finding implies that an increase of R&D spending by 1% will reduce inefficiency (or promote efficiency) by about 0.6%–0.9%. This finding supports the argument of Lome et al. (2016) and Ting et al. (2016) postulating that R&D spending will promote better economic performance as the firms boost competitive advantage by making differentiation from their competitor. As the R&D aims to motivate firms to keep innovating the novel production approach, it enforces better managerial skills which in turn promotes technical efficiency. This finding is strengthened by the correlation illustration across subsector between R&D spending and technical efficiency in Figures 5 and 6.

Interesting results are shown by the interaction between R&D spending and several firm characteristics, namely capital ownership, the level of wages, and dummy for high tech and medium tech. The effect of capital ownership itself is negative across the models, concluding that foreign firms perform better efficiency performance than the domestic firms. This finding is consistent with prior

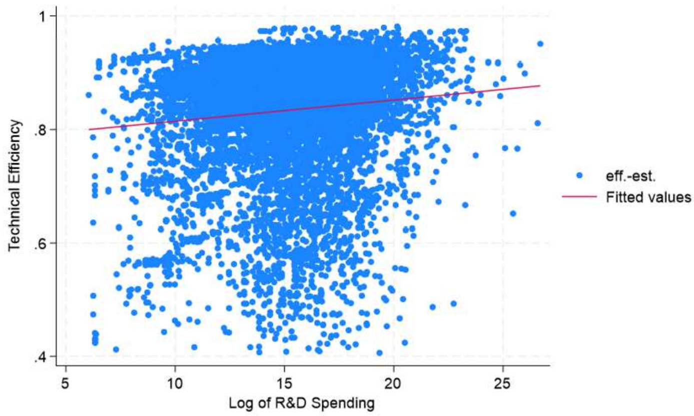

Figure 5: Correlation of Log of R&D Spending to The Technical Efficiency

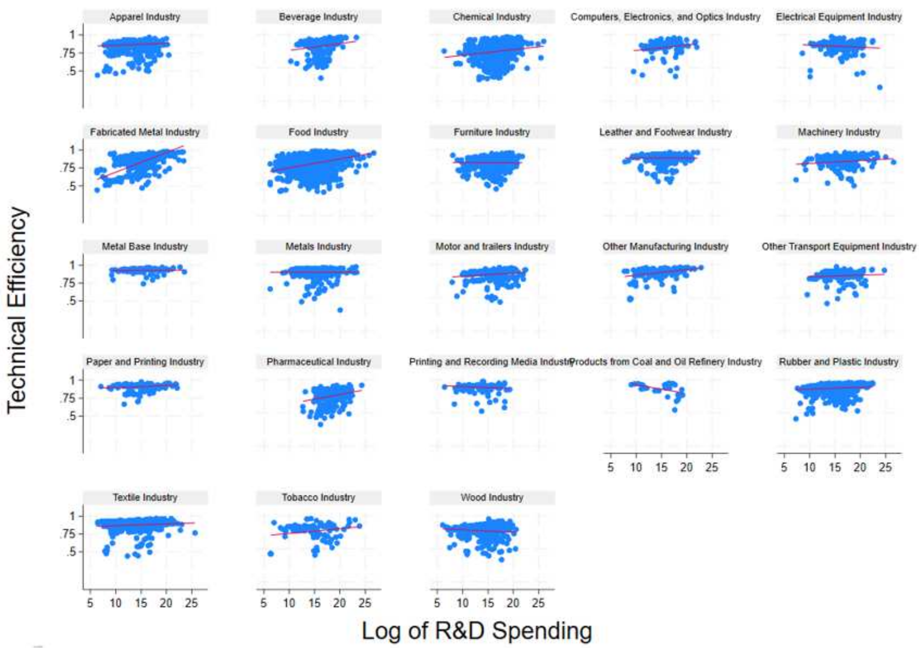

Figure 6: Correlation of Log of R&D Spending to The Technical Efficiency Across Subsector

claims such as Sari (2019). Moreover, the negative effect of foreign ownership to the inefficiency is then strengthened by its interaction with R&D spending, implying that R&D spending owned by foreign firms promotes more efficiency than R&D spending from domestic firms. This finding supports prior study of Agovino et al. (2018) suggesting the evidence to which the foreign firms are more likely to be closer to the world technology frontier as they remain under control of the parent company.

The effect of dummy for high tech and medium high-tech is positive, indicating that high tech and medium high-tech firms are less efficient than the medium low tech and low-tech group. This finding is strengthened by its interaction with R&D spending and implies that the R&D spending of high-tech and medium high-tech group do not promote better efficiency improvement. A plausible reason of this result is because the intensity of technology in the subsector may affect to the technological progress instead of technical efficiency representing the managerial expertise. In this sense, managerial improvement does not necessarily require advanced technology intensity.

The effect of wages level can proximate absorptive capacity. The negative effect demonstrates that wages level promotes efficiency. As the absorptive capacity also represents the degree to which skilled workers are employed in a firm, the negative impact concludes that it will encourage efficiency improvements of the firms, supporting prior studies such as Sugiharti et al. (2022), Yasin (2022), and Yasin & Sari (2022). However, we do not capture similar effect when wages level interacts with R&D spending. A plausible reason is the possibility for firm to outsource the R&D activities which affect the relative benefits and costs of external sourcing relative to the in-house R&D, as suggested by Love & Roper (2002). In other words, when the R&D spending is allocated under outsource scheme which does not affect wages level and absorptive capacity development of the firm (Cohen & Levinthal, 1989), it then makes sense that higher wages level and R&D spending do not contribute positively to the firms' technical efficiency. Nonetheless, possibility for which in-house and external R&D are complement rather than substitute remain requiring further investigation (see Bertrand, 2009; Cassiman & Veugelers, 2006).

In this regard, we then analyze the marginal effect of R&D in the inefficiency effect by using first differential of inefficiency with respect to R&D spending only for Model 4 to capture to which degree an increase of R&D spending under absorptive capacity level will promote technical efficiency. The result is illustrated in Figures 7 and 8. According to Figures 7 and 8, the marginal effect of R&D spending to the technical efficiency remains positive for all strategies, revealing the robust estimate of our estimation where the R&D affects positively to the firm's efficiency performance.

For control variables, such as import, conclude that importer performs better efficiency score than that non importer. This finding supports the argument of Esquivias & Harianto (2020) arguing that as by being importer, firms may have access to the high quality raw materials which in turn imposes them to apply stringent standard of production approach to avoid inefficiency and induces more competition pressure in the domestic markets, as also suggested by Yasin (2022).

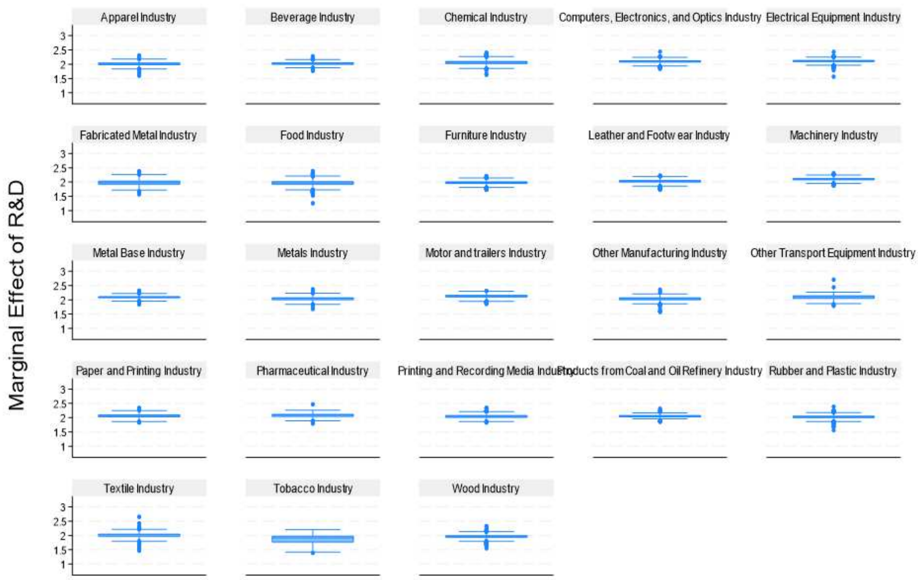

Figure 7: Marginal Effect of R&D in Model 4 Across Subsector

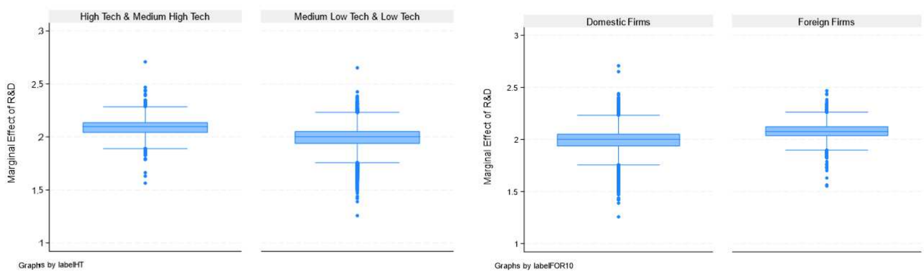

Figure 8: Marginal Effects of R&D in Model 4 Across Technology Intensity and Capital Ownership

Meanwhile, export is shown statistically significant in encouraging efficiency in Model 2, revealing that exporter is also more efficiency than that non exporter. This finding is consistent with hypothesis of learning-by-exporting in which firms will perform better once they enter the international markets through export activities (Atkin et al., 2017; De Loecker, 2013; Pane & Patunru, 2021). Furthermore, firms with labour more than 99 (large company) are not statistically different with firms with less than 99 workers (medium company).

4. Conclusion and Implication

We have demonstrated the effect of R&D spending to the efficiency performance of the manufacturing industry in Indonesia. The finding reveals the robust positive effect of R&D spending to the efficiency performance, which implies that firms allocating more R&D spending will perform better efficiency due to, for example, managerial expertise improvements. An interesting finding is shown by the interaction model for which larger R&D allocated by foreign firm will boost better efficiency than that allocated by domestic firms, supporting prior arguments that foreign firm can be booster of innovation as they are more likely to be closer to the world technology frontier.

According to the abovementioned findings, there are several policy implications. First, as the positive effect of R&D to the efficiency is captured under the support of foreign firms, we recommend that the intensification of in-house R&D rather than external R&D through outsourcing. The strategy for in-house R&D will impose firm to organize the cost and benefit structure in such ways to obtain better efficiency. In this sense, the improvement for human resource through training and skill development will also be conducted, rather than merely taking the ready-to-use product from outsourced R&D activities that may limit the knowledge transfer. Moreover, evidently, foreign firms is more likely to obtain financial supports from their parent company for their R&D. It may then cause rivalry effect for local firms under market liberalism. Hence, policies encouraging R&D efforts to local firms are also required, such as tax incentives. Furthermore, learning-based R&D spending should consider the appropriate level of capabilities to ensure R&D investment can be converted effectively and efficiently into productivity gains.

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