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Foreign direct investment, efficiency, and total factor productivity: Does technology intensity classification matter?

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Abstract

Purpose — We examine whether the foreign direct investment (FDI) in promoting technical efficiency is controlled by the sector classifications based on the technology intensity (High Technology, Medium-High Technology, Medium-Low Technology, and Low Technology).

Methods — We use the Indonesian firm-level dataset of the large and medium manufacturing survey from 2007 to 2015 and employ the time-varying stochastic production frontier.

Findings — We reveal that FDI, technology intensity and absorptive Capacity significantly affect firms' production and efficiency. We also found that the Indonesian manufacturing industry from 2007 to 2015 experienced positive Total Factor Productivity growth, where High-Technology sectors experienced the largest magnitude among others. Meanwhile, technological progress stemming from FDI is enjoyed more by Low Technology sectors. Meaning to say, technology intensity classification does not matter to technological progress.

Implication — The host country's government should focus on industries with high technical capabilities to accelerate FDI gains for the firms. Simultaneously, human capital improvement also needs to be intensified, for instance, through training or human development, so that firms with lower technical capability can catch up and, consequently, receive similar benefits from FDI activities.

Originality — Our study accommodates the research gap by including the FDI effect in both productivity and efficiency in a single equation. Many studies merely categorize technology intensity following the stochastic production frontier estimation to obtain technical efficiency or TFP growth. In this sense, those studies did not control the impact of the technology-specific effect.

Keywords — FDI, manufacturing, Indonesia, stochastic production frontier.

Introduction

The debate on whether foreign investment benefits the host's economy in the form of technology diffusion has attracted many researchers. Most of them claimed that foreign investment is a major channel of technology transfers from developed countries to developing countries (Baltabaev, 2014; Zhao & Zhang, 2010). In terms of more technical issues, some studies also suggested that the benefits of FDI can be effectively gained to develop advanced managerial expertise and scale-

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production knowledge that lead to production efficiency improvement (Mastromarco & Ghosh, 2009; Sari, 2019; Smeets, 2008; Yang, Chen, & Huang, 2013).

However, theoretical arguments indicate that the effect of technology diffusion stemming from FDI might be conditional and complementary to other factors such as human capital investment and specified subsector characteristics. The high quality of human capital will promote FDI benefits as it increases absorptive capacity, enabling technology diffusion to be quickly taken in (Carbonell & Werner, 2018). For the case of subsector characteristics, there may be different effects resulting from FDI upon high and low technology intensity sectors. The technology diffusion caused by FDI is greater in the high technology sectors than in low-technology ones as it relies on technology creation and research and development (R&D) intensity (Keller, 2010). In this sense, technological progress and the appropriateness of technology are claimed as sector-specific (Fu & Gong, 2011). Therefore, the conventional approach to identifying the effect of technology diffusion caused by FDI on economic performance without considering specific technology intensity may be unclear.

Given any considerable potential effect of FDI on economic performance, a systematic analysis that distinguishes technology intensity is essential. However, there are not many previous robust studies that have devoted efforts to investigating any detected FDI's effect on technology intensity in the case of Indonesia. The United Nations Conference on Trade and Development (UNCTAD) recorded that, as of 2014, the Indonesian global FDI inflows were noted in the 14th place with more than 23 billion USD (Gopalan, Hattari, & Rajan, 2016). This amount increased by approximately 20% compared to that in 2013. Therefore, this evidence raises urgent questions–*"In the case of the Indonesian manufacturing sector, do large FDI inflows matter?"* If it does matter, "*is it technology-intensity sectors oriented?*"

This study investigates the effect of FDI on firms' technical efficiency and production distinguished in high-, medium-high, medium-low and low-technology sectors in Indonesia. FDI's effect on technical efficiency helps measure total factor productivity (TFP) growth decomposed from technological change and scale efficiency change. To acknowledge the composition of TFP growth, this study prefers stochastic frontier estimation because it recognises 'the best practice' aligning the frontier at which well-performed firms will stay, leading to more variation in productivity scores (Farrell, 1957).

This study contributes to the literature in several ways. Firstly, unlike many prior studies examining the FDI effect on firms' productivity or efficiency, our study accommodates the research gap by including the FDI effect on productivity and efficiency in a single equation. This model refers to the study of (Sari, Khalifah, & Suyanto, 2016). Secondly, many studies, notably for Indonesian cases, merely categorize technology intensity following the stochastic production frontier estimation to obtain technical efficiency or TFP growth. In this sense, those studies did not control the impact of the technology-specific effect. This approach leads to FDI bias that may affect efficiency and productivity and the firms' technology intensity classification. In this study, we include technology-specific to avoid this bias.

Methods

Data

This study uses firm-level data from the large and medium manufacturing sector (IBS) annually surveyed by the Indonesian Central Bureau of Statistics from 2007 to 2015. The Indonesian Central Bureau of Statistics defines manufacturing firms as large and medium firms which empower more than 100 labourers for large firms and between 20 to 99 labourers for medium firms. The number of firms may change over time due to some exiting the industry. Nonetheless, selecting balanced panel data may limit the number of firms estimated in this study. Therefore, the unbalanced-panel data consists of 120,477 observations with a minimum number of 12,418 manufacturing establishments in 2010 and a maximum number of 13,850 establishments in 2011.

There are two divisions of variables in this study. The first division includes the main variables, e.g. total output, capital (approximated by the fixed assets of a firm such as land, building, machinery, equipment, and vehicles), number of labourers, energy (approximated by fuel and lubricants used in a year) and raw material. Except for the number of labourers, all variables are in Rupiah. The second division has two sub-divisions, namely the key exogenous variables: a foreign firm that proxies FDI, dummies of technology intensity (high, medium-high, medium-low, and low intensity) and absorptive Capacity. There are other exogenous variables referred to in some previous studies: age of firm (Machmud, Nandiyanto, & Dirgantari, 2018; Suyanto & Salim, 2010), export (Atkin, Khandelwal, & Osman, 2017; De Loecker, 2013; Mok, Yeung, Han, & Li, 2010), imported raw material intensity obtained from the ratio of imported raw material and total materials (Sari, 2019; Sari et al., 2016), and firm size obtained from the market share of the firm in the industry. Table 1 reports the statistics descriptive of all variables employed in this study.

Table 1. Descriptive Statistics

Variables	Units		2007	2008	2009	2010	2011	2012	2013	2014	2015
The Main Variables											
Output (Y)	Billion Rupiah	Mean	14.85	31.79	43.50	41.86	51.49	58.09	109.63	68.87	74.91
		Std. Deviation	154.28	509.07	439.54	516.98	542.31	441.01	864.95	568.98	696.00
Capital (K)	Billion Rupiah	Mean	7.3	15.0	1010.7	52.8	74.9	103.6	161.9	486.9	116.0
		Std. Deviation	98.7	292.2	105598.8	1928.4	2418.1	4924.4	8162.6	15054.4	4809.2
Labour (L)	Workers	Mean	134.3	148.3	154.9	172.8	180.4	189.8	194.3	193.7	189.3
		Std. Deviation	544.3	579.6	591.2	665.0	642.0	657.1	671.1	759.4	793.2
Material (M)	Billion Rupiah	Mean	8.3	17.7	24.5	23.5	28.6	30.7	57.0	34.0	35.3
		Std. Deviation	51.3	225.1	250.4	387.5	377.8	198.3	518.3	255.9	268.2
Energy (E)	Billion Rupiah	Mean	0.37	0.89	1.02	0.79	1.17	1.40	2.36	1.73	1.71
		Std. Deviation	5.50	24.51	17.74	12.03	19.68	17.90	30.02	30.44	25.98
Exogenous Variables											
Technology Intensity	Dummy	High Technology	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
		Std. Deviation	0.11	0.12	0.13	0.13	0.13	0.13	0.13	0.13	0.13
		Medium-High Technology	0.05	0.06	0.06	0.07	0.07	0.07	0.08	0.08	0.08
		Std. Deviation	0.22	0.24	0.24	0.26	0.26	0.26	0.27	0.27	0.27
		Medium-Low Technology	0.18	0.19	0.19	0.19	0.19	0.20	0.20	0.19	0.19
		Std. Deviation	0.38	0.39	0.39	0.39	0.39	0.40	0.40	0.39	0.39
		Low Technology	0.74	0.72	0.71	0.71	0.70	0.70	0.69	0.70	0.70
		Std. Deviation	0.43	0.44	0.45	0.45	0.45	0.45	0.45	0.45	0.45
Foreign Direct Investment/Foreign Ownership	Dummy	Mean	0.06	0.07	0.07	0.08	0.08	0.09	0.08	0.09	0.10
		Std. Deviation	0.23	0.26	0.26	0.27	0.28	0.28	0.28	0.29	0.29
Absorptive Capacity (absp)	Ratio	Mean	14.97	15.18	15.65	15.51	14.81	16.24	16.79	16.06	16.19
		Std. Deviation	1.06	1.06	0.95	0.93	2.13	0.70	0.65	0.76	0.74
Age of Firm (age)	years	Mean	15.52	16.71	17.81	18.95	20.10	21.18	22.27	23.17	24.10
		Std. Deviation	11.62	11.78	11.89	11.96	12.18	12.21	12.29	12.21	12.19
Export (expr)	Dummy	Mean	0.19	0.17	0.15	0.14	0.14	0.12	0.14	0.12	0.13
		Std. Deviation	0.40	0.38	0.35	0.35	0.35	0.32	0.35	0.32	0.34
Imported Raw Material (imp)	Ratio	Mean	0.06	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.08
		Std. Deviation	0.06	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.08
Firm Size (Fsize)	Ratio	Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		Std. Deviation	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Number of Observations			12,418	13,814	13,737	13,071	13,850	13,585	13,360	13,337	13,305

Note: Mean=arithmetical average, Std. Dev.=standard deviation.

FDI can be set in some proxies to capture the foreign diffusion in the firm. In this study, the percentage of foreign-capital ownership share is considered as the proxy of FDI (see: Sari, 2019; Sari et al., 2016; Yasin, 2021). The percentage of foreign share ownership in a firm consists of several categories: 5% (Haddad & Harrison, 1993), 10% (IMF, 2004), 20% (Djankov & Hoekman, 2000), or at least any amount of positive foreign ownership in a firm (Narjoko & Hill, 2007). This study only refers to the 20% to estimate TFP growth and decomposition. However, the 5% indicator is also considered to examine the robustness check of the estimated model.

The dummy variables of high, medium-high, medium-low, and low technology stem from the sector classification based on technology intensity proposed by OECD (2011). The classification is referred to in the two digits of the Indonesia Standard Industrial Classification

(ISIC) of 2009. It is worth noting that IBS data before 2010 referred to ISIC 2005, while ISIC 2009 was referred to in the 2010 IBS and later. During this transition, a firm might change its industrial classification. Therefore, this study's 2007-2009 observations need to be converted into ISIC 2009. The classification is summarised in Table 2.

Table 2. Classification of High-Technology and Low-Technology

High Technology		Medium-High Technology		Medium-Low Technology		Low Technology	
Code	Subsector	Code	Subsector	Code	Subsector	Code	Subsector
21	Pharmaceutical Industry	20	Chemical Industry	23	Fabricated Metal Industry	10	Food Industry
26	Computers, Electronics, and Optics Industry	27	Electrical Equipment Industry	24	Metal Base Industry	11	Beverage Industry
		28	Machinery Industry	25	Metals Industry	12	Tobacco Industry
		29	Motor and trailers Industry	22	Rubber and Plastic Industry	13	Textile Industry
		30	Other Transport Equipment Industry	19	Products from Coal and Oil Refinery Industry	14	Apparel Industry
						15	Leather and Footwear Industry
						16	Wood Industry
						17	Paper and Printing Industry
						18	Printing and Recording Media Industry
						31	Furniture Industry
						32	Other Manufacturing Industry

Source: OECD (2011)

Empirical Strategy

This study uses Transcendental Logarithmic (Translog) as the main stochastic production frontier model. The use of Translog is more flexible as it recognises a non-fixed substitution elasticity and fewer constraints than those recognised in a general logarithm linear model, e.g. Cobb-Douglas (Christensen, Jorgenson, & Lau, 1973). Moreover, the Translog function does not inflict constant elasticity substitution as Cobb-Douglas does (Kumbhakar & Wang, 2005; Wang & Wong, 2012). Therefore, Translog conveys more insights into the estimation. The stochastic production frontier for panel data with the exogenous variable in this study can be specified as follows:

$$y_{it} = \beta_0 + \sum_{n=1}^{N} \beta_n xn_{it} + \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N} \beta_{nm}\, xn_{it} xm_{it} + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + \sum_{m=1}^{N} \beta_{nt}\, xn_{it} t_{it} + \sum_{k=1}^{K} \beta_k Zk_{it} + v_{it} - u_{it} \quad (1)$$

Where y is the total output, xn and xm represent inputs consisting of capital (k), labour (l), energy (e) and raw materials (r). All output and inputs are expressed in the natural logarithm (ln) and deviation from their geometric means. The subscript i and t denote i-th firm and t-the year. Zk represents exogenous variables such as the dummies of technology intensity (High, Medium-High, Medium-Low, and Low Technology), FDI, absorptive Capacity, the interacting variable of technology intensity with FDI and absorptive Capacity, the interacting variable of FDI with absorptive Capacity, age of firm, dummy export, imported material intensity and firm size. v_{it} is the SF model's random variable assumed as $iid.N(0, \sigma_v^2)$, and u_{it} is a non-negative random variable assumed as the half-truncated normal $(N^+(\mu_i, \sigma_u^2))$ in distribution. u_{it} is also the inefficiency parameter that captures the inefficiency effects specified below.

$$u_{it} = \delta_0 + \sum_{k=1}^{K} \delta_k Zk_{it} + \omega_{it} \quad (2)$$

Where δ_k represents the coefficients of inefficiency effects that consist of all exogenous variables, and ω_{it} is an error term in the inefficiency equation.

The stochastic frontier approach is challenging to estimate as it requires precise specification forms and causes instability of numerical and statistical samples in the infinite samples (Sari, 2019). To maintain the stability of the numerical and statistical samples, an additional test, e.g. the generalised log-likelihood test (Kumbhakar et al., 2015), is needed to select the proper specification, rather than the Translog function, of the stochastic production function. This study refers to another alternative of the production function: Cobb-Douglas (CD). A null hypothesis (H_0) is the CD model that omits the coefficients of time, time-squared and interacting input with time ($\beta_{nm} = \beta_{nt} = \beta_{tt} = \beta_t = 0$). The log-likelihood test is decided by comparing the likelihood ratio statistic from each model. The log-likelihood statistic is determined from $\lambda = -2[l(H_0) - l(H_1)]$, where $l(H_0)$ is the log-likelihood statistic of the CD model and where $l(H_1)$ is the log-likelihood value of Translog. The null hypothesis is rejected if the λ statistic is less than the χ^2 table with degrees of freedom equal to the number of parameters involved in the restrictions.

The estimated coefficients in Eq. (1) cannot be directly interpreted (Sari et al., 2016), but these coefficients can be used to measure the output elasticity of each input. The calculation is specified as follows:

$$\varepsilon_{nit} = \frac{\partial y_{it}}{\partial x n_{it}} = \beta_n + \frac{1}{2}\Sigma_{n=1}^{4}\Sigma_{m=1}^{4}\beta_{nm} x m_{it} + \beta_{nt} t \tag{3}$$

Where ε_{nit} is the elasticity for each input at each data point. From each output elasticity, the standard return to scale elasticity can be calculated as follows:

$$\varepsilon_{Tit} = \Sigma_{n=1}^{N}\varepsilon_{nit} \tag{4}$$

Where ε_{Tit} is the total elasticity of inputs for each firm and period.

Some studies in the literature emphasised that high technology may generate not only technological progress but also develop managerial expertise and scale-production knowledge, which contributes to enhancing both technical efficiency and scale efficiency (Kokko & Kravtsova, 2008; Sari et al., 2016; Smeets, 2008). In this sense, different technology intensities may affect scale efficiency change. Following the example of the study of Kumar and Russell (2002) and Sari et al. (2016), this study depends on the decomposition of TFP growth: Technical Efficiency Change (TEC), Technical Change (TC) and Scale Efficiency Change (SEC).

The first component of TFP growth is technical efficiency change (TEC) obtained from the growth of technical efficiency (TE). Obtained from the stochastic production frontier in Eq. (1), technical efficiency measures the ratio of the realised output to the maximum potential output. The estimation of TE is illustrated in Eq. (5a-5d):

$$TE_{it} = \frac{y_{it}}{\hat{y}_{it}} \tag{5a}$$

$$= \frac{f(x_{it}, z_{it}; \beta).\exp\,(v_{it} - u_{it})}{f(x_{it}, z_{it}; \beta).\exp(v_{it})} \tag{5b}$$

$$= \exp\,(-u_{it}) \tag{5c}$$

$$= \exp\,(-\delta_k Z k_{it} - \omega_{it}) \tag{5d}$$

Where y_{it} is the realised output and $\hat{y}_{it}$ is the maximum potential output. As TE is the ratio of y_{it} and $\hat{y}_{it}$, it ranges between 0 and 1. When TEs are closer to 1, the realised outputs are closer to their optimal output value. Then, TEC can be defined as follows:

$$TEC_{it,t-1} = \ln\left(\frac{TE_{it}}{TE_{it-1}}\right) \times 100\% \tag{6}$$

Where $\ln\left(\frac{TE_{it}}{TE_{it-1}}\right)$ is the natural logarithm of the technical efficiency of firm i at the period t over the technical efficiency of the period $t-1$.

The second component of TFP growth is technical change (TC), which captures the condition of the production frontier's shifting. This shifting reflects the technological progress embodied in the capital and labour input to depict the effect of technology in improving factor productivity over time (Sengupta, 1995). TC can be functionally derived from the partial derivative with respect to time, as follows:

$$\frac{\partial y_{it}}{\partial t} = \beta_t + \beta_{tt}t + \beta_{nt}xn_{it} \tag{7}$$

Then, TC can be formed by:

$$TC_{it,t-1} = 0.5\left[\left(\frac{\partial y_{i,t-1}}{\partial t}\right) + \left(\frac{\partial y_{i,t}}{\partial t}\right)\right] \times 100\% \tag{8}$$

The third component of TFP growth is scale efficiency change (SEC), which is associated with a firm's production scale. SEC considers the elasticity of output from each input in Eq. (3) and total elasticity in Eq. (4) to construct a scale factor that is functioned as follows:

$$SF_{it} = \frac{\varepsilon_{Tit}-1}{\varepsilon_{Tit}} \tag{9}$$

at each data point. SEC between periods t and $t-1$ is calculated from the summation of the average of the scale factor between two periods multiplied by the change in the respective input usage. It can be formulated as follows:

$$SEC_{it,t-1} = \frac{1}{2}\sum_{n=1}^{N}[(SF_{it}\varepsilon n_{it} + SF_{it-1}\varepsilon n_{it-1})(xn_{it} - xn_{it-1})] \times 100\% \tag{10}$$

Therefore, TFP growth can be calculated as follows:

$$TFPg_{it,t-1} = TEC_{it,t-1} + TC_{it,t-1} + SEC_{it,t-1} \tag{11}$$

Results and Discussion

Table 3 documents the generalised log-likelihood test decision to choose this study's most suitable production frontier. By referring to α =1% in χ^2 table, the result shows that λ>χ^2 table, which therefore determines the Translog specification as a suitable model to be furtherly analysed.

Table 3. Hypothesis testing of various production functions

Model	CD (df=16) $H0: \beta_{nt} = 0$
Translog (H1)	38499.89
Critical Value of χ^2 at $\alpha = 1\%$	5.81
Decision	Translog

Table 4 and Table 5 report the estimated coefficients on the production function and inefficiency effects of the exogenous variables from 3 different models[1]. Model 1 refers to the Translog production function using foreign ownership (FOR) 20%, Model 2 refers to the Translog production function using FOR 5%, and Model 3 refers to the Cobb Douglas production function using FOR 20%. The focus is firstly on identifying the main exogenous variables. The Coefficients of technology intensities, namely Medium-High Technology, Medium-Low Technology, and Low Technology, show the negative significance for all models in the production function. This finding implies that the firms' production categorized as high technology sector are averagely higher than that firms categorized as Medium-High Technology, Medium-Low Technology, and Low Technology. However, this result contrasts the inefficiency effects functions in Table 5, where the coefficients of Medium-High Technology, Medium-Low Technology, and Low Technology reveal significant and negative magnitude. These results conclude that firms categorized as High Technology sector are less efficient than that Medium-High Technology, Medium-Low Technology, and Low Technology firms. The coefficients of FDI from Model 1 and Model 2 are

[1] The results for input coefficients are reported in the Appendix to save space.

identified as positively significant in promoting productivity. Accordingly, the magnitude of FDI in Model 1 is larger than that in Model 2. This finding suggests that foreign firms have larger output production than local firms. However, there is no significant effect of FDI. It affects inefficiency partially.

Table 4. The Estimation of Stochastic Production Frontier on The Production Function

	Dependent Variable= Firms' Outputs					
	Model 1		Model 2		Model 3	
	Coeff	Standard Error	Coeff	Standard Error	Coeff	Standard Error
Medium-High Technology (MHT)	-0.882***	0.239	-1.475***	0.229	-1.981***	0.285
Medium-Low Technology (MLT)	-1.015***	0.223	-1.408***	0.220	-1.295***	0.258
Low Technology (LT)	-0.832***	0.222	-1.248***	0.217	-1.888***	0.254
Foreign Direct Investment (FDI)	0.838***	0.127	0.720***	0.122	0.200	0.149
FDI × MHT	0.111**	0.050	0.088*	0.050	-0.008	0.057
FDI × MLT	0.037	0.049	0.061	0.046	-0.089	0.056
FDI × LT	-0.045	0.048	-0.014	0.043	-0.075	0.053
Absorptive Capacity (Absp)	0.076***	0.014	0.051***	0.013	0.051***	0.016
FDI × Absp	-0.038***	0.007	-0.033***	0.007	0.007	0.008
Absp × MHT	0.049***	0.015	0.084***	0.014	0.113***	0.017
Absp × MLT	0.044***	0.014	0.067***	0.014	0.063***	0.016
Absp × LT	0.034***	0.014	0.058***	0.013	0.095***	0.015
Age	-0.001***	0.000	-0.001***	0.000	-0.001***	0.000
Export	0.012**	0.006	0.007	0.006	-0.005	0.007
Import	0.125***	0.010	0.138***	0.010	0.064***	0.012
Firm Size	15.668***	0.518	17.635***	0.544	10.747***	0.434

Note: *** is significance at 1%, ** is significance at 5%, * is significance at 10%.

Table 5. The Estimation of Stochastic Production Frontier on The Inefficiency Function

	Dependent Variable= Inefficiency					
	Model 1		Model 2		Model 3	
	Coeff	Standard Error	Coeff	Standar d Error	Coeff	Standard Error
Medium-High Technology (MHT)	-19.632***	0.706	-20.926***	0.721	-21.431***	0.795
Medium-Low Technology (MLT)	-23.783***	0.573	-22.780***	0.586	-25.226***	0.576
Low Technology (LT)	-22.692***	0.529	-22.699***	0.518	-24.708***	0.548
Foreign Direct Investment (FDI)	-0.360	0.652	1.042	0.640	-5.480***	0.735
FDI × MHT	0.818***	0.174	0.891***	0.192	1.727***	0.195
FDI × MLT	3.356***	0.171	3.518***	0.178	2.854***	0.212
FDI × LT	2.300***	0.177	2.365***	0.190	2.294***	0.191
Absorptive Capacity (Absp)	-1.021***	0.032	-0.968***	0.032	-1.142***	0.034
FDI × Absp	0.252***	0.037	0.165***	0.036	0.499***	0.040
Absp × MHT	1.000***	0.043	1.062***	0.043	1.045***	0.049
Absp × MLT	1.040***	0.035	0.974***	0.035	1.140***	0.034
Absp × LT	0.969***	0.032	0.963***	0.032	1.109***	0.033
Age	0.011***	0.001	0.010***	0.001	0.003***	0.001
Export	0.220***	0.045	0.097**	0.049	0.025	0.035
Import	3.415***	0.047	3.346***	0.047	3.325***	0.051
Firm Size	39.492***	0.575	41.825***	0.599	30.161***	0.537

Note: ***, **, * denote significance at 1%, 5%, and 10% level respectively. Standard errors are in parenthesis.

A similar finding is also shown by the coefficient of Absorptive Capacity, which is positive for the production function in all models. This result implies that a higher allocation of labour costs, such as wages, overtime, accident allowance and training, fosters a firm's productivity. This effect is strengthened by the result of the inefficiency effects function, where absorptive Capacity has a negative impact on technical inefficiency. This suggests that a higher labour cost will boost a firm’s technical efficiency. Mastromarco and Ghosh (2009) and Henry, Kneller, and Milner (2009) argued that the existing number of human capital is an essential factor for higher technology absorption as the quality of workers will be assessed by this indicator. Since absorptive Capacity also includes the cost of training, spending on labour training might also positively contribute to promoting firms' efficiency and productivity.

The interacting variables between technology intensity & FDI, technology intensity & absorptive Capacity, and absorptive Capacity & FDI are robust impacts on the production function. According to Model 1, the interacting variable between FDI and MHT is found significant, but it is discovered insignificant on the MLT and LT. This finding can be interpreted as a higher FDI does not affect Medium-Low and Low Technology sectors in promoting firms' production. The result of Model 2 strengthens this finding. The inefficiency effect function demonstrates that most of the coefficients of interacting terms between technology intensity and FDI are positive. It means that the effect of FDI in promoting efficiency is primarily effective for the High Technology sector as a benchmark. This result supports the finding of Walheer and He (2020) using the observation of the high technology firms. They argued that firm ownership is essential in explaining Chinese manufacturing firms' technical efficiency and technology gap. Foreign-owned firms not only shape the sectoral technology metafrontier but also set the standard for technical efficiency.

The effects of the interaction variable between technology intensities and absorptive capacity positively affect firms' production in all models. This can be interpreted as the allocation of labour cost is effective in encouraging production for only Medium-High, Medium-Low, and Low Technology sectors. Conversely, these effects are not pertinent in terms of technical efficiency. The coefficients of technology intensities and absorptive capacity in the inefficiency equation are significantly positive. This concludes that the more allocation of labour costs is more effective for High Technology in improving technical efficiency. This finding is not surprising as an increase in labor cost per worker often represents the increasing ability of workers to absorb external knowledge and technologies (Orlic, Hashi, & Hisarciklilar, 2018). In this regard, a higher-skilled labor allocation in the High Technology group leads to greater efficiency as skilled professionals are required for research and development (R&D). Meanwhile, lower technology groups are found less rigorous, signalling that those groups are less engaged in R&D and advanced production activities than higher-tech firms.

The last variable to be analysed is the interaction variable between absorptive Capacity and FDI. Surprisingly, the result in the production function shows a negative coefficient for Model 1 and Model 2, which suggests that a higher absorptive capacity for a foreign firm will decrease productivity. However, this study observed a different effect of the interaction between FDI and absorptive Capacity on technical inefficiency. Similarly, the inefficiency function reveals that FDI and higher absorptive Capacity will decrease technical efficiency by 25.2%, 16.5%, and 49.9%, respectively, for each model. This finding indicates that foreign firms are relatively not benefited by a higher allocation of labour costs to boost efficiency. The plausible reason for this finding is referred to the study by Javorcik et al. (2012), revealing that foreign firms have offered higher salaries to attract skilled workers. In this regard, foreign firms do not require to allocate more costs for training that will reduce their efficiency performance.

The other exogenous variables in this study show relatively the same effect among the three models. First, the coefficient of firm age in the production function is negative, which means an older firm tends to experience decreasing productivity. This impact is also evidently found in the inefficiency effects equation by which the firm's age positively impacts technical inefficiency. In other words, an older firm tends to be less efficient than a younger one. This finding is in line with the hypothesis of the liability of obsolescence. According to this hypothesis, the effect of firm age decreases firms' efficiency due to their failure to adapt to the environmental evolution in the industry, like failing to adopt a newer technology which might lead to inefficient production (Coad, 2018; Le Mens, Hannan, & Pólos, 2015).

Surprisingly, an exporting firm tends to reduce technical efficiency less than a non-exporting firm does. This finding aligns with Mok et al. (2010), arguing that exporters will benefit from export activities if only they take up a dominant portion of their total sales. Otherwise, exporters will handle large costs of transactions and demanding technical barriers to the trade, decreasing their benefits. The coefficient of Imp shows a significant positive effect on the production function of all models. Still, the positive impact of imported material intensity on technical efficiency can not be captured. This result supports the finding of Yasin (2021), revealing that more intensity of imported materials leads to less efficient performance. The finding related to firm size is relatively not surprising as it shows a vigorous positive impact on productivity. However, a larger firm is found less efficient than a smaller one; thus, this effect does not promote firms' technical efficiency.

The coefficients of inputs are reported in Appendix Table 8. These coefficients are not directly interpretable in the economy, but they can be used to estimate the output elasticity with respect to each input. Table 6 conveys output elasticity that captures how much output will increase if the level of input increases. By comparing the elasticity of output with respect to capital (EK), labour (EL), energy (EE) and raw material (EM), it is found that output is mainly more driven by material than by capital, energy, or labour.

Table 6. Elasticity of Output

		Domestic Firm	Foreign Firm
High Technology	EK	0.055	0.044
	EL	0.278	0.241
	EE	0.082	0.065
	ER	0.637	0.667
	Etotal	1.051	1.017
Medium-High Technology	EK	0.048	0.036
	EL	0.260	0.212
	EE	0.082	0.068
	ER	0.661	0.691
	Etotal	1.050	1.006
Medium-Low Technology	EK	0.065	0.043
	EL	0.311	0.235
	EE	0.104	0.077
	ER	0.602	0.667
	Etotal	1.082	1.022
Low Technology	EK	0.053	0.048
	EL	0.279	0.253
	EE	0.076	0.076
	ER	0.660	0.648
	Etotal	1.067	1.023

Note: EK, EL, EE, and ER denote output elasticity with respect to capital, labour, energy and raw material. Etotal=EK+EL+EE+ER. The measurements are obtained from the unbalanced panel observation.

The following analysis concerns the estimation of TFP growth and its decompositions: technical efficiency change (TEC), scale efficiency change (SEC) and technical change (TC). Table 7 reports this estimation for foreign and domestic firms and the categories of R&D intensity.

The result reported in Table 7 reveals that, on averagely, the manufacturing industry in Indonesia from 2007-2015 experienced a positive TFP growth of 3.59%. This magnitude stems from the component of TC at 2.8%, TEC by 0.99% and SEC by 0.68%. Looking at the capital ownership for the whole period, the result shows that the TFP growth of foreign firms categorized as High Technology is the largest amongst all categories at 7.07%. However, by dividing TFP growth into the foreign and domestic firms, the domestic firms have a higher TFP than foreign firms by 3.64%.

Table 7. The Average of Total Factor Productivity Growth and Its Components

Firm	Technology Intensity	TFPg	TC	TEC	SEC
Foreign Firms	HT	7.077	2.985	3.897	0.194
	MHT	3.429	2.296	1.237	-0.105
	MLT	2.056	2.636	-0.648	0.065
	LT	2.816	3.554	-0.881	0.150
	All Foreign Firms	3.073	3.048	-0.051	0.079
Domestic Firms	HT	3.750	3.100	-0.066	0.715
	MHT	3.552	2.304	0.716	0.532
	MLT	3.727	3.241	-0.325	0.812
	LT	3.625	2.718	0.185	0.729
	All Domestic Firm	3.643	2.802	0.112	0.733
All Firms		3.596	2.822	0.991	0.680

Note: TEC, TC, SEC, and TFPg are the arithmetic average of the annual rate in percentage. HT denotes High Technology, MHT denotes Medium High Technology, MLT denotes Medium Low Technology, and LT denotes Low Technology.

Table 8. The Estimation of Stochastic Production Frontier

	Model 1		Model 2		Model 3	
	Coeff	SE	Coeff	SE	Coeff	SE
k	0.054***	0.002	0.054***	0.002	0.056***	0.001
l	0.174***	0.005	0.176***	0.005	0.271***	0.002
e	0.070***	0.002	0.069***	0.002	0.088***	0.001
r	0.701***	0.002	0.701***	0.002	0.643***	0.001
k^2	0.006***	0.000	0.006***	0.000	-	-
l^2	0.041***	0.002	0.040***	0.002	-	-
e^2	0.018***	0.000	0.018***	0.000	-	-
r^2	0.072***	0.000	0.073***	0.000	-	-
$k \times l$	0.028***	0.001	0.030***	0.001	-	-
$k \times e$	0.006***	0.000	0.006***	0.000	-	-
$k \times r$	-0.039***	0.001	-0.040***	0.001	-	-
$l \times e$	0.013***	0.001	0.014***	0.001	-	-
$l \times r$	-0.116***	0.001	-0.120***	0.001	-	-
$e \times r$	-0.045***	0.001	-0.046***	0.001	-	-
t	0.062***	0.003	0.062***	0.003	-	-
$t \times k$	-0.003***	0.000	-0.003***	0.000	-	-
$t \times l$	-0.001***	0.000	-0.001***	0.000	-	-
$t \times e$	0.018***	0.001	0.018***	0.001	-	-
$t \times r$	0.002***	0.000	0.002***	0.000	-	-
t^2	-0.008***	0.000	-0.008***	0.000	-	-
Sigma-Square (σ^2)	4.960***	0.019	5.030***	0.021	3.705***	0.008
Gamma (γ)	0.971***	0.000	0.971***	0.000	0.941***	0.000
Log-Likelihood Ratio	-84155.51		-84091.98		-103405.46	

Note: Models 1-3 refer to Translog model with foreign ownership (FOR) 5% (Model 1), 10% (Model 2), and 20% (Model 3). Models 4-6 refer to Hick-Neutral, Cobb-Douglas, and No Technological Progress with FOR 5%. ***, **, * denote significance at 1%, 5%, and 10% level respectively. Standard errors are in the parenthesis.

Both foreign firms categorized as Medium-Low and Low Technology averagely experience negative TEC. In terms of this indicator, foreign firms show an averagely lower magnitude than domestic firms. The result shows that foreign firms in the High Technology category have the largest average of TEC among others at 3.89%. In comparison, foreign firms in the Low Technology category show the lowest growth by -0.88%. This finding strengthens Table 5, revealing that foreign firms with high technology perform better efficiently. This finding is consistent with Fu and Gong (2011), who employed a Chinese-firm-level dataset despite using different observations. Although FDI does not contribute to higher technical efficiency for foreign High Technology sectors (see the inefficiency equation in Table 5), foreign firms in High Technology sectors tend to grow faster than others during the periods of interest.

Foreign and domestic firms are relatively different in scale efficiency change (SEC). Foreign firms experience a positive SEC of 0.07%, whereas the negative SEC is experienced by the Medium-High Technology sector at -0.10%. Meanwhile, domestic firms averagely show a positive SEC of 0.73%, whereas Medium-Low Technology sectors contribute 0.81% on this magnitude.

This study addresses the finding regarding the technical change, which can reflect how the technological progress of firms developed. The results related to technical change in foreign and domestic firms show that the technological progress experienced by foreign firms is relatively larger than that experienced by domestic ones. This is not surprising as foreign firms may have more advanced technology to produce outputs, and thus, their shifting frontier process is faster.

However, an intriguing result reveals that the Low Technology sectors enjoy foreign ownership benefits mainly. This finding is surprising since, according to some studies, the technology diffusion caused by FDI is associated with high-technology intensity (Keller, 2010). There are three possible reasons for this result. The first plausible reason is the low technical capabilities of human resources in Indonesia. The investment of multinational enterprises (MNEs) can take place anywhere. Still, the investment in the High Technology sectors surely needs more stringent standards that might lead to a slower shifting of high-technology firms. In this sense, theories of human capital investment as a complementary factor to foreign investment are, indeed, relevant (see: Carbonell & Werner, 2018; Lucas, 1988; Rebelo, 1991; Romer, 1986).

The second reason is that the Low Technology sectors have received many foreign investments. This means that more foreign support is given through, for instance, High Technology transfer to Low Technology sectors. This is in accordance with the studies of Kokko (1994) and Liu, Siler, Wang, and Wei (2000), concluding that regardless of the classification of the industry (e.g. low-technology industry or high-technology industry), firms' technical capabilities are more likely to determine the effectiveness of the technology transfer obtained from FDI activities.

The third reason is related to the type of foreign firms. Foreign firms are more likely to affiliate with parent companies headquartered in foreign countries. In this case, a parent company may give its subsidiaries the access merely to apply and adapt advanced technology (Fu & Gong, 2011). Meanwhile, the parent company continues its core technology development in the headquarters. In this sense, a foreign High Technology sector cannot achieve a higher technical change.

Conclusion

This study has demonstrated the effects of FDI (represented by the incoming foreign firm), technology intensity (i.e. High, Medium-High, Medium-Low, and Low Technology sectors) and absorptive Capacity on the technical efficiency and productivity of the manufacturing firms in Indonesia. The stochastic production frontier estimation reveals that FDI, technology intensity and absorptive capacity alone promote firms' production, but only absorptive capacity promotes technical efficiency. The models adopted in this study concluded that the interacting term between technology intensity and FDI has a negative impact on firms' technical inefficiency. It means that sectors categorized as High Technology incorporated with foreign ownership tend to have higher technical efficiency. The result shows that, on averagely, the manufacturing industry in Indonesia from 2007 to 2015 experienced positive TFP growth. The result also shows that the technological progress experienced by foreign firms is relatively larger than that experienced by domestic ones. In this sense, international technology diffusion through FDI might successfully occur because foreign firms can make a faster frontier shifting process.

Finally, this study has many important implications. Obtaining FDI benefits, such as transfer of knowledge or technology diffusion, is not a simple matter. It requires many complementary factors, such as technical capabilities or absorptive Capacity, even if a firm is categorised as a High Technology sector. Firms with lower technical capability can catch up and receive similar benefits from FDI activities. In this sense, the host country's government should focus on the industries that have had high technical capabilities to accelerate FDI gains for the firms. However, simultaneously, human capital improvement also needs to be intensified, for instance, through training or human development.

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