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Article

# Determinants of $CO_2$ Emission Intensity: Manufacturing Firm-Level Evidence in Indonesia

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***Abstract***

The Indonesian economy has improved with the manufacturing sector as its primary growth driver. However, along with this development, the country inevitably faces environmental issues such as increased carbon emissions. Based on the firm-level dataset from the Indonesian large and medium manufacturing sector, this paper investigates the main factors related to the $CO_2$ emission intensity of manufacturing firms. The emission carbon data is obtained by calculating the fuel consumption of plants converted into carbon dioxide emissions using emission factors. The result shows that the trend of carbon emission had increased, but the carbon emission intensity had improved. Performing panel data framework, this study uses OLS, 2SLS, and fixed effect model in analyzing the determinants of $CO_2$ intensity. The result of the FE regression suggests that larger firms are emission efficient compared to small-sized firms. Similarly, capital- and labor-intensive firms are less carbon-intensive. Furthermore, firms that spend more on maintenance have emitted more, perhaps due to the adoption of high maintenance equipment by emission-intensive firms requiring more expenses.

**Keywords:** fossil fuels; CO2 intensity; Indonesia; manufacturing; panel data; fixed effect.

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## I. Introduction

Climate change has become an issue of concern for humanity for many years. According to the World Health Organization (2018), climate change would have caused 250.000 deaths per year between 2030 and 2050. Also, it would cost health around US$ 2-4 billion per year by 2030. On the environmental side, the increase of heat in the atmosphere will result in sea-level rise, flooding, forest fires, drought, and even species extinction (Intergovernmental Panel on Climate Change-IPCC, 2018). Indonesia also faces the climate change threat, which has impacted various aspects of its economy and development. As an archipelagic country with thousands of small islands and low-lying areas, Indonesia is the most vulnerable country affected by global warming. The loss of small islands because of the increase in sea level, the tidal flooding in big cities, and the rise of sea surface temperature in Java and Eastern Indonesia's seas are just a few examples of the consequences of global warming. Indeed, these conditions have cost highly.

Carbon dioxide emissions primarily cause global warming. The IPCC reports that human activities have caused global warming of approximately 1.0$^{o}$C above pre-industrial levels, increasing at 0.2$^{o}$C per decade. These activities, such as manufacturing operations, heating, transportation operation, and electricity generation, mostly use fossil fuels as their energy sources. Yet, fossil fuels combustion that releases carbon dioxide emissions is the largest share of climate change contributors. The International Energy Agency (IEA) in 2017 claimed that the use of energy was the largest source of emissions with an estimated share of 68%, followed by large-scale biomass burning, agriculture, and industrial processes at 14%, 12%, and 7%, respectively. Although the global demand for fossil fuels (coals, oils, and natural gas) is undeniably still high, some European countries have already shifted to renewable energy. As the leading country in renewable energy consumption, Germany has moved to use renewable energy at 12.74% of its total energy consumption. The United Kingdom, Sweden, Spain, and Italy have replaced fossil fuels with renewable energy at 11.95%, 10.96%, 10.17%, and 8.8%, respectively (Gordon, 2019). However, the expectation of the global demand for fossil fuels in 2021 increases by 6.2% (oil), 4.5% (coal), and 3.2% (natural gas), with the growth concentrated in emerging markets (IEA, 2021).

Many studies show that the high fossil energy consumption coincides with the rapid economic growth in developing countries, which increases carbon emission levels (Vo *et al.*, 2019; Hwang and Yoo, 2012; Sahu and Narayanan, 2010). However, some literature suggests that economic growth causes deterioration in the initial stage, but after adopting high technologies, it might lead to environmental improvement. The International Energy Agency (IEA) recently stated that emerging markets account for over two-thirds of global carbon emissions. Its levels in 2021 are predicted to increase as the world economy gradually recovers from the Covid-19 pandemic. As the largest economy in Southeast Asia, Indonesia also faces the issue of the accumulation of carbon dioxide in the environment.

The Indonesian economy has grown rapidly after economic reform in trade and investment in the mid-1980s. The reform boosted the manufacturing sector as the primary growth driver that pushed GDP to grow at an average of 8% per year (Kuncoro, 2018). Now, Indonesia is ranked 16$^{th}$ as the biggest economy, with a GDP of US$ 1.12 trillion as of 2019 (World Bank, 2021). In addition, the manufacturing industry contributes 19.7% of GDP in the same year. However, along with the rapid economic development, Indonesia inevitably faces excessive energy demand and environmental issues such as pollution. IEA (2017) states that Indonesia is one of Asia's most significant emissions contributors, after China and India. Emissions grew 230% faster than the global level at 56.5% from 1990 to 2015 (Hastuti *et al.*, 2020).

The increasing carbon emissions concern pushes the author to investigate the driving forces affecting the $CO_2$ emission level in Indonesian manufacturing, concentrating on firm characteristics. Thus, this paper tries to examine whether foreign ownership affects the emissions intensity; whether larger enterprises benefit from its economies of scale and thus release fewer emissions per unit of output than smaller enterprises; whether firms with higher export intensity are less emission-intensive; whether levels of maintenance expenditure affect pollution intensity; and whether capital intensive and labor-intensive firms emit less per unit of output.

A previous study in Indonesia examining the pollution-haven and halo hypothesis by Brucal *et al.* (2017) shows that firms with foreign shareholders increase total energy consumption and $CO_2$ emissions due to the increasing production scale or expansion. Thus, it decreases the firms' energy intensity and emissions intensity, implying that they improve their efficiency in using energy inputs to produce a unit of output with lower energy and carbon content. Meanwhile, Ramstetter and Narjoko (2014) argue that the correlation between plant ownership and total energy intensity was generally weak. Soytas *et al.* (2007) examine the association between carbon dioxide emissions, energy consumption, and income level in the US. They found that energy use is the prominent contributor to emissions, but the association between income and carbon emissions is not significant. Furthermore, other existing literature using a standard OLS approach suggests that exports activity has a significant negative relation to $CO_2$ emission intensity, meaning exporters firms appear to have better environmental performance than non-exporters (Cole *et al.*, 2013).

Since the study on a panel approach at the firm level in Indonesia is limited, it is important to research the impact of firm characteristics on $CO_2$ emissions using plant-level data. The unavailability of carbon dioxide emission data at the plant level might be one of the reasons why there is no recent study in this literature at the firm level, particularly in Indonesia. To the best of our knowledge, this paper is the first study in Indonesia that uses a data survey of manufacturing firms to calculate carbon emissions and further analyze determinants of carbon dioxide emissions intensity. Besides, the micro-level data might generate more reliable findings than the macro-level data since the macro data come from the supply side of the energy. Hence, it may not represent the actual consumption of the firm. Thus, this research presents the results of estimating the $CO_2$ emission from firms by comparing OLS, 2SLS, and fixed effects (FE) models from 2011- to 2014 by following the bottom-up sectoral approach by IPCC Guidelines (2006) associating it with the firm characteristics.

The remainder of the paper is organized as follows. Section II reviews the relevant literature related to carbon emission intensity and empirical study. Section III introduces the data collection and research methodology: estimation of $CO_2$ intensity, OLS estimation approach, 2SLS estimation, and fixed-effects. Section IV reports the empirical results and their discussions. Lastly, section V provides some conclusions.

## II. Literature Review

With the increase of concern in environmental degradation, a growing empirical literature has examined the cause of emissions levels. Sahu and Mehta (2018) investigate the determinants of carbon dioxide emission intensities of manufacturing firms in India. Firm-level data for carbon dioxide emissions is not available; thus, they calculated the emission coefficient based on the IPCC reference approach. They used fixed and random effects models and found that firms that allocate more expenses in research and development activities are more energy and emission efficient. A similar result by Cole et al. (2005) shows that emissions intensity is significantly negative to the firm's capital and research and development expenses. In addition, Sahu and Mehta (2018) found that repair intensity is significantly positive to emission intensity. Intuitively, the higher firms spend money on machine maintenance, the better the quality of the machine; thus, the production processes have become more efficient and will produce less waste. Moreover, without proper care and repair, it may cause the downgrade of the machine, which causes a higher consumption of energy per unit product.

Firms do not have allocation invested in reducing emissions to pursue profit maximization. According to the pollution haven hypothesis, pollution-intensive industries that emit more pollution are likely to move from strictly regulated nations to less-regulated nations. Thus, the foreign firms might emit more pollution compared to local firms. On the other hand, the pollution halo hypothesis suggests that foreign firms positively affect the environment due to their cleaner technologies than their local counterparts. Several studies, however, provide inconclusive results. In 2014, Jiang *et al.* examined the main factors of emission intensity level for three types of prominent pollutants in China: sulfur dioxide, wastewater, and soot. They used a firm-level dataset from the manufacturing sector covering over 100 cities in China. China's Ministry of Environment Protection provides the manufacturing pollution dataset with 2862 (in 2006) and 4261 (in 2007) firms. This database is only a sample of all firms in China, with the manufacturing plants giving a self-report of their emission data. They found that multinational enterprises have lower pollutant emission intensity than state-owned enterprises (SOEs). Eskeland and Harrison (2003) also found a similar result: multinational enterprises are more energy-efficient than state-owned firms and apply superior technology. Also, foreign firms are more likely to avoid negative impressions or perceptions in one country, such as the image of polluting industries. On the other hand, a study in Ghana by Cole *et al.* (2008) suggested that foreign ownership has no influence on increasing fuel consumption and total energy use but only increases the electricity use.

Firm size is one of the components of firm heterogeneity in affecting the intensity of pollution emissions. Larger firms with bigger scale economies might consume more efficient fuel and generate low carbon emissions. Besides, compared to small firms, they have more flexibility to adopt new efficient technology without worrying about financial constraints. Cole *et al.* (2005) found that Japanese firms' pollution negatively affects firm size and productivity. A similar result by Jiang *et al.* (2014) shows that larger firms with more educated workers tend to emit less.

Furthermore, Cole *et al.* (2005) suggested that firms reliant on machinery tend to emit more than firms that rely on labor. This is because capital-intensive firms may engage in certain complex industrial sectors which generate more emissions per unit of energy. Moreover, capital intensity seems to have a positive correlation to energy intensity (Papadogonas *et al.*, 2007) due to a positive association between capital intensity and pollution intensity. However, Sahu and Mehta (2018) found that capital intensity in Indian manufacturing firms has no association with emission intensity. However, the bigger firms, the more flexible they are in adopting new technology and doing research and development. Besides, big firms are likely to keep their positive image by being environmentally-friendly enterprises.

The argument for the relationship between labor intensity and emission intensity is uncertain. On the one hand, firms with high-skilled labor (to operate high technology) tend to be more efficient and less energy-intensive than lower-skill industries. On the other hand, low-skilled industries could be more energy efficient because high-skilled sectors typically emit more pollution due to their complex industrial processes. Cole *et al.* (2005) found that an increase in labor intensity will increase pollution intensity within an industry. In contrast, Xie *et al.* (2018) suggested that labor intensity has not led to a significant boost in reducing carbon dioxide emissions in China's western region.

Richter and Schiersch (2017) examine carbon dioxide emission intensity by focusing on firms' exporting activity by using a unique panel dataset for manufacturing firms in Germany. They calculate $CO_2$ emission intensities and capital stocks for each firm. The data consist of information on the usage of fifteen different fuels types at the firm level in unit kWh. They can calculate $CO_2$ emissions accurately by transforming fuel inputs to $CO_2$ emissions using the emissions factors for each fuel. The main finding suggests a negative relation between export intensity and emission intensity. Exporters can sell more products for the same amount of emitted carbon dioxide than non-exporting firms. A study by Holladay (2010) found that exporting firms emit less pollution than their non-exporting enterprises in the same industry. This is because exporting leads to an increasing number of production and hence lower emission intensity. A similar result by Cole *et al.* (2013) in examining Japanese manufacturing firms shows that export activity negatively correlated to $CO_2$ emission intensity. The more firms depend on exports, the lower their pollution intensity. In their study, export activity is measured as the share of products sold outside the country.

## III. Data and Methodology

### 3.1. Data

This research uses secondary data from Indonesia's Large and Medium-Scale Manufacturing Firms Annual Survey (LMM) conducted by Statistics Indonesia. The 2011-2014 dataset provides establishment-level data for all manufacturing firms (foreign and domestic firms) with 20 or more workers annually. The dataset is classified based on five digits Indonesian Standard of Industrial Classification Code (ISIC). The advantage of using the LMMs survey dataset is its comprehensiveness and detailed data up to sub sectors which gives an advantage in manufacturing subsector analysis. Data based on questionnaires of LMMs have detailed information on energy consumption of fuels and electricity consumption in terms of money values and physical quantities, and other firm characteristics variables, such as ownership details, industry classification, workers wage, total workers, and value-added. The dataset basically pools four cross-sectional, then I construct panel data by merging the dataset. However, the number of observations for each period might vary because it depends on the number of new firms and firms that do not continue their business. Therefore, this results in an unbalanced panel dataset.

**Table 1.** Descriptive Statistics of Variables

| Firm characteristics | Mean | Std Dev | Min | Max |
|---|---|---|---|---|
| Carbon intensity | 0.0123 | 2.3780 | 0 | 547.327 |
| Capital intensity | 2.5810 | 57.6541 | 0 | 5750 |
| Export intensity | 12.623 | 118.0618 | 0 | 34469.110 |
| Labor intensity | 0.2827 | 0.8904 | 0 | 56.999 |
| Maintenance intensity | 0.0610 | 0.5041 | 0 | 97.869 |
| Firm size | 5.61e+07 | 5.79e+08 | 1004 | 5.38e+10 |
| Number of observations | | 95,189 | | |

**Source:** Author calculation from the Large and Medium Manufacturing Survey dataset

The dependent variable is carbon intensity obtained by calculating using IPCC guidelines, whereas its determinants are capital intensity, export intensity, labor intensity, maintenance intensity, and firm size. Table 1 shows the descriptive statistics of each variable. With 95.189 firm-year observations, the mean carbon intensity is 0.0123 with a standard deviation of 2.3780. Capital intensity and export intensity have a mean of 2.5810 and 12.623, with a standard deviation of 57.6541 and 118.0618, respectively. The high standard deviation figures mean that the capital intensity and export intensity range spread out.

**Table 2.** Descriptive Statistics Disaggregated per Firm Ownership

| Firm characteristics | Domestic Firms | | | | Foreign Firms | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std Deviation | Min | Max | Mean | Std Deviation | Min | Max |
| Carbon intensity | 0.1734 | 2.5426 | 0 | 547.327 | 0.1497 | 1.1228 | 0 | 52.852 |
| Energy intensity | 11.211 | 314.145 | 0 | 40041.75 | 38.859 | 649.458 | 0 | 48507.96 |
| Capital intensity | 2.3809 | 53.9933 | 0 | 5092.698 | 4.4713 | 84.7460 | 0 | 5750 |
| Export intensity | 9.8340 | 123.2569 | 0 | 344469.1 | 33.1125 | 40.0740 | 0 | 195.521 |
| Labor intensity | 0.2971 | 0.8924 | 0 | 53.399 | 0.1463 | 0.8600 | 0 | 56.999 |
| Maintenance int | 0.5489 | 0.2450 | 0 | 40.288 | 0.1191 | 1.4436 | 0 | 97.869 |
| Firm size | 3.73e+07 | 4.46e+08 | 1004 | 4.90e+10 | 2.33e+08 | 1.26e+09 | 7415 | 5.38e+10 |
| Number of observations | | 86,077 | | | | 9112 | | |

**Source:** Data processed from the Large and Medium Manufacturing Survey dataset

Whereas Table 2 depicts a descriptive summary of the dummy variable, firm ownership status, classified into two groups: foreign firms and non-foreign firms. We can observe that there are more domestic firms (90.43%) than foreign firms (9.57%). On export activity, foreign firms are export intensive compared to local firms. Further, we find that local firms are labor-intensive, while multinational firms are more capital-intensive. Interestingly, foreign firms spend less on maintenance activity compared to local firms. This is probably because foreign enterprises are capital intensive and have already adopted higher-quality technology, leading to efficient energy-saving and less cost in maintenance. Finally, the variable firm size shows the value of firms' net sales, which can be seen that large or foreign firms (0.1497) have lower carbon intensity than domestic firms (0.1734). Table 3 presents the definition of the variables.

**Table 3.** Definition of Variables

| Variable | Definition |
|---|---|
| Carbon intensity | Natural log of $CO_2$ emission/total sales |
| Capital intensity | Natural log of total fixed asset/total sales |
| Export intensity | Natural log of total export/total sales |
| Labor intensity | Natural log of total wages/total sales |
| Maintenance intensity | Natural log of total expenses on maintenance/total sales |
| Firm size | Natural log of total net sales |

### 3.2. Methodology

#### 3.2.1. Estimation of $CO_2$ emission intensity

The calculation of carbon dioxide emissions based on fossil fuel combustion follows the 2006 IPCC Guideline methodologies. Firstly, I calculate total energy consumption at the firm level by adding all fossil fuels consumption with corresponding energy conversion values. Since the data available of fuel usage are in volume or mass units (kg, liter), then it needs to be converted into energy units (e.g., Joules). To convert the unit into energy units requires calorific values. The IPCC Guideline uses net calorific values (NCVs) in units of TJ/Gg. Default NCV values to convert to a unit of terajoules are presented in **Table 4.** The conversion formula is given by:

$$FC_{j,t}^{i}(TJ) = FC_{j,t}^{i}(physical\ unit)x\ NCV_i \tag{1}$$

**Table 4.** The Default Net Calorific Value and Carbon Emission Factors

| Energy sources | NCV (TJ/Gg) | Carbon emission factors (kg/TJ) |
|---|---|---|
| Gasoline | 44.3 | 69300 |
| Diesel | 43.0 | 74100 |
| Kerosene | 43.8 | 71900 |
| Coal | 26.44[1] | 96920[1] |
| Coal briquettes | 20.7 | 97500 |
| Gas | 48 | 56100 |
| LPG | 47.3 | 63100 |
| Lubricants | 40.2 | 73300 |

[1] The average value of NCV and carbon emission factor of anthracite, coking coal, other-bituminous coal, sub-bituminous coal, and lignite.

**Source**: IPCC Guideline (2006)

Since there is no data on $CO_2$ emission at the firm level, plant-level data on fuel consumption has been converted into carbon dioxide emission using emission factors (equation 2). After that, we estimate carbon emissions intensity by dividing the total $CO_2$ emissions for each plant by the total value added by each plant (equation 3).

$$CE_{j,t} = \sum_i FC^i_{j,t}\ x\ NCV_i\ x\ CF_i\ x\ COF_i x\ (\frac{44}{12}) \tag{2}$$

$$CEI_{j,t} = \frac{CE_{j,t}}{value\ added\ of\ the\ product\ during\ the\ year} \tag{3}$$

where $i$ denotes the various fuels/electricity, $t$ represents the time in years, $CE_{j,t}$ means total carbon emissions of firm $j$ in year $t$, $FC^i_{j,t}$ denotes the total energy consumption of fuel type $i$ by firm $j$ in year $t$, $NCV_i$ represents net calorific values of fuel type $i$. $CF_i$ is the carbon emission factor of fuel type $i$, $COF_i$ is the carbon oxidation factor with the default of equal 1 for all fuels, and $CEI_{j,t}$ is the carbon dioxide emission intensity of firm $j$ in year $t$.

**Figure 1** presents the trend of the value-added and energy consumption of Indonesian manufacturing from 2011 to 2014. The total energy consumption decreased from about 750,000 TJ (2011) to 430,000 TJ (2013) but slightly increased again to about 450,000 TJ (2014). The industry value-added shows an increasing trend from year to year, from 70 million US$ (2011) to 119 million USD (2014).

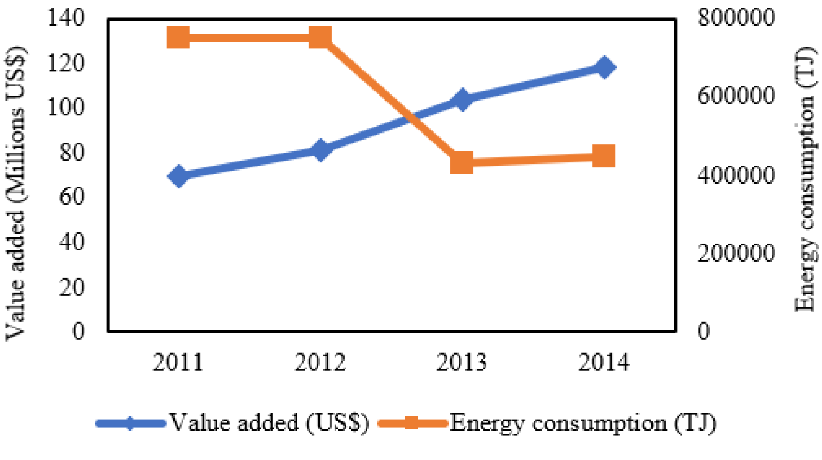


**Figure. 1** Energy Consumption and Value-Added of the Indonesian Manufacturing Industry

**Figure 2** illustrates the total energy and emissions intensity of manufacturing firms. Similar to energy intensity, $CO_2$ emission intensity is estimated by dividing the firm's added value. The trend of energy intensity is linear to the trend of $CO_2$ intensity during the study period. When the energy intensity has declined over time, the $CO_2$ intensity has decreased. However, although the carbon emissions intensity has declined from 2011 to 2014, carbon emissions have increased **(Figure 3)**. Thus, it is clear that the decline in emission intensity is due to the rise in value-added.

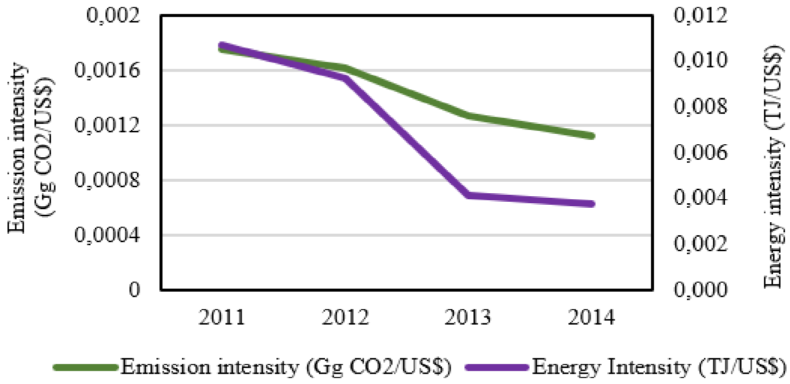


**Figure. 2** Energy Intensity and Emissions Intensity of the Indonesian Manufacturing Industry

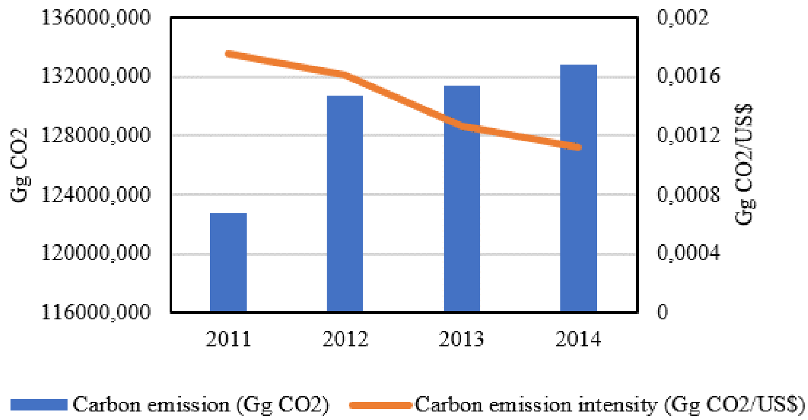


**Figure. 3** Carbon Emissions and Carbon Emissions Intensity of the Indonesian Manufacturing Industry

### 3.2.2. Ordinary Least Squares (OLS) regression

After the first step of the $CO_2$ intensity calculation, I apply four econometrics methods: OLS, 2SLS, fixed effects, and fixed effect-instrumental variables to answer the research questions of determinants of $CO_2$ emissions intensity. As the benchmark model, firstly, this study estimates the equation using OLS regression; however, the estimation might be biased due to endogeneity issues. The OLS regression model is as follows:

$$\ln(CEI)_{j,t} = \alpha + \beta_1 ln(fsize)_{j,t} + \beta_2 ln(export)_{j,t} + \beta_3 ln(cap)_{j,t} + \beta_4 ln(labor)_{j,t} + \beta_5 ln(maintenance)_{j,t} + \beta_6 (dummy\ ownership)_{j,t} + \delta_t + \varepsilon_{j,t} \quad (4)$$

$CEI_{j,t}$ denotes carbon emission intensity for firm $j$ in at time $t$, and $(fsize)_{j,t}$ is firm size for firm $j$ in at time $j$, $(export)_{j,t}$ is export intensity for firm $j$ in at time $t$, $(cap)_{j,t}$ is capital intensity for firm $j$ in at time $t$, $(labor)_{j,t}$ is labor intensity for firm $j$ in at time $t$,

$(maintenance)_{j,t}$ is maintenance for existing infrastructure intensity for firm $j$ in at time $t$, $(dummy\ ownership)_{j,t}$ is binary dummy with 1 for foreign ownership, 0 otherwise, $\delta_t$ is year fixed effect, and $\varepsilon_{j,t}$ is the stochastic disturbance term.

Furthermore, this study also tries to analyze how the interaction between explanatory variables affects the outcome variable. I set two interaction term variables: ownership and export intensity; and maintenance intensity and capital intensity. The models' estimation could look like the following:

$$\begin{aligned}\ln(CEI)_{j,t} = \alpha &+ \beta_1 ln(fsize)_{j,t} + \beta_2 ln(export)_{j,t} + \beta_3 ln(cap)_{j,t} + \beta_4 ln(labor)_{j,t} + \\ &\beta_5 ln(maintenance)_{j,t} + \beta_6 (dummy\ ownership)_{j,t} + \\ &\beta_7 (dummy\ ownership)_{j,t} * ln(export)_{j,t} + \delta_t + \varepsilon_{j,t}\end{aligned} \tag{5}$$

$$\begin{aligned}\ln(CEI)_{j,t} = \alpha &+ \beta_1 ln(fsize)_{j,t} + \beta_2 ln(export)_{j,t} + \beta_3 ln(cap)_{j,t} + \beta_4 ln(labor)_{j,t} + \\ &\beta_5 ln(maintenance)_{j,t} + \beta_6 (dummy\ ownership)_{j,t} + \\ &\beta_7 (maintenance)_{j,t} * ln(cap)_{j,t} + \delta_t + \varepsilon_{j,t}\end{aligned} \tag{6}$$

### 3.2.3. Two-Stage Least Squares (2SLS) regression

As the OLS estimates may suffer from endogeneity problems such as reverse causality, omitted variable bias, and selection bias, which may cause inconsistent estimates and lead to misleading interpretations, I apply the 2SLS regressions model with an instrumental variable. Although I predict that the relationship/causal link runs from firm characteristics to carbon emission intensity, reverse causality is possible. For instance, while a large firm size is likely to emit less emissions due to its features, the level of $CO_2$ intensity might affect firm size as well. As the firm's release high emissions to the atmosphere, the government forces them to reduce their emissions; hence, they need to spend more money on technology or hire skilled workers that can affect their profit, thus their firm size. Moreover, selection bias and unobserved heterogeneity might also affect the result estimations, such as firms culture. Therefore, to address these concerns, I employ an instrumental variable.

There are some conditions to finding a useful instrument. The first condition is the instrument should correlate with the treatment variable (firm size). Second, the instrument variable must be correlated to the outcome variable ($CO_2$ emissions intensity) through the suspected endogenous variable (firm size) and not correlate with error terms. For example, a recent study by (Kabir *et al.*, 2021) uses 'signatories of the Kyoto protocol' as an instrumental variable to investigate the reverse causality of carbon emission and default risk. While finding a valid instrumental variable is challenging, I employ the compensation expenses (social allowance and pension for workers) as the instrumental variable. While the total compensation expenses are expected to impact firm size significantly, the compensation itself is not expected to affect $CO_2$ intensity directly. Birindelli *et al.* (2019), in investigating the impact of women CEOs on environmental performance, also use 2SLS random-effects methods and apply the log of the board member compensation as an instrument. Nuber and Velte (2021) also used a similar instrument in examining board gender and carbon emissions. They used total pensions scaled to the number of employees as an instrument. In the first stage of 2SLS, I regress firm size on the compensation expenses and other independent variables (equation 7). Then in the second stage, I regress $CO_2$ intensity with an instrumental variable (equation 8).

$$\ln(fsize)_{j,t} = \alpha + \beta_1 ln(compensation)_{j,t} + \beta_2 ln(export)_{j,t} + \beta_3 ln(cap)_{j,t} + \beta_4 ln(labor)_{j,t} + \beta_5 ln(maintenance)_{j,t} + \beta_6 (dummy\ ownership)_{j,t} + \delta_t + \varepsilon_{j,t} \quad (7)$$

$$\ln(CEI)_{j,t} = \alpha + \widehat{\beta_1} ln(fsize)_{j,t} + \beta_2 ln(export)_{j,t} + \beta_3 ln(cap)_{j,t} + \beta_4 ln(labor)_{j,t} + \beta_5 ln(maintenance)_{j,t} + \beta_6 (dummy\ ownership)_{j,t} + \delta_t + \varepsilon_{j,t} \quad (8)$$

## IV. Result and Discussion

### 4.1. Ordinary least square regression

Table 5. reports the findings of OLS and interaction term regression in analyzing the relationship between $CO_2$ intensity and several explanatory variables such as capital intensity, labor intensity, firm size, export intensity, maintenance intensity, and ownership status. Column (1) shows OLS estimation where $CO_2$ intensity is the dependent variable. I added a year dummy to control for time-specific fixed effects. In addition, Bu *et al.* (2019) argue that since firms normally develop year by year, the serial autocorrelation issue might exist, making the model suffer from heterogeneity due to the huge variation across firms. Therefore, I also apply robust standard error for correlation across firms within the firm level. Since the equation uses logarithms, the effect of independent variables on $CO_2$ intensity is expressed as an elasticity which describes how $CO_2$ intensity varies in percentage terms in response to a one percentage point change in a certain explanatory variable. The labor intensity, firm size, and export intensity negatively correlate with $CO_2$ intensity at a 1% significance level. Other factors held constant, a 1% increase in labor intensity, $CO_2$ intensity decrease by 0.061%. Furthermore, a decrease of 0.132% in $CO_2$ intensity is associated with a 1% rise in firm size. Similarly, other things equal, an increase of 1% in export intensity would follow by a decrease of 0.025% in $CO_2$ intensity. Conversely, with a 1% rise in maintenance intensity, $CO_2$ intensity increased by 0.107%. Meanwhile, other variables, capital intensity and ownership status show insignificant results.

Although the firm size, labor intensity, export intensity, and maintenance intensity have significantly affected $CO_2$ intensity, the effect of interaction between independent variables on the outcome might differ. To examine this possibility, I set two interaction terms in equation (5) with ownership status and export activity and equation (6) with the interaction of maintenance intensity and capital intensity as interaction variables. The reason for deciding on this interaction variable is due to the insignificant variable of ownership in the OLS and FE model. On the other hand, many works of the literature suggest that foreign firms are likely to have low $CO_2$ intensity (Jiang *et al.*, 2014; Eskeland and Harrison, 2003). Therefore, I try to interact the ownership variable with the export intensity variable since, in the descriptive analysis, foreign firms are export intensive. Foreign firms are likely larger firms that can adopt cleaner technologies for their production. In addition, export-intensive firms are also cleaner since they need to meet the standard environmentally friendly products by importer country's regulation. Thus, the expected effect of the export activity of foreign firms would decrease $CO_2$ intensity. Columns (2)-(4) show regression results by adding ownership and export intensity as the interaction terms. The estimated coefficients for the interaction terms appear significantly negative throughout the estimations. These results suggest that foreign firms with export activity decrease the $CO_2$ intensity by 0.043%, 0.036% (after only controlling capital intensity), and 0.059% (by controlling firm size).

**Table 5.** OLS Regressions and the Interaction Term

| | **Baseline** | **Interaction term** | | | | | |
|---|---|---|---|---|---|---|---|
| **Variables** | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** |
| Capital intensity | -0.008 | -0.008 | 0.016*** | | 0.037*** | 0.034*** | 0.045*** |
| | (0.006) | (0.006) | (0.006) | | (0.012) | (0.012) | (0.012) |
| Labor intensity | -0.061*** | -0.061*** | | | -0.060*** | | 0.018*** |
| | (0.005) | (0.005) | | | (0.005) | | (0.005) |
| Firm size | -0.132*** | -0.133*** | | -0.105*** | -0.132*** | -0.119*** | |
| | (0.005) | (0.005) | | (0.005) | (0.005) | (0.005) | |
| Export intensity | -0.025*** | -0.017*** | -0.040*** | -0.015** | -0.025*** | | |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | | |
| Maintenance intensity | 0.107*** | 0.107*** | | | 0.120*** | 0.116*** | 0.107*** |
| | (0.005) | (0.005) | | | (0.006) | (0.006) | (0.006) |
| Ownership | -0.049 | 0.028 | -0.162*** | 0.102** | -0.052 | | -0.351*** |
| | (0.039) | (0.052) | (0.051) | (0.052) | (0.039) | | (0.036) |
| Ownership*exp intensity | | -0.043** | -0.036** | -0.059*** | | | |
| | | (0.018) | (0.018) | (0.018) | | | |
| Maintenance*cap intensity | | | | | 0.011*** | 0.012*** | 0.011*** |
| | | | | | (0.003) | (0.003) | (0.003) |
| Constant | 2.187*** | 2.191*** | 0.067*** | 1.569*** | 2.239*** | 2.176*** | 0.481*** |
| | (0.073) | (0.073) | (0.007) | (0.070) | (0.074) | (0.072) | (0.026) |
| Year effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 95,189 | 95,189 | 95,189 | 95,189 | 95,189 | 95,189 | 95,189 |
| R-squared | 0.367 | 0.368 | 0.351 | 0.359 | 0.368 | 0.366 | 0.357 |
| Adj. R^2 | 0.367 | 0.367 | 0.351 | 0.359 | 0.368 | 0.366 | 0.357 |
| Prob>F | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Furthermore, I also set another interaction term between maintenance intensity and capital intensity. This is because the sign of maintenance intensity is positively significant (baseline column), different from the expected sign. Theoretically, firms that spend more money on maintenance tend to emit less carbon. However, since the sign of maintenance intensity on $CO_2$ intensity is positive, it is suspected that firms with complex machines (this type of firm might tend to generate more emissions) need more money to maintain the equipment infrastructure. Therefore, I set the interaction term of maintenance intensity and capital intensity to investigate their different effect on the outcome. Capital-intensive firms are likely to have higher maintenance intensity; thus, if the reasoning behind emission-intensive firms adopting complex machines generating high carbon emissions is proper, then I expect a positive sign of the interaction term. On the baseline column, capital intensity is insignificant, while after adding the interaction term on columns (5)-(7), the capital intensity becomes positively significant. The interaction terms for all regression also positively affected $CO_2$ intensity, meaning that capital intensive firms spending more money on machinery maintenance emit more emissions.

### 4.2. Two-stage least square (2SLS) regression

In the basic equation (3), $CO_2$ intensity is the dependent variable. The result shows a negative relationship between $CO_2$ emission intensity and firm size. However, the results may suffer from endogeneity problems. Therefore, I employ 2SLS regression with compensation as the instrumental variable to address this issue. **Table 6.** column (1) presents the first stage regression results, revealing that compensation as the instrument variable positively impacts firm size, which shows that the instrument is relevant in the first stage. In addition, the first stage regression test suggests that the critical value of the F-statistic for weak identification is higher than the critical Stock-Yogo value. It means that we reject the null hypothesis that the instrument is weak.

**Table 6.** Two-stage least square regression

| Dependent variable | (1) First stage regression | (2) Second stage regression |
|---|---|---|
| | Firm size | $CO_2$ intensity |
| Compensation | 0.099*** | - |
| | (0.002) | |
| Capital intensity | -0.069*** | -0.005 |
| | (0.005) | (0.006) |
| Labor intensity | -0.547*** | -0.033*** |
| | (0.005) | (0.011) |
| Export intensity | 0.161*** | -0.034*** |
| | (0.006) | (0.007) |
| Maintenance intensity | 0.065*** | 0.103*** |
| | (0.005) | (0.005) |
| Ownership | 1.547*** | -0.133*** |
| | (0.034) | (0.050) |
| Firm size | - | -0.084*** |
| | | (0.018) |
| Constant | 12.901*** | 1.555*** |
| | (0.025) | (0.236) |
| Observations | 95,189 | 95,189 |
| R-squared | 0.392 | 0.366 |
| Adj. R^2 | 0.392 | 0.366 |
| F-Statistic for weak identification | 3606 | - |
| Year effects | Yes | Yes |

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The Hausman test was employed to test the existence of endogeneity. The result shows the significant statistics meaning that the variable is endogenous, justifying using two-stage instrumental variable regressions. The Hausman test also shows that the coefficient estimator of 2SLS is consistent. However, Cameron and Trivedi (2009) argue that the IV estimator can be less efficient than the OLS estimator. Column (2) presents second stage regression results, showing the impact of firm size on CO2 intensity, which is negatively significant at level 1%. Comparing the result between OLS regression (Table 5. column 1) and 2SLS regression (Table 6. column 2), firm size, labor intensity, export intensity, and maintenance intensity confirm the similar results regarding both sign and significance. However, the impact of variable ownership on CO2 intensity becomes negatively significant at level 1%. Controlling for potential endogeneity by implementing IV might explain the inconsistencies in estimation.

### 4.3. Fixed effect (FE) and fixed effect instrumental variable (FE-IV)

Table 7 presents the results of regression FE (column 1) and FE-IV (column 2), which show slightly different results. While all the signs of variables between both models are the same, the significance of labor intensity yields different results. In the FE model, labor intensity has a significant relationship with $CO_2$ intensity; on the other hand, in the FE-IV estimation, the coefficient is insignificant. Furthermore, variable ownership in FE-IV becomes insignificant, while in the 2SLS model, it is significant at 1%. After performing the Hausman test, the result is insignificant, which means that the FE and FE-IV estimates are not significantly different; thus, the FE model is preferable. This might be because the instrument variable is weak.

**Table 7.** Fixed effects and fixed effect instrumental variable regression

| **Variables** | **(1) FE** | **(2) FE-IV** | **(3) 2SLS** |
|---|---|---|---|
| Capital intensity | -0.074*** | -0.094** | -0.005 |
| | (0.007) | (0.038) | (0.006) |
| Labor intensity | -0.031*** | -0.048 | -0.033*** |
| | (0.006) | (0.032) | (0.011) |
| Firm size | -0.315*** | -0.405** | -0.084*** |
| | (0.010) | (0.168) | (0.018) |
| Export intensity | 0.004 | 0.002 | -0.034*** |
| | (0.012) | (0.012) | (0.007) |
| Maintenance intensity | 0.071*** | 0.061*** | 0.103*** |
| | (0.007) | (0.020) | (0.005) |
| Ownership | -0.091 | -0.081 | -0.133*** |
| | (0.082) | (0.084) | (0.050) |
| Constant | 4.788*** | 6.028*** | 1.555*** |
| | (0.139) | (2.298) | (0.236) |
| Observations | 95,189 | 95,189 | 95,189 |
| R-squared | 0.573 | | 0.366 |
| Number of psid | 28,115 | 28,115 | |
| R-sq: within | 0.573 | 0.572 | |
| R-sq: between | 0.151 | 0.135 | |
| R-sq: overall | 0.340 | 0.318 | |
| Adj. R^2 | 0.573 | | 0.366 |
| Prob>F | 0 | 0 | |
| F | 6338 | | |
| Corr | -0.119 | -0.195 | |
| sigma_u | 1.449 | 1.508 | |
| sigma_e | 1.326 | 1.327 | |
| Rho | 0.544 | 0.563 | |
| F-Statistic for weak identification | | | 3606 |
| Year effect | Yes | Yes | Yes |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In column 1, capital intensity, labor intensity, firm size, and maintenance intensity are significant at level 1%. On the other hand, export intensity and firm ownership are insignificant. An increase of 1% in labor intensity, $CO_2$ intensity would decrease by 0.031%, and other factors held constant. Labor intensity is significantly negative, implying that labor-intensive firms are emission efficient. This might be because the labor-intensive industry is typically non-complex and does not generate much pollution. Capital intensity also has negative implications on emission intensity, meaning firms with more capital are emitting less. A decrease of 0.074% in $CO_2$ intensity is associated with a 1% rise in capital intensity. It indicates that firms with a bigger plant, high technology, and/or bigger properties are cleaner than small capital industries.

Further, with a 1% rise in firm size, $CO_2$ intensity decreased by 0.315%, meaning big firms are more emission efficient or emit less than small firms. With the advantages of high profit, bigger firms can invest in cleaner technology and research and development to improve their performance. On the other hand, maintenance intensity positively affects emissions intensity. 1% rise in maintenance intensity, $CO_2$ intensity increase by 0.107%. It implies that firms with more expenses in maintenance emit more emissions. However, the reason is not clear. Theoretically, firms that spend more money on machinery maintenance would emit less since the equipment is regularly being maintained. Perhaps, the large amount of money spent on maintenance is a sign that emission-intensive firms adopt complex machines generating high carbon emissions. Meanwhile, other variables, capital intensity and ownership status show insignificant results.

## V. Conclusion and Recommendation

Fossil fuels as an energy source are undeniably important for economic growth and human life. However, aside from their importance in providing energy, overconsumption of fossil fuels, especially for combustion processes, will increase emissions levels in the atmosphere. Although some mitigation action to address this issue has already been determined, the demand for fossil fuels is still high in some countries, including Indonesia. As the manufacturing sector is the main consumer of fossil fuels, this paper tries to analyze the energy intensity of manufacturing sub-sectors in Indonesia and examine the determinants of $CO_2$ emission intensity at the firm level. The unavailability of data on plant emissions requires the author to calculate $CO_2$ emissions from firms' fuels consumption based on IPCC Guidelines 2006.

From 2011 to 2014, the trend of the total energy consumption has decreased, and the total value addition of products has increased. This leads to the decreasing energy intensity, meaning that the firm uses less energy to produce a product. While the energy intensity has declined over time, the $CO_2$ intensity has decreased as well. However, the reduction of $CO_2$ intensity is not because of the decrease in the total carbon emission; instead, it increases over time.

This study employs OLS, 2SLS, FE, and FE-IV models to test the hypothesis of the determinants of $CO_2$ intensity. The results among all regressions are slightly similar regarding significance and sign. While the use of compensation as an instrument variable might generate a weak instrument, the ownership and export intensity variables show their significance in the 2SLS model. However, labor intensity, export intensity, and ownership become insignificant after inserting the instrument into the FE-IV model. Furthermore, using the FE model, this study found that capital intensity, labor intensity, firm size, and maintenance intensity are significant at 1%. The big firm size is more emission efficient or emits less than the small firm. Capital- and labor-intensive firms are less carbon-intensive. These results might indicate that big firms may spend on clean technology and invest in highly skilled labor to operate the technology, which will result in emission efficiency. Conversely, maintenance intensity shows a positive effect on emission intensity. While the reason might be unclear, we assume that the maintenance expenses are spent on the complex machine which is adopted by the emission-intensive firms.

Lastly, we hope that this study will provide some insight to Indonesia's policymakers in picturing the condition of energy and emissions in the manufacturing sector. I would like to highlight that the policymakers should focus on industrial sub-sectors which contribute to high energy and emissions intensity. This is important since carbon emission has increased, even though its $CO_2$ intensity has declined. Moreover, the findings of determinants of $CO_2$ intensity might become a foundation for how policymakers formulate the regulations related to firms' emissions.

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