Jurnal Presipitasi
Media Komunikasi dan Pengembangan Teknik Lingkungan
e-ISSN: 2550-0023

Vol 23, No 1, 2026, 95-114
Article available at [homepage presipitasi]()

Original Research Article

Economic Activity and Greenhouse Gas Emissions: An Empirical Study of the Indonesian Manufacturing Industry

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Abstract
Manufacturing industry plays significant role in the Indonesian economy. However, this sector was the largest contributor to greenhouse gas (GHG) emissions in 2022, reaching 38% of total emissions released by all sectors. The purposes of this study are to identify characteristics and trends of economic activity and GHG emissions from fuel consumption across 24 manufacturing subsectors, and to analyze the effect of some economic variables on GHG emissions of the manufacturing industry in Indonesia. Economic variables from 2012-2022, including machinery maintenance intensity, labor intensity, resource-use intensity, value-added, and GHG intensity, were analyzed using descriptive statistics and fixed-effect model panel regression. The results show that labor intensity in the manufacturing subsector tends to decline, while resource use intensity and value-added are increasing. Meanwhile, machinery maintenance intensity shows considerable variation without consistent concentration in particular subsectors. Panel data regression indicates that maintenance intensity and labor intensity have significant positive effect on GHG intensity, while resource-use intensity and value-added have significant negative effect. Based on these results, interventions on economic variables can influence GHG emission levels. This study recommends fiscal policy interventions, such as subsidies for environmentally friendly equipment and incentives for green industries, to strengthen the performance of environmentally friendly industries.

Keywords: Data panel regression; economic variables; greenhouse gases emission; manufacturing industry

1. Introduction

Climate change is one of the environmental issues that is currently being widely discussed at the global level. The global temperature has increased by up to 1.1°C compared to the temperature conditions in 1850–1900, within only ten years, from 2011 to 2020 (Calvin et al., 2023). The rise in global temperature that leads to climate change is driven by the increasing accumulation of greenhouse gases (GHGs) in the atmosphere. GHGs actually play an important role in maintaining the Earth's warmth. However, when their concentration becomes excessive, GHGs can cause the Earth's temperature to become too high due to their ability to trap atmospheric radiation. One of the GHGs that has a major influence on climate change is carbon dioxide (CO_2), which can be produced naturally as well as through human activities (IPCC, 2021).

The manufacturing industry is one of the human activities that produces CO_2. The process of converting raw materials into products requires energy. As explained in the Second Law of Thermodynamics, there is entropy or residue resulting from the process of energy transformation, which in this case includes CO_2 emissions. There are two types of emissions: direct emissions, which are generated directly from fuel consumption, and indirect emissions, which originate from energy consumption in other sectors such as electricity use (Zhou et al., 2023).

Indonesia's economy is highly dependent on the manufacturing industry, as indicated by the proportion of its value-added to the Gross Domestic Product (GDP), which reached 20.39% in 2023 (Statistics Indonesia, 2024a). The sector's performance growth is also positive, recording the highest figure in ASEAN at 52.9 (Coordinating Ministry for Economic Affairs, Republic of Indonesia, 2024). The growth of the manufacturing industry in Indonesia is also indicated by an increase in the production index of Large and Medium Industries, which reached 2.41% in 2023 (Statistics Indonesia, 2024b). The number of industries also increased from 30,115 industries in 2018 to 31,776 industries in 2022 (Badan Pusat Statistik, 2024c).

The growth of the industrial economy drives an increase in the consumption of raw materials and fuels, which can lead to higher greenhouse gas (GHG) emissions. However, once a certain level of economic development is reached, the amount of emissions tends to decline. This condition is explained by the Environmental Kuznets Curve Theory, which states that at a low level of economic development, pollution tends to be high until it reaches a certain maximum point, after which it decreases in line with improvements in economic conditions or income (Grossman, 1994). The industrial sector contributed 38% of Indonesia's GHG emissions in 2022, making it the highest among all sectors—even higher than the energy sector—as shown in Figure 1 (Statistics Indonesia, 2025).

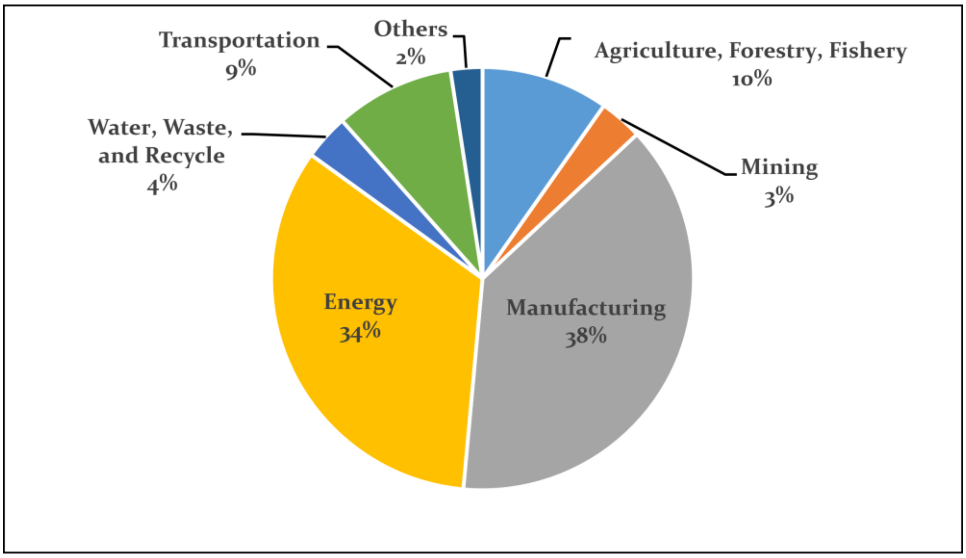

Figure 1. Sectoral contribution to greenhouse gas emissions in Indonesia in 2022

Source: *Statistics indonesia, 2025*

Emission control strategies have been extensively designed by the Government of Indonesia, including in the Enhanced Nationally Determined Contribution (ENDC), which targets an emission reduction of up to 31.89% without international assistance and 43.2% with international support. In addition, there are also more technical regulations, such as those related to emission standards and green industry implementation. However, climate change is a complex issue because the factors influencing it are highly diverse and therefore need to be examined from multiple perspectives. Existing policies must also be continuously adjusted by considering the various determinants that may affect emissions.

Several studies discussing the relationship between economic activity and GHG emissions in the industrial sector have mostly focused on the macro level, using variables such as GDP, production index, value-added, and industrial output (Kumar Dahal et al., 2023; Mulatsih, 2022; Osobajo et al., 2020; Rosita et al., 2024). However, specific research analyzing manufacturing subsectors using long-term panel data and linking them to economic variables such as labor intensity, machinery maintenance intensity, resource use intensity, and value-added is still limited. Meanwhile, manufacturing sub-sectors are not homogeneous, and each has different economic characteristics and emission contributions.

The purposes of this study are to identify characteristics and trends of economic activity and GHG emissions from fuel consumption across 24 manufacturing industry subsectors, and to analyze the effect of some economic variables on GHG emissions of the manufacturing industry in Indonesia. This research is expected to contribute to providing empirical data related to the role of economic variables on emissions in the manufacturing industry and provide evidence-based recommendations to support emission control in the Indonesian manufacturing industry.

2. Methods

2.1. Data Collection

The data in this study were obtained from the publications of *Statistics of Indonesia Manufacturing Industry* and *Indicator of Indonesia Manufacturing Industry*, published by Statistics Indonesia, which were derived from the annual survey of the manufacturing industry. This data is the result of an annual survey on the manufacturing industry, which includes data on fuel consumption (both fossil and non-fossil), maintenance costs, labor expenditures, output value, input value, and value-added. There are 24 (twenty-four) manufacturing sub-sectors according to the *Indonesia Industrial Standard Classification of All Economic Activities* (ISIC) 2-digit code used in this study (Table 1). The research year was selected for 10 (ten) years, from 2012 to 2022. However, the year 2016 was excluded because there was no similar publication that provided data on fuel consumption for that year, so the GHG intensity could not be calculated completely. To maintain panel data consistency and estimation validity, the year 2016 was removed from the sample. This exclusion still produces a long and representative data series that adequately reflects the dynamics of Indonesia's manufacturing sub-sectors.

Table 1. List of manufacturing industry subsectors based on the 2-digit code of the Indonesian Industrial Standard Classification

Code	Description	Code	Description
10	Food products	22	Rubber and plastic products
11	Beverages	23	Other non-metallic mineral products
12	Tobacco products	24	Basic metals
13	Textiles	25	Fabricated metal products, except machinery and equipment
14	Wearing apparel	26	Computer, electronic, and optical products
15	Leather and related products	27	Electrical equipment
16	Wood and products of wood and cork (except furniture)	28	Machinery and equipment n.e.c.

Code	Description	Code	Description
17	Paper and paper products	29	Motor vehicles, trailers, and semi-trailers
18	Printing and reproduction of recorded media	30	Other transport equipment
19	Coke and refined petroleum products	31	Furniture
20	Chemicals and chemical products	32	Other manufacturing
21	Basic pharmaceutical products and pharmaceutical preparations	33	Repair and installation of machinery and equipment

There are three types of variables used in this study: dependent variables, independent variables, and control variables. The dependent variable is GHG intensity. Meanwhile, the independent variables reflect the economic conditions of the manufacturing industry. Two independent variables were selected based on research by Constantia (2022), which are labor intensity (LI) and value-added (VA). However, this study differs from Constantia in that it covers a longer time series, whereas the previous study only covered data from 2011 to 2014. Furthermore, the previous study also aimed to determine the most appropriate statistical regression model for analyzing the influence of economic activity on industrial emissions. Other independent variables added to this study are machinery maintenance intensity (MMI) and resource use intensity (RI). Meanwhile, the fossil fuel consumption variable is used as a control variable.

The four selected independent variables are chosen to represent the influence of economic activity in the manufacturing industry on emission reduction (Table 2). The MMI variable shows the amount of expenditure on machinery maintenance relative to the output value. This variable is used to indicate whether the maintenance efforts undertaken by the industry have resulted in emission reductions. It is considered that maintenance does not not only prevents production failures but also increases energy efficiency and reduces emissions (Orošnjak et al., 2025). The LI variable is defined as the ratio of labor expenditure to output, or in other words, the extent of labor's contribution to industrial production. Some industries are known as labor-intensive, which can have both positive and negative effects on emissions, due in part to mechanization as a means of reducing emissions. (Aldas et al., 2024; S. Zhang et al., 2023a). The third variable, RI, represents the ratio of input costs to output costs. Industrial production processes require inputs in the form of resources, which then produce outputs in the form of products and waste, one of which is emissions. Therefore, the most resource-efficient industries are known to be more productive because they optimize the use of their resource inputs, thereby reducing waste production (Tang and Bruneau, 2025). This variable is expected to show how efficiently Indonesian industries utilize existing resources and how this efficiency affects emissions. The final independent variable is value-added (VA), which has often been used as an indicator of industrial economic growth (Altomonte et al., 2011; Ramirez et al., 2005; Soytas and Sari, 2007). Thus, VA can be a suitable variable to show whether industrial economic growth in Indonesia is in line with emission reduction efforts.

Table 2. Research variables

Variable	Code	Definition
Machinery maintenance intensity	MMI	The ratio of the value of purchases, production, or repairs of fixed capital in the form of machinery and equipment to output
Labor intensity	LI	The ratio of labor expenditure to output
Resource use intensity	RI	The ratio of input value to output value
Value-added	VA	The difference between the input value and output value (excluding labor wages) is an indicator of value-added or profit from a business activity

Variable	Code	Definition
Fossil fuel consumption	FOS	The amount of fossil fuel consumed by each manufacturing industry sub-sector within one (1) year
GHG Intensity	GHG-I	The amount of GHG emissions (CO_2e from CO_2, CH_4, and N_2O) per output

2.2. Data Analysis

The calculation of GHG emissions in this study includes the consumption of fossil and non-fossil fuels. The types of fuels include oil fuels (gasoline, diesel oil, kerosene, gas oil, fuel oil, and/or biodiesel), coal (including coal briquettes), gaseous fuels (natural gas and LPG), and biomass.

First, emissions of each greenhouse gas were calculated by incorporating the emission factors of each fuel type using Equation 1. The types of greenhouse gases calculated in this study include carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4).

Equation 1:

$$E = FC\ x\ EF$$

In Equation 1, E refers to emission, where the unit value is measured in tons, while FC is fuel consumption in terajoules, and EF is the emission factor, for which the unit value is in tons/Terajoule. The emission factor represents the amount of emissions released per unit of fuel consumption. The emission factors for each type of fuel are presented in Table 3. The limitations of national emission factors prompted this study to use a combination of national and global emission factors for each greenhouse gas.

Table 3. Emission factor (EF)

Fuel type	Emission factor (ton/ Terajoule)		
	Carbon dioxide	**Methane[2]**	**Nitrous oxide[2]**
Gasoline	72.6[1]	0.003	0.0006
High-speed diesel/ Automotive diesel	74.433[3]	0.003	0.0006
Industrial diesel oil	74.067[3]	0.003	0.0006
Marine fuel oil/ residual fuel oil	75.167[3]	0.003	0.0006
Biofuel (B100)	70.8[1]	0.003	0.0006
Coal	99.718[3]	0.01	0.0015
Coal briquettes	97.5[1]	0.01	0.0015
Natural gas	57.64[3]	0.001	0.0001
Liquefied Petroleum Gas	71.87[4]	0.001	0.0001
Biomass	0*	0.03	0.004
Kerosene	73.7[4]	0.003	0.0006

Sources:
[1]*(Ministry of Environment Republic of Indonesia, 2012)*
[2]*(IPCC, 2006)*
[3] *(Ministry of Energy and Mineral Resources, Republic of Indonesia, 2020)*
[4]*(The Fiscal Policy Agency, 2013)*
**accounted for in the AFOLU sector, and therefore not recalculated in the industrial sector.*

We then continue to convert them into a single unit of measurement, carbon dioxide equivalent (CO_2e), with the estimation specification in Equation (2).

Equation 2:

$$CO_2e = (ECO_2\ x\ GWPCO_2) + (ECH_4\ x\ GWPCH_4) + \ (EN_2Ox\ GWPN_2O)$$

Here in equation 2, CO2e is the carbon dioxide equivalent in tons CO2e. Emissions counted previously from equation 1 are then used to calculate CO2e, which includes ECO2 or carbon dioxide emission in tons, ECH4 or methane emission in tons, and ENO2 or nitrous oxide emission in tons. Each emission type is multiplied by the global warming potential (GWP). GWPCO2 refers to the global warming potential of CO2, for which the value is set at 1. While GWPCH4 represents the global warming potential of CH4, where the value for fossil is set at 29.8 and 27 for non-fossil types. The last is GWPN2 or global warming potential of N2O, for which the value is set at 273.

These GWP values are applied to convert different greenhouse gases into a common unit, enabling a consistent comparison of their overall impact on climate change. This approach ensures that the contribution of each gas is appropriately weighted based on its relative warming effect, allowing for a more comprehensive representation of total emissions in terms of CO2e.

Data analysis in this study employs descriptive statistical tests and panel data regression. In this study, Stata 17 is used as the software for statistical analysis. Descriptive statistical tests are conducted to observe the distribution of each research variable, while panel data regression is used to analyze the relationship between the dependent and independent variables using panel data. Panel data are a combination of cross-section and time-series data, with a structure illustrated in Table 4 (cells are intentionally left blank). We analyzed the data from all subsectors within a single panel data regression, so the regression was not estimated separately for each subsector.

Table 4. Panel data structure

Subsectors code (ID)	Year	Machinery Maintenance intensity (MMI)	Labor intensity (LI)	Resource use intensity (RI)	Value-added (VA)	Consumption of fossil fuel (FOS)	Greenhouse gases intensity (GHG-I)
10	2012	...	...	...	...	...	...
10	2013	...	...	...	...	...	...
10	2014	...	...	...	...	...	...
10	2015	...	...	...	...	...	...
10	2017	...	...	...	...	...	...
10	2018	...	...	...	...	...	...
10	2019	..	...	...	...	...	...
10	2020	...	...	...	...	...	...
10	2021	...	...	...	...	...	...
10	2022	...	...	...	...	...	...
11	2012	...	...	...	...	...	...
11	2013	...	...	...	...	...	...
11	2014	...	...	...	...	...	...
11	2015	...	...	...	...	...	...

Note*: rows continue for all subsectors and years*

Prior data validation is conducted to ensure that the panel dataset is accurate and consistent for further analysis. It consists of assessing data completeness and detecting any missing values across all variables, identifying potential outliers, verifying the consistency of measurement units and variable definitions to ensure uniformity across observations, checking for duplicated entries, and evaluating the economic and logical coherence of each variable. Based on data validation, there are no missing values, outliers, or duplicate records in the dataset. All variable units are verified and ensured to be consistent. There is no negative value that fulfills logical validity.

Several methods are commonly used to estimate panel data regression models, namely the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM). To determine the most appropriate method for the research data, several preliminary tests need to be conducted, including the Chow test, Hausman test, and Lagrange Multiplier test, in order to ensure that the selected model is valid and methodologically rigorous. The Chow test is the first test to determine whether the model is appropriate to use. We will select the models based on the p-value, where CEM will be selected if the p-value > 0.05 and FEM will be selected if the p-value < 0.05. The Hausman test tells us whether REM or FEM is appropriate to use. We will use REM if the p-value > 0.05, and FEM if the p-value < 0.05. Lastly, we conduct a Lagrange Multiplier test to determine whether CEM or REM is better to use. CEM will be selected if the p-value > 0.05, while REM will be selected if the p-value < 0.05.

While the descriptive analysis utilizes each variable in its original unit, the variables in panel data regression analysis are first transformed using a logarithmic (log) equation to avoid heteroskedasticity. This transformation standardizes the unit of the variables and allows the coefficients to be interpreted as elasticities. Prior variable units for RI, MMI, and LI are the cost-to-cost ratio (IDR to IDR), so these variables are already unitless. Meanwhile, VA is in billion IDR, and GHG-I is in ton CO_2e per billion IDR. However, the log transformation further synchronized the data units and supports stable estimation so that different variable units do not affect the validity of the regression analysis.

After choosing the model, we continue to perform classical assumption tests, including multicollinearity and heteroskedasticity tests. These tests were conducted to ensure that the model used is valid and reliable. A model is valid and reliable when the p-value for each variable of the multicollinearity test, evaluated using the Variance Inflation Factor (VIF), is less than 0.85, and the p-value for the heteroskedasticity test, based on the Breusch-Pagan test, is greater than 0.05. The regression equation used is presented in Equation 3.

Equation 3:

$$log\ (GHG\ I_{it}) = \alpha_0 + \beta_1 log\ MMI_{it} + \beta_2 log\ LI_{it} + \beta_3 log\ RI_{it} + \beta_4 log\ VA_{it} + \beta_5 log\ FOS_{it} + \varepsilon_{it}$$

In equation 3, we will use the natural form of logarithm, which will be presented with Log in each variable. The dependent variable, GHG intensity in ton CO2e, is written as GHG-I variables. Other independent variables are MMI or machinery maintenance intensity, LI or labor intensity, RI or resource use intensity, and VA or value-added, while FOS is the control variable that represents fossil fuel consumed. Some intercepts used in equation 3 are α_0 for the intercept coefficient, β for the variable coefficient, ε present as the error term, and subscript i denotes the subsectors and t denotes the time period. Additionally, the use of the logarithmic form aims to normalize the data distribution and reduce heteroscedasticity, allowing for a more robust estimation of the relationships between variables.

Each coefficient is later interpreted under the assumption that all other variables in the model remain constant. This approach allows the estimated coefficients to represent the isolated contribution of each predictor to the dependent variable. Validation of the interpretation is carried out qualitatively by comparing the direction of the relationships obtained with findings from previous studies. The research flow diagram is shown in Figure 2.

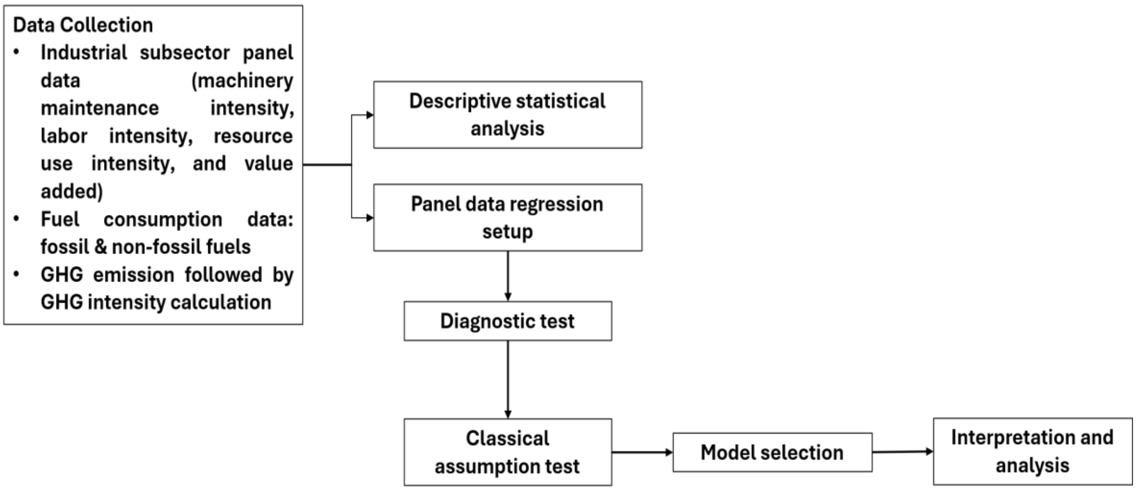

Figure 2. Research flow diagram

3. Result and Discussion

3.1. Model Selection

The results of the model selection tests consistently indicate that the Fixed Effect Model (FEM) is the most appropriate panel data model for this study. Based on the Chow Test and Hausman Test, both pooled OLS and random-effects assumptions are rejected (Table 5). The classical assumption tests further support the robustness of the chosen model. Multicollinearity is not detected as all VIF values are within the acceptable standards, and the heteroskedasticity test indicates that the data do not exhibit variance irregularities (Table 6). Overall, the diagnostics confirm that the Fixed Effects Model provides the most reliable estimation for this study.

Table 5. Chow test dan hausman test

Test	Null Hypothesis (H_0)	Statistic	Prob>Chi2/F	Decision	Selected Model
Chow Test	Pooled OLS is better	F(23,211) = 5.15	0.000	Reject H_0	Fixed Effect
Hausman Test	Random Effect is better	$X^2(5)$ = 76.49	0.000	Reject H_0	Fixed Effect
Fixed Effect Model Significance	All coefficients = 0 (no effect)	F(5,211) = 1,739.96	0.000	Reject H_0	Fixed Effect model is significant

Table 6. Classical assumption test

Multicollinearity Test (Variance Inflation Factor)		
Variable	**VIF**	**1/VIF**
MMI	1.23	0.81
LI	1.69	0.59
RI	1.32	0.76
VA	1.72	0.58
FOS	1.60	0.63
Mean VIF	1.51	Multicollinearity does not occur
Heteroskedasticity (Breusch-Pagan)		

Multicollinearity Test (Variance Inflation Factor)		
Statistic Chi²	**Prob > Chi²**	**Decision**
2.04	0.1536	Heteroskedasticity does not occur

3.2. Economic Conditions and Manufacturing Industry Emissions

The variables of machinery maintenance intensity, labor intensity, resource use intensity, and Value-added are used to represent the economic activity of each manufacturing industry sub-sector. Another variable, namely manufacturing industry emissions, is used to describe the environmental pressure exerted by the industry.

3.2.1. Machinery Maintenance Intensity

Machinery maintenance intensity (MMI) indicates the ratio between the expenditure on fixed capital in the form of machinery repair, construction, or maintenance, and the total output received by the sub-sector per year. These costs are essential in manufacturing industries, which are characterized by the use of machinery, to fully restore machine performance or to partially repair it in order to maintain production (Ben-Salem et al., 2015).

Based on the result, this value varies considerably, as the highest value each year is never held by the same sub-sector (Figure 3). The highest intensity was experienced by the printing and reproduction of recorded media industry sub-sector (ISIC 18) in 2015, with a value reaching 3.32. Other sub-sectors also experienced their peak machinery maintenance intensity around 2014–2015. Although there has been an increase in the last three years, the value has not reached the level observed in 2014–2015.

A relatively similar pattern can be seen in the sub-sector of coke and refined petroleum products (ISIC 19), which consistently shows the lowest intensity values compared to other sub-sectors. Meanwhile, the highest average machinery maintenance cost ratio during the ten-year observation period was recorded in the chemicals and chemical products industry sub-sector (ISIC 20), followed by the electrical equipment industry sub-sector (ISIC 27), and the printing and reproduction of recorded media industry sub-sector (ISIC 18). This condition may indicate high machinery dependence in these sub-sectors.

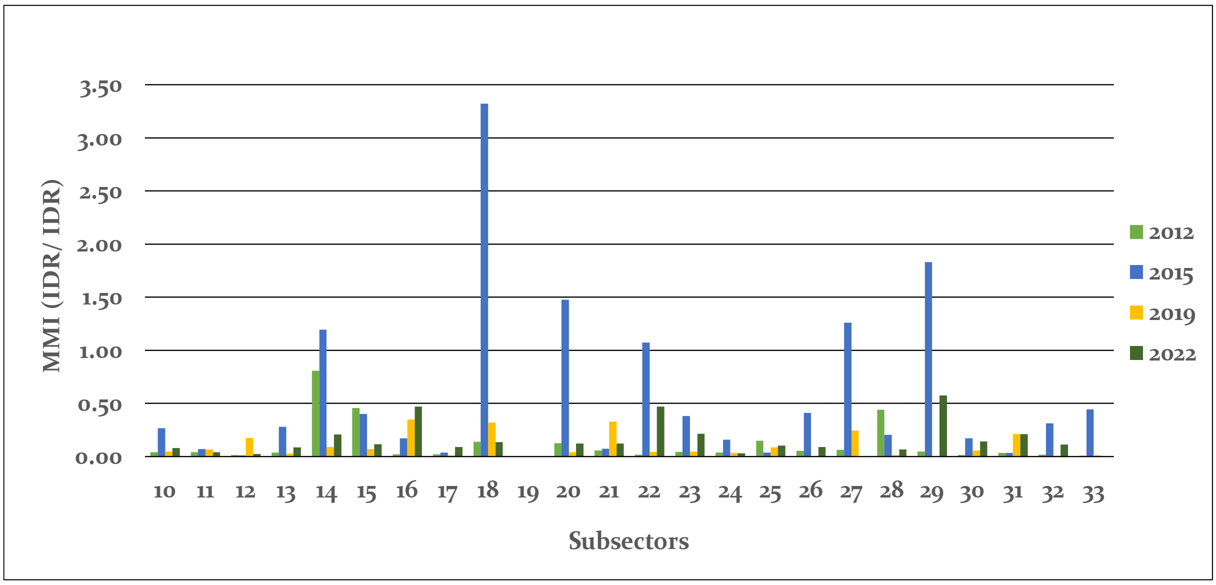

Figure 3. Machinery maintenance intensity in the manufacturing industry (2012-2022)

3.2.2. Labor Intensity

Labor intensity (LI) as a ratio of labor expenditures to output indicates the differences in labor-dependent production structures. Higher labor intensity indicates a worsening economic condition in the industry. This is because the cost incurred for labor increases while the output value remains constant or decreases. On average, as shown in Figure 4, labor intensity across all sub-sectors generally declined, as seen in the food industry sub-sector (ISIC 10), the coke and refined petroleum products sub-sector (ISIC 19), and the other transport equipment industry sub-sector (ISIC 30). Although there has been an increase in recent years, the value remains lower than before 2017.

The highest labor intensity occurred in the furniture industry sub-sector (ISIC 31) in 2012. However, based on the average value, the highest labor intensity throughout the observation period occurred in the other manufacturing industry sub-sector (ISIC 32). Conversely, the coke and refined petroleum products industry (ISIC 19) had the lowest average labor intensity among all sub-sectors. The decline in labor intensity was observed in nearly all manufacturing industry sub-sectors. The utilization of more efficient and innovative technologies has been identified as one of the driving factors behind this condition (Lu et al., 2021; Zhu et al., 2024).

(Jiang et al., 2024) stated that there are two main channels through which machine technology affects labor in the manufacturing industry. The first is the productivity effect, where machines make the production process more efficient, and the second is the output scale effect, which occurs when efficient and low-cost production drives companies to significantly increase their production volume. Thus, the low labor intensity in the coke and refined petroleum products sub-sector reflects the dominance of the productivity effect over the output scale effect. This occurs because technology replaces labor without being fully offset by production capacity expansion.

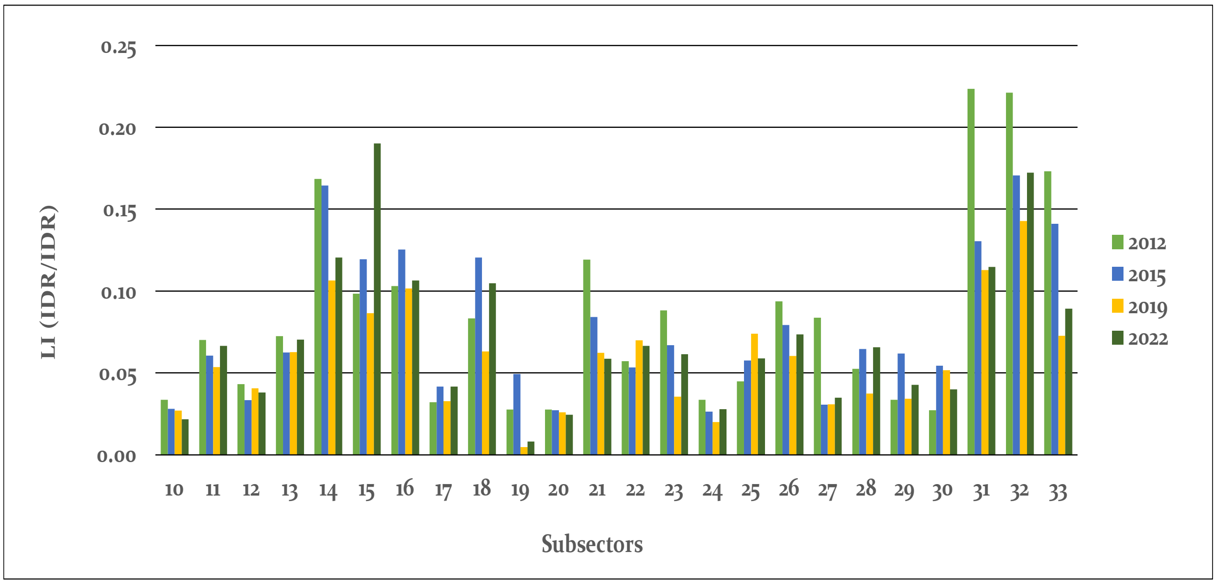

Figure 4. Labor intensity in the manufacturing industry (2012-2022)

3.2.3. Resource Use Intensity

Resource use intensity (RI), as a ratio of input to output, measures the degree of dependence on material and intermediate inputs. This value can determine whether an industry is resource-intensive or resource efficient, as it indicates how a sub-sector utilizes resources as efficiently as possible to produce maximum output — the smaller the value, the more optimal the use of available resources (Hernandez et al., 2017; Sarfraz et al., 2023).

This figure is derived from data on input efficiency per output for large and medium industries published by Statistics Indonesia. The fluctuation in resource use intensity values is shown in Figure 5. Several sub-sectors consistently exhibited resource use intensity values above 50% throughout the observation period. These include the food industry sub-sector (ISIC 10), the textile industry sub-sector (ISIC 13), the rubber, rubber goods, and plastics industry sub-sector (ISIC 22), the basic metal industry sub-sector (ISIC 24), and the fabricated metal products, except machinery and equipment industry sub-sector (ISIC 25). Thus, it was found that the five sub-sectors spend more on input costs than the output costs, making them less efficient in using their resources.

Inefficiencies in resource utilization in the textile industry are related to the dominance of domestic auxiliary raw materials, where the use of domestic raw materials covers 42,34% of the total production costs required. The high dependence on raw material inputs makes it difficult for the textile industry to achieve efficient production, even when its production capacity has been increased (Asmara et al., 2014). In fact, the improvement of the textile industry's performance largely depends on its ability to produce output efficiently (Chen et al., 2023). More efficient resource use, with intensity values below 50% during the observation period, was observed in the beverage industry sub-sector (ISIC 11) and the apparel industry sub-sector (ISIC 14). Meanwhile, other sub-sectors tended to fluctuate within the range of 22% to 66.8%.

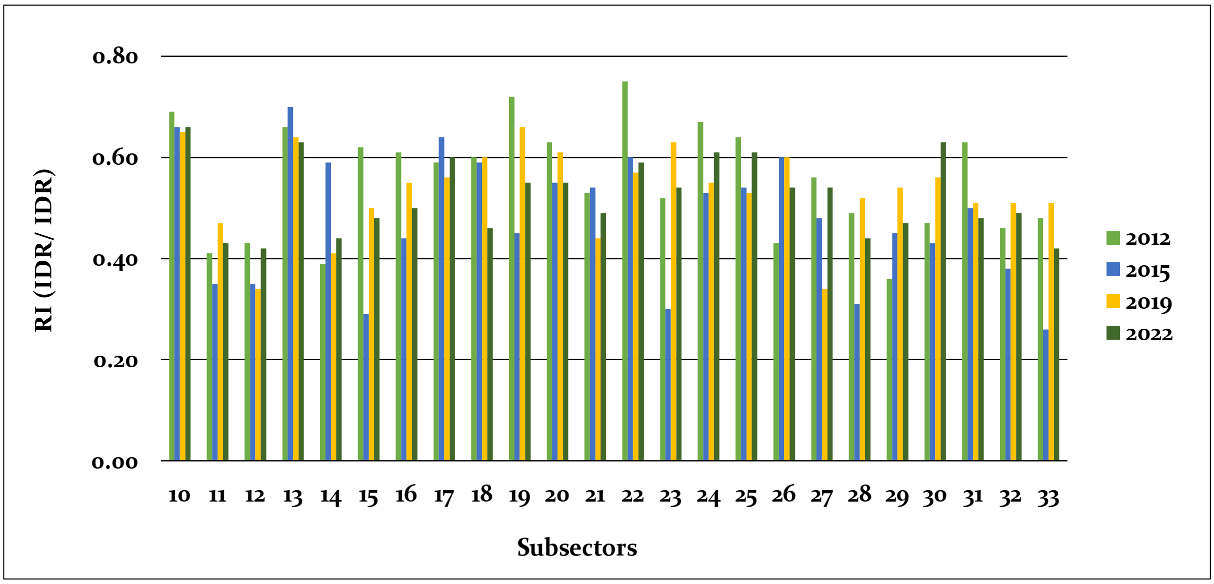

Figure 5. Resource use intensity in the manufacturing industry (2012-2022)

3.2.4. Value-added

The main objective of a business or activity is essentially to generate profit. In the manufacturing industry, such profit is obtained by increasing the value-added (VA) of a commodity. Value-added is defined as the increase in the value or price of a commodity through processing, transportation, or storage (The Fiscal Policy Agency, 2012). Therefore, value-added serves as an important indicator for assessing a company's success in implementing effective and efficient industrial management by maximizing output and minimizing input (reducing operational and investment costs) (Moesa, 2017).

The total value-added obtained by large and medium manufacturing industries from 2012 to 2022 tended to increase across almost all sub-sectors (Figure 6). Several sub-sectors experienced a decline in value-added in 2020 during the COVID-19 pandemic but recovered in 2021, such as the tobacco industry sub-sector (ISIC 12), the wearing apparel industry sub-sector (ISIC 14), and the leather, leather goods, and footwear industry sub-sector (ISIC 15). Some sub-sectors consistently dominated the highest annual value-added throughout the observation period. The food industry sub-sector (ISIC 10) had the highest total value-added compared to other sub-sectors. Even the COVID-19 pandemic did not significantly reduce the output produced by the food industry sub-sector, as evidenced by the continued increase in its VA value over the study years. This condition was driven by the larger number of business units in the food industry sub-sector compared to others. Other sub-sectors that also dominated and continued to experience increases in value-added were the chemicals and chemical products industry sub-sector (ISIC 20) and the basic metal industry sub-sector (ISIC 24). This indicates the presence of positive economic potential within these sectors.

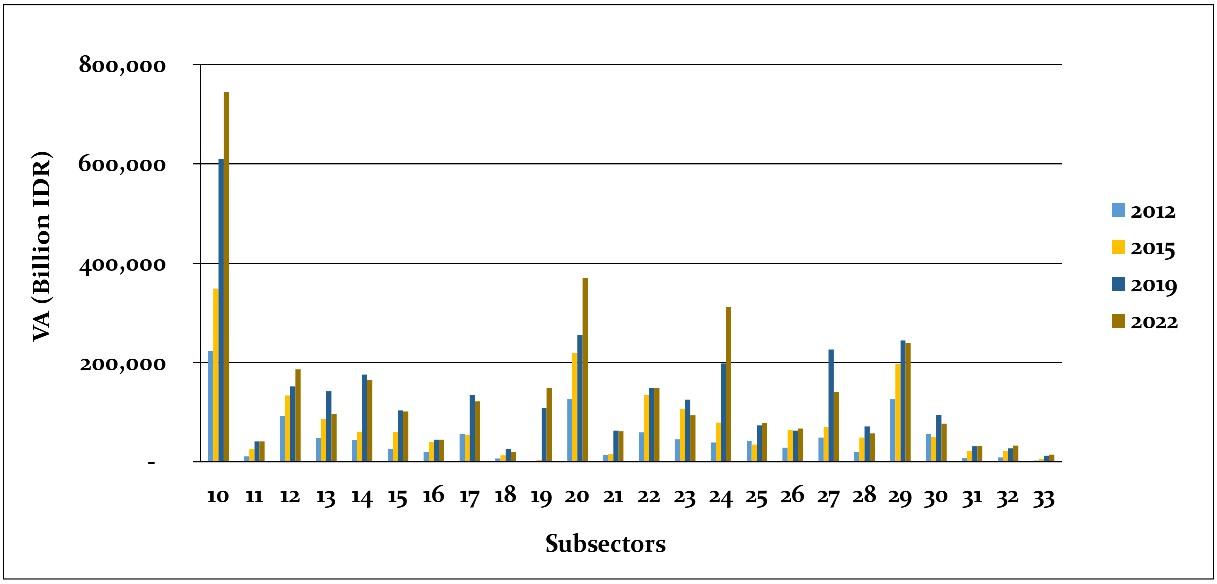

Figure 6. Value-added in the manufacturing industry (2012-2022)

3.2.5. GHG Intensity

Every economic activity generates waste or residues, including emissions. This study uses greenhouse gas (GHG) emission intensity (GHG-I), which indicates the amount of GHG emissions produced from fuel consumption per unit of output in each manufacturing industry sub-sector. A higher GHG-I indicates a less environmentally friendly industry, as it produces greater GHG emissions for every unit of output. In this context, GHG-I serves as a crucial indicator for evaluating the environmental performance of industrial activities, particularly in terms of energy efficiency and emission control. Lower GHG-I values reflect more efficient fuel use and cleaner production processes, which contribute to reducing the overall environmental impact of the manufacturing sector and support sustainable industrial development.

The GHG-I across subsectors is displayed in Figure 7. The GHG-I in the non-metallic mineral products industry sub-sector (ISIC 23) shows a different trend compared to other sub-sectors. Its value tends to increase and has become the highest among all sub-sectors in 2022. This condition is due to the relatively higher coal consumption in this sub-sector, which results in higher GHG emissions. One of the dominant industries in this sub-sector is the cement industry, which is known to be one of the most energy-intensive industries in Indonesia (Panjaitan et al., 2020). However, in general, Figure 7 shows that almost all manufacturing industry sub-sectors in Indonesia experienced a decline in GHG intensity. This result is in line with the overall economic conditions in Indonesia's manufacturing sector. Based on GDP and emissions data from Statistics Indonesia, although GDP tends to increase, emissions intensity has consistently declined, indicating that total emissions growth is smaller than GDP growth (Figure 8). Research by Prastiyo et al. (2020) also shows that Indonesia has passed the turning point phase of the Environmental Kuznets Curve (EKC) when viewed from the overall sector, which shows an increase in the rate of economic growth that has been accompanied by a decrease in the rate of emissions per capita.

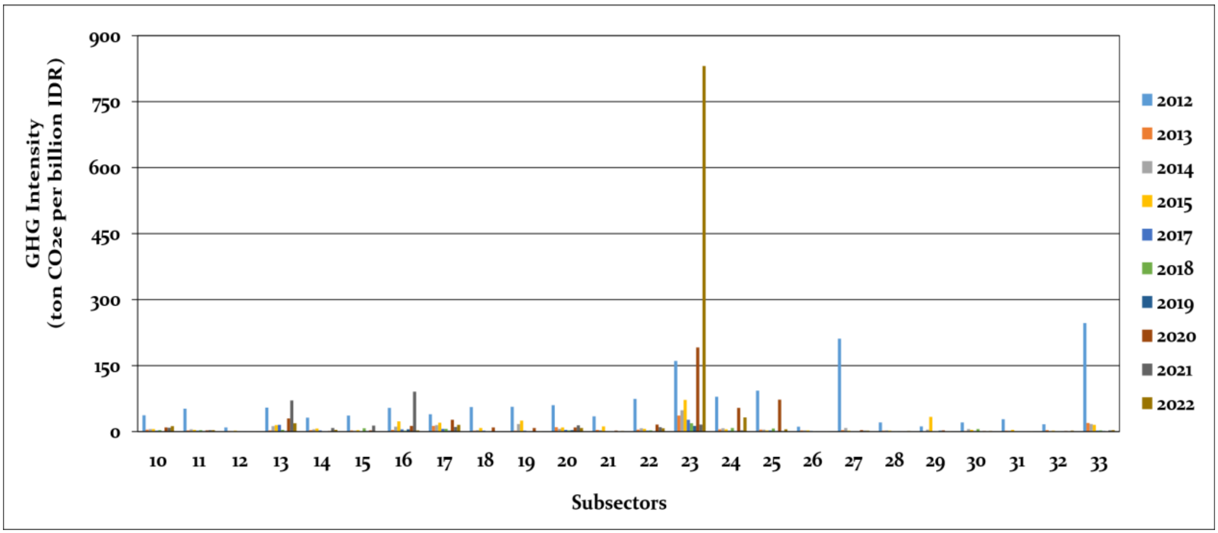

Figure 7. Greenhouse gas intensity in the manufacturing industry (2012-2022)

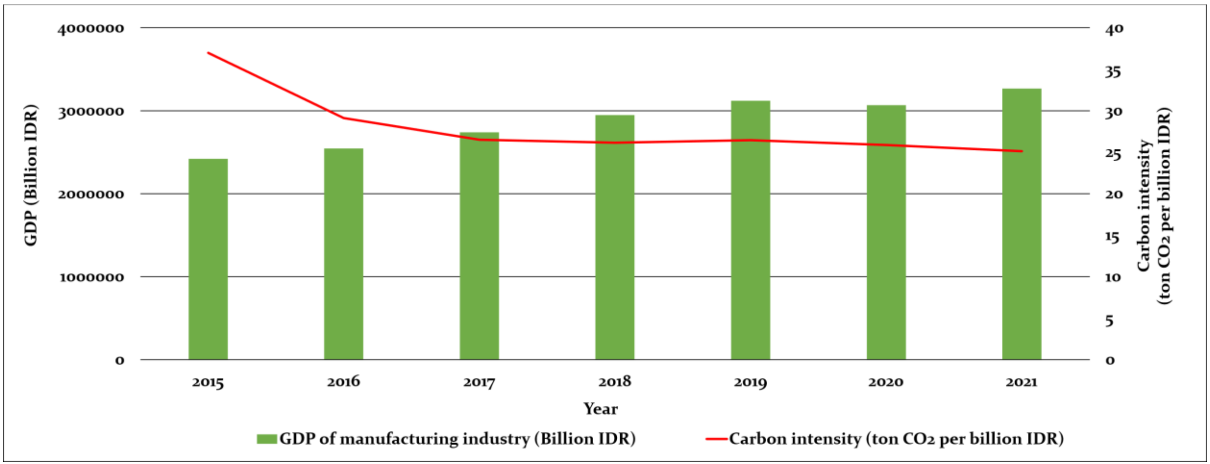

Figure 8. Comparison between gross domestic product and carbon intensity in the manufacturing industry

Indonesia's success in surpassing the EKC turning point indicates that the government has made progress in implementing GHG reduction strategies within the country's manufacturing industry. Some of these strategies include the energy mix policy outlined in the National Energy Plan (Government of Indonesia, 2017), the implementation of green industry standards that consider the availability of natural resources and/or environmental carrying capacity (Government of Indonesia, 2018), as well as environmental supervision, enforcement, and compliance programs.

3.3. The Effect of Economic Variables on GHG Emissions

Statistical data processing shows that the influence of economic variables on GHG emissions in the manufacturing industry can be observed using the fixed effect model (Table 7). The fixed effect model was chosen not only because the results of the Chow and Hausman tests support it, but also because, theoretically, this model is more suitable for studying manufacturing sub-sectors that have heterogeneous characteristics. Each industrial sub-sector has fundamental differences in terms of cost structure and energy intensity; therefore, it is assumed that there are fixed and unobserved individual effects. The estimation results using the fixed effect model can control sub-sector–specific factors that remain constant over time, allowing the analysis results to better reflect the pure influence of economic variables on GHG emissions. All independent variables, both jointly and partially, show a significant influence on the dependent variable. This indicates that changes in GHG intensity are not only affected by fossil fuel consumption, but are also influenced by the economic conditions of the manufacturing industry.

Table 7. Result of panel regression (fixed effect model)

Variable	β Coefficient	t-stat	p-value	Effect
ln MMI	0.0188117	2.15	0.033	Significantly positive
ln LI	0.6259126	9.82	0.000	Significantly positive
ln RI	-0.4019979	-4.15	0.000	Significantly negative
ln VA	-0.5379548	-12.37	0.000	Significantly negative

The modeling results show an R-squared value of 0.9008 with a significance level of 0.000. This indicates that 90.08% of the variation in GHG intensity can be explained by the independent variables of the model–the log form of fixed capital purchases, log of labor intensity, log of efficiency, and log of value-added–with the control variable being fossil fuel consumption. The p-values of all variables obtained are <0.05, indicating that the influence given is statistically significant and serves as evidence that all independent variables have a strong influence on GHG intensity.

Every 1% increase in the MMI will increase GHG-I by 0.018817%. This result is consistent with a study by Constantia (2022), who stated that this occurs because the incurred costs are spent on more complex machine repairs often found in industries that produce higher emissions.

A 1% increase in LI is followed by an increase in GHG-I by 0.6259126. The positive and significant relationship between labor intensity and GHG emissions indicates that labor-incentive subsectors tend to produce higher emissions (S. Zhang et al., 2023b). This increase occurs because rising labor costs reduce companies' investment in a greener production, such as environmentally friendly machinery or emission control devices (Li et al., 2023; M. Zhang et al., 2023).

In contrast to MMI and LI, a negative relationship was found between RI and GHG-I, with the value of the β Coefficient is -0.4019979. This finding shows that the role of input cost substitution, as the largest proportion of costs in the manufacturing industry often comes from raw materials rather than fossil fuels. In other words, higher input costs do not always correspond to increased energy consumption but rather reflect a stronger dependence on domestic raw materials. For example, in energy-intensive industries such as the basic metal industry (ISIC 24), the proportion of fuel costs ranged from 1.6% to 11.41% during the study period, while in the textile industry, it ranged from 3.35% to 15.7%. Hence, this finding should be interpreted with caution, as it may also indicate production inefficiency that is not directly reflected in emission levels, such as dependence on high-cost or imported raw materials, which happened in textile industries (Rohman et al., 2025). Moreover, material inefficiency and high operational and material handling costs can also affect production inefficiency (Indrawati and Ridwansyah, 2015).

A negative relationship is also found between VA and GHG-I, with the value of the β Coefficient is -0.537954. The decline in GHG-I as a result of increased VA illustrates that the economic development of Indonesia's manufacturing industry is generally in line with emission reduction programs, as discussed earlier. One of the factors is that some manufacturing industries in Indonesia have implemented Green Business Practices that involve the act of using efficient and renewable energy, as well as waste management. Textiles sub-sector (ISIC 13) and also chemicals and chemical products sub-sector (ISIC 19) are two industries that are highly adopting this concept as their operational activity produces huge environmental impacts (Wilana and Naryoto, 2024) Green Business Practices concept is also aligned with National Energy Plan programs by the Government of Indonesia, as it focuses on implementing the green industry standards. Other regions, such as Europe, have experienced similar conditions due to the implementation of renewable energy use, technological advancement, and energy efficiency (Fida and Saeed, 2023).

3.4. Emission Control Policies in the Manufacturing Industry

A significant relationship was found between MMI, RI, LI, and VA with GHG-I in the manufacturing industry. This finding provides evidence that emission control strategies in the manufacturing sector, from an economic perspective, are closely related to operational and human resource aspects. The cost structure in the manufacturing industry is highly dependent on several factors, such as optimizing machine performance, increasing labor productivity, and resource-efficient utilization. Interventions at the input and production process levels are very important in reducing GHG emissions.

Based on the findings of this study, increasing value-added, accompanied by increasing production volume and maintaining minimal energy consumption, can reduce GHG intensity. Therefore, the appropriate program to implement is energy efficiency. Energy efficiency refers to the optimal use of energy to increase productivity, reduce costs, and minimize waste production. Those benefits can be achieved through the adoption of energy-efficient machines and the implementation of efficient and effective production systems. Energy efficiency also contributes to economic growth by reducing input costs in fuel consumption, which then generates long-term profits and strengthens industrial competitiveness (Marchi et al., 2017).

Furthermore, high machine maintenance intensity also tends to result in high GHG intensity. For this, the implementation of Sustainable Maintenance Practice (SMP) is a program worth considering. The principle of SMP lies in better machine maintenance, not only targeting operational and technical functions, but also scooping socio-economic and environmental aspects, including emissions (Orošnjak et al., 2025). The use of appropriate technology is also important, as it enables lower maintenance costs and ensures that machines operate optimally and produce minimal emissions (Madreiter et al., 2024).

Labor productivity is also a key factor in emission reduction, especially for countries with large populations like Indonesia (Bangun, 2017). The increasing number of workers, which in turn increases the expenditure for the manufacturing industry, is expected to contribute significantly to value-added. Several programs can be applied, such as human resource development programs that focus on training to improve leadership skills, employee commitment, performance, and financial resource management (Farrukh et al., 2019). Labor-intensive industries, according to several studies, tend to be industries that do not utilize mechanization in their equipment, thus requiring greater energy in their production processes. However, this strategy cannot rely solely on the operational aspect; it must be supported by improvements in human resource capacity so that workers become more prepared and understand the urgency of resource and environmental management (Brüggemann et al., 2019; Büth et al., 2018).

Government policy also plays a key role in the success of emission reduction efforts from the economic side. One strategy that can be implemented is providing economic incentives for industries that are committed to or have undertaken carbon reduction efforts. However, Indonesia's particular regulation that clarifies the technical regulation of economic incentives for emission reduction in the industrial sector has not yet been implemented. Existing initiatives, such as The Green Industry Standard and the Green Industry Award, do not specifically provide fiscal incentives.

Incentives may be offered in the form of capital subsidies—such as for purchasing energy-efficient machinery or air pollution control facilities—or through tax reduction policies (Wang et al., 2021; Q. Zhang et al., 2023). This government intervention is important because the primary focus of a business is to maximize profits; therefore, environmental costs should be considered as an opportunity to add value to the products they produce rather than a financial burden (Sari, 2023; Wicaksono, 2024). Government subsidies are expected to increase the internalization of environmental costs by companies and foster sustainable economic activity (Hibiki, 2024; Wang et al., 2025).

4. Conclusions

The results of the study indicate that overall, economic performance in the Indonesian manufacturing industry tends to improve, as evidenced by increased value-added and decreased labor intensity. However, resource intensity also increases, accompanied by considerable variation in machine maintenance intensity, although it does not show the highest or lowest concentration in a particular subsector. The results of panel data regression using a fixed-effect model show that machine maintenance intensity and labor intensity have a positive and significant relationship (β = 0.0188117; 0.6259126) with GHG intensity, while the variable resource intensity and value-added have a negative and significant relationship (β = −0.4019979; −0.5379548) with GHG intensity. These findings show that emissions from the manufacturing industry in Indonesia are currently determined not only by fuel or energy consumption, but also by economic factors. Interventions in input and production process aspects—such as energy efficiency, sustainable maintenance practices, and improvement of labor capacities—are key strategies for controlling GHG emissions in the manufacturing industry. These strategies can be implemented together with fiscal policy interventions, such as subsidies for environmentally friendly production equipment and incentives for industries implementing energy efficiency efforts, to strengthen the performance of environmentally friendly industries. Further research is recommended to analyze emission projections under various scenarios, considering policy interventions that can be implemented in Indonesia. Such work can include more datasets, such as projections of economic growth, production output, policy interventions, and cost-benefit analysis, to enable a more comprehensive assessment of industrial emissions.

Acknowledgement

This research was supported by a publication grant from the Center for Environmental Study, Universitas Gadjah Mada, number 1225/UN1/PSLH/HK.08.00/2025, which contributed to the implementation and completion of this study. The authors gratefully acknowledge this support.

Ethnic Statement

The authors of this article did not perform any studies with human participants.

CRediT Author Statement

Annisa Ayu Fawzia: Conceived and Designed Analysis, Collected Data, Contributed and Analysis Tools, Performed Analysis, Wrote Paper, Formatting. **Aulia Valerie Fawzia:** Collected Data, Contributed and Analysis Tools, Economic Analysis, Wrote Paper. **Emilya Nurjani:** Theoretical guidance, Wrote Paper. **Benarifo Ahmada:** Industrial analysis, Wrote Paper.

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