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The Dynamic of Economic Growth, Manufacturing, FDI, and Carbon Emissions: A Vector Error Correction Model Analysis

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Abstract: By increasing environmental issues related to climate change, there is a need for studying the impacts of economic growth, manufacturing, and foreign direct investments on carbon emissions in rapidly growing countries such as Indonesia. This paper studies the dynamic impacts of economic growth, manufacturing, FDI, and carbon emissions in the period of 1994-2023 using Vector Error Correction Model (VECM). Unit root, cointegration and Granger causality tests are used in this paper to investigate both equilibrium relationships and dynamic impacts. The findings of this paper show the existence of significant cointegration relationship among the variables. Economic growth negatively affects carbon emissions in both the short and long run, which shows that economic growth leads to better environmental conditions. On the other hand, manufacturing positively affects carbon emissions in both the short and long runs, and FDI has a positive effect on carbon emissions in both the periods, which suggests that the growth of industries and FDI is still being done in carbon-intensive sectors. These findings suggest that sustainable economic growth requires greening of industries and strict environmental policies.

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INTRODUCTION

Indonesia has experienced very quick industrialization over the last ten years because of its manufacturing industry growth, mineral processing, infrastructure development, and foreign investments. The process has helped the economy to grow quickly, improve export competitiveness, and provide jobs (Akbar et al., 2025; Surya et al., 2021). Nevertheless, because of industrial activities, the country's energy needs have increased, mostly in terms of fossil fuel utilization, which contributed to high CO_2 emissions. In 2023, Indonesia became the leader in CO_2 emissions among all ASEAN states. The aforementioned factors indicate that there is a great need for finding a balance between the development of the industrial sector and environmental protection through the adoption of cleaner production techniques, alternative energy sources, and CO_2 emissions reduction strategies.

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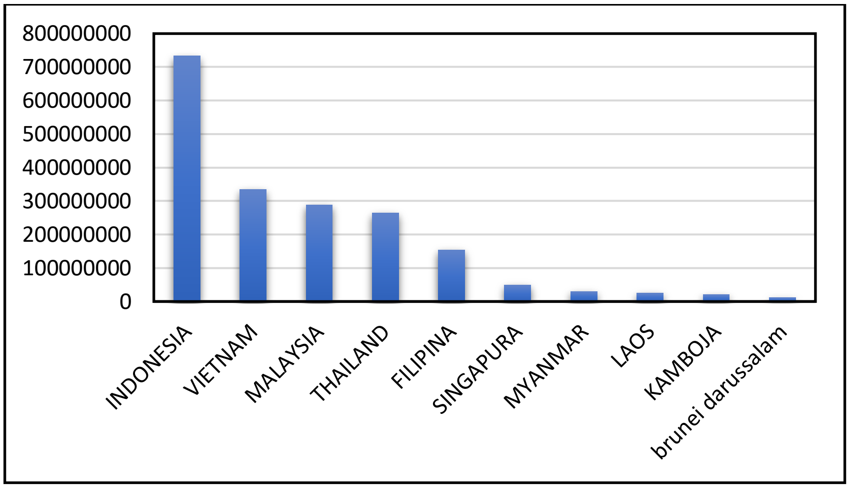

Figure 1. Tren Carbon Dioxide in ASEAN Countries 2023 (tones)
Source: data process (2026)

Figure 1 shows carbon dioxide (CO_2) emissions in ASEAN nations for 2023, showing large differences in terms of CO_2 emissions. Indonesia had the largest amount of CO_2 emissions of all nations, with emissions of 733.2 million metric tons, compared to the second largest nation, Vietnam, which had 334.7 million metric tons of emissions. Malaysia and Thailand were also major contributors with 288.8 million metric tons and 264.4 million metric tons of CO_2 respectively, while Brunei Darussalam showed the lowest CO_2 emissions with 11.8 million metric tons. The large emissions of Indonesia can be attributed to the large population size, extensive industries, fast economic growth rate, and use of fossil fuels.

A close link between economic growth and carbon emissions is one of the topics to consider in environmental economics due to the occurrence of a negative environmental externality. There can be costs incurred to the environment in the processes of economic production, which might be overlooked in the prices set, thus causing a social cost in the form of carbon emissions. The concept of the Environmental Kuznets Curve (EKC) adds another perspective to the issue as it implies that there will be deterioration in the state of the environment in the early stages of economic development, whereas it will improve in the late stages thanks to improved technology and policies (Ahmed et al., 2023; Khan et al., 2022; Oprea et al., 2025). Economic growth in developing countries is often associated with the rapid growth in manufacturing along with increased FDI flows, which will increase the capabilities of production, industrial output, and employment. Growth in manufacturing, caused by FDI, is the main catalyst of economic growth via the increased rate of industrialization and diffusion of technologies. Still, the increase in industrial activity increases energy consumption, which involves the use of fossil fuels, thus causing additional greenhouse gas emissions and rising CO_2 levels. Intensive industry causes climate change, degradation of ecosystems, and low environmental quality. Empirical studies conducted recently imply that the pollution haven hypothesis will become strengthened by FDI as it attracts highly polluting industries to the states with weaker environmental regulations, thus causing more carbon emissions in the early stages of economic development (Wencong et al., 2023).

Economic growth, industrialization, and FDI are well known to be leading causes of carbon emission because all these elements have impacts on production, energy consumption, and industrialization (Miah et al., 2025; Nguyen et al., 2026). Fast economic growth increases demand for products and services, whereas industries consume huge amounts of energy, mostly from non-renewable energy sources. Likewise, FDI promotes industrialization through increasing production capacity and other infrastructure. Hence, it becomes clear that the above-mentioned factors are strongly linked to carbon emissions.

There exists a direct correlation between industrial development and increased carbon emissions, since industrial activities require high energy usage, which in most cases is generated from fossil fuels. With an increase in manufacturing output, more energy is used, more fuel burnt, and the manufacturing process increases, hence causing the emission of more greenhouse gases (Hoa et al., 2024; Qiao et al., 2024; Yamaka et al., 2021). This is because the uncontrolled growth of manufacturing without any use of cleaner technology may cause environmental degradation through air pollution and climate change. Cement industries, steel, chemical industries, petroleum refineries, and pulp and paper factories are some of the main sources of carbon emissions from industrial processes due to their high energy usage.

FDI acts as an important tool that drives economic development and industrialization in developing countries such as Indonesia. However, higher levels of FDI will increase carbon emissions especially if they are directed towards industries which are both energy intensive and pollution intensive (Adekunle et al., 2026). In general, developing countries have plenty of natural resources, cheaper labor, and weaker environmental regulation policies, making them good locations for the carbon intensive production process. This explains the Pollution Haven Hypothesis theory. According to this theory, multinational corporations relocate their polluting production processes to nations with relaxed environmental regulations (Esmaeili et al., 2023). Therefore, while FDI enhances economic development and industrialization, it increases the use of fossil fuels and environmental degradation.

While there is no shortage of literature on the interplay between carbon emissions and economic determinants in Indonesia, there is still limited information available that is conclusive in nature. The reason for this phenomenon may be attributed to the fact that previous literature has focused on the impact of economic growth, manufacturing development, and foreign direct investments separately. Because Indonesia is undergoing an industrial revolution, being the largest carbon emitter in the ASEAN region, it becomes crucial for an analysis of the combined impact of these variables to be conducted. Such an analysis will help in getting a better insight into the trade-offs between economic growth, manufacturing, FDI, and environmental sustainability. Past studies present a mixed set of results: one set of results suggests that economic growth positively impacts carbon emissions Miah et al. (2025) report that economic growth positively affects carbon emissions in both the short and long term, while others Hoa et al. (2024) suggest that economic growth can reduce carbon emissions. Yang et al. (2021) find that manufacturing increases carbon emissions. Regarding the environmental impact of FDI, Pradhan et al. (2021) found that FDI inflows improved environmental quality by reducing degradation, challenging the pollution haven hypothesis. Similarly, Qamri et al. (2022) concluded that the pollution haven hypothesis does not apply in Asian economies, indicating that increased FDI inflows can promote economic development without necessarily worsening environmental degradation.

This research seeks to explore the contribution of economic growth, manufacturing industry development and foreign direct investment in generating carbon emissions in Indonesia. The use of Vector Error Correction Model (VECM) in this research is informed by the existence of cointegration of variables that implies a long-run equilibrium relationship. The VECM model takes care of the short-run and long-run dynamics as well as correcting any disequilibrium using the error correction term. This methodology will allow a complete analysis of the interaction between economic growth, manufacturing, foreign direct investment (FDI) and carbon emissions. Besides, the outcomes of the research will not only be of benefit to academic literature but also will give valuable information to policy makers to find a balance between economic development and the protection of environment. Being aware of the important role of the interplay of these variables will be critical as Indonesia develops its manufacturing industry while facing increasing demands to reduce greenhouse gases emission.

RESEARCH METHOD

In this study, a quantitative research design using time-series data (secondary data) will be used that will be extracted from the World Bank, UNCTAD, and WDI databases. The data for the period of 1994-2023 will be analyzed and the country of study will be Indonesia. In total, four dependent variables are included in the analysis: CO_2, GDP, MNC, and FDI. Carbon emissions are measured in metric tons. Economic growth is captured through GDP in terms of constant 2015 US dollars (constant 2015 US$). Manufacturing will be measured through added manufacturing value, also in terms of constant 2015 US dollars (constant 2015 US$). Foreign direct investments will be estimated as net FDI inflows, Balance of Payments (BoP), measured in current US dollars (current US$). All variables have been collected from official international databases to provide reliable and consistent empirical analysis. Vector Error Correction Model (VECM) is applied in the research as a main analytical method. The reason why it is suitable for this paper is that it can capture both the short-term dynamic and long-run equilibrium relationship between endogenous variables as well as their interaction without making any predetermined assumptions about direction of causality (Giannone et al., 2015; Guay & Pelgrin, 2023). The vector error correction model will be specified as follows:

$$\Delta CO2_t = \sum_{i=1}^{p-1} \beta_i \, \Delta CO2_{t-i} + \sum_{i-1}^{p-1} \gamma_i \, \Delta GDP_{t-i} + \sum_{i-1}^{p-1} \gamma_i \, \Delta MNC_{t-i} + \sum_{i-1}^{p-1} \delta_i \, \Delta FDI_{t-i} \, \emptyset ECT_{t-1} + \varepsilon_t \ldots\ldots\ldots\ldots (1)$$

Where Δ is the first differential operator, α is a constant, βi,γi,δi are short run coefficients, ECT_{t-1} is the error correction term (from the cointegration results), ϕ is the adjustment coefficient towards long-run equilibrium and ε_t is the error term. The strong point for VECM estimation is the coefficient of the error correction teonem ($\emptyset ECM_{t-1}$). The error correction model was used to measure the speed of adjustment.

The next stage consisted of determining the optimal lag length by applying several model selection criteria: the Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), and Hannan–Quinn Information Criterion (HQ). The optimal lag was selected based on the criterion that received the strongest overall support. Once the appropriate lag structure was established, the stability of the vector autoregression (VAR) model was assessed using the inverse roots of the autoregressive (AR) characteristic polynomial. The use of this diagnostic test ensured that all the characteristic roots lie within the unit circle; hence, the stability of the model was achieved. This made the IRF and FEVD analysis credible.

The VECM formulation is correct if the stability assumption holds true for the VAR process from which the model is formulated. As per the test proposed by Fokianos et al. (2022), the condition for stability will hold true if the characteristic roots are such that their moduli are less than one. From the stability test results, it was established that all the roots are within the unit circle, implying dynamic stability of the estimated VAR model. The Johansen cointegration test results reveal that the trace statistic values are greater than those of the 5% critical values, thereby implying at least one cointegration relationship between the variables. This outcome shows that the long run equilibrium is there, hence, making it possible to use the VECM to estimate the short- and long-term dynamics. Granger causality tests will be done to identify the causality direction between economic growth, manufacturing, foreign direct investment and carbon emissions. Impulse response function will be estimated to determine the nature, direction, and persistency of the response of the variables in relation to innovations of other variables. Forecast Error Variance Decomposition (FEVD) will also be undertaken to find out the portion of forecast error variance that is due to innovations of each endogenous variable. All empirical analysis will be done with the help of STATA 17 software.

RESULTS AND DISCUSSION

Data Stationary Test Result

However, before the estimation of the empirical model, it is necessary to verify the stationarity of all the variables in order to avoid any biased results from the regression. Unit roots in panel data cause inconsistency and incorrect statistical inference since the variables can display trend behavior through time. Therefore, in order to solve the problem, a stationarity test was conducted in order to determine the order of integration of the variables under consideration. The Augmented Dickey Fuller (ADF) unit root test was employed in order to verify the stationarity of the variables. The findings of the test are summarized in Table 1.

Table 1. Stationary Test Result

Variables	Stationery Test				Stationer
	ADF Statistic				
	Level	Prob	First Diff	Prob	
CO2	0.292	0.9770	-7.393	0.000	First Difference
GDP	1.609	0.9979	-4.220	0.000	First Difference
MNC	1.126	0.9954	-4.634	0.001	First Difference
FDI	-1.450	0.5580	-7.450	0.000	First Difference

Source: Data processed (2026)

The outcome of the Augmented Dickey Fuller test reveals that all variables (CO2, GDP, MNC and FDI) are non-stationary at their levels (p-value>0.05), but stationary after first difference (p-value<0.05). It shows that all variables are integrated of order one (I(1)). Therefore, the Johansen cointegration test was conducted to ascertain the type of model that will be used; either Vector Error Correction Model (VECM) if there is cointegration, or Vector Autoregressive model (VAR) if there is no cointegration.

Lag Optimum

Lag length was obtained using different criteria, namely Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criteria (AIC), Schwarz Bayesian Information Criteria (SBIC), and Hannan-Quinn Information Criteria (HQIC). The lag length chosen by most of the above criteria was deemed to be the one most suited to model estimation. From Table 2 below, the smallest value in each criterion has been put into an asterisk (*) indicating the most favorable lag length. Since most of the criteria chose lag 1 as the best, the latter was chosen for further analysis.

Table 2. Determining Lag Optimum

Lag	LR	FPE	AIC	HQIC	SBIQ
0	-	3.4e+56	141.514	141.574*	141.701*
1	23.086	4.6e+56	141.811	142.11	142.745
2	32.534	4.8e+56	141.794	142.331	143.475
3	47.063	3.5e+56	141.291	142.060	143.72
4	44.795*	3.2e+56*	140.865*	141.881	144.041

Source: Data processed (2026)

The above table illustrates the optimal selection of lags in accordance with the criteria of LR, FPE, AIC, HQIC, and SBIC. Lag 4 is selected as optimal in accordance with LR (44.795), FPE (3.2 x 1056), and AIC (140.865). However, in accordance with HQIC (141.574) and SBIC (141.701), lag 0 is selected as optimal. Lag 4 is selected because several criteria recommend its selection. It makes it possible to incorporate the dynamic relationship between D(CO2), D(GDP), D(MNC), and D(FDI). Stability of the VECM model is verified through checking the inverse roots of the AR characteristic polynomial. In accordance with Fokianos et al. (2022), VECM system can be regarded as stable (stationary) if the modulus of each root is less than one. As follows from the stability test results represented in Table 4, the modulus of all characteristic roots is less than one, having the maximum value equal to 0.976345. The results obtained prove the fact that the VECM model satisfies the requirements concerning stability and stationarity.

Table 3. Stability Test Results

Root	Modulus
.9763448	.976345
.7087796 - .5549554i	.900191
.7087796 - .5549554i	.900191
-.1043232 + .8890624i	.895162
-.1043232 - .8890624i	.895162
-.8623406	.862341
.839107 + .1371627i	.850244
.839107 - .1371627i	.850244
-.7305301 + .324036i	.799171
-.7305301 - .324036i	.799171
.5111269 + .6040289i	.791266
.5111269 - .6040289i	.791266
.1270278 + .6121948i	.625235
.1270278 - .6121948i	.625235
-.3788925 + .4013142i	.551917
-.3788925 - .4013142i	.551917

Source: Data processed (2026)

Cointegration Test

The Johansen cointegration test determines whether the time series variables have an equilibrium relationship in the long run. The existence of cointegration is verified by the fact that the trace statistics are higher than the critical value at the 5% level.

Table 4. Johansen Cointegration Test Result

Hypothesized	Eigenvalue	Trace Statistic	Critical Value (5%)
0	NA	86.9236	47.21
1	0.71646	49.1113	29.68
2	0.66057	16.6967	15.41
3	0.36510	3.0681*	3.76
4	0.09722		-

Source: Data processed (2026)

The results of Johansen cointegration test on the variables carbon emissions, economic growth, manufacturing and foreign direct investment are provided in Table 4. The values of trace statistics of the first three cases, which are 86.9236, 49.1113 and 16.6967, are greater than their corresponding 5% critical values, so that the null hypothesis of no cointegration is rejected. However, the value of the fourth trace statistic is smaller than its 5% critical value; hence, the null hypothesis cannot be rejected.

Engel Granger Causality Test

The Engle-Granger causality test was applied in assessing the causal relationships that exist between D(CO2), D(GDP), D(MNC) and D(FDI). It is a statistical method that indicates whether one variable can be used to predict the other. From Table 5, it is evident that there exists Granger causality between the variables at 5% level of significance. The Granger Causality test determines the effects of economic growth (D(GDP)), multinational corporations (D(MNC)) and foreign direct investment (D(FDI)) on carbon emissions (D(CO2)), and whether carbon emissions affect the other variables.

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Table 5. Engel-Granger Causality Test Results

Null Hypothesized	chi2	Prob
D (CO2) influenced by D (GDP)	102.17	0.000
D (CO2) influenced by D (MNC)	93.513	0.000
D (CO2) influenced by D (FDI)	42.599	0.000
D (CO2) influenced by D (GDP), D (MNC), D (FDI)	146.15	0.000
D (GDP) influenced by D (CO2)	8.617	0.071
D (GDP) influenced by D (MNC)	22.543	0.000
D (GDP) influenced by D (FDI)	10.787	0.029
D (GDP) influenced by D (CO2), D (MNC), D (FDI)	44.814	0.000
D (MNC) influenced by D (CO2)	16.171	0.003
D (MNC) influenced by D (GDP)	28.984	0.000
D (MNC) influenced by D (FDI)	18.897	0.001
D (MNC) influenced by D (CO2), D (GDP), D (FDI)	67.159	0.000
D (FDI) influenced by D (CO2)	5.3923	0.249
D (FDI) influenced by D (GDP)	9.5529	0.049
D (FDI) influenced by D (MNC)	9.2396	0.255
D (FDI) influenced by D (CO2), D (GDP), D (MNC)	23.699	0.022

Source: Data processed (2026)

Table 5 provides the Engel-Granger causality test results that show significant causal relationships between carbon emissions, economic growth, manufacturing activity, and foreign direct investments. The economic growth, manufacturing activities, and foreign direct investment all significantly affect carbon emissions individually and jointly ($p < 0.01$). This means that these variables play a considerable role in affecting environmental quality. The economic growth is significantly affected by manufacturing activities and foreign direct investments, but carbon emissions have a marginal effect on it at the 10% level of significance. The manufacturing activities are significantly affected by carbon emissions, economic growth, and foreign direct investments, demonstrating a significant dependence of industrial development on macroeconomic conditions. The foreign direct investments are significantly affected by economic growth and the joint impact of carbon emissions, economic growth, and manufacturing activities, but not the individual impact of carbon emissions and manufacturing activities on it.

VECM Estimation

The results of the short-run estimation of the VECM are provided in Table 6, focusing on the impact of changes in GDP, MNC, and FDI on carbon emissions D(CO2). According to the results, the error correction term is negative and statistically insignificant. This implies that carbon emissions do not make an adjustment towards long-run equilibrium following short-run changes.

Table 6. Short-Run Estimation Result

Variable	` Coeff.	Std. Error	z	p-value	Significance
ECT (-1)	-2.365789	.4685149	-5.05	0.000***	Significant
D (CO2 (-1))	.7371596	.3533728	2.09	0.037**	Significant
D (CO2 (-2))	.162942	.2400994	0.68	0.499	Not significant
D (CO2 (-3))	-.0061997	.1378427	-0.04	0.964	Not significant
D (GDP (-1))	-963840.1	204125.7	-4.71	0.000***	Significant
D (GDP (-2))	-103607.3	254251.6	-0.43	0.666	Not significant
D (GDP (-3))	-279697.2	202639.7	-1.36	0.175	Not significant
D (MNC (-1))	.0185785	.0039612	4.69	0.000***	Significant
D (MNC (-2))	.0009162	.0052018	0.18	0.860	Not significant
D (MNC (-3))	.0037028	.0042417	087	0.383	Not significant

Variable	` Coeff.	Std. Error	z	p-value	Significance
D (FDI (-1))	.0053436	.0011937	4.48	0.000***	Significant
D (FDI (-2))	.004749	.0010675	4.45	0.000***	Significant
D (FDI (-3))	.0018056	.0007639	2.36	0.018**	Significant
Constant	26557.4	3081313	0.01	0.993	Not significant

Notes: ** = *** p<0.01, ** p<0.05, * p<0.10
Source: Data processed (2026)

Short-term dynamics are modeled using the error correction form of the Vector Error Correction Model (VECM) whereby the first difference of every endogenous variable is modeled based on the error correction term and first difference of all endogenous variables. The short-run equation is given below:

$$\begin{aligned} D(CO2) \;\; = & -2.365789\mathrm{ECT}_{t-1} + .7371596\mathrm{D(CO2)}_{t-1} \\ & + .162942\mathrm{D(CO2)}_{t-2} - .0061997\mathrm{D(CO2)}_{t-3} - 963840.1\mathrm{D(GDP)}_{t-1} \\ & - 103607.3 - 279697.2\mathrm{D(GDP)}_{t-3} + .0185785\mathrm{D(MNC)}_{t-1} + .0009162\mathrm{D(MNC)}_{t-2} \\ & + .0037028\mathrm{D(MNC)}_{t-3} + .0053436\mathrm{D(FDI)}_{t-1} + .004749\mathrm{D(FDI)}_{t-2} \\ & + .0018056\mathrm{D(FDI)}_{t-3} \end{aligned}$$

The calculated short run VECM indicates that carbon emission depends on the effect of short run and long run dynamics. The value of the error correction term (ECT) is negative and statistically significant (−2.365789; $p < 0.01$). The coefficient indicates that about 236.58% of short-run disequilibrium is corrected within one period, reflecting a rapid return to equilibrium. Carbon emissions are persistent, as the first lag of (D(CO2)) is positive and significant (0.7372), meaning previous increases tend to continue. Economic growth ($D(GDP)_{t-1}$) has a significant negative effect on carbon emissions, so higher short-run economic growth is linked to lower emission growth. In contrast, manufacturing activity ($D(MNC)_{t-1}$) and foreign direct investment ($D(FDI)_{t-1}$, $D(FDI)_{t-2}$, $D(FDI)_{t-3}$) significantly increase emissions. The other lagged terms are statistically insignificant, indicating limited short-run effects.

Table 7. Long-Run Estimation Result

Variable	` Coeff.	Std. Error	z	p-value	Significance
D(GDP)	-281851.8	70798.7	-3.98	0.000***	Significant
D(MNC)	.1149622	.0016667	2.98	0.003***	Significant
D(FDI)	.0023245	.000748	3.11	0.002***	Significant
Constant	-2.30e+07				

Source: Data processed (2026)
Notes: ** = *** p<0.01, ** p<0.05, * p<0.10

The VECM is formulated based on the estimated long-run cointegrating relationship among carbon emissions (CO_2), economic growth D(GDP), manufacturing activity D(MNC), and foreign direct investment D(FDI). By normalizing the cointegrating vector on carbon emissions D(CO2) = 1, the long-run equilibrium equation can be expressed as follows:

$$D(C02) = -2.30x10^7 - 281851.8D(GDP) + 0.1149622D(MNC) + .0023245D(FDI)$$

Table 7 presents the long-run cointegrating equation that defines the equilibrium relationship among carbon emissions (D(CO2)), economic growth (D(GDP)), manufacturing activity (D(MNC)), and foreign direct investment (D(FDI)). The results indicate that all three variables have significant long-term effects on carbon emissions. Economic growth is associated with a negative coefficient, indicating that sustained growth reduces carbon emissions, likely due to technological progress, improved energy efficiency, and stronger environmental management. In contrast, manufacturing activity and foreign direct investment both have positive coefficients, suggesting that industrial expansion and increased investment inflows raise carbon emissions, likely through higher energy use and production intensity.

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It is clear that the results indicate that economic growth reduces environmental degradation, whereas production activities and FDI raise carbon emissions.

Impulse Responds Function

As shown by the Impulse response analysis, the effects on carbon emissions of shocks to the explanatory variables. These include economic growth D(GDP), manufacturing D(MNC), and foreign direct investments D(FDI). The Impulse response function shows the effects on carbon emissions aftershocks to each of the explanatory variables. An increase in carbon emissions means that there is an increase in D(GDP).

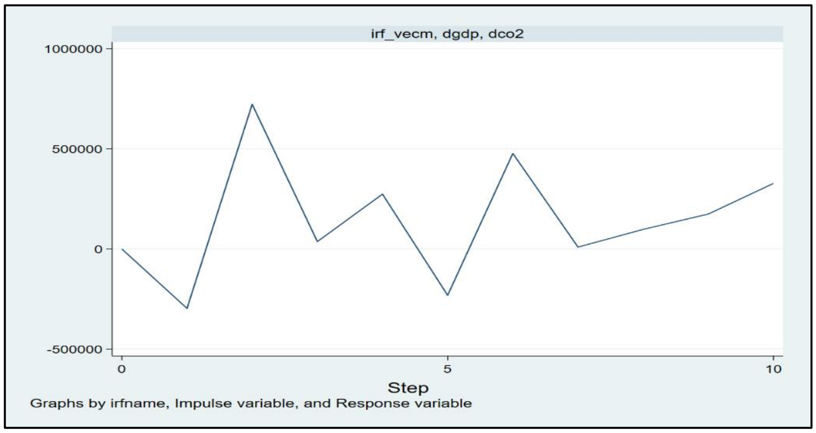

Figure 2. IRF D(GDP) to D(CO2)
Source: data process (2026)

Impulse response function (IRF) illustrates the reaction of carbon emissions to a shock in economic growth of one standard deviation for a period of ten intervals. Carbon emissions decrease in the first interval, implying a transient negative effect. For the second interval, the response turns very positive, suggesting that economic growth spurs activity that emits more carbon into the environment. For subsequent intervals, the response fluctuates, demonstrating short-run instability in the effect of economic growth on carbon emissions. At the end of the forecast horizon, the response becomes positive but lower, signifying that economic growth shock triggers a lasting but stabilizing positive response in carbon emissions.

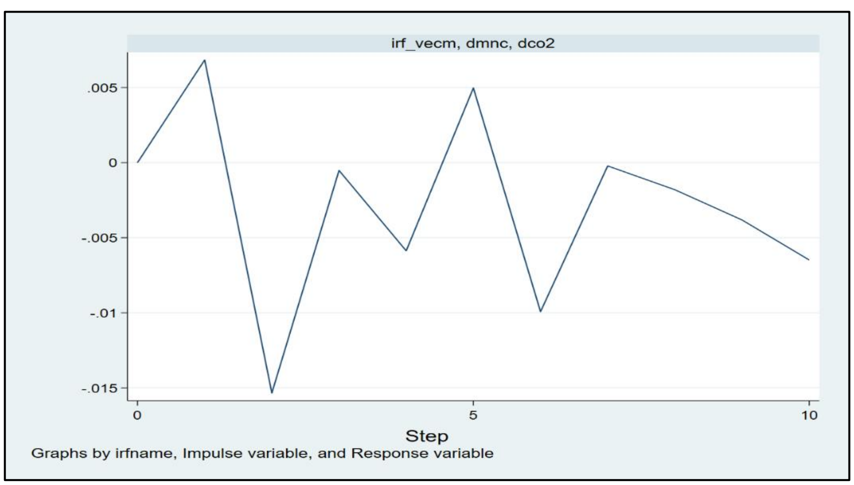

Figure 3. IRF D(MNC) to D(CO2)
Source: data process (2026)

Impulse Response Function is provided in Figure 3, which demonstrates the dynamics of carbon emissions' reaction to one standard deviation of manufacturing activities during ten periods. Carbon emissions go up during the first period, which means that there is an instant increase after a manufacturing shock. Then, the response goes down and changes sign from positive to negative and vice versa until the end of the forecast horizon. Such dynamics show that the short-term relationship between manufacturing activities and carbon emissions is unstable due to constant adjustments in industrial output and energy consumption. During the last periods, the response stays negative, which suggests that manufacturing shocks lose their influence and approach the long-run equilibrium.

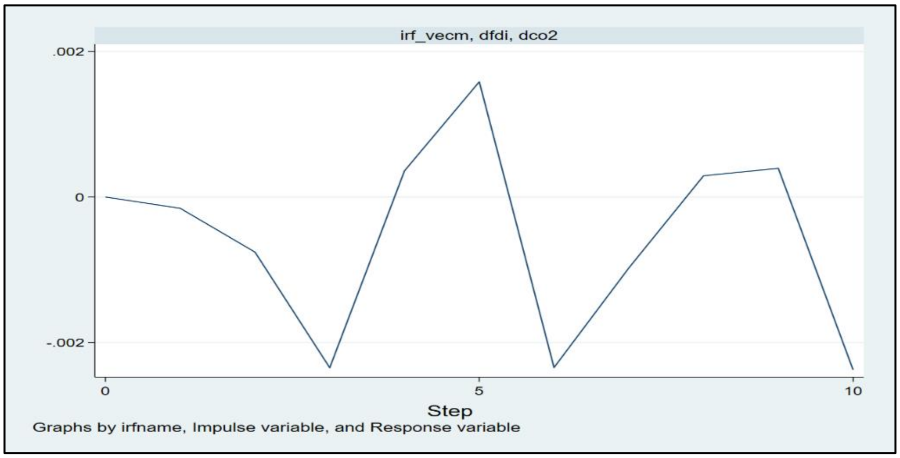

Figure 4. IRF D(FDI) to D(CO2)
Source: data process (2026)

The graph presented in Figure 4 captures the reaction of carbon emissions to an increase by one standard deviation of foreign direct investments over a period of ten intervals. There is an initial dip in the response because an increase in investments does not cause emissions to rise. The response is minimized at the third interval and subsequently increases positively until it peaks at the fifth interval. This suggests a delayed effect on the environment. In the subsequent intervals, the response becomes inconsistent due to the short-term dynamics of investments and production.

Forecast Error Variance Decomposition

The Forecast Error Variance Decomposition (FEVD) method provides a complement to the impulse responses analysis through measuring the contribution of each endogenous variable in the forecast error variance of D(CO2) at various forecasting horizons. Table 10 indicates that the variance of D(CO2) is basically driven by its own shocks over the forecasting period. In the beginning, 100 percent of the forecast error variance comes from the shocks of D(CO2), demonstrating the high persistence of carbon emissions. The effect of other variables increases over time, but carbon emissions continue to be the main determinants of their variance.

Tabel 8. Forecast Error Variance Decomposition (FEVD)

Step	D(CO2)	D(GDP)	D(MNC)	D(FDI)
1	1	0	0	0
2	.863446	.000543	.133039	.002971
3	.626291	.007324	.339897	.026488
4	.500617	.010813	.27692	.211651
5	.485053	.013006	.292543	.209397
6	.430496	.013241	.295883	.26038
7	.367403	.009848	.309822	.312927
8	.371034	.010769	.298146	.320052
9	.372923	.012883	.295905	.318289

10	.391905	.012843	.288077	.307177

Source: data process (2026

The D(GDP), D(MNC), and D(FDI) all make up the forecast error variance of D(CO2), with their contributions fluctuating with respect to forecast horizons. D(MNC) is the most important external contributor at the second forecast horizon, contributing about 13.30% of the variance of D(CO2), compared to a smaller share of 0.30% and 0.05% by D(FDI) and D(GDP). Starting from the fourth forecast horizon, D(FDI) becomes the most important external contributor to the variance of D(CO2), with its maximum contribution of 32.01% at the eighth horizon before declining slightly to 30.72% in the tenth horizon. However, D(MNC) contributes more or less equally to the variance of D(CO2) at around 27.69% to 33.99%, implying a relatively constant effect on the carbon emissions. D(GDP) makes the least contribution to the forecast error variance of D(CO2), making just a little below 1% at every horizon of forecasting.

The results from the FEVD show that the forecast variance of D(CO2) is fully explained by its own shocks, representing 100% in the first period. The effect decreases considerably over time, falling down to 39.19% in the tenth period. As far as the long run periods are concerned, D(MNC) and D(FDI) become the leading factors for variation, providing 28.81% and 30.72%, respectively, while D(GDP) represents just 1.28%. It can be said that although carbon emissions start being affected by their own shocks, multinational companies and foreign direct investments become more relevant. In comparison, economic growth exerts a relatively minor effect, suggesting that investment-related external factors have a greater impact than aggregate output growth on long-term carbon emission fluctuations.

DISCUSSION

The Nexus Economics Growth and Carbon Emission

The relationship between economic growth and carbon emissions is a key issue in environmental economics, especially when considering negative externalities. It is possible that economic activity will create environmental expenses that will not be incorporated in the price due to carbon emission. On the other hand, economic growth will foster technical progress and higher energy efficiency, and it will result in stricter regulation of environmental problems. According to the VECM estimation results, economic growth plays an important role in decreasing carbon emissions in the short and long run. This proves that economic development of the examined economy is now connected to the use of more advanced technologies, energy efficiency, and efficient environmental policy. Hence, even though economic activity creates negative externalities in the environment, economic growth helps to overcome these problems in the future.

These findings are consistent with Dogan & Seker (2016), Destek & Sarkodie (2019), and Churchil et al. (2018) which suggest that economic development can reduce carbon emissions through technological progress, increased energy efficiency, and stricter environmental regulations. Economic development is associated with innovation, enhanced efficiency, policy improvement, and moving towards greener industries. Therefore, economic development does not necessarily lead to carbon emissions, as progress in the field of production and environmental management can counterbalance the effect of economic development on the environment.

The Nexus Manufacturing and Carbon Emission

Manufacturing activity has a positive and statistically significant impact on carbon emissions in both the short and long term. These findings are consistent with Xu & Lin (2016) and Avenyo & Tregenna (2022), The reason for this correlation is that during the initial stages and mid-stages of economic growth, environmental degradation results because of the high use of energy intensive technology in manufacturing industries. Even though the advancement in technology can solve this problem, emissions from manufacturing continue to rise otherwise.

Industrial activities influence the carbon emission process, which is positive and statistically significant in both the short and long run periods. In the short run period, it can be observed that only the first lag of the industrial activities significantly increases the carbon emission level which shows that any changes in the levels of industrial production result in more energy usage and consequently in the increased level of fossil fuels consumption. In the long run period, the positive coefficient shows that the ongoing growth in the levels of industrial activities leads to a constant increase in the level of carbon emissions. This can be explained by means of the theory of negative externalities according to which the process of industrial production leads to the appearance of some additional environmental cost which is not included in the production cost of the firm.

The Nexus Foreign Direct Investment and Carbon Emission

The effects of globalization have made it important to study the environmental effects of foreign direct investment. Foreign Direct Investment may help countries grow economically by raising productivity, capital, and technology transfer, but its effects will be influenced by the type of investments and production processes involved. From the negative externality theory framework, FDI could cause environmental harm that would not be included in the private production costs incurred by the firms, especially when the foreign investments are in carbon-emitting industries. In this paper, it has been found that FDI causes an increase in carbon emissions in the short run and long run. From 1994 to 2023, the positive relationship implies that foreign investment causes production processes that produce a lot of environmental externalities and not enough clean technologies have been put in place to counter the emissions.

These findings align with empirical evidence that FDI often leads to higher carbon emissions, especially in developing and emerging economies. While some studies, such as Singhania & Saini (2021), Bulus & Koc (2021) and Marques & Caetano (2020), have observed the contrary where foreign direct investment decreases emissions, foreign direct investment in Indonesia contributes to the increasing carbon emissions in the short run and in the long run. This occurs mainly due to the fact that FDI in Indonesia takes place in energy-intensive industries such as manufacturing and processing industries. In the short run, an increase in foreign direct investment increases production capabilities, which leads to increased use of fossil fuels and thus, emissions of CO_2. In the long run, the growth in industries leads to an increase in dependency on carbon-intensive energy resources, such as coal, which continues to dominate the energy supply in Indonesia.

CONCLUSION

The study findings in the long run, economic growth contributes negatively to carbon emissions owing to technological innovation, energy efficiency and environmental laws and policies. On the other hand, the levels of carbon emissions are high because of manufacturing activities and foreign investments as they tend to be concentrated in carbon intensive industries. In the short run, the findings are consistent where economic growth decreases carbon emissions while manufacturing activities and foreign investments increase carbon emissions. Thus, the study shows that the environmental externality related to manufacturing and FDI is a negative one, since both processes have the effect of increasing carbon emissions. The results of the research demonstrate that the cost created by environmental externality in relation to industrial production and FDI has not been internalized yet.

Several policy implications emerge from the results. First, economic growth has been shown to reduce CO2 emissions makes it crucial to ensure growth through innovations and green technology. Second, the positive effect of the manufacturing sector shows that it is important to increase efforts to transform the industry through introducing cleaner technology and machinery, energy efficiency, and strict regulation. Third, the positive influence of FDI means that investment policy needs to focus on investing only in sustainable and environmentally friendly projects. It is necessary for policymakers to create green screens of investment projects, provide incentives for low-carbon foreign investment, and ensure that foreign investors satisfy some environmental criteria. Moreover, it is possible to use fiscal incentives, green finance, and carbon pricing as means of encouraging firms to reduce their carbon emissions. Hence, it is important to incorporate environmental criteria in industry and investment policy.

REFERENCES

Adekunle, I. A., Taiwo, S., Uwilingiye, J., & Aworinde, O. (2026). Does FDI turn 'Dirtier' at higher growth levels? Evidence from non-linearities and threshold effects. *Energy Policy*, *216*, 115419. doi:https://doi.org/10.1016/j.enpol.2026.115419

Ahmed, M., Huan, W., Ali, N., Shafi, A., Ehsan, M., Abdelrahman, K., . . . Fnais, M. S. J. S. (2023). The Effect of Energy Consumption, Income, and Population Growth on CO2 Emissions: Evidence from NARDL and Machine Learning Models.

Akbar, M., Ridho, M., Pranata, D., Alfarizi, & Sakuntala, D. (2025). Analysis of the Economic Growth Gap in 2025 (Case Study of Developed Countries Vs Developing Countries). *Indonesian Journal of Entrepreneurship and Startups*, *3*, 11-20. doi:10.55927/ijes.v3i1.13557

Avenyo, E. K., & Tregenna, F. (2022). Greening manufacturing: Technology intensity and carbon dioxide emissions in developing countries. *Applied Energy*.

Bulus, C., & Koc, S. (2021). The effects of FDI and government expenditures on environmental pollution in Korea: the pollution haven hypothesis revisited. *Environmental Science and Pollution Research*, *28*, 1-16. doi:10.1007/s11356-021-13462-z

Churchil, S. A., Inekwe, J., Ivanovski, K., & Smyth, R. (2018). The environmental Kuznets curve in the OECD: 1870–2014. *Energy Economics*, *75*, 389-399. doi:10.1016/j.eneco.2018.09.004

Destek, M. A., & Sarkodie, S. A. (2019). Investigation of environmental Kuznets curve for ecological footprint: The role of energy and financial development. *Science of The Total Environment*, *650*, 2483-2489. doi:https://doi.org/10.1016/j.scitotenv.2018.10.017

Dogan, E., & Seker, F. (2016). Determinants of CO2 emissions in the European Union: The role of renewable and non-renewable energy. *Renewable Energy*, *94*, 429-439. doi:https://doi.org/10.1016/j.renene.2016.03.078

Esmaeili, P., Balsalobre Lorente, D., & Anwar, A. (2023). Revisiting the environmental Kuznetz curve and pollution haven hypothesis in N-11 economies: Fresh evidence from panel quantile regression. *Environmental Research*, *228*, 115844. doi:https://doi.org/10.1016/j.envres.2023.115844

Fokianos, K., Fried, R., Kharin, Y., & Voloshko, V. (2022). Statistical analysis of multivariate discrete-valued time series. *Journal of Multivariate Analysis*, *188*, 104805. doi:https://doi.org/10.1016/j.jmva.2021.104805

Giannone, D., Lenza, M., & Primiceri, G. E. (2015). Prior Selection for Vector Autoregressions. *The Review of Economics and Statistics*, *97*(2), 436-451. doi:10.1162/REST_a_00483 %J The Review of Economics and Statistics

Guay, A., & Pelgrin, F. (2023). Structural VAR models in the Frequency Domain. *Journal of Econometrics*, *236*(1), 105466. doi:https://doi.org/10.1016/j.jeconom.2023.04.009

Hoa, P. X., Xuan, V. N., & Thu, N. T. P. (2024). Factors affecting carbon dioxide emissions for sustainable development goals – New insights into six asian developed countries. *Heliyon*, *10*(21), e39943. doi:https://doi.org/10.1016/j.heliyon.2024.e39943

Khan, I., Hou, F., Zakari, A., Irfan, M., & Ahmad, M. (2022). Links among energy intensity, non-linear financial development, and environmental sustainability: New evidence from Asia Pacific Economic Cooperation countries. *Journal of Cleaner Production*, *330*, 129747. doi:https://doi.org/10.1016/j.jclepro.2021.129747

Marques, A., & Caetano, R. (2020). The impact of foreign direct investment on emission reduction targets: Evidence from high- and middle-income countries. *Structural Change and Economic Dynamics*, *55*. doi:10.1016/j.strueco.2020.08.005

Miah, M. D., Islam, M. S., & Raihan, A. (2025). Dynamic impact of economic growth, energy use, foreign direct investment and population on greenhouse gas emission in Bangladesh. *Innovation and Green Development*, *4*(4), 100259. doi:https://doi.org/10.1016/j.igd.2025.100259

Nguyen, T. H. P., Vu, T. T., Vu, T. A., & Le, H. P. (2026). The effects of FDI and energy consumption on economic growth, environmental degradation, and sustainable development: Global evidence. *Environmental Challenges*, *24*, 101576. doi:https://doi.org/10.1016/j.envc.2026.101576

Oprea, S., Adela, B., & Georgescu, I. (2025). Investments, Economics, Renewables and Population Versus Carbon Emissions in ASEAN and Larger Asian Countries: China, India and Pakistan. *Sustainability*, *17*. doi:10.3390/su17146628

Pradhan, A., Sachan, A., Sahu, U., & Mohindra, V. (2021). Do foreign direct investment inflows affect environmental degradation in BRICS nations? *Environmental Science and Pollution Research*, *29*. doi:10.1007/s11356-021-15678-5

Qamri, G. M., Sheng, B., Adeel-Farooq, R., & Alam, G. M. (2022). The criticality of FDI in Environmental Degradation through financial development and economic growth: Implications for promoting the green sector. *Resources Policy*, *78*, 102765. doi:10.1016/j.resourpol.2022.102765

Qiao, R., Liu, X., Gao, S., Liang, D., GesangYangji, G., & Xia, L. (2024). Industrialization, urbanization, and innovation: Nonlinear drivers of carbon emissions in Chinese cities. *Applied Energy*.

Singhania, M., & Saini, N. (2021). Demystifying pollution haven hypothesis: Role of FDI. *Journal of Business Research*, *123*, 516-528. doi:https://doi.org/10.1016/j.jbusres.2020.10.007

Surya, B., Menne, F., Sabhan, H., Suriani, S., Abubakar, H., & Idris, M. (2021). Economic Growth, Increasing Productivity of SMEs, and Open Innovation. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(1), 20. doi:https://doi.org/10.3390/joitmc7010020

Wencong, L., Kasimov, I., & Saydaliev, H. B. (2023). Foreign direct investment and renewable energy: examining the environmental Kuznets curve in resource-rich transition economies. *Renewable Energy*.

Xu, B., & Lin, B. (2016). Reducing carbon dioxide emissions in China's manufacturing industry: a dynamic vector autoregression approach. *Journal of Cleaner Production*, *131*, 594-606. doi:https://doi.org/10.1016/j.jclepro.2016.04.129

Yamaka, W., Phadkantha, R., & Rakpho, P. (2021). Economic and energy impacts on greenhouse gas emissions: A case study of China and the USA. *Energy Reports*, *7*, 240-247. doi:10.1016/j.egyr.2021.06.040

Yang, M., Wang, E.-Z., & Hou, Y. (2021). The relationship between manufacturing growth and CO2 emissions: Does renewable energy consumption matter? *Energy*, *232*, 121032. doi:https://doi.org/10.1016/j.energy.2021.121032