Analysis Of The Impact Of Energy Consumption And Economic Performance On Carbon Dioxide Emissions In Indonesia Using Error Correction Mechanism

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ABSTRACT

Lately, Indonesia has been intensively developing its domestic economy. Industrial development began to be started, which attracted investors to invest. However, this massive economic development is causing an increase in CO_2 emissions. This study intends to capture the effects of primary energy consumption per capita and economic performance represented by Gross Domestic Product (GDP), Foreign Direct Investment (FDI), and International Trade Openness on CO_2 emissions in Indonesia from 1990–2022, in the short-run and long-run, using Error Correction Mechanisms (ECMs) analysis. In the long-run, energy consumption and GDP significantly affect CO_2 emissions in Indonesia. Meanwhile, in the short-run, only energy consumption and Error Correction Term (ECT) have a significant effect on CO_2 emissions. Moreover, from the ECT coefficient, it is known that the speed of adjustment to return to equilibrium is 95.08% in the first year after the shock.

Keywords: CO_2 emissions, ECM, energy consumption, GDP, investment, trade openness.

INTRODUCTION

For an extended period, environmental pollution has persisted as an unresolved major issue. According to Jones (2023), the era of global warming has transitioned into what is now termed global boiling. Unfortunately, this shift is undesirable, as global warming signifies a significant increase in the Earth's temperature. The World Meteorological Organization (2023) has identified that this temperature surge is expected to persist, reaching its pinnacle in July 2023, marking it as the hottest month in recorded history. Consequently, this situation is contributing to climate chaos across various regions worldwide.

The World Meteorological Organization (2023) highlights that the primary driver behind global boiling and ensuing climate chaos is the escalating concentration of greenhouse gas (GHG) pollution. This pollution, comprising various gases like carbon dioxide (CO_2), methane (CH_4), nitrogen oxide (N_2O), and sulfur hexafluoride (SF_6), poses a threat to the environment as it accumulates in the Earth's atmosphere without proper breakdown. Despite its diverse composition, CO_2 emerges as the most influential gas in this mix.

According to a recent publication by the European Commission (2023), findings indicate that in 2022, the preeminent contributor to global GHG emissions was CO_2, primarily stemming from the combustion of fossil fuels. This source accounts for a staggering 71.6% of the total GHG emissions. This pattern isn't confined to global trends; it also significantly characterizes Indonesia's GHG landscape.

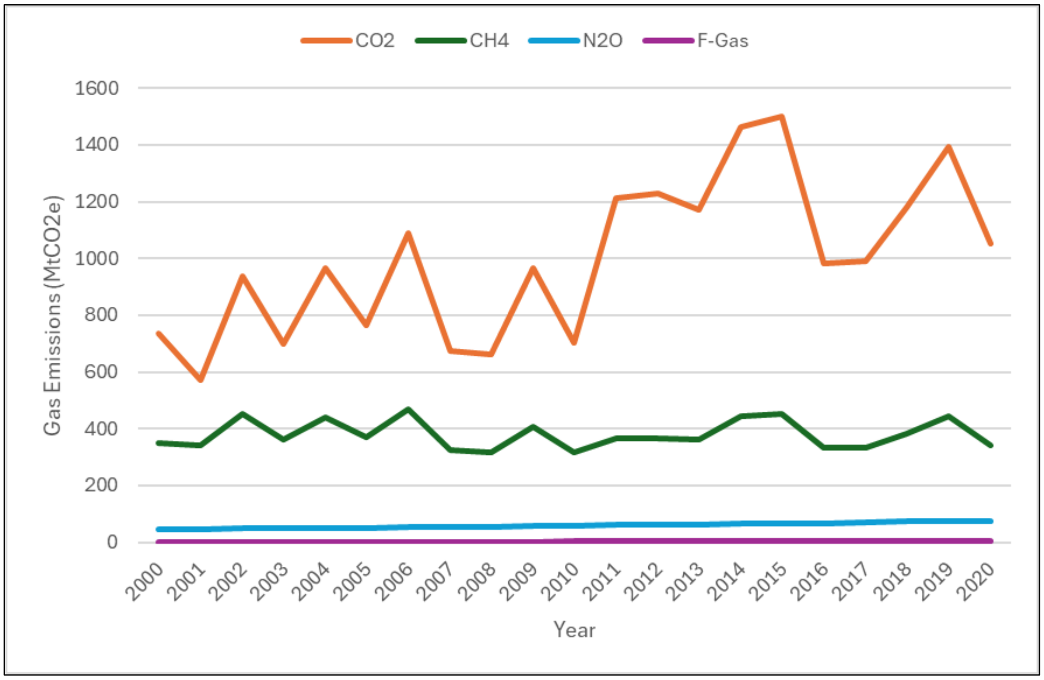

Figure 1. Development of Greenhouse Gas Emissions in Indonesia
Source: World Resources Institute

Based on Figure 1, it becomes evident that CO_2 gas emissions exhibit a fluctuating pattern. In the period spanning from 2000 to 2010, the data appears devoid of a discernible trend, indicating a lack of consistent yearly increments in CO_2 gas emissions. However, a noteworthy shift occurs post-2011, where CO_2 emissions undergo a rapid and unmistakable upward trajectory. This observation indicates a significant and relatively consistent increase in CO_2 emissions during the period from 2011 to 2020.

The British Petroleum Company's publication in 2022 states that the surge in atmospheric CO_2 emissions is intrinsically linked to the escalating annual energy consumption, encompassing both renewable and non-renewable sources. As of now, energy consumption remains predominantly influenced by the oil and mining sectors. As cited in the Energy Institute's publication (2023), carbon emissions stemming from energy consumption experienced a notable 0.9% increase in 2022 compared to the preceding year, reaching 34.4 Giga Tons of CO_2. Furthermore, global energy consumption witnessed a 2.8% rise in 2019. When compared to prior years, these numbers show a consistently high level, indicating that the majority of the world's energy consumption still comes from carbon-based energy sources, or what is popularly known as carbon-based energy.

According to Mirzaei & Bekri (2017), there's a concerning trend where the demand for carbon-based energy is expected to outpace the actual energy production. This imbalance necessitates a continual expansion of production processes to keep up with market demands. Monitoring and control mechanisms are vital in managing this evolving production landscape. Karunia et al. (2023) emphasize that as production processes increase, so do the resulting emissions. This aligns with Noor & Saputra's (2020) findings that indicate intensified industrial development leads to the emergence of new industries and drives economic activities within the industrial sector. These interconnected dynamics highlight the need for a nuanced approach to address the evolving complexities of energy demand, production, and their environmental impacts.

Beyond advancements in the industrial sector, there is a concurrent surge in economic activity. The economic vitality of a nation is often encapsulated in its Gross Domestic Product (GDP) per capita figures. GDP represents the average added value generated through the production of goods and services by each resident in a country during a specified period. A higher GDP per capita is generally anticipated to enhance the quality of life for each resident. However, not all improvements in the quality of life align with environmentally friendly practices, particularly in countries categorized as Emerging Markets with lower-middle income statuses or in the midst of development.

Research by Tsandra et al. (2023) reveals a positive (unidirectional) relationship between the rise in GDP per capita and the volume of CO_2 emissions in countries classified as emerging markets. This aligns with the findings of Nikensari et al. (2019), suggesting that countries in the lower-middle income category tend to witness an uptick in CO_2 emissions as their GDP per capita increases. This correlation arises from the absence of advanced, environmentally friendly technology to support existing economic activities. In the context of Indonesia, which is currently classified as a lower-middle-income country, significant challenges lie ahead. Striking a balance between economic improvement and the reduction of CO_2 emissions necessitates a concerted effort to adopt more environmentally friendly technologies.

To bolster economic progress and advance into a more developed nation, the investment matrix remains a pivotal factor, playing a crucial role in sustaining economic growth within a country. As cited by Yu & Xu (2019) in Jufri & Bahri (2022), for developing nations such as Indonesia aspiring to achieve energy-efficient industries through indigenous technology, substantial investments, including foreign direct investment (FDI), become imperative. FDI can pave the way for newfound opportunities, enabling developing nations to elevate their industries and technologies to environmentally sustainable levels.

However, in certain instances, such as highlighted in the research by Chandio et al. (2018), the upsurge in foreign capital inflows tends to exacerbate environmental degradation. Furthermore, according to Hergert & Marton (2017), the emergence of Foreign Direct Investment (FDI) serves as a strategy for developed nations to outsource "dirty industries" to economically less developed countries. This phenomenon transpires due to a lack of control over the allocated capital, leading to FDI, which ideally should ameliorate conditions, inadvertently fostering the proliferation of new factories and industries that are environmentally unfriendly.

Beyond the realm of capital investments, economic advancement manifests through the escalating volume of commercial transactions or trade. The intensification of trade activities, however, raises concerns about a concomitant rise in pollution, particularly when environmental considerations are not integrated into these transactions. According to Retno et al. (2021), within the ASEAN nations, heightened openness to international trade yields a positive effect on the environment by curbing CO_2 emissions. This positive outcome stems from government policies centered on maintaining and observing sustainable, environmentally friendly development practices. On the other side, Nanda P. and Djoni (2021) posit a positive correlation between trade openness and CO_2 emissions per capita in the Indonesian context. This study also underscores the imperative for Indonesia to foster more environmentally friendly technological innovations and implement stringent environmental regulations for businesses to adhere to.

Based on the foundations mentioned earlier, a research initiative was launched to examine the influence of several key variables, specifically per capita primary energy consumption, GDP, FDI, and

International Trade Openness, on CO_2 emissions in Indonesia from 1990 to 2022. This investigation considers both short-term and long-term effects, utilizing the Error Correction Mechanism (ECM) analysis for a comprehensive understanding. Distinguishing itself from previous studies, this research extends its timeframe up to 2022 and incorporates variables that represent economic aspects from both production and consumption perspectives.

METHOD

This study used secondary data from the Statistical Review of World Energy 2023, World Bank's official website, and The Emissions Database for Global Atmospheric Research (EDGAR). The data consisted of yearly time-series observations in Indonesia from 1990 to 2022, totaling 32 observations. The study analyzed two types of variables, namely predictor variables and response variables, to obtain long-term and short-term regression effects. CO_2 emissions per capita was the only response variable, which was influenced by four predictor variables, including primary energy consumption per capita (Karunia et al., 2023), GDP per capita (Tsandra et al., 2023), foreign direct investment (Chandio et al., 2018), and trade openness (Retno et al., 2021). The definition of variables, types of units, and the origin of the data used are detailed in Table 1.

Table 1. Definition of Variables, units, and data sources used

Variable	Definition	Unit	Data sources
CO_2	CO_2 emissions per capita	T/per Capita	EDGAR
EC	Primary energy consumption per capita	gigajoule/ per capita	Statistical Review of World Energy 2023
GDP	GDP per capita (constant 2015 US$)	thousand US dollars/per capita	World Bank
FDI	*Foreign Direct Investment*	Trillion US Dollars	World Bank
Trade	International trade openness	% GDP	World Bank

This study applies quantitative research methods with two types of analysis: descriptive analysis and inference analysis. The descriptive analysis is presented in the form of statistical summary tables and line charts that show the time series data from 1990-2022. The statistical summary table elucidates the distribution of data, including the minimum value, maximum value, average, and standard deviation of each variable used. On the other hand, line charts are used to illustrate the trend of change in response variables from year to year. The inference analysis method applied in this study is a time series analysis method called Error Correction Mechanism (ECMs). Hanke & Wichern (2014) explain that the ECM model can be used to identify the presence of long-term and short-term effects of predictor variables on response variables and determine the amount of adjustment required in the short term to attain long-term equilibrium.

Before analyzing with an ECM model, stationary testing of all variables is required. The dataset is considered as stationary if it has constant mean and constant variance. According to Franses (1998), it is said that either mean or variance is not constant, then it includes weak stationary which is not essentially stationary. To test stationarity, an Augmented Dickey-Fuller (ADF) Test was conducted. As described in theory by Gujarati & Porter (2009), this test involves adding (augmenting) the lagged value of the dependent variable to the ΔY_t Dickey-Fuller equation.

The objective of this test is to examine whether there is a root unit in the data. If the data used contains a root unit in it, the data will be deemed non-stationary (failed to reject H0). The models in the ADF test follow the equation as listed below:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta Y_{t-i} \quad (1)$$

with Δ symbolizes the value of *First Difference* The variables used and *t* are variables that indicate the trend value. In this test, the form of the hypothesis taken is

$H_0 : \delta = 0$ (contain unit root, nonstationary)
$H_1 : \delta < 0$ (not contain unit root, stationary)

Meanwhile, to test whether there is a trend in the data, the following hypothesis are used

$H_0 : \beta_2 = 0$ (there is no trend, strong stationary)
$H_1 : \beta_2 \neq 0$ (there is trend, weak stationary)

After the data is tested for stationarity, modeling is carried out using the Error Correction Mechanism (ECM). ECM was first applied by J.D. Sargan. However, its use was corrected for its imbalance which was later re-popularized by Engle and Granger. This improved model can be used if the variables entered in the model are detected not to be stationary at the level, but can fall into the stationary category when *differentiating* at the same difference level. Based on Gujarati & Porter (2009), Granger's representation theorem states that if the variables Y and X are cointegrated, their relationship can be expressed as ECM. Based on the results of the cointegration test, a long-term regression equation was obtained in this study as follows:

$$CO_{2t} = \alpha_0 + \alpha_1 EC_t + \alpha_2 GDP_t + \alpha_3 FDI_t + \alpha_4 Trade_t + e_t \quad (2)$$

with α_i is the i-th parameter coefficient, t is time and is an error that satisfies classical assumptions. In ensuring that the variables are cointegrated and have a stable long-term relationship, it is necessary to test the residual stationarity of the long-term model. To check residual stationarity in long-term equations, a test method is carried out e_t Augmented Dickey Fuller (ADF*)* which has the same procedures and hypotheses as before, but without testing the presence or absence of trends in them. If the residual is stationary, it can be interpreted that the response variables and predictors are cointegrated, so the short-term model (ECM) can be estimated with the following equation:

$$\Delta CO_{2t} = \alpha_0 + \alpha_1 \Delta EC_t + \alpha_2 \Delta GDP_t + \alpha_3 \Delta FDI_t + \alpha_4 \Delta Trade_t + e_t \quad (3)$$

with *Δ* is differentiation, $ECT_t = \hat{e}_{t-1}$ is the value of the lag of 1 period of the residual that can be reflected into the form of deviation or equilibrium error from the previous period (t-1). The model is said to be stable if the value of the ECT(α_5) parameter coefficient is significant and is at a value of less than 0.

After obtaining short-term model estimates, the next step of analysis is testing and checking classical assumptions. Assumptions that need to be met are the assumptions of normality, homoscedasticity, non-autocorrelation, and checking non-multicollinearity. In this study, the Jarque-Bera normality test was used in testing the normality of the error distribution. Furthermore, an autocorrelation test is carried out to detect random error autocorrelation in the t-th period with the previous period *(t-1).* Gujarati and Porter (2009) explain that to avoid some of the weaknesses of the Durbin-Watson Test, Breusch and Godfrey developed the autocorrelation test so it can be used in non-stochastic, higher-order autoregressive, and regression *simple* or *higher-order moving averages* from *white noise*. After testing the non-autocorrelation assumption, a homoscedasticity test was conducted to test for the homogeneity of residual's variance. Neter et al. (1983) revealed that this test assumes that residuals are independent and normally distributed. Furthermore, multicollinearity checking is intended to ensure that predictor variables do not have a strong correlation between predictor variables in the same model. The method used to detect the occurrence of multicollinearity is the value of *Variance Inflation Factors* (VIF). According to Neter et al. (1983), these factors are able to explain how much the variance of the estimator coefficient increases compared to when the predictor variables are not linearly related.

More clearly, hypotheses in testing assumptions can be seen in the following table:

Table 2. Classical Assumption Testing Hypothesis

Assumption	H_0	H_1	**Critical Region**
Residual Normality	$\varepsilon_t \sim N(0, \sigma^2)$	$\varepsilon_t \nsim N(0, \sigma^2)$	Reject H_0 if *p-value<0.05*
Homoscedasticity	$E(\varepsilon_t{}^2 \vert X) = \sigma^2$	$E(\varepsilon_t{}^2 \vert X) \neq \sigma^2$	Reject H_0 if *p-value<0.05*
Non-Autocorrelation	$\rho = 0$	$\rho \neq 0$	Reject H_0 if *p-value<0.05*

Source: Neter et al., 1983.

RESULTS AND DISCUSSION

Descriptive Analysis

Before doing inferential analysis, descriptive analysis using line diagrams was carried out to see the general condition of CO_2 emissions per capita in Indonesia in 1990–2022, with visualization in the following figure.

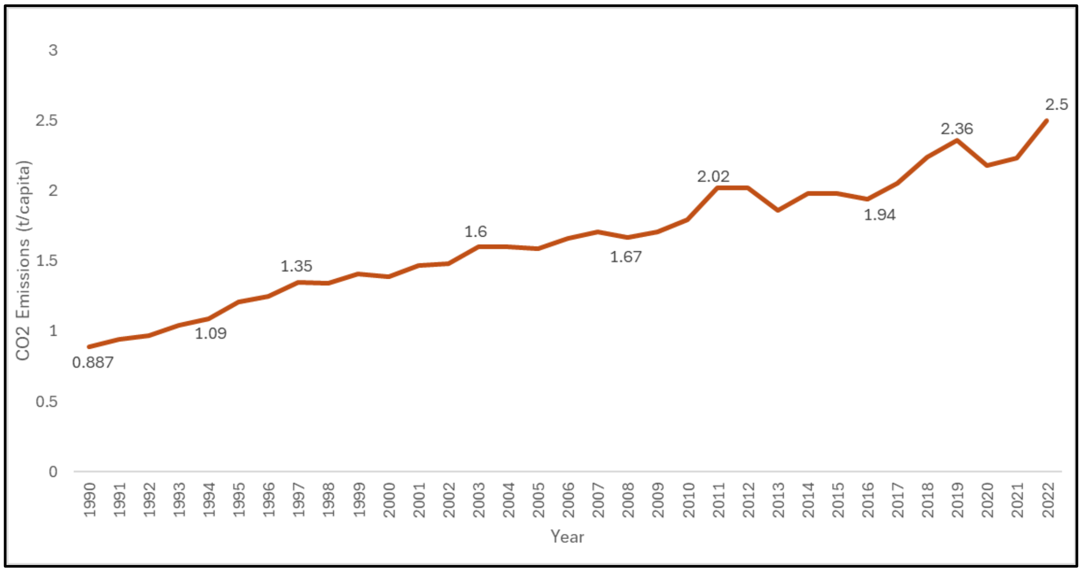

Figure 2. Condition of CO_2 Emissions per Capita in Indonesia in 1990–2022
Source : Emissions Database for Global Atmospheric Research

From Figure 2, it can be seen that the movement of CO_2 emissions per capita in Indonesia every year over the last 32 years has increased to reach 2.5 tons per capita in 2022.

To determine the minimum value, maximum value, mean, and standard deviation for each variable, descriptive analysis was carried out using summary statistics.

Table 3. Summary Statistics

Variable	Min	Max	Mean	Std.Dev
CO_2	0.8870	2.5000	1.6520	0.4320
	(in 1990)	(in 2022)		
EC	11.8000	35.5000	22.2879	5.7083
	(in 1990)	(in 2022)		
GDP	1.4836	4.0736	2.5451	0.8034
	(in 1990)	(in 2022)		
FDI	-0.0046	0.0251	0.0093	0.0096
	(in 2000)	(in 2014)		
Trade	32.9722	96.1862	52.8274	11.9173
	(in 2020)	(in 1998)		

Table 3 shows that the lowest values for CO_2 emissions per capita, primary energy consumption per capita, and GDP per capita occurred in 1990, and the highest values were in 2022. Then the FDI variable reached its lowest figure in 2000, while the highest figure was in 2022. Meanwhile, the trade openness variable has a minimum value in 2020 and a maximum value in 1998.

Inferential Analysis

1. Pre-estimation Test

Before estimating the model and conducting the analysis, stationary testing and cointegration testing are performed. Stationary test and cointegration test are conducted as follows:

a) Stationarity Test

Stationarity test using ADF Test is conducted on *Level* and *First Difference* to examine each of the variables. Data is classified into stationary when the mean and variance of the data are constant. A constant variance is indicated by the absence of a trend in the ADF Test model. A significant trend coefficient in the model would render the variable weakly stationary and considered non-stationary. Using the Augmented Dickey-Fuller (ADF) method at a 5% significance level, the test results are as shown in the following table:

Table 4. Summary of Stationary Test

Variable	p-value	trend's p-value	Conclusion
Level			
CO_2 (t/capita)	0.0822	0.0035**	Non-stationary
EC (gigajoule/capita)	0.2595	0.0139**	Non-stationary
GDP (thousands US Dollar/capita)	0.9332	0.1644	Non-stationary
FDI (trillion US Dollar)	0.1567	0.0169**	Non-stationary
Trade openness (% GDP)	0.0338**	0.0221	Non-stationary
First difference			
CO_2 (t/capita)	0.0000**	0.8627	Stationary
EC (gigajoule/capita)	0.0002**	0.7942	Stationary
GDP (thousands US Dollar/kapita)	0.0077**	0.1580	Stationary
FDI (trillion US Dollar)	0.0000**	0.7579	Stationary
Trade (% GDP)	0.0000**	0.7304	Stationary

Note: ** sig. in $\alpha = 5\%$

Based on Table 4, it can be concluded that all of the variables do not satisfy stationarity at *Level*, but exhibit stationarity in the *First Difference*.

b) Cointegration Test

The result of the long-run regression estimation or the cointegrating regression are shown in Table 5:

Table 5. Result of Long-Run Regression

Variable	Coefficient	Std Error	t-Statistics	p-value
Constant	-0.1024	0.0863	-1.1869	0.2452
EC (gigajoule/capita)	0.0542	0.0039	13.6804	0.0000**
GDP (thousands US Dollar/capita)	0.1702	0.0380	4.4777	0.0000**
FDI (trillion US Dollar)	0.6702	1.7855	0.3753	0.5969
Trade (% GDP)	0.0020	0.0011	1.8555	0.5058
R-squared	0.9893			
Adjusted R-squared	0.9878			
F-statistics	649.9562			
Prob (F-statistics)	0.0000**			

Dependent variable: CO_2 Emission (t/capita)
Note: ** sig. in $\alpha = 5\%$

In Table 5, the p-value for the simultaneous test is 0.0000 which indicates that at a 5% significance level, this implies that at least one variable among the independent variables significantly influences the per capita CO_2 emissions in Indonesia in the long-run. On the other hand, in partial terms, the results show that only two independent variables, namely Primary Energy Consumption and GDP, significantly affect the amount of per capita CO_2 emissions in Indonesia in the long term.

Then, based on the results in the above table, a long-run regression model is obtained as follows.

$$(\widehat{CO_2})_t = -0.1024 + 0.0542EC_t + 0.1702GDP_t + 0.6702FDI_t + 0.0020Trade_t \tag{4}$$

The equation above must undergo a cointegration test to check whether the response and predictor variables are cointegrated. To conduct the cointegration test, the test is performed on the residuals of the long-run estimation. The predictor and the response variable is cointegrated when the residuals are stationary at *Level*. The results of the residual stationarity test using the ADF method show a probability value of 0.0001. Based on the result obtained, at the 5% significance level, it is concluded that the residuals of the above long-run regression model are stationary at level. This implies that the variables used in the model have a long-run relationship or can be considered cointegrated.

2. Error Correction Model (ECM) Estimation

After conducting the stationary test and cointegration test, short-run regression is estimated. The estimation results are presented in the following Table 7.

Table 7. Result of ECM Estimation (Short-run Regression)

Variable	Coefficient	Std. Error	t-Statistics	p-value
Constant	0.0162	0.0113	0.7461	0.1667
EC (gigajoule/capita)	0.0481	0.0059	8.0635	0.0000**
GDP (thousands US Dollar/capita)	0.0141	0.1151	0.1227	0.9032
FDI (trillion US Dollar)	1.9725	1.6426	1.2008	0.2406
Trade (% GDP)	0.0006	0.0008	0.7317	0.4709
ECT(-1)	-0.9508	0.2084	-4.560	0.0001**
R-squared	0.8053			
Adjusted R-squared	0.7679			
F-statistic	21.5117			
Prob(F-statistic)	0.0000			

Dependent variable: CO_2 Emission (t/capita)
Note: ** sig. in $\alpha = 5\%$

Based on the table containing the processed data outputs above, a short-run regression equation is obtained as follows:

$$\Delta(\widehat{CO_2})_t = 0.0162 + 0.0481\Delta EC_t + 0.0141\Delta GDP_t + 1.9725\Delta FDI_t + 0.0006\Delta Trade_t - 0.9508ECT_{t-1} \quad (5)$$

The estimation results indicate that the coefficient of the Error Correction Term (ECT) with a lag of 1 is negative and significantly partial to the model. A negative ECT value less than 1 indicates that the formed ECM model is valid or appropriate. The coefficient of ECT(-1) of -0.9508 can also be interpreted as the speed of adjustment in the short-run model being 0.9508, or in other words, 95.08% of the adjustment or correction from short-run fluctuations towards the long-run equilibrium occurs in the first year and 4.92% occurs in subsequent periods.

Based on the the model estimation, the adjusted R-squared value of the above model is 0.7679. This value implies that 76.79% of the variation in per capita CO_2 emissions in Indonesia can be explained by the variables of per capita primary energy consumption, per capita GDP, FDI, and trade openness.

The results of the simultaneous F-test lead to the conclusion that, at a significance level of 5%, at least one independent variable significantly influences the dependent variable. Based on the partial test, it is found that, at a significance level of 5%, per capita primary energy consumption is significant in the short-run regression model. Moreover, per capita GDP, FDI, and trade openness do not significantly affect per capita CO_2 emissions in Indonesia.

3. Assumption Test

The short-term regression model that has been obtained is then checked for non-multicollinearity and classical assumption tests. The tests of classical assumptions are normality, non-autocorrelation, and homoscedasticity, with the results of the tests on the model that has been obtained explained as below.

a) Normality Test

The results of normality testing with the Jarque Bera Test are shown in figure 3 below.

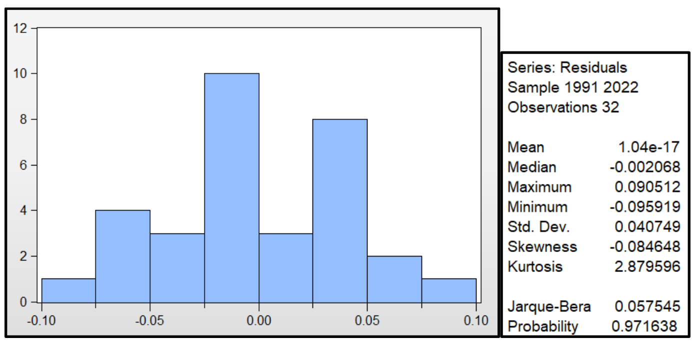

Figure 3. Result of Jarque-Bera Test
Source : Processed Data by Eviews 12 (2023)

Based on Figure 3, it is obtained that the resulting significance level of Jarque Bera test is in the range above the 5% significance level, namely 0.9716, so a decision can be made that H_0 fails to be rejected or the assumption of normally distributed errors is fulfilled.

b) Non-Multicollinearity Checking

The results of the non-multicollinearity check are shown in Table 8 below.

Table 8. Non-Multicollinearity Check Results

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.00013	2.08498	NA
D(EC)	0.00003	1.55598	1.24072
D(GDP)	0.01325	3.01794	1.61455
D(FDI)	2.69801	1.25053	1.18769

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
D(Trade)	0.00000	1.27186	1.27123
ECT(-1)	0.04346	1.07100	1.06082

Source : processed data

Based on Table 8, it can be said that the VIF values of all predictor variables used are in a fairly small range and below 10. This means that there is no strong or very strong correlation between predictor variables, or, in other words, that the assumption of non-multicollinearity is satisfied.

c) Non-Autocorrelation and Homoscedasticity Test

Non-autocorrelation and Homoscedasticity test results are shown in table 9 below.

Table 9. Result of Non-Autocorrelation and Homoscedasticity Test

Test	P-value
Non-autocorrelation	0.3024
Homoscedasticity	0.4414

Source : processed data

The Breusch-Godfrey Serial Correlation LM Test for non-autocorrelation and the Breusch Pagan Godfrey Test for homoscedasticity produced p-values that were above the accepted significance level, namely 5%, so that it could be concluded that the resulting random error had no autocorrelation and heteroscedasticity did not occur in the model used, so that the assumptions of non-autocorrelation and homoscedasticity were fulfilled.

4. Interpretation and policy implication

Based on partial tests listed in table 5 and table 6, the variables of primary energy consumption and GDP affect the amount of CO_2 emissions in Indonesia in the long term. With a coefficient value of 0.0542 for the primary energy consumption variable, it means that every time there is an increase in primary energy consumption of 1 gigajoule per capita, in the long run it will have an impact on increasing CO_2 per capita by 0.0542% assuming other predictor variables are constant. Then with a coefficient value of 0.1702 for the GDP variable, it shows that every increase in GDP of 1 thousand US dollars per capita, in the long run it will have an impact on increasing CO_2 per capita by 0.1702% assuming other variables are constant.

In the short term, only primary energy consumption per capita had a significant effect in the model. The value of the primary energy consumption coefficient per capita is 0.0481 means that if there is an increase in energy consumption by 1 gigajoule per capita, then CO_2 emissions per capita will increase by 0.0481% assuming other predictor variables are constant.

Thus, it is obtained that Indonesia is still in the pre-industrial economy and has not yet reached the highest peak of its economy. Indonesia's economy must continue to be improved but by continuing to pay attention to the environment. For this reason, the government can make policies to overcome this, including by diversifying energy sources. It is used to reduce dependence on certain primary energies that can increase CO_2 emissions. To maintain energy consumption as needed but prevent emissions from increasing, one way is to change carbon-based fuels into the energy that more environmentally friendly. The government can design certain regulations, such as carbon taxes or emission limits to regulate companies engaged in sectors that produce a lot of CO_2 emissions. In addition, the government can also make policies that encourage energy efficiency, both in the industrial and household sectors, for example, by incentivizing the use of more environmentally friendly technology and can build infrastructure that supports energy efficiency.

CONCLUSION

Based on tests with the Error Correction Model (ECM), using a 5% significance rate and a total of 32 years of observations, it determines that energy consumption and GDP per capita have a significant impact on Indonesia's CO_2 emissions in the long term, while other variables (FDI and Trade Openness) do not. Furthermore, with the same significance, it has been found that in the short-term estimates, only the energy consumption variable has a significant influence on the amount of CO_2 per capita emission in Indonesia. The short-term correction effect obtained was -0.9508. In other words, the rate of correction or model adjustment needed to be able to return to a balanced position after a shock occurred was 95.08% in the first year and 4.92% in the subsequent period.

The significant amount of primary energy consumption that has a positive impact on Indonesian CO_2 emissions suggests that as the amount of energy consumed increases, the number of carbon dioxide emissions will increase as well. It shows that Indonesia is still in a pre-industrial economy and has not reached its economic peak. That is, in order to maximize existing economic growth by keeping an eye on the environment, Indonesia still needs to make extra efforts. To be able to prevent rising emissions while maintaining energy consumption as needed, one way is to create more environmentally friendly alternative energy.

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