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Analyzing the Linkage between CO2 Emissions, Economic Growth, Energy Intensity and Consumption: A VECM Model Application

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Abstract: Indonesia is one of the 198 countries which in 1992 signed the United Nations Framework Convention on Climate Change (UNFCCC). UNFCCC formulated international agreements to reduce global greenhouse gas emissions as an effort to combat rising global temperatures. However, in 2022, Indonesia currently is one of the largest carbon dioxide emitters in the world with a total carbon emission of 728.88 million Tons of CO2 and occupies the 6th position in the world. Fossil fuels are still used as the main energy source in Indonesia to support economic growth with a contribution of 87,7 percent. This research aims to analyze the shape of the relationship between CO2 emissions and economic growth, and to analyze the relationship between CO2 emissions, economic growth, energy intensity, and renewable energy consumption in Indonesia. Regression modeling is used in finding the shape of the relationship between CO2 emissions and economic growth, which resulted in a monotonically increasing relationship. Vector Error Correction Model (VECM) is used to analyze the relationship between CO2 emissions, economic growth, energy intensity, and renewable energy consumption, which found that in the long run economic growth and energy intensity will increase CO2 emissions with the parameters are positively significant to CO2 emission. Meanwhile, an increase in renewable energy consumption will reduce CO2 emissions with the parameter is negatively significant to CO2 emission. However, in the short term only energy intensity has a significant effect on CO2 emissions. With this research, it can be determined how to mitigate CO2 emissions and reducing the impact of the rising greenhouse gas emissions on environment.

Keywords: CO2 emission, Economic Growth, Energy Intensity, Renewable Energy, VECM

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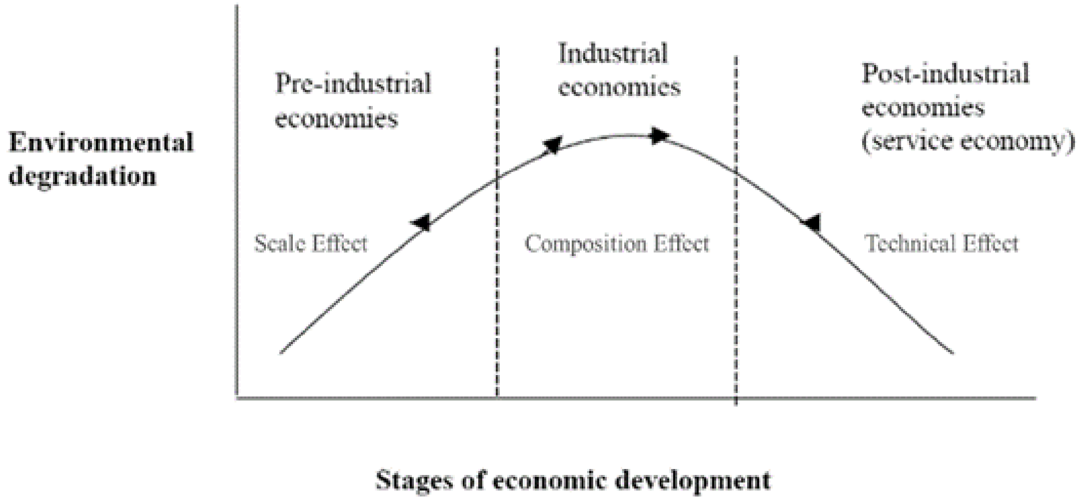
Introduction

Since the early 90s, conferences on how to address climate change have been intensified, it involves the ratification of the United Nations Framework Convention on Climate Change (UNFCCC) during the UN Conference on Environment and Development in 1992. UNFCC has now been ratified by 198 countries and resulted in international agreements including the Kyoto Protocol and the Paris Agreement (Kuh, 2018). These agreements generally aims to reduce global greenhouse gas emissions in an effort to combat rising in global temperature. Indonesia signed the UNFCC on June 5, 1992. Therefore, Indonesia is one of the countries committed to reducing emissions. Indonesia's response to the Paris Agreement in December 2015 regarding keeping the average global temperature increase below 2°C in the pre-industrialization period was the passing of Undang-undang No. 16 Tahun 2016. The law commits Indonesia to a 29 percent reduction in emissions within 2030 through Indonesia's own efforts and a 41 percent reduction with international assistance. This commitment was increased in the The National Medium-Term Development Planning 2020-2024. Indonesia is targeting a 31,89 percent reduction by its own efforts and a 43,20 percent reduction with international assistance by 2030. Indonesia's commitment to reducing emissions is also strengthened by Net Zero Emission targeting in 2060 as stated in Nationally Determined Contribution (NDC) at the 26th Conference of the Parties to the UNFCCC (COP26) in Gasglow (Kementerian ESDM, 2021). Net Zero Emission (NZE) is a reduction of greenhouse gas emissions released into the atmosphere to near zero with the remainings being able to be reabsorbed by the earth.

Indonesia is one of the members of the Group of Twenty (G20). The G20 is an international economic cooperation forum that has members with large economies in the world comprising of 19 countries and 1 European Union (Kemenkeu, 2022). G20 economies collectively contribute 85 percent to Gross World Product (GWP) (Tripathi, 2023). Based on World Development Indicators data by the World Bank, Indonesia in 2022 occupies the 16th position with the world's largest Gross Domestic Product (GDP). Indonesia has a GDP of 1.32 trillion US dollars or a contribution of 1,3 percent of the world's gross domestic product. According to Acheampong and Opoku (2023), economic activities involve the use of large amounts of energy to drive economic growth. Most of the energy used from the past until now comes from fossil fuels such as coal, oil, and natural gas which is a major source of CO2 emissions and significant contributor to climate change. As supported by Waheed et al. (2019), energy consumption especially from non-renewable energy like fossil fuels causes CO2 emissions and this condition us often found in developing countries.

Likewise, Indonesia occupies the 6th position in the world as an emitter. In 2022, Indonesia's CO2 emissions reach 728.88 million tons of CO2 ($MtCO_2$), which contributes of 1,96 percent to the world's total CO2 emissions. This high level of CO2 emissions is a cause for concern because efforts to mitigate CO2 emissions will be difficult to achieve. The use of energy obtained from renewable sources is a solution in reducing the impact on the environment. It is because renewable energy, recognized as carbon-free, can ensure energy security and lower emissions (Raihan & Tuspekova, 2022). Indonesia currently still uses energy derived from burning fossil fuels, especially coal and natural gas as the main energy source in the industrial sector (IESR, 2023). Indonesia's primary energy supply from renewable energy in 2022 is 12,3 percent. The contribution of renewable energy is still quite small compared to energy derived from fossil fuels such as oil, coal and gas which has a value of 87,7 percent (Kementerian ESDM, 2023). Efficient energy use in a country can also help minimize risks to the environment. Energy efficiency contributes to less energy consumption as well as a reduction in greenhouse gases released into nature (Akdag & Yıldırım, 2020). Energi efficiency in country's economy is calculated through energy intensity measurements.

The relationship between CO2 emissions and economic growth is explained in the Environmental Kuzntes Curve (EKC) hypothesis. The EKC hypothesis posits that CO2 emissions will keep rising until the average income hits a turning point, after which environmental quality will start to improve or CO2 emissions will decline as income continues to grow. According to Panayotou (2003), The EKC hypothesis or the inverted-U relationship between environmental degradation and economic growth, parallels Kuznets's theory on the relationship between income and inequality. At early stages of development, environmental degradation is minimal, primarily due to subsistence economic activities and the limited production of biodegradable waste. As agriculture and resource extraction become more intensive and industrialization progresses, resource depletion and waste production escalate. In advanced stages of development, there is a shift towards information-based industries and services, alongside the adoption of technologies that enhance quality of life more efficiently.



Source: Panayotou, 2003

Figure 1. Stages of Economic Development

The inverted U-shaped curve can also be classified into scale, composition, and technique effects. The scale effect signifies that economic advancement initially harms the environment, as heightened production and consumption of fossil fuels in industrial processes lead to elevated emissions. The composition effect suggests that economic progress either benefits or harms the environment based on structural shifts within the economy away from carbon-intensive industries. The technical effect indicates that economic growth benefits the environment, as high-income nations transition from traditional, polluting technologies to cleaner alternatives (Sarkodie & Strezov, 2019).

Research conducted by Aslam et al. (2021), aims to explore the relationship between industrialization, GDP per capita, trade openness, population density, and CO2 emissions. This study also aims to identify the Environmental Kuznets Curve hypothesis in China during the period 1962-2018. Using the AutoRegressive Distributed Lag model (ARDL), this study found that there is an inverted-U EKC relationship characterized by a significant linear form of GDP per capita with a positive sign and a significant quadratic form of GDP per capita with a negative coefficient sign on CO2 emissions. It means that GDP per capita will lead to an increase in CO2 emissions until a certain level of GDP per capita (*turning point*), an increase in GDP per capita will decrease the level of CO2 emissions. In addition, this study found that population density, industrialization, and trade openness will increase CO2 emissions and GDP per capita will reduce CO2 emissions in the long run.

On other hand Zhang (2021) in researching China during period 1974-2014 to analyze the relationship between CO2 emissions and income, found that using an ARDL model, compared to the conventional EKC hypothesis form (U-shape), there is an N-shape relationship between CO2 emissions and GDP per capita in China. The N-shaped Environmental Kuznets Curve (EKC) implies that the original EKC hypothesis does not hold

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in the long term, as beyond a certain income threshold, further increases in income may once again lead to a positive relationship between economic growth and environmental degradation

The study on the Environmental Kuznets Curve (EKC) conducted by (Caporin et al., 2024) for Central Asian Countries during the period 1995-2018 using Fully Modified Ordinary Least Squares (FMOLS) reveal evidence of a linear Kuznets relation between carbon dioxide emissions, and gross domestic product. There is no evidence of a U-shaped or N-shaped Kuznets relation for Central Asia. The findings indicate that only a linear relationship, where GDP is significantly positive on CO2 emissions, was found. Meaning that as GDP increases, CO2 emissions also increase or a growth in GDP still causes CO2 emission.

In determining the relationship between GDP and CO2 emissions, policymakers must ascertain whether a nation's economy follows a conventional (inverted U-shaped) EKC pattern, and if it has, whether the critical turning point has been reached. (Munir et al., 2020). However, in reality, many studies, as well as the aforementioned points have found relationships other than the inverted U-shape between the two variables. These include a linear relationship, a quadratic relationship (U-Shaped or inverted U-shaped), and a cubic relationship (N-Shaped or inverted N-shaped) which is a expansion of the relationship form in the EKC hypothesis (Hatmanu et al., 2022). So, it is necessary to identify the form of the relationship between CO2 emissions and economic growth in order to formulate appropriate policies to mitigate CO2.

Analysis of the relationship between CO2 emissions, economic growth, and energy use is increasingly being conducted, such as research conducted by, Namahoro et al. (2021) Zhou (2023)**,** Raihan et al. (2022), and Shahbaz et al. (2013). Namahoro et al. (2021) in researching Africa continent on the level of income and regional in 1980-2018 using panel cross-sectional augmented distributed lags (CS-DL) method found that Energy intensity and economic growth cause CO2 emissions, while renewable energy reduces CO2 emissions at the regional level and income level, as well as at the African level. Through the causality test, it is found that there is a bidirectional relationship between CO2 emissions and GDP, CO2 emissions and energy intensity, and CO2 emissions and renewable energy in certain regions.

The study conducted by Zhou (2023) in researching dynamic relationship and causality between economic growth, energy consumption, and CO2 emissions in provinces and cities along the Yangtze River Economic Belt in 2000-2018. This study using panel vector autoregression (PVAR) analysis method found that economic growth in the previous period increased energy consumption and CO2 emissions in the current period, as well as energy consumption in the previous period accelerated economic growth and CO2 emissions in the current period, while CO2 emissions in the previous period only resulted in increased energy consumption in the current period. This study found bidirectional relationships in CO2 emissions and energy consumption and in energy consumption and economic growth.

Meanwhile, the study conducted by Raihan et. al. (2022) in researching dynamic impacts of economic growth, fossil fuel energy use, renewable energy use, and agricultural productivity on CO 2 emissions in Nepal in 1990-2019 using Ordinary Least Squares (DOLS) method found that an increase in economic growth and fossil fuel energy would increase CO2 emissions. However, an increase in renewable energy use and agricultural productivity may lead to CO2 emissions reduction in the long run.

These studies found different directions of relationship between these variables. in addition to previous research in researching the linkage between economic growth, energy use and CO2 emissions, research conducted by Wang et al., (2011), Tiwari, (2012), Salahuddin and Khan (2013), Jian et al. (2019) also found different directions of relationship between these variables. Some studies use energy intensity variables such as those conducted by Shahbaz et al. (2015) and Appiah et al. (2019). While others use renewable energy consumption variables such as in research by Raihan & Tuspekova (2022) and Apergis et al. (2010). However, there are few studies that include both energy intensity and renewable energy consumption. This study that being conducted simultaneously includes the variables of CO2 emissions, economic growth, energy intensity, and renewable energy consumption. This study analyzes the relationship between variables using the Vector Error Correction Model. This study differentiates the analysis method between variable linkages and the identification of the EKC relationship form. The identification of the form of the EKC relationship is done using linear and polynomial regression models. This study analyzes Indonesia in the latest conditions with annual data from 1965 to 2022. The coverage of this data is quite extensive which comes from various open sources and not only relying on data available in the World Development Indicators by the World Bank as in most studies, such as those conducted by Tiwari (2012), Salahuddin and Khan (2013), Raihan et al. (2022), Shahbaz et al. (2015), Appiah et al. (2019), and Raihan and Tuspekova (2022b).

Therefore, this study aims to analyze the shape of the relationship between CO2 emissions and economic growth, and to analyze the relationship between CO2 emissions, economic growth, energy intensity, and renewable energy consumption in Indonesia.

Research Method

This research uses secondary data obtained from various open sources, namely the global Carbon Atlas for CO2 Emissions data, the World Bank for Gross Domestic Product and Total Population data, and Our World in Data for energy consumption data. Indonesia's time series data during the period 1965 to 2022 is used in the study. The variables used in the study include CO2 emissions per capita and Gross Domestic Product per capita which were obtained from emissions data and GDP data divided by the total population that are used in the identification of the EKC hypothesis relationship. To analyze the relationship between CO2 Emissions, Economic Growth, Energy Intensity, and Renewable Energy Consumption, the variables of CO2 emissions, Gross Domestic Product, Energy Intensity which were obtained from total primary energy consumption divided by GDP, and Renewable Energy Consumption which were obtained from the summation of energy data from renewable sources are used. The variables used in this study are in the form of natural logarithms.

In identifying the shape of the EKC relationship in Indonesia, regression analysis is used, both linear and polynomial regression models. The models to be identified are as follows:

1. Linear Regression Model

$$\boxed{\ln(\text{CO2 Kapita})_t = \alpha_0 + \alpha_1 \ln(\text{PDB Kapita})_t + \varepsilon_t} \quad (1)$$

2. Second Degree Polynomial Regression (Quadratic)

$$\boxed{\ln(\text{CO2 Kapita})_t = \alpha_0 + \alpha_1 \ln(\text{PDB Kapita})_t + \alpha_2 (\ln(\text{PDB Kapita}))_t^2 + \varepsilon_t} \quad (2)$$

3. Third Degree Polynomial Regression (Cubic)

$$\boxed{\ln(\text{CO2 Kapita})_t = \alpha_0 + \alpha_1 \ln(\text{PDB Kapita})_t + \alpha_2 (\ln(\text{PDB Kapita}))_t^2 +} \\ \boxed{\alpha_3 (\ln(\text{PDB Kapita}))_t^3 + \varepsilon_t} \quad (3)$$

Description:

ln (CO2 Kapita)	: natural logarithm of CO2 emissions per capita
ln (PDB Kapita)	: natural logarithm of GDP per capita
$(\ln(\text{PDB Kapita}))^2$	: quadratic of natural logarithm of GDP per capita
$(\ln(\text{PDB Kapita}))^3$	: cubic of natural logarithm of GDP per capita
α_0	: intercept
$\alpha_1,\alpha_2,\alpha_3$	: regression model parameters
ε_t	: *error term*
t	: period of time (1965,1966,...,2022)

The stages of analyzing linear regression models and polynomial regression models are as follows:

1. Stationarity test for variables natural logarithm of CO2 emissions and GDP per capita with Augmented Dickeu Fuller (ADF) to check whether the data is stationary. Non-

stationary data will result in spurious and misleading regression results. (Gujarati & Porter, 2009). The ADF equation model is as follows

$$\boxed{\Delta Y_t=\beta_1+\beta_2 T+\delta Y_{t-1}+\sum_{i=1}^{m}\alpha_i\Delta Y_{t-1}+\varepsilon_t} \quad (4)$$

Hypothesis:
H_0:δ=0 (there is a unit root or the time series data is not stationary)
H_1:δ<0 (time series data is stationary)
With the criterion of rejecting the null hypothesis if the ADF statistic is greater than its critical value, which indicates that the data is stationary.

2. Regress 3rd degree polynomial regression model, 2nd degree polynomial model, and linear regression models which are written in equations (3), (2), and (1), respectively. Regression parameter estimation using the *Ordinary Least Square* (Gujarati & Porter, 2009)
3. Conduct a partial test (student-t test) to find out which variables have a significant effect on the dependent variable with the following equation:

$$\boxed{t_j=\frac{\hat{\alpha}_j}{SE(\hat{\alpha}_j)}\sim t_{(n-p-1)}} \quad (5)$$

With $\hat{\alpha}_j$ is the estimated coefficient of j-th variable and $SE(\hat{\alpha}_j)$ is standard error of the estimated coefficient of j-th variable. Criterion of rejecting the null hypothesis ($t_j>t_{\alpha(n-p-1)}$) indicates that the variable is significant to the dependent variable (Gujarati & Porter, 2009).
4. Testing the classical assumptions of regression so that the regression model is unbiased, consistent, and produces precise estimates. These assumptions include normality, homoscedasticity, non-autocorrelation, and non-multicollinearity.
   a. Normality
   Normality testing is done with the Jarque-Bera test which is carried out to determine whether the regression model error is normally distributed or not. With the following hypothesis:
   $H_0:\varepsilon_t\sim N(0,\sigma^2)$ error are normally distributed
   $H_1:\varepsilon_t\nsim N(0,\sigma^2)$ error are not normally distributed
   The criterion for rejecting the null hypothesis is when Jarque Bera value is greater than the value of $\chi^2_{\alpha,2}$
   b. Homoscedasticity
   Homoscedasticity testing is done with the Breusch Pagan Godfrey test. Homoscedasticity indicates a condition in which the variance of the error is consistent across time (Gujarati & Porter, 2009). The hypothesis of this test is as follows:
   $H_0:Var(\varepsilon_t)=\sigma^2$ (variance error is constant / homoskedastic)
   $H_1:Var(\varepsilon_t)\neq\sigma^2$ (variance error is not constant / heteroscedastic)
   The criterion for rejecting the null hypothesis is the value of χ^2_{value} is greater that the value of $\chi^2_{\alpha,p-1}$
   c. Non-Autocorrelation
   Testing the assumption of non-autocorrelation is done with the Breusch Godfrey Langrange Multiplier (LM Test). The hypothesis of this test is as follows:
   H_0: $\rho_1=\rho_2=...=\rho_p=0$ (no autocorrelation occurs)
   H_1: at least one $\rho_j\neq0$, j=1,2,...,p(autocorrelation occurs)
   The criterion for rejecting the null hypothesis if the value of the BG statistic is greater than the value of the $\chi^2_{\alpha,p}$
   d. Non-Multikolinearity
   Multicollinearity is a condition where there is a correlation between independent variables (Gujarati & Porter, 2009). Multicollinearity detection can use the Variance Inflation Factors (VIF) value. If $VIF_i>10$, it means that there is a high

correlation between the i-th independent variable and the other i-th independent variables (multicollinearity occurs).

To analyze the relationship between CO2 emissions, economic growth, energy intensity, and renewable energy consumption in Indonesia, The Vector Error Correction Model (VECM) is employed, which is a constrained version of VAR designed for non-stationary yet cointegrated data. In the VECM specification, the long-term relationship among endogenous variables is restricted to converge towards their cointegrating relationship, while permitting the presence of short-run dynamics. (Juanda & Junaidi, 2011). The VECM analysis stages are as follows:

1. Conduct stationarity testing of natural logarithm variables of CO2 Emissions, Gross Domestic Product, Energy Intensity, and Renewable Energy Consumption with Augmented Dickey Fuller (ADF). This stationarity test is to determine the VAR model used whether VAR in level or VAR in difference.
2. Optimum lag selection is based on LR (sequential modified Likelihood Ratio test statistic), AIC (Akaike Information Criterion), SC (Schwarz Information Criterion), FPE (Final Prediction Error), and HQ (Hannan-Quinn information criterion) criteria. These lag selection criteria are based on the lag that has the largest LR value, as well as the smallest AIC, SC, FPE, and HQ values (Juanda & Junaidi, 2011).
3. Checking the stability of the optimum lag using the inverse root value of the characteristic Autoregressive polynomial. If all roots of the polynomial function have a modulus value of less than one, then it can be said that the VAR system fulfills a stable or stationary condition.
4. Testing for cointegration with Johansen Cointegration. If there is cointegration then the model used is VECM. However, if there is no cointegration then the model used is VAR in difference. This test uses the trace statistics value or maximum eigenvalue. With the following hypothesis:

Trace Statistics:	*Maximum Eigenvalue*
$H_0(r_0)$: rank($\mathbf{\Pi}$)=r_0	$H_0(r_0)$: rank($\mathbf{\Pi}$)=r_0
$H_1(r_0)$: rank($\mathbf{\Pi}$)>r_0	$H_1(r_0)$: rank($\mathbf{\Pi}$)=r_0+1

   The criteria for rejecting the null hypothesis if the trace statistics or maximum eigenvalue is greater than Johansen and Juselius critical points. When r_0=0, reject H_0 on trace statistics means there is at least 1 cointegration vector. Next, tests will be conducted for r_0=1, fails to reject H_0 meaning there is 1 cointegration vector. However, reject H_0 meaning there are at least 2 cointegration vectors. This test will be repeated until the null hypothesis fails to reject.
5. Estimating the selected model, if the selected model is VECM then the long-term equation is as follows:

$$\ln CO2_t = \alpha_0 + \sum_{j=1}^{k} \alpha_{1j} \ln CO2_{t-j} + \sum_{j=1}^{k} \alpha_{2j} \ln PDB_{t-j} + \sum_{j=1}^{k} \alpha_{3j} \ln IE_{t-j} + \sum_{j=1}^{k} \alpha_{4j} \ln KET_{t-j} + \varepsilon_{CO2,t} \quad (6)$$

$$\ln PDB_t = \beta_0 + \sum_{j=1}^{k} \beta_{1j} \ln CO2_{t-j} + \sum_{j=1}^{k} \beta_{2j} \ln PDB_{t-j} + \sum_{j=1}^{k} \beta_{3j} \ln IE_{t-j} + \sum_{j=1}^{k} \beta_{4j} \ln KET_{t-j} + \varepsilon_{PDB,t} \quad (7)$$

$$\ln IE_t = \gamma_0 + \sum_{j=1}^{k} \gamma_{1j} \ln CO2_{t-j} + \sum_{j=1}^{k} \gamma_{2j} \ln PDB_{t-j} + \sum_{j=1}^{k} \gamma_{3j} \ln IE_{t-j} + \sum_{j=1}^{k} \gamma_{4j} \ln KET_{t-j} + \varepsilon_{IE,t} \quad (8)$$

$$\ln KET_t = \theta_0 + \sum_{j=1}^{k} \theta_{1j} \ln CO2_{t-j} + \sum_{j=1}^{k} \theta_{2j} \ln PDB_{t-j} + \sum_{j=1}^{k} \theta_{3j} \ln IE_{t-j} + \sum_{j=1}^{k} \theta_{4j} \ln KET_{t-j} + \varepsilon_{KET,t} \quad (9)$$

The short-term equation model is as follows:

$$\Delta \ln CO2_t = a_0+\lambda_1\hat{\varepsilon}_{CO2,t-1}+\sum_{j=1}^{k} a_{1j}\Delta \ln CO2_{t-j} + \sum_{j=1}^{k} a_{2j}\Delta \ln PDB_{t-j} + \sum_{j=1}^{k} a_{3j}\Delta \ln IE_{t-j} + \sum_{j=1}^{k} a_{4j}\Delta \ln KET_{t-j} + v_{1t} \quad (10)$$

$$\Delta \ln PDB_t = b_0+\lambda_2\hat{\varepsilon}_{PDB,t-1}+\sum_{j=1}^{k} b_{1j}\Delta \ln CO2_{t-j} + \sum_{j=1}^{k} b_{2j}\Delta \ln PDB_{t-j} + \sum_{j=1}^{k} b_{3j}\Delta \ln IE_{t-j} + \sum_{j=1}^{k} b_{4j}\Delta \ln KET_{t-j} + v_{2t} \quad (11)$$

$$\Delta \ln IE_t = \omega_0+\lambda_3\hat{\varepsilon}_{IE,t-1}+\sum_{j=1}^{k} \omega_{1j}\Delta \ln CO2_{t-j} + \sum_{j=1}^{k} \omega_{2j}\Delta \ln PDB_{t-j} + \sum_{j=1}^{k} \omega_{3j}\Delta \ln IE_{t-j} + \sum_{j=1}^{k} \omega_{4j}\Delta \ln KET_{t-j} + v_{3t} \quad (12)$$

$$\Delta \ln KET_t = \varphi_0+\lambda_4\hat{\varepsilon}_{KET,t-1}+\sum_{j=1}^{k} \varphi_{1j}\Delta \ln CO2_{t-j} + \sum_{j=1}^{k} \varphi_{2j}\Delta \ln PDB_{t-j} + \sum_{j=1}^{k} \varphi_{3j}\Delta \ln IE_{t-j} + \sum_{j=1}^{k} \varphi_{4j}\Delta \ln KET_{t-j} + v_{4t} \quad (13)$$

Description:

ln CO2 : natural logarithm of CO2 emissions
ln PDB : natural logarithm of GDP
ln IE : natural logarithm of Energi Intensity
ln KET : natural logarithm of Renewable Energi Consumption
t : period of time (t =1965,1966,...,2022)
k : optimum lag length
ε_{it} : long-run equation error term (i=CO2,PDB,IE,KET)
$\alpha_0,\beta_0,\gamma_0,\theta_0$: long-run equation intercept
$\alpha_i,\beta_i,\gamma_i,\theta_i$: long-run equation parameters (i=1,2,3,4)
λ_i : speed of adjustment (i=1,2,3,4)
$\hat{\varepsilon}_{i,t-1}$: long-run equation residuals ((i = CO2, PDB, IE, KET)
v_{it} : short-run equation error term (i=1,2,3,4)
a_0,b_0,ω_0,ϕ_0 : short-run equation intercept
a_i,b_i,ω_i,ϕ_i : Short-run equation parameters (i=1,2,3,4)

6. Conduct a diagnostic test to see the white noise residuals of the estimated model with Augmented Dickey Fuller (ADF). White noise residuals is condition when the residuals have a mean value of zero and variance σ^2, and there is no autocorrelation (Juanda & Junaidi, 2011).
7. Conduct an Impulse Response Function (IRF) analysis to see the effect of shocks om the variables in the system at current time and in several future periods

Results and Discussions

Analysis of the Shape of the Relationship between Economic Growth and CO2 Emissions

Table 1. Stationarity Testing ADF

Variable	Data at level		Data at first difference	
	Test Statistics	P-Value	Test Statistics	P-Value
Ln CO2 Kapita	-2,100384	0,5344	-8,066344	0,0000**
Ln PDB Kapita	-2,597283	0,2831	-5,877817	0,0000**
Ln PDB Kapita^2	-0,708424	0,9674	-6,102288	0,0000**
Ln PDB Kapita^3	1,961189	1,0000	-5,675212	0,0001**

**) Significant at α=5%, *) Significant at α=10%

Stationarity testing with Augmented Dickey Fuller (ADF) uses an equation model that includes intercept and trend. Stationarity testing on level data does not show any significant variables. It means that the variables are not stationary at the data level so that stationarity testing is carried out on the first difference data. Stationarity testing on the first difference data shows that the variables have been stationary. It can be seen from all variables that are significant at the 5 percent significance level. The stationary variables will be subjected to regression analysis to determine the shape of the relationship between CO2 emissions and

GDP per capita. There are three models performed, namely linear regression models, 2nd, and 3rd degree polynomial regression models.

Table 2. Third Degree Polynomial Regression (Cubic) Estimation

Dependent Variable: Δ(Ln (CO2 Kapita))				
Variable	***Coefficient***	**Std. Error**	**t-Statistic**	**P-value**
Δ(Ln(PDB Kapita))	1,012237	0,345769	2,927492	0,0050**
Δ((Ln (PDB Kapita))^2)	-0,476485	0,327728	-1,453904	0,1519
Δ((Ln (PDB Kapita))^3)	0,293209	0,230157	1,273953	0,2082
C	0,005853	0,013619	0,429752	0,6691

**) Significant at α=5%, *) Significant at α=10%

Table 2. Second Degree Polynomial Regression (Quadratic) Estimation

Dependent Variable: Δ(Ln (CO2 Kapita))				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**P-value**
Δ(Ln(PDB Kapita))	1,065388	0,345217	3,086137	0,0032**
Δ((Ln (PDB Kapita))^2)	-0,135017	0,189662	-0,711884	0,4796
C	0,009171	0,013444	0,682189	0,4980

Table 4. Linear Regression Model Estimation

Dependent Variable: Δ(Ln (CO2 Kapita))				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**P-value**
Δ(Ln (PDB Kapita))	0,928571	0,285483	3,252628	0,0020**
C	0,009925	0,013342	0,743898	0,4601

The estimation results of the cubic regression model to identify the form of N-shaped or inverted N-shaped relationship is shown in Table 2. It shows that only the variable Δ(Ln(PDB Kapita)) is significant to Δ(Ln(CO2 Kapita)). There is no significant relationship between the quadratic and the cubic of economic growth variables with CO2 emissions growth variable. In this model monotonically increasing relationship is found. Where, the growth of CO2 emissions will increase often with increasing GDP per capita growth.

Caporin et al., (2024) stated that the linearity might not be surprising as it might be interpreted as evidence of all countries being in the first phase of the N-shaped and U-shaped curve, which might be locally approximated by a linear relationship. These results are consistent with that of Bekhet and Othman, (2018) for Malaysia.

To see the quadratic relationship, which is U-shape or inverted U-shape, a 2nd degree polynomial regression analysis was conducted. Table 3, shows that there is an inverted U shape relationship indicated by a positive Δ(Ln(PDB Kapita)) coefficient and a negative Δ((Ln (PDB Kapita))^2) coefficient. However, the variable Δ((Ln (PDB Kapita))^2) is not significant to CO2 emissions growth. Therefore, the relationship between CO2 emissions growth and Indonesia's economic growth in this model also has a positive linear relationship.

This finding is in line with research conducted by Lean dan Smyth (2010) in examining ASEAN-5 which found that Indonesia's pollutant emissions increased monotonically with income levels. Research conducted by Chandran dan Tang (2013) whom also examined ASEAN-5 found similar results for the relationship between CO2 emissions and GDP per capita. The study states that the relationship between CO2 emissions and income in Indonesia tends to be linear. According to Chandran dan Tang (2013), the rejection of the conventional relationship shape of the EKC hypothesis (inverted U-shaped) in Indonesia, Malaysia, and Thailand is because these countries are developing countries that have not yet reached the desired income level to achieve the inverted U-shaped relationship established by the EKC hypothesis. The results obtained from the quadratic equation regression are not in line with the research conducted by Sugiawan and Managi (2016) in examining Indonesia who found an inverted-U relationship between GDP per capita and CO2 emissions from the quadratic equation model. Next, modeling will be done for the linear regression model.

From Table 4, it is known that the variable Δ(Ln(PDB Kapita)) is significant to Δ(Ln(CO2 Kapita)) at the 5 percent significance level. It means that economic growth significantly affects emissions growth. The linear regression model shows that CO2 emissions growth and economic growth have a monotonically increasing relationship or there is an increasing relationship between the two variables which were shown by a positive (Ln(PDB Kapita)) coefficient. When there is an increase in economic growth, the growth of CO2 emissions will also increase. The increase in CO2 emissions indicates an increase in environmental degradation.

The results of modeling to identify the form of this linear relationship are in line with research conducted by Sugiawan and Managi (2016), in examining Indonesia. This study also found a monotonically increasing relationship between economic growth and per capita income variables in the linear model equation. However, the study by Sugiawan and Managi found an inverted-U relationship between GDP per capita and CO2 emissions from its quadratic equation model, which is not in line with the results of this study. Therefore, it can be concluded that the relationship between CO2 emissions growth and Indonesia's GDP per capita growth is positive linear or has a monotonically increasing relationship.

Table 5. Classical Assumptions of Regression Models

Assumption (H_0)	Test	P-value		
		Linear Regression Model	Quadratic Regression Model	Cubic Regression Model
Normality	Jarque-Bera	0,2970	0,3459	0,2512
Homoscedasticity	Breusch-Pagan-Godfrey	0,6066	0,8370	0,9011
Non-Autocorrelation	Breusch Godfrey LM-Test	0,9430	0,7525	0,6974

Non-Multicollinearity Assumption					
Linear Regression Model		Quadratic Regression Model		Cubic Regression Model	
Variable	VIF	Variable	VIF	Variable	VIF
Δ(Ln (PDB Kapita))	1,0000	Δ(Ln(PDB Kapita))	1,4491	Δ(Ln(PDB Kapita))	1,4706
		$\Delta((\text{Ln (PDB Kapita)})^2)$	1,4491	$\Delta((\text{Ln (PDB Kapita)})^2)$	4,3768
				$\Delta((\text{Ln (PDB Kapita)})^3)$	4,2279

From Table 5, it shows that with a significance level of 5 percent it fails to reject the null hypothesis for the normality assumption test with Jarque-Bera, the homoscedasticity assumption test with Breusch Pagan Godfrey, and the non-autocorrelation assumption test with Breusch Godfrey LM-test. Meanwhile, the detection of multicollinearity using VIF found that all variables in each model have VIF <10 or the assumption of non-multicollinearity is met.

The Relationship between CO2 Emissions, Economic Growth, Energy Intensity, and Renewable Energy Consumption

Table 6. ADF Stationarity Test

Variable	Data at level		Data at first difference	
	Test Statistics	P-Value	Test Statistics	P-Value
Ln CO2	-1,728221	0,7257	-8,074392	0,0000**
Ln PDB	-1,998211	0,5895	-5,847691	0,0001**
Ln IE	-0,989282	0,9372	-5,577959	0,0001**
Ln KET	-2,180770	0,4907	-8,955650	0,0000**

**) Significant at α=5%, *) Significant at α=10%

In analyzing with the Vector Autoregressive (VAR) model which is a time series analysis, data stationarity is required. The data used in the VAR model is required to be stationary (Juanda & Junaidi, 2011). Checking data stationarity in the selection of VAR models is necessary to determine whether the VAR model used is VAR in level or VAR in difference or VECM if there is cointegration. Based on ADF stationarity, it is known that the variables are not stationary in level data. Stationarity testing on first difference data found that all variables are stationary at first difference at 5 percent significance level. Next, the optimum lag selection will be carried out to determine the order of the VAR model.

Table 7. Lag Selection Criterion

Lag	LogL	LR	FPE	AIC	SC	HQ
0	3,291572	NA	1,21e-05	0,026238	0,173570	0,083058
1	299,9732	538,4222*	3,70e-10*	-10,36938*	-9,632716*	-10,08528*
2	314,7926	24,69905	3,90e-10	-10,32565	-8,999663	-9,814270
3	327,2191	18,86990	4,57e-10	-10,19330	-8,277983	-9,454638
4	346,2768	26,11606	4,29e-10	-10,30655	-7,801901	-9,340604

Table 7 contains the optimum lag selection criteria, it is found that lag 1 has the largest LR value, as well as the smallest AIC, SC, FPE, and HQ values. Therefore, the selected lag in the modeling is lag 1 which will then be checked for stability. The stability of VAR modeling with a predetermined lag optimum is useful to check whether the model has been stable (stationary) or not.

Table 8. *AR Roots*

Root	Modulus
0,993085	0,993085
0,915140	0,915140
0,830429	0,830429
0,651188	0,651188

The stability of VAR modeling with a predetermined optimum lag is useful to check whether the model has stabilized (stationary) or not. Based on the AR Roots Table, it can be seen that all roots have a modulus value that is less than one. This means that the VAR with order 1 has been stable or stationary. Furthermore, to determine whether the selected model is VAR in difference or VECM, cointegration testing is conducted. If there is cointegration then VECM modeling will be selected.

Table 9. Johansen Cointegration Test

Null Hypothesis	Trace		Maximum Eigenvalue	
	Trace Statistics	P-value	Max-Eigen Statistics	P-value
$r = 0$	59,19001	0,0030**	33,92031	0,0067**
$r \leq 1$	25,26970	0,1520	16,23508	0,2114
$r \leq 2$	9,034622	0,3622	6,546074	0,5441
$r \leq 3$	2,488548	0,1147	2,488548	0,1147

**) Significant at α=5%, *) Significant at α=10%

Based on the Johansen cointegration test, it is known that there is at most 1 cointegration among the variables. This indicates that the variables lnCO2, LnPDB, LnIE, and LnKET are cointegrated or have a long-term relationship. Therefore, modeling using VECM. In the analysis with VECM, it is possible to estimate the long-term Johansen cointegration equation.

Table 10. Estimation of Long-Run Equation

Dependent Variable: Ln $CO2_{t-1}$				
Variable	Coefficient	Std. Error	t-Statistic	P-value
Ln PDB_{t-1}	1,125804	0,02840	-39,6468	0,000000**
Ln IE_{t-1}	0,430701	0,05051	-8,52644	0,000000**
Ln KET_{t-1}	-0,064511	0,01795	3,59312	0,000725**

C	-1,343805

**) Significant at α=5%, *) Significant at α=10

The long-term equation is as follows:

$$\boxed{\ln CO2_{t-1} = -13438 + 1{,}1258 \ln PDB_{t-1} + 0{,}4307 \ln IE_{t-1} - 0{,}0645 \ln KET_{t-1}} \quad (14)$$

Based on Table 10, it is known that at the 5 percent significance level all variables significantly affect CO2 emissions in the long run. Gross domestic product and energy intensity variables have a positive significant effect on CO2 emissions in the long run. Meanwhile, renewable energy consumption has a negative effect on the CO2 emissions in the long run. When there is an increase in gross domestic product by 1 percent, CO2 emissions will increase by 1,13 percent. Likewise, when there is an increase in energy intensity by 1 percent, CO2 emissions will increase by 0,43 percent. Meanwhile, when renewable energy consumption increases by 1 percent, CO2 emissions will decrease by 0,06 percent. This is in line with research conducted by Namahoro et al. (2021) in examining Africa which found that renewable energy consumption significantly contributed to reducing CO2 emissions as well as energy intensity was found to significantly increase CO2 emissions. However, this study found the relationship between economic growth and CO2 emissions to have mixed effects (positive and negative) across African regions, incomes, and panels.

An increase in GDP that increases emissions is in line with research by Shahbaz dkk. (2013) in researching Indonesia which found that economic growth increases CO2 emissions and is a major contributor to CO2 emissions. The estimation results of this long-term equation are also in line with research conducted by Shahbaz et al. (2015) in examining Portugal which found that energy intensity and economic growth have a positive influence on CO2 emissions. Therefore, it can be said that energy intensity and economic growth are the main causes of CO2 emissions. This research suggests that CO2 emissions can be reduced at the expense of economic growth or by encouraging energy efficiency or the use of energy-efficient technologies in increasing domestic production.

In addition, the results of this study are also in line with research conducted by (X. Zhang et al. (2023) in examining the country of Morocco, where it was found that an increase in energy intensity significantly contributes to CO2 emissions in the long term and short term. Meanwhile, an increase in renewable energy consumption will reduce CO2 emissions in the long term and short term. Zhang et al. suggested based on empirical findings that to reduce CO2 emissions can be through energy efficiency which can be done by optimizing the energy consumption structure and using clean energy.

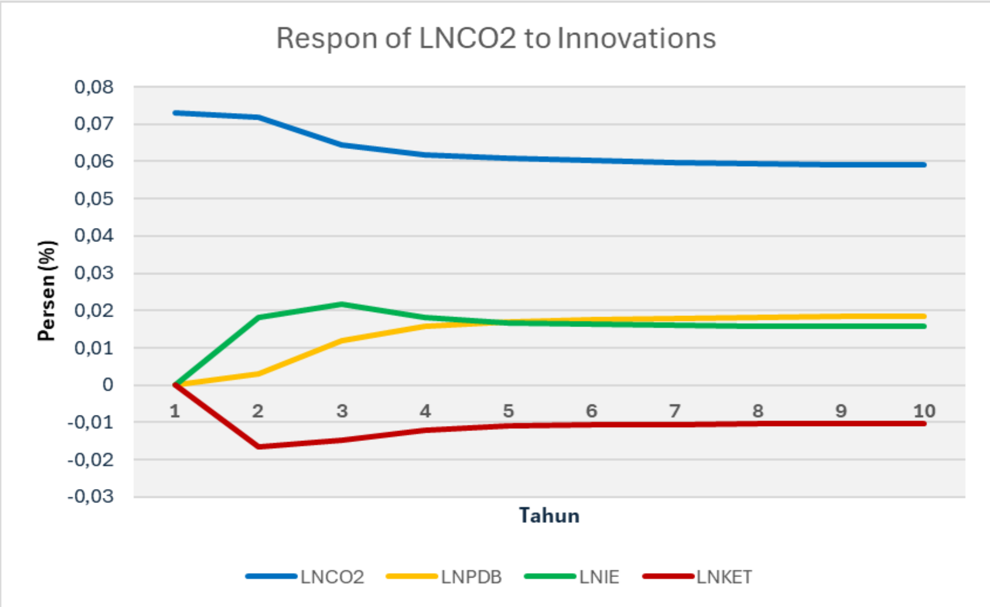
Table 11. Estimation of VECM equation

Dependent Variable: $\Delta \ln CO2_t$				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**P-Value**
$\widehat{\varepsilon_{t-1}}$	-0.446805	0.191606	-2.331898	0.0207**
$\Delta \ln CO2_{t-1}$	-0.015718	0.195589	-0.080361	0.9360
$\Delta \ln GDP_{t-1}$	0.178604	0.366374	0.487491	0.6264
$\Delta \ln IE_{t-1}$	0.500657	0.279036	1.794236	0.0743*
$\Delta \ln KET_{t-1}$	-0.062113	0.048696	-1.275529	0.2036
C	0.054310	0.019396	2.800052	0.0056**

**) Significant at α=5%, *) Significant at α=10

The VECM estimation results in Table 11 show that in the short term, only the variable of energy intensity growth has a significant effect on CO2 emission growth. Economic growth, and renewable energy consumption growth variables are not significant to the growth of CO2 emissions at the 10 percent significance level. This indicates that energy intensity causes CO2 emissions in the short term. Shahbaz, et al. (2015) said that an increase in energy intensity can harm the environment if energy production still depends on energy derived from fossil fuels.

Short-term equation estimation shows that the equation $\Delta \ln CO2_t$ has a negative and significant long-run residual coefficient. This coefficient value shows the speed of adjustment. This value means that the short-term imbalance will be corrected by 44.68 percent for each period. Juanda and Junaidi (2011) said that in the VECM model, there is a gradual correction through short-term adjustment to the deviation from the long-term equilibrium model. Next, it will be conducted the ADF test whether the residuals of VECM modeling meet the white noise assumption. It was found that the residuals of the VECM estimation results met the assumption of white noise, namely with a stationary modeling residual value with a p-value of (0.0000).



Sumber: *Output* Eviews12 *Student Version Lite*, retrieved

Figure 2. Response of CO2 Emission Variables to Shocks (*Shock*)

Impulse Response analysis is used to determine the response of a variable when there is a shock to the variable itself or shocks that occur to other variables. Figure 2 shows the response of CO2 emissions to shocks. In the first year, there is no response of CO2 emissions to shocks that occur in GDP, energy intensity and renewable energy consumption where CO2 emissions in the first year only respond to shocks that occur to CO2 emissions themselves. In year 2 CO2 emissions began to respond to shocks that occurred in these variables. CO2 emissions generally respond positively to shocks that occur in CO2 emissions itself, GDP, and energy intensity. While shocks that occur in renewable energy consumption are negatively responded by CO2 emissions. The response of CO2 Emissions to shocks that occur in renewable energy consumption is in line with research conducted by Tiwari (2011) which found that shocks to renewable energy consumption have a negative impact on CO2 emissions. This study also found that shocks to GDP have a positive impact on CO2.

Conclusions

The relationship between CO2 emissions growth and economic growth in Indonesia for the period 1965-2022 is monotonically increasing, which means that when there is an increase in economic growth, emissions growth will also increase. In Indonesia, the causes of CO2 emissions in the long run are GDP and energy intensity. Meanwhile, the one that contributes to reducing CO2 emissions is renewable energy consumption. However In the short term, it found that the causes of CO2 emissions in Indonesia are energy intensity.

In order to control CO2 emissions in the process of economic development, Indonesia must replace the extensive economic growth mode (quantitative increase in inputs) with intensive economic growth (productivity increase). This can be achieved by developing low-consumption industries and limiting the development of industries with high levels of energy consumption. The Indonesian government can increase the presence of such low-consumption industries with policies such as tax breaks and rebates to support the increase in national income.

In an effort to reduce environmental impacts, the government should encourage the use of renewable energy consumption as a substitute for energy derived from fossil fuels, and develop clean energy. Renewable energy includes energy derived from solar, wind, water, waves, as well as biomass and geothermal. The government can provide support in the form of tax intensive, capital, technology, and protection aspects.

Energy use efficiency efforts can also be carried out as a way to reduce CO2 emissions, namely by reducing energy consumption derived from fossil fuels which are the largest contributor to CO2 emissions. The use of more energy-efficient technologies in the production process can support an environment free from damage. The government can invest in energy-efficient technologies and encourage energy conservation efforts.

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