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Factors influencing carbon emissions in Indonesia : Dynamic model approach

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ABSTRACT

This study aims to determine the relationship between GRDP growth, Gross Fixed Capital Formation, trade value, added value of the industrial sector and energy consumption to increasing carbon dioxide emissions in Indonesia. The secondary data used for research comes from World Development Indicators, the Indonesian Central Bureau of Statistics, and regional financial reports for the period 1988-2020. The analytical tool used in this study uses the Error Correction Model regression to analyze short-term and long-term relationships between research variables. The results of the study show that in the long term GDRP growth, industrial added value, and energy consumption are the main drivers of increasing carbon dioxide emissions in Indonesia. In the short term, growth in GDRP and consumption of petroleum are driving increased carbon dioxide emissions. The government must be firm with the Presidential Regulation concerning the Application of Carbon Economic Value to Achieve Nationally Determined Contribution Targets and Control of Greenhouse Gas Emissions in National Development. The basic principles and strategies that the government must pay attention to are reducing emissions in urban transportation by limiting the number of vehicles that are not roadworthy and diverting fossil energy to electricity.

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1. INTRODUCTION

Entering the 21st century the increasing concentration of pollutants in the earth's atmosphere has created a serious threat to the destruction of the ozone layer and the occurrence of various dramatic climate changes as implied by the phenomenon of global warming (Todaro & Smith, 2009). To reduce environmental risks, global emissions must be limited to near safe limits. The responsibility for reducing emissions must be shared fairly across the international community. According to data from the United States Aeronautics and Space Administration (NASA), the concentration level of carbon dioxide (CO2) in the global atmosphere has reached an average of 417.6 parts per million (ppm) on May 17, 2022. This figure has increased by around 6.2%. compared to 2011. The increase also consistently occurs every year, as shown in the graph. If traced further,

according to NASA, the concentration of CO2 in the atmosphere today has even increased by around 50% compared to the beginning of the industrial era in 1750. Increasing levels of CO2 in the atmosphere have the potential to increase the temperature of the earth's surface, which can then trigger climate change, natural disasters, and have an impact on to the disruption of economic activity.

The main source of the greenhouse effect is the burning of fossil energy (oil, gas and coal) by motorized vehicles and industrial machinery. The biggest contributor to air pollution and takes the longest time to decompose naturally in the atmosphere and has the highest concentration level is carbon dioxide. In 2017, estimated carbon dioxide emissions were 487 million tons (MtCO2) per year in Indonesia, an increase of 4.7 percent from 2016 (Global Carbon Project (GCP), 2017). In 2017 Indonesia contributed 1.34 percent of the world's total CO2 emissions of 36,153 million tons (MtCO2). In 2018, there was a 2 percent increase in CO2 emissions from 2017. This carbon emission consists of burning oil, cement production, and changes in land use such as forest fires or deforestation. In 2021 total energy consumption in Indonesia will reach 909.24 million barrels of oil equivalent (BOE). Based on data from the Ministry of Energy and Mineral Resources (ESDM), energy consumption in Indonesia edged up 0.4% compared to 2020 of 905.6 million BOE.

According to a WMO-UNEP assessment, current pollutant emission patterns would raise global temperatures by 0.3 degrees Celsius every decade, or 3 degrees Celsius (5.4 degrees Fahrenheit), through the end of the 21st century (Todaro, 1999). The study suggests that to restore CO2 and CFC concentrations to their current levels, human activities that cause increased emissions at current levels must be reduced by up to 60 percent. Even though the statistical evidence that appears to be a trend of global warming is inadequate, the potential for climate change with all its dire consequences has generated a series of demands and calls for preventive policies to address the current global warming problem. Economic growth, PMTB, trade value, industrial added value, and energy consumption affect Indonesia's carbon dioxide emissions. Regression using the Error Correction Model is utilized. The secondary data used comes from World Development Indicators, the Indonesian Central Bureau of Statistics, as well as the regional financial reports of the Indonesian Ministry of Finance for 1988-2020.

The rapid increase in the production of carbon emission pollutants has led to an increase in the concentration of gases which causes the greenhouse effect and depletion of the ozone layer. Since the start of the industrial revolution until the 1960s (Todaro & Smith, 2009) the global concentration of carbon dioxide has increased by 26 percent. The UNCHE was held in Stockholm, Sweden, in 1972 to address air pollution. The UN convened 114 nations for the first environmental summit. This conference is also the first step in efforts to save the environment globally. Topics raised in this environmental conference are pollution, climate change, ozone depletion, use and management of marine and water resources, widespread deforestation, desertification and soil degradation, hazardous waste, and biodiversity depletion. The conference's Agenda 21 recommendations cover new ways to educate, conserve natural resources, and participate in designing an environmentally sound economy or sustainable economic development. The overall goal of Agenda 21 is to create a safe, secure, and dignified life.

Numerous scholars have conducted research on the correlation between economic growth, PMTB, trade value, industry added value, and energy consumption and the rise in carbon dioxide emissions during the developmental process. The aforementioned researchers have explored this topic in depth. Research conducted by (Shrestha et al., 2009) concluded that economic growth is the main factor of economic development and has an impact on increasing CO2 emissions in ten countries (namely Australia, China, India, Japan, Malaysia, Pakistan, South Korea, Singapore, Thailand, and Vietnam). Impact Economic growth will increase the intensity of electricity use to become a major factor of development in Bangladesh, Indonesia, and the Philippines. Structural changes

to power plants as the main contributor to changes in CO2 emissions in Sri Lanka and New Zealand. Another study conducted by (He et al., 2022) concluded that economic growth is the main driver in increasing carbon dioxide.

According to research by (Zhu & Gao, 2019), energy consumption structure, urbanization rate, and per capita GDP all contribute to the transportation sector's carbon emissions. There exists an inverse correlation between the degree of technological advancement and economic trade openness, and the utilization of carbon emissions within the transportation sector. A study conducted by (Wang & Geng, 2015) found that the tertiary industry's contribution to the overall GDP and urban per capita income has an indirect positive impact on carbon emissions. The mitigation of carbon emissions stemming from municipal solid waste (MSW) can be achieved significantly through the processes of incineration and composting.

Examining the factors that contribute to CO2 emissions in Latin America is the aim of study by (Panait et al., 2022). The research findings indicate that foreign investment and the inflow of development aid funds have a significant influence on the levels of carbon dioxide emissions. The research carried out by (Xu et al., 2014) investigated the diverse determinants that influence the carbon emissions arising from the consumption of non-renewable energy sources in China. The research results suggest that the main contributor to carbon emissions is the production of electricity, which is associated with both industrial structure and energy consumption. In China and India, energy consumption affects renewable energy more than CO2 emissions (Ahmed et al., 2022). Substituting non-renewable energy sources with renewable ones and reducing coal use might reduce carbon dioxide emissions while sustaining economic growth.

According to (Xu et al., 2016), carbon emissions come from product and service production. Transportation emits carbon after industry. (Al-mulali, 2012) examined the main drivers of CO2 emissions in twelve Middle Eastern countries: Bahrain, Egypt, Iran, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syria, UAE, and Yemen. The research found that total primary energy consumption, net inflows of foreign direct investment, GDP, and total commerce increase CO2 emissions throughout development. According to a research by (Chandran & Tang, 2013), long-term elasticity shows that income and transportation energy use affect CO2 emissions, but FDI does not. Economic development affects ASEAN CO2 emissions. Transportation energy regulation may reduce carbon dioxide emissions. Urbanization and energy use positively affect CO2 emissions (Abbasi et al., 2020). This shows that urbanization and energy use face long-term environmental quality issues.

Researchers (Liu & Feng, 2022) and (Omri & Saidi, 2022) examined the connection between CO2 emissions and unemployment. Liu and Feng's study determined that there exists a positive correlation between unemployment rates in the Middle East and CO2 emissions. This implies that a rise in the quantity of unemployed individuals may result in a corresponding increase in CO2 emissions. In various regions across the globe, namely Africa, America, Europe, and Asia-Pacific, there exists a negative correlation between unemployment and CO2 emissions. This implies that a rise in unemployment levels is likely to result in a decrease in CO2 emissions. Overall, there is a lack of empirical evidence indicating any correlation between unemployment and CO2 emissions within the Middle East and Asia-Pacific region. The research conducted by (Omri & Saidi, 2022) reveals a bidirectional correlation between the amplification of worth in the agricultural sector and the discharge of carbon dioxide. There is a unidirectional correlation between emissions and industrial value added in both the short and long term. Additionally, there is a unidirectional correlation between value added services and CO2 emissions.

Based on previous research, it is interesting to examine the impact of economic development/macro variables on carbon dioxide emissions in Indonesia. The impact of development that has been felt so far in developing countries is unsustainable economic

development (development that has an environmental impact). The difference between this research and previous research is; a) the variables used use collaboration from various previous studies (very few studies use industry added value variables); b) most studies use panel data models and multiple regression, in this study using dynamic models.

2. RESEARCH METHOD

According to (Enders, 2004), regression using non-stationary time series data yields erroneous conclusions. This phenomenon of regression arises due to a relatively high coefficient of determination despite the lack of any meaningful relationship between the independent and dependent variables. The significant coefficient of determination evident in the two time series variables can be ascribed to the existence of a trend, rather than a causal association between the variables. The current investigation employs the subsequent model :

$$ECO2 = \beta o+\beta_1 GDPt+\beta_2 GFCFt+\beta_3 IVAt+\beta_4 TRADEt+\beta_5 OCt+\acute{\varepsilon}t \quad (1)$$

Where:
ECO2 = Carbon Dioxide Emissions
GDP = Gross Domestic Product
GFCF = Gross Fixed Capital Formation
IVA = Industry Value Added
TRADE = Trade Value
OC = Oil Consumption
ἐt = residuals
β = Regression Coefficient

The linear combination of the dependent and independent variables may be stationary even if their data are not. Equation (1) may be rewritten as:

$$\acute{\varepsilon}t = ECO2-\beta o-\beta_1 GDPt-\beta_2 GFCFt-\beta_3 IVAt-\beta_4 TRADEt-\beta_5 Oct \quad (2)$$

The noise element of the linear combination is. When the variable t remains constant, it can be inferred that the dependent and independent variables exhibit cointegration or a sustained long-term relationship. This assertion is substantiated in cases where the two variables exhibit non-stationarity at the fundamental level but demonstrate stationarity at a comparable level of differentiation. The present investigation scrutinized the concept of cointegration by means of the Engle-Granger cointegration test. Cointegration refers to the linear combination between two variables in time series data that exhibit non-stationarity at one level but stationarity at another. Despite the existence of a prolonged association between the two variables, there may not be an equilibrium in the immediate correlation between them. This imbalance means that what economic actors want is not necessarily the same as what happens. To overcome this imbalance, a model is made to include adjustments to carry out imbalance corrections which are referred to as error correction models. This model was first introduced by Sargan and then developed by Hendry until finally popularized by Engle-Granger. The purpose of utilizing this particular model is to address the challenge of non-stationarity and linear regression in the context of time series data. In order to examine this model, we propose a long-term relationship model between the ECO2 variable and the independent variable, as outlined below:

$$ECO2t = \beta o+\beta 1 GDPt+ \beta 1 GFCFt+ \beta 1 IVAt+ \beta 1 TRADEt+ \beta 1 OCt \quad (3)$$

If ECO2t has a different value from the balance value, the difference between the left and right sides in Equation (3) is:

$$ECt = ECO2t-\beta o-\beta 1GDPt- \beta 1GFCFt- \beta 1IVAt- \beta 1TRADEt- \beta 1OCt \quad (4)$$

This Ect difference value is referred to as the unbalance error. If ECt is zero, then ECt and the independent variables are in balance. Because ECt and its independent variables are rarely found in a state of equilibrium, an unbalanced or short-term relationship is observed by incorporating the element of ECt's inertia and its independent variables. Suppose you have the following equation:

$$ECO2t = bo+b1GDPt-1-b2GFCFt-1-b3IVAt-1-b4TRADEt-1-b4OCt-1 +\Phi ECO2t-1+\dot{\varepsilon}t \; ; \; 0<\phi<1 \quad (5)$$

$$\Delta ECO2t=b1GDPt-b2GFCFt-b3IVAt-b4TRADEt-b4OCt+\Phi ECO2t-\lambda(ECO2t-1-\beta o-\beta 1GDPt-1-\beta 2GFCFt-1-\beta 3IVAt-1-\beta 4TRADEt-1-b4OCt-1)+\dot{\varepsilon}t \quad (6)$$

In Equation (6) you can enter the lag of the first level or also the lag at a higher level. In Equation (5) the impact is that the ECO2 value takes time to fully adjust to the variation of the independent variables. From Equation (7), there is $-\lambda(ECO2t-1-\beta o-\beta 1GDPt-1-\beta 2GFCFt-1-\beta 3IVAt-1-\beta 4TRADEt-1-b4OCt-1)$ in Equation (6) which is interpreted as a balance error from the previous period t -1. Equation (6) explains that changes in ECO2 in the current period are affected by changes in the independent variable and the imbalance error in the previous period. Equation (6) is the first level of ECM with parameter λ is the adjustment parameter, parameter b describes the short-term effect and parameter β describes the long-term effect. The lowered ECM is known as the two-stroke model from Engle-Granger. According to Engle Granger, if the independent and dependent variables are not stationary but cointegrated, then the relationship between the two variables can be explained by the ECM model.

3. RESULTS AND DISCUSSIONS

Using regression with time series data requires data to be in stationary form. Stationary data is data whose variations and auto variance are always the same when the data is used in a study. Stationary data will produce a more stable time series regression model. If the data used in the model is not stationary, it is necessary to reconsider the validity and stability of the regression results. The results of the regression equation obtained from data that are not stationary cause an oblique regression. Sharp regressions have strong coefficients of determination but no significant relationship between independent and dependent variables ((Gujarati, 2004); (Basuki, 2017)).

An ADF (Augmented Dicky Fuller) test with a five percent significance criterion determines if the data are steady. Based on the results presented in Table 1, it can be inferred that the t-ADF value pertaining to the data level surpasses the MacKinnon critical value. Therefore, it can be deduced that the data employed in the analysis is non-stationary and contains unit roots. The test for unit roots is conducted at the level of first-order differencing or lower. This test is carried out on the unit root test, if it turns out that the data is not stationary in the first degree (Price & Insukindro, 1994), the test is carried out in the first differential form. The following test is a stationarity test with the DF test at the first level of differentiation. From Table 1 for the first Different data, it is stationary, this can be seen in the probability value of ADF winning which is less than 5 percent.

Table 1. Stationary Test Results

Group unit root test Summary
Series : EC02, GDP, GFCF, IVA, TRADE, OCT
Date : 05/30/22 Time : 11:55
Sample : 1988 2020

Method	Data Level		First Different	
	Statistic	Prob.**	Statistic	Prob.**
Null : Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.06649	0.4735	-10.7964	0.0000
Null : Unit root (assumes individual unit root process)				
Im, Pesaran and Shiw W-stat	0.65121	0.7425	-11.7819	0.0000
ADF – Fisher Chi-Square	15.5820	0.2111	119.297	0.0000
PP – Fisher Chi-Square	14.7963	0.2528	145.080	0.0000

Source: Data Analysis Results, 2022

In Figure 1a, 1b, 1c, 1d, 1e and 1f with the 1st difference test for ECO2, GDP, GFCF, IVA, TRADE and OCT, all variables are stationary at the 1st difference. This can be seen in the t statistic for ADF < of prob 0.01. Furthermore, after all the data is fulfilled in the 1st difference, then a cointegration test is carried out. The preliminary evidence of a long-term association (cointegration) in the utilized model is its successful completion of the cointegration examination. The results of the cointegration test are derived by generating a residual through the utilization of the Ordinary Least Squares (OLS) regression method. Then the residual results are tested by looking at the Augmented Dicky Fuller value at the level, if the ADF probability is less than 0.05 then a cointegration relationship has occurred.

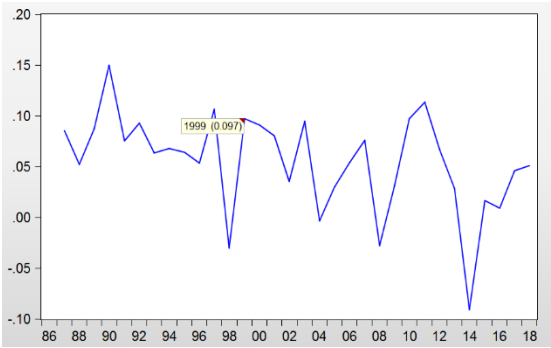

Figure 1 : Stationary ECO2 Variable at the first differentiation

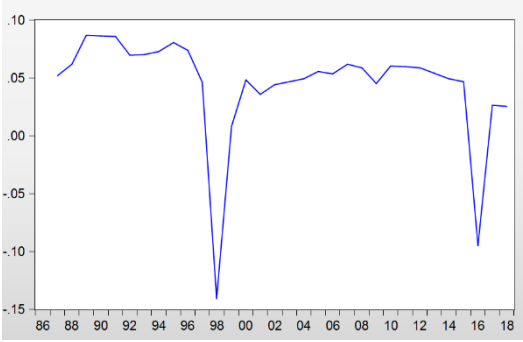

Figure 2 : Stationary GDP Variable at the first differentiation

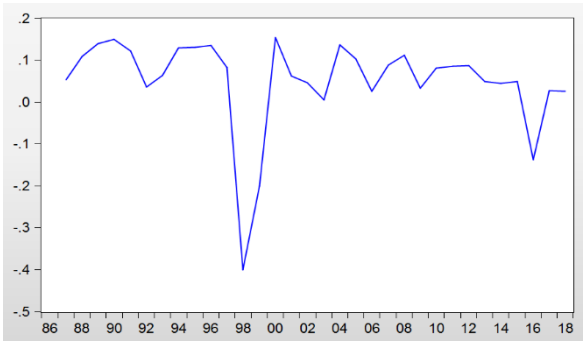

Figure 3: Stationary GFCF Variable at the first differentiation

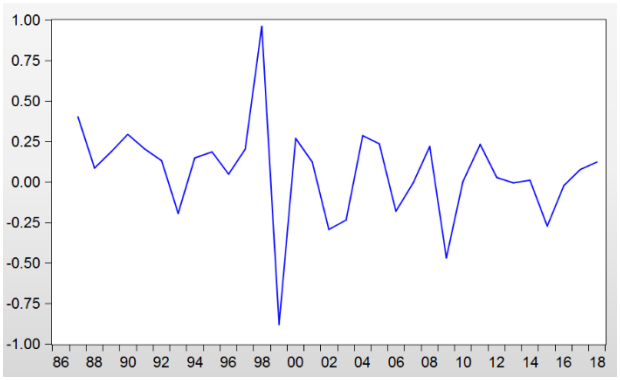

Figure 4: Stationary IVA Variable at the first differentiation

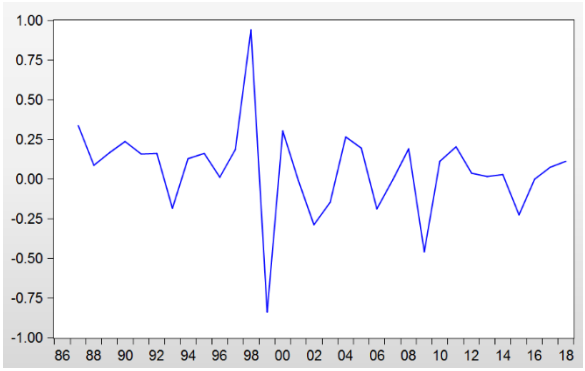

Figure 5: Stationary TRADE Variable at the first differentiation

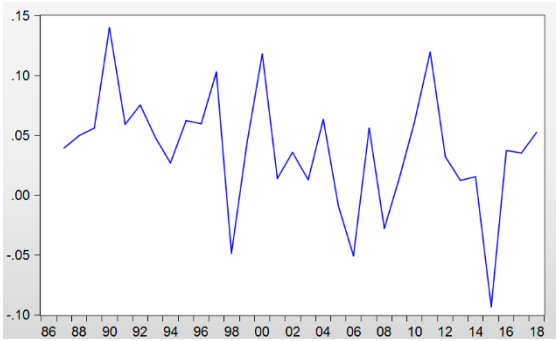

Figure 6: Stationary OCT Variable at the first differentiation

Upon conducting the DF test, as presented in Table 2 and Figure 2, it is possible to determine the stationarity of the residual (ECT) at the level. This can be achieved by examining the t-statistical value and assessing its significance at a critical value of 5% (Prob 0.0003). Based on the statistical analysis, it can be deduced that the observed probability value of 0.0003 is lower than the predetermined significance level of 0.05. Therefore, it can be concluded that the data under consideration demonstrates cointegration.

Table 2 Integration Test Results

Null Hypothesis : ECT has a unit root			
Exogenous : Constant			
Lag Legth : 0 (Automatic – based on SIC, maxlag = 8)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.39759	0.0015
Test critical values :	1% level	-3.65373	
	5% level	-2.95711	
	10% level	-2.61743	
*MacKinnon (1996) one-sided p-values			

Source: Data Analysis Results, 2022

It is required to evaluate the traditional ECM model assumptions after doing a short-term regression (Gujarati, 2004). The conventional method of assessing assumptions involves conducting an autocorrelation test, heteroscedasticity test, and multicollinearity test.

Table 3. Classical Assumption Test

Breusch-Godfrey Serial Correlation LM Test :			Heteroskedasticity Test : Breusch-Pagan-Godfrey		Ramsey RESET Test	
F-statistic	Prob. F(2,23)	0.3315	Prob. F (6,25)	0.668	t-statistic	0.6608
Obs*R-squared	Prob. Chi-Square (2)	0.2311	Prob. Chi-Square (6)	0.612	F-statistic	0.6608

Source: Data Analysis Results, 2022

According to Table 3, the Breusch-Godfrey Serial Correlation LM test technique detects traditional assumption violation tests for autocorrelation issues utilizing Obs*R-squared values. The regression model has no autocorrelation since the Obs*R-squared value is 0.2311 or above 0.05. Breusch-Pagan-Godfrey detected heteroscedasticity with an Obs*R-squared probability of 0.612. The model has no heteroscedasticity since Obs*R-squared is over 0.05. The equation model is linear since the Ramsey RESET Test F value is 0.6608 or more than 0.05.

Table 4. Multicollinearity Test

	LECO2	LGDP	LGFCF	LIVA	LOCT	LTRADE
LECO2	1.0000	0.8793	0.8292	0.7499	0.8921	0.7730
LGDP	0.8793	1.000	0.8799	0.6755	0.8640	0.7080
LGFCF	0.8292	0.8799	1.0000	0.6156	0.8142	0.6501
LIVA	0.7499	0.6755	0.6156	1.0000	0.7951	0.8925
LOCT	0.8921	0.8640	0.8142	0.7951	1.0000	0.8172
LTRADE	0.7730	0.7080	0.6501	0.8925	0.8172	1.0000

Source: Data Analysis Results, 2022

Table 4 shows how to find multicollinearity using partial correlation between independent variables. Table 4 reveals all variables have correlation matrices < 0.85. This correlation value implies no model multicollinearity. If the regression is used for prediction or forecasting, multicollinearity is not necessarily negative since a high coefficient of determination indicates a successful prediction or forecast. Multicollinearity does not occur in regression models with strong coefficients of determination and slope significance. The greater the lag in time series regression, the stronger the correlation between independent variables or model multicollinearity. The ECT imbalance correction coefficient (-1) of -0.7281 is often referred to as an imbalance error in the dynamic model (Widarjono, 2007). If the ECT (-1) coefficient is zero, then Y and X are always in balance. The coefficient of this unbalance value explains how fast it takes to get the balance value.

Table 5 Regression Result

Long-Term				Short-Term			
Dependent Variable : LOG(ECO2) Method : Least Squares Sample : 1988 2020				Dependent Variable : D(LOG(ECO2)) Method : Least Squares Sample : 1988 2020			
Variable	Coefficient	t-Statistic	Prob.	Variable	Coefficient	t-Statistic	Prob.
LOG(GDP)	1.1369	7.2438	0.000***	D(LOG(GDP))	1.1447	3.6347	0.0013***
LOG(GFCF)	-0.4443	-5.4284	0.000***	D(LOG(GFCF))	-0.4051	-3.1536	0.0042***
LOG(IVA)	0.3301	2.8879	0.0075***	D(LOG(IVA))	0.1997	1.4604	0.1566
LOG(TRADE)	-0.3883	-3.0126	0.0056***	D(LOG(TRADE))	-0.2084	-1.4420	0.1617
LOG(OCT)	0.7315	6.0814	0.000***	D(LOG(OCT))	0.6890	5.5568	0.000***
				ECT(-1)	-0.7281	-3.6822	0.0011***
C	-21.0876	-19.4000	0.000***	C	-0.0025	-0.2154	0.8312
R-squared	0.997	Mean Depd_Var	19.417	R-squared	0.6803	Mean Depd_Var	0.0550
F-statistic	1678.097***	DW Stat	1.564	F-statistic	8.8652***	DW Stat	1.8616

Source: Data Analysis Results, 2022

The error correction model is designed to achieve equilibrium among economic variables over an extended period. In the event of a short-term imbalance within a given period, such as a year, the error correction model will automatically make adjustments in subsequent periods to rectify the imbalance (Engle & Granger, 1987). The residual coefficient (-1) or ECT (-1) must be significant with a probability of 0.05 in order for the ECM model to be considered valid. In the event that the coefficient fails to attain statistical significance at a significance level of 0.05, it can be concluded that the model is not valid and additional refinement of the econometric model specifications is necessary. According to Table 5, the model's Error Correction Term (ECT) coefficient has statistical significance at a probability level of 0.0011, below the customary threshold of 0.05. The results support the Error Correction Model (ECM). The balance figure of -

0.7281 shows that the 1988-2020 carbon dioxide emission imbalance adjustment was slow.

The ECT value (-1) of -0.7281 implies that a 100% imbalance in the past would reduce carbon dioxide (Co2) emissions by 72.81%. These data suggest that CO2 emissions take 7-8 years to balance 100%. Table 5 shows that Indonesia's long-term and short-term GDP increases CO2 emissions. This is supported by the results of research conducted by (Zhu & Gao, 2019) which states that GDP per capita has a positive relationship to carbon dioxide emissions in the transportation industry sector. Meanwhile, another study conducted by (Wang & Geng, 2015) states that the level of tertiary industry in overall GDP and urban per capita income has an indirect positive relationship with carbon dioxide emissions.

The Gross Fixed Capital Formation (GFCF) represents a crucial expenditure component of the Gross Domestic Product (GDP). It serves as an indicator of the extent to which the economy invests in generating new value rather than consuming it. Based on Table 5, the GFCF has an influence both in the long term and in the short term in reducing carbon dioxide emissions. According to research by (Ahmed et al., 2022) renewable energy has the least influence on CO2 emissions in China and India whereas energy consumption has the biggest impact. The findings of our study are consistent with this finding. Over the past twenty years, the adverse effects of environmental degradation, global warming, and climate change have had a detrimental impact on human existence. Examples of environmental issues include floods, robbery, air pollution, water pollution, soil pollution, extreme climate change, and extreme weather patterns. Multiple analytical findings indicate a surge in global warming and climate alteration attributed to the progressively pervasive ecological degradation in diverse nations, including Indonesia, resulting from economic advancement. The Indonesian government has implemented a green economy scheme as a primary approach for economic conversion in the medium to long run, with the aim of expediting economic recuperation following the Covid-19 pandemic and fostering the establishment of comprehensive and sustainable economic growth. The green economy will encompass the adoption of a carbon price policy, which will involve the establishment of a carbon cap and trade system, as well as the implementation of a carbon tax program by the year 2023.

Added Value for Industry increases long-term carbon dioxide emissions but has no short-term impact. Long-term trade value will lower CO2 emissions. According to (Xu et al., 2016), the industrial sector emits the most carbon, followed by transportation. In Bahrain, Egypt, Iran, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syria, UAE, and Yemen, (Al-mulali, 2012) evaluated the primary variables affecting CO2 emissions. Total primary energy consumption, net foreign direct investment, GDP, and total trade increase CO2 emissions. President Joko Widodo also pledged to cut greenhouse gas (GHG) emissions by 29% with business as usual in 2030 and 41% with international aid at the 21st UNFCCC 2015 in Paris. In 2008, a 2.5% biodiesel mix was mandated. Biodiesel reached 7.5% in 2010. From 2011 to 2015, biodiesel climbed from 10% to 15%. All connected industries adopted B20 on January 1, 2016.

Fuel consumption both in the long term and in the short term has an influence on increasing carbon dioxide emissions. When viewed from the type of energy, the transportation subsector is a fuel user of around 47% in Indonesia. Currently the Government of Indonesia is very committed to the issue of climate change. One of them is by issuing carbon tax regulations in Indonesia (Presidential Decree 98 of 2021 concerning the Economic Value of Carbon, Law No. 7 of 2022 concerning Harmonization of Taxes which regulates carbon taxes), so whoever pollutes he is the one who pays, supports emission reduction, encourages investment and innovation.

4. CONCLUSION

The results of the research above show that in the short term and long-term Domestic Income Products and use of fossil energy affect the increase in carbon dioxide emissions in Indonesia. Meanwhile, in the long term, investment and trade have a negative effect on carbon dioxide emissions. One of the ways that the government should do is divert the use of energy and transportation to reduce the primary carbon footprint. In addition, carbon emissions can also be reduced by using renewable energy sources to generate the required electricity. Based on the results of this study, it is expected that the government must be firm with the Presidential Regulation concerning the Implementation of Carbon Economic Value to Achieve Nationally Determined Contribution Targets and Control of Greenhouse Gas Emissions in National Development. The Indonesian government should be able to reduce carbon emissions by 41% with international support by 2030. Basic principles and strategies for reducing emissions in urban transportation by limiting the number of vehicles that are not roadworthy and diverting fossil energy to electricity.

This research has the limitation that it does not include the need for fossil energy imported from outside, so that the research results can predict the security of Indonesian fossil energy (estimated energy crisis) in the future.

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