Environmental Kuznets Curve in ASEAN: Effects of Growth, Trade, Renewable Energy, and Industrialization

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Abstract. This study explored the effects of trade openness, economic growth, renewable energy consumption, and industrialization on carbon dioxide emissions in five developing ASEAN countries from 1991 to 2020. A dynamic panel model was used for data analysis, incorporating cross-sectional dependence tests, panel unit root tests, and panel cointegration methods. Estimations were conducted using FMOLS, DOLS, and Sys-GMM techniques for accuracy. Results indicated that trade openness significantly reduced carbon emissions by facilitating access to clean technologies and promoting environmental sustainability. Economic growth followed the Environmental Kuznets Curve (EKC) pattern, with emissions rising in the early stages of growth and decreasing as income levels increased. Industrialization was found to increase emissions in the long term, while renewable energy consumption effectively reduced them. The findings underscore the critical role of trade openness, renewable energy investments, and strict industrial policies in reducing carbon dioxide emissions, emphasizing their importance for sustainable development in ASEAN countries.

Keywords: Trade Openness, Economic Growth, Renewable Energy, Industrialization, CO_2, EKC.

1 Introduction

Environmental degradation is a serious threat to the sustainability of all living things on this planet, and its impacts are already being felt around the world. This phenomenon is no longer just a local issue, but a global challenge that requires serious attention. The uncontrolled utilization of natural resources has led to alarming environmental degradation [1].

Continued human activities in exploiting natural resources have led to a significant decline in environmental quality [2, 3]. This uncontrolled exploitation has negative effects on the environment, including pollution, global warming, land degradation and biodiversity loss [4]. The historical dimension of human interference in the environment is critical to understanding current unsustainable practices. Over time, the impacts of environmental degradation have become more pronounced, raising the question of whether we are heading in the right direction.

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The importance of environmental awareness has increased in the last decade, especially with the significant increase in global temperatures. Climate change has become a challenge whose reality is now being felt in the 21st century [5]. The environmental crisis not only poses a direct impact on ecosystems, but also stimulates deep questions about our active role in the management of the planet. The extent to which global awareness can drive concrete actions to address climate change and environmental degradation is an important question that needs to be answered [6, 7].

Climate change has broad and complex environmental, economic and social impacts. Significant increases in temperature can result in changes in weather patterns, rising sea levels, decreased availability of natural resources, and threats to biodiversity [8]. In addition, climate change also affects economic sectors such as agriculture, fisheries, and tourism [9].

The worldwide impacts of climate change can be identified through a number of factors, one of which is greenhouse gas (GHG) emissions. Carbon dioxide (CO_2) is the largest contributor to the GHG spectrum, accounting for about 80 percent of total emissions [10]. Decades of research reinforce the view that GHG emissions from human activities have been the main driver of the increase in global average temperature over the last 100 years [11–13].

The ASEAN region is one that is experiencing serious environmental degradation, such as climate change, forest destruction, land degradation, air and water pollution, and biodiversity loss (ASEAN, 2018). To address these issues and achieve the Sustainable Development Goals (SDGs), ASEAN countries have been cooperating on the environment since 1977. This cooperation is guided by the ASEAN Socio-Cultural Community (ASCC) Blueprint 2025, which includes conservation and sustainable management of natural resources, eco-friendly cities, climate change mitigation and adaptation, waste management, and increased community awareness and participation [14].

Data from the World Bank on CO_2 emissions in ASEAN over the period 2000-2019 shows that the average growth of CO_2 emissions in the region increased year on year [15]. Over the past decade, the average growth of CO_2 emissions in ASEAN has been around 5.9%. This figure reflects the significant impact of ongoing economic activity and population growth in the region.

ASEAN plays an important role in contributing to total CO_2 emissions in the East Asia and Pacific region. In 2019, ASEAN accounted for around 10.6% of total CO_2 emissions in the region [15]. This data indicates that ASEAN has a significant influence on the dynamics of CO_2 emissions in the region. With continued economic growth and a growing population, ASEAN's role in the context of CO_2 emissions is expected to continue to be important in the coming years.

In this context, the Environmental Kuznets Curve (EKC) hypothesis becomes relevant to analyze the relationship between economic growth and environmental degradation. The EKC proposes that in the early stages of economic growth, environmental degradation and GHG emissions increase with industrialization and urbanization. However, after reaching a certain income level, people start to demand a cleaner environment, and more efficient technologies are applied, so emissions start to decline [16, 17].

Economic growth is closely linked to energy consumption and GHG emissions. Stronger economic development requires higher levels of energy consumption, especially from fossil energy sources that generate CO [18]. This relationship is often reinforced by trade openness, where countries that are more open to international trade tend to experience increased economic activity and industrialization, which can increase GHG emissions [19]. Industrialization plays a key role in increasing GHG emissions in developing countries, including in ASEAN. The industrialization process often relies on the use of fossil energy and less efficient technologies, which contributes to increased CO_2 emissions [20, 21].

However, the increased use of renewable energy offers opportunities to reduce GHG emissions. Renewable energies such as solar, wind and bioenergy can replace the use of fossil fuels and reduce negative impacts on the environment [22]. Several studies show that increased consumption of renewable energy contributes to improved air quality and reduced CO_2 emissions [23, 24].

ASEAN countries show significant differences in their contribution to CO_2 emissions. Over the past 10 years, Indonesia, Thailand and Vietnam have been the largest contributors to CO_2 emissions in the region. Indonesia, as the country with the largest population in ASEAN, contributed about 34% of the total CO_2 emissions in ASEAN during the period. This was followed by Thailand at around 15.1% and Vietnam at around 11.7%. Malaysia, the Philippines and Singapore are also among the largest contributors to CO_2 emissions. [15]. These countries' contributions highlight the need for concerted efforts to reduce negative environmental impacts and implement sustainable policies to reduce CO_2 emissions in ASEAN.

Considering these factors, this study aims to analyze the influence of economic growth, trade openness, renewable energy use, and industrialization on increasing greenhouse gas emissions in ASEAN countries. A deeper understanding of this relationship is important to formulate effective policies in achieving sustainable economic growth without compromising environmental quality.

2 Literature Review

2.1 Economics and CO_2 Emissions

The relationship between economic growth and CO_2 emissions is complex and varies across countries and regions [25–28]. Several studies have shown that economic growth leads to an increase in CO_2 emissions due to intensive energy use, especially in the short term [28, 29]. Increased industrial activity and reliance on fossil fuels as the economy expands are major factors in this. However, in the long run, the relationship between GDP and CO_2 emissions tends to be negative as the development of low-carbon technologies enables production with lower emissions [29]. This suggests that technological progress and improved energy efficiency can decouple economic growth from environmental degradation. The environmental consequences of GDP growth in relation to CO_2 emissions are significant, with a direct relationship between CO_2 emissions and economic growth [29, 30]. The elasticity of CO_2 emissions with respect to GDP suggests the existence of an Environmental Kuznets Curve, indicating that at high levels of income and economic growth, improvements in environmental conditions may occur [30]. This phenomenon implies that when an economy reaches a certain prosperity, there is a tendency to invest more resources in sustainable practices and technologies that reduce environmental impacts.

2.2 Trade Openness and CO_2 Emissions

The relationship between trade openness and CO_2 emissions is complex and varies across contexts and regions. Some studies show that trade openness generally increases CO_2 emissions in newly industrialized countries and developing countries with high CO_2 emissions, indicating long-term environmental degradation [31, 32]. For example, in Oman, GDP per capita and trade openness have a positive impact on CO_2 emissions, suggesting that economic growth and trade expansion contribute to environmental degradation [33, 34]. Conversely, in developed countries, trade openness can reduce CO_2 emissions; studies show that in the largest emitting countries of the developed world, trade liberalization appears to improve environmental quality [32]. Trade openness supports carbon neutrality in rich countries, contributing to global carbon neutrality after passing certain structural tipping points [35].

In addition, research has identified a non-linear relationship between trade openness and CO_2 emissions. There is an inverted U-shaped relationship where emissions initially increase with trade expansion but decrease after reaching a certain threshold [36]. This suggests that in the early stages of trade liberalization, environmental degradation may occur due to industrial growth, but after a certain point, further openness leads to environmental improvements through technology transfer and better environmental practices. The impact of trade openness on CO_2 emissions is also heterogeneous across regions and income groups. For example, trade openness reduces carbon intensity in high and lower-middle income groups, but increases it in upper-middle income groups [37]. In Africa, trade openness increases CO_2 emissions in North, South and West Africa, but has negative effects in East and Central Africa [38].

2.3 Renewable Energy and CO_2 Emissions

The effect of renewable energy on CO_2 emissions has been widely studied, revealing some important insights. An increase in renewable energy consumption significantly reduces CO_2 emissions; for example, a 1% increase in renewable energy consumption can lead to a 0.98% decrease in CO_2 emissions [39]. Similarly, a 10% increase in renewable energy consumption reduces per capita CO_2 emissions by 2.2% [40]. The effectiveness of renewable energy in reducing CO_2 emissions is more pronounced when countries surpass certain thresholds in renewable energy consumption, especially in developed countries with strong institutions [41]. In addition, different types of renewable energy have different impacts on CO_2 emissions; increased investment in wind energy reduces CO_2 emissions, while investment in solar energy and bioenergy can increase emissions due to multiplier effects [42].

Some studies suggest that the effect of GDP on CO_2 emissions is negligible, challenging the traditional view that economic growth always leads to an increase in emissions [43]. Therefore, policymakers are encouraged to promote renewable energy and trade openness to achieve effective CO_2 emission reductions [28, 44]. The effect of renewable energy on CO_2 emissions also varies by region; for example, in Sub-Saharan Africa, increased renewable energy use significantly lowers CO_2 emissions [44]. While in China, renewable energy development has been shown to substantially reduce CO_2 emissions [45].

2.4 Industrialization and CO_2 Emissions

Industrialization has a significant impact on CO_2 emissions, contributing to environmental degradation in many regions. In general, industrialization leads to an increase in CO_2 emissions. For example, in Europe and Central Asia, a 10% increase in industrial value added as a percentage of GDP results in a 2.6% increase in CO_2 emissions [40]. Similar trends are observed in India, Indonesia, Côte d'Ivoire and Tanzania, where industrial growth is positively associated with increased CO_2 emissions [46–49].

However, there are factors that can mitigate the negative effects of industrialization on CO_2 emissions. Renewable energy consumption, for example, can mitigate these impacts. A 10 percentage point increase in renewable energy consumption reduces per capita CO_2 emissions by 2.2% in Europe and Central Asia [40]. In addition, industrial competitiveness and economic freedom are negatively associated with CO_2 emissions in high-income countries, suggesting that these factors can promote environmental sustainability [50]. The impact of industrialization on CO_2 emissions also varies by region. In developing countries, medium- and high-tech manufacturing industries are associated with lower emissions compared to low-tech industries [51]. In Africa, although industrialization directly increases CO_2 emissions, its indirect effects through increased per capita income can lead to a reduction in overall emissions [52].

3 Methodology

3.1 Data

The current study uses panel data on CO_2 emissions, trade openness, GDP per capita, renewable energy consumption, and industrialization, covering the period from 1991 to 2020. The data is sourced from the World Development Indicators (WDI, 2024), and the analysis includes five developing ASEAN countries that have complete data available for the given time frame: Indonesia, Malaysia, Thailand, Philippines and Vietnam.

3.2 Econometric Methodology

Researchers using panel data often assume that differences between cross-sectional units can be addressed by using constants. However, individual disparities due to varying economic frameworks may still exist. Ignoring these differences can bias results and lead to incorrect conclusions. Therefore, this study incorporates tests for cross-sectional dependence, series stability using panel unit root tests, and long-term relationships through panel cointegration methods. If cointegration exists among the variables, techniques such as Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), and System Generalized Method of Moments (SGMM) are employed to measure the long-term elasticity between dependent and independent variables. The GMM estimator addresses endogeneity issues in regressors by using differences between endogenous and exogenous regressors as lags in the instrumental variables set [53].

This research utilizes the SGMM estimator, which integrates historical instruments and lagged values of the dependent variable. [54]. SGMM is suitable for dynamic panel data as it eliminates endogeneity arising from potential relationships between independent variables and the error term. [55]. FMOLS and DOLS effectively address endogeneity among regressors and serial correlations in error terms. FMOLS adopts a non-parametric approach by not considering lags and leads of explanatory variables, while DOLS includes them [56]. DOLS is more effective and efficient in small samples [57]. DOLS also addresses cross-dependence by obtaining country-specific coefficients and producing balanced, efficient, and consistent outcomes. [58] . To handle heterogeneity in cointegrated long-run panels, Ye et al. [59] proposed weighted criteria for DOLS and FMOLS techniques.

Cross-sectional dependence and slope homogeneity. The first step of this study is to analyze a panel dataset to understand its characteristics, focusing on cross-sectional dependence and slope homogeneity [60]. This analysis helps determine the appropriate panel unit root tests, cointegration tests, and estimators for further analysis stages. To examine cross-sectional dependence among the data, the study employs Pesaran's CD test [61, 62]. However, Juodis and Reese [63] found that the CD test may over-reject the null hypothesis in the presence of semi-strong or strong latent factors. To address this, they propose a two-step test resulting in the CDW statistic, which adjusts for over-rejection but may lack statistical power due to randomization.

To improve the test's power, Juodis and Reese [63] modify the CDW statistic by incorporating a screening component from Fan et al. [64], leading to the CDW+ test. Additionally, Pesaran and Xie [65] note that while the standard CD test is valid for weak latent factors, it over-rejects with stronger factors. They introduce the CD* test, a bias-corrected version of the CD statistic that remains valid regardless of latent factor strength. Consequently, this study employs the CDW, CDW+, and CD* tests to robustly examine cross-sectional dependence in panel data with semi-strong or strong latent factors.

Panel unit root tests. Panel unit root tests have gained popularity among researchers analyzing panel data due to their increased statistical power compared to standard unit root tests conducted on individual time series. Traditional unit root tests often assume independence among cross-sectional units, which can lead to size distortion and limited power when cross-sectional dependence exists-common in regional or panel data.

To address this issue, second-generation unit root tests have been developed that account for cross-sectional dependence. Among these, Pesaran's [66] Cross-sectionally Augmented Im, Pesaran, and Shin (CIPS) test is widely utilized. The CIPS test enhances the traditional panel unit root testing procedure by incorporating cross-sectional averages of the variables, effectively capturing cross-sectional dependence. [67]. This makes the CIPS test more robust and suitable for panel data where cross-sectional units may be correlated, providing more reliable results in the presence of cross-sectional dependence.

3.3 FMOLS, DOLS, and Sys-GMM

Economic growth, trade openness, renewable energy and industrialization have varying impacts on CO_2 emissions. In the short term, economic growth increases emissions due to fossil fuel use, but in the long term low-carbon technologies can reduce emissions [29]. Trade openness tends to increase emissions in developing countries but can reduce emissions in developed countries through the adoption of clean technologies [32]. Renewable energy consumption significantly reduces emissions, especially in developed countries and regions such as China and Sub-Saharan Africa [39]. Industrialization increases CO_2 emissions, but renewable energy consumption and industrial efficiency can mitigate this impact, especially in high-tech sectors [51]. The CO_2 emissions model can be expressed in linear form as follows:

CO2it=fTOit,GDPPCit,GDPPC2it,REit,INDit (SEQ "equation" \n * MERGEFORMAT 1)

where CO2 refers to carbon dioxide emissions (metric tons). RE, TO, GDPPC, GDPPC2, and IND are the explanatory variables, representing renewable energy consumption (% of total final energy consumption), trade openness (exports + imports/GDP), GDP per capita (constant 2015 US$), GDP per capita squared (quadratic term), and industrialization (industry value added as % of GDP), respectively.

i Indicates country i=1,,N

t Indicates time (t=1991,,2020)

The empirical model of the variables is represented by the following equation:

CO2it=0+1TOit+2GDPPCit+3GDPPC2it+4REit+5INDit+it (SEQ "equation" \n * MERGEFORMAT 2)

where (0) and (it) are the intercept and error terms. Besides, (1,2,3,4,5) indicate the coefficients.

The FMOLS estimator makes adjustments to the standard OLS to provide unbiased and efficient estimates. The FMOLS estimator can be expressed as:

FMOLS=i=1Nt=1TXitXit'-1i=1Nt=1TXityit+Δuit(SEQ "equation" \n * MERGEFORMAT 3)

The FMOLS estimator is used to obtain consistent and efficient estimates of the relationship between the dependent and independent variables in a panel data context. In the FMOLS model, N represents the number of cross-sectional units (e.g., countries or companies), and iii is used to identify each unit. T represents the time periods, and t indicates each specific time point. The double summation over i and t ensures the model utilizes all available data points, capturing variability across units and over time. While uitt is a correction term for endogeneity and serial correlation. This correction ensures robustness in estimating long-term relationships in non-stationary panel data.

Dynamic Ordinary Least Squares (DOLS) is also used to estimate the long-run relationships between CO_2 emissions and the explanatory variables. DOLS augments the regression equation by incorporating lead and lagged differences of the independent variables, effectively addressing endogeneity and serial correlation. The general form of the DOLS model is:

yit=Xitβ+k=-qqXit-kk+it (SEQ "equation" \n * MERGEFORMAT 4)

where yit represents CO_2 emissions, Xitis the vector of independent variables Xit-k are the lead, lagged differences of the independent variables, and itis the error term and kare the corresponding coefficients. The inclusion of the lead and lag differences helps ensure that the estimates are efficient and unbiased, capturing the long-term equilibrium relationships among the variables.

The System Generalized Method of Moments (Sys GMM) is used to capture the dynamic aspect of CO_2 emissions, addressing potential endogeneity issues that arise due to the correlation between the independent variables and the error term. The general form of the Sys GMM model is:

yit=αyit-1+Xitβ+it (SEQ "equation" \n * MERGEFORMAT 5)

Where, yit-1is the lagged dependent variable, Xitrepresents the matrix of explanatory variables, and it is the error term. Sys GMM uses lagged values of the dependent and independent variables as instruments, providing consistent and efficient parameter estimates. This helps in dealing with the dynamic nature of CO_2 emissions, ensuring that the impact of past emissions on current levels is properly captured.

4 Result

4.1 Descriptive Statistical Analysis

As a first step, descriptive statistical analysis was conducted to understand the basic characteristics of the data used. Descriptive statistics provide an overview of the distribution, mean, and variability of the data, which is important in ensuring the validity of the econometric model assumptions.

Table 1. Variable Descriptive Statistics

Variable	O bs	Mean	Std. dev.	Min	Max
	15	11.906	0.732	9.893	13.313
LNCO2	0	2	7	3	5
	15	105.17	47.41	32.97	220.40
TO	0	85	83	22	68

LNGDPPC	150	8.0290	0.6294	6.5488	9.3160
LNGDPPC2	150	64.8578	10.1370	42.8872	86.7881
LNRE	150	3.0869	0.9250	0.6931	4.3241
IND	150	38.0389	4.9959	23.7944	48.5303

Source: Data processed by researchers, 2024

From Table 1, it can be seen that the average CO_2 emissions (LNCO2) is 11.9062 with a standard deviation of 0.7327, indicating moderate variation across countries and time. Trade openness (TO) has an average of 105.1785%, with a standard deviation of 47.4183, indicating significant differences in the level of trade openness between countries. Other variables also show variations that reflect the different economic and energy conditions in seven ASEAN countries.

Cross-Sectional Dependence Test. Before conducting further analysis, it is important to test whether the panel data has cross-sectional dependence. This dependency can affect the efficiency of estimation and the validity of statistical inference [61]. The tests used include Pesaran's CD test, CDW, CDW+, and CD*.

Table 2. Cross-Sectional Dependence Test Results

Variables	CD	p-value	CDW	p-value	CDW+	p-value	CD*	p-value
LNCO2	16,410	0,000	-3,4404	0,001	48,460	0,000	2,850	0,004
TO	4,300	0,000	4,910	0,000	27,900	0,000	2,660	0,008
LNGDPPC	16,920	0,000	-3,36	0,001	50,150	0,000	4,580	0,000

			0					
LNRE	8,360	0,000	-2,990	0,003	23,440	0,000	0,760	0,448
IND	5,630	0,000	-0,500	0,617	23,360	0,000	2,410	0,016

Source: Data processed by researchers, 2024

The test results in Table 1 show that most variables have significant cross-sectional dependence, with a p-value of less than 0.05. For instance, the LNCO2 variable has a CD value of 16.410 with a p-value of 0.000, indicating strong dependence between cross-sectional units. Only the CDW test for the IND variable had a p-value greater than 0.05 (p-value = 0.617), suggesting that no significant cross-sectional dependence was found for this variable. However, overall, cross-sectional dependence is present in the data, so the estimation method should take this into account.

Slope Heterogeneity Test. The slope heterogeneity test is conducted to check whether the regression coefficients vary across countries, which may affect the interpretation of the results [60].

Table 3. Slope Heterogeneity Test Results

	Delta	p-value	Delta (HAC)	p-value (HAC)
Value	125,720	0,0000	49,910	0,0000
adj.	143,590	0,0000	57,000	0,0000

Source: Data processed by researchers, 2024

The statistical values of Delta and Delta adj. which are significant at the 1% level (p-value = 0.0000) indicate significant slope heterogeneity. This means that the assumption of slope homogeneity is not met, and the regression coefficients differ across countries. Therefore, the estimation model should accommodate this heterogeneity to produce accurate estimates.

Panel Stationarity Test. To avoid pseudo regression, a stationarity test on panel data is required. The CIPS test is used because it considers cross-sectional dependence [61].

Table 4. CIPS Panel Stationarity Test Results

Variable	Level	First Difference
LNCO2	-2.097	-4.590***
TO	-1.041	-4.691***
LNGDPPC	-2.910***	-3.196***
LNGDPPC2	-2.756***	-3.386***
LNRE	-0.286	-3.484***
IND	-2.585***	-5.878***

**** p<0.01, ** p<0.05, * p<0.1 in the table represent the probability of no unit root at first difference*
Source: Data processed by researchers, 2024

The results in Table 4, indicate that at level, all variables are non-stationary as the CIPS statistical value is greater than the critical value. After the first differentiation, all variables become stationary with significant CIPS statistical values (p-value < 0.05). This indicates that the variables are integrated of order one (I(1)), so cointegration analysis can be conducted.

Panel Cointegration Test. The cointegration test is conducted to examine the existence of a long-run relationship between the dependent and independent variables. Pedroni's test was used in this study (Pedroni, 2004).

Table 5. Pedroni Cointegration Test Results

	Statistic	**p-value**
Modified Phillips-Perron t	1.792	0.037
Phillips-Perron t	-4.954	0.000
Augmented Dickey-Fuller t	-1.432	0.076

Source: Data processed by researchers, 2024

The results in Table 5, two of the three cointegration test statistics show significance at the 5% level. The Modified Phillips-Perron t value is 1.7921 with a p-value of 0.0366 and the Phillips-Perron t is -4.9542 with a p-value of 0.0000. This indicates cointegration between CO_2 emissions and the independent variables. Although the Augmented Dickey-Fuller t-value is not significant (p-value = 0.0761), the presence of cointegration can still be concluded as the majority of tests support the alternative hypothesis.

Estimation of Long-Term Elasticity. After confirming the existence of cointegration, model estimation is performed using Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), and System Generalized Method of Moments (Sys-GMM) methods. These methods were chosen to address endogeneity and autocorrelation issues, as well as to capture dynamics in panel data [56, 57].

In Table 6, trade openness has a significant negative effect on CO_2 emissions in the long and short run. In the FMOLS and DOLS models, the TO variable has coefficients of -0.0024 and -0.0051 respectively, significant at the 1 percent level. This indicates that increasing trade openness decreases CO_2 emissions significantly in the long run. In the Sys-GMM model, TO is also negatively significant (-0.0004) at the 10 percent significance level, although the effect is smaller in the short term. The economic growth variable and its square show a non-linear relationship with CO_2 emissions, supporting the Environmental Kuznets Curve (EKC) hypothesis. In the FMOLS model, LNGDPPC has a significant positive effect (4.8620) at the 1 percent level, while $LNGDPPC^2$ has a significant negative effect (-0.2351) at the same level. This suggests that CO_2 emissions increase in the early stages of economic growth but decrease after reaching a certain income level. In the Sys-GMM model, a similar pattern is found with LNGDPPC significantly positive (0.8178) and $LNGDPPC^2$ significantly negative (-0.0482) at the 1 percent level, suggesting that the EKC relationship holds also in the short run.

Industrialization has a significant positive effect on CO_2 emissions in the long run but is not significant in the short run. In the FMOLS and DOLS models, the IND variable has a significant positive coefficient (0.0117 and 0.0359) at the 1 percent level, indicating that increased industrial activity increases CO_2 emissions. However, in the Sys-GMM model, the effect of IND is not significant, as the impact of industrialization takes longer to significantly affect emissions. Renewable energy use has a significant negative effect on CO_2 emissions in the long run, but is insignificant in the short run. In the FMOLS and DOLS models, the LNRE variable has a significant negative coefficient (-0.6273 and -1.0309) at the 1 percent level, indicating that an increase in renewable energy consumption significantly reduces CO_2 emissions. In the Sys-GMM model, the effect of LNRE is not significant. In the Sys-GMM model, the lag variable of CO_2 emissions has a significant positive coefficient (0.9288) at the 1 percent level, indicating the persistence of CO_2 emissions in the short term.

Table 6. Estimation Results of FMOLS, DOLS, and Sys-GMM

VARIABLES	(1) FMOLS	(2) DOLS	(3) Sys-GMM
L.LNCO2	-	-	0.9288***
			(0.0150)
TO	-0.0024***	-0.0051***	-0.0004*
	(0.0001)	(0.0005)	(0.0002)
LNGDPPC	4.8620***	-0.2356	0.8178***
	(0.1079)	(0.8612)	(0.2124)
LNGDPPC2	-0.2351***	0.1032*	-0.0482***
	(0.0076)	(0.0583)	(0.0129)
IND	0.0117***	0.0359***	0.0023
	(0.0005)	(0.0033)	(0.0015)
LNRE	-0.6273***	-1.0309***	0.0029
	(0.0124)	(0.1387)	(0.0175)

Constant	-9.3853*** (0.3518)	11.0242*** (3.3135)	-2.5976*** (0.8001)
R-squared	0.9990	0.9997	-

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*
Source: Data processed by researchers, 2024

5 Discussion

5.1 Trade Openness on CO_2 Emissions

Trade openness contributes to reducing carbon dioxide emissions in both the short and long term. The results show that increased trade openness allows countries to access more efficient and environmentally friendly technologies from their trading partners. This can reduce carbon dioxide emissions through the adoption of clean technologies and better production practices [37, 38]. In the long run, these positive effects become more significant as new technologies and practices take time to be implemented and have a noticeable impact on reducing emissions. In addition, trade openness increases international competition, encouraging companies to improve energy efficiency and reduce waste to remain competitive in the global market [35]. In the short term, despite its smaller impact, trade openness still plays a role in reducing emissions through improved operational efficiency and early adoption of cleaner technologies.

Economic Growth on CO_2 Emissions. The relationship between economic growth and carbon dioxide emissions follows the pattern of the Environmental Kuznets Curve (EKC). In the early stages of economic growth, increased economic activity is often associated with increased carbon dioxide emissions. This is due to industrialization and urbanization that increase fossil energy consumption and energy-intensive industrial activities [29]. However, after reaching a certain level of development, people and governments start to care more about the environment and have the resources to invest in green technologies and implement stricter environmental regulations [29, 30]. As a result, carbon dioxide emissions begin to decline despite continued economic growth. In the long run, this effect becomes more pronounced due to investments in green technologies and a shift towards a less energy-intensive, service-based economy. In the short term, this relationship may be less pronounced as structural changes in the economy take time to significantly affect emissions [27].

Industrialization on CO_2 Emissions. Industrialization has different impacts on carbon dioxide emissions in the short and long term. In the long term, increased industrial activity contributes to increased carbon dioxide emissions. This is due to increased energy production and consumption in the industrial sector, especially when the energy comes from fossil fuels [40, 47]. Industrialization drives economic growth but often ignores environmental impacts, especially in developing countries that focus on economic expansion. In the short term, the impact of industrialization on emissions may be insignificant as changes in industrial activity do not immediately affect emission levels in a substantial way [49]. In addition, the implementation of more efficient and cleaner industrial technologies takes time and investment, so the positive effects on emissions reductions will only be felt in the long term.

Renewable Energy on CO_2 Emissions. The use of renewable energy plays an important role in reducing carbon dioxide emissions, especially in the long term. Renewable energies such as solar, wind and biomass are replacing the use of fossil fuels that produce high emissions. Increased consumption of renewable energy significantly lowers carbon dioxide emissions as these energy sources are cleaner and more sustainable [39, 68]. In the long term, investments in renewable energy infrastructure and shifts in energy policy have a greater impact on reducing emissions. However, in the short term, the effect may not be significant because the adoption of renewable energy takes time for infrastructure development, technology adjustment, and changes in consumer behavior [41]. Challenges such as high initial investment costs and technological limitations may also hinder the direct impact of renewable energy on emission reductions in the short term.

Persistence of CO_2 Emissions. Carbon dioxide emissions from the previous period have a significant influence on current emissions, indicating the persistence of emissions in the short term. This reflects that the economic structure and dependence on fossil fuels do not change drastically in a short period of time. [28]. Industry and the transportation sector, which are major contributors to emissions, typically have infrastructure and technologies that are not easily replaced in the short term, so carbon dioxide emissions are likely to persist over time unless there are strong policy interventions or significant changes in energy technologies. This persistence emphasizes the importance of consistent and sustained implementation of environmental policies to achieve significant emissions reductions.

6 Conclusion

The conclusion of this study shows that trade openness, economic growth, industrialization, and renewable energy use have a significant influence on carbon dioxide emissions. Trade openness reduces emissions by providing access to clean technologies and efficient practices, while economic growth shows a non-linear pattern where emissions increase in the early stages but decrease as the economy develops. Industrialization increases emissions in the long run, while renewable energy is effective in reducing emissions, especially in the long run. Emissions from previous periods also show persistence, signaling a strong reliance on fossil energy. These results emphasize the importance of policies to promote trade openness, investment in renewable energy, and industry regulation to control carbon dioxide emissions sustainably. The government needs to encourage a faster energy transition and implement stricter regulations in the industry to minimize negative environmental impacts. Collaboration between the public and private sectors is also needed to accelerate the adoption of green technologies and achieve emission reduction targets.

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