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Can CO2 emissions cease growing in Côte d'Ivoire? An empirical analysis of the effects of economic growth, energy consumption, industrialization, and urbanization in the presence of structural breaks

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ABSTRACT

This paper aims at examining the effects of economic growth, energy use, industrialization, and urbanization on carbon dioxide (CO2) emissions in Côte d'Ivoire over the period from 1970 to 2016. It also analyzes the conditions under which these emissions can cease growing. We used cointegrating regression models, like the fully modified ordinary least square (FMOLS), the canonical cointegration regression (CCR), and the dynamic ordinary least square (DOLS), to figure out the long-run coefficients. The vector error correction model (VECM) is used in the causality analysis. Finally, we carried out an analysis of the conditional thresholds for reducing CO2 emissions. The results indicate that there is a long-term, significant positive relationship between economic growth, energy use, urbanization, and industrialization, as well as carbon dioxide emissions, in the presence of structural breaks. In other words, they increase CO2 emissions in Côte d'Ivoire. The causality analysis results reveal a long-term bidirectional causal link between industrialization and CO2 emissions, as well as long-term unidirectional causal links from each independent variable to CO2 emissions. The conditional threshold analysis for reducing CO2 emissions shows that under the current economic conditions of the country, pollution will continue to increase. Our findings corroborate the conclusions of COP28, the most recent United Nations conference on climate change. Therefore, a good carbon dioxide pricing or taxation policy for polluting industries, law enforcement and regulations, and the implementation of effective strategies for the promotion and development of clean and renewable energy use will effectively reverse the trend in Côte d'Ivoire.

Contribution/ Originality: This study is valuable and unique because it shows that without strong and practical commitments, atmospheric pollution from carbon dioxide will continue to rise in Côte d'Ivoire's current economic conditions.

1. INTRODUCTION

In recent decades, there has been a growing awareness about the problems of degradation of the natural environment due to emissions of CO2 and other particles in the atmosphere. The number of Conferences of the Parties (COPs) held on the issue is indicative of the extent of the debate on the subject. According to the sixth assessment report of the Intergovernmental Panel on Climate Change (IPCC), greenhouse gases (GHGs) have increased by about 70% since the 1970s, as have the risks associated with global warming. The human influence on global warming is unequivocal. Experts predict global warming of 1.5 to 2.5°C in the coming decades but before 2040, with widespread adverse effects on agriculture, natural ecosystem balance, and public health (IPCC, 2021).

Each country participates in global warming in one way or another and feels the adverse effects of climate change. Côte d'Ivoire, despite possessing abundant resources for electricity production, relies on fossil fuels and non-renewable energy sources like oil, oil derivatives, and gas to partially meet its energy needs and sustain its economic growth. Unfortunately, this growth generates significant amounts of GHGs and is driven by massive industrialization, transport, and agricultural development (Keho, 2015). Despite the ratification of the United Nations Framework Convention on Climate Change (UNFCCC) in 1994, Côte d'Ivoire's GHG emissions are on the rise. These include carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), nitrogen oxides (NO_x), and carbon monoxide (CO) (Ministry of the Environment Water and Forestry, 2000). The World Development Indicators (2021) database shows that total GHG emissions for Côte d'Ivoire in 2019 were 24860 kiloton (kt) CO_2 equivalent, while they were 24350 kt in 2018 and 18880 kt in 2011. In particular, carbon dioxide emissions have increased by more than 77% over the last three decades, leading to the deterioration of air quality in urban areas (Senzele, 2022). Since the early 1970s, researchers have developed a framework to analyze the environmental impact of human activities. This framework, known as the Impact = Population, Affluence, and Technology (IPAT model), focuses on the effects of population, affluence (or economic growth), and the technology used to produce goods. However, today, many determinants are often included in the analyses, such as income level, energy use structure, deforestation, renewable energy and non-renewable energy consumption, electricity consumption, technical efficiency, energy efficiency, industrial structure, and macroeconomic factors such as urbanization, trade openness, globalization, foreign direct investment, and the quality of institutions (see, for example, (Fei, Dong, Xue, Liang, & Yang, 2011; Muhammad & Khan, 2021; Muhammad, Khan, Khan, & Khan, 2021)).The objective of this study is to analyze the effect of urbanization, industrialization, fossil fuel energy consumption, and economic growth on CO_2 emissions in Côte d'Ivoire based on data from 1970 to 2016.

We also analyze the conditions under which these emissions can stop growing. The study will allow us to better appreciate the human influence on pollution and make appropriate proposals. To do so, we first use different econometric techniques to analyze the data collected. These are unit root and cointegration tests. After that, we use three cointegrating regression models—FMOLS (fully modified ordinary least squares), CCR (canonical cointegration regression), and DOLS (dynamic ordinary least squares)—to figure out the long-term elasticities when there are breaks in the structure. We also analyze causal associations between variables through VECM Granger causality, variance decomposition, and impulse response function techniques. The empirical findings broadly support the literature on carbon dioxide pollution determinants. Economic growth, industrialization, urbanization, and fossil fuel consumption contribute to CO_2 emissions in Côte d'Ivoire.

The causality analysis reveals long-term bidirectional associations between CO_2 emissions and industrialization, as well as unidirectional associations between the four variables and CO_2 emissions. However, our research deviates from earlier studies by delving deeper into the conditions for reversing this trend and devising strategies to lower carbon dioxide emissions. Indeed, with the extensive models considering the interactive variables, the results show that under current economic conditions, urbanization, energy use, and industrial activities, carbon dioxide emissions will continue to increase in Côte d'Ivoire.

Therefore, we believe that new specific measures, including law enforcement and regulations, carbon pricing or taxation, the promotion and development of clean energy, and the use of renewable energy, are necessary to reduce and reverse the trend of emissions. All these actions will help Côte d'Ivoire gradually exit the "fossil fuel era."

The rest of the paper is organized as follows: In Section 2, we provide a brief literature review. In Section 3, we present the empirical research strategy. Section 4 presents the results and facilitates discussions. In Section 5, we extend the model to analyze conditional thresholds. Section 6 concludes the paper and provides policy implications.

2. LITERATURE REVIEW

In this section of the paper, we briefly review the literature on the relationships between CO2 emissions and various human activity variables, including economic growth, fossil fuel consumption, industrialization, and urbanization. Our goal is to investigate the effects of these variables on the evolution of CO2 emissions in Côte d'Ivoire, better understand the nature of the relationships, and propose appropriate solutions to reduce pollution and protect the environment. We also analyze the conditions under which these emissions can stop growing. For this, we will focus on empirical methods and results.

The literature has extensively examined the relationship between economic growth and environmental carbon dioxide pollution. Most of the papers were interested in analyzing the existence of an EKC-shape parabolic relationship between CO2 emissions and growth (see, (Boamah et al., 2017; Halicioglu, 2009; Halkos & Gkampoura, 2021; Jun et al., 2021; Martınez-Zarzoso & Bengochea-Morancho, 2004; Younici & Belhadi, 2021; Zilio & Recalde, 2011)) or nonlinear relationships between CO2 emissions and other variables (Raheem & Kazeem, 2015).

These papers aim to investigate whether CO2 emissions rise with income until they reach a certain level of economic development, after which they gradually decrease. In other words, the authors seek to verify whether populations become more protective of the environment when the average standard of living improves and the economies of the countries prosper.

However, alongside this type of work, there are others who focus solely on analyzing the existence, type, and strength of a monotonic linear relationship between economic growth and CO2 emissions. The majority of these establish a strong, monotonically increasing relationship between CO2 emissions and income. This means that the more growth there is, the higher the carbon dioxide concentration in these countries.

For example, Kahia, Jebli, and Belloumi (2019) analyze the impact of renewable energy consumption and economic growth on carbon dioxide emissions for a panel of 12 East and North African countries over the period 1980-2012. They use a Panel Vector Autoregressive (PVAR) model and show that economic growth leads to environmental degradation (CO2 emissions), while renewable energy use, international trade, and foreign direct investment flows lead to a decrease in CO2 emissions. The same is true of the study by Khan, Teng, and Khan (2019) in Pakistan over the period 1965 to 2015. Those authors use dynamic Auto-Regressive Distributed Lag (ARDL) simulation and show that a 1% increase in per capita income generates an increase in CO2 emissions in both the short and long run. They advocate the use of renewable energy sources.

The monotonically increasing relationship between Gross Domestic Product (GDP) and carbon dioxide emissions has also been verified by the work of Osobajo, Otitoju, Otitoju, and Oke (2020) for 70 countries over the period from 1994 to 2013 using the Panel OLS and Fixed effects (FE) models, by Begum, Raihan, and Said (2020) for Malaysian time series, over the period 1990-2016 using the DOLS model, by Muhammad and Khan (2021) for a panel of 170 countries in the world over the period 1990-2018 using the Generalized Method of Moment (GMM) and FE models, by Muhammad et al. (2021) for the BRICS (Brazil, Russia, India, China, South Africa) countries over the period 1991-2018 using the FE, GMM and system GMM models. Regarding the relationship between energy consumption and CO2 emissions, some work, such as Foster and Elzinga (2016) shows that energy production and use are likely a source of a larger share of CO2 emissions. Indeed, in a world of increasing population growth, the energy requirements induced by meeting ever-increasing human needs lead to CO2 emissions and climate change. According to Tzete, Djibie, Julius, and Tsalefac (2022) oil is the first source of energy; it provides for 33% of the world's energy, followed by coal (27%) and gas (21%). Indeed, this is the reason why many scientists (see for example, (Alshehry & Belloumi, 2015; Jun et al., 2021; Osobajo et al., 2020; Stern, 2004)) argue that reducing CO2 emissions requires reducing energy intensity through shifts to less energy-intensive industries and the development and promotion of clean technologies.

In this study, we are also interested in industrial activity, another determinant of emissions highlighted in the literature. Industries consume huge amounts of fossil fuel for their operations, including hydrocarbons such as diesel and lubricating oils. According to Naili and Morsli (2021) a large share of CO_2 emissions comes from the oil and gas industry, including mining, refining, storage, and transportation. Several studies in different regions have confirmed that industrial activities contribute to the degradation of the environment's quality. This is Keho (2015) case in Côte d'Ivoire. He observes that the more a country industrializes, the higher its CO_2 emissions. He finds that trade openness and industrialization are complementary to the degradation of environmental quality in Côte d'Ivoire. Wang, Shi, Li, and Wang (2011) used an error correction model in a heavy industrial structure and found that a 1% increase in industrial production leads to about 0.278% and 0.147% growth in CO_2 emissions in the long and short runs, respectively.

The urbanization variable is particularly important in understanding the evolution of CO_2 emissions. Indeed, for Africa, which is trying to become westernized, strong urbanization leads to strong demographic growth and consequently increases energy needs. African countries are experiencing high population growth and increased energy demand, with rates exceeding 2.5% (Tzete et al., 2022). The literature also highlights the heterogeneous effects of urbanization on carbon dioxide emissions, depending on the level of economic development, the rate of industrialization, energy consumption, and many other parameters, such as the age distribution of the population. For example, Poumanyvong and Kaneko (2010) examine the impact of urbanization on CO_2 emission and energy use in 99 countries over the period from 1975 to 2005. They show that the magnitude of the positive effect of urbanization on CO_2 emissions, and energy use depends on the level of economic development. The impact is more pronounced in middle-income countries than in other countries. The impact is more pronounced in middle-income countries than in other countries. Meanwhile, Fan, Liu, Wu, and Wei (2006); Zhu and Peng (2012) and Jensen, Lugauer, and Sadler (2014) differentiate the effects of urbanization based on the age distribution of the population. Fan et al. (2006) show, for example, that the proportion of the population with ages between 15 and 64 exerts a negative effect on CO_2 emissions in low-income countries, while the effect is positive in other country groups. Zhu and Peng (2012) show that the younger the population, the higher the rate of CO_2 emissions in China from 1978 to 2008.

On the other hand, some works, such as Sharma (2011) instead find that urbanization has a negative effect on the CO_2 emission rate in high-income countries as well as middle-income countries. Overall, urbanization has direct and indirect effects on CO_2 emissions that would be interesting to examine.

Finally, it should be noted that several studies, such as Al-Mulali and Ozturk (2015) and Raheem and Ogebe (2017) emphasize the existence of an interrelationship between urbanization, energy consumption, and industrialization and their direct and indirect adverse effects on CO_2 emissions and the environment.

3. METHODOLOGY

3.1. Model Specification and Data

3.1.1. The Model

Our model is based on the Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model reformulated by Dietz and Rosa (1997) and inspired by the conventional IPAT framework proposed in the early 1970s to quantify the environmental impact of human activities. According to I=PAT model, environmental impact (I) is estimated by the product of three factors, namely population (P), affluence (A), and technology (T). The STIRPAT model reformulation is given by:

$$I_t = aP_t^b A_t^c T_t^d \mu_t \qquad (1)$$

Here, the environmental impact I is given by CO_2 emissions, A by GDP per capita, and P by the urban population. T is a vector of two variables, namely industrialization and fossil energy consumption. We expand the model by including fossil energy consumption because it is mostly used for social organization, household activities, transport, and power generation. We use the empirical log-linear form below, which reduces skewness in time series data and produces better results. A similar approach was used in Shahbaz and Rahman (2010); Murshed, Ferdaus, Rashid, Tanha, and Islam (2021) and Jin, Ahmed, Pata, Kartal, and Erdogan (2023).

$$ln\,CO2_t = a_0 + a_1 ln\,GDP_t + a_2 ln\,ENE_t + a_3 ln\,IND_t + a_4 ln\,URB_t + \varepsilon_t \qquad (2)$$

Where $t = 1, ..., T$ periods. The study spans a 47-year period from 1970 to 2016. The error term ε_t is such that $\varepsilon_t \sim iid\ (0, \sigma^2)$. All variables are expressed in natural logarithm to reduce skewness in the time series data and produce better results in the estimates. The dependent variable is *ln*CO2, which represents CO2 emissions. The other four variables are the explanatory variables: *ln*GDP is the per capita income, *ln*IND is the industrialization variable, *ln*ENE is the fossil fuel consumption, and finally *ln*URB represents the urbanization rate. We expect the following signs for the coefficients to be estimated: $a_1 > 0$, $a_2 > 0$, $a_3 > 0$, and $a_4 > 0$. In other words, we suspect that each of these variables is a source of increased CO2 emissions. If the results confirm this intuition, it would be interesting to analyze, in a second step, the conditions under which we can observe a decrease in carbon dioxide emissions in Côte d'Ivoire.

3.1.2. Data and Variables

The description of the variables used and the data source are presented in Table 1. All data series are from the World Bank's World Development Indicators (WDI) database. The trend for each series is shown in Figure 1.

Table 1. Description of variables.

Variables	Symbols	Descriptions and units of measurement	Periods	Data source
CO2 emissions	*CO2*	CO2 emissions in kilo tons	1970-2016	WDI (World bank)
GDP per capita	*GDP*	GDP per capita in constant 2010 US dollars	1970-2016	WDI (World bank)
Industrialization	*IND*	Value added industries as % of GDP	1970-2016	WDI (World bank)
Energy consumption	*ENE*	Fossil fuel consumption as % of total	1970-2016	WDI (World bank)
Urbanization	*URB*	Urban population as % of total population	1970-2016	WDI (World bank)

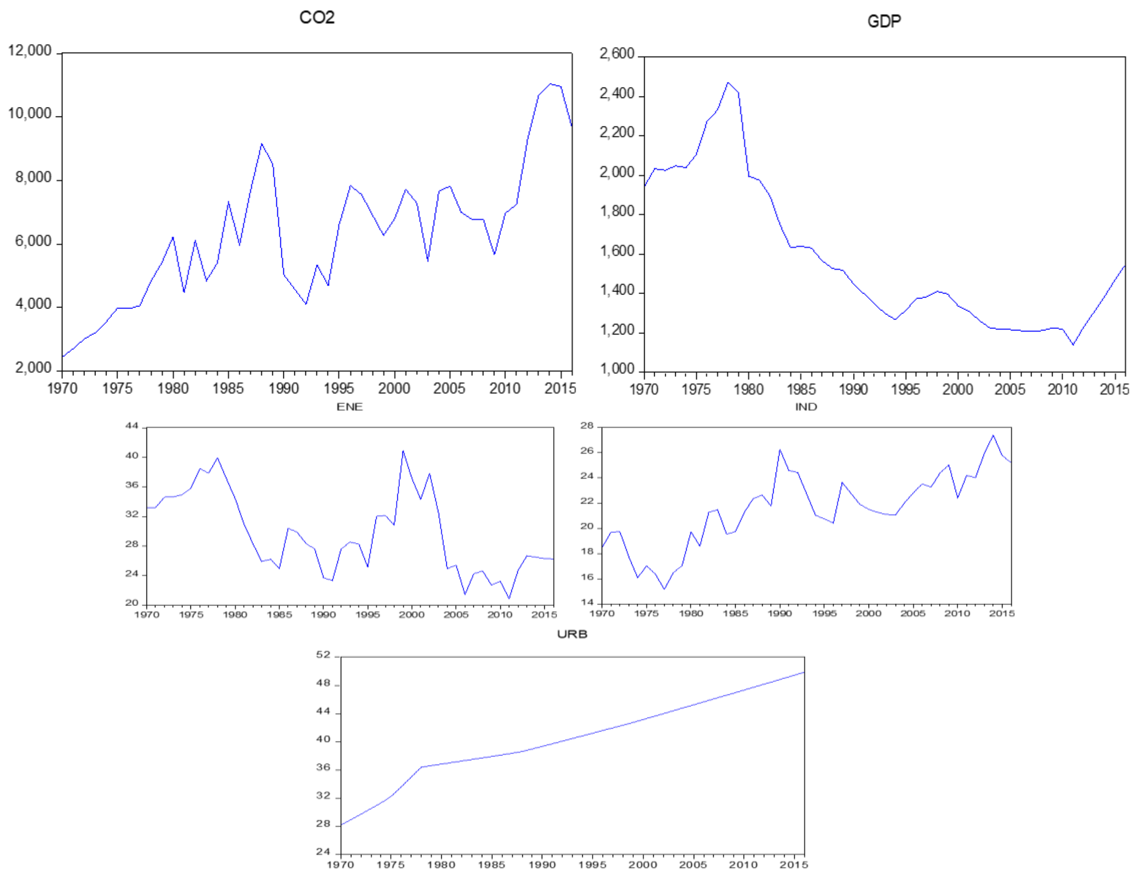


Figure 1. Trend of variables (CO2: Carbon emissions, GDP: Gross domestic product, ENE: Energy consumption, IND: Industrialization, URB: Urbanization).

3.1.2.1. Dependent Variable

CO_2 emissions are defined as the release of carbon dioxide into the atmosphere over a period of time. Carbon dioxide is a colorless, odorless, and non-toxic gas formed during carbon combustion and the breathing of living organisms. It is a greenhouse gas (GHG) that contributes to global warming. This study expresses CO_2 emissions in kilotons (kt). CO_2 emissions in Côte d'Ivoire experienced remarkable growth in the 1980s until today due to several reasons, including deforestation, mining, and the use of oil and gas.

3.1.2.2. Independent Variables

GDP per capita in constant 2010 US dollars provides the income variable. Taking it on a per capita basis allows us to see the share of wealth held by everyone, considering demographic fluctuations. The country's first general downward trend in GDP since 1980 is due to the crisis that occurred that same year. The devaluation of the CFA franc (Communauté Financière Africaine) explains the second decline in 1994. The serious post-election crisis in 2011 caused GDP to fall to its lowest level. Since 2012, Côte d'Ivoire has experienced an economic upturn that explains this new phase of growth in its GDP. The ENE variable represents fossil fuel consumption as a percentage of the total. According to studies such as OECD (2007) CO_2 emissions from fossil fuels (diesel and gasoline) are almost proportional to their carbon content, with the conversion rate from C to CO_2 varying between 95 and 99.5%. Thus, with a weighting coefficient considering the respective carbon content of gasoline (2.401 kg CO_2 / liter) and diesel (2.622 kg CO_2 / liter), it is easy to estimate the CO_2 emissions from the total quantity of the fossil fuel consumed. The country's various crises have caused ups and downs in energy consumption. The peak in 2000 was due to the high production of electricity and heat from burning coal in the Azito thermal power plant. The IND variable, a proxy for the country's level of industrialization, represents the value added of industries as a percentage (%) of GDP. According to the IPCC (2014) industry represents one of the main large sectors of the world economy contributing to CO_2 emissions, with an estimated share of about 21%. The industrialization dynamic began in Côte d'Ivoire in the 1970s and continues to grow due to external openings. Finally, the URB variable represents the urban population as a percentage (%) of the total population. In Côte d'Ivoire, as in several African countries, the increase in the rate of urbanization is due to an increase in the consumption of the middle class of urban populations. The urbanization rate increased from 17.7% in 1960 to more than 50% in 2018. Côte d'Ivoire is the third-most urbanized country, behind Cameroon and Ghana (Mondiale, 2019). Urbanization and industrialization are often linked and are direct and indirect sources of CO_2 emissions (Raheem & Ogebe, 2017; Xu & Lin, 2015).

The summary statistics and correlation matrix between variables are reported in Table 2 and Table 3, respectively. The CO_2 emissions variable is the most volatile, while the industrialization rate variable is the least volatile, with respect to the different standard deviations. In the Pearson correlation matrix, the correlation coefficients between the regressors *ln*IND, *ln*URB, and the regressor *ln*GDP are close to or above 0.8, suspecting multicollinearity. However, the calculation of the variance inflation factors (VIF) shows VIF values that are all less than 5. This means that there is no severe multicollinearity.

Table 2. Descriptive statistics.

Variables	Obs.	Mean	Std. dev.	Min.	Max.	Skewness	Kurtosis
*ln*CO2	47	8.689	0.361	7.800	9.309	-0.479	2.774
*ln*GDP	47	7.338	0.223	7.037	7.812	0.634	2.107
*ln*ENE	47	3.377	0.178	3.038	3.710	0.095	1.935
*ln*IND	47	3.060	0.141	2.718	3.310	-0.557	2.719
*ln*URB	47	3.689	0.149	3.338	3.909	-0.593	2.698

Table 3. Correlation matrix between variables and variance inflator factors (VIFs).

Variables	*ln*CO_2	*ln*GDP	*ln*ENE	*ln*IND	*ln*URB	VIF
*ln*CO2	1					-
*ln*GDP	-0.596***	1				3.853
*ln*ENE	-0.408***	0.633***	1			2.024
*ln*IND	0.633***	-0.794***	-0.698***	1		3.604
*ln*URB	0.846***	-0.807***	-0.553***	0.753***	1	3.191

Note: *** indicate the significance level at 1%.

3.2. Econometric Techniques

3.2.1. Unit Root Tests

We use two tests, the unit root test of Zivot and Andrews (1992) or ZA test and the unit root test of Perron and Vogelsang (1992) or PV test. Unlike traditional unit root tests (such as the Augmented Dickey and Fuller (1981) or ADF test, Phillips and Perron (1988) or PP test, and Kwiatkowski, Phillips, Schmidt, and Shin (1992) or KPSS test), the ZA and PV tests capture one endogenous structural break between series and avoid estimation biases.

The ZA test develops three models (model A allowing a break in the intercept, model B allowing a break in the trend, and model C allowing a break in both the intercept and the trend), such as:

Model A:

$$\Delta x_t = a + a_{t-1} + bt + cDU_t + \sum_{j=1}^{k} d_j\, \Delta x_{t-j} + \mu_t \qquad (3)$$

Model B:

$$\Delta x_t = b + bx_{t-1} + ct + bDT_t + \sum_{j=1}^{k} d_j\, \Delta x_{t-j} + \mu_t \qquad (4)$$

Model C:

$$\Delta x_t = c + cx_{t-1} + ct + dDU_t + dDT_t + \sum_{j=1}^{k} d_j\, \Delta x_{t-j} + \mu_t \qquad (5)$$

With DU representing the dummy of the change in the intercept, such that DUt = 1 if (t > SB) and 0 otherwise. DTt is the dummy of the change in the slope of the trend function, with DTt = t-SB if (t > SB) and 0 otherwise; SB is the break year. In this study, we use model C. We chose this model because it has the advantage of having a stationary function with a unique change in both the intercept and trend function of the variable.

In the PV unit root test, we perform the procedure in the presence of additive outliers (AO model) and innovative outliers (IO model) relative to the data mean, given that the data frequently exhibit irregularities and errors. Indeed, Perron and Vogelsang (1992) expanded upon Perron (1989) test, proposing an alternative method for break date selection that maximizes the absolute value of the t statistic on the break coefficient. The AO and IO models assume, respectively, that the mean change is sudden and gradual.

The ZA and PV tests, in addition to identifying an endogenous break date in the series, estimate the properties of stationarity under the null hypothesis of the presence of a unit root in the series versus the alternative hypothesis of stationarity in the presence of a break.

3.2.2. Cointegration Tests

We use two cointegration tests: a more traditional one that neglects structural breaks in the series (Johansen test) and one that considers them (Gregory-Hansen test). The Johansen (1988) cointegration test procedure is based on the maximum likelihood method. It relies on the determination of the rank (r) of the matrix $\prod$. The rank (r) represents the number of long-run vectors or cointegrating relationships. It is obtained from two likelihood ratio statistics: the trace statistic and the maximum eigenvalue statistic. The trace statistic is given by:

$$\text{Trace}\ (Ho(r)/H1(k)) = -T\ \sum_{t=r+1}^{P} \ln(1 - \emptyset_i) \qquad (6)$$

$\emptyset_i$ being the ith maximum estimated eigenvalue. It tests the null hypothesis of cointegration Ho(r) : rank ($\prod$) = r against the alternative hypothesis $H1$ (k) : rank ($\prod$) = k. As for the maximum eigenvalue statistic, it is given by:

$$\emptyset_{max}\ (Ho(r)/H1(r+1)) = -T\ (1 - \emptyset_{r+1}) \qquad (7)$$

It tests the null hypothesis Ho(r): rank ($\prod$) = r against $H1$ (r): rank ($\prod$) = r +1. For these two statistical tests, the null hypothesis of no-cointegration is rejected when the calculated statistic is lower than the critical value.

According to Gregory and Hansen (1996) the residual-based cointegration test admits one structural break in the cointegrating vector. The test procedure proposes three alternative models: model (C) with a shift in level, model (C/T) with a shift in level and trend, and model (C/S) with a shift in regime:

Model (C):

$$y_t = \mu_0 + \mu_1\varphi_{t\tau} + \mu_2 x_t + \varepsilon_t, \qquad t = 1, \dots, n \qquad (8)$$

Model (C/T):

$$y_t = \mu_0 + \mu_1\varphi_{t\tau} + \beta t + \mu_2 x_t + \varepsilon_t, \qquad t = 1, \dots, n \qquad (9)$$

Model (C/S):

$$y_t = \mu_0 + \mu_1\varphi_{t\tau} + \mu_2 x_t + \mu_3 x_t \varphi_{t\tau} + \varepsilon_t, \qquad t = 1, \dots, n \qquad (10)$$

Where φ_t is a dummy variable such that $\varphi_{t\tau}$= 1 if t > [nτ] or 0 if t ⩽ [nτ], and $\tau \in$ (0,1) is the (relative) time at the breakpoint. In Model (C), $\mu 0$ is the intercept before rupture and μ_1 is the change in intercept at rupture. In Model (C/T), the break only affects the intercept but contains a trend. In Model (C/S), μ_2 is the cointegrated slope coefficient before the break and μ_3 is the change in the cointegrated slope coefficient at the time of the break.

To test the null hypothesis of non-cointegration against the alternative hypothesis of cointegration in the presence of an unknown break, the ADF^*, Za^* and Zt^* statistics tests proposed by Gregory and Hansen (1996) are used:

$$ADF^* = \inf_{\tau \in T} ADF(\tau)\ ;\ Z_a{}^* = \inf_{\tau \in T} Z_a(\tau)\ ;\ Z_t{}^* = \inf_{\tau \in T} Z_t(\tau) \qquad (11)$$

The null hypothesis is rejected if the ADF^*, Za^* or Zt^* statistical tests are smaller than the critical values in the Gregory and Hansen (1996) table. Note that in the Gregory and Hansen cointegration test, there is no appropriate table of critical values for more than four independent variables.

3.2.3. Estimates of Long-Run Elasticities

To estimate the long-run coefficients, we use long-run estimation techniques for the cointegrating vector. These are the three fully efficient single-equation cointegrating regression models, including Phillips and Hansen (1990) fully modified ordinary least squares (FMOLS), Stock and Watson (1993) dynamic ordinary least squares (DOLS), and Park (1992) canonical cointegrating regression (CCR). Compared to the OLS estimator and other cointegrating approaches, these models overcome endogeneity bias and information distortion (i.e., serial correlations in the error terms) (Adom & Kwakwa, 2014; Kwakwa, Adu, & Osei-Fosu, 2018; Narayan & Narayan, 2004). Specifically, the FMOLS and CCR estimators correct for endogeneity bias semi-parametrically, while the DOLS estimator corrects for it parametrically. The CCR model is similar to FMOLS; the difference is that the former focuses only on data transformation, while the latter focuses on both data and parameter transformation (Adom, Amakye, Barnor, & Quartey, 2015). According to Montalvo (1995) the DOLS estimator performs consistently better than FMOLS and CCR. However, they are all applicable only when all variables are integrated of order 1. Following Adom and Kwakwa (2014) and Kwakwa et al. (2018) the FMOLS estimator can be obtained as follows:

$$\widehat{\emptyset}_{FMOLS} = \left(\sum_{t=1}^{T} Z_t Z_t'\right)^{-1}\left(\sum_{t=1}^{T} Z_t Y_t^+ - T\hat{J}^+\right) \qquad (12)$$

Where $Z_t = (X_t', D_t')$, $Y_t^+ = Y_t - \hat{\lambda}_{ox}\hat{\lambda}_{xx}^{-1}\Delta x_t$ represents the transformed data or correction term for endogeneity, $\hat{\lambda}_{ox}$ and $\hat{\lambda}_{xx}$ are the estimates of the kernel of the long-run covariance, $\hat{J}^+ = \hat{\Delta}_{ox} - \hat{\lambda}_{ox}\hat{\lambda}_{xx}^{-1}\hat{\Delta}_{xx}$ is the estimated bias correction term for the serial correlation and $\hat{\Delta}_{ox}$ and $\hat{\Delta}_{xx}$ are the estimates of the kernel of the one-sided long term covariances.

As for the CCR estimator, it is given by:

$$\widehat{\emptyset}_{CCR} = \left(\sum_{t=1}^{T} Z_t^* Z_t^{*\prime}\right)^{-1} \sum_{t=1}^{T} Z_t^* Y_t^* \qquad (13)$$

Where $Z_t^* = (X_t^{*\prime}, D_t^{\prime})$, $X_t^* = X_t - (\hat{\Sigma}^{-1}\hat{\Lambda}_2)\hat{V}_t$ and $Y_t^* = Y_t - (\hat{\Sigma}^{-1}\hat{\Lambda}_2\beta + [\hat{\eta}_{22}^{-1}\hat{\omega}_{21}])^{\prime}\hat{V}_t$ are the transformed data, $\hat{\beta}$ is an estimate of the coefficients of the cointegrated equation obtained using static OLS, $\hat{\Lambda}_2$ is the second column of $\hat{\Lambda}$ and $\hat{\Sigma}$ is the estimated contemporary covariance matrix of the residuals (Hamilton, 1994).

Finally, the estimation technique DOLS involves an augmentation of the cointegrating regression with q lags and r leads from ΔX_t such that the new error term in the cointegrating equation is orthogonal to the entire innovation history of the stochastic regressor (Belke & Czudaj, 2010): $Y_t = X_t^{\prime}\beta + D_{1t}^{\prime}\gamma_1 + \sum_{j=-q}^{r}\Delta X_{t+j}^{\prime}\delta + v_{1t}$ where β is the long-run elasticity and δ represents the coefficients of the I(1) regressors in difference ΔX_t with lags and leads. The DOLS estimator is then given by:

$$\hat{\phi}_{DOLS} = (\hat{\beta}^{\prime}, \hat{\gamma}_1^{\prime})^{\prime} \qquad (14)$$

Although they use different correction mechanisms, the three cointegrating regression techniques are asymptotically equivalent.

3.2.4. VECM Granger Causality Test

When the results show the existence of cointegrating relationships between the variables, we need to analyze the causality between the series. To do this, we use the vector error correction model (VECM) approach proposed by Granger (1969) and Engle and Granger (1987). The advantage of this model is that it both captures the causal relationships between the cointegrated parameters and distinguishes between the long-run and short-run relationship in Granger causality. This approach is required when the series are integrated of order 1 as in this study (see unit root test results in Table 4 and 5). Within the framework of Model 2, we can model the empirical equation as follows:

$$(1-L)\begin{bmatrix}\ln CO2_t\\ \ln GDP_t\\ \ln ENE_t\\ \ln IND_t\\ \ln URB_t\end{bmatrix} = \begin{bmatrix}a_1\\ a_2\\ a_3\\ a_4\\ a_5\end{bmatrix} + \sum_{i=1}^{p}(1-L)\begin{bmatrix}b_{11i}b_{12i}b_{13i}b_{14i}b_{15i}\\ b_{21i}b_{22i}b_{23i}b_{24i}b_{25i}\\ b_{31i}b_{32i}b_{33i}b_{34i}b_{35i}\\ b_{41i}b_{42i}b_{43i}b_{44i}b_{45i}\\ b_{51i}b_{52i}b_{53i}b_{54i}b_{55i}\end{bmatrix} \times \begin{bmatrix}\ln CO2_{t-1}\\ \ln GDP_{t-1}\\ \ln ENE_{t-1}\\ \ln IND_{t-1}\\ \ln URB_{t-1}\end{bmatrix} + \begin{bmatrix}a\\ b\\ d\\ f\\ J\end{bmatrix} ECT_{T-1} + \begin{bmatrix}e_{1t}\\ e_{2t}\\ e_{3t}\\ e_{4t}\\ e_{5t}\end{bmatrix} \qquad (15)$$

Where (1-L) is the difference operator. The statistical significance of the elasticity parameters α, β, δ, ϕ and ϑ attached to the lagged error correction term ECT_{T-1} when using t-statistics provides information about the long-run causal associations between the variables. The statistical significance of the F-statistics, using the Wald test, of the elasticity parameters b11i, b12i, ... , $b55i$ attached to the lagged terms of the explanatory variables (in first difference) give information about the short-run causality between the variables.

It is also desirable to check whether the two sources of causality are jointly significant (i.e., long- and short-run causality). Finally, the ε_{1t}, ε_{2t}, ε_{3t}, ε_{4t} and ε_{5t} are the error terms assumed to be homoscedastic, i.e., of constant variance.

3.2.5. Variance Decomposition and Impulse Response Function

The VECM Granger causality test only shows the causal relationship between variables within the sample period. It therefore does not determine the relative strength of the causal effect beyond the selected time period and is unable to determine how much feedback exists from one variable to another (Shahbaz, Khraief, Uddin, & Ozturk, 2014; Shahbaz, Zeshan, & Afza, 2012; Shan, 2005).

We will add the innovative accounting approach (IAA) with error variance decomposition and impulse response function techniques to our analysis to make up for the problems with the VECM Granger causality method. The two methods constitute two exercises that allow us to synthesize the essential information contained in a VAR system's internal dynamics. They measure the relative influence of different shocks on each variable's dynamics at different horizons.

Pesaran & Shin (1999) specifically use the error variance decomposition method to explain the variance of an endogenous variable due to innovative (simultaneous) shocks from other variables. It thus estimates the contribution of one variable's innovation to another's fluctuations. Its main advantage is that it produces better results than other traditional approaches (Engle & Granger, 1987). The VAR system solely determines the order of the variables, making it insensitive to this.

As for the impulse response function, it indicates how long and to what extent the dependent variable reacts to shocks from the independent variables. For both techniques, the amplitude is interested in the shock effects over 10 periods, i.e., 10 years. This horizon represents the time required for the variables to return to their long-term levels.

4. EMPIRICAL RESULTS AND DISCUSSIONS

4.1. Study of the Stationarity

The results of the Zivot and Andrews (1992) and Perron and Vogelsang (1992) unit root tests taking into account endogenous structural breaks in the series are reported in Table 4 and 5 respectively.

In the first difference, all variables are stationary, and both the intercept and the trend have a structural break date. In other words, the variables are all of order 1.

Table 4. Results of Zivot-Andrews structural break unit root test.

Variables	Zivot-Andrews structural break in both the intercept and trend unit root test				Decision
	Level		First difference		
	t-statistic	Time break	t-statistic	Time break	
*ln*CO2	-5.459	1990	-8.146***	1993	I (1)
*ln*GDP	-2.446	2007	-6.715***	1979	I (1)
*ln*ENE	-3.521	1996	-7.959***	2003	I (1)
*ln*IND	-4.084	1980	-8.254***	1984	I (1)
*ln*URB	-4.629	1978	-18.753***	1979	I (1)

Note: *** indicate the significance level at 1%. Here, we use the model C.

Table 5. Results of Perron-Vogelsang structural break unit root test.

Variables	Perron-Vogelsang structural break in both the intercept and trend unit root test								
	Level				First difference				Decision
	Additive outliers		Innovational outliers		Additive outliers		Innovational outliers		
	t-stat	tb	t-stat	tb	t-stat	tb	t-stat	tb	
*ln*CO2	-4.642	1989	-4.473	1989	-8.846***	1990	-9.140***	1990	I (1)
*ln*GDP	-2.556	1981	-1.992	2012	-4.985**	1982	-5.514***	2011	I (1)
*ln*ENE	-3.462	1995	-5.128*	1985	-8.365***	2004	-8.075***	2004	I (1)
*ln*IND	-3.598	1981	-3.456	1992	-8.216***	1990	-8.125***	1990	I (1)
*ln*URB	-5.576*	1984	-15,54*	1991	-5.716***	1984	-29.00***	1998	I (1)

Note: ***, ** and * indicate the significance level at 1%, 5% and 10% respectively. tb = time break.

Note that unlike stationary $I(0)$ variables, first-order integrated variables do not generally provide information in the long run. To establish a long-run relationship between economic growth, fossil fuel consumption, industrialization, urbanization, and the CO2 variable in Côte d'Ivoire, we will examine cointegration. After that, we proceed to the Lag order selection test. The result recorded in Table 6 shows that the optimal lag (p) is 2. This test is useful for the implementation of the VECM Granger causality model.

Table 6. Lag order selection.

VAR lag order selection criteria						
Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	146.719	NA	9.44e-10	-6.591	-6.386	-6.516
1	365.013	375.668	1.19e-13	-15.582	-14.353*	-15.128
2	399.374	51.142*	8.06e-14*	-16.017*	-13.764	-15.186*
3	422.472	29.006	1.00e-13	-15.928	-12.652	-14.720
4	445.850	23.921	1.41e-13	-15.853	-11.552	-14.267

Note: * indicates lag order selected by the criterion.
According to the different information criteria in the table, sequential modified LR test statistic (each test at 5% level) (LR), Final prediction error (FPE), Akaike information criterion (AIC), Schwartz information criterion (SC) and Hannan- Quinn information criterion (HQ), the optimal lag length (p) is 2.

4.2. Study of Cointegration

4.2.1. Johansen Cointegration Test

Table 7 reports the results of the Johansen cointegration test. They confirm the existence of at least one long-run relationship or cointegrating equation among the variables in the estimated model.

Table 7. Results of Johansen cointegration test.

Hypothesis	Trace statistic	Critical value at 0.05	Max-eigen statistic	Critical value at 0.05
None*	88.850 [a]	60.061	45.279 [a]	30.439
At most 1*	43.570 [b]	40.174	24.740 [b]	24.159
At most 2	18.830	24.275	11.514	17.797
At most 3	7.3156	12.320	6.393	11.224

Note: *denotes rejection of the null hypothesis (No-cointegration between variables) at the 0.05 level. Trace test and Max-eigenvalue statistics indicate 2 cointegration equations. ([a]) and ([b]) indicate the significance level at 1% and 5% respectively (MacKinnon, Haug, & Michelis, 1999) p-values).

4.2.2. Gregory-Hansen Cointegration Test

Table 8 gives the results of the Gregory and Hansen (1996) cointegration test. We use the Bayesian Information Criterion (BIC) as the lag choice method.

The results of the GH test, the ADF* and Zt* statistics tests confirm the existence of a cointegrating relationship between the variables in the presence of a structural break at the 10% significance level, in the case of the model (C) with a shift in level and the model (C/S) with a shift in regime. As a result, we can estimate the long-term effects of the model's variables.

Table 8. Results of Gregory-Hansen cointegration test with one structural break.

Type of shift	ADF*	Zt*	Za*	Time break (ADF)	Cointegration
Level (C)	-5.51*	-5.57*	-37.86	1990	Yes
Level and trend (C/T)	-5.57	-5.63*	-38.34	1990	No
Regime (C/S)	-6.27*	-6.34*	-45.05	1990	Yes

Note: * indicate the significance at 10% level. GH test critical values for m=4 : model 1 (C) 1% : -6.05, 5% : -5.56, 10% : -5.31 ; model 2 (C/T) 1% : -6.36, 5% : -5.83, 10% : -5.59 ; model 3 (C/S) 1% : -6.92, 5% : -6.41, 10% : -6.17.

4.3. Results of the Long-Run Estimates

The results of the long-run estimates are presented in Table 9. The three estimation methods—FMOLS, CCR, and DOLS—show the same trends. The estimated coefficients of the variables economic growth, fossil fuel consumption, industrialization, and urbanization are positive and globally significant, as demonstrated by the works of Khan et al. (2019), Begum et al. (2020), Muhammad and Khan (2021) and Muhammad et al. (2021).

In particular, urbanization has a substantial positive effect on carbon emissions. A 1% increase in urban population generates a more than proportional increase of 2.47%, 2.37%, and 1.42% in CO2 emissions at the 1% significance level, respectively, with the FMOLS, CCR, and DOLS estimators. This is in line with the strong association between urbanization and CO2 emissions, as shown in the correlation matrix in Table 3. These results are consistent with the results of Alam, Fatima, and Butt (2007) and Poumanyvong and Kaneko (2010) who found a positive relationship between the rate of urbanization and the rate of CO2 emissions, respectively, in Pakistan and a group of 99 countries.

Table 9. Long-run coefficients based on FMOLS, CCR and DOLS estimators.

Estimation models	FMOLS		CCR		DOLS	
Independant variables	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
*ln*GDP	0.567**	2.153	0.538**	2.098	0.544**	2.200
*ln*ENE	0.392*	1.668	0.422*	1.759	0.485**	2.349
*ln*IND	0.788*	1.883	0.909**	2.096	0.754	0.989
*ln*URB	2.473***	6.287	2.376***	10.599	1.421***	3.264
DUM1990	-0.038	-0.177	0.028	0.102	-0.520	-1.060
C	-8.352*	-2.461	-8.259*	-2.518	-4.211	-1.059
R-squared	0.699		0.688		0.880	
Adjusted R-squared	0.662		0.649		0.777	
S.E. of regression	0.197		0.201		0.149	
Long-run variance	0.039		0.039		0.014	

Note: ***,** and * indicate the significance level at 1%, 5% and 10%. We estimate long-run covariances with Bartlett Kernel and Andrews Bandwith. Especially for DOLS, we use fixed leads and lags specification (Lead=1 and lag=1). DUM represents the dummy variable.

But these results are contrary to those of Keho (2015), who found a significant negative effect of urbanization on CO2 emissions in Côte d'Ivoire over the period 1970-2010. According to the author, although urbanization generates environmental pollution, it participates in the objectives of sustainable development; this would be through easier access in urban areas to advanced technologies and new knowledge that improve energy efficiency. For us, this argument is fragile, especially in the context of Côte d'Ivoire where technological development is not very dynamic and the integration of innovations is still weak.

The results in Table 9 also show that an economic growth of 1% increases the level of air pollution by CO2 by more than 0.5%, with a significance level of 5%, whatever the estimator considered. As for fossil fuel consumption, it generates an increase in the level of CO2 emissions of about 0.4%. The positive effects of these two variables have been highlighted in the literature (see for example, (Jalil & Mahmud, 2009; Nahoua, 2021; Shahbaz et al., 2014)). Thus, there is indeed a monotonically increasing relationship between income and CO2 emissions in Côte d'Ivoire over the study period. As for the industrialization variable, the results indicate that only the FMOLS and CCR estimators exhibit positive and significant coefficients at the 10% and 5% levels, respectively. The effect of industrialization on CO2 emissions is almost proportional to its levels of increase. The more the country industrializes, the higher its CO2 emissions become. Industrialization thus contributes to the degradation of environmental quality in Côte d'Ivoire. This result is consistent with Keho (2015).

Finally, the dummy variable DUM1990, which captures the period of structural break, shows statistically insignificant effects on CO2 emissions in Côte d'Ivoire, whatever the estimator considered. Indeed, in order to consider the break in the 1990s highlighted by the Gregory-Hansen (G-H) cointegration test, we introduced the dummy variable DUM1990 in the regression equation to be estimated. With this result, we can say that the causes of the break in 1990, notably the stabilization reforms, liberalization, massive privatization, and the socio-political crisis, did not have a significant influence on the evolution of CO2 emissions. Furthermore, when we compare all these post-break results, including the dummy variable, with those of the pre-break estimates, not including the dummy variable, we find that the econometric tests are more robust for the post-break estimates (i.e., higher R^2 and Adjusted-R^2 and lower long-run variance, whatever the estimator considered).

4.4 Results of the VECM Granger Causality Test

The presence of cointegration among the variables implies causal relationships among the variables. The relational directions between economic growth, fossil fuel consumption, industrialization, urbanization, and CO2 emissions allow for better articulation of environmentally friendly economic growth policies.

Table 10 reports the results of the vector error correction model (VECM) used to analyze the short-run and long-run causal relationships between the variables.

Table 10. VECM Granger causality analysis.

Dependent variables	Direction of Granger causality					Long run
	Short run					
	***ln*CO2**	***ln*GDP**	***ln*ENE**	***ln*IND**	***ln*URB**	***ECT*$_{t-1}$**
*ln*CO2	–	3.318* (0.068)	0.043 (0.834)	0.309 (0.578)	4.154** (0.041)	- 0.320*** (-2.888)
*ln*GDP	0.021 (0884)	–	0.071 (0.788)	0.824 (0.363)	14.537*** (0.0001)	0.096*** (3.743)
*ln*ENE	1.178 (0.277)	1.425 (0.232)	–	0.153 (0.695)	0.008 (0.926)	–
*ln*IND	1.159 (0.281)	5.194** (0.022)	0.046 (0.829)	–	6.561** (0.014)	- 0.084* (-1.953)
*ln*URB	0.077 (0.780)	0.041 (0838)	0.081 (0.775)	1.383 (0239)	–	–

Note: ***, ** and * indicate the significance level at 1%, 5% and 10%, respectively.

We note that only the estimated coefficients of the lagged error correction terms for the CO2 emissions and industrialization equations are negative and statistically significant. Their respective values of -0.320 and -0.084 indicate that the shocks experienced by the system converge to the long-run equilibrium at a low speed for the CO2 emissions equation and at a very low speed for the industrialization equation. In other words, in the long run, economic growth, energy consumption, industrialization, and urbanization Granger cause carbon emissions (see green arrows in Figure 3). Similarly, there is a long-term causality from carbon emissions, economic growth, energy consumption, and urbanization to industrialization (see blue arrows in Figure 3). Thus, we have long-run bidirectional causality between carbon emissions and industrialization. Furthermore, Table 10 shows that, although the lagged error correction term in the GDP equation is significant, it does not indicate long-run causality with the other variables because its coefficient does not have the right sign. In the short run, we infer a unidirectional Granger causality from income to CO2 emissions and industrialization. So, the previous long-run analysis shows that these short-run causal associations continued into the long run. This supports the positive relationship between economic growth and CO2 emissions. In Côte d'Ivoire, economic growth significantly influences emissions, leading to the emergence of various economic activities that produce greenhouse gases. Finally, we have three short-run unidirectional causalities from urbanization to per capita income, CO2 emissions, and industrialization (see Figure 2). From the perspective of our research topic, the logic of the causality scheme in Figure 1 and Figure 2 demonstrates that the variables under study strongly influence CO2 emissions. But, at the socio-economic level, the increase in CO2 emissions could result in rising temperatures, ecosystem disruption, and adverse effects on human health. Note that the causality analysis in the short and long run shows the importance of urbanization in the evolution of CO2 in Côte d'Ivoire.

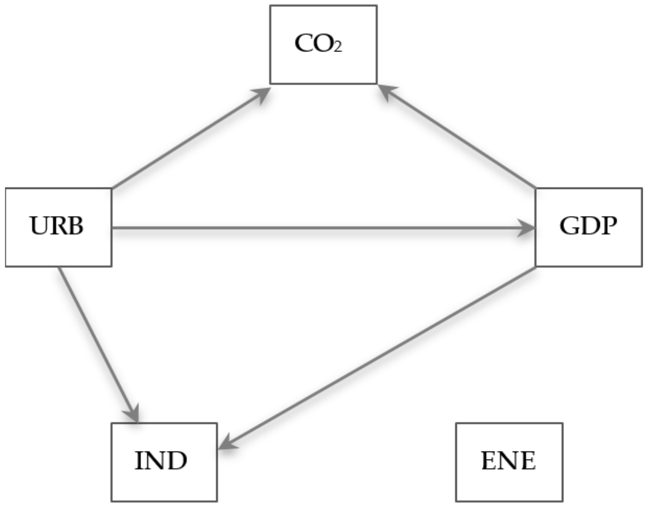


Figure 2. Short-run causal links.

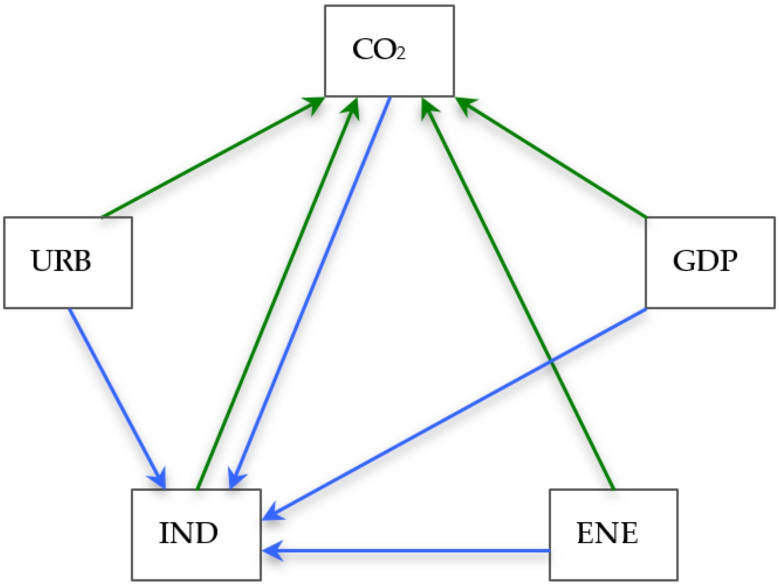


Figure 3. Long-run causal links.

To go further and check the robustness of VECM, we use error variance decomposition and impulse response function methods to determine the relative strength of the causal effect of the variables beyond the selected period. We will thus measure the relative influence of the different shocks on the dynamics of each variable.

4.5. Variance, Decomposition, and Impulse Response

Table 11 describes the results of the variance decomposition approach. They show that in the short run, i.e., in the third year, the innovation or shock on CO2 emissions explains 90.38% of the variation in CO2 (own shock), while the income shock causes 3.84% of CO2 emissions; the contribution of fossil fuel consumption, industrialization, and urbanization is 0.084%, 1.88%, and 3.79% of the CO2 emissions, respectively. In the long run, which is the tenth year, the shock on CO2 emissions accounts for 78.41% of the variation in CO2 (the own shock). The shocks to income, fossil fuel consumption, and industrialization cause low levels of variation in CO2 emissions, at 5.03%, 0.42%, and 2.91%, respectively, compared to the contribution of urbanization, which accounts for 13.21% of CO2 emissions. This result is consistent with previous estimates that showed a significant effect of urbanization on emissions in Côte d'Ivoire. All these results underline that economic growth, fossil fuel consumption, industrialization, and especially urbanization contribute to CO2 emissions in Côte d'Ivoire.

We also note that in the long run, CO_2 emissions, fossil fuel consumption, industrialization, and urbanization explain economic growth at 21.66%, 4.42%, 2.74%, and 29.98%, respectively. Shocks on CO_2 emissions, GDP per capita, industrialization, and urbanization contribute to 4.02%, 14.28%, 0.39%, and 4.97% of the change in fossil fuel consumption, respectively. CO_2 emissions, GDP per capita, fossil fuel consumption, and urbanization explain industrialization at 11.85%, 6.19%, 18.43%, and 18.10%, respectively. Finally, the shocks on CO_2 emissions, GDP per capita, fossil fuel consumption, and industrialization contribute to urbanization at 2.40%, 7.66%, 2.78%, and 1.91%, respectively.

The results in Figure 4 describe the impulse responses using the Cholesky technique. In periods 1 and 2, a shock to GDP initially has a small positive impact on CO_2. Then, the response gradually decreases until the ninth period, beyond which it reaches its equilibrium value. A shock to fossil fuel consumption does not have a significant impact on CO_2 until period 7, after which the response increases slightly until period 10. A shock to industrialization initially decreases CO_2 emissions; CO_2 emissions gradually increase until period 7 reaches the equilibrium value and remains positive. Initially, a shock to urbanization decreases CO_2 emissions until the second period. Then, emissions rise, reaching the equilibrium region in the third period, and continue to rise throughout the remainder of the analysis period. Thus, the results of the impulse response test confirm those of the variance decomposition. In other words, economic growth, fossil fuel consumption, industrialization, and urbanization contribute to CO_2 emissions in Côte d'Ivoire.

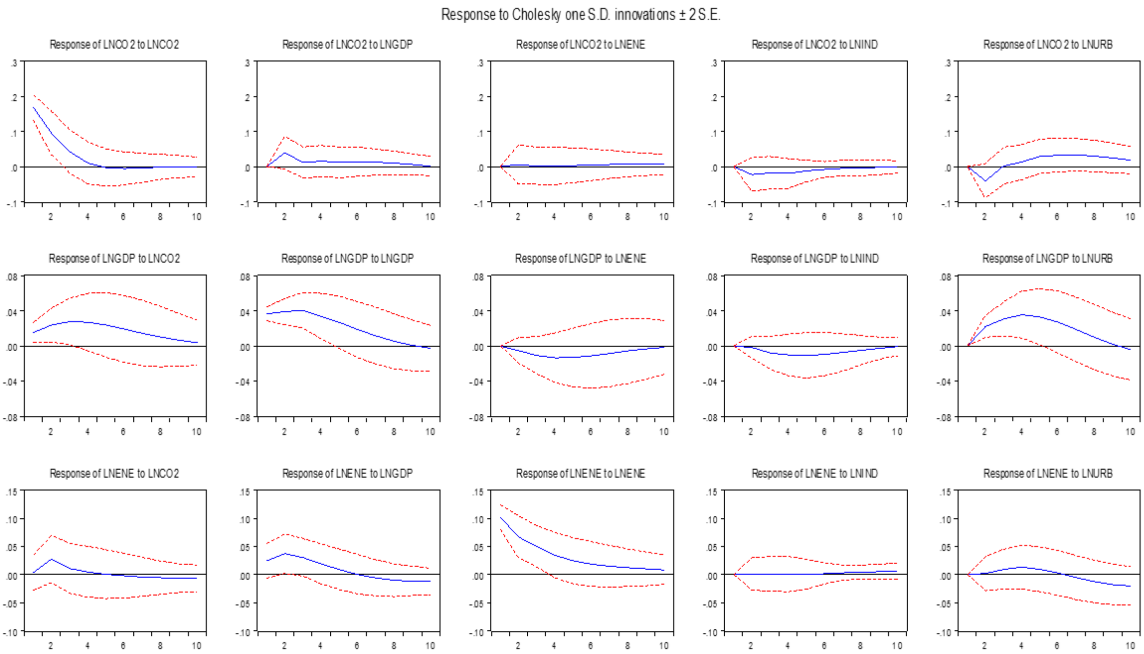
In particular, the two IAA techniques demonstrate that urbanization has a positive and significant impact not only on CO_2 emissions but also on per capita income, industrialization, and, to a lesser extent, fossil fuel use. Thus, per capita income, industrialization, and energy use may influence the transmission of urbanization's effects to CO_2 emissions, and vice versa. In the remaining section of the paper (section 5), we continue our analysis of how urbanization affects CO_2 emissions based on factors such as economic development (income), industrial structure and intensity (industrialization), and fossil fuel consumption, and vice versa.

Table 11. Variance decomposition of the five variables.

Variance decomposition of LNCO2:						
Period	S.E.	LNCO2	LNGDP	LNENE	LNIND	LNURB
1	0.168	100.000	0.000	0.000	0.000	0.000
2	0.202	90.961	3.727	0.085	1.228	3.996
3	0.208	90.387	3.846	0.084	1.888	3.793
4	0.210	88.780	4.317	0.088	2.723	4.091
5	0.213	86.550	4.491	0.105	2.984	5.867
6	0.216	84.083	4.771	0.158	3.040	7.946
7	0.219	81.768	4.957	0.224	3.000	10.048
8	0.221	80.059	5.063	0.291	2.959	11.626
9	0.223	78.983	5.065	0.354	2.930	12.666
10	0.224	78.415	5.032	0.420	2.914	13.216
Variance decomposition of LNGDP:						
Period	S.E.	LNCO2	LNGDP	LNENE	LNIND	LNURB
1	0.039	14.936	85.063	0.000	0.000	0.000
2	0.064	19.052	68.403	0.637	0.053	11.853
3	0.087	20.298	58.399	1.813	0.840	18.647
4	0.105	20.680	50.603	2.875	1.513	24.327
5	0.117	20.789	46.031	3.577	2.073	27.527
6	0.124	20.960	43.319	4.003	2.423	29.293
7	0.127	21.214	41.958	4.240	2.627	29.958
8	0.128	21.475	41.399	4.363	2.721	30.039
9	0.129	21.645	41.240	4.415	2.751	29.947
10	0.129	21.669	41.175	4.421	2.747	29.985
Variance decomposition of LNENE :						
Period	S.E.	LNCO2	LNGDP	LNENE	LNIND	LNURB
1	0.105	0.102	5.396	94.501	0.000	0.000

2	0.132	4.311	11.154	84.513	0.002	0.0177
3	0.145	4.122	13.576	81.864	0.007	0.429
4	0.151	3.908	14.087	80.847	0.006	1.149
5	0.154	3.785	13.968	80.765	0.007	1.473
6	0.155	3.753	13.767	80.985	0.019	1.473
7	0.156	3.784	13.739	80.818	0.059	1.597
8	0.157	3.853	13.890	79.880	0.135	2.241
9	0.159	3.939	14.105	78.265	0.235	3.454
10	0.162	4.023	14.280	76.376	0.341	4.977
Variance decomposition of LNIND :						
Period	S.E.	LNCO2	LNGDP	LNENE	LNIND	LNURB
1	0.054	3.192	5.797	6.433	84.576	0.000
2	0.064	3.993	4.301	6.585	74.385	10.734
3	0.072	11.702	4.398	11.117	60.339	12.441
4	0.077	13.315	4.554	14.785	52.606	14.738
5	0.080	12.924	5.317	17.212	49.535	15.010
6	0.081	12.609	5.517	18.456	48.531	14.885
7	0.081	12.560	5.478	19.022	48.153	14.784
8	0.082	12.455	5.526	19.132	47.660	15.226
9	0.083	12.189	5.800	18.893	46.706	16.411
10	0.084	11.856	6.196	18.435	45.404	18.107
Variance decomposition of LNURB :						
Period	S.E.	LNCO2	LNGDP	LNENE	LNIND	LNURB
1	0.005	0.386	17.101	0.071	0.704	81.735
2	0.010	0.210	16.468	0.018	1.967	81.335
3	0.015	0.122	13.815	0.008	2.240	83.813
4	0.020	0.095	11.934	0.020	2.331	85.617
5	0.023	0.104	10.307	0.096	2.312	87.179
6	0.025	0.176	8.987	0.286	2.257	88.291
7	0.027	0.374	8.011	0.636	2.177	88.800
8	0.028	0.780	7.459	1.178	2.085	88.496
9	0.029	1.458	7.363	1.908	1.991	87.277
10	0.030	2.409	7.666	2.782	1.910	85.230

Note: S.E means standard error; LNCO2 is *ln*CO2; LNGDP is *ln*GDP; LNENE is *ln*ENE; LNIND is *ln*IND; LNURB is *ln*URB.



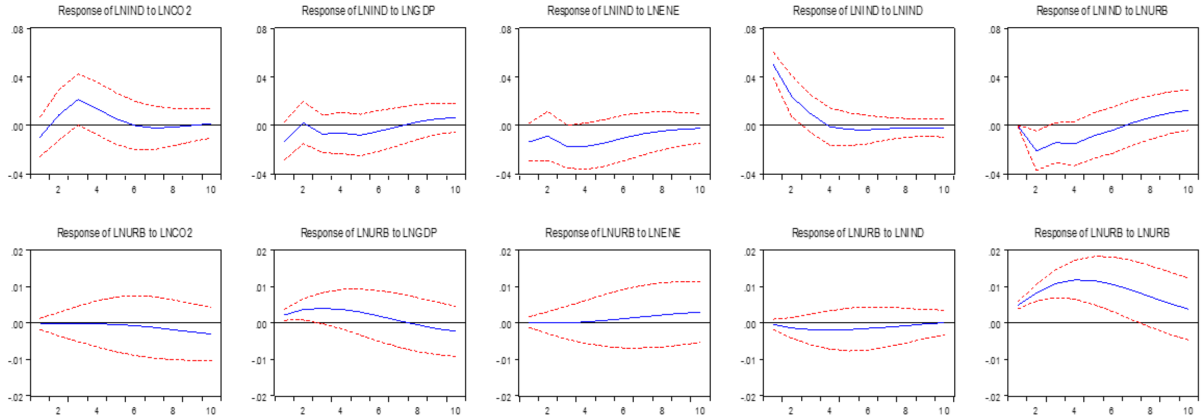


Figure 4. Impulse response function.

5. EXTENSION

In the extension of the paper, we analyze the impact of the interaction between urbanization (URB) and the other three explanatory variables, GDP, ENE, and IND, on CO2 emissions. The objective is to deduce the threshold conditions imposed on the URB variable for the other explanatory variables, GDP, ENE, and IND, to reduce the amounts of CO2 emissions and vice versa. To do this, we introduce interaction terms (in bold) into the original model 2 and consider modified models 3, 4, and 5 below.

Model 3:

$$ln\,\mathrm{CO2}_t = b_0 + b_1 ln\,\mathrm{GDP}_t + b_2 ln\,\mathrm{ENE}_t + b_3 ln\,\mathrm{IND}_t + b_4 ln\,\mathrm{URB}_t + b_5 ln\,\mathrm{GDP}_t * ln\,\mathrm{URB}_t + \varepsilon_t \quad (16)$$

Model 4:

$$ln\,\mathrm{CO2}_t = c_0 + c_1 ln\,\mathrm{GDP}_t + c_2 ln\,\mathrm{ENE}_t + c_3 ln\,\mathrm{IND}_t + c_4 ln\,\mathrm{URB}_t + c_5 ln\,\mathrm{ENE}_t * ln\,\mathrm{URB}_t + \varepsilon_t \quad (17)$$

Model 5:

$$ln\,\mathrm{CO}_{2t} = d_0 + d_1 ln\,\mathrm{GDP}_t + d_2 ln\,\mathrm{ENE}_t + d_3 ln\,\mathrm{IND}_t + d_4 ln\,\mathrm{URB}_t + d_5 ln\,\mathrm{IND}_t * ln\,\mathrm{URB}_t + \varepsilon_t \quad (18)$$

The long-run coefficients are estimated only with the FMOLS and CCR estimators to simplify the analysis. The results are reported in Table 12.

Table 12. Estimation results of the modified models with FMOLS and CCR.

Models	**Model 3**		**Model 4**		**Model 5**	
Variables	**FMOLS**	**CCR**	**FMOLS**	**CCR**	**FMOLS**	**CCR**
*ln*GDP	-14.791*** (-2.778)	-14.339*** (-2.865)	0.7863*** (2.792)	0.707*** (2.686)	0.993*** (3.114)	0.876*** (3.054)
*ln*ENE	0.272 (1.110)	0.290 (1.185)	-18.530*** (-3.009)	-19.455*** (-2.960)	0.374 (1.440)	0.349 (1.347)
*ln*IND	0.296 (0.695)	0.475 (1.041)	0.364 (0.867)	0.524 (1.204)	15.073** (2.016)	16.536* (1.876)
*ln*URB	-28.120** (-2.638)	-27.290*** (-2.719)	-14.333** (-2.606)	-15.413** (-2.571)	14.672** (2.310)	15.477** (2.156)
*ln*URB**ln*GDP	4.137*** (2.865)	4.001*** (2.990)				
*ln*URB**ln*ENE			5.009*** (3.064)	5.258*** (3.012)		
*ln*URB**ln*IND					-3.883** (-1.911)	-4.241* (-1.796)
C	107.246*** (2.691)	103.904*** (2.742)	54.906** (2.656)	58.995** (2.608)	-56.236** (-2.303)	-58.711** (-2.136)
R-squared	0.730	0.722	0.717	0.706	0.688	0.687
Adjusted R-squared	0.696	0.687	0.682	0.670	0.649	0.648
S.E. of regression	0.187	0.190	0.191	0.195	0.201	0.201
Long-run variance	0.042	0.042	0.042	0.042	0.048	0.048

Note: T-statistics are reported in parentheses; ***,** and * indicate the significance level at 1%, 5% and 10% respectively. We estimate Long-run covariances with Bartlett kernel and Andrews's bandwith.

The significant results of the long-term estimates of the three models show that the effect of the variables GDP, ENE, and IND on CO_2 emissions does depend on the rate of urbanization. Similarly, the effect of the urbanization variable on CO_2 emissions depends on the values taken by GDP, ENE, and IND. We can then calculate the conditional thresholds for the levels of URB, GDP, ENE, and IND needed to see a decrease in carbon dioxide emissions in the country. With model 3, the condition on GDP for URB to generate a decrease in CO_2 emissions is given by GDP < $e^{(b4/b5)}$ while the condition on URB for GDP to generate a decrease in emissions is given by URB < $e^{(b1/b5)}$. With model 4, the condition on ENE for URB to generate a decrease in CO_2 emissions is given by ENE < $e^{(c4/c5)}$; the condition on URB for ENE to generate a decrease in emissions is given by URB < $e^{(c2/c5)}$. Finally, with model 5, the condition on IND for URB to generate a decrease in CO_2 emissions is given by IND < $e^{(d4/d5)}$ and the condition on URB for IND to generate a decrease in emissions is given by URB < $e^{(d3/d5)}$. The calculated threshold conditions are reported in Table 13.

Table 13. Conditional thresholds for reducing CO_2 emissions.

Title of the condition	FMOLS	CCR
Conditions on URB for GDP to lead to a decrease in CO_2 emissions	URB < 9.717 %	URB < 9.736 %
Conditions on GDP for URB to lead to a decrease in CO_2 emissions	GDP < 18.476 $ US	GDP < 18.544 $ US
Conditions on URB for ENE to lead to a decrease in CO_2 emissions	URB < 10.054 %	URB < 10.073 %
Conditions on ENE for URB to lead to a decrease in CO_2 emissions	ENE < 7.778 %	ENE < 7.790 %
Conditions on URB for IND to lead to a decrease in CO_2 emissions	URB < 10.549 %	URB < 10.59 %
Conditions on IND for URB to lead to a decrease in CO_2 emissions	IND < 10.269 %	IND < 9.929 %

Table 13 confirms that the urbanization-pollution relationship depends on economic growth, industrial structure, and fossil fuel use. Urbanization will lead to a decrease in the level of CO_2 if and only if the level of income per capita is very low and less than 18.5 US$, if the amount of fossil fuel consumed represents less than 9.7% of the energy consumed, or if the industrialization rate of the economy is less than 10%. However, the Ivorian economy has already surpassed all three of these threshold levels. In other words, the country's urbanization will continue to increase, as will air pollution.

Symmetrically, Table 13 shows that economic growth, industrial development, and fossil fuel use would result in lower CO_2 emissions if and only if the level of urbanization is less than 10% overall. This result clearly indicates that these three variables will also continue to increase carbon dioxide emissions, as the average urbanization rate over the study period is above 10% and continues to grow. All of these results show that, in the current state of the Ivorian economy's functioning, carbon dioxide air pollution in Côte d'Ivoire will continue to increase unless the country takes appropriate measures. Indeed, the current socio-economic context of Côte d'Ivoire is very dynamic and conducive to investment. The current socio-economic context of Côte d'Ivoire is favorable and likely to attract more polluting activities due to the creation of new industries. This favorable economic situation leads to an increase in the purchasing power of the middle class, a change in consumption patterns, and a greater production of pollution waste (Ministry of Environment and Sustainable Development, 2016). As a result, reversing the trend in CO_2 emissions necessitates specific measures.

6. CONCLUSION

This study dealt with the empirical analysis of the relationship between CO_2 emissions and economic growth, industrialization, fossil fuel consumption, and urbanization in the case of Côte d'Ivoire over the period 1970-2016. It also analyzes the conditions under which these emissions can stop growing. The data used is from the World Bank's

World Development Indicators database. For the preliminary analysis of the data, we used econometric techniques, including two unit-root tests (ZA and PV), two cointegration tests (Johansen and GH), and finally the Granger VECM method as well as IAA techniques to assess the causal associations and their intensity. Estimates of the long-run coefficients were made using the cointegrating regression techniques FMOLS, CCR, and DOLS in the presence of structural breaks.

The results broadly support the literature on the determinants of carbon dioxide pollution. They confirm that economic growth, industrialization, urbanization, and fossil fuel consumption have a positive effect on CO_2 emissions in Côte d'Ivoire. The effects of urbanization are more marked. Massive migrations from rural areas to cities, the expansion of urbanized territories, the evolution of economic structures, transportation means, and energy consumption, all contribute to urbanization in Côte d'Ivoire and are significant sources of pollution. As for fossil fuels (oil and gas) and their harmful effects on pollution, we note that Côte d'Ivoire consumes a lot of them, like other African countries. For instance, in 2019, Côte d'Ivoire consumed approximately 8,028.47 kilotons of oil equivalent (ktoe) to fuel various activities such as road transport and manufacturing, accounting for 74.7% of primary energy supplies (Ministry of Petroleum Energy and Renewable Energy, 2020). Finally, we should note that the development of energy-intensive industries follows increasing urbanization and population growth, significantly contributing to the rise in CO_2 emissions. The causality analysis shows that CO_2 emissions and industrialization are linked in two directions over the long term. The four variables are linked in one direction to CO_2 over the long term, and there are also short-term links that only go in one direction.

The primary contribution of this study stems from the outcomes of the modified model estimates included in the extension. The results show that under the current economic, urbanization, energy use, and industrial conditions of the country, carbon dioxide emissions will continue to grow indefinitely. This is why COP 28, the latest United Nations climate change conference, ended with an unprecedented call for a rapid, fair, and equitable transition away from fossil fuels. The Ivorian authorities must implement specific policies to significantly reduce carbon dioxide emissions. To achieve this, we recommend a sound carbon pricing policy as well as strategies for promoting and developing clean and renewable energy. With regard to the carbon pricing policy, or carbon tax, we note that there is already an environmental tax in Côte d'Ivoire. However, this tax does not currently include any taxation on GHG emissions. Nevertheless, an attempt was made in 2016 to account for this. We developed scenarios for projecting potential carbon tax revenues based on a psychologically acceptable price per ton of CO_2. With a starting carbon price of 1,000 CFA francs and a more ambitious price of 2,500 CFA francs, the cumulative revenue from the carbon tax would be 493.5 billion and 1,233.7 billion CFA francs, respectively (Ministry of Environment and Sustainable Development, 2016). This amount could have contributed to financing adaptation and CO_2 reduction measures. As for the promotion and development of clean and renewable energy, this will require the establishment of the necessary institutional regulations to remove market barriers to large-scale clean and renewable energy investments. Regulatory instruments will thus provide incentives for the diffusion of clean technologies and contribute to reversing the pollution trend. On the other hand, the Ivorian industry will have to invest in an operational change by integrating clean production technologies. This means, for example, reducing the use of polluting energy in favor of renewable or less polluting energy. All economic actors, including companies, households, and the public sector, will ultimately be responsible for the costs of environmental pollution resulting from their actions. The polluter-pays principle can facilitate a swift shift in behavior through the implementation of laws and regulations. Finally, the authorities will have to prioritize economic growth based on knowledge by strongly integrating innovation in order to improve labor efficiency, physical capital productivity, and energy efficiency. All these actions will help the country gradually exit the "fossil fuel era."

This study opens several avenues of research, including the question of whether carbon dioxide emissions are a limiting factor for the country's economic development or whether the country could accommodate them. If the country has to live with these CO_2 emissions, we must model and estimate the optimal level of emissions to preserve the country's sustainable economic development. One of the limitations of this study is the limited availability of data during the study period. The same data availability problem prevented us from exploring new pollution proxies, such as the ecological footprint and load capacity factors used in recent developments in the field of study.

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