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Effects Of Renewable Energy Consumption And Economic Growth On Carbon Intensity In Africa: Moment Quantile Regression Approach

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Abstract
The Paris Agreement has accelerated a global push towards reducing carbon emissions, with Africa facing unique challenges and opportunities in this regard. Despite abundant renewable energy resources, many African countries continue to rely heavily on carbon-intensive energy sources, which not only exacerbate environmental degradation but also impede socio-economic development. The main objective of this study is to analyse the relationship between renewable energy consumption and carbon intensity utilizing panel data from 34 African countries from 1995 to 2022. The specific objectives of this study are to investigate the contribution of renewable energy consumption to carbon intensity in Africa, to investigate the contribution of economic growth to carbon intensity in Africa, and to investigate the validity of the EKC hypothesis for the analysed sample of African countries. Using an ex-post-facto research design, this study analysed an extended STIRPAT model incorporating carbon intensity, renewable energy consumption, per capita GDP (and its quadratic term), domestic credit, and natural resources rent. The study utilized secondary data sourced from the World Bank's World Development Indicators (WB-WDI) and the Global Financial Development (GFD) database compiled by the World Bank. The analysis included second-generation econometric methods such as cross-sectional dependence-augmented panel unit root and cointegration tests and employed fixed effects regression with Driscoll-Kraay standard errors (DK-FE) and the novel method of moment's quantile regression (MM-QR). The empirical results show that a 1% increase in renewable energy consumption decreases carbon intensity between -0.23% in the lowest quantile to -0.19% in the highest quantile of carbon intensity. Per capita GDP, on the other hand, exhibits a strong positive relationship with carbon intensity, while the squared term of per capita GDP shows a mitigating effect, supporting the Environmental Kuznets Curve (EKC) hypothesis. The study also finds positive but insignificant effects of domestic credit and rent.

Keywords: *Renewable energy consumption, Carbon intensity, EKC hypothesis, Cross-sectional dependence, Method of moment quantile regression, Africa*

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I. Introduction

The global demand for energy has grown steadily, driven by population growth, industrialization, and economic development (Bhuiyan, Zhang, Khare, et al., 2022; Emenekwe, Okereke, Nnamani, et al., 2022). From the mid-20th century to the present, global primary energy consumption has increased significantly, reflecting the critical role energy plays in modern economies (Bhuiyan et al., 2022). However, this growth has been predominantly fuelled by fossil fuels-oil, coal, and natural gas—which, while economically beneficial, are major contributors to carbon dioxide (CO_2) emissions (Soeder, 2021). The extraction, processing, and consumption of fossil fuels have led to increased atmospheric CO_2 levels, contributing to global warming and climate change(IEA, 2021a; Soeder, 2021). The international policy discourse has increasingly focused on mitigating CO_2 emissions to combat the climate crisis (IEA, 2021a).

CO_2 emissions are a key driver of the greenhouse effect, leading to severe environmental consequences such as rising sea levels, extreme weather events, and disruptions to ecosystems and human health (Strauss, Orton, Bittermann, et al., 2021). Recognizing these threats, the 26thConference of Parties (COP26) to the United Nations Framework Convention on Climate Change (UNFCCC) saw nations commit to limiting global temperature rise to 1.5 degrees Celsius by 2030 (IPCC, 2018). This commitment underscores the need for all countries, irrespective of their development stage, to decouple CO_2 emissions from their economic and demographic trajectories. Yet, with energy demand continuing to rise, achieving climate-neutral targets remains a formidable challenge for many economies, partly because of the indispensable role of energy in driving economic growth (Emenekwe, Okereke, et al., 2022; Lallana, Bravo, Le Treut, et al., 2021; Le Treut, Lefèvre, Lallana, & Bravo, 2021).

Africa stands at a pivotal juncture in its economic development, challenged by the dual imperatives of promoting growth and sustainability. The continent's energy consumption patterns are critically linked to its environmental and economic outcomes, especially in terms of carbon intensity which has direct implications for global climate change (IEA, 2021a; Kaya, 1990).Recent shifts in global energy landscapes, driven by technological advancements and international environmental agreements, have urged African nations to reconsider their energy strategies to significantly lower carbon emissions, thus contributing to achieving the Sustainable Development Goals (SDGs), particularly SDG 7, which aims for affordable, reliable, sustainable, and modern energy for all (IEA, 2021b; World Bank, IEA, IRENA, UNSD, 2021).

Since the Paris Agreement (COP26), there has been a global push towards reducing carbon emissions, with Africa facing unique challenges and opportunities in this regard. Despite abundant renewable energy resources, many African countries continue to rely heavily on carbon-intensive energy sources, which not only exacerbate environmental degradation but also impede socio-economic development. Recent studies highlight significant disparities in energy consumption patterns across the continent, with renewable energy underutilized despite its potential to reduce carbon emissions and enhance energy security (IEA, 2022). As the continent grapples with the adverse effects of climate change, including droughts and resource depletion, optimizing energy consumption to minimize carbon intensity becomes imperative. This context underscores the critical need to examine how increasing renewable energy consumption can influence carbon intensity and support Africa's green growth aspirations.

Moreover, the role of economic factors, such as GDP per capita, in influencing carbon emissions, introduces additional layers to the problem. Studies have indicated Environmental Kuznets Curve (EKC) in some regions, where emissions increase with economic growth up to a point before declining as income continues to rise (Emenekwe, Onyeneke, & Nwajiuba, 2021; Grossman & Krueger, 1995; Nwani, 2022). However, the applicability of the EKC in African contexts remains contested, with evidence suggesting diverse trajectories depending on country-specific factors (Ayad, Lefilef, & Ben-Salha, 2023; Onifade, 2022; Ouédraogo, Peng, Chen, & Hashmi, 2022).

Also, the existing literature provides limited insight into how variations in economic growth, credit availability, and natural resources rent affect the relationship between renewable energy consumption and carbon intensity across different economic quantiles within the continent. Thus, this study aims to explore the extent to which renewable energy consumption and economic growth influence carbon intensity,and the validity of the EKC hypothesis across various African economies.

II. Literature Review

Brief conceptual literature

Renewable energy refers to energy derived from natural processes that are replenished constantly, such as solar, wind, hydro, and biomass(IRENA, 2019). Unlike fossil fuels, renewable energy sources produce little to no greenhouse gas emissions during operation, making them pivotal in the transition towards a low-carbon economy. The adoption of renewable energy technologies is influenced by various factors, including policy frameworks, economic incentives, technological advancements, and institutional capacities. In the African context, the abundant availability of renewable resources presents a significant opportunity for reducing carbon intensity and promoting sustainable development(IEA, 2021a).Economic growth, typically measured as GDP per capita, is a fundamental driver of development, influencing energy consumption patterns and environmental impact(Grossman & Krueger, 1995). In the early stages of economic growth, energy consumption—and consequently, carbon emissions—tend to increase as industrial activities and economic output expand(Grossman & Krueger, 1995). However, the relationship between economic growth and environmental impact is complex and may follow different trajectories depending on the stage of development and the adoption of cleaner technologies. Carbon intensity is defined as the amount of carbon dioxide emissions produced per unit of economic output, typically measured as CO_2 emissions per GDP(Kaya, 1990; Our World in Data, 2020). It serves as a critical indicator of an economy's environmental efficiency and its progress towards decarbonization. High carbon intensity signifies a heavy reliance on fossil fuels and inefficient energy use, whereas lower carbon intensity indicates a cleaner and more sustainable energy mix(Our World in Data, 2020). Reducing carbon intensity is essential for mitigating climate change and achieving international environmental targets (IEA, 2021a).

Theoretical Review

Understanding the relationship between renewable energy consumption and environmental outcomes involves several theoretical frameworks and hypotheses that provide insights into the complex dynamics of energy use, economic growth, and environmental impact. This section reviews the dominant theoretical frameworks relevant to this research, including the IPAT and STIRPAT models and the Environmental Kuznets Curve (EKC) hypothesis.

IPAT and STIRPAT models

The IPAT model, formulated by Ehrlich and Holdren(1971), specifies a mathematical identity that expresses environmental impact (I) as the product of Population (P), Affluence (A), and Technology (T): ($I=P\times A\times T$). However, Apeaning (2021) argues that ethical concerns often undermine the effectiveness of using population control as a mitigation tool.

The simplicity of the IPAT model makes it a useful starting point for understanding the macro-level drivers of environmental impact, including carbon emissions. Building on IPAT, Dietz andRosa(1997)developed the STIRPAT model (Stochastic Impacts by Regression on Population, Affluence, and Technology) to incorporate stochastic elements and provide a more flexible analytical framework:$I=aP^b\times A^c\times T^d$. In this model, coefficients b, c, and d can be estimated empirically, allowing for the examination of non-linear relationships and the influence of other factors. The STIRPAT model is particularly relevant for analysing the impact of renewable energy consumption on carbon emissions, as it can account for variations in technological advancements and economic conditions across different countries.

Environmental Kuznets Curve (EKC) hypothesis

The Environmental Kuznets Curve (EKC) hypothesis, proposed by Grossman and Krueger(1995), posits that the relationship between environmental degradation and economic growth follows an inverted U-shape. In the initial stages of economic growth, environmental degradation and pollution increase, but after reaching a certain level of income per capita, the trend reverses, and further economic growth leads to environmental improvement. This hypothesis suggests that as countries develop, they initially prioritize economic growth over environmental concerns, but eventually, increased wealth and technological advancements enable them to invest in cleaner technologies and environmental protection measures.

The effectiveness of economic growth in reducing CO_2 emissions depends significantly on a country's level of development(Frodyma, Papież, & Śmiech, 2022; Nwani, Usman, Okere, & Bekun, 2023). Typically, nations are more inclined to decouple CO_2emissions from economic growth once they achieve a certain per capita income level (Frodyma et al., 2022). Although technology is recognized as the most effective means to reduce CO_2 emissions (Apeaning, 2021), the original *IPAT* equation did not clearly define this technological factor (York, Rosa, & Dietz, 2003). Waggoner and Ausubel (2002) addressed this by refining the concept of technology to include the technological structure of the energy mix, thereby extending the impact equation (*IPAT*).

Empirical Review

Econometric testing of the impact of PAT on CO_2 emissions has been the focus of numerous empirical studies across various regions and periods. This review synthesizes findings from key studies to understand this dynamics. Emenekwe, Onyeneke, and Nwajiuba (2021) analysed the effects of financial development (FD) and economic growth on carbon dioxide (CO_2) emissions in 37 Sub-Saharan African (SSA) countries from 2000 to 2016. The strategy checked for cross-sectional dependence and causality using second-generation analytical techniques. The estimation technique was the pooled mean group ARDL and the dynamic generalized method of moment estimator. The findings indicate that overall FD reduces CO_2 emissions in the region and supports the environmental Kuznets curve (EKC) hypothesis. Specifically, the results reveal that a 1 unit increase in the overall FD index results in a 2.867% reduction in CO_2 emissions over the long run.

Emenekwe, Onyeneke, Nwajiuba, Anugwa, and Emenekwe(2023)investigated the drivers of CO_2 emissions from both consumption and production across 103 nations, emphasizing the roles of renewable energy use, financial market progress, per capita income growth, and population size. Utilizing the method of moments quantile regression and fixed effects model with Driscoll–Kraay standard errors, the study reveals a reduction in CO_2 emissions with increased renewable energy adoption. Furthermore, financial development leads to decreased emissions. However, growth in income and population are associated with higher CO_2 emissions. Specifically, a 1% increase in renewable energy consumption decreases consumption-based CO_2 emission by 0.2–2.1%.

Namahoro, Wu, Xiao, and Zhou(2021 a) examined the asymmetric relationship between renewable energy consumption, economic growth, and carbon emissions in Sub-Saharan Africa from 1995 to 2018. Using the Non-linear Autoregressive Distributed Lag (NARDL) model, they found that increases in renewable energy consumption significantly reduce carbon emissions, while economic growth impacts emissions differently across countries, highlighting the critical role of renewable energy in mitigating carbon intensity.

Musah, Kong, Mensah, Antwi, and Donkor(2020) investigated the nexus between carbon emissions, renewable energy consumption, and economic growth in ECOWAS countries from 1980 to 2016. Employing the Panel Vector Autoregression (PVAR) model, they discovered bidirectional causality between renewable energy consumption and economic growth. Their findings underscore that renewable energy consumption contributes to reducing carbon emissions, supporting the transition to a greener economy in West Africa.

Bekun, Emir, and Sarkodie(2019) focused on Nigeria from 1980 to 2014, exploring the relationship between energy use, economic growth, and carbon emissions using the ARDL bounds testing approach. They concluded that renewable energy consumption significantly reduces carbon emissions, whereas economic growth increases emissions. This suggests the need for policies that promote sustainable economic growth alongside increased renewable energy use.

Adewuyi and Awodumi (2017) explored biomass energy consumption, economic growth, and carbon emissions in Sub-Saharan Africa from 1980 to 2015 using the Generalized Method of Moments (GMM). They found that biomass energy consumption reduces carbon emissions, while economic growth has a dual effect, initially increasing but eventually reducing emissions as economies mature.Adams and Acheampong (2019) analyzed the role of renewable energy in reducing carbon emissions in 22 African countries from 1990 to 2014 using the Fixed Effects Model. Their findings indicated that renewable energy consumption significantly reduces carbon emissions, and they emphasized the importance of supportive policies to enhance renewable energy adoption.

Kahia, Jebli, and Belloumi(2019) examined the impact of renewable energy consumption on economic growth and carbon emissions in North Africa from 1980 to 2015 using the Autoregressive Distributed Lag (ARDL) model. They concluded that renewable energy consumption reduces carbon emissions and positively influences economic growth, reinforcing the benefits of renewable energy adoption. Odhiambo (2011) analyzed the causal relationship between energy consumption, carbon emissions, and economic growth in South Africa using Granger causality tests. He found that while energy consumption drives economic growth, it also increases carbon emissions, indicating a trade-off between growth and environmental sustainability.

Inal, Addi, Çakmak, et al.(2022) explored the impact of globalization and renewable energy on carbon emissions in Africa using the Generalized Method of Moments (GMM). They found that renewable energy consumption and globalization reduce carbon emissions, highlighting the importance of integrating global best practices in energy policies.

Namahoro et al.(2021 b) investigated the effects of energy intensity, renewable energy, and economic growth on carbon emissions in East Africa from 1990 to 2019 using the Panel Cointegration approach. Their findings indicated that renewable energy consumption significantly reduces carbon emissions, while economic growth increases emissions, particularly in the short term.Esso and Keho (2016) examined the long-run and short-run relationships between energy consumption, economic growth, and carbon emissions in 12 Sub-Saharan African countries from 1970-2010 using the ARDL bounds testing approach. They concluded that renewable energy consumption reduces carbon emissions, but economic growth increases emissions.

Ekwueme et al. (2021) analyzed the carbon emission effects of renewable energy utilization in Nigeria using the ARDL model. Their results showed that renewable energy consumption significantly reduces carbon emissions, and economic growth impacts emissions non-linearly, consistent with the EKC hypothesis. (Omoke, Nwani, Effiong, Evbuomwan, and Emenekwe(2020)investigated the asymmetric dynamic effects of financial development on ecological footprint in Nigeria over the period 1971–2014 using the nonlinear autoregressive distributed lag (NARDL) framework. The results show that in Nigeria, an increase in financial development has significant reducing effect on ecological footprint and vice versa. Further, the analysis shows that economic growth, energy consumption, urbanization, and economic globalization are all drivers of environmental sustainability in Nigeria.

III. Methodology

The study adopted panel data regression analysis because of the heterogeneous nature of the data involved. A cross sectional and time series data were drawn from some selected African countries.

Model specification

The model in this study has its origin in the IPAT and STIRPART described in Section 0. As noted, Dietz and Rosa (2003) redefined the IPAT identity was into astochastic model, STIRPAT, whose algebraic form is as follows:

$$I = aP^b \times A^c \times T^d \tag{1}$$

The constant, a, scales the function; b, c and d are the exponents of P,A, and T, respectively, and are to be derived using appropriate econometric techniques to aid policy inferences. Following existing empirical studies(Emenekwe et al., 2023; Nwani, 2022; Waggoner & Ausubel, 2002), this study defines T as a function of the technological structure of the energy mix and other variables of interest relevant to the specific study. Specifically, we use Renewable energy consumption, domestic credit, and total natural resources rent to proxy T and thereby extend Eq. (1). Following the empirical literature thatdo not explore the population (P) in-depth, this study divides both sides of the Eq. (1) by P to obtain per capita values. Thus, taking algebraic and natural logarithmic (*ln*) transformation of the components yields the following expression for empirical investigation:

$$\ln CI_{i,t} = \beta_0 + \beta_1 \ln Renew_{i,t} + \beta_2 \ln GDPpc_{i,t} + \beta_3 \ln Credit_{i,t} + \beta_4 \ln Rent_{i,t} + \varepsilon_{i,t} \qquad 2)$$

where impacts *(I)* are represented by CO_2emissions per unit of GDP (i.e., emission intensity of economic growth, ln*CI*), affluence (*A*) is represented by per capita GDP (ln*GDPpc*), technology (*T*) is represented by renewable energy consumption as a percentage of total final energy consumption (ln*Renew*), credit to the domestic economy (ln*Credit*), and natural resources rent (ln*Rent*).“i, t” refers to the ithcountry in year $t$and $\varepsilon$is the error term. $\beta_0$is the intercept of the functional relationship and $\beta_0 \dots \beta_5$are the coefficients of the explanatory variables to be estimated. The “ln” symbol indicates that all the variables are defined in their natural logarithmic form. The interactions between CI and *GDPpc*, as the economy progress along the development path, could follow an inverted U-shaped curve according to the EKC hypothesis(Grossman & Krueger, 1995). Hence, we extend Eq. (2) to include the quadratic term of per capita GDP (*GDPpc*) in the functional equation:

$$\ln CI_{i,t} = \beta_0 + \beta_1 \ln Renew_{i,t} + \beta_2 \ln GDPpc_{i,t} + \beta_3 \ln GDPpc_{i,t} + \beta_4 \ln Credit_{i,t} + \beta_5 \ln Rent_{i,t} + \varepsilon_{i,t} \qquad 3)$$

a priori expectations:$\beta_1$is expected to have a negative sign to indicate that $Renew$ reduces CI. Furthermore, a valid inverted U-shaped curve only exists if $\beta_2 > 0$ and $\beta_3 < 0$. For β_4 domestic credit has different signs (Emenekwe et al., 2021). It is, however, expected that increased domestic credit allocation would lead to increased investment and adoption of energy efficient processes that reduce carbon intensity. For, β_5, existing related studies have suggested different signs (Shittu, Adedoyin, Shah, & Musibau, 2021). It is however expected that β_5 willhave a positive sign to indicate that natural resource extraction createssustainability concerns in the case of African economies.

Data sources

This study uses balanced panel data from 34 African countries selected based data availability from 1995 to 2022 (see list of countries and data in Table A1 in the Appendix). To measure carbon intensity (*CI*), CO_2 emissions kilogram per 2015 US$ of GDP is used, for per capita income (*GDPpc*), GDP per capita in constant 2015 US$ is used, renewable energy consumption (*Renew*) is calculated as a percentage of total final energy consumption, domestic credit is measured as while natural resource rent (*Rent*) is defined in the form of derived rents as a percentage of GDP. Data on these variables are from the World Development Indicators (WDI) database compiled by the World Bank. Domestic credit is proxied by credit supply by deposit money banks to government and state-owned enterprises as a percent of GDP, and the data is obtained from the Global Financial Development (GFD) database compiled by the World Bank.

Estimation techniques

The estimation techniques consist of the following estimation steps:

Test for cross-sectional dependence (CSD)

Because African countries share similar economic characteristics, shocks in one country can spill over to the other countries in the panel. As a result, testing for the presence of cross-sectional dependence (CSD) in the panel data series is recommended and can be achieved using the technique proposed by Pesaran (2004). The CSD statistic of the Pesaran (2004) test is given as follows:

$$CSD = \sqrt{\frac{2T}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}} \qquad 4)$$

where T = (1995, . . ., 2022), N represents the number of cross-sections, which in the case of this study is limited to the 34 African countries in the panel and $\hat{\rho}_{ij}$represents the correlation among the derived residuals of the cross-sectional panel units. The presence of CSD is tested under H_0: cross-section independence.

Panel unit root test

This study employs the panel unit root test proposed by Pesaran (2007). The objective is to identify the stationarity features of the variables. Pesaran (2007) extended the Dickey-Fuller (DF) regression model to account for potential cross-sectional dependence in the panel data series. The CSD Augmented DF statistic (CADF) is calculated as:

$$\Delta y_{i,t} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + \varepsilon_{i,t} \tag{5}$$

where $\Delta$is the difference operator, $\bar{y}_t$is the average of the target variable for Nobservations. Based on Eq.(5), a cross-sectional augmented Im-Pesaran-Shin (CIPS) test with the following statistics is calculated:

$$CIPS = \frac{1}{N}\sum_{I=1}^{N} CADF_I \tag{6}$$

For a more robust CIPS statistic, Pesaran (2007) recommends additional tests to determine the truncated version of the CIPS statistic as follows:

$$CIPS\text{-}TR = \frac{1}{N}\sum_{I=1}^{N} CADF_I^* \tag{7}$$

Where $CADF_I^*$ suggests that the derived CIPS statistic has been truncated to limit the effect of extreme values that could result from the size of T not being sufficiently large.

Cointegration test

To test if the variables based on the empirical model specifications exhibit a long-run relationship, the error-correction-based cointegration test by Westerlund (2007), which is significantly efficient in the presence of cross-sectional dependency, is used. The baseline equation is given as follows:

$$\Delta Y_{i,t} = u_i' d_t + \lambda_i\left(Y_{i,t-1} - \beta' X_{i,t-1}\right) + \sum_{j=1}^{k} \emptyset_{ij}\, \Delta Y_{i,t-j} + \sum_{j=1}^{k} \gamma_{ij}\, \Delta X_{i,t-j} + \varepsilon_{i,t} \tag{8}$$

In Equation (8), $\lambda_i$provides an estimate of the speed of error-correction toward the long-run equilibrium (Westerlund, 2007). Four (4) statistics can be derived from the above equation:

$$G_t = \frac{1}{N}\sum_{i=1}^{N} \frac{\widehat{\omega_i}}{se(\widehat{\omega_i})} \tag{9}$$

$$G_a = \frac{1}{N}\sum_{i=1}^{N} \frac{T\widehat{w_i}}{1 - \sum_{j=1}^{k} \omega_{ij})} \tag{10}$$

$$P_t = \frac{\widehat{\omega}}{se(\widehat{\omega})} \tag{11}$$

$$P_t = T\widehat{\omega} \tag{12}$$

Two group statistics; $G_t$defined by Eq.(9) and $G_a$defined by Eq.(10), test whether a long-run relationship exists in at least one cross-sectional unit. The $P_t$defined by Eq.(11) and $P_a$defined by Eq.(12) provide statistics for testing the presence of a long-run relationship in the entire panel. The null hypothesis of no cointegration in the entire panel is rejected when one or both panel statistics are statistically significant.

Panel parameters estimation

To estimate Equations (3), two panel estimation techniques are used: regression with Driscoll-Kraay standard errors (DK-R) and the panel quantile regression model with fixed effects via the method of moments (MM-QR). Each of these techniques makes assumptions that address estimation issues that can affect the validity of the derived parameter estimates. The DK-R derives slope coefficients that are heteroskedastic and robust to very general forms of cross-sectional dependence (Driscoll & Kraay, 1998). Depending on how the error term ($\varepsilon_{i,t}$) is treated, DK-R can estimate three different models: pooled (constant effect) model (DK-PL), fixed effects model (DK-FE) and the GLS random effects model (DK-RE) which assumes the error term be a random variable. Using the Hausman test, the more efficient and appropriate DK-R model can be selected. The DK-R technique, however, models only the mean of the dependent variable. Since the normality check in Table 1 indicates that *CI* is not normally distributed, the DK-R model may not produce sufficient policy-relevant information for the low and high carbon intensity countries, and the MM-QR technique, which takes distributional heterogeneity into account, is used. The MM-QR model as formulated by Machado and Silva (2019) produces heterogeneous and distributional effects across quantile locations of the dependent variable. The conditional quantile $Q_\gamma(\tau|X)$ for a location-scale model is defined as:

$$Q_\gamma(\tau|X_{it}) = \alpha_i + \delta_i qi(\tau) + X_{it}'\varphi + Z_{it}'\gamma q(\tau)$$

13)

where X_{it}' is a vector of regressors, and $\alpha_i + \delta_i qi(\tau)$ is the scalar coefficient of the quantile-τ fixed effect at τ, which are time-invariant parameters whose heterogeneous effects are allowed to vary across the quantiles of *Y*. Equation (13) can be used to model the functional relationship defined in Equations (3) as follows:

$$Q_{\ln CI_{i,t}}(\tau|a_i, \varepsilon_{it}, X_{i,t}) + \alpha_{i\tau} + \varphi_{1a\tau}\ln Renew_{i,t} + \varphi_{2a\tau}\ln GDPpc_{i,t} + \varphi_{3a\tau}\ln GDPpc_{i,t} + \varphi_{4a\tau}\ln Credit_{i,t} + \varphi_{5a\tau}\ln Rent_{i,t} + \varepsilon_{i,t} \quad 14)$$

where $Q_{\ln CI_{it}}(\tau|a_i, \varepsilon_{it}, X_{i,t})$ is the conditional quantile of *CI* with the scalar coefficient $(a_i(\tau))$ for the distributional effect at τ. To examine the effect of an explanatory variable, for example *Renew*, on *CI*, τ is set between 0 and 1. This produces the impact of *Renew* at the selected point in the conditional distribution of *CI*. For instance, setting τ = 0.25 produces the 25thquantile equation for the distribution of *CI*.

IV. Results Presentation And Analysis

Descriptive Statistics

Table 1 shows the summary statistics and tests for normality. Carbon intensity has an average value of 0.3867, which is higher than the median of 0.2929, indicating a right-skewed distribution. This skewness suggests that most countries have relatively low carbon intensity, but a few outliers with values as high as 1.4950 significantly raise the average, highlighting disparities in industrial activities and energy use patterns.

Similarly, GDP per capita shows a pronounced disparity, with an average of 2,052.3820, significantly higher than the median of 1,146.4000, and a wide range from a minimum of 217.0597 to a maximum of 10,956.9450. This difference and broad range point to economic variations among the countries, where a few are much wealthier compared to the majority. The substantial standard deviation of 1,998.2703 further underscores this economic divergence.

Domestic credit as a percentage of GDP also exhibits considerable variability, with values ranging from 0 to 142.4220. The mean of 25.5791 is much higher than the median of 14.1574, indicating that while some countries have robust financial systems providing substantial business credit, others are markedly restricted.

Renewable energy consumption is another key variable, showing a left-skewed distribution where the median of 73.6600 is higher than the mean of 60.8246. This suggests that while the majority of countries rely heavily on renewable energy, a few with very low usage, with the minimum at just 0.0600, significantly pull the mean down. The maximum consumption recorded is 96.7300, illustrating the varied extent of renewable energy integration into national energy policies across the continent.

Table 1. Descriptive Statistics and tests for normality.

Variable	Mean	Median	Std. Dev.	Min	Max
CI	0.3867	0.2929	0.2779	0.0621	1.4950
Renew	60.8246	73.6600	29.5887	0.0600	96.7300
GDPpc	2,052.3820	1,146.400	1,998.2703	217.0597	10,956.9450
GDPpcsq	8,201,006	1,314,234	15,600,000	47114.91	120,000,000
Credit	25.5791	14.1574	27.5278	0.0000	142.4220
Rent					
Skewness / Kurtosis test for normality					
				———— joint ———	
		Pr(skewness)	Pr(Kurtosis)	chi2(2)	Prob > chi2
CI		0.0000	0.0000	251.18***	0.0000
Renew		0.0000	0.0000	170.04***	0.0000
GDPpc		0.0000	0.0000	209.39***	0.0000
GDPpcsq		0.0000	0.0000	498.17***	0.0000
Credit		0.0000	0.0000	261.11***	0.0000
Rent		0.0000	0.0000	170.04***	0.0000
Note: Number of observations is 918. ***p < 0.01 indicates rejection of normality condition in the distribution at 1% significance level.					

The probability values for both skewness and kurtosis are 0.0000 for all the variables., and the Chi-square statistics for variables (carbon intensity [251.18], GDP per capita [209.39], GDP per capita square [498.17], domestic credit [261.11], renewable energy consumption [170.04], and natural resources rent [170.04])are highly significant (Prob > chi2 = 0.0000). This significance indicates a strong rejection of the normality hypothesis for all the variables at the 1% level. The previous summary statistics had suggested a right-skewed distribution, and this test confirms that the distribution also deviates from normality in terms of peakness (kurtosis).

CSD, unit root, cointegration and model selection tests

CSD results

The results in

Table **2**and Table 3 show that the null hypothesis of no CSD is rejected for all variables. The Pesaran (2004, 2015)CSD test is the main employed to assess whether there is cross-sectional dependence among the panel data units, under the null hypothesis, there is weak cross-section dependence, while the alternative hypothesis is there is strong cross-section dependence.

Table 2. Pesaran (2004, 2015)test for weak cross-sectional dependence (CSD)

	CD	CDw	CDw	CD*
Residuals	19.5900	-1.8800	1335.5500	4.8800
	(0.0000)	(0.0600)	(0.0000)	(0.0000)

Note:H_0: weak cross-section dependence. H_1: strong cross-section dependence.*p*-values in parenthesis.
References: CD: Pesaran (2004, 2015); CDw:Juodis and Reese(2022); CDw+:CDw with power enhancement fromFan, Liao, and Yao (2015); CD*: Pesaran and Xie(2023). Implemented using *xtcd2* command in Stata 16.

Table 3. Estimation of Cross-Sectional Exponent (alpha)

Variable	Alpha	Std. Err.	[95% Conf. Interval]	
ln*CI*	0.5272	0.0394	0.4500	0.6044
ln*Renew*	0.8964	0.0402	0.8176	0.9751
ln*GDPpc*	0.9808	0.0505	0.8819	1.0797
ln*GDPpcsq*	0.9807	0.0857	0.8127	1.1488
ln*Credit*	0.8615	0.0566	0.7506	0.9724
ln*Rent*	0.8648	0.0245	0.8168	0.9128

Note: 0.5 <= alpha < 1 implies strong cross-sectional dependence. Implemented estimation using *xtcse2* command in State 16

The test statistic of 19.5900 for the residualswith a *p*-value of 0.0000 suggests that we must reject the null hypothesis of weak cross-section dependence for the model and accept the alternative hypothesis of strong cross-sectional dependence. This result implies significant cross-sectional dependence, meaning that model variables share common shocks or influences across different countries, which could be due to economic, environmental, or policy similarities.

Estimation of Cross-Sectional Exponent (Alpha)(Fan et al., 2015):The alpha values estimate the degree of cross-sectional dependence: ln*CI*: An alpha of 0.5272 indicates moderate cross-sectional dependence. This value is just above the lower threshold of 0.5, suggesting some level of shared variation among countries, though less pronounced than in other variables. ln*Renew*, ln*GDPpc*, ln*GDPpcsq*, ln*Credit*, ln*Rent*: These variables have alpha values close to or above 0.8, with ln*GDPpc* and ln*GDPpcsq* nearing or exceeding 0.98, indicating very strong cross-sectional dependence. Such high values of alpha confirm that these variables are highly sensitive to common external factors affecting the panel units, reinforcing the findings from the CD test. Therefore, cross-sectional dependence is confirmed in the data series of all the variables.

Unit root result

Because cross-sectional dependence is present among the variables, cross-sectionally augmented unit root techniques are used to identify the stationarity properties of the variables. The results are presented in

Table **4**.

Table 4. Cross-Sectional Augmented Panel Unit Root Tests

CIPS										
		Level I(0)			**1st Difference I(1)**			**5% Critical Value**		
Variables		**Constant**	**C and T**		**Constant**	**C and T**		**Constant**	**C and T**	**Decision**
ln*CI*		-1.9114	-1.9016		-3.0090	-3.4094		-2.1400	-2.6500	I(1)
ln*Renew*		-1.4336	-1.4545		-3.7868	-3.6299		-2.1400	-2.6500	I(1)
ln*GDPpc*		-1.9504	-2.4029		-2.9463	-3.0937		-2.1400	-2.6500	I(1)
ln*GDPpcsq*		-1.9110	-2.5486		-2.8635	-3.0649		-2.1400	-2.6500	I(1)
ln*Credit*		-2.0757	-3.6659		-3.0331	-3.7452		-2.1400	-2.6500	I(1)
ln*Rent*		-1.5330	-2.0078		-3.7001	-3.1229		-2.1400	-2.6500	I(1)
CIPS-TR										
		Level I(0)			**1st Difference I(1)**			**5% Critical Value**		
Variables		**Constant**	**C and T**		**Constant**	**C and T**		**Constant**	**C and T**	**Decision**
ln*CI*		-1.9114	-2.3623		-2.9444	-3.3458		-2.1400	-2.6500	I(1)
ln*Renew*		-1.4336	-2.6045		-3.7123	-3.4378		-2.1400	-2.6500	I(1)

ln*GDPpc*		-1.9504	-2.5562		-2.9344	-2.9904		-2.1400	-2.6500	I(1)
ln*GDPpcsq*		-1.9110	-2.6197		-2.8011	-2.9597		-2.1400	-2.6500	I(1)
ln*Credit*		-2.07565	-2.1346		-3.0331	-3.7452		-2.1400	-2.6500	I(1)
ln*Rent*		-1.4985	-2.0078		-3.6071	-3.0826		-2.1400	-2.6500	I(1)
Note: H_0: variable has a unit root; C and T stands for constant and trend; *** indicate rejection of H_0 at 1% level of significance. Software: Eviews version 12.										

Both tests, the CIPS (Cross-Sectional Im, Pesaran, and Shin test) and the CIPS-TR (truncated version of CIPS), are designed to account for cross-sectional dependencies in panel datasets, enhancing the reliability of unit root testing in such contexts. The tests were conducted both at levels ($I(0)$) and at first differences ($I(1)$) for each variable. For each test condition, critical values at the 5% significance level are provided for scenarios with only a constant (Constant) and with both a constant and a trend (C and T).

Decision on Stationarity:$I(1)$ Decision: All variables—ln*CI*, ln*Renew*, ln*GDPpc*, ln*GDPpcsq*, ln*Credit*, and ln*Rent*—were determined to be integrated of order 1 ($I(1)$), based on the test results.

This determination is made when the unit root test statistics at levels are higher (less negative) than the respective critical values, failing to reject the null hypothesis of a unit root; and the test statistics at first differences are lower (more negative) than the respective critical values, leading to rejection of the null hypothesis, thus confirming stationarity at first differences.

Cointegration test result

The Westerlund (2007) ECM panel cointegration test results, as presented in

Table **5**, provide strong evidence of a long-term equilibrium relationship among the variables in the model. This test includes four key statistics: two targeting the group (G_t and G_a) and two assessing the panel as a whole (P_t and P_a).The G_t statistic, at a *p*-value of 0.0900, suggests a marginal indication of cointegration within certain groups, showing a weak yet notable presence of a long-term relationship at the 10% significance level. Conversely, the G_a statistic is highly significant with a *p*-value of 0.0000, robustly confirming cointegration within at least one group in the panel. This strong result underscores that certain countries or clusters share common economic and environmental dynamics.

For the panel-wide tests, P_t and P_a both demonstrate significant evidence of cointegration, with P_t at a *p*-value of 0.0400 and P_a at a *p*-value of 0.0000. These findings indicate that the variables share a common stochastic trend across the entire panel, reinforcing the concept of interconnectedness among the economic and environmental factors across all countries studied.

Thus, for this set of African countries, a long-run relationship exists between carbon emission intensity of economic growth, renewable energy consumption, per capita GDP, domestic credit, and natural resource rent.

Table 5. Westerlund (2007) ECM panel cointegration test

Test Statistics	Value	Robust *P*-Value
G_t	-2.4550	0.0900
G_a	-10.6180***	0.0000
P_t	-14.8230*	0.0400
P_a	-9.4930***	0.0000
Note: Robust *p*-values are based on 100 bootstrap replications of the critical values. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively. The *Ho* is no cointegration. Implemented estimation using *xtwest* command in State 16.		

Model selection test results

The results of the Hausman test (

Table **6**), with a Chi-square statistic of 40.1300 and a *p*-value of 0.0000, significantly indicate a systematic difference in the coefficients between the fixed effects and random effects models. This finding leads to the rejection of the null hypothesis that differences in coefficients across these models are not systematic. Given this result, the fixed effects model is the appropriate choice for your analysis. Thus, the results from Hausman test reveal that the fixed effects model (DK-FE) is a more appropriate DK-R model for estimating the model.

Table 6. Hausman test

Test: H_0: difference in coefficients not systematic
Chi2 (5) = 40.1300
Prob>chi2 = 0.0000

The Variance Inflation Factor (VIF) test results for the model (

Table **7**) indicate that multicollinearity is not a significant concern among the variables. The VIF values for ln*Renew*, ln*GDPpc*, ln*Credit*, and ln*Rent*(at 2.33, 1.73, 1.80, and 1.08) suggest a modest level of correlation with other variables well below the threshold commonly associated with severe multicollinearity concerns, typically around 10(Emenekwe & Emodi, 2022). Further, the mean VIF across all variables is 1.74, indicating that, on average, there is no pronounced multicollinearity in the model. This suggests that the regression estimates should be stable and reliable, without the distortions often caused by high multicollinearity.

Table 7. Variance inflation factor test for multicollinearity

Variable	VIF	1/VIF
ln*Renew*	2.3300	0.4286
ln*PCgdp*	1.7300	0.5783
ln*Credit*	1.8000	0.5548
ln*Rent*	1.0800	0.9254
Mean VIF	1.7400	

Results from panel regression techniques

The parameter estimates are summarized in

Table 8 and Table 9. Specifically, estimates in

Table 8 evaluate the DK-FE model's the mean effect of the explanatory variables while those in Table 9 assess the MM-QR estimates for distributional heterogeneity in the effects of the explanatory variables in the selected African countries. In Table 9, three groups of quantiles are defined: the lower quantile (Qtile_10 and Qtile_25); the median quantile (Qtile_50); and the upper quantile (Qtile_75 and Qtile_90).

Table 8 presents the conditional mean estimates. Log of renewable energy consumption (ln*Renew*): A one percent increase in ln*Renew* is associated with a 0.2136 percent decrease in ln*CI*. This relationship is statistically significant (*p*-value = 0.0000), implying a strong negative relationship between renewable energy consumption and carbon intensity, all else equal. The quantile regression results in Table 9 are consistent with conditional mean estimates of

Table 8. In other words, the MM-QR estimates show that a 1 percent increase in ln*Renew* decreasesln*CI* irrespective of the quantile location of a country in the distribution. However, the results reveal that the magnitude of reduction by increased renewable energy consumption is largest in the lower quantileof carbon intensity (-0.2278, -0.2224) compared to the median quantile (-0.2143) and higher quantile (-0.2052, -0.1991).

Log of economic growth per capita (ln*GDPpc*): A one percent increase in ln*GDPpc* is associated with a 0.6359 percent increase in ln*CI*. The relationship is statistically significant (*p*-value = 0.0000), implying a strong positive relationship between economic per capita and carbon intensity. In other words, increasing economic growth per capita appears to increase carbon intensity, all else equal.The quantile regression results in Table 9 are consistent with conditional mean estimates of

Table 8. In other words, the MM-QR estimates show that a 1 percent increase in ln*GDPpc* increases ln*CI* irrespective of the quantile location of a country in the distribution. However, the results reveal that the magnitude of increase by increased economic growth per capita is largest in the lower quantile of carbon intensity (0.7084, 0.6809) compared to the median quantile (0.6397) and higher quantile (0.5930, 0.5621).

Square of economic growth per capita (ln*GDPpcsq*): from

Table 8, a one percent increase in ln*GDPpcsq* is associated with a 0.0538 percent decrease in lnCI. This relationship is statistically significant (*p*-value = 0.0000), implying a strong negative relationship between square of economic growth and carbon intensity, all else equal.The quantile regression results in Table 9 are consistent with conditional mean estimates of

Table 8. In other words, the MMQR estimates show that a 1 percent increase in ln*GDPpcsq* decreases ln*CI* irrespective of the quantile location of a country in the distribution. However, the results reveal that the magnitude of reduction by increased renewable energy consumption is largest in the lower quantile of carbon intensity (-0.0582, -0.0565) compared to the median quantile (-0.0540) and higher quantile (-0.0512, -0.0493).

Log of Domestic Credit (ln*Credit*): from

Table 8, the coefficient of lnCredit is positive (0.0031) and statistically insignificant at the 5% level (*p*-value = 0.2870). The quantile regression results in Table 9 are consistent with conditional mean estimates of

Table 8. In other words, the MMQR estimates show that a 1 percent increase in ln*Credit* increases ln*CI* irrespective of the quantile location of a country in the distribution. However, the results are statistically insignificant at the 5% level.Log of total natural resources rent (ln*Rent*): from

Table 8, the coefficient of ln*Rent*is positive (0.0087) and statistically insignificant at the 5% level (*p*-value = 0.1300). The quantile regression results in Table 9 are consistent with conditional mean estimates of

Table 8. In other words, the MMQR estimates show that a 1 percent increase in ln*Rent*increases ln*CI* irrespective of the quantile location of a country in the distribution. However, the results are statistically insignificant at the 5% level.

Table 8. Fixed-effects regression with Driscoll-Kraay (DK-FE) standard errors

Variables	Coefficient	Std. Err.	t	P>|t|	[95% Conf. Interval]	
ln*Renew*	-0.2136	0.0289	-7.3900	0.0000	-0.2730	-0.1542
ln*GDPpc*	0.6359	0.0810	7.8500	0.0000	0.4694	0.8025
ln*GDPpcsq*	-0.0538	0.0068	-7.8600	0.0000	-0.0679	-0.0397
ln*Credit*	0.0031	0.0029	1.0900	0.2870	-0.0028	0.0090
ln*Rent*	0.0087	0.0056	1.5600	0.1300	-0.0027	0.0202
Constant	-0.6327	0.1771	-3.5700	0.0010	-0.9968	-0.2686
Number of groups = 34						
F(5, 26) = 13.07						
Prob > F = 0.0000						
Within R^2 = 0.2744						

Note:Fixed effects model (FE-DK) is implemented using the *xtscc* command (with options, fe lag()) in Stata 16. Maximum lag: 1. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Table 9. Method of moments quantile regression (MM-QR) results

Variables	Location	Scale	Qtile_10	Qtile_25	Qtile_50	Qtile_75	Qtile_90
ln*Renew*	-0.2136***	0.0094	-0.2278***	-0.2224***	-0.2143***	-0.2052***	-0.1991***

	(0.0155)	(0.0095)	(0.0180)	(0.0156)	(0.0153)	(0.0197)	(0.0241)
	[-13.7500]	[0.9900]	[-12.6600]	[-14.2400]	[-13.9600]	[-10.4300]	[-8.2700]
ln*GDPpc*	0.6359***	-0.0482	0.7084***	0.6809***	0.6397***	0.5930***	0.5621***
	(0.0601)	(0.0369)	(0.0696)	(0.0604)	(0.0594)	(0.0761)	(0.0932)
	[10.5800]	[-1.3100]	[10.1800]	[11.2700]	[10.7700]	[7.7900]	[6.0300]
ln*GDPpcsq*	-0.0538***	0.0029	-0.0582***	-0.0565***	-0.0540***	-0.0512***	-0.0493***
	(0.0044)	(0.0027)	(0.0051)	(0.0044)	(0.0043)	(0.0056)	(0.0068)
	[-12.2300]	[1.0900]	[-11.4200]	[-12.7800]	[-12.4200]	[-9.1900]	[-7.2200]
ln*Credit*	0.0031	0.0019	0.0002	0.0013	0.003	0.0048	0.006
	(0.0039)	(0.0024)	(0.0045)	(0.0039)	(0.0038)	(0.0049)	(0.0060)
	[0.8100]	[0.8100]	[0.0500]	[0.3400]	[0.7800]	[0.9800]	[1.0100]
ln*Rent*	0.0087**	0.0023	0.0052	0.0065	0.0085**	0.0108*	0.0123*
	(0.0044)	(0.0027)	(0.0051)	(0.0044)	(0.0043)	(0.0055)	(0.0068)
	[2.0000]	[0.8700]	[1.0300]	[1.4900]	[1.9800]	[1.9500]	[1.8200]
Constant	-0.6327***	0.1763	-0.8974***	-0.7968***	-0.6463***	-0.4757*	-0.3627
	(0.1947)	(0.1197)	(0.2255)	(0.1957)	(0.1925)	(0.2465)	(0.3019)
	[-3.2500]	[1.4700]	[-3.9800]	[-4.0700]	[-3.3600]	[-1.9300]	[-1.200]
Observations	918	918	918	918	918	918	918
No. of groups	34	34	34	34	34	34	34

Note: MM-QR is implemented using the mmqreg command (with option, absorb(idcode), q(10, 25, 50, 75, 90) in Stata 16. Standard errors in (); t-statistics in []. *, ** and *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

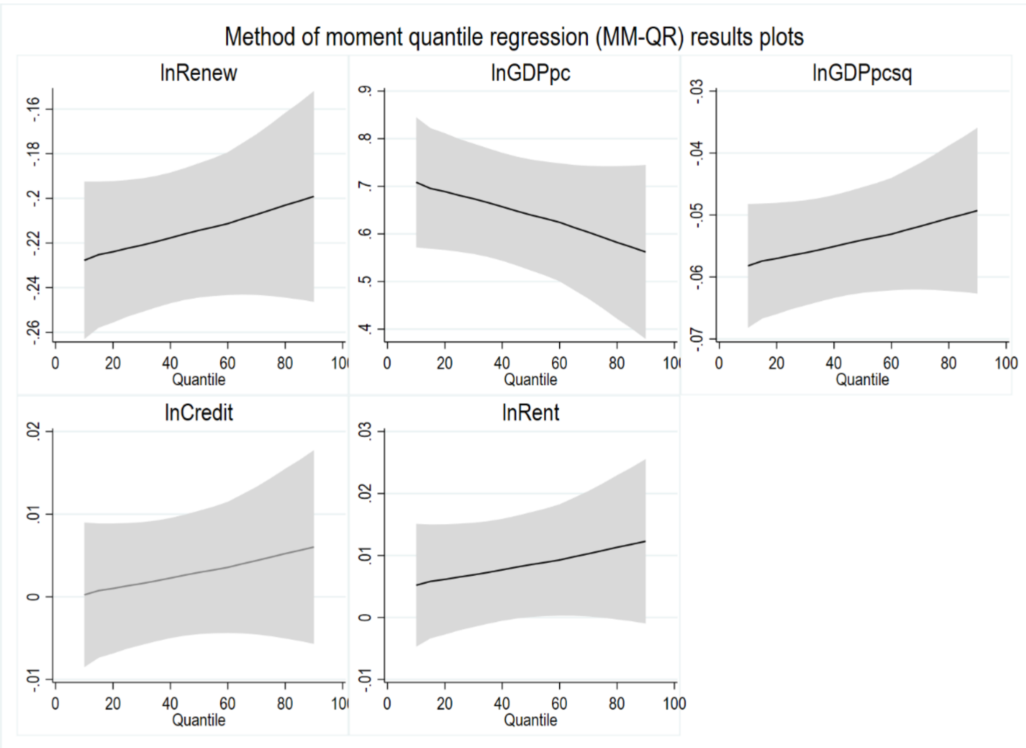

Figure 1. Quantile regression plots for estimates in Table 9
Source: Author's compilation using Stata 16.

V. Implication Of Results

Renewable energy consumption and carbon intensity in Africa

The coefficient of renewable energy consumption (ln*Renew*) is negative and statistically significant across all the quantiles. Thus, irrespective of a country's location on the quantile distribution, the use of renewable energy offers a low-to-zero-carbon path to economic growth, however, with a greater contribution to greening economic output in the lowerquantile countries. In line with SDG 7.2, African countries would need to augment policy choices with the target of increasing the amount of renewables in the energy consumption mix, especially in the more carbon-intensive economies such as South Africa, Egypt, Algeria, and Nigeria(Global Carbon Budget, 2023). This finding is consistent with a prior expectation and existing studies (Elom, Onyeneke, Ankrah, et al., 2024; Emenekwe, Onyeneke, & Nwajiuba, 2022; Emenekwe et al., 2023; Wang, Jiang, Li, Zhang, & Zhang, 2023).

Economic growth, its squared term, and carbon intensity

The coefficient estimates for ln*GDPpc* are positive and highly statistically significant across all quantiles. The squared term, ln*GDPpcsq*, has a statistically significant negative coefficient across all the quantiles. Together, the EKC's predicted inverted U-shaped curve between environmental impacts and per capita GDP is confirmed across all quantiles of ln*CI*. In other words, economic growth is predicted to increase carbon emissions in African economies in the early phases of development and will require attaining a certain level of income to bend the curve and induce a change away from a carbon-intensive growth pattern and toward a more resource-efficient and environmentally friendly growth pattern. This results is in line with recent empirical works in the that found evidence of an inverted U-shaped relation which validates the presence of the EKC hypothesis(Emenekwe, Onyeneke, et al., 2022; Iorember, Goshit, & Dabwor, 2020; Nwani, 2022). Conversely, it differs from other studies that found evidence of a contradicting result, especially a U-shaped relationship between economic growth and its squared term on environmental sustainability 22 selected African countries(Arogundade, Hassan, & Bila, 2022).

Domestic credit and carbon intensity in Africa

Although a 1 percent increase in ln*Credit*is shown to have a positive effect on ln*CI*across estimation techniques, the effects are statistically insignificant irrespective of the quantile location of a country in the distribution. These estimates differ from other studies which find a statistically significant relationship between domestic credit and carbon emissions (Emenekwe, Onyeneke, et al., 2022; Nwani, 2022; Omoke et al., 2020).

Total natural resources rent and carbon intensity in Africa

Similar to the preceding discussion, a 1 percent increase in lnRent is shown to have a positive effect on ln*CI* across estimation techniques. This indicates that the negative environmental effects of relying on natural resource extraction outweigh its economic benefits in Africa. However, the effects are statistically insignificant irrespective of the quantile location of a country in the distribution. These estimates differ from other studies which find a statistically significant relationship between natural resources rent and environmental sustainability. For instance, one study showed that natural resources mitigate environmental degradation(Shittu et al., 2021), while another showed they intensify emissions in the BRICS economies(Nathaniel, Yalçiner, & Bekun, 2021).

Policy Recommendations

Enhance Renewable Energy Policies: Given the significant impact of renewable energy consumption on reducing carbon intensity, it is recommended that African nations strengthen their policies in support of renewable energy. This includes investing in renewable energy infrastructure, providing incentives for clean energy projects, and setting more ambitious targets for renewable energy in the national energy mix.Economic Growth and Environmental Sustainability: To ensure that economic growth translates into environmental benefits, it is essential to implement policies that encourage not just growth but sustainable growth. This can involve promoting technologies that reduce the carbon intensity of production processes, enhancing energy efficiency, and investing in research and development for sustainable practices.

Further Research on Credit and Resource Rent: The findings suggest that the roles of domestic credit and natural resources rent in influencing carbon intensity are not clear-cut. Further research should explore these relationships in more detail, examining the specific mechanisms through which credit and resource rent might affect environmental outcomes. This could help in designing targeted interventions that utilize financial and natural resources in ways that support environmental sustainability.Policy Integration: Integrating environmental considerations into all areas of economic policy-making can ensure that efforts to reduce carbon intensity are embedded within broader economic planning and development strategies. This holistic approach is vital for achieving sustainable development goals.

References

[1] Adams, S., & Acheampong, A. O. (2019). Reducing Carbon Emissions: The Role Of Renewable Energy And Democracy. Journal Of Cleaner Production. Https://Doi.Org/10.1016/J.Jclepro.2019.118245

[2] Adewuyi, A. O., & Awodumi, O. B. (2017). Biomass Energy Consumption, Economic Growth And Carbon Emissions: Fresh Evidence From West Africa Using A Simultaneous Equation Model. Energy, 119, 453–471. Https://Doi.Org/10.1016/J.Energy.2016.12.059

[3] Apeaning, R. W. (2021). Technological Constraints To Energy-Related Carbon Emissions And Economic Growth Decoupling: A Retrospective And Prospective Analysis. Journal Of Cleaner Production, 291. Https://Doi.Org/10.1016/J.Jclepro.2020.125706

[4] Arogundade, S., Hassan, A. S., & Bila, S. (2022). Diaspora Income, Financial Development And Ecological Footprint In Africa. International Journal Of Sustainable Development \& World Ecology, 29, 440–454. Https://Api.Semanticscholar.Org/Corpusid:249204619

[5] Ayad, H., Lefilef, A., & Ben-Salha, O. (2023). A Revisit Of The Ekc Hypothesis In Top Polluted African Countries Via Combining The Armey Curve Into The Kuznets Curve: A Fourier Ardl Approach. Environmental Science And Pollution Research International, 30(33), 81151–81163. Https://Doi.Org/10.1007/S11356-023-27980-5

[6] Bekun, F. V., Emir, F., & Sarkodie, S. A. (2019). Another Look At The Relationship Between Energy Consumption, Carbon Dioxide Emissions, And Economic Growth In South Africa. Science Of The Total Environment. Https://Doi.Org/10.1016/J.Scitotenv.2018.11.271

[7] Bhuiyan, M. A., Zhang, Q., Khare, V., Mikhaylov, A., Pinter, G., & Huang, X. (2022). Renewable Energy Consumption And Economic Growth Nexus—A Systematic Literature Review. Frontiers In Environmental Science, 10, 1–21. Https://Doi.Org/10.3389/Fenvs.2022.878394

[8] Dietz, T., & Rosa, E. A. (1997). Effects Of Population And Affluence On Co2 Emissions. Proceedings Of The National Academy Of Sciences, 94(1), 175–179. Https://Doi.Org/10.1073/Pnas.94.1.175

[9] Driscoll, J., & Kraay, A. (1998). Consistent Covariance Matrix Estimation With Spatially Dependent Panel Data. The Review Of Economics And Statistics, 80(4), 549–560. Https://Econpapers.Repec.Org/Repec:Tpr:Restat:V:80:Y:1998:I:4:P:549-560

[10] Ehrlich, P. R., & Holdren, J. P. (1971). Impact Of Population Growth. Science, 171(3977), 1212–1217. Http://Www.Jstor.Org/Stable/1731166

[11] Elom, C. O., Onyeneke, R. U., Ankrah, D. A., Deffor, E. W., Ayerakwa, H. M., & Uwaleke, C. C. (2024). Achieving Carbon Neutrality In Africa Is Possible: The Impact Of Education, Employment, And Renewable Energy Consumption On Carbon Emissions. Carbon Research, 3(1), 24. Https://Doi.Org/10.1007/S44246-024-00102-7

[12] Emenekwe, C. C., & Emodi, N. V. (2022). Temperature And Residential Electricity Demand For Heating And Cooling In G7 Economies: A Method Of Moments Panel Quantile Regression Approach. In Climate (Vol. 10, Issue 10). Https://Doi.Org/10.3390/Cli10100142

[13] Emenekwe, C. C., Okereke, C., Nnamani, U. A., Emodi, N. V., Diemuodeke, O. E., & Anieze, E. E. (2022). Macroeconomics Of Decarbonization Strategies Of Selected Global South Countries: A Systematic Review. Frontiers In Environmental Science, 10. Https://Doi.Org/10.3389/Fenvs.2022.938017

[14] Emenekwe, C. C., Onyeneke, R. U., & Nwajiuba, C. U. (2021). Financial Development And Carbon Emissions In Sub - Saharan Africa. Environmental Science And Pollution Research, 29(13), 19624–19641. Https://Doi.Org/10.1007/S11356-021-17161-7

[15] Emenekwe, C. C., Onyeneke, R. U., & Nwajiuba, C. U. (2022). Financial Development And Carbon Emissions In Sub-Saharan Africa. Environmental Science And Pollution Research, 29(13), 19624–19641. Https://Doi.Org/10.1007/S11356-021-17161-7

[16] Emenekwe, C. C., Onyeneke, R. U., Nwajiuba, C. U., Anugwa, I. Q., & Emenekwe, O. U. (2023). Determinants Of Consumption-Based And Production-Based Carbon Emissions. Environment, Development And Sustainability. Https://Doi.Org/10.1007/S10668-023-04311-9

[17] Esso, L. J., & Keho, Y. (2016). Energy Consumption, Economic Growth And Carbon Emissions: Cointegration And Causality Evidence From Selected African Countries. Energy. Https://Doi.Org/10.1016/J.Energy.2016.08.010

[18] Fan, J., Liao, Y., & Yao, J. (2015). Power Enhancement In High-Dimensional Cross-Sectional Tests. Econometrica, 83(4), 1497–1541. Https://Doi.Org/Https://Doi.Org/10.3982/Ecta12749

[19] Frodyma, K., Papież, M., & Śmiech, S. (2022). Revisiting The Environmental Kuznets Curve In The European Union Countries. Energy, 241, 122899. Https://Doi.Org/Https://Doi.Org/10.1016/J.Energy.2021.122899

[20] Global Carbon Budget. (2023). National Fossil Carbon Emissions 2023 V1.0. Https://Globalcarbonbudget.Org/Carbonbudget2023/

[21] Grossman, G. M., & Krueger, A. B. (1995). Economic Growth And The Environment*. The Quarterly Journal Of Economics, 110(2), 353–377. Https://Doi.Org/10.2307/2118443

[22] Iea. (2021a). Net Zero By 2050: A Roadmap For The Global Energy Sector. Https://Www.Iea.Org/Reports/Net-Zero-By-2050

[23] Iea. (2021b). World Energy Outlook-2021. Sdg7 Access To Electricity And Clean Cooking Database. Https://Www.Iea.Org/Data-And-Statistics/Data-Product/Sdg-Access-To-Electricity-And-Clean-Cooking-Database

[24] Iea. (2022). Africa Energy Outlook. Paris, France: International Energy Agency. Https://Www.Iea.Org/Reports/Africa-Energy-Outlook-2022

[25] Inal, V., Addi, H. M., Çakmak, E., Torusdağ, M., Çalışkan, M., Inal, V., Addi, H. M., Çakmak, E., Torusdağ, M., & Çalışkan, M. (2022). The Nexus Between Renewable Energy, Co2 Emissions, And Economic Growth: Empirical Evidence From African Oil-Producing Countries. Energy Reports. Https://Doi.Org/10.1016/J.Egyr.2021.12.051

[26] Iorember, P. T., Goshit, G. G., & Dabwor, D. T. (2020). Testing The Nexus Between Renewable Energy Consumption And Environmental Quality In Nigeria: The Role Of Broad-Based Financial Development. African Development Review-Revue Africaine De Developpement, 32(2), 163–175. Https://Doi.Org/10.1111/1467-8268.12425

[27] Ipcc. (2018). Summary For Policymakers. In V. Masson-Delmotte, P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P. R. Shukla, A. Pirani, Moufouma-Okia, W. C. Péan, R. Pidcock, S. Connors, J. B. R. Matthews, Y. Chen, X. Zhou, M. I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, & T. Waterfield (Eds.), Global Warming Of 1.5°C: An Ipcc Special Report On The Impacts Of Global Warming Of 1.5°C Above Pre-Industrial Levels And Related Global Greenhouse Gas Emission Pathways, In The Context Of Strengthening The Global Response To The Threat Of Climate Change, (Pp. 3–24). Cambridge University Press. Https://Doi.Org/10.1017/9781009157940.001

[28] Irena. (2019). Off-Grid Renewable Energy Solutions To Expand Electricity Access: An Opportunity Not To Be Missed. International Renewable Energy Agency. Https://Www.Irena.Org/-/Media/Files/Irena/Agency/Publication/2019/Jan/Irena_Off-Grid_Re_Access_2019.Pdf?Rev=1dcdb820bde543ffa37022ef7758999e

[29] Juodis, A., & Reese, S. (2022). The Incidental Parameters Problem In Testing For Remaining Cross-Section Correlation. Journal Of Business & Economic Statistics, 40(3), 1191–1203. Https://Doi.Org/10.1080/07350015.2021.1906687

[30] Kahia, M., Jebli, M. Ben, & Belloumi, M. (2019). Analysis Of The Impact Of Renewable Energy Consumption And Economic Growth On Carbon Dioxide Emissions In 12 Mena Countries. Clean Technologies And Environmental Policy. Https://Doi.Org/10.1007/S10098-019-01676-2

[31] Kaya, Y. (1990). Impact Of Carbon Dioxide Emission Control On Gnp Growth : Interpretation Of Proposed Scenarios. Https://Api.Semanticscholar.Org/Corpusid:135282880

[32] Lallana, F., Bravo, G., Le Treut, G., Lefèvre, J., Nadal, G., & Di Sbroiavacca, N. (2021). Exploring Deep Decarbonization Pathways For Argentina. Energy Strategy Reviews, 36. Https://Doi.Org/10.1016/J.Esr.2021.100670

[33] Le Treut, G., Lefèvre, J., Lallana, F., & Bravo, G. (2021). The Multi-Level Economic Impacts Of Deep Decarbonization Strategies For The Energy System. Energy Policy, 156, 112423. Https://Doi.Org/Https://Doi.Org/10.1016/J.Enpol.2021.112423

[34] Machado, J. A. F., & Silva, J. M. C. (2019). Quantiles Via Moments. Journal Of Econometrics, 213(1), 145–173. Https://Doi.Org/Https://Doi.Org/10.1016/J.Jeconom.2019.04.009

[35] Musah, M. B., Kong, Y., Mensah, I. A., Antwi, S. K., & Donkor, M. (2020). The Link Between Carbon Emissions, Renewable Energy Consumption, And Economic Growth: A Heterogeneous Panel Evidence From West Africa. Environmental Science And Pollution Research. Https://Doi.Org/10.1007/S11356-020-08488-8

[36] Namahoro, J. P., Wu, Q., Xiao, H., & Zhou, N. (2021). The Impact Of Renewable Energy, Economic And Population Growth On Co2 Emissions In The East African Region: Evidence From Common Correlated Effect Means Group And Asymmetric Analysis. Energies. Https://Doi.Org/10.3390/En14020312

[37] Namahoro, J. P., Wu, Q., Zhou, N., & Xue, S. (2021). Impact Of Energy Intensity, Renewable Energy, And Economic Growth On Co2 Emissions: Evidence From Africa Across Regions And Income Levels. Renewable & Sustainable Energy Reviews. Https://Doi.Org/10.1016/J.Rser.2021.111233

[38] Nathaniel, S. P., Yalçiner, K., & Bekun, F. V. (2021). Assessing The Environmental Sustainability Corridor: Linking Natural Resources, Renewable Energy, Human Capital, And Ecological Footprint In Brics. Resources Policy, 70, 101924. Https://Doi.Org/Https://Doi.Org/10.1016/J.Resourpol.2020.101924

[39] Nwani, C. (2022). Financing Low-Carbon Growth In Africa: Policy Path For Strengthening The Links Between Financial Intermediation, Resource Allocation And Environmental Sustainability. Cleaner Environmental Systems, 6, 100082. Https://Doi.Org/Https://Doi.Org/10.1016/J.Cesys.2022.100082

[40] Nwani, C., Usman, O., Okere, K. I., & Bekun, F. V. (2023). Technological Pathways To Decarbonisation And The Role Of Renewable Energy: A Study Of European Countries Using Consumption-Based Metrics. Resources Policy, 83, 103738. Https://Doi.Org/Https://Doi.Org/10.1016/J.Resourpol.2023.103738

[41] Odhiambo, N. M. (2011). Economic Growth And Carbon Emissions In South Africa: An Empirical Investigation. Journal Of Applied Business Research. Https://Doi.Org/10.19030/Jabr.V28i1.6682

[42] Omoke, P. C., Nwani, C., Effiong, E. L., Evbuomwan, O. O., & Emenekwe, C. C. (2020). The Impact Of Financial Development On Carbon, Non-Carbon, And Total Ecological Footprint In Nigeria: New Evidence From Asymmetric Dynamic Analysis. Environmental Science And Pollution Research. Https://Doi.Org/10.1007/S11356-020-08382-3

[43] Onifade, S. T. (2022). Retrospecting On Resource Abundance In Leading Oil-Producing African Countries: How Valid Is The Environmental Kuznets Curve (Ekc) Hypothesis In A Sectoral Composition Framework? Environmental Science And Pollution Research International, 29(35), 52761–52774. Https://Doi.Org/10.1007/S11356-022-19575-3

[44] Ouédraogo, M., Peng, D., Chen, X., & Hashmi, S. H. (2022). Testing The Mineral Resources-Induced Environmental Kuznets Curve Hypothesis In Africa. Natural Resources Research, 31(5), 2435–2459. Https://Doi.Org/10.1007/S11053-022-10060-9

[45] Our World In Data. (2020). Kaya Identity: Drivers Of Co_2 Emissions. Https://Ourworldindata.Org/Grapher/Kaya-Identity-Co2?Country=~Owid_Wrl

[46] Pesaran, M. H. (2004). General Diagnostic Tests For Cross Section Dependence In Panels. University Of Cambridge, Faculty Of Economics, Cambridge Working Papers In Economics No. 0435.

[47] Pesaran, M. H. (2007). A Simple Panel Unit Root Test In The Presence Of Cross-Section Dependence. Journal Of Applied Econometrics, 22(2), 265–312. Https://Doi.Org/10.1002/Jae.951

[48] Pesaran, M. H. (2015). Testing Weak Cross-Sectional Dependence In Large Panels. Econometric Reviews, 34(6–10), 1089–1117. Https://Doi.Org/10.1080/07474938.2014.956623

[49] Pesaran, M. H., & Xie, Y. (2023). A Bias-Corrected Cd Test For Error Cross-Sectional Dependence In Panel Data Models With Latent Factors.

[50] Shittu, W., Adedoyin, F. F., Shah, M. I., & Musibau, H. O. (2021). An Investigation Of The Nexus Between Natural Resources, Environmental Performance, Energy Security And Environmental Degradation: Evidence From Asia. Resources Policy, 73, 102227. Https://Doi.Org/Https://Doi.Org/10.1016/J.Resourpol.2021.102227

[51] Soeder, D. J. (2021). Fossil Fuels And Climate Change Bt - Fracking And The Environment: A Scientific Assessment Of The Environmental Risks From Hydraulic Fracturing And Fossil Fuels (D. J. Soeder (Ed.); Pp. 155–185). Springer International Publishing. Https://Doi.Org/10.1007/978-3-030-59121-2_9

[52] Strauss, B. H., Orton, P. M., Bittermann, K., Buchanan, M. K., Gilford, D. M., Kopp, R. E., Kulp, S., Massey, C., Moel, H. De, & Vinogradov, S. (2021). Economic Damages From Hurricane Sandy Attributable To Sea Level Rise Caused By Anthropogenic Climate Change. Nature Communications, 12(1), 2720. Https://Doi.Org/10.1038/S41467-021-22838-1

[53] Waggoner, P. E., & Ausubel, J. H. (2002). A Framework For Sustainability Science: A Renovated Ipat Identity. Proceedings Of The National Academy Of Sciences, 99(12), 7860–7865. Https://Doi.Org/10.1073/Pnas.122235999

[54] Wang, J., Jiang, C., Li, M., Zhang, S., & Zhang, X. (2023). Renewable Energy, Agriculture, And Carbon Dioxide Emissions Nexus: Implications For Sustainable Development In Sub-Saharan African Countries. Sustainable Environment Research, 33(1), 31. Https://Doi.Org/10.1186/S42834-023-00193-8

[55] Westerlund, J. (2007). Testing For Error Correction In Panel Data*. Oxford Bulletin Of Economics And Statistics, 69(6), 709–748. Https://Doi.Org/Https://Doi.Org/10.1111/J.1468-0084.2007.00477.X

[56] World Bank, Iea, Irena, Unsd, I. (2021). Tracking Sdg 7: The Energy Progress Report. World Bank.

[57] York, R., Rosa, E. A., & Dietz, T. (2003). Stirpat, Ipat And Impact: Analytic Tools For Unpacking The Driving Forces Of Environmental Impacts. Ecological Economics, 46(3), 351–365. Https://Doi.Org/Https://Doi.Org/10.1016/S0921-8009(03)00188-5