Energy 260 (2022) 124951

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Discerning the role of renewable energy and energy efficiency in finding the path to cleaner consumption and production patterns: New insights from developing economies

Muhammad Shahbaz [a], Chinazaekpere Nwani [b], Festus Victor Bekun [c,d,*], Bright Akwasi Gyamfi [e], Divine Q. Agozie [f]

[a] Department of International Trade and Finance, School of Management and Economics, Beijing Institute of Technology, Beijing, China
[b] Department of Economics and Development Studies, Alex Ekwueme Federal University, Ndufu-Alike, Ebonyi State, Nigeria
[c] Faculty of Economics Administrative and Social Sciences, Department of International Logistics and Transportation, Istanbul Gelisim University, Istanbul, Turkey
[d] Adnan Kassar School of Business, Department of Economics, Lebanese American University, Beirut, Lebanon
[e] Economic and Finance Application and Research Center, İStanbul Ticaret University, Turkey
[f] University of Ghana, Business School, Dept. of Operations and Management Information Systems, Ghana

ARTICLE INFO

Keywords:
Energy efficiency
Renewable energy
Production and consumption-based CO_2 emissions
Developing economies

ABSTRACT

This study provides empirical evidence on the relationship between energy efficiency and production- and-consumption based carbon emissions by assessing the impact of population size, income, and clean energy on the carbon dioxide (CO_2) emissions function. Method of Moments Quantile Regression (MM-QR) and Augmented Mean Group (AMG) estimators are applied to observe long-term associations between the variables, and Dumitrescu-Hurlin (DH) Ganger causality test is used to identify the direction of causality. Findings reveal that, across all specifications, energy intensity and population size have positive (increasing) impact on both estimates of CO_2 emissions while renewable energy use has a negatively significant impact and stronger on consumption-based estimates. The presence of an inverted U-shaped curve in the relationship between per capita income and CO_2 emissions, as predicted by the Environment Kuznets curve (EKC) hypothesis, only exists when CO_2 emissions are calculated based on production pattern. Further empirical analysis based on DH causality tests show a bidirectional causality between energy intensity and production-based CO_2 emissions, population size and consumption-based CO_2 emissions, per capita income and consumption-based CO_2 emissions, and energy intensity and renewable energy use. In addition, a unidirectional causality runs from per capita income to production-based CO_2 emissions, and from energy intensity and renewable energy use to consumption-based CO_2 emissions. This analysis outlines a paradigm for the formulation of a green development strategy in developing economies via energy and environmental resources.

1. Introduction

Ongoing global developments consistently highlight the need for cleaner and sustainable production and consumption patterns if the atmospheric warmings and potential ecological, physical and health implications are to be mitigated [1]. In addition, many strategic policies have been under consideration at different levels and among national and international bodies, which advocate for an increased dependence on clean energy sources. For example the United Nations (UN), has extensively pushed for the achievement of its sustainable development goals (like SDG 7) which underscores the need for an increased use of clean energy across the globe. Through an SDG 7 target of increasing clean energy utilization (SDG Target 7.2) and doubling energy efficiency rates among countries (SDG Target 7.3), the big question is whether these policy targets impact the attainment of climate change mitigation goals (SDG 13). Experts highlight energy efficiency and renewable energy as crucial factors that can facilitate the achievement of climate [2] change mitigation targets [1]. For instance, employing efficient technologies and mechanisms that boost energy-saving options (e.g. gas

* Corresponding author. Faculty of Economics Administrative and Social sciences, Department of International Logistics and Transportation, Istanbul Gelisim University, Istanbul, Turkey.

E-mail addresses: muhdshahbaz77@gmail.com (M. Shahbaz), nwani.chinazaekpere@funai.edu.ng (C. Nwani), fbekun@gelisim.edu.tr (F.V. Bekun), bagyamfi@ticaret.edu.tr (B.A. Gyamfi), dagozie@ug.edu.gh (D.Q. Agozie).

https://doi.org/10.1016/j.energy.2022.124951
Received 13 November 2021; Received in revised form 20 April 2022; Accepted 24 July 2022
Available online 13 August 2022

List of nomenclature/abbreviations

EKC	Environmental Kuznets curve
SDG	Sustainable Development Goals
MM-QR	Method of Moments Quantile Regression
DH	Dumitrescu-Hurlin
AMG	Augmented Mean Group
CO_2	carbon dioxide emissions
UN	United Nations
STIRPAT	Stochastic Impacts by assessing the Relationship between Population, Affluence, Technological innovation
CD	Cross-section dependence
CADF	Cross-sectionally Augmented Dickey-Fuller unit root test
ECM	Error correction model
P	Population (in Millions)
REn	Renewable energy
EnI	Energy intensity
PrdCE	Production-based CO_2 emissions
ConCE	Consumption-based (trade adjusted) CO_2 emissions
PCI	Affluence measured
GDP	Economic growth

boilers, electric bicycles) can reduce per unit energy demand of economic output to alleviate the global pressure on energy consumption [3]. Energy sources considered clean include wind, geothermal, and solar energy, among others, offer another path toward the reduction in the dependence of economic activities on fossil fuels [4].

In line with the set objectives of SDG 7 (Increasing the proportion of renewable or clean energy production globally) and 13 (doubling the improvement rates of energy efficiency among countries), this study examines the energy intensity, renewable energy, and CO_2 emissions nexus. It focuses on environmental conditions in developing countries, particularly, in Africa, Asia, the Latin America, and the Caribbean. This study, by this step, extends the literature on the phenomenon at hand from two perspectives. First, the strand of studies that have examined the relationship [5] between energy intensity and carbon pollution [6], and the others that have considered the renewable energy utilization [7] and CO_2 emission [8] nexus [5]. The gap [9]left by these two groups of studies is whether increasing the share of renewable energy in the energy mix could have significant reduction effect on the intensity of energy use (i.e. improves energy efficiency). Thus, this study extends extant literature through an empirical examination of the role of clean or renewable energy consumption in reducing energy intensity through the lens of selected developing economies. Taking this additional step is necessary, considering that recent developments in the renewable energy sector show that most forms of renewable energy also offer efficiency gains [11].

This study shows novelty in three aspects. Foremost, it extends to the current scheme of literature on the relationship between renewable energy, energy efficiency and environment, and its causal association. This study, by analyzing the heterogeneous effects of renewable energy, energy efficiency on environment, particularly for developing economies presents new insights on a nascently explored issue. Thus, the study extends the global debate on energy efficiency and its impact on environment for developing countries. This topic has important policy significance for the growth, sustainability, and efficiency in emerging economies. Further, this study explores, beyond economic contribution, the contribution of energy efficiency to climate recovery (sustainability). Moreover, empirical discussions in the literature have largely shown interest on modeling CO_2 emissions related to domestic production activities (i.e. emissions embodied in territorial production activities). A key limitation of a production-based measure of CO_2 emission is that it fails to account for the growing environmental impact of international trade and its diverse effects on consumption patterns and lifestyles, particularly in developing economies [12]. Most developed countries pay attention to services and knowledge-based sectors that possess lower carbon potential and, as such, have de-materialized their production processes, improved transportation systems, and substituted travel time to achieve greater energy efficiency [13]. Hence, economic engagements differ significantly in developed and developing economies. Dirty industries have shifted production activities abroad, boosting extractive activities (e.g. mining, construction, oil, and gas) and low-technologically driven production processes that mostly occur in developing economies [13]. Thus, this present study takes these varying conditions into account. Recent literature concludes that attributing CO_2 emissions from productive activities in developing countries places a strong limitation on environmental policy choices as CO_2 generation is highly embedded in these production activities and is worsened by their final consumers [12]. Therefore, this study focuses on developing economies, which have received little attention on this issue in policy and from an existing literature point of view, shedding more insights and evidence from a consumption-based perspective for policy formulation on the total lifecycle of emissions [15]. Further, looking at the estimations of the Global Carbon Project (GCP), it is revealed that many developing economies generate more CO_2 emissions in their consumption than production (i.e. net importers of CO_2 emissions) [16]. According to the most recent GCP data, more than 80% of African and South American countries are net importers of CO_2 emissions. In addition, this study shies from traditional econometric models and adopts the Moments Quantile Regression (MM-QR) and the Augmented Mean Group (AMG) estimators to evaluate the relationships between endogenous and exogenous variables in the long run. It also employs the Dumitrescu-Hurlin Ganger causality approach to examine causality between the variables. These second-generation estimators are superior to conventional first-generation estimation techniques. For instance, the MM-QR and second-generation panel regression techniques are the most effective for reducing heterogeneity and cross-sectional issues.

The rest of this paper is organized as follows: Section-II, reviews existing literature. Then a detailed explication of the methodological procedure is shown in Section-III. Section-IV presents the empirical analysis, results, and discussion. Section-V presents conclusions with policy implications.

1.1. Literature review

The perceived impact of efficient production and [17] clean energy [9] utilization has [18] received [19] considerable attention from Ref. [7] scholars and [20]experts from various [5] domains in the literature [10]. Largely, several extant works support the notion that energy intensity contributes to the growth of carbon emissions. For example, using data from 53 middle-income economies over the period 1991–2013, Lin et al. [21] revealed that energy intensity increases CO_2 emissions. Ghazali and Ali [22] drew a similar conclusion that energy intensity increased carbon emissions, using a panel of 10 newly industrialized economies. However, Irfan et al. [6] identified a different long-run condition among South Asian economies over a decade for the period of 1990–2014 using the reciprocal of energy intensity to define efficiency in energy use in south Asia. Their study revealed a significant negative long-run impact on energy intensity and carbon emissions in the region. Subsequently, production of clean or renewable energy is highlighted as a path to reducing CO_2 emissions. For example, Nguyen and Kakinaka [7], and Ulucak et al. [10] among others, studied the relationship between renewable energy utilization and CO_2 emissions from different countries over different periods. They employed a panel of 107 countries over the period 1990–2013, Inglesi-Lotz and Dogan [8] employed data from 10 African states for the period 1980–2011, Hanif et al. [9] used 25 developing Asian economies for the period of

1990–2015 while others like Ulucak et al. [10] examined all OECD member states for the period of 1980–2016. The results from Nguyen and Kakinaka [7] revealed renewable or clean energy utilization facilitates CO_2 emissions among low-income countries while it reduces CO_2 emissions in middle-income and high-income countries. Ulucak et al. [10] confirmed the existence of EKC and adverse environmental effects of non-renewable energy utilization. However, this result is contrary to evidence found among OECD states, where renewable energy use had no significant mitigation effect on CO_2 emission. Further, Hanif et al. [9] and Irfan et al. [6] found increasing renewable energy sources in the consumption mix significantly reduces CO_2 emissions among selected sub-Saharan African states and Asian and South Asian states respectively.

Further empirical discussion from some recent studies focusses on the heterogeneous effect of efficient energy production and clean energy indicators on CO_2 emissions across diverse economies. By seeking to extend the EKC framework, Akram et al. [5] investigated the heterogeneous effect of clean energy utilization on carbon emissions in 66 developing economies over the period of 1990–2014. Analysis from this study validated the inverted U-shaped relationship as predicted by the EKC hypothesis but reveals a stronger prediction at the upper quantiles. In addition, the estimates revealed that energy efficiency and renewable or clean energy have reduction effects on carbon emissions on all quantiles, with the mitigation effect of improving energy efficiency being stronger at upper quantiles while renewable energy provides stronger mitigation effect in countries at lower quantiles. Xu and Lin [2] employed the data from 30 Chinese provinces and showed that energy efficiency has stronger mitigation effect at the lower quantile provinces of CO_2 emission scale. For the transport sector in China, Haung et al. [60] observed that energy intensity contributes to growth of emissions with greater impact observed at upper quantiles. Further, Anwar et al. [23] observed how clean and unclean (non-renewable) energy generation affects the environment among ASEAN countries between 1990 and 2018. This examination also validated the EKC hypothesis. In that, non-renewable energy utilization contributes to CO_2 emissions in all the countries while clean (renewable) energy showed a mitigation effect only in countries within the lower quantiles of CO_2 emission scale.

In view of the above discussion, there are still gasps in the existing literature. Existing studies have largely studied CO_2 emissions related to fossil fuels in domestic production, while neglecting the perspective of the increasing impact of trade-induced consumption patterns on environment among less developed states. Further, policy considerations on the potential contribution of energy intensity and renewable energy use are limited. Therefore, to contribute to these deficiencies in the literature, this examination applies a non-aggregated CO_2 emissions data to cater for the varying effects of production and usage trends among developing states.

2. Methodology

2.1. Analytical framework and model specification

The STIRPAT (Stochastic Impacts by Assessing the Relationship between Population, Affluence, Technological Innovation) forms the analytical basis for modelling the impacts of human-environment related activities [24] is defined for a panel data using the following mathematical equation:

$$lnI_{it} = a_0 + \alpha_1 lnP_{i,t} + \alpha_2 lnA_{i,t} + \alpha_3 lnT + \varepsilon_{it} \tag{1}$$

The parameters I P and A, represent environment, population size and affluence respectively while T is

a measure of technological progress. "*ln*" indicates the logarithmic presentation of the variables, i represents the cross-sectional country index and t indicates time index for the period covered, a_0 is constant of equation-1, a_i (with $i = 1\ldots3$) are coefficients to be estimated, and ε is error term. I is defined as carbon emissions (CE), affluence (A) is measured using per capita income (PCI) while technological progress (T) is explained by cleaner energy transition indicators. Specifically, this study examines the effectiveness of SDG target 7.2 (Increasing the proportion of renewable or clean energy production globally) and SDG target 7.3 (Doubling the improvement rates of energy efficiency among countries) in mitigating carbon related environmental sustainability challenges in developing economies. The extended STIRPAT equation-1 can be written as follows:

$$lnCE_{it} = a_0 + \alpha_1 lnP_{i,t} + \alpha_2 lnPCI_{i,t} + \alpha_3 lnEnI_{i,t} + \alpha_4 lnREn_{i,t} + \varepsilon_{it} \tag{2}$$

In equation-2, EnI is for SDG indicator 7.3.1 (energy intensity measured in terms of primary energy and GDP) while REn is for SDG indicator 7.2.1 (renewable energy share in total final energy consumption). This study considers carbon emissions (CE) from two perspectives: production-based emissions (PrdCE) and consumption-based emissions (ConCE). The following model specifications are derived for empirical investigation:

$$lnPrdCE_{it} = a_0 + \alpha_1 lnP_{i,t} + \alpha_2 lnPCI_{i,t} + \alpha_3 lnEnI_{i,t} + \alpha_4 lnREn_{i,t} + \varepsilon_{it} \tag{3}$$

$$lnConCE_{it} = a_0 + \alpha_1 lnP_{i,t} + \alpha_2 lnPCI_{i,t} + \alpha_3 lnEnI_{i,t} + \alpha_4 lnREn_{i,t} + \varepsilon_{it} \tag{4}$$

Next, equation-3 and 4 are augmented with the square of per capita income (PCI) to account for the assumptions of Environmental Kuznets Curve (EKC) hypothesis. The EKC framework predicts an inverted U-shaped relationship between CO_2 emissions and per capita income, suggesting that economic activities are more carbon intensive at the early stage of growth but reverses after certain level of income is achieved [25]. The following STIRPAT augmented EKC model specifications are therefore derived for additional empirical investigation:

$$lnPrdCE_{it} = a_0 + \alpha_1 lnP_{i,t} + \alpha_2 lnPCI_{i,t} + \alpha_3 lnPCI^2_{i,t} + \alpha_4 lnEnI_{i,t} + \alpha_5 lnREn_{i,t} + \varepsilon_{it} \tag{5}$$

$$lnConCE_{it} = a_0 + \alpha_1 lnP_{i,t} + \alpha_2 lnPCI_{i,t} + \alpha_3 lnPCI^2_{i,t} + \alpha_4 lnEnI_{i,t} + \alpha_5 lnREn_{i,t} + \varepsilon_{it} \tag{6}$$

where PCI^2 is the square of per capital income. Depending on the value of α_2, the coefficient of PCI and the value of α_3, the coefficient of square (PCI^2), equation-4 and 5 can produce different functional relationships. The EKC is only one of these possible functional outcomes, which exists when the value of α_2 is positive ($\alpha_2 > 0$) and the value of α_3 is negative ($\alpha_3 < 0$). Further empirical steps are considered to determine whether renewable energy can be used to reduce the intensity of energy use in developing economies. The model is specified in equation-7:

$$lnEnI_{it} = a_0 + \alpha_1 lnCE_{i,t} + \alpha_2 lnP_{i,t} + \alpha_3 lnA_{i,t} + \alpha_4 lnREn_{i,t} + \varepsilon_{it} \tag{7}$$

2.2. Data

The data on the consumption-production-based carbon emissions data was accessed from the Global Carbon Budget report (see Table 1). The World Bank data on world development indicators was used to collect data per capita GDP, population size (both indicators of affluence) (CD-ROM, 2021) while the data on energy intensity and renewable energy consumption from the WDI repository and the SDG Indicators repository. This study focuses on developing economies in Africa, Asia and Latin America and the Caribbean. Only countries with available data for all the identified variables over the period of 1995–2019 are included in the panel. Based on the condition of data availability, a balanced panel consisting of forty (40) countries is constructed. The countries are listed in Appendix-A.

3. Definition of variables and source of data

ConCE is for Consumption-based (trade adjusted) CO_2 emissions (in million tonnes); **PrdCE** is for Production-based CO_2 emissions (in (million tonnes). Data on ConCE and PrdCE are from the Global Carbon Budget [16] available at https://doi.org/10.5194/essd-11-1783-2019; **P** is for population (in Millions), Total, Data collected from the World Development Indicators (WDI), World Bank; **PCI** is for affluence measured using GDP per capita (Constant 2010 US$) data collected from WDI of World Bank; **EnI** is for Energy intensity level of primary energy (megajoules per constant 2011 purchasing power parity GDP); **REn** is for Renewable energy consumption (% of total final energy consumption). Data on **EnI** and **REn** are from two sources; 1995–2015 from WDI, World Bank (available at https://databank.worldbank.org/source/world-development-indicators#advancedDownloadOptions) while estimates for 2016 and 2017 are from the SDG Indicators Global Database, United Nations available online at: https://unstats.un.org/sdgs/indicators/database/.

Basic descriptive statistics on the variables are summarised in Table-2. The mean CO_2 emissions based on estimates of domestic territorial production activities (PrdCE) approximates to 108.89 million tonnes (Mt), but individually, estimates vary between 0.79 mt and 2259.68 mt. Comparatively, the mean as well as the maximum estimates are higher when CO_2 emissions are calculated based on trade-induced consumption demands, specifically at 112.86 mt and 2456.95 mt, respectively. This suggests, against existing empirical evidence that consumption-based CO_2 emissions could offer more reliable implications for understanding the environmental impacts of these developing economies. As highlighted in Figure- 1, there are also vast differences in the intensity of energy use and the size of renewable energy in the energy mix among the countries, with countries like Saudi Arabia, South Africa, Jordan, and Malaysia deriving less that 20% of their energy mix from renewable energy sources while for few others like Zambia, Tanzania and Burkina Faso, renewable energy sources constitute a major proportion of the energy mix. Jarque-Bera test, based on the Skewness and Kurtosis of the distribution, rejects the null hypothesis of normality in the series of all the variables. Also, Fig.1 indicates a non-symmetric distribution for PrdCE and ConCE. Clearly, the distribution of the variables varies significantly from their mean values.

Table-1
Summary of studies on the role of renewable energy and energy efficiency.

Author	Variable	Findings
[50]	Renewable energy, energy intensity improvements, total final consumption, CO_2 emission, energy efficiency,	Renewable energy and energy efficiency, combined with electrification of end-uses reduces CO_2 emissions
[51]	Consumption, income, renewable energy, total factor productivity, trade	Non-rejection of EKC hypothesis emphasized the impact of renewable energy.
[52]	EKC Hypothesis, Institutional quality, CO_2 emissions, energy consumption, economic growth	The EKC hypothesis is valid in South Africa, renewable energy decreases CO_2 emissions
[53]	Institutional quality, green innovation, and energy efficiency	Significant positive influence of both green innovation and institutional quality on energy efficiency
[54]	Human capital trade renewable energy Investment innovative activity	Renewable energy promotes innovation through investment, trade, and human capital. Cleaner energy and energy efficiency has a significant impact on innovation.
[55]	Carbon dioxide emissions, GDP per capita, renewable energy	Renewable energy reduces carbon dioxide emissions.
[56]	Renewable energy, CO_2, foreign direct investment, urbanization, ICT use, GDP	An inverted U-shape relationship between economic growth and environmental degradation
[57]	Renewable energy, real income, CO_2	Renewable energy mitigates emissions; however, the interaction effect stays positive
[58]	Renewable energy, coal rent, CO_2, Economic development, energy utilization	Renewable energy, has a negative and significant impact on CO_2 emissions
[59]	Biomass energy, FDI, trade flow, economic growth	Renewable energy usage in the long run reduces pollution and negatively correlates with CO_2 emissions level

3.1. Estimation techniques

3.1.1. Preliminary tests

The required preliminary tests include: (i) cross-section dependence (CD) test, (ii) unit root tests (iii) and a slope heterogeneity test. Specifically, as a robust assessment measure for both large and small cross-sectional dimensions, this study conducts the Pesaran test [26]. Then the Cross-sectional Augmented IPS test of Pesaran [27] and Cross-sectionally Augmented Dickey-Fuller (CADF) test developed by Pesaran [23] are employed for a panel unit root analysis. Finally, to check for slope heterogeneity in the panel data, this study employs the Pesaran and Yamagata test [29].

3.2. Cointegration test

For the purposes of assessing cointegration, after establishing the integration order, this analysis applies the Westerlund cointegration procedure [30] The [31] Westerlund (2005, 2007) cointegration procedure is underpinned by the assumption that constructs or factors exist in a first order of integration, thus it is based on the error correction mechanism assumption. Thus, the expression used for the rectification of errors in this panel study is expressed in equation-2:

$$\triangle Y_{it} = \pi_i d_i + \theta_i \left(Y_{it-1} + \gamma_i^* X_{it-1}\right) + \sum_{j=1}^{m} \theta_{ij} \triangle Y_{it-j} + \sum_{j=0}^{m} \delta_{ij} \triangle X_{it-j} + \varepsilon_{it} \tag{8}$$

From equation-8, the expression $\pi_i^* = (\pi_{1i}, \pi_{2i})^*$, depicts the parameter vector, while $d_t = (1-t)^*$, and θ_i represent the deterministic mechanisms, and the respective error correction parameter. To identify the existence of cointegration [30],a Least Square based estimator, Westerlund [31]) test procedure and their respective significance of the adjustment term θ_i of ECM is employed. In the mathematical model in equation-8, these statistics are grouped into the group and panel statistics. Thus, Gτ depicts the mean statistics of the group, whereas Gα expresses the derivations from the expressions in equation-3 and 4:

$$G\tau = \frac{1}{N} \sum_{i=1}^{N} \frac{\hat{\propto} i}{SE(\hat{\propto} i)} \tag{9}$$

$$G\alpha = \frac{1}{N} \sum_{i=1}^{N} \frac{T \hat{\propto} i}{\hat{\propto} i(1)} \tag{10}$$

where, $\hat{\propto} i$ is denoted by $SE(\hat{}\propto i)$ as standard error. The semiparametric kernel technique of $\propto i(1)$ is $\hat{\propto} i(1)$.

$$P\tau = \frac{\hat{\propto} i}{SE(\propto i)} \tag{11}$$

$$P\alpha = T\hat{\alpha} \tag{12}$$

Equation-5 and 6 show other two panel estimation procedure used in this study to show evidence of cointegration in the study's entire panel. It is noteworthy that, the procedures delineated in this study possess substantial use by extant [32] works in the literature [33].

3.2.1. Parameter estimation using Augmented Mean Group (AMG) estimator

From the ensuing discussion, this study applies a robust estimation procedure that helps to account for cross-sectional dependency in series data. Specifically, the Augmented Mean Group (AMG) heterogenous panel estimator of Eberhardt and Bond; and Eberhardt and Teal [34]. This [35] procedure is modelled in the mathematical function in

Table-2
Definition of variables, source of data and descriptive statistics.

Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability	Observations
ConCE	112.86	15.58	2456.95	0.62	266.53	5.05	34.95	43036.28	0.00	920
PrdCE	108.89	20.24	2259.68	0.79	246.61	4.98	33.94	40492.08	0.00	920
P	69.58	20.49	1338.66	1.47	183.08	5.47	33.65	40610.75	0.00	920
PCI	3480.95	2097.92	21399.10	215.17	3752.78	2.28	9.44	2390.38	0.00	920
EnI	6.39	5.15	44.71	2.12	4.39	3.03	16.98	8898.94	0.00	920
REn	45.04	38.96	94.27	0.01	29.37	0.20	1.63	77.91	0.00	920

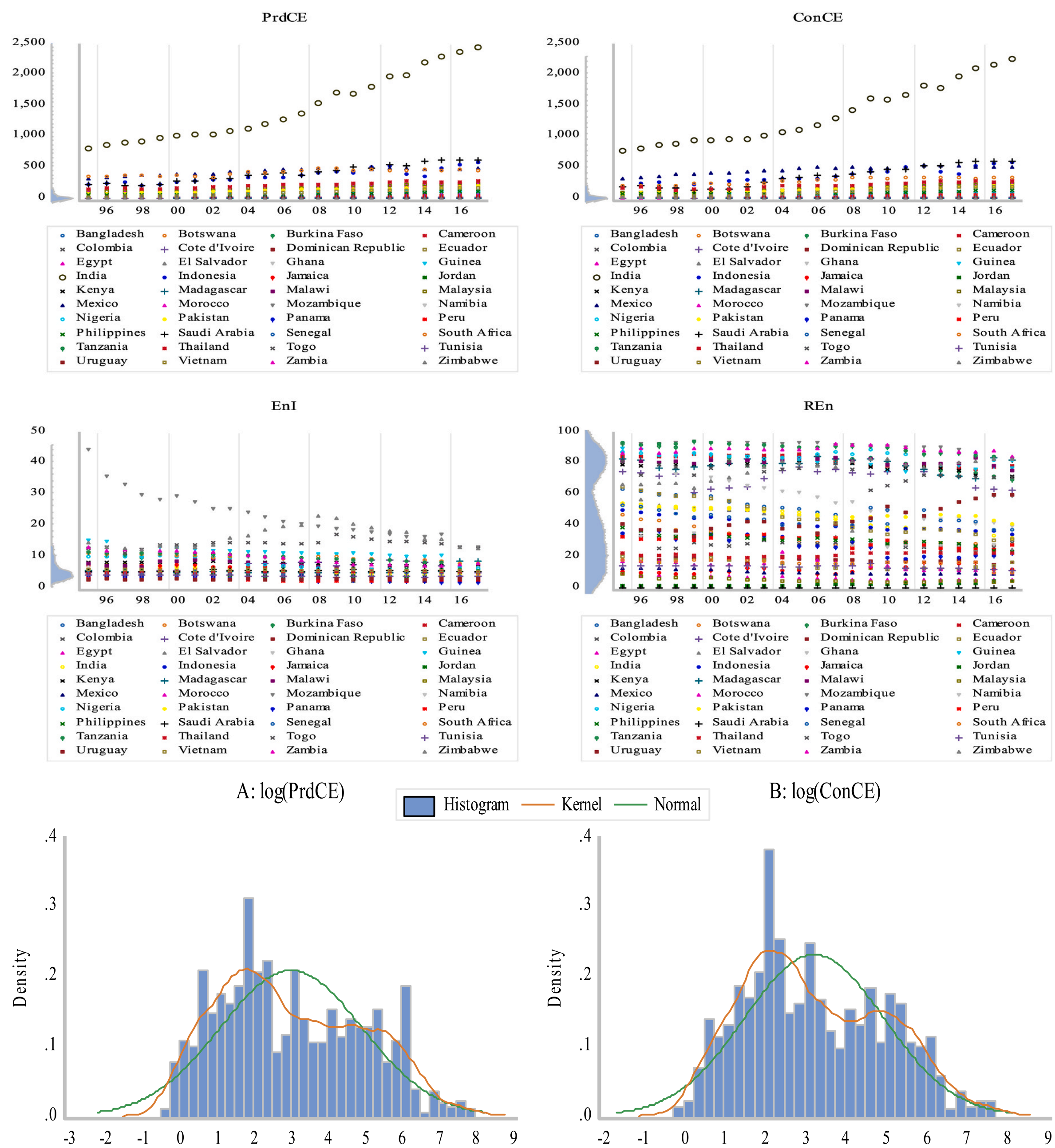

Figure-1. a Distributional Plots of Key Variables. **b. Distributional –Kernel and Normality Plots of CO_2 Emissions.**

equation-13:

$$\Delta Y_{it} = \alpha_i + \beta_i \Delta X_{it} + \sum_{t=1}^{T} \pi_t D_t + \varphi_i UCF_t + \mu_{it} \tag{13}$$

The OLS estimator of the differenced equation-13 is used to produce AMG estimator shown in equation-14. φ_i represents the estimated gradient parameters of X_{it} variable in equation-13.

$$\text{AMG} = \frac{1}{N} \sum_{i=1}^{N} \varphi_i \tag{14}$$

3.2.2. Distributional heterogeneity analysis using method of Moments Quantile Regression (MM-QR) approach

The MM-QR is implemented to investigate the sectoral and heterogeneous influence throughout quantiles [36]. The Quantile regressions provide more reliable predictions compared with simple regressions. Particularly, when the relationship between two parameters seems unlikely or non-existent [37]. To further improve the model estimations, this study employed the MM-QR with a static impact in line with Machado and Silva [38]. A quantile regression is not sensitive to Ref. [39] potential unseen heterogeneity [40]. The MM-QR approach permits detection of partial heterogeneous covariance effects in a parsimonious fashion. This approach is effective in conditions that have several consequences of human actions and endogenous response variable MM-QR method is also simple to use because it provides non-crossing predictions of the regression quantiles. For estimating the contingent quantiles Q_Y (τ/X), the estimate is given by:

$$Y_{it} = \alpha_i + X_{it}'\beta + (\delta_i + Z_{it}'\gamma)\, U_{it} \tag{15}$$

and the probability, P $\{\delta_i + Z_{it}'\gamma > 0\} = 1$. $(\alpha, \beta, \delta, \gamma')'$ are factors for the analysis. (α_i, δ_i), i = 1 … …, n, shows the individuals I fixed impact and Z is the k-vector of recognised factor of X which are differentiable alterations with component l given by:

$$Z_l = Z_l\,(X),\ l = 1 \ldots k \tag{16}$$

where, *Xit* id the proxy of any fixed *i* is independent across time (t). *Uit* is a proxy distributed across individuals (i) and across time (t) which are normalized to satisfy the moment situation but does not imply limit as show in equation-15 show as:

$$Q_Y\,(\tau/\mathbf{X_{it}}) = (\alpha_i + \delta_i q(\tau)) + X_{it}'\beta + Z_{it}'\gamma q(\tau) \tag{17}$$

From equation-17, X_{it} represents vector of explanatory factors which are per capital income (P) and its square (PCI), energy intensity (EnI) as well as renewable energy share (Ren). Q_Y (τ/X_{it}) represents the dependent variables in this analysis which are, production-based CO_2 emissions (PrdCE) and consumption-based CO_2 emissions (ConCE).

3.2.3. Panel causality test

This analysis tests the causal relationship and the respective direction among the variables using the Dumitrescu-Hurlin [41] modified Granger [42] non-causality test which accommodates heterogeneity and CD in panel data. The Granger causality test is based on the following equation:

$$Y_{it} = \delta_i + \sum_{k=1}^{p} \beta_{1ik} Y_{i,t-k} + \sum_{k=1}^{p} \beta_{2ik} X_{i,t-k} + \varepsilon_{it} \tag{18}$$

From equation-18, β_{2ik} and β_{1ik} denote the regression coefficients and autoregressive parameters for individual panel variable *i* at time *t* respectively. Following the assumption of a balance panel of observation for the variable Y_{it} and X_{it}, the null hypothesis of non-existent causality among the variables was assessed or compared with the alternate hypothesis of heterogenous causality in the panel investigation.

Based on the above steps, the analytical framework in Fig. 2 is constructed to guide empirical analysis.

3.3. Empirical results

The cross-sectional dependence (CD) test proposed by Pesaran [26] is employed to assess the possible dependence among the variables across 40 developing economies. The empirical results in Table- 2 reject

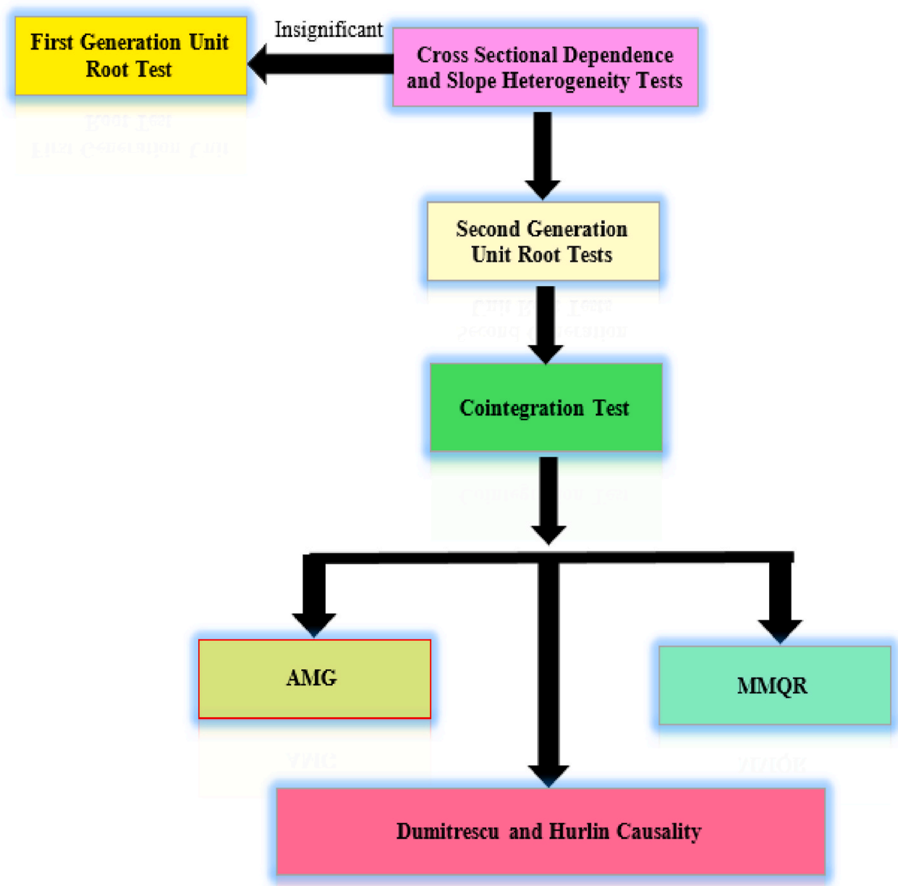

Figure-2. Flow of analysis.

the null hypothesis. Thus, no cross-sectional dependence among the selected variables at 1% significance level. Therefore, each variable contains cross-sectional dependence, indicating that shocks in one country spread to other countries in panel. Next, the analysis employs 2nd-generation panel unit root tests to examine the stationarity properties of the variables. These tests include: CIPS and CADF. The empirical results show the presence of unit root in the variables at level form but at first difference, reject the null hypothesis of unit root for all the variables (see Table- 3). Table- 4 presents observations from the Pesaran and Yamagata [29] test for slope heterogeneity. The test results herein suggest a rejection of the null hypothesis of slope homogeneity in all model specifications. Thus, there is a slope heterogeneity concern in panel data.

A stationary test at first difference is conducted for all the variables to test for the presence of a long run relationship between the variables. Then the Westerlund [30] cointegration test is performed to evaluate the existence of cross-sectional dependence. In addition, as an extension to the analysis procedure, a second-generation error-correction technique, based on the cointegration is also performed. Results from the two tests are presented in Table- 5. Westerlund [30] test results show that all panels are cointegrated. Further, p-values for test statistics from the Westerlund [31] error-correction based cointegration test show that the null hypothesis is rejected for the *Gt* test statistic, providing evidence that cointegration exists in at least one of cross-sectional units (i.e. in at least one group). Of more importance is the rejection or otherwise of the null hypothesis for the panel test statistics. Observing the results for *Pt* test statistic shows that the null hypothesis of no cointegration is rejected in all the model specifications, providing evidence that cointegration exists among the variables for the whole panel. The analysis further uses the Augmented Mean Group estimation, which caters for the existence of cross-sectional dependence and heterogeneity in the panel data to estimate the parameters of the model specifications. The derived estimates are therefore highly robust, unbiased, and efficient for various combinations of cross-section and time dimensions even when considered with non-stationary data and in the absence of cointegration [35]. To account for distributional heterogeneity in the panel, the MM-qreg technique is employed, defining three sections of quantiles: the lower quantile (qtile_25th); the median quantile (qtile_50th) and the upper quantile (qtile_75th).

The empirical results from the modelling of production-based carbon emissions are presented in Table- 7. Starting with the environmental impact of population, the coefficient of *ln*P showed a positive coefficient and statistically significant at 1% level across all specifications, irrespective of the estimation technique used. Based on STIRPAT augmented EKC model, a 1% increase in population size increases production-based CO_2 emissions by 1.40%. From the MM-qreg estimates, the environmental impact of increasing population size is stronger in developing economies at the lower quantile of *ln*PrdCE distribution. Further, the coefficient of per capita income (*ln*PCI) in extended STIRPAT model is positive and statistically significant at 1% level and indicates a 1.11% increase in production-based CO_2 emissions in response to a 1% increase in per capita income (*ln*PCI). In specification-5, the model is augmented with the square of per capita income (*ln*PCI^2) to accommodate the EKC hypothesis. The results show valid an inverted U-shaped curve in the relationship between income per capita and production-based CO_2 emissions in the sampled developing countries. MM-qreg estimates show that an inverted U-shaped curve in the relationship between income per capita and production-based CO_2 emissions is valid irrespective of the quantile location of the countries and affirms the findings of Saint [43], Gokmenoglu and Taspinar [44]. Again, this result reinforces the Environmental Kuznets curve hypothesis which suggests that there is a direct connection between an increasing standard of living and environmental degradation [45]. The coefficient of energy intensity (*ln*EnI) is positive and statistically significant at 1% level across all specifications. From the AMG estimates in model specification-5, a 1% increase in energy intensity increases production-based CO_2 emissions by 0.71%. Conversely, a 1% increase in energy efficiency reduces production-based CO_2 emissions by 0.71%. MM-qreg estimates show that the environmental impact of energy intensity is stronger in developing economies at the lower quantile of *ln*PrdCE distribution. This finding affirms the studies of Emir and Bekun [46], Shahbaz et al. [45], Ulucak and Khan [48] that also confirms that, energy intensity increases pollution (see Table 6) (see Table 5).

The coefficient of renewable energy consumption (*ln*REn) is negative and statistically significant at 1% level across all specifications. The AMG estimates in model specification-5 show that a 1% increase in the use of renewable energy decreases production-based CO_2 emissions by 0.35% while MM-qreg estimates highlight stronger mitigation effect in countries at the lower quantiles of *ln*PrdCE distribution. This observation makes important revelations referring from previous studies of Alola and Alola [48], who propose that increased consumption of renewable energy mitigates CO_2 emissions. The empirical results in Table- 7 show AMG estimations for the extended STIRPAT specification. It is observed that a 1% rise in the size of population (*ln*P) raises consumption-based CO_2 emissions by 1.90% while MM-qreg estimates provide further evidence to indicate stronger environmental impact in developing economies at the lower quantile of *ln*ConCE distribution. The estimates of the STIRPAT specification, show that a significant positive relationship also exists between per capita income and consumption-based CO_2 emissions. In specification 6, the model is augmented with the square of per capita income (*ln*PCI^2) to accommodate the EKC hypothesis. From the estimates, income per capita (*ln*PCI) reveals a positive effect with statistical significance attained at 10% level. The coefficient of square (*ln*PCI^2) is negative as expected, but statistically insignificant. The MM-qreg estimates show that *ln*PCI and *ln*PCI^2 have statistically insignificant coefficients in countries at the lower (MM-qtile_25) and upper (MM-qtile_25) quantiles of the *ln*ConCE distribution. For the median quantile (MM-qtile_50) of the distribution, the estimates confirm a monotonically increasing relationship between per capita income and consumption-based CO_2 emissions as also suggested by AMG estimates. This finding corroborates with surveys of studies on the divergence in the evidence across countries on the EKC hypothesis due to differences in measures of environmental indicators. It is therefore interesting to note that the EKC hypothesis does hold for consumption-based CO_2 emissions in the selected developing economies. Looking at the coefficient of *ln*EnI in Table- 8, a positive and statistically significant relationship exists between the intensity of energy use and consumption-based CO_2 emissions. From the AMG estimates, a 1% increase in energy intensity contributes by 0.60% increase in consumption-based CO_2 emissions. Again, this indicates that a 1% increase in the rate of improvement in energy efficiency will reduce consumption-based CO_2 emissions by 0.60%. MM-qreg estimates show that energy intensity has stronger impact in countries at the lower quantiles of *ln*ConCE distribution. The estimates also show a negative and statistically significant coefficient for renewable energy consumption (*ln*REn) across all the specifications. The AMG estimates in model specification show that a percentage increase in renewable energy

Table-3
Pesaran (2004, 2015) cross-section dependence analysis.

Variable	CD-test	p-value	average joint	mean ρ	mean abs(ρ)
*ln*PrdCE	92.435	0.000	23.00	0.69	0.80
*ln*ConCE	93.593	0.000	23.00	0.70	0.76
*ln*P	132.793	0.000	23.00	0.99	0.99
*ln*PCI	93.919	0.000	23.00	0.70	0.76
*ln*PCI^2	94.045	0.000	23.00	0.70	0.76
*ln*EnI	46.158	0.000	23.00	0.34	0.56
*ln*REn	36.835	0.000	23.00	0.28	0.55

Note: All the variable apart from PU underwent logarithmic transformation; Under the null hypothesis of cross-section independence, CD ~ N(0,1); ***p < 0.01, **p < 0.05, *p < 0.1; P-values close to zero indicate data are correlated across panel groups.

Table-4
Panel unit root analysis.

Variables	Panel A: CIPS (Pesaran, 2007) unit-root test				Panel B: CADF (Pesaran, 2003) unit root test				Decision
	Level I (0)		1st Difference I (1)		Level I (0)		1st Difference I (1)		
	Without Trend	With Trend	Without Trend	With Trend	Without Trend	With Trend	Without Trend	With Trend	
*ln*PrdCE	−2.225**	−2.717**	−4.682***	−4.733***	−1.486	−1.744	−3.369***	−3.391***	I (1)
*ln*ConCE	−2.307***	−2.762***	−4.761***	−4.783***	−1.706	−2.156	−3.548***	−3.660***	I (1)
*ln*P	−1.656	−2.480	−2.214**	−4.428***	−1.487	−1.039	−3.641***	−5.716***	I (1)
*ln*PCI	−1.732	−2.008	−3.348***	−3.651***	−1.101	−1.407	−2.548***	−2.999***	I (1)
*ln*PCI^2	−1.696	−1.935	−3.296***	−3.618***	−1.082	−1.417	−2.484***	−2.954***	I (1)
*ln*EnI	−1.786	−2.193	−4.457***	−4.601***	−0.840	−1.384	−2.876***	−2.897***	I (1)
*ln*REn	−1.878	−2.047	−4.338***	−4.488***	−1.674	−1.625	−2.900***	−3.048***	I (1)

Note: ***p < 0.01, **;0 .05; * 0.1. The null hypothesis assumes for CADF assumes all series are non-stationary in a heterogeneous panel all with cross-sectional dependence.

Table-5
Pesaran and Yamagata (2008) slope heterogeneity analysis.

Specifications	Delta tilde ($\triangle$)	Adjusted delta tilde ($\triangle_{Adj}$)
1.1. *ln*PrdCE	21.979*** [0.000]	25.565*** [0.000]
1.2. *ln*PrdCE (EKC)	17.632*** [0.000]	21.140*** [0.000]
2.1. *ln*ConCE	19.624*** [0.000]	22.825*** [0.000]
2.2. *ln*ConCE (EKC)	16.062*** [0.000]	19.258*** [0.000]
3.1. *ln*EnI with *ln*PrdCE	27.345***[0.000]	31.806***[0.000]
3.2. *ln*EnI with *ln*ConCE	28.698***[0.000]	33.380***[0.000]
P-values in parentheses; ***p < 0.01; ** 0.05; *0.1.		

Table-6
Panel cointegration analysis.

Specifications				
Panel A: Westerlund (2005) panel cointegration test				
	Some panels		All Panels	
1.1. *ln*PrdCE	−3.1620***[0.0008]		−1.9070**[0.0283]	
1.2. *ln*PrdCE (EKC)	−3.7742***[0.0001]		−2.1642**[0.0152]	
2.1. *ln*ConCE	−3.5330***[0.0002]		−1.8509**[0.0321]	
2.2. *ln*ConCE (EKC)	−3.8987***[0.0000]		−2.0681**[0.0193]	
3.1. *ln*EnI with *ln*PrdCE	−2.9772*** [0.0015]		−1.9084**[0.0282]	
3.2. *ln*EnI with *ln*ConCE	−2.7528*** [0.0030]		−1.8325**[0.0334]	
Panel B: Westerlund (2007) Error-correction panel cointegration test				
	Gt Value [Robust p-value]	Ga Value [Robust p-value]	Pt Value [Robust p-value]	Pa Value [Robust p-value]
1.1. *ln*PrdCE	−2.944*** [0.000]	−2.512 [0.968]	−12.262*** [0.000]	−2.129 [0.768]
1.2. *ln*PrdCE (EKC)	−3.218*** [0.000]	−1.415 [0.980]	−15.992*** [0.000]	−1.262 [0.712]
2.1. *ln*ConCE	−3.240*** [0.000]	−2.110 [0.996]	−14.066***[0.000]	−2.129 [0.684]
2.2. *ln*ConCE (EKC)	−3.771*** [0.000]	−1.266 [0.992]	−27.998*** [0.000]	−1.848 [0.596]
3.1. *ln*EnI with *ln*PrdCE	−3.243*** [0.000]	−3.048 [0.831]	−15.659*** [0.000]	−2.678 [0.800]
3.2. *ln*EnI with *ln*ConCE	−3.122*** [0.000]	−2.557 [0.958]	−12.478*** [0.000]	−2.349 [0.996]

The Robust P-Values are from 250 bootstrapping of critical values under null hypothesis of no cointegration. ***p < 0.01, **p < 0.05, *p < 0.1 indicate the level at which the null hypothesis is not accepted.

utilization reduces consumption-based CO_2 emissions by 0.39% while MM-qreg estimates highlight stronger mitigation effect at the upper quantiles of *ln*ConCE distribution.

The empirical results from further empirical analyses are provided in Table- 9. Specifically, this step is taken determine whether renewable energy can be used to reduce the intensity of energy (i.e. increase the rate of improvement in energy efficiency) in developing economies. From the estimates, *ln*REn has a negative coefficient with statistical significance achieved at 5% level. Looking at the coefficient across the two specifications reveals that increasing the amount of renewable energy in energy mix by 1% could reduce the intensity of energy by 0.19%–0.24%. Conversely, it means that a 1% increase in the amount of renewable energy in energy mix increases energy efficiency by 0.19%–0.24%. Interestingly, the estimates also confirm a significant positive relationship between sources of CO_2 emissions (i.e. *ln*PrdCE and *ln*ConCE) and energy intensity in these economies. The empirical results in Table- 10 show the causal linkages among the variables. In Panel-A, the null hypothesis that *ln*EnI does not cause *ln*PrdCE is rejected at 1% level of significance. The null hypothesis that *ln*PrdCE does not cause *ln*EnI is as well rejected at 5% level of significance. These results imply the existence of bidirectional causal relationship between energy intensity and production-based carbon emissions. Surprisingly, no significant causal relationship exists between renewable energy use and production-based CO_2 emissions in this group of developing economies. Other causal linkages include a unidirectional causality that runs from population size and per capita income to production-based CO_2 emissions. In Panel-B, a unidirectional causality runs from energy intensity and renewable energy use to consumption-based CO_2 emissions. The causality between population size and consumption-based CO_2 emissions is bidirectional. Also, bidirectional causality exists between per capita income and consumption-based CO_2 emissions but not with the squared term, in which case, the null hypothesis that *ln*ConCE does not Granger-cause *ln*PCI^2 is not rejected. Another interesting finding is the bidirectional causal relationship between energy intensity and renewable energy use (see Panel-C). A summary scheme for the causality is highlighted in Fig. 3.

4. Conclusion and policy implications

The transition to a low-carbon economy is an essential component of the sustainable development (UNSDG-7.13) agenda. Increasing the share of renewable energy in energy mix (SDG Target 7.2) and doubling the rate of improvement in energy efficiency (SDG Target 7.3) are among many policy options currently considered to have the potential to facilitate the transition to green economy especially for developing and emerging blocs. In this study, the nexus between the intensity of energy use, an indicator of energy efficiency (see SDG indicator 7.3.1), renewable energy use (see SDG indicator 7.2.1), and CO_2 emissions is examined based on a STIRPAT augmented model that also incorporates the EKC specification. The environmental impacts of developing

Table-7
Parameter estimates for production-based carbon emissions.

Variables	1.1	1.2a	1.2b	1.2c	1.2d
	Extended STIRPAT model	STIRPAT Augmented EKC model			
	AMG	AMG	MM-qtile_25	MM-qtile_50	MM-qtile_75
*ln*P	1.6453***	1.4000***	1.1276***	1.1049***	1.0806***
	(0.1637)	(0.1242)	(0.0586)	(0.0515)	(0.0573)
	[10.049]	[11.274]	[19.254]	[21.439]	[18.858]
*ln*PCI	1.1091***	13.8423***	3.0739***	3.2512***	3.4414***
	(0.0978)	(4.3567)	(0.2304)	(0.2028)	(0.2252)
	[11.338]	[3.177]	[13.342]	[16.033]	[15.280]
*ln*PCI^2	.	−0.7347***	−0.1359***	−0.1473***	−0.1595***
	.	(0.2846)	(0.0140)	(0.0123)	(0.0137)
	.	[-2.582]	[-9.692]	[-11.932]	[-11.633]
*ln*EnI	0.6532***	0.7102***	0.5134***	0.4826***	0.4495***
	(0.1012)	(0.1084)	(0.0474)	(0.0417)	(0.0463)
	[6.457]	[6.550]	[10.839]	[11.575]	[9.704]
*ln*REn	−0.3182***	−0.3530***	−0.2195***	−0.2061***	−0.1917***
	(0.0970)	(0.0992)	(0.0321)	(0.0283)	(0.0314)
	[-3.280]	[-3.560]	[-6.828]	[-7.285]	[-6.094]
Constant	−30.6989***	−74.6321***	−31.7251***	−31.9403***	−32.1712***
	(3.7095)	(18.0813)	(1.2872)	(1.1327)	(1.2597)
	[-8.276]	[-4.128]	[-24.647]	[-28.199]	[-25.538]
Observations	920	920	920	920	920
Number of ID	40	40	40	40	40

Note: Standard errors in ( ); t-statistics in [ ]; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table-8
Parameter estimates for consumption-based carbon emissions.

Variables	2.1	2.2a	2.2b	2.2c	2.2d
	Extended STIRPAT model	STIRPAT Augmented EKC model			
	AMG	AMG	MM-qtile_25	MM-qtile_50	MM-qtile_75
*ln*P	1.6325***	1.9008***	1.5882***	1.4764***	1.3739***
	(0.2927)	(0.3314)	(0.0966)	(0.0767)	(0.0781)
	[5.578]	[5.735]	[16.441]	[19.256]	[17.595]
*ln*PCI	1.3181***	8.7412*	1.1262	0.9763*	0.8388
	(0.1768)	(5.0472)	(0.7014)	(0.5573)	(0.5686)
	[7.457]	[1.732]	[1.606]	[1.752]	[1.475]
*ln*PCI^2		−0.3556	−0.0074	−0.0000	0.0067
		(0.3295)	(0.0463)	(0.0368)	(0.0375)
		[-1.079]	[-0.159]	[-0.001]	[0.179]
*ln*EnI	0.4865***	0.6000***	0.5470***	0.4626***	0.3851***
	(0.1179)	(0.1176)	(0.0896)	(0.0711)	(0.0725)
	[4.125]	[5.101]	[6.105]	[6.504]	[5.312]
*ln*REn	−0.5801***	−0.3851***	−0.2252***	−0.2486***	−0.2700***
	(0.1432)	(0.1280)	(0.0702)	(0.0558)	(0.0569)
	[-4.050]	[-3.010]	[-3.207]	[-4.456]	[-4.745]
Constant	−29.1393***	−61.2523**	−32.1571***	−29.2054***	−26.4985***
	(4.5514)	(26.4167)	(3.1485)	(2.4995)	(2.5476)
	[-6.402]	[-2.319]	[-10.213]	[-11.685]	[-10.401]
Observations	920	920	920	920	920
Number of ID	40	40	40	40	40

Note: Standard errors in ( ); t-statistics in [ ]; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

economies in Latin America, Asia, the Caribbean, and Africa form the scope for the empirical analysis. Based on available data on the variables, a panel consisting of 40 countries is constructed for the study. To provide a more complete picture of total lifecycle emissions, this study used both production and consumption-based measures of carbon emissions. Results revealed that population size drives CO_2 emissions in developing economies. It establishes an inverted U-shaped association between income per capita and production-based CO_2 emissions, thus validating the EKC hypothesis. The coefficient of energy intensity is positive and significant across all specifications. Renewable energy utilization shows a negative effect, significant at 0.01 across all specifications. The analysis observed bidirectional causality between energy intensity and production-based CO_2 emissions. A unidirectional causality runs from population size and per capita income to production-based CO_2 emissions. A unidirectional causality runs from energy intensity and renewable energy use to consumption-based CO_2 emissions. The causality between population size and consumption-based CO_2 emissions is bidirectional. Bidirectional causality also exists between per capita income and consumption-based CO_2 emissions. Another interesting finding is the bidirectional causal relationship between energy intensity and renewable energy use.

Taking cognizance of the current findings, several important inferences can be made. First, the results highlight the need for policymakers to consider the increasing importance of energy efficiency as a crucial consideration for CO_2 emissions mitigation. Many developing economies face difficulties in producing electric power and increase access to cleaner energy options or even optimize their production. At present, many countries have made attempts at trying to reduce adverse environmental actions to curb the negative impacts on the global environment. This action to an extent has inspired other countries have

Table-9
Parameter estimates for energy intensity.

	(3.1)	(3.2)
Variables	AMG (*ln*EnI with *ln*PrdCE)	AMG (*ln*EnI with *ln*ConCE)
*ln*PrdCE	0.3157***	–
	(0.0662)	–
	[4.766]	–
*ln*ConCE	–	0.1527***
	–	(0.0408)
	–	[3.742]
*ln*P	−1.0281***	−0.8505***
	(0.1909)	(0.1547)
	[-5.386]	[-5.498]
*ln*PCI	−0.9607***	−0.9016***
	(0.0545)	(0.0678)
	[-17.644]	[-13.296]
*ln*REn	−0.1893**	−0.2424**
	(0.0918)	(0.0979)
	[-2.063]	[-2.475]
Constant	26.4521***	22.5458***
	(2.8945)	(2.5231)
	[9.139]	[8.936]
Observations	920	920
Number of ID	40	40

Note: Standard errors in ( ); t-statistics in [ ]; ***p < 0.01, **p < 0.05, *p < 0.1.

remained passive toward this objective. Many countries possess large deposits of resources that can facilitate the production and sustenance of renewable energy but have been unexplored or completely unexplored by these countries. Non-renewable energy consumption, which increases carbon emissions is observed to be an important driver for energy generation and consumption among developing economies. For instance, according to Shahbaz et al. [32], many sub-Saharan African states are found to be heavily dependent on coal for electricity generation. Unfortunately, the African continent alone is estimated to generate over 1750 TWh of hydropower and 14,000 MW of geothermal energy sources. Yet only about 7% this capacity has been utilized [45]. Thus, the focus of countries should be to use green energy drive economic development and prosperity. Beyond hydroelectric power and geothermal sources of electric power, other environmentally friendly energy sources exist to augment these somewhat traditional energy generation options. A challenge to this realization is the unbalanced dynamics of energy politics in many developing economies, which is especially crucial because of issues of resource distribution, and use in developing countries. This burden is often borne by all and sundry, even in some cases a spill-over tends to extend the cost and burden to immediate neighbours. Therefore, the effect of negative energy production options makes the issue of environmental degradation, pollutant emissions and climate change challenge is affected by all. Thus, government policy and communication of these policy briefs ought to be effective to facilitate public understanding of environmental issues and concerns and understanding of the role of households toward the fight against greenhouse gas emissions. Governments and other stakeholders need to lend support to positive environmental goals such as afforestation and landscaping to radically reduce pollution volumes across the globe [49]. Moreover, the result of the significant role of energy intensity in reducing CO_2 emissions should be maintained as s a vital consideration to ensure that, present and future energy demands are responsibly met in line with global sustainability targets. Specifically, this study observes that energy intensity drives pollution among the countries considered in this study. Thus, it can also be surmised that increased energy intensity suggests evidence of improper utilization of energy. Energy advances by R&D investment will lower energy intensity of energy industry and thus less carbon pollution economic experts need to promote research and development on enhancing energy usage and ecological sustainability. Moreover, R&D related investments will be a crucial means toward coping with the overreliance of fossil fuels. However, a final consideration, is to facilitate the urgent need for policy and strategy to ensure

Table-10
Dumitrescu and Hurlin (2012) Granger non-causality analysis.

Null hypothesis	W-bar Statistic	Z-bar stat. statistic	90% critical value	P-value
Panel A: Production-based CO_2 emissions				
*ln*P does not Granger-cause *ln*PrdCE	22.1141	34.2281	37.6522	0.1600
*ln*PrdCE does not Granger-cause *ln*P	23.0465	36.0929***	21.0511	0.0100
*ln*PCI does not Granger-cause *ln*PrdCE	8.2111	19.6413***	8.8513	0.0000
*ln*PrdCE does not Granger-cause *ln*PCI	9.0554	8.1109	10.2222	0.2800
*ln*PCI^2 does not Granger-cause *ln*PrdCE	8.1832	19.5531***	9.9832	0.0000
*ln*PrdCE does not Granger-cause *ln*PCI^2	9.0109	8.0217	12.1455	0.4400
*ln*EnI does not Granger-cause *ln*PrdCE	4.0195	13.5037***	6.9559	0.0000
*ln*PrdCE does not Granger-cause *ln*EnI	3.1517	9.6226**	8.0681	0.0300
*ln*REn does not Granger-cause *ln*PrdCE	8.2713	6.5427	10.8211	0.4700
*ln*PrdCE does not Granger-cause *ln*REn	2.8539	8.2908	9.1047	0.1700
Panel B: Consumption-based CO_2 emissions				
*ln*P does not Granger-cause *ln*ConCE	19.5107	42.6304***	21.1631	0.0000
*ln*ConCE does not Granger-cause *ln*P	10.4907	19.3408***	5.3533	0.0000
*ln*PCI does not Granger-cause *ln*ConCE	14.4816	18.9633***	12.2003	0.0000
*ln*ConCE does not Granger-cause *ln*PCI	4.5133	7.9478*	7.6995	0.0800
*ln*PCI^2 does not Granger-cause *ln*ConCE	14.5584	19.1168***	9.6426	0.0000
*ln*ConCE does not Granger-cause *ln*PCI^2	4.4705	7.8124	7.9515	0.1100
*ln*EnI does not Granger-cause *ln*ConCE	3.6110	11.6768***	7.6624	0.0000
*ln*ConCE does not Granger-cause *ln*EnI	8.2884	6.5768	10.8821	0.3800
*ln*REn does not Granger-cause *ln*ConCE	10.2981	10.5962***	8.8317	0.0200
*ln*ConCE does not Granger-cause *ln*REn	8.7940	7.5880	11.6965	0.3200
Panel C: Nexus between energy intensity and Renewable Energy				
*ln*REn does not Granger-cause *ln*EnI	3.0134	9.0042**	6.1638	0.0300
*ln*EnI does not Granger-cause *ln*REn	11.9623	13.9246***	10.4541	0.0100

Note: ***p < 0.01, **p < 0.05, *p < 0.1; Optimal number of lags (AIC lags tested: 1 to 5). * p-values using bootstrap replications for 90% critical value.

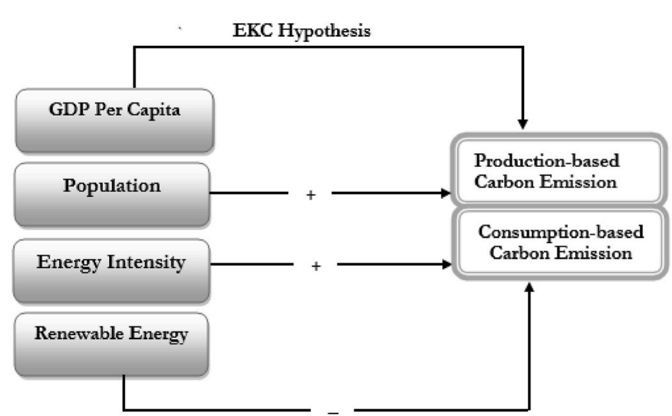

Fig. 3. Graphical analysis of framework.

climate and energy industries be supervised more strictly to become more ecologically responsible. This can be achieved through enforcing technical expansion and growth policies that lend themselves to actionable R&D and innovative initiatives.

The validity of the EKC hypothesis among the selected countries in this study for production-based CO_2 implies that these developing states require substantial efforts and action to minimize adverse effects of increased income levels on environment. Given the fact that the countries under consideration are all developing nations and are still struggling with their growth paths, it is necessary to build institutional mechanisms required to develop and implement effective strategic decisions and environment-relative regulations to achieve sustained environments without compromising their fragile economic development trajectories. However, along the path of the consumption-based analysis of carbon emissions, the analysis rejects the presence of EKC, this could be a source of concern for most of these developing states understudy. Thus, the move toward transitioning to clean energy sources like renewable energy is pertinent considering the implicit effects cleaner environments. Therefore, practitioners and other stakeholders must seek a shared meaning, and concerted efforts toward realizing the dynamic shift to cleaner energy sources and technologies by improving the share of energy mix for fossil-fuels to renewable energy sources.

Credit author statement

Chinazaekpere Nwani: Conceptualization; Writing – original draft; Formal analysis; Methodology; **Muhammad Shahbaz**: Validation; Visualization; Investigation; Supervision. **Bright Akwasi Gyamfi**: Writing – original draft; Writing, Validation; Divine Q. Agozie: Data curation; Writing – original draft. **Festus Victor Bekun**: Visualization; Supervision, and Corresponding.

Appendix-A: List of Sampled Developing Countries by Region

S/N	AFRICA	S/N	ASIA	S/N	Latin America and the Caribbean
1	Botswana	22	Bangladesh	32	Colombia
2	Burkina Faso	23	India	33	Dominican Republic
3	Cameroon	24	Indonesia	34	Ecuador
4	Cote d'Ivoire	25	Jordan	35	El Salvador
5	Egypt	26	Malaysia	36	Jamaica
6	Ghana	27	Pakistan	37	Mexico
7	Guinea	28	Philippines	38	Panama
8	Kenya	29	Saudi Arabia	39	Peru
9	Madagascar	30	Thailand	40	Uruguay
10	Malawi	31	Vietnam		
11	Morocco				
12	Mozambique				
13	Namibia				
14	Nigeria				
15	Senegal				
16	South Africa				
17	Tanzania				
18	Togo				
19	Tunisia				
20	Zambia				
21	Zimbabwe				

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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