Modelling Sustainable Energy Transition in BRICS+ Countries: A Smoothed Common Correlated Effects Instrumental Variable Quantile Regression Approach

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Abstract

The collective goal of achieving net-zero emissions in the coming decades has sparked considerable debate in recent years. The nature of the energy transition in fossil fuel-dependent economies suggests the presence of both implicit and explicit gaps in country-level commitments to the transition. Utilizing data from 1996 to 2019 from the BRICS+ bloc, this study investigates the heterogeneous effects of key economic and environmental factors on energy transition across the distribution of energy transition levels using a smoothed quantile instrumental variable regression model with common correlated effects (CCE) adjustments. The analysis incorporates macroeconomic, environmental and governance variables, while addressing endogeneity through instrumental variables, such as fossil fuel reserves and temperature anomalies. The results reveal significant heterogeneity in the relationships across quantiles. Specifically, CO_2 emissions exhibit a consistently negative impact on energy transition, with the effect fluctuating across the distribution. GDP and population growth negatively influence energy transition, with stronger effects at higher quantiles, indicating structural constraints in high-transition countries. Notably, the heterogeneity of inflation effects, though insignificant, suggests dynamic economic pressures at varying energy transition levels. These findings underline the importance of targeted, quantile-specific policy interventions to accelerate energy transition, emphasizing decarbonization and market reforms. The CCE adjustments ensure robustness by accounting for cross-sectional dependence, and sensitivity analyses confirm the validity of the results. This study contributes to the growing literature on sustainable energy by providing novel insights into the distributional dynamics of energy transition drivers.

Keywords: Energy transition analysis, CO_2 emissions policies, instrumental variables, common correlated effects, quantile regression

JEL codes: O13; Q43; C26.

1.0 **Introduction**

The global transition towards a low-carbon future has emerged as one of the important pathways for countries to revolutionize existing energy systems, restructure economies towards sustainable economic development, and contribute to reducing global warming levels to 1.5°C (IEA, 2023). Although these outcomes reflect long-term transformations across economies, they resonate with myriad short-to-medium term implications, including recurrent cost changes to different energy technologies, changes to global energy market dynamics, and shifts in investment away from fossil fuels to renewable energy resources (Gerasimchuk et al., 2019). These evolving dynamics present enormous opportunities for the new BRICS bloc (also termed BRICS+), which together wield vast energy resource potential to cooperate in building a more robust and resilient clean energy future (Kaur et al., 2023; Kazelko & Semeghini, 2024; Wen et al., 2024).

Navigating the energy transition in BRICS+ countries require setting ambitious plans and targets given the historical fossil fuel energy dominance of the bloc for decades. This evolving trend warrants further long-term structural changes across economic sectors and energy systems (IEA, 2023; IRENA, 2024). Available data show that the energy transition curve (share of renewable energy consumption (RE) to the share of fossil fuel consumption (NRE)) of BRICS+ countries reflect a mildly significant progress in the transformation of energy systems (see Fig. 1). While the energy transition movement of member countries such as the UAE, Brazil, China, South Africa, Indonesia and India shows an uneven transformation from 1996 to 2019, that of Iran, and Russia indicates a relatively smoothed-out transformation. The historical energy transition curve of the latter countries shows lackluster additions to renewable energy compared to fossil fuels. Similar to Iran, Russia is considered to have attached low priority to the transition away from fossil fuels, adding only 0.5% of renewable energy to its energy mix below the 2.5% target in 2020 (Godzinska & Pastukhova, 2022). By contrast, China and India have made significant strides in the global renewable energy market in recent years. For instance, China ranks among the leading countries in terms of the use of clean energy technologies, accounting for 50% of wind capacity additions, 60% of global EV sales, and 45% of global solar PV capacity additions (IEA, 2023).

Before its recent expansion, the bloc began showing signs of becoming a major political and economic power (Wen et al., 2024), thereby changing the dynamics of the existing global geopolitics (Godzinska & Pastukhova, 2022). BRICS posted an average GDP growth rate of 6.6% in 2021, surpassing both the EU and the US, which recorded GDP growth rates of 6.01% and 5.95%, respectively, according to data from the World Bank. China and India, the two fastest-growing economies of the bloc, recorded GDP growth rates of 8.45% and 9.05%, respectively, in 2021. Additionally, the inclusion of new members in the bloc increased its share of the global population to 45%, indicating a 4-percentage point increase in population growth prior to expansion. While these high-performing macroeconomic indicators tailwind the bloc's anticipated dominance in the global economy, this raises concerns about the accompanying rise in carbon emission growth and the changing dynamics of the bloc's energy transition process. According to the IEA (2023), China is the largest producer and consumer of fossil fuels, contributing to approximately one-third of global CO_2 emissions. Fig. 2 shows that China's CO_2 emissions began to rise rapidly, close to the turn of the 21st century, and have since continued on a positive trajectory due to ongoing rapid urbanization and industrialization. Similarly, the CO_2 emission paths of Egypt, UAE, Russia, and Iran mimic those of China, albeit in relative terms, emissions growth occurs at a diminishing rate (see Fig. 2). To this end, although investments in RE have been rising over the past decade, carbon dioxide emissions have continued to rise (see Fig. 3). The rise of RE and non-RE public investments in Brazil is accompanied by inverted V-shaped per capita CO_2 emissions. Likewise, the rise in public investment in RE over the past decade is not reflected in the decline of per capita CO_2 emissions in China, India, and South Africa as these countries are faced with rising per capita CO_2 emissions.

In line with the urgency of global energy transition in recent decades, various scholars have studied the determinants of energy transition using quantitative approaches (Akarsu & Gümüşoğlu, 2019; Akintande et al., 2020; J. Li et al., 2020; Taghizadeh-Hesary & Rasoulinezhad, 2020). In this vein, the majority of studies have explored specific aspects or dimensions of energy transition, such as renewable energy consumption (or fossil fuel energy consumption) of economies (Ackah & Kizys, 2015; Akarsu & Gümüşoğlu, 2019; Akintande et al., 2020; Sadorsky, 2009), while others use the World Economic Forum (WEF) energy transition index, clean energy production index, sustainable energy development index, and green quality of energy mix index, among others as proxies for energy transition (Kuc-Czarnecka et al., 2021; Lau et al., 2023; Zambrano-Monserrate, 2024). Furthermore, some studies have examined the relationship between energy transition and macroeconomic variables including trade openness, population size, economic growth, energy prices, globalization, and economic complexity (Majumder et al., 2023; Owjimehr & Samadi, 2022; Wen et al., 2024).

There is vast literature on the determinants of the energy transition pattern of countries; however, evidence on the impact of several macroeconomic variables on energy transition in countries remains inconclusive. Regarding the energy transition-growth nexus, there is a lack of consensus, as some studies indicate a U-shaped relationship (Akarsu & Gümüşoğlu, 2019; Damette & Marques, 2019; Ergun & Rivas, 2023). Considering the energy-transition-CO_2 nexus, the literature demonstrates the heterogenous effects of CO_2 emissions on energy transition (Lau et al., 2023; Zambrano-Monserrate, 2024). The literature is replete with studies that examine the relationship between energy transition and population growth; however, the effect is mixed (Akintande et al., 2020; Owjimehr & Samadi, 2022; Taghizadeh-Hesary & Rasoulinezhad, 2020). Studies investigating the relationship between energy transition and exchange rate have found heterogenous effects (Deka et al., 2023; Shah et al., 2022). While these studies have been carried out mostly in developed economies, there is a dearth of literature on the factors that determine energy transition patterns in emerging economies, specifically, the new BRICS bloc. More importantly, the recent expansion of the BRICS bloc presents several dynamics that shape the bloc's energy future in terms of clean energy trade and investment (Kazelko & Semeghini, 2024), thus influencing the significance of this study.

This study contributes to the literature in several ways. For instance, this study models the influencing factors of energy transition drawn from the novel theoretical model of Taghizadeh-Hesary and Rasoulinezhad (2020) for the BRICS+ economic bloc from 1996-2019. Unlike their study, this study incorporates covariates, such as ecological footprint, inflation rate, real oil price and political stability. In addition, we employ a smoothed (CCE) IV-QR model as an ideal econometric technique. The smoothed (CCE) IV-QR framework accounts for unobserved heterogeneity, heterogeneous covariate effects, and deals with cross-sectional dependence and endogeneity issues which are useful in obtaining unbiased and consistent estimates.

The remainder of this paper is organized as follows. Section 2 reviews the existing literature. Section 3 discusses the theoretical model used in the study, explores the methodology, and outlines the data description and model specifications. Section 4 presents a detailed analysis of the results obtained. Finally, Section 5 concludes the paper, summarizing the main findings of the study.

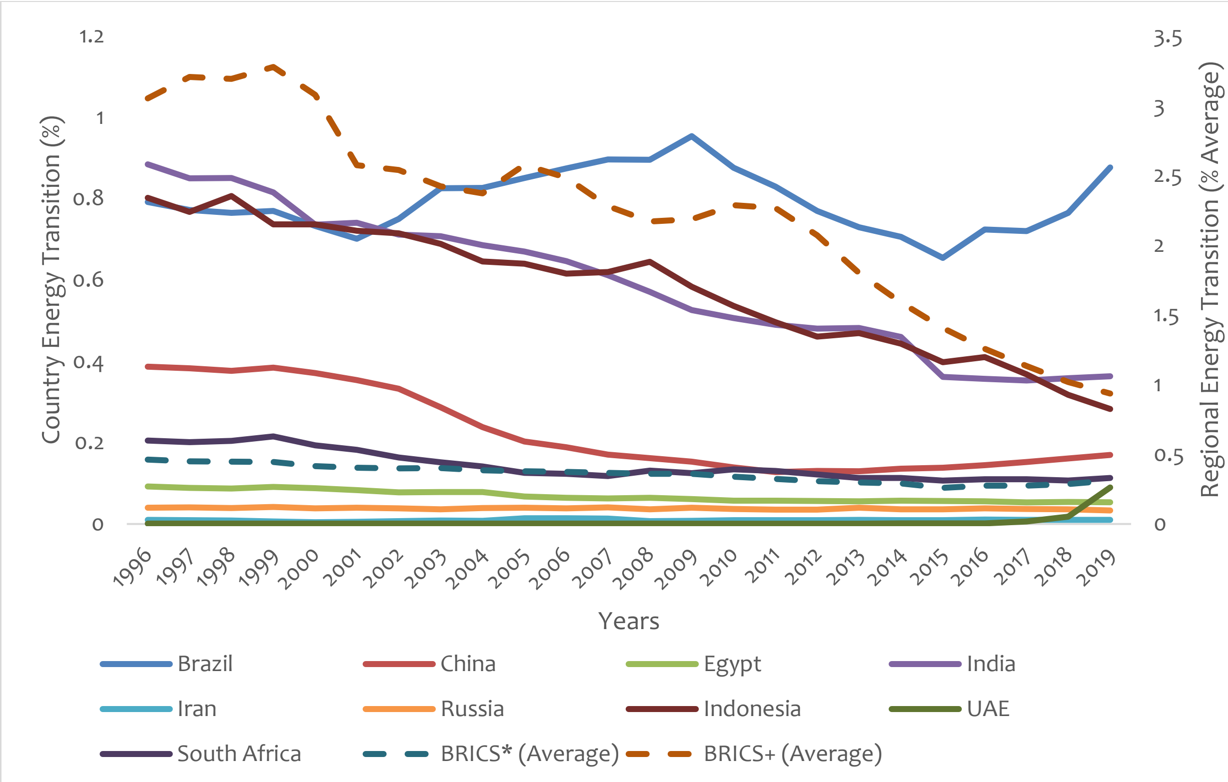

Fig. 1 *Energy Transition in Selected BRICS+ countries, 1996-2019*

Source: Authors' construct based on data from World Bank and BP's Statistical Review 2019

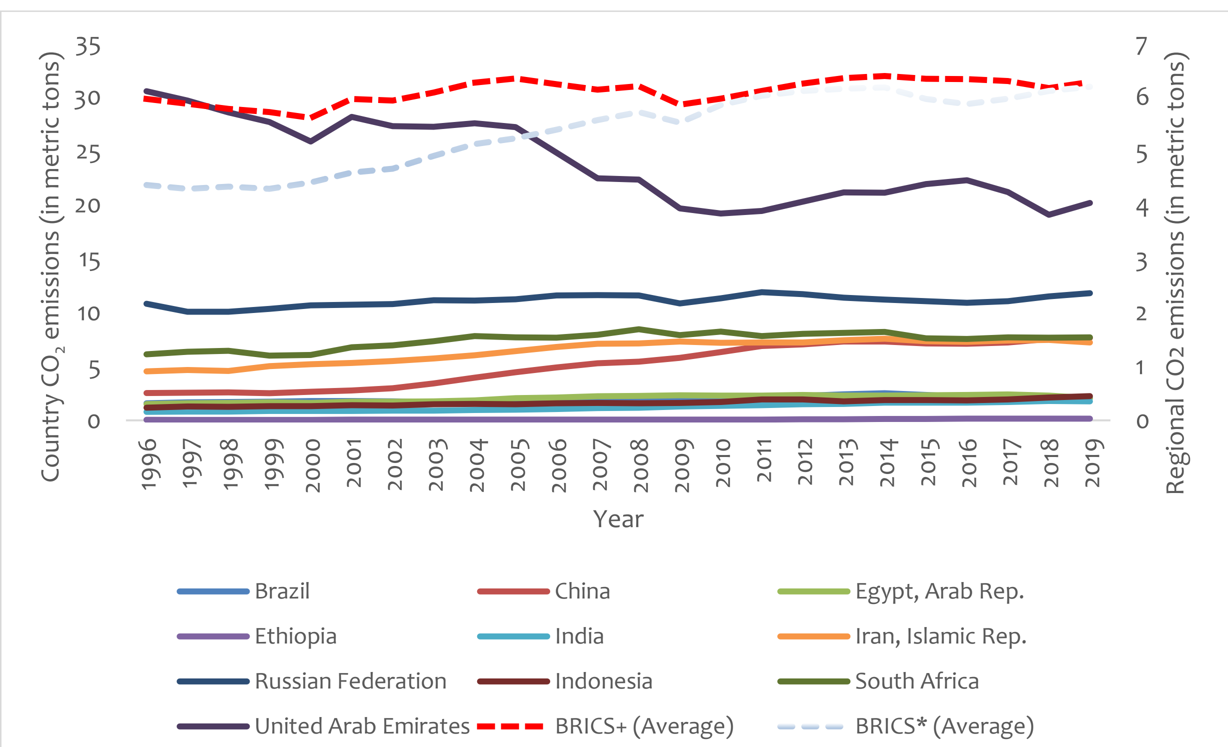

Fig. 2 *Carbon dioxide Emissions in BRICS+ Countries, 1960-2019*

Source: Authors' construct based on World Bank data

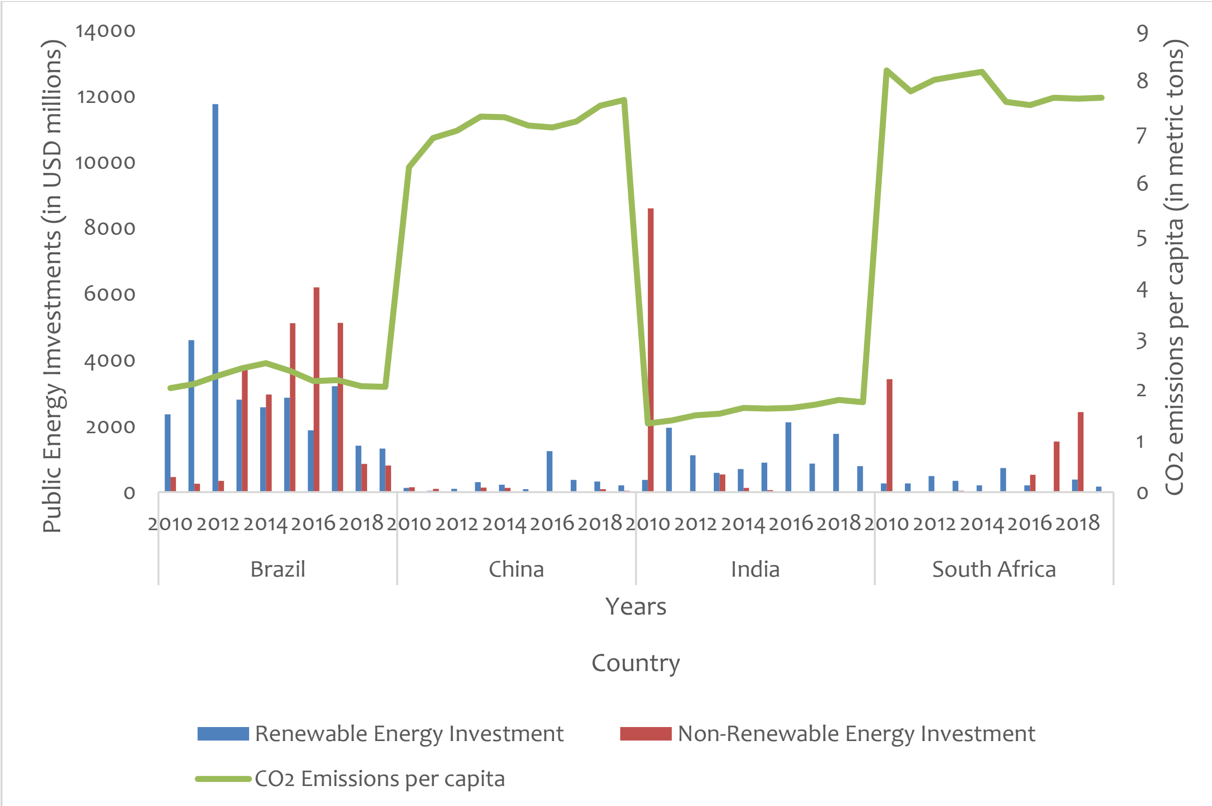

Fig. 3 *CO_2 emissions and public energy investments in selected BRICS+ Countries, 2010-2020*

Source: Authors' construct based on IRENA Public Investment Data

2.0 **Literature Review**

An assessment of the broad literature on energy transition shows an increase in studies examining the drivers of energy transition (Ergun & Rivas, 2023; Lau et al., 2023; Zambrano-Monserrate, 2024). A combination of factors, including, but not limited to, specific individual and multi-country contexts and multi-year horizons, have informed the use of different methodological approaches to investigate the relationship between several macroeconomic variables and energy transition. Most studies have used causality and cointegration tests to examine these relationships (Damette & Marques, 2019; Dissanayake et al., 2023; Hwang & Sánchez Díez, 2024; J. Li et al., 2020; Shah et al., 2022). Moreover, some studies have used system GMM techniques to analyse these relationships, however, such an approach requires larger panels to ensure robust results. Studies that use quantile regression techniques woefully ignore the presence of reverse causality between regressors and the outcome variable resulting in biased results (Adebayo et al., 2024; Afshan et al., 2022). Akin to the rigor required in studies capturing these effects, the smoothed (CCE) instrumental variables (IV) quantile regression framework is considered a suitable approach; however, to the best of our knowledge, no study has employed this approach in analyzing the energy transition dynamics in the new BRICS bloc.

According to Garcia-Casals et al. (2019), energy transition, as reflected in renewable energy consumption and energy efficiency coupled with deep electrification of end-uses, has the potential to boost global GDP in the long run. The results were obtained by employing the E3ME macro-econometric modelling of energy transition for IRENA member states from 2018 to 2050. Specifically, the authors find that a 90% reduction in energy-related carbon dioxide emissions could result in a maximum 1.5% increase in GDP in 2031, but eventually decline to 1% by 2051. This indicates a diminishing return on GDP from the energy transition. Investigating energy transitions in the EU and Switzerland from 1990 to 2018, Muco et al. (2021) confirmed the above results, noting that, an increase in energy use associated with economic growth tends to reduce energy efficiency and increase production costs, thus diminishing GDP growth.

Combining cointegration and causality tests in examining the relationship between energy transition index and CO_2 emissions in 26 OECD countries from 1970-2015, Zambrano-Monserrate (2024) found that clean energy production reduces CO_2 emissions in both the short-run and long-run. Additionally, bidirectional causality exists between the energy transition indicator and CO_2 emissions. Likewise, Taghizadeh-Hesary and Rasoulinezhad (2020) discovered that economic growth positively impacts energy transition, whereas CO_2 emissions have an inverse relationship with energy transition. The authors capture the energy transition measure as the ratio of renewable energy consumption to non-renewable energy consumption. In addition, in both sub-sample groups (i.e., high- and upper-middle-income, and low and lower-middle-income groups) an increase in population lowers the energy transition process. Again, the rate of ET acceleration was higher for high and upper-middle-income economies because of the greater relative income surplus that aids high-level green financing in these economies, thus facilitating the demand for RE. This result was achieved through a generalized method of moments (GMM) estimation using data on 45 Asian economies over the period 1993–2018. However, the exchange rate was found to be insignificant in the ET process, whereas population growth showed a positive association with renewable energy consumption.

Similarly, Rasoulinezhad et al. (2020) assessed the impact of geopolitical risk on ET in Russia using an ARDL bounds testing method over the period 1993–2018 and found a long-run negative impact of economic growth, population growth, and inflation rate on energy transition in Russia, while CO_2 emissions, geopolitical risk, exchange rate and financial openness have positive impacts on energy transition movement in the country. Furthermore, the results indicate that in the short run, the relationship between energy transition improvement and economic growth, CO_2 emissions, population growth, and inflation rate is negative, while geopolitical risk, exchange rate and financial openness are the only variables that accelerate energy transition in the country.

Hwang and Sánchez Díez (2024) analyzed the impact of renewable energy transition on green economic growth using panel data of 14 Latin American economies form 2003–2020. The results indicate that renewable energy transition propels economic growth and also confirms heterogeneity in the effects established due to geographical location, fossil fuel dependence and mineral resource dependence. Additionally, the authors analyzed the mediating effects between renewable energy and green economic growth. They concluded that capital investment, dependence on hydropower electricity production, residential electricity consumption per capita, human capital, and formal job creation play mediatory roles in the renewable energy transition and green growth nexus. Amid these dynamics, they also find a negative spatial spillover effect of the renewable energy transition in Latin America.

Akintade et al. (2020) used Bayesian Model Averaging (BMA) procedures to examine the determinants of renewable energy consumption from 1996–2016 in the five most populous African economies. They found a positive nexus between population growth, urban population, energy demand/use and electricity power demand, and energy transition. Despite incorporating thirty-four covariates into the model, in the final analysis, they found that GDP growth, oil-producing status, land surface area, political stability, corruption control, rule of law, oil demand, school enrolment (tertiary), agriculture, urban population, and government effectiveness drive renewable energy consumption. Subsequently, by exploring RE demand dynamics in Africa, Ackah & Kizys (2015) found that RE demand in oil-rich African countries is significantly affected by real income per capita, carbon emissions per capita, and RE prices. The result is consistent in all three models (a random effects model, a fixed effects model and a dynamic panel data model) estimated with data covering 1985–2010. To estimate RE demand, the authors used metric tonnes equivalent of RE sources, including the sum of hydro, geothermal, wind, solar, industrial waste, municipal waste, biomass, biofuels, and charcoal. A positive association was found for real income per capita, implying the availability of sufficient funds to support renewable energy adoption. They also found a negative association between CO_2 emissions and RE demand and attributed this to a decline in biomass, which is a component of RE following an increase in carbon dioxide emissions.

Chen et al. (2020) explored the relationship between renewable energy consumption and economic growth using a sample of 103 countries from 1995–2015. The authors adopted a panel threshold model for the analysis. The results show differing effects: beyond a predetermined threshold level, renewable energy consumption has a positive effect on economic growth in developing economies and non-OECD countries. Below a determined threshold level, the effect of renewable energy consumption on economic growth becomes negative. For developed economies, the authors find no significant effect between renewable energy consumption and economic growth, whereas the result is positively significant for OECD countries.

Yu and Guo (2023) investigated the driving factors of green energy transition in China using quarterly time-series data from 2000–2020. The authors employed a bootstrap autoregressive distributed lag (BARDL) to examine the relationships between economic policy uncertainty, technological innovation, ecological governance, and economic growth. Affirming a long run association between the variables, the authors found that economic policy uncertainty and economic growth inhibit the progress of the green energy transition, while technological innovation and environmental governance play a pivotal role in promoting the green energy transition in China.

3.0 **Methodology**

This section is divided into two parts. The first part discusses the theoretical model of the study while the second part details the data and variables used as well as the empirical model and strategy of the study.

3.1 Theoretical Model

Based on the theoretical framework developed by Taghizadeh-Hesary and Rasoulinezhad (2020), we examine a basic two-sector model comprising the industry sector and household/residential sector. We further assume that the demand for energy sources—both renewable and non-renewable—originates from these two sectors, and that electricity generated from these energy sources within the economy is entirely consumed by them. We adopt the energy transition definition of Edenhofer et al. (2012) as the structural shift in existing energy systems towards modern energy. Consequently, the energy transition process within the economy reflects a mix of renewable and non-renewable energy sources. The energy inputs utilized by the industrial sector represent the proportion of renewable and non-renewable energy sources employed in the production process. Similarly, a household's demand for or consumption of energy resources reflects a combination of energy goods derived from both renewable and non-renewable sources. Thus, households derive utility from consuming a diverse bundle of goods sourced from renewable and non-renewable energy sources.

3.1.1 Industry Sector

Pokrovski (2003) proposed an extension of the conventional neoclassical growth model to include consumed energy, referred to as productive energy (ET). The way productive energy enters the production function is not only by adding to the cost of production but also by enhancing the value generated during the production process (Lee et al., 2008; Lee & Chang, 2007; Pokrovski, 2003).

We illustrate the industry's output with a basic Cobb-Douglas production function at a constant returns to scale (CRS) while introducing productive energy, in this case, which is the share of RE consumption to non-RE consumption into the function given by:

$$Y_t^I = F(A_t, K_t, L_t, ET_t) = A_t\left(K_t^{\alpha} L_t^{\beta} (ET_t^I)^{1-\alpha-\beta}\right), 0 < \alpha < 1, 0 < \beta < 1 \quad (1)$$

Where Y^I is the total output of industry, A represents exogenous total factor productivity, K denotes the capital input, L denotes the labor input, ET^I denotes energy inputs used in industrial production, which depicts the energy transition (share of renewables to non-renewables) in the industrial sector, α is the elasticity of production of capital, β is the elasticity of production of labor, and the elasticity of production of energy inputs is equal to $1 - \alpha - \beta$. is the total output of industry.

Furthermore, following Edenhofer et al.'s (2012) definition of energy transition, the economy's energy transition is given by:

$$ET_t = \frac{REC_t}{NREC_t} \quad (2)$$

Where REC_t is the renewable energy consumption and $NREC_t$ is the non-renewable energy consumption in the industry.

The industry sector faces a cost function as follows:

$$C_t = r_t K_t + w_t L_t + e_t (P_t^E + T_t) ET_t^I \quad (3)$$

Where C_t is the industry's cost of production, r denotes the interest rate of capital, K denotes the capital input, w denotes the wage rate, L denotes the labor input, e denotes the exchange rate, P^E denotes energy price and T denotes the environmental costs associated with transporting energy resources (we use CO_2 emissions as a proxy).

Accordingly, firms maximize their profits as follows:

$$Max\ \pi_t = P_t^Y Y_t - r_t K_t - w_t L_t - e_t(P_t^E + T_t)ET_t^I \tag{4}$$

Where π is the industry sector's profit, P^Y is the price of the final products, r denotes the interest rate of capital, w denotes the wage rate, e denotes the exchange rate, P^E denotes energy price and T denotes the transportation environmental cost of energy resources.

By substituting Eq.1 into Eq.4 and solving the first differential with respect to ET, the resulting equation becomes:

$$\frac{\partial \pi_t}{\partial ET_t^I} = (1 - \alpha - \beta)\frac{P_t^Y Y_t^I}{ET_t^I} - e_t(P_t^E + T_t) = 0 \tag{5}$$

Making ET^I the subject in Eq.5, the industry's energy transition becomes:

$$ET_t^I = (1 - \alpha - \beta)\frac{P_t^Y Y_t^I}{e_t(P_t^E + T_t)} \tag{6}$$

From Eq.6, it is evident that, the industry's energy transition is a function of the elasticities of production of labour and capital, the price of final industry products, real output of industry, energy price, exchange rate and energy transportation environmental costs.

3.1.2 Household Sector

Let C_t and ET_t^H be the time-varying indices of household consumption of non-energy goods and energy goods respectively. Generally, household derives utility from the consumption of both non-energy and energy goods. The household energy demand is represented by the following utility function:

$$U_t = (C_t, ET_t^H) = \frac{1}{1-\rho}(C_t)^{1-\rho} + \frac{1}{1-\tau}(ET_t^H)^{1-\tau} \tag{7}$$

Households maximize their utility subject to a budget constraint given by:

$$Y_t^H = P_t^C C_t + e_t(P_t^e + T_t)ET_t^H \tag{8}$$

Where Y^H is the total income of households, P^C represents the price of non-energy goods, P^E represents the price of energy goods, which is determined by energy price, e represents the exchange rate and T represents the transportation environmental cost of energy goods.

To maximize the utility of households, the household's Lagrange function is set up as follows:

$$L = U(C_t, ET_t^H) - \varphi\{P_t^C C_t + e_t(P_t^E + T_t)ET_t^H - Y_t^H\} \tag{9}$$

The first-order differential with respect to ET^H, C, and φ are given as follows:

$$\frac{\partial L}{\partial ET_t^H} = U^I(ET_t^H) - \varphi\{e_t(P_t^E + T_t)\} = 0 \tag{10}$$

$$\frac{\partial L}{\partial C_t} = U^I(C_t) - \varphi(P_t^C) = 0 \Rightarrow \varphi = \frac{U^I(C_t)}{P_t^C} \tag{11}$$

$$\frac{\partial L}{\partial \varphi} = Y_t^H = P_t^C + e_t(P_t^E + T_t)ET_t^H \quad (12)$$

Substituting φ from Eq. 11 into Eq. 10 and solving for ET_t^H, the household's energy transition becomes a function of electricity tariff, exchange rate, transportation environmental costs of energy and the income level of households as expressed in eq. 13 below.

$$ET_t^H = f(P_t^E, e_t, T_t, Y_t^H) \quad (13)$$

The total energy demand of the economy is given by:

$$ET_t = ET_t^I + ET_t^H \quad (14)$$

From Eq.14, the total energy demand of the economy is expressed below

$$ET_t = f(P_t^E, P_t^Y, e_t, T_t, Y_t) \quad (15)$$

Where P^E denotes electricity tariff, P^Y denotes the price of final industry products, e denotes the exchange rate, T represents environmental costs associated with transportation of energy, and Y is the total GDP of the economy which constitutes the total industrial output, (Y^I) and the income level of households (Y^H).

3.2 Data and Variables of the Study

This study utilized an annual panel dataset from 1996–2019. The data were obtained from multiple sources including the World Bank's World Development Indicators (WDI) and BP's Statistical Review 2017-2019, the Global Footprint Network (GFN), Energy Institute Statistical Review, Worldometer and Berkeley Earth. Due to the recent expansion of BRICS (now referred to as BRICS+), which includes five additional countries, the study focused data on full members of the bloc as at January 2025: Brazil, Russia, India, China, South Africa, Egypt, Ethiopia, Iran, UAE and Indonesia. Based on the theoretical model, this study posits that energy transition—defined as the ratio of renewable energy consumption to non-renewable energy consumption—is the dependent variable. Similarly, the independent variables include exchange rate, GDP, real oil prices (used as a proxy for energy prices), and CO_2 emissions. The study incorporates control variables such as population growth rate, political stability and ecological footprint.

Regarding the proxy for energy prices, real oil price is an appropriate proxy due to its significant role in shaping global energy markets. As a dominant energy source, oil price influences other energy markets and is associated with electricity prices and energy consumption (Alola et al., 2023). Additionally, using real oil price ensures that energy price changes are consistent over time. Kilian (2009) stressed that oil price shocks are key drivers of energy price volatility, amplifying their suitability as a proxy. In the context of BRICS+ countries, where fossil fuels play a critical role, real oil prices capture volatility and trends in energy costs, making them particularly suitable for this study.

Table 1. Definition of Variables

Variables	Log Transformation of the variables	Definition	Database
Energy transition (et)	let	$\frac{\%Renewable\ energy\ cons.}{\%Fossil\ fuel\ \ energy\ cons.}$	WDI / BP
CO_2 Emissions (co2_e)	lco2	Metric tons per capita	WDI
Population growth (pop)	lpop	Annual percentage growth rate of population	WDI
Exchange rate (ex)	lex	Official exchange rate (LCU per US$, period average)	WDI
GDP	lgdp	Annual percentage growth rate of GDP	WDI
Inflation rate (infl)	linfl	Consumer prices (annual %)	WDI
Ecological footprint (eco_fp)	leco_fp	Global Footprint Network	GFN
Political Stability (pol_stab)	lpol_stab	estimates	WDI
Real Oil Price (r_oil_px)	lr_oil_px	$ per barrel	EISR
Fossil fuel reserves (foss_res)	lfoss_res	Proved oil reserves (thousand million barrels)	EISR /Worldometer
Temperature anomalies (temp)	ltemp	Degree celsius	BE

Notes: WDI World Development Indicators

BP BP Statistical Review

GFN Global Footprint Network

EISR Energy Institute Statistical Review

BE Berkley Earth

3.3 Econometric Model Specification

Based on the variables for the study and the theoretical foundation underpinning their selection, the multivariate econometric specification can be written as:

$$et_{it} = \gamma + \delta co2_{it} + \omega pop_{it} + \varphi ex_{it} + \rho gdp_{it} + \sigma infl_{it} + \alpha r\_oil\_px_{it} + \beta pol\_stab_{it} + \pi eco\_fp_{it} + \varepsilon_{it} \tag{16}$$

We adopt a log-transform of the model due to the non-normality of the data. The log-transform of the model is expressed in Eq.17 as follows:

$$let_{it} = \gamma + \delta lco2_{it} + \omega lpop_{it} + \varphi lex_{it} + \rho lgdp_{it} + \sigma linfl_{it} + \alpha lr\_oil\_px_{it} + \beta pol\_stab_{it} + \pi leco\_fp_{it} + \varepsilon_{it} \tag{17}$$

Where γ is the intercept term, ω, φ, ρ, σ, α, β, π are the slope coefficients and ε is the error term. Additionally, i represents the cross-section of countries and t represents the time period.

3.3.1 Smoothed (common correlated effects) Instrumental Variable Quantile Regression Model

Introduced by Koenker and Bassett (1978), the standard quantile regression model estimates the effects of a given set of covariates at the conditional quantiles of the dependent variable (Fitzenberger & Wilke, 2015). Canay (2011) argues that the ability to account for unobserved heterogeneity and the varying effects of covariates is one of the many powerful features of the quantile regression model. However, the standard quantile regression model does not address issues of endogeneity and cross-sectional dependence associated with panel data. Against this backdrop, the IV-QR model proposed by Chernozhukov and Hansen (2006) which utilizes an inverse quantile regression estimator (IQR) have been widely adopted to deal with endogeneity issues of the standard QR model. Despite its advantages, the IV-QR quantile regression model has other limitations including its inability to account for cross-sectional dependence and the fact that it does not yield smooth estimators as there are jumps in the path of the estimator (Fernandes et al., 2021), given the quantile objective function to be minimized. The objective function of the (unsmoothed) IV-QR model faces complications in solving for high-order approximations of the sampling distribution of the objective function (Kaplan & Sun, 2017). In resolving these two limitations, we take a step further to adopt a smoothed instrumental variables quantile regression approach proposed by Kaplan and Sun (2017), and adjust the model with common correlated effects following Harding and Lamarche (2014) approach. The common correlated effects adjustment of the smoothed IV-QR model is based on cross-sectional averages of the dependent and independent variables following an adjustment of Pesaran (2006) model.

With the exception of the static (CCE) IV-QR model developed by Harding and Lamarche (2014), recent literature have predominantly focused on dynamic (CCE) QR panel models with lagged dependent variables and interactive effects (Galvao, 2011; Harding et al., 2020; Zheng et al., 2024). These models have been shown to provide consistent estimates where the panel timeseries and cross-sectional units are large ($T, N \rightarrow \infty$). A necessary condition for the consistency of parameters among such models is that the number of cross-sectional averages must be greater or equal to the number of unobserved common factors. However, Kapetanios et al. (2011) posited that for short panels where the number of unobserved common factors is less or equal to the number of dependent and independent variables combined, there is known improvement of the static CCE estimator and tests on the model.

We specify the model akin to Harding and Lamarche (2014) as follows:

$$y_{it} = \alpha' d_{it} + \beta' x_{it} + \gamma_i{}' f_t + u_{it}, \quad i = 1, \ldots\ldots, N; t = 1, \ldots\ldots., T \tag{18}$$

$$d_{it} = \pi'_1 w_{it} + \pi'_2 x_{it} + \pi'_3 f_{it} + \pi'_4 \gamma_i + \pi'_5 \gamma_i f_t + v_{it} \tag{19}$$

Where y_{it} is the outcome variable of interest for subject i at time t, d is a vector of k_1 endogenous variables, x is a vector of k_2 exogenous independent variables, f_t is the vector of r unobserved common time-varying factors, γ is an $r \times 1$ vector of country-specific factor loadings. Both γ_i and f_t are latent variables, the parameter of interest is α and u is the disturbance term. In the second equation d is correlated with a vector of $m \geq k_1$ instruments w, the exogenous variables x, and the latent variables γ and f. We assume that the variable v is stochastically dependent on u.

We rewrite Eq. (18) in a matrix form for convenience as follows:

$$y = D\alpha + X\beta + F\gamma + u \tag{20}$$

where y is an $NT \times 1$ vector, D is an $NT \times k_1$ matrix, X is an $NT \times k_2$ matrix, and F is an $NT \times r$ matrix. From the above, the IV estimator for α can be obtained in two steps form:

$$y(\alpha) = y - D\alpha = X\beta + F\gamma + W\psi + \varepsilon \tag{21}$$

Where W is a matrix of instruments, and the latent term F is approximated by cross-sectional averages of dependent and independent variables.

We then substitute Eq. (19) into Eq. (18) and sum over the cross-sectional dimension of the model to obtain Eq. (22) below:

$$\bar{z}_t(\tau) = C_1 \bar{w}_t + C_2(\tau)\bar{x}_t + (\bar{C}_3 + \bar{C}_4 \bar{\gamma}')f_t + \bar{C}_5 \bar{\gamma} \tag{22}$$

Where $\bar{z}_t(\tau)$ is the cross-sectional average of $z_{it}(\tau) = (y_{it}, d'_{it})'$, and $C_1 = (\alpha'\pi'_1, \pi'_1)'$, $C_2(\tau) = (\alpha'\pi'_2 + \beta(\tau)')', \ \pi'_1)'$, $\bar{C}_3 = N^{-1}\sum_{i=1}^{N}((\pi'_{3i}\alpha)', \pi'_{3i})'$, $C_4 = (\alpha'\pi_4 + 1, \pi_4)'$, $\bar{\gamma} = N^{-1}\sum_{i=1}^{N}\gamma_i$ and $C_5 = (\alpha'\pi_5, \alpha'\pi_5)$.

Now, to estimate the quantile regression model with cross-sectional averages and endogenous covariates, we specify the objective function as follows:

$$Q_{it}(\alpha, \tau, \beta, \delta, \lambda) = \rho_\tau(y_{it} - \tilde{d}'_{it}\alpha - x'_{it}\beta - \hat{f}'_t(\tau)\delta - \widehat{\Phi}'_{it}(\tau)\lambda) \tag{23}$$

Where $\rho_\tau(\omega) = \omega(\tau - G\left(-\frac{\mu}{h}\right)(\omega \leq 0))$ is the standard loss function, $G(*)$ is a smoothing function and h is the smoothing parameter or bandwidth (Kaplan & Sun, 2017). From Eq. (24), we note that unknown common factors are approximated by the term $f_t(\tau) = \psi(\tau; \bar{z}_t, \bar{w}_t, \bar{x}_t, 1)$, which is a known parametric function of cross-sectional averages of the endogenous and exogenous variables. Hence $\hat{f}'_t(\tau)$ in Eq. (25) is a vector that includes an intercept and the cross-sectional variables $\hat{\bar{z}}(\tau)_t$, $\bar{w}_t$ and $\bar{x}_t$. $\tilde{d}'_{it} = (d'_{it}, \bar{d}'_t)'$. Then, we instrument the vector $\check{d}_{it}$ by the vector of instruments $\widetilde{w}'_{it} = (w'_{it}, \bar{w}'_t)'$. Therefore, $f_t(\tau)$ is defined as $\psi(\tau; \bar{y}_t, \bar{x}_t, 1)$. The second term $\Phi_{it}(\tau) = \Phi(\tau; w_{it}, x_{it}, f_{it}, \lambda_i)$ is a vector of transformations of instruments.

We minimize the objective function above as follows:

$$\{\hat{\beta}(\tau, \alpha), \hat{\delta}(\tau, \alpha), \hat{\lambda}(\tau, \alpha)\} = argmin_{\beta,\lambda,\delta} \sum_{t=1}^{T}\sum_{i=1}^{N} Q_{it}(\alpha, \tau, \beta, \delta, \lambda) \tag{24}$$

Then we solve for the coefficient of the endogenous regressor, by finding the value of α.

3.4 Empirical Strategy

Given potential reverse causality between energy transition and CO2 emissions which may lead to endogeneity problems and likely bias our results, we employed a smoothed (CCE) instrumental variables quantile regression approach (CCE IV-QR) to resolve these problems.

Since the instrumental variables quantile regression method is robust to heterogeneity, we estimate the τ_{th} quantile of the dependent variable (et), ranging from the 10th to 80th quantile, as a linear function of the endogenous variable ($co2_{it}$), a vector of covariates including control variables (X_{it}), a vector of unobserved common time-varying factors (f_t), a vector of country-specific factor loadings (γ_i) and error term (μ_{it}).

$$Q_{et}\tau = \alpha_\tau co2_{it} + \beta X_{it} + \gamma_i f_t + \mu_{it} \tag{25}$$

We further assume $et_{it}$to be predicted by the following equation, given that $co2_{it}$ is correlated with the error term (μ_{it}) based on eq.19.

$$co2_{it} = \pi_1 w_{it} + \pi_2 x_{it} + \pi_3 f_{it} + \pi_4 \gamma_i + \pi_5 \gamma_i f_t + v_{it} \tag{26}$$

Where w_{it} is a vector of instruments for $co2_{it}$, both γ_i and f_t are latent variables and v_{it} is the disturbance term.

We then substitute Eq.26 into Eq.25 to obtain cross-sectional averages as in Eq.22 and estimate the quantile objective function as follows:

$$Q_{it}(\alpha, \tau, \beta, \delta, \lambda) = \rho_\tau(et_{it} - \alpha_\tau co2_{it} - \beta_\tau X_{it} - \delta f_t(\tau) - \lambda \phi_{it}(\tau)) \tag{27}$$

From the above, we minimize the quantile objective function by including a smoothing function as follows:

$$argmin \sum_{i=1}^{T} \sum_{i=1}^{N} \rho_\tau(et_{it} - \alpha_\tau co2_{it} - \beta_\tau X_{it} - \delta f_t(\tau) - \lambda \phi_{it}(\tau)), \rho_\tau(\omega) \equiv [\tau - G\left(-\frac{\mu}{h}\right)] \tag{28}$$

Where $(*)$ is the quantile loss function, $G(*)$ is the smoothing function, and then we solve for the coefficient of $\alpha_\tau$through the minimization problem.

With regards to our model, we selected fossil fuel reserves and temperature anomalies as our instruments as they both correlate with the endogenous variable (CO_2 emissions). To ensure robustness of our instruments, we use the correlation matrix in Table 2, as well as diagnostic tests from our smoothed (CCE) IV-QR model to verify the strength and exogeneity of both instruments.

Fossil fuel reserves are a critical determinant of CO_2 emissions, as they represent the potential for future carbon release upon combustion. Russel (2016) highlights that the potential CO_2 emissions from existing fossil fuel reserves far exceed the carbon budget necessary to limit global warming, underscoring their direct impact on emissions. Additionally, Mazza and Canuto (2024) model the association between fossil fuel reserve depletion and future CO_2 concentrations, demonstrating the direct connection between exploitation of fossil fuel reserve and CO_2 emissions. Likewise, temperature anomalies serve as a theoretically sound and empirically relevant instrument for CO_2 emissions in our analysis. Temperature anomalies represent a direct and measurable outcome of cumulative CO_2 emissions, which happen to be the primary driver of anthropogenic climate change. Temperature anomalies are exogenous to short-term country-level energy transition efforts, as they occur due to long-term historical emissions. Studies that have successfully employed climatic variables like temperature anomalies as instruments in similar contexts include Burke et al. (2015) and Dell et al. (2012).

Moreover, given that our data is unbalanced, we employed varied forms of linear interpolation, based on the structure of variables to fill missing values. Interpolation was selected because it preserves the temporal structure of the data and minimizes disruptions to underlying trends (Knutsen, 2012). This method is particularly suited for variables which exhibit gradual and continuous changes over time. Furthermore, linear interpolation avoids the introduction of spurious variability or bias, as it relies only on existing observations within the series. Additionally, to ensure the robustness of our results, we conducted sensitivity analyses, including comparisons with non-interpolated dataset, which excluded missing years. The results confirmed that interpolation did not significantly influence the conclusions of our analysis.

4.0 Empirical Results

This section presents the descriptive statistics, diagnostic tests, empirical findings and a thorough discussion of results.

4.1 Descriptive Statistics

Table 2 presents the descriptive statistics for the variables and the pairwise correlation matrix. Among the variables, energy transition (et), exchange rate (ex), carbon dioxide emissions (co_2), population growth (pop), real oil price (r_oil_px), inflation rate (infl), and ecological footprint (eco_fp) are all positively skewed, with real oil price exhibiting a long right-tailed distribution, as indicated by the kurtosis value. In contrast, economic growth (gdp) and political stability (pol_stab) are negatively skewed, suggesting that the distribution of the data is more peaked than a normal distribution. According to the correlation matrix, the exchange rate, carbon dioxide, population growth rate, inflation rate, and real oil price all exhibit a negative correlation with energy transition, and carbon dioxide emissions showing a particularly strong negative association. Conversely, GDP and ecological footprint show a weak positive association with energy transition.

Table 2. Descriptive Statistics

Variable	Obs	Min	Max	Mean	Std. Dev.	Skewness	Kurtosis
et	223	0.001	29.699	2.158	6.303	3.174	11.595
ex	240	1.005	4.20E+04	2384.071	6299.992	3.741	19.386
co2_e	240	0.048	30.523	6.099	6.938	1.801	5.75
pop	240	-0.460	18.128	1.751	2.195	4.743	31.308
r_oil_px	240	-6.03E+04	5.68E+07	1.76E+06	5.90E+06	5.252	38.558
gdp	240	-13.127	1.42E+01	4.778	3.852	-0.622	4.753
infl	240	-16.267	85.746	9.008	10.244	3.387	23.028
pol_stab	210	-2.095	0.995	-0.645	0.706	0.513	2.849
eco_fp	240	2.89E+07	4.81E+09	7.00E+08	1.04E+09	2.631	9.555
foss_res	240	0.428	158.400	40.355	49.517	1.015	2.438
temp	240	-0.126	2.432	0.978	0.469	0.579	3.658

Pairwise Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) et	1.000										
(2) ex	-0.121	1.000									
(3) co2_e	-0.298	-0.067	1.000								
(4) pop	0.158	-0.062	0.392	1.000							
(5) r_oil_px	-0.092	0.657	-0.102	-0.065	1.000						
(6) gdp	0.239	-0.186	-0.145	0.005	-0.030	1.000					
(7) infl	-0.015	0.252	-0.063	-0.042	-0.009	-0.228	1.000				
(8) pol_stab	-0.342	-0.238	0.679	0.314	-0.073	-0.123	-0.399	1.000			
(9) eco_fp	-0.189	-0.144	-0.077	-0.283	-0.093	0.296	-0.186	0.013	1.000		
(10) foss_res	-0.281	0.378	0.658	0.083	0.081	-0.250	0.266	0.185	-0.113	1.000	
(11) temp	-0.071	0.250	0.284	-0.073	0.169	-0.106	-0.021	-0.004	0.052	0.444	1.000

4.1.1 Cross-Sectional Dependence Test

The cross-sectional dependence (CD) test is an important diagnostic tool for panel data analysis. Given that our dataset has a limited number of cross-section units (*N*) and time periods (*T*) (i.e., *N, T* < 30) (Thombs, 2022), with more time series units than cross-section units, we employed the Breusch and Pagan (1980) LM cross-sectional dependence test. As shown in Table 3, we obtained a CD statistic of 227.251 with a p-value below the 1% significance level, leading us to reject the null hypothesis that there is no cross-sectional dependence. Therefore, we conclude that there is strong cross-sectional dependence within the panel of countries.

Table 3. Breusch-Pagan LM Test of Independence

Cross-Sectional Dependence	Statistic	p-value
Model	227.251	0.000***

*** *p*<0.01, ** *p*<0.05, * *p*<0.10

4.1.2 Panel Unit Root Test

Following the conclusions drawn from the cross-sectional dependence test, a panel unit root test was necessary to assess the suitability of the model for estimation (Tugcu, 2018). This crucial diagnostic test identifies the presence of stationarity or non-stationarity in both covariates and dependent variables. We employed a second-generation panel unit root test, specifically Pesaran Cross-Sectional Augmented Dickey-Fuller (PESCADF) test to determine the stationarity of the variables (Pesaran, 2003, 2007). The results presented in Table 4 indicate that the test without trend display lr_oil_px, lgdp and linfl stationary at levels whereas the test with trend shows same pattern (lr_oil_px, lgdp and linfl) of stationary variables. Based on the p-values of these variables, we could not reject the null hypothesis of no unit root at 1% significance level. However, when expressed as first difference, all variables exhibit stationarity, with and without a trend term implying that the data series are integrated of mixed order *I(0) and I(1)*.

Table 4. Pesaran's cross-sectional augmented Dickey Fuller (Pescadf) test

	Constant		Constant & Trend	
Variable	T-bar	*p*-value	T-bar	*p*-value
let	-0.755	0.999	-1.127	1.000
lex	-2.106	0.130	-2.171	0.682
lpop	-1.649	0.641	-2.456	0.309
lr_oil_px	-2.610***	0.003	-2.953***	0.014
lgdp	-2.843***	0.000	-3.200***	0.001
lco2	-1.491	0.810	-1.648	0.988
linfl	-2.687***	0.001	-3.471***	0.000
lpol_stab	-1.565	0.737	-2.179	0.671
leco_fp	-1.995	0.222	-2.134	0.725
Δlet	-3.520***	0.000	-3.806***	0.000
Δlex	-3.083***	0.000	-4.163***	0.000
Δlpop	-3.627***	0.000	-3.886***	0.000
Δlr_oil_px	-4.041***	0.000	-4.056***	0.000
Δlgdp	-4.115***	0.000	-4.028***	0.000
Δlco2	-3.487***	0.000	-3.581***	0.000

Δlinfl	-4.210***	0.000	-4.161***	0.000
Δlpol_stab	-3.121***	0.000	-4.472***	0.000
Δleco_fp	-3.312***	0.000	-3.231***	0.001

*** $p<0.01$, ** $p<0.05$, * $p<0.10$
Source: Authors' Computation

4.1.4 Panel Cointegration Test

Table 5 presents the results of the Pedroni test for co-integration. As a residual-based test, the Pedroni test for cointegration better explains cointegration relationships (Gutierrez, 2003). Pedroni test for cointegration tests the null hypothesis of no cointegration and allows for heterogeneity in the long-run covariance matrix and slope coefficients. As presented in Table 5, we find that the modified Philips-Perron test, Philips Perron test and the Augmented Dickey-Fuller test, all have probability values less than 1% significance level, indicating that we reject the null hypothesis of no cointegration. To confirm the results, we showed that in appendix Table 12, the Westerlund cointegration test and Kao test presented p-values less than 1% significance level. This indicates the presence of cointegration between variables in the model.

Table 5. Pedroni Cointegration Test

Modified Phillips-Perron *t*	4.124***	0.000
Phillips-Perron *t*	2.848***	0.002
Augmented Dickey-fuller *t*	3.015***	0.001

*** $p<0.01$, ** $p<0.05$, * $p<0.10$

4.1.5 Smoothed (CCE) Instrumental Variable Quantile Estimation

After performing the preliminary tests, the smoothed IV-QR estimation proposed by Kaplan and Sun (2017), and which we adjust to include cross-sectional averages is estimated as in Harding and Lamarche (2014) to obtain a static (CCE) IV-QR model. The CCE IV-QR approach utilizes cross-sectional averages of the variables to capture the shared unobserved effects across cross-sectional units (Eibinger et al., 2024). The inclusion of cross-sectional averages, as a requirement for panel estimations based on a common correlated effects (CCE) approach allow for inferences that not only deal with cross-sectional dependence in panels but remains robust to variables with mixed orders of integration and cointegration (Kapetanios et al., 2011). The CCE approach can be utilized in panels with small sample sizes, providing robust and reliable inferences (Eibinger et al., 2024; Kapetanios et al., 2011). We present robustness checks by comparing the results of Kaplan and Sun (2017) smoothed estimating equations (SEE), Chernozhukov and Hansen (2006) inverse quantile regression (IQR) estimator and results from instrumental variable two-stage least squares (2SLS) model to indicate reliability of our results. Full results for the quantiles are reported to provide a comprehensive representation of the heterogeneous effects of the independent variables across the energy transition distribution. We complement these results with visual presentations of the distribution while comparing results for the smooth estimating equations estimator and inverse quantile estimator (see appendix Fig. 4).

Based on the empirical findings presented in Table 6, we observe that the smoothed estimating equations estimator displays variables exhibiting heterogeneity across quantiles. The results indicate a significantly strong negative relationship between lco2 and let across all quantiles of the energy transition distribution at 1% significance level. This relationship suggests that higher levels of CO_2 emissions are associated with lower progress in energy transition, reflecting the detrimental impact of carbon-intensive economies on clean energy adoption. Notably, this effect fluctuates across the distribution from -1.710% at the 10th quantile to -1.450% at the 80th quantile. The effect declines from the 10th quantile to the 40th quantile and rises from the 50th to the 70th quantiles before declining sharply at the 80th quantile. Similarly, the estimated coefficient of lex indicates a consistent negatively significant association across the distribution (0.10 – 0.80). This relationship suggests that exchange rate fluctuations are associated with declining energy transition progress. The results demonstrate heterogeneity across the distribution, indicating that a 1% increase in the exchange rate leads to a 0.151% decline in energy transition at the 10th quantile, slightly rising at the 40th quantile, and declining through to the 80th quantile (0.079% respectively).

With regards to the relationship between economic growth (lgdp) and energy transition (let), we find a significant negative effect across the distribution. This suggests that a 1% increase in GDP yields a 0.150% decrease in energy transition at the 10th quantile, and then declines slightly at the 40th quantile (-0.160%). The effect rises sharply to 0.191% decrease at the 50th quantile to the 70th quantile, and again slows down to 0.188% decrease at the 80th quantile. The relationship between population growth rate (lpop) and energy transition reflects a negative effect across the distribution, albeit the results exhibit statistical significance at the 80th quantile only. The results suggest that a 1% increase in lpop leads to a 0.184% decrease in energy transition among countries with lower energy transition levels (10th quantile). This negative effect increases to -0.100% at the 50th quantile, and sees a further rise to -0.240% in countries at advanced-energy transition levels (80th quantile). Furthermore, the results reflect a statistically insignificant effect between real oil prices and energy transition across the quantile distribution. Despite this, we find a modest but increasing positive effect throughout the distribution, indicating that a 1% rise in real oil price yields a 0.002% increase in energy transition in countries with lower energy transition levels and gradually increases to 0.030% in countries with high energy transition levels. For the relationship between inflation rate and energy transition, we find an insignificant but fluctuating effect across the lower end and extreme upper end of the distribution. At lower quantiles (10th quantile), the effect is negative (-0.019%), turns positive afterwards (0.009% at 20th quantile) and becomes negative (-0.014% at 30th quantile). Beyond the 30th quantile, the effect turns positive, increasing through to the 70th quantile. However, at the 80th quantile, the effect turns negative (-0.048%). Likewise, the results reflect a statistically insignificant but modest positive effect between political stability and energy transition across the quantile distribution, increasing from 0.040% at the 10th quantile to 0.072% at the 80th quantile. Between ecological footprint and energy transition, we find a positively significant effect across the distribution, albeit this effect diminishes in countries with moderate and advanced-energy transition levels. This suggests that a 1% increase in ecological footprint yields a 0.665% increase in energy transition at the 10th quantile, 0.577% increase at the 50th quantile, and 0.299% increase at the 80th quantile.

Table 6. Smoothed (CCE) IV-Quantile Regression Model

	SEE Estimator							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	q10	q20	q30	q40	q50	q60	q70	q80
lco2	-1.710***	-1.667***	-1.638***	-1.641***	-1.656***	-1.654***	-1.647***	-1.450***
	(0.099)	(0.098)	(0.063)	(0.036)	(0.038)	(0.042)	(0.116)	(0.153)
lex	-0.151**	-0.138**	-0.133***	-0.135***	-0.110**	-0.046	-0.089	-0.079**
	(0.064)	(0.054)	(0.032)	(0.032)	(0.048)	(0.039)	(0.059)	(0.038)
lgdp	-0.150*	-0.167*	-0.190***	-0.160***	-0.191**	-0.229***	-0.233*	-0.188*
	(0.083)	(0.090)	(0.059)	(0.062)	(0.081)	(0.077)	(0.136)	(0.105)
lpop	-0.184	-0.097	-0.093	-0.109	-0.100	-0.083	-0.200	-0.240**
	(0.146)	(0.140)	(0.094)	(0.085)	(0.098)	(0.082)	(0.196)	(0.119)
lr_oil_px	0.002	0.004	0.004	0.003	0.003	0.007	0.015	0.030
	(0.009)	(0.016)	(0.010)	(0.011)	(0.014)	(0.016)	(0.045)	(0.030)
linfl	-0.019	0.009	-0.014	0.037	0.046	0.048	0.007	-0.048
	(0.058)	(0.071)	(0.062)	(0.061)	(0.065)	(0.063)	(0.192)	(0.139)
leco_fp	0.665***	0.636***	0.642***	0.589***	0.577***	0.560***	0.493***	0.229
	(0.072)	(0.077)	(0.049)	(0.061)	(0.069)	(0.065)	(0.146)	(0.166)
lpol_stab	0.040	0.031	0.032	0.048	0.065	0.089	0.122	0.072
	(0.145)	(0.124)	(0.086)	(0.098)	(0.100)	(0.098)	(0.115)	(0.074)
let_mean	-0.052	0.157	0.306	0.396	0.449	0.452	0.734	0.315
	(0.777)	(0.754)	(0.541)	(0.594)	(0.643)	(0.631)	(1.323)	(0.631)
lr_oil_px_mean	0.032	0.057	0.047	0.067*	0.069	0.061	0.047	-0.017
	(0.039)	(0.041)	(0.037)	(0.040)	(0.049)	(0.052)	(0.114)	(0.056)
linfl_mean	0.019	-0.104	-0.088	-0.251	-0.245	-0.219	-0.084	0.172
	(0.171)	(0.222)	(0.236)	(0.248)	(0.273)	(0.289)	(0.399)	(0.271)
lpol_stab_mean	0.144	0.152	0.095	0.123	0.031	-0.144	-0.171	-0.321
	(0.166)	(0.204)	(0.186)	(0.225)	(0.297)	(0.322)	(0.577)	(0.340)
Constant	-13.683***	-12.745***	-12.256***	-10.837***	-10.382***	-9.935***	-7.669*	-3.176
	(1.274)	(1.406)	(1.431)	(1.597)	(2.002)	(2.091)	(4.006)	(3.055)
Obs	240	240	240	240	240	240	240	240

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.10$

From the IQR estimator in Table 9, we check the robustness of our SEE estimator and observe that overall, the IQR estimator displays similar effects to the SEE estimator, however, there is differences in coefficient values of the variables. This underlying difference is because both estimators approximate the original moment condition in different ways. The latter (SEE) uses kernel approach to approximate the original estimation equation. For the relationship between lco2 and let, the results indicate a significantly strong negative relationship across all quantiles of the energy transition distribution at 1% significance level. This relationship suggests that higher levels of CO_2

emissions are associated with lower progress in energy transition, reflecting the detrimental impact of carbon-intensive economies on clean energy adoption. Notably, this effect fluctuates across the distribution from -1.703% at the 10^{th} quantile, declines at the 20^{th} quantile, rises at the 30^{th} and 40^{th} quantiles and declines to -1.637% at the 50^{th} quantile. It then rises at the 60^{th} quantile and falls at the 70^{th} quantile through to the 80^{th} quantile (-1.461%). This means that for countries at lower-and-mid-transitions, the results indicate a mixed effect of CO2 emissions. Subsequently, the percent decline in CO_2 emissions at the higher quantiles shows that the effect of CO2 emissions is minimal in countries at advanced stages of the energy transition. Similarly, the estimated coefficient of lex indicates a fluctuation in the magnitude of the negative effect across the distribution (0.10 – 0.80). While this relationship suggests that exchange rate fluctuations are associated with declining energy transition progress, there is heterogeneity in the specific effects across the distribution.

With regards to the relationship between economic growth (lgdp) and energy transition (let), we find a significant negative effect across the distribution. This suggests that a 1% increase in GDP yields a 0.132% decrease in energy transition at the 10^{th} quantile, and then declines to 0.168% and 0.164% at the 40th and 50^{th} quantiles. The effect, then rises again through to 0.229% decrease at the 80^{th} quantile. The relationship between population growth rate (lpop) and energy transition reflects a negative effect across the distribution, albeit the results exhibit statistical significance at the 80^{th} quantile only. This means that a 1% increase in lpop leads to a 0.186% decrease in energy transition among countries with lower energy transition levels (10^{th} quantile). This negative effect decreases initially across the 20^{th} and 30^{th} quantiles, and increases from the 40^{th} and 50^{th} quantiles. The effect declines at the 60^{th} quantile and sees a further rise to -0.181% in countries at advanced-energy transition levels (80^{th} quantile). Between ecological footprint and energy transition, we find a positively significant effect across the distribution, albeit this effect diminishes in countries with moderate to advanced-energy transition levels. This suggests that a 1% increase in ecological footprint yields a 0.687% increase in energy transition at the 10^{th} quantile, 0.528% increase at the 50^{th} quantile, and 0.220% increase at the 80^{th} quantile.

In addition, as a robustness check, the IV two-stage least squares regression model in Table 9 yields similar results to the smoothed (CCE) IV-QR model at the median (50^{th} quantile). The findings indicate a strong negative relationship between carbon dioxide emissions (lco2) and energy transition. Specifically, a 1% increase in lco2 results in a 1.672% decline in energy transition. We find a significant negative association between exchange rate and energy transition at 1% significance level. This suggests that a 1% increase in the exchange rate leads to an approximate 0.105% decrease in energy transition. The results indicate a strong negative effect of population growth on energy transition, with a 1% increase in population growth resulting in a 0.145% decrease in energy transition. Intuitively, a rising population signifies an increasing demand for energy sources. Additionally, the findings reveal a negative effect of economic growth (-0.210%) on energy transition, a -0.034% effect of inflation rate on energy transition and a 0.008% effect of real oil price on energy transition. Regarding ecological footprint, the results indicate that a 1% increase in ecological footprint corresponds to a 0.544% increase in the energy transition.

From Appendix Table 12, the post-estimation test of endogenous effects displays four hypotheses being tested. For the test of the null hypothesis of no effect, the Kolmogorov-Smirnoff statistic is 48.331 which is greater than the critical value of 2.47. Thus, at a 95% confidence level, we reject the null hypothesis and conclude that the specified endogenous variable (lco2) has some effect on energy transition. For the test of the null hypothesis of constant effect, the Kolmogorov-Smirnoff statistic is 2.293 which is greater than the critical value of 2.245. Thus, we reject the null hypothesis at a 95% confidence level and conclude that the effects of CO_2 emissions on energy transition varies across the estimated quantiles. Regarding the test of the null hypothesis of dominance, the statistic of 26.495 is greater than 2.259. Hence, we reject the null hypothesis and conclude that the effects of CO_2 emissions are not strictly positive across the estimated quantiles. For the test of the null hypothesis of exogeneity, the Kolmogorov-Smirnoff statistic is 3.319 which is greater than the critical value of 2.187. Thus, we reject the null hypothesis and conclude that lco2 is endogenous.

From Appendix Table 13, the post-estimation results of the Pesaran cross-sectional dependence test justifies the inclusion of cross-sectional averages in our model as the CD-statistic (-0.775) displays an insignificant result with a p-value of 0.4387 which is greater than 1% significance level. We reject the null hypothesis of strong cross-sectional dependence within our model. Cross-sectional averages were included to address potential unobserved common factors that could introduce bias. Although the averages (let_mean, lr_oil_px_mean, linfl_mean, and lpol_stab_mean) were statistically insignificant, we retained them for the robustness of our results.

4.1.6 Robustness Checks

Table 7. Instrumental Variable Quantile Regression (IQR Estimator)

	IQR Estimator							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	q10	q20	q30	q40	q50	q60	q70	q80
lco2	-1.703***	-1.625***	-1.636***	-1.646***	-1.637***	-1.655***	-1.629***	-1.461***
	(0.089)	(0.074)	(0.065)	(0.034)	(0.036)	(0.042)	(0.071)	(0.175)
lex	-0.172***	-0.143***	-0.132***	-0.140***	-0.111**	-0.038	-0.032	-0.059*
	(0.055)	(0.036)	(0.033)	(0.032)	(0.050)	(0.041)	(0.035)	(0.034)
lgdp	-0.132**	-0.189***	-0.222***	-0.168***	-0.164*	-0.251***	-0.252**	-0.229
	(0.061)	(0.054)	(0.053)	(0.061)	(0.085)	(0.078)	(0.108)	(0.147)
lpop	-0.186	-0.075	-0.060	-0.104	-0.133	-0.077	-0.119	-0.181*
	(0.119)	(0.103)	(0.097)	(0.086)	(0.115)	(0.078)	(0.101)	(0.107)
lr_oil_px	-0.002	-0.000	0.004	-0.003	0.001	-0.000	0.013	0.020
	(0.008)	(0.009)	(0.010)	(0.011)	(0.013)	(0.015)	(0.023)	(0.024)
linfl	0.005	-0.014	-0.035	0.048	0.076	0.040	0.065	-0.008
	(0.053)	(0.068)	(0.060)	(0.057)	(0.062)	(0.061)	(0.093)	(0.142)
leco_fp	0.687***	0.700***	0.681***	0.571***	0.528***	0.560***	0.470***	0.220
	(0.056)	(0.045)	(0.046)	(0.061)	(0.082)	(0.066)	(0.104)	(0.191)
lpol_stab	0.063	0.041	0.030	0.055	0.083	0.097	0.097	0.084
	(0.118)	(0.098)	(0.087)	(0.098)	(0.133)	(0.105)	(0.106)	(0.096)
let_mean	0.022	0.095	0.193	0.322	0.174	0.460	0.435	0.336
	(0.660)	(0.517)	(0.530)	(0.560)	(0.645)	(0.614)	(0.573)	(0.575)
lr_oil_px_mean	0.019	0.016	0.034	0.079**	0.053	0.081*	0.018	-0.017
	(0.033)	(0.032)	(0.035)	(0.039)	(0.055)	(0.049)	(0.067)	(0.055)
linfl_mean	-0.001	-0.009	-0.051	-0.244	-0.208	-0.165	0.034	0.253
	(0.160)	(0.208)	(0.229)	(0.238)	(0.278)	(0.291)	(0.279)	(0.290)
lpol_stab_mean	0.055	0.098	0.068	0.139	0.038	-0.046	-0.363	-0.237

	(0.147)	(0.187)	(0.189)	(0.223)	(0.272)	(0.305)	(0.398)	(0.310)
Constant	-13.698***	-13.780***	-13.153***	-10.674***	-9.962***	-10.166***	-8.079***	-3.171
	(1.155)	(1.295)	(1.424)	(1.557)	(2.097)	(1.991)	(2.627)	(3.544)
Obs	240	240	240	240	240	240	240	240

Robust standard errors in parentheses
*** *p<0.01, ** p<0.05, * p<0.10*

Table 8. Instrumental Variable 2 Stage Least Squares Estimation
Instrumental Variable (2SLS) Estimation Results

let	Coefficient	Robust std. err.	z	P>z	[95% conf.	interval]
lco2	-1.671***	0.032	-51.490	0.000	-1.735	-1.608
lex	-0.105***	0.024	-4.290	0.000	-0.153	-0.057
lgdp	-0.210***	0.052	-4.020	0.000	-0.313	-0.108
Lpop	-0.192***	0.069	-2.800	0.005	-0.326	-0.057
lr_oil_px	0.008	0.016	0.520	0.605	-0.023	0.039
linfl	-0.034	0.056	-0.610	0.545	-0.144	0.076
leco_fp	0.545***	0.043	12.540	0.000	0.459	0.630
lpol_stab	0.082	0.064	1.280	0.199	-0.043	0.207
let_mean	0.641	0.485	1.320	0.186	-0.309	1.592
lr_oil_px_mean	0.065	0.042	1.540	0.124	-0.018	0.147
linfl_mean	-0.019	0.215	-0.090	0.930	-0.441	0.403
lpol_stab_mean	0.005	0.204	0.020	0.981	-0.395	0.405
_cons	-9.441***	1.456	-6.480	0.000	-12.295	-6.587

*** *p<0.01, ** p<0.05, * p<0.10*

4.1.6 Discussion

CO_2 emissions and energy transition: The results indicate a consistently significant negative relationship between CO_2 emissions (lco2) and energy transition (let). This highlights the role of carbon emissions as a deterrent to progress in energy transition. The varying effect across quantiles—ranging from -1.710% at the 10th quantile to -1.450% at the 80th quantile, with marginal increases from -1.641% at the 40th quantile to -1.656% at the 50th quantile—indicates that the impact of CO_2 emissions is not uniform across the distribution of energy transition progress. The negative relationship suggests that higher carbon emissions are associated with lower levels of energy transition progress. However, the observed amplification and subsequent marginal rise across quantiles imply that the marginal effect of CO_2 emissions differs depending on a country's energy transition status. At lower quantiles (10th quantile), **c**ountries at the early stages of energy transition face significant challenges in reducing carbon emissions, as their energy systems are heavily reliant on fossil fuels.

This is consistent with the results of Lau et al. (2023), Taghizadeh-Hesary and Rasoulinezhad (2020), and Zambrano-Monserrate (2024), who find that countries with high carbon emissions typically exhibit slower adoption of renewable energy technologies due to structural reliance on carbon-intensive infrastructure. The marginal rise in the negative effect between the 40th and 50th quantiles may indicate that, mid-transition countries after sometime experience difficulties in reducing carbon emissions due to technological, institutional, or financial constraints. This aligns with Grubert and Hastings-Simon (2022), who posit that mid-transition countries experience bottlenecks, such as the cost of replacing fossil-fuel-based infrastructure and limited public support for transition policies. At higher quantiles (80th quantile), **t**he declining negative effect suggests that countries with advanced energy transition programs may have decoupled CO_2 emissions from economic activity through greater reliance on renewables and energy efficiency measures. This finding diverges from Friedrichs and Inderwildi (2013), who argue that even high-transition countries struggle to mitigate carbon emissions entirely due to economic and industrial pressures. The observed fluctuation in the 40^{th} and 50^{th} quantiles may reflect heterogeneity in institutional capacity or policy implementation across countries.

The results have critical implications for policymakers aiming to accelerate energy transition while addressing carbon emissions. Low-transition countries require international assistance in the form of technology transfers, green financing, and capacity-building programs to overcome structural reliance on fossil fuels. Policies must focus on reducing CO_2 emissions while promoting affordable and accessible renewable energy options. The Paris Agreement provides a framework for encouraging such efforts through nationally determined contributions (NDCs). High-transition countries must prioritize policies that address residual CO_2 emissions, such as carbon capture and storage (CCS) and advanced energy efficiency measures.

Exchange rate and energy transition: The results reveal a significant negative relationship between the exchange rate (lex) and energy transition (let). This effect declines in magnitude as we move up the quantile distribution, from -0.151% at the 10th quantile to -0.079% at the 80th quantile. However, there are fluctuations at the 40^{th} quantile and 70^{th} quantiles, though the effects of these marginal increases are greater at the lower quantile than at the higher quantile. Overall, the diminishing negative impact suggests that the role of exchange rate fluctuations is more pronounced in countries at the lower stages of energy transition compared to those at higher stages. At lower quantiles (10th Quantile), the exchange rate has a stronger negative impact in countries with low levels of energy transition. This is likely because countries at early stages of energy transition often rely on imports of renewable energy technology, infrastructure, and expertise, making them more vulnerable to exchange rate volatility. A depreciation of the domestic currency increases the cost of importing these critical inputs, slowing the energy transition process.

This finding aligns with Yazdanie et al. (2024) who emphasize that exchange rate fluctuations significantly affect the scale and timing of renewable energy investments in developing economies due to high import dependency. At higher quantiles (80th Quantile), the negative impact of exchange rate fluctuations declines in countries more advanced in energy transition levels. These countries often have a stronger domestic renewable energy industry or have diversified their energy mix, reducing their reliance on imported technology. The marginal rise at the 70^{th} quantile may indicate that advanced countries may also face negative repercussions of exchange rate fluctuations. The findings align with Hong et al. (2024), who find that exchange rate effects remain significant even in advanced economies. Meanwhile the declining effect at the 80^{th} quantile may suggest that structural factors, such as energy self-sufficiency and economic resilience, may mitigate this vulnerability. Cherni and Jouini (2017) posit that currency depreciation adversely affects renewable energy investments in emerging economies, a finding that supports the stronger impact at lower quantiles in this study. Similarly, Li et al. (2023) note that volatile exchange rates deter long-term renewable energy infrastructure projects due to increased costs and uncertainty. However, the diminishing effect at higher quantiles (80th quantile) observed here contrasts with Deka et al. (2023), who argue that exchange rate volatility can have persistent negative effects across all stages of renewable energy development. This difference could be attributed to the inclusion of cross-sectional dependence adjustments in this study, which account for structural factors that mitigate exchange rate sensitivity.

The results underscore the need for exchange rate stabilization and support mechanisms to facilitate energy transition. For low-transition countries (lower quantiles), policies aimed at stabilizing exchange rates, such as targeted monetary interventions or hedging mechanisms, can reduce the cost of renewable energy imports. International financial support, such as concessional loans or grants, could shield developing countries from exchange rate risks when procuring renewable energy technology. On the other hand, advanced-transition countries (higher quantiles) should focus on fostering domestic renewable energy industries to reduce reliance on imports, thereby insulating themselves from exchange rate fluctuations. For instance, countries like Germany and Denmark, which lead in renewable energy adoption, have robust local industries producing renewable energy technologies, reducing their exposure to currency volatility.

GDP and energy transition: The results demonstrate a negative relationship between GDP and energy transition across all quantiles, suggesting that higher levels of GDP are associated with slower rates of energy transition. This finding may be reflective of structural challenges in high-GDP economies, where significant reliance on fossil fuels has created institutional and infrastructural inertia. This aligns with York and McGee (2017) study which argue that economically advanced countries face barriers in achieving energy transitions due to their embedded dependence on carbon-intensive energy systems. However, the findings contrast with research on low-income countries, such as Bhattacharya et al. (2016), which shows that rising GDP in developing countries supports energy transition by enabling investments in renewable energy technologies. The growing magnitude of the negative effect—from -0.150% at the 10th quantile to -0.229% at the 60th quantile—indicates that this relationship strengthens as energy transition levels increase. At lower levels of energy transition, the weaker negative relationship suggests that GDP has a less restrictive effect, potentially because low-transition countries are at earlier stages of adopting renewable energy, where initial efforts are relatively straightforward and less costly.

This pattern aligns with Fowlie and Meeks (2021), who find that low-transition countries benefit from low-hanging fruit opportunities such as improving energy efficiency or utilizing small-scale renewable projects. As countries progress toward higher levels of energy transition, the negative effect of GDP intensifies. This may reflect that high-GDP countries with advanced infrastructure rely heavily on fossil fuels, making transitions increasingly complex as more ambitious goals are pursued. Additionally, initial renewable energy investments (e.g., solar and wind) are relatively inexpensive, but scaling up to cover larger portions of energy demand becomes progressively harder. This finding corresponds to Jenkins et al. (2018), who highlight the challenges of decarbonizing high-income economies due to structural barriers.

This result may reflect possible trade-offs in policy and economic priorities where economies with higher GDP typically have higher energy demand, making it harder to meet this demand solely with renewable energy sources. High-GDP countries often prioritize maintaining economic growth, which may temporarily conflict with energy transition goals. This is in line with Grossman and Krueger's (1995) growth-environment dilemma. However, as countries approach advanced stages (70th and

80th quantile) of the transition we see declines in GDP effect on energy transition. This is in line with Sadorsky (2009), who suggests that high-GDP economies can accelerate energy transition by leveraging greater financial capacity to fund advanced green technologies. The results may also reflect the economies of scale that advanced economies may enjoy in reaching higher levels of energy transition which can help them have some respite from the negative effect of increasing GDP growth on the transition. Policymakers in advanced economies need to address entrenched barriers by incentivizing innovation through providing subsidies for green technologies that address large-scale energy needs. Countries should reform policies to align economic growth strategies with energy transition goals. International cooperation to share best practices and technologies may help high-GDP countries overcome barriers to transition. For instance, Peters et al. (2020) argue that collaborative renewable energy projects in developed countries can accelerate the global transition.

Population growth and energy transition: The results indicate a consistent negative relationship between population (lpop) and energy transition (let). This suggests that population growth or density is negatively associated with progress toward energy transition. A larger population often increases energy demand, particularly in developing economies where traditional energy sources (e.g., coal, oil) dominate. This dependence creates pressure on governments to prioritize meeting energy needs over transitioning to renewable sources, consistent with the energy access vs. energy sustainability trade-off discussed by Smil (2017). This finding aligns with Taghizadeh-Hesary and Rasoulinezhad (2020), who argue that higher population growth increases reliance on non-renewable energy, especially in economies that lack adequate investment in renewable infrastructure. Similarly, York et al. (2003) emphasize that larger populations are often associated with higher CO_2 emissions, which correlates with delayed energy transition. The effect of lpop on let shows significant heterogeneity across the energy transition distribution. At lower quantiles (10th quantile), the negative effect of population is strongest (-0.184%) at the lower end of the energy transition spectrum. This suggests that in countries with low levels of energy transition, population growth is a significant barrier to progress. These countries often have limited financial resources to invest in renewable energy and a greater dependence on traditional energy sources to meet basic energy needs.

These results are consistent with Hanif et al. (2019), who note that population growth in developing economies exacerbates delays in energy transitions due to competing priorities such as energy access and poverty reduction. However, this effect eases from the 20th quantile and picks up again only at the 40th quantile (-0.109%) and falls to -100% and -0.083% at the 50th and 60th quantiles, indicating that in countries with moderate levels of energy transition, the population's impact on energy transition is mixed. These countries are likely benefiting from investments in renewable energy technologies which help reduce the energy burden from population growth and enhanced policies for energy efficiency in populous regions. This partly aligns with Jones et al. (2015), who found that even middle-income countries with moderate energy transitions still face population-related constraints due to urbanization-driven energy demands. Likewise, the findings diverge from the studies of Akintande et al. (2020) as well as Owjimehr and Samadi (2022), who identified a positive association between population size and renewable energy consumption. At higher quantiles (70th and 80th quantiles), the negative relationship strengthens again (-0.200% and -0.220% respectively), reflecting renewed challenges for high-transition countries. These challenges may include overburdened Infrastructure and diminishing returns. This pattern mirrors results from York and Rosa (2003) study, which showed that larger populations place disproportionate pressure on environmental systems, even in countries with advanced green energy policies. The findings reveal a non-linear relationship between population and energy transition, with the strongest negative effects observed at the tails of the energy transition distribution. This reflects the dual nature of population as both a driver of energy demand and a constraint on renewable energy deployment. At lower quantiles, countries with low energy transition levels are caught in a cycle of high population growth, increasing energy demand, and insufficient investment in renewables. At higher quantiles, population pressures in high-transition countries reflect the limits of existing infrastructure to meet large-scale demand sustainably.

The results suggest that population dynamics play a critical role in shaping energy transition outcomes, necessitating tailored policy approaches. For low-transition countries, policies should prioritize balancing energy access with investments in renewables to ensure population growth does not exacerbate dependence on fossil fuels. Studies like Liddle and Lung (2010) recommend expanding distributed renewable energy systems (e.g., solar home systems) in rural and rapidly growing regions. For high-transition countries, Investments in advanced grid systems and large-scale renewable installations are essential to meet the demands of large populations. Additionally, Peters et al. (2020) highlights that encouraging sustainable consumption patterns can help mitigate the strain of population growth.

Ecological footprint and energy transition: The results indicate a consistently significant positive relationship between ecological footprint (leco_fp) and energy transition (let). This suggests that countries with a higher ecological footprint are more likely to engage in energy transition. However, the declining effect across quantiles—from 0.665% at the 10th quantile to 0.229% at the 80th quantile—indicates that the marginal impact of ecological footprint on energy transition weakens as countries achieve higher levels of energy transition. For countries with low energy transition levels, a high ecological footprint could serve as a wake-up call, motivating policy actions and public demand for transitioning to renewable energy. For countries already progressing in energy transition, the diminishing effect might reflect diminishing returns or saturation, where additional pressure from ecological footprint has a smaller impact due to established energy transition systems. The declining effect across quantiles may reflect different country-specific dynamics, such as levels of economic development, institutional capacity, or public awareness. A high ecological footprint is often associated with excessive resource exploitation and environmental degradation, which can drive policy reforms to promote clean energy. Countries in this group may also face international pressure, such as climate agreements or trade penalties linked to environmental performance, motivating stronger action.

This result aligns with York and Rosa (2003), who find that countries with larger ecological footprints tend to adopt more stringent environmental policies in response to higher environmental stress. On the other hand, high-transition countries (80th Quantile) which have advanced energy transition programs in place may already have implemented robust policies that address the ecological footprint, leaving limited room for additional impact. The declining effect may also indicate that energy transition becomes more complex or costly at higher levels, as countries approach technological or policy frontiers. This finding differs from Knight and Schor (2014), who demonstrate that the ecological footprint consistently motivates sustainable development across all stages of transition. The observed decline in the marginal effect may indicate heterogeneity in institutional readiness or resource constraints.

Policymakers in these countries should leverage the environmental urgency reflected by a high ecological footprint to prioritize investments in renewable energy infrastructure and incentives.

International collaborations, such as technology transfer agreements, can further enhance the effectiveness of such initiatives. For countries at advanced stages of energy transition, marginal gains may require breakthroughs in storage technologies, smart grids, and energy efficiency improvements, which go beyond conventional renewable adoption. Wiedmann et al. (2020) emphasize the need for high-transition countries to adopt a systemic approach to energy transition, focusing on long-term sustainability beyond just reducing ecological footprint.

Inflation and energy transition: The results reveal a heterogenous but insignificant relationship between inflation (linfl) and energy transition (let). This reflects a negative relationship at 10th quantile (-0.019%) and then turns positive at the 20th quantile (0.009%) and thereafter turns negative at 30th quantile (-0.014%). Subsequently, from the 40th to the 70th quantile, the results remain positive until the 80th quantile where it turns negative (-0.048%). With negative effects at lower and upper quantiles and positive effects at intermediate quantiles, the results reflect the dynamic nature of inflation's impact, contingent upon the stage of energy transition development. At the 10th quantile, the negative relationship may stem from inflation-induced investment constraints in countries with low energy transition levels. In contrast, the positive effects observed between the 20th and 70th quantiles suggest that moderate inflation may stimulate energy transition through enhanced liquidity and reduced real interest rates. However, the return to a negative relationship at the 80th quantile indicates that inflation may hinder further progress in countries with advanced energy transition levels, potentially due to rising maintenance costs or crowding out of green investments.

These findings align with studies highlighting the dual role of inflation in energy transition. Sadorsky (2010) emphasize the negative effects of inflation on energy investments, particularly in low-transition countries. Similarly, Omri et al. (2015) along with Ibrahim and Law (2016) demonstrate that inflation's impact is heterogeneous, depending on institutional quality and economic structure. The positive effects observed at intermediate quantiles are consistent with Baek (2016) coupled with that of Bildirici and Kayıkçı (2013), who argue that mild inflation can promote green investments under conducive macroeconomic conditions. These findings underscore the importance of tailored inflation management policies to support energy transition. For low-transition countries, stabilizing inflation is critical to fostering green investments. In contrast, intermediate-transition countries may benefit from leveraging mild inflation, while advanced-transition countries should prioritize controlling inflation to sustain progress

5.0 Conclusion

Energy transition has become a pressing issue in recent years. The current study presents a comprehensive and nuanced investigation into the factors driving energy transition. The study makes valuable contributions to the sustainable energy transition literature and enhances our understanding of the complex nature of the energy transition dynamics of the expanding BRICS bloc. Utilizing annual data from 1996 to 2019, the study analyzes the energy transition dynamics of the 10 full members of BRICS. The study employs the smoothed (CCE) IV-QR regression framework to empirically examine the heterogeneous relationships between energy transition and key macroeconomic, environmental, and governance variables. We uncover significant insights that contribute to the broader understanding of factors influencing sustainable energy transitions.

Our findings highlight the multifaceted role of economic, environmental, and structural factors. For instance, the negative relationship between CO_2 emissions and energy transition, which fluctuates across the distribution, underscores the heterogeneity in the impact of CO_2 emissions on energy transition. Similarly, the heterogeneous impact of inflation and GDP on energy transition reflects the varying capacities of countries at different stages of transition to respond to macroeconomic challenges. While inflation adversely affects low-transition countries, moderate inflation appears to stimulate progress in intermediate-transition economies, aligning with prior evidence on the liquidity-enhancing effects of controlled inflation. Similarly, the positive but declining impact of ecological footprint suggests that environmental pressures initially drive energy transition efforts but become less pronounced as countries achieve higher levels of transition. Our methodological approach accounts for cross-sectional dependence and unobserved heterogeneity, ensuring robust and reliable results. By incorporating cross-sectional averages and addressing potential endogeneity through appropriate instruments, such as fossil fuel reserves and temperature anomalies, we provide an empirically grounded framework that aligns with the realities of interconnected global energy systems. Robustness checks from the inverse quantile regression framework and IV two-stage least squares model further validate the robustness of our findings. Sensitivity analyses for the reduced data also confirms the appropriateness of the interpolated data and methodological adjustments.

The policy implications of this research are profound. Governments and international organizations must prioritize tailored interventions that consider the stage-specific challenges of energy transition. Policies aimed at reducing CO_2 emissions, stabilizing inflation, and leveraging moderate energy pricing are critical for fostering sustainable energy systems. Additionally, targeted support for low-transition countries is essential to overcome structural barriers and accelerate their progress toward clean energy adoption. This study contributes to the growing body of literature on energy transition by offering a granular understanding of the drivers and barriers across the distribution of energy transition levels. By situating our findings within existing research, we reconcile varying perspectives and provide actionable insights for policymakers and researchers. Future research could extend this framework by exploring the role of emerging technologies, geopolitical dynamics, and global energy markets in shaping the trajectory of energy transitions. With regards to methodological rigor, novel methodological approaches such as the dynamic (CCE) IV-QR framework can be explored to compare and expand the findings of this study. Furthermore, a comparison between the BRICS+ bloc and other developed economic blocs such as the EU would add valuable contributions to the literature.

In conclusion, our findings emphasize the complex interplay of economic, environmental, and institutional factors in driving energy transitions, highlighting the need for coordinated, context-specific strategies to achieve global sustainability goals. These insights serve as a foundation for advancing both academic discourse and practical policymaking in the critical quest for a sustainable energy future.

Appendices

Table 9. Smooth (CCE) IV-QR Model with reduced data (non-interpolated data)

	Smooth Estimator			IQR Estimator		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	q20	q50	q80	q20	q50	q80
lco2	-1.607***	-1.639***	-1.499***	-1.599***	-1.638***	-1.423***
	(0.064)	(0.043)	(0.204)	(0.069)	(0.046)	(0.172)
lex	-0.136***	-0.134***	-0.079*	-0.147***	-0.128***	-0.080**
	(0.031)	(0.037)	(0.042)	(0.032)	(0.039)	(0.040)
lgdp	-0.226***	-0.218***	-0.278**	-0.221***	-0.217**	-0.202
	(0.055)	(0.083)	(0.140)	(0.052)	(0.087)	(0.131)
lpop	-0.012	-0.059	-0.126	-0.006	-0.091	-0.139
	(0.104)	(0.113)	(0.138)	(0.100)	(0.117)	(0.126)
lr_oil_px	0.007	0.019	0.037	0.004	0.013	0.035
	(0.011)	(0.015)	(0.033)	(0.011)	(0.016)	(0.031)
linfl	-0.037	-0.019	-0.287	0.004	0.008	-0.270
	(0.073)	(0.071)	(0.209)	(0.093)	(0.070)	(0.209)
leco_fp	0.690***	0.580***	0.246	0.728***	0.572***	0.160
	(0.048)	(0.100)	(0.201)	(0.049)	(0.104)	(0.163)
lpol_stab	0.073	0.155	0.057	0.063	0.155	0.023
	(0.137)	(0.224)	(0.062)	(0.134)	(0.227)	(0.044)
let_mean	0.254	0.235	0.463	0.140	0.119	0.377
	(0.246)	(0.404)	(0.484)	(0.247)	(0.398)	(0.441)
lr_oil_px_mean	0.040	0.032	-0.001	0.019	0.013	-0.001
	(0.041)	(0.061)	(0.070)	(0.040)	(0.063)	(0.064)
linfl_mean	-0.138	0.006	0.297	-0.110	0.136	0.255
	(0.248)	(0.379)	(0.348)	(0.244)	(0.395)	(0.290)
lpol_stab_mean	0.071	-0.137	-0.329	0.052	-0.275	-0.174
	(0.209)	(0.337)	(0.395)	(0.226)	(0.353)	(0.347)
Constant	-13.286***	-10.939***	-3.068	-14.131***	-11.044***	-1.651
	(1.061)	(2.408)	(3.441)	(1.095)	(2.591)	(2.844)
Observations	193	193	193	193	193	193

Robust standard errors in parentheses

**** p<0.01, ** p<0.05, * p<0.10*

Note: intermediate quantiles are omitted as they show similar trends

Table 10. Pesaran's CD-Test for Cross-sectional Dependence

Variable	CD-test	p-value	average joint T	mean ρ	mean abs(ρ)
residual	7.718***	0.000	24.000	0.230	0.560

****p<0.01, **p<0.05, *p<0.10*

Table 11. Tests for Cointegration

	Statistic	P-value
Kao test		
Modified Dickey-Fuller *t*	5.148***	0.000
Dickey-Fuller *t*	9.939***	0.000
Augmented Dickey-Fuller *t*	5.495***	0.000
Unadjusted modified Dickey-Fuller *t*	6.615***	0.000
Unadjusted Dickey-Fuller *t*	8.325***	0.000
Westerlund test		
Variance ratio	2.176***	0.015

****p<0.01, **p<0.05, *p<0.10*

Fig. 4 Coefficient plot for endogenous variable (lco2)

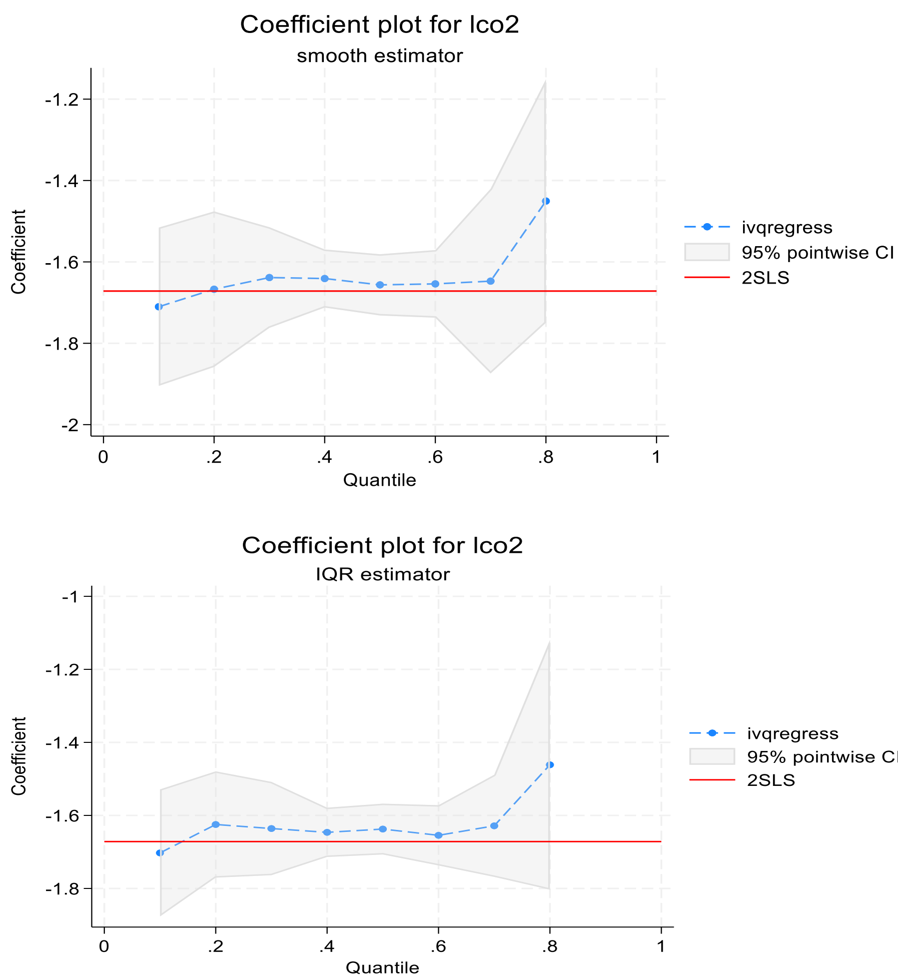

Table 12. Tests for endogenous effects

Null hypothesis	KS-Statistic	95% critical values
No effect	48.331	2.470
Constant effect	2.293	2.245
Dominance	26.495	2.259
Exogeneity	3.319	2.817

Note: If the KS statistic < critical value, there is insufficient evidence to reject the null hypothesis. (KS = Kolmogorov–Smirnov)

Table 13. Post-Estimation Pesaran's CD Test

Variable	CD-test	p-value	average joint T	mean ρ	mean abs(ρ)
Res	-0.775	0.438	24.00	-0.02	0.29

****p<0.01, **p<0.05, *p<0.10*

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