Received: 15 April 2024 | Revised: 8 August 2024 | Accepted: 18 August 2024

DOI: 10.1002/mde.4377

RESEARCH ARTICLE

WILEY

Striding towards a greener future: Unlocking the potential of natural resources and employment dynamics in green energy transition in sub-Saharan Africa

Kingsley I. Okere[1] | Stephen Kelechi Dimnwobi[2,3] | Ismail O. Fasanya[1]

[1]School of Economics and Finance, University of the Witwatersrand, Johannesburg, South Africa

[2]Department of Economics, Nnamdi Azikiwe University, Awka, Nigeria

[3]Strategy, Execution and Evaluation (SEE) Office, Awka, Nigeria

Correspondence
Kingsley I. Okere, School of Economics and Finance, University of the Witwatersrand, Johannesburg, South Africa.
Email: kingsley.okere@wits.ac.za

Abstract

The adoption and utilization of renewable energy offer potential benefits such as enhanced energy efficiency, cost savings, and ecological advantages. However, a key research question addressed in this analysis is whether natural resource rent and employment dynamics influence renewable energy consumption in Africa. Previous research has predominantly focused on the aggregate employment rate, overlooking the nuances of labor diversity across sectors and employment types. Hence, this study evaluates the importance of natural resource rent and employment in driving the transition to green energy in sub-Saharan Africa from 1991 to 2022. It employs the innovative method of moments quantile regression (MMQR) model for this purpose. The findings reveal a positive connection between natural resource rent and the adoption of green energy. When considering employment types, the study observes that self-employment and wages/salaried workers undermine clean energy utilization. Moreover, the study highlights that employment across key economic sectors also plays a role. While employment in the agriculture and service sectors fosters green energy utilization, employment in the industrial sector impedes renewable energy consumption. To advance the development of green energy in Africa, this study underscores a range of policy options.

1 | INTRODUCTION

The urgency of addressing environmental degradation has become paramount on the global stage, requiring immediate and concerted action (Çakmak et al., 2024; Ezenekwe et al., 2024). The combustion of fossil fuels for energy production has been a major contributor to the escalation of carbon emissions, leading to disruptions in weather patterns and environmental upheavals (Dimnwobi et al., 2021; Okere et al., 2024). The increasing negative effect of this crisis on humanity and the ecosystem necessitates the shift to eco-friendly lifestyles (Liu & Lu, 2023). This transition is essential for reducing ecological damage and guaranteeing a carbon-free future. To meet this crucial demand, renewable energy has emerged as a viable means of attaining a green society (Jin & Huang, 2024; Olanrewaju et al., 2019; Onuoha et al., 2023a). While the shift towards clean energy is critical and widely encouraged, the significant upfront costs involved in these projects can also make it difficult for nations to embrace these initiatives (Li & Tong, 2024; Omoju et al., 2024; Onuoha et al., 2023b). Natural resource rents, which act as a financial reservoir, present a potent option for economies to advance the utilization of green energy options (Han et al., 2023). The prudent utilization of revenue from resource rents to fund green energy can create a financial buffer, thereby reducing the increased risk linked with high upfront expenses for green alternatives. The revenue from these resources can also be employed to fund incentives or inducements for clean energy technologies, thereby making them more affordable and widely accessible (Han et al., 2023; Yuan et al., 2023). Employment also plays a vital role in stimulating the widespread usage of green energy (Zhao & Luo, 2017). The expansion in employment levels can boost purchasing power and economic stability, which will enable enterprises and individuals to fund eco-friendly energy options (Przychodzen & Przychodzen, 2020). Additionally, employment growth could contribute to more prosperous and stable societies that can champion and enforce green energy strategies (Karmaker et al., 2023).

Sub-Saharan Africa (SSA) provides an excellent context for assessing the influence of natural resources, employment, and clean energy consumption for at least three critical reasons. First, the region depends significantly on conventional biomass, which accounts for 66% of the final energy use in these economies (International Energy Agency [IEA], 2020). Notwithstanding the region's huge potential for renewable energy, it is yet to be fully exploited. For instance, in 2018, renewables accounted for 26% of power generation, 8% of final energy use, and 7% of the total primary energy supply (International Renewable Energy Agency [IRENA], 2020). The region also has one of the world's richest solar resources, but it currently only boasts around 5 GW of solar photovoltaic (PV), representing less than 1% of the global share of solar PV (IEA, 2019). This underlines the significant underemployment of clean energy potential in the region. Besides, since 2000, clean energy consumption as a portion of overall energy use in SSA has been decreasing (World Bank, 2023). The major concern for this underutilization of clean energy in this region is that they are the worst hit by the climate crisis despite making a negligible contribution to global carbon emissions (Dimnwobi, Okere, Onuoha, et al., 2023). Additionally, the region, unlike its developed counterparts, has a weak adaptation framework to climate change. SSA economies are signatories to the Paris climate agreement, which strives to lessen global emission levels. Green energy possesses the potential to mitigate the emission level and address the energy access divide in the region owing to the significant green energy resources (Dimnwobi, Madichie, et al., 2022). Therefore, there is a pressing requirement to advocate for the development and utilization of clean energy in Africa. Second, natural resource rents provide an avenue that can be utilized to further develop the region's green energy sector. SSA boasts significant resource reserves. For instance, Nigeria, Angola, and Gabon, among others, have vast oil, diamond, and gold reserves (Nwani et al., 2023). The huge resource deposits in these economies also translate to a significant contribution to the region's economic growth. In 2021, natural resource rents as a share of GDP in SSA stood at 10%, which is significantly more than the world's average of 3% (World Bank, 2023). The abundance of these resources in this region provides a notable prospect for SSA to pivot towards sustainable energy. Tactical and judicious use of revenue derived from these resources can propel investments towards the development of robust green energy networks.

Third, as per the World Bank's data, the employment-to-population ratio in SSA is 62% higher than the world's average of 56% (World Bank, 2023). The agricultural sector continues to provide a major source of employment in the region, with its contributions in 2021 standing at 52%, reducing slightly from 56% in 2011 (World Bank, 2023). Relatedly, the service sector contributed 37% to employment in 2021, increasing from 34% in 2011. Additionally, industrial employment also witnessed a moderate uptick, climbing to 12% in 2021, relative to 10% in 2011 (World Bank, 2023). These significant employment dynamics in this region provide favorable conditions for individuals to enhance their economic resources. The expansion of employment across multiple sectors will increase financial security, thereby increasing the likelihood of funding and embracing green technologies. These dynamics set the groundwork for the progression towards eco-friendly lifestyles across the region.

Our research enriches the literature in several ways. First, this research is a pioneering effort to assess the influence of employment and natural resources on the clean energy transition in Africa. This study not only shows the dynamics influencing the green transition but also fills the void in the literature. Second, unlike other studies that have employed aggregate employment rate, our research adopts a more comprehensive approach by utilizing employment across the key economic sectors (industry, services, and agriculture) as well as employment types (wage and salaried workers and self-employed individuals). Third, previous studies have been dominated by studies using conditional mean estimates; our study employs the method of moments quantile regression (MMQR). This advanced technique estimates the relationships at different quantiles of renewable energy, which is the dependent variable. This study provides informed suggestions that will aid African economies in expediting the adoption of renewable energy technologies, thereby bolstering climate stabilization.

The study will follow the subsequent structure. Section 2 provides the pertinent literature. Section 3 encompasses the data sources and methods, while Section 4 comprises the findings and discussion. Finally, Section 5 presents the conclusion and policy recommendations.

2 | LITERATURE REVIEW

This section of the study is divided into four segments. The first part encompasses the theoretical foundation. The second segment is on the nexus between natural resources and clean energy, while the third component focuses on the green energy effects of employment dynamics. The last part of this section documents the shortcomings of previous studies.

2.1 | Theoretical underpinning

The resource curse hypothesis states that resource-rich economies usually encounter poor development outcomes relative to their counterparts with fewer resources. This paradox is driven by the fact that these economies rely significantly on their natural assets, resulting in corruption, economic instability, and disregard for other critical sectors of the economy (Jin & Huang, 2024). Relating this theory to clean energy, this resource curse can manifest in diverse aspects. First, nations with enormous resources might not be motivated to fund sustainable energy owing to their substantial income emanating from exporting fossil fuels. This can hamper the shift to green energy sources, as stakeholders benefiting from these conventional fuels would frustrate this change (Zhang et al., 2023). Second, institutions can be eroded with a surge in resource revenues, resulting in weak governance and systemic corruption, which can undermine the establishment of infrastructure and strategies to drive sustainable energy projects. Third, the economic uncertainty linked with the volatility of commodity prices can deflect funds and attention away from extended funding in green energy, as the priority of the government may be stabilizing the economy in the short term over clean energy development (Li & Tong, 2024). Lastly, economic diversification and innovative activities can be suppressed, as these resource-abundant nations may not have the incentive to expand alternative sectors, including sustainable energy, leading to sluggish progress in the uptake of green energy. These factors impede the transition to clean energy in nations blessed with natural resources. On the flip side, neoclassical growth theory underlines the criticality of labor, capital accumulation, and technological advancements in promoting economic advancement (Halkos & Psarianos, 2016). This theory can be applied to explain how employment shapes the adoption of sustainable energy (Fanti & Manfredi, 2009). First, increased employment levels may result in improved income, which likely enhances the demand for clean energy. Income has been identified in the literature as one of the drivers of clean energy uptake (Onuoha et al., 2023a, 2023b). Second, labor force expansion can bolster the diversification of the economy, minimizing the dependence on conventional energy options and stimulating a reliable and sustainable energy outlook (Deng et al., 2023). Third, enhancing employment levels can boost funding for green energy as governments and businesses react to the growing appeal for clean energy options (Halkos & Psarianos, 2016). Fourth, employment growth often leads to an expansion of the requisite skilled manpower, which may boost innovation as well as enhance the efficiency of eco-conscious technologies (Durani et al., 2023).

2.2 | Natural resources–renewable energy consumption nexus

Resource rent can provide diverse economies with the resources to fund green energy. However, studies on the nexus between natural resources and sustainable energy, so far, have yet to reach a consensus. Beginning with studies that report that natural resources facilitate the green transition, Ma et al. (2023) find that the utilization of natural resources facilitates the transition to more environmentally friendly energy sources in OECD countries. This suggests the potential for natural resource in the shift towards greener energy in developed economies. Zhang et al. (2024) align with this outcome by showing that higher resource rents stimulate the adoption of clean energy in China. Ahmadov and van der Borg (2019) confirm that natural resources support the green transition in the European Union. This is also related to the outcome in N-11 economies by Yuan et al. (2023), demonstrating that increased embracement of renewable energy is facilitated by natural resources. Likewise, Olaniyi and Odhiambo (2024) observed that resource-rich African economies are driven towards clean energy development by their abundant natural resources. In a broader context covering 162 nations, Han et al. (2023) conclude that clean energy utilization is stimulated by natural resources. Focusing on a specific resource rent, Olanrewaju et al. (2019) disclose that natural gas rents positively influence green consumption in African economies, while Liu and Lu (2023) report that oil and forest rents are positively associated with BRICS's renewable electricity production.

Differing from the foregoing, some other studies uncover that natural resources may not always promote green energy uptake. This is because resource abundance often generates severe economic reliance on conventional fuels, which impedes the funding and policy backing required for the establishment of green energy infrastructure. For instance, Shinwari et al. (2022) reveal a negative relationship between natural resource volatility and investment in renewable energy in China. Relatedly, Dingru et al. (2022) concluded that natural resource rents play a negligible role in fostering the growth of Africa's renewable energy sector. Their findings suggest that these rents have little impact on facilitating the transition to green energy.

Therefore, this study evaluates the following null hypothesis:

Hypothesis 1. Natural resource rent has no significant impact on the green energy transition.

2.3 | Employment–renewable energy consumption nexus

This assessment of the literature in this segment is divided into two streams. The first strand is on the clean energy effect of employment dynamics showing how employment promotes or undermines the utilization of clean energy. In the other part, we document literature that assesses the reciprocal connection showcasing the influence of clean energy utilization on generating employment possibilities. This strand focuses on how employment drives clean energy utilization; however, the literature on this nexus is still limited. For instance, Przychodzen and Przychodzen (2020) affirm that rising unemployment, which is declining employment levels spur clean energy production. This is quite different from the finding of Karmaker et al. (2023) in the top remittance-receiving economy demonstrating that employment is essential in the transition to clean energy. In a single-country context, Zhao and Luo (2017) report that the utilization of sustainable energy is significantly encouraged by employment.

There has been a significant disparity in research focus, as prior studies have majorly concentrated on how clean energy consumption drives employment generation, but the effect of employment in stimulating the uptake of clean energy has not been given adequate research attention. This stream of studies documents the nexus between sustainable energy and employment dynamics. Henriques et al. (2016) appraise the influence of clean energy on employment generation in Portugal, indicating that sustainable energy promotes job creation. Analogously, Arvanitopoulos and Agnolucci (2020) report that sustainable energies are essential for the United Kingdom's employment growth. Relatedly, Füllemann et al. (2020) reveal using Switzerland's data that clean energy boosts employment. Khobai et al. (2020) conclude that South Africa's employment opportunities respond favorably to the development of green energy. This is also related to outcomes derived in China by Chen (2019) and Liu et al. (2023), who affirm that renewable energy consumption fosters labor market expansion. In a wider context, Proença and Fortes (2020) and Ortega et al. (2020) establish the enhancing effect of green energy on employment growth in European Union nations. Likewise, Osei et al. (2022) find that clean energy positively influences job creation in both European and Asian economies, but the effect is stronger in the European countries.

Diverging from earlier research, some other studies argue that clean energy does not enhance employment growth. For instance, Saboori et al. (2022) find that increased utilization of clean energy is linked to a rise in unemployment in the United States, indicating that a shift towards higher renewable energy consumption potentially reduces employment rates. Muniyoor (2020) investigates the impact of investing in solar energy on job creation in India, observing no notable positive response. Similarly, Çelik (2021) illustrates the lack of a correlation between clean energy transition and work creation in the US economy.

In line with the foregoing, this research assesses the following null hypothesis:

> **Hypothesis 2.** Employment has no significant effect on clean energy consumption.

2.4 | Research gap

The preceding discussion reveals an increasing trend of studies aiming to forecast green energy utilization through the lenses of natural resources and employment dynamics. However, significant shortcomings are still evident in the literature necessitating additional research attention. First, the literature majorly concentrates on economies other than Africa, ignoring the challenges faced in transitioning to clean energy. Despite the region's increasing exposure to the adverse effects of the climate crisis, huge resource endowment, and employment patterns, studies in this context are still not available. Hence, this underlines the critical need for research addressing this lacuna. Second, the criticality of employment in promoting the green energy transition receives limited attention in the literature, particularly in the African context. Previous research has majorly assessed how the utilization of clean energy influences employment, neglecting the reciprocal connection wherein employment growth fosters sustainable green energy development. Third, studies on the employment–green energy nexus have primarily employed aggregate employment measures, ignoring the diverse labor landscape across sectors and employment categories. Another limitation of prior works is the use of linear econometric models, thereby neglecting the nonlinear relationship between the variables.

These shortcomings are addressed in this study by assessing the effect of natural resources and employment on clean energy in Africa. The transition to sustainable energy provides a pathway Africa can utilize to achieve carbon neutrality. Furthermore, this research contributes to the limited studies on the connection between employment and green energy. It diverges from previous research by considering labor diversity across various sectors and employment types. Specifically, it analyzes employment in key economic sectors—agriculture, services, and industry—as well as among self-employed individuals and wage/salaried workers. Finally, the study employs the MMQR technique to examine the asymmetric relationship between natural resources, employment, and renewable energy consumption. This approach enables the exploration of this nexus across the conditional distribution of renewable energy consumption, facilitating the identification of appropriate policy responses.

3 | METHODOLOGY

3.1 | Model design

The underlying theoretical basis for modeling renewable energy using employment and natural resource rent as independent variables is rooted in comprehending the dynamic relationship between economic, social, and environmental factors that shape the transition to renewable energy. This transition is encapsulated by the equation $I = P * A * T$, as proposed by Holdren and Ehrlich (1974) and York et al. (2003). This equation serves as an environmental impact model that is well-suited for econometric analysis and can be easily explained from an economic standpoint. In this model, I represents environmental impact or pollution, P represents population, A represents affluence, and T represents technology and serves as a channel through which other variables can be incorporated into the model. The same relationship can be expressed in this study as follows:

$$lnREN_{it} = \beta_0 + \beta_1 lnNRR_{it} + \beta_2 lnEMP_{it} + \varepsilon_{it} \tag{1}$$

The variables are expressed in logarithmic form,[1] denoted by "*ln*." The subscripts i and t correspond to country ith in year t, while ε represents the stochastic error term. *NRR* indicates natural resources rent, *EMP* indicates a vector of employment from primary industry (agriculture, forestry, and fishing, expressed as a percentage of GDP) (*asemp*), secondary industry (construction, mining, manufacturing, energy, and water utilities sectors, expressed as a percentage of GDP) (*isemp*), and tertiary industry (services, expressed as a percentage of GDP) (*ssemp*), self-employed (*selfemp*), and wage and salaried (*wsw*).

The presence of carbon transfer in renewable energy systems can stem from various structural conditions such as different physical, technological, and socioeconomic factors. With this in mind, we consider the influence of other factors in our model specification for this empirical analysis. One such additional factor we examine is the level of economic development. Research suggests an inverted U-shaped relationship between renewable energy and economic growth in

Africa. In this context, the association between renewable energy deployment and economic growth initially demonstrates positive effects. However, beyond a certain threshold, further increases in economic growth may undermine the green energy transition. To account for this, we include per capita GDP in our analysis, both as a standalone variable and as a squared term. Similar studies conducted by Nwani (2022) and Çakmak et al. (2024) have adopted a similar approach. Thus, the model is re-specified as follows:

$$lnREN_{it} = \beta_0 + \beta_1 lnGDPC_{it} + \beta_2 lnGDPCSQ_{it} + \beta_3 lnNRR_{it} + \beta_4 lnEMP_{it} + \varepsilon_{it} \tag{2}$$

The inverted U-shaped curve of the EKC hypothesis is valid if $\beta_1 > 0$ and $\beta_2 < 0$. The intercept of the functional relationship is denoted as β_0, while $\beta_1 \dots \beta_4$ represent the coefficients associated with the explanatory variables. These coefficients serve to explain the individual effects of the variables on renewable energy. We expect the underlining elasticities as $\beta_3 > 0$ and $\beta_4 > 0$.

3.2 | Data sources and description statistics

To conduct empirical analysis, this study used annualized panel datasets from 44 African nations (see Appendix A) that span the years 1991–2022. With a bigger cross-sectional (N) dimension and a significant time dimension (T), a macropanel framework was used as a consequence. Reliable conclusions were ensured by implementing the appropriate stages for a framework ($N > T$). Notably, the study's parameters were set in accordance with the data that were available. Table 1 provides more tables with details on the pertinent panel series.

Renewable energy consumption is used as the dependent variable. Clean energy mitigates pollution, resulting in a healthier environment and enhanced public health (Onuoha et al., 2023a). The utilization of green energy conforms to numerous SDGs, specifically Goal 7 (sustainable and inexpensive energy) and Goal 13 (climate action) (Onuoha et al., 2023b). We utilize employment in services, industry, and agriculture, as well as salaried workers and self-employed workers as the independent variables. These variables holistically document employment across critical economic sectors and different kinds of work arrangements. Service, industry, and agriculture employment indicate labor distribution across key economic sectors, offering an understanding of economic composition and development, while self-employed and wage and salaried workers showcase diverse patterns of employment security and income stability, underlining differences in the conditions of employment and likely vulnerabilities. Natural resource rent is also employed as an independent variable. Resource rent can impact clean energy by offering the needed support to invest in eco-conscious technologies, as governments could utilize resource revenues to fund sustainable energy initiatives (Zhang et al., 2024). On the flip, increased rents from non-renewable options could lower the speed of shifting to clean energy, as resource-rich nations may prioritize immediate economic benefits over long-term sustainability. Economic growth is also another variable utilized in the study, as an expansion in income can facilitate the rapid transition to green energy (Onuoha et al., 2023a).

3.3 | Estimation techniques

The current study utilized a diverse range of panel econometric approaches to provide thorough empirical insights into the research questions. Following that, comprehensive explanations of all relevant approaches are presented below.

3.3.1 | Cross-sectional dependency test and slope heterogeneity tests

To determine the eventual cross-sectional dependency and heterogeneous slope, the study utilized various techniques. These techniques included the Pesaran (2015) average correlation coefficients CD test technique as well as a set of recently proposed weak CD toolkits. The weak CD toolkits used were the CD Pesaran (2015), CD_w (Juodis & Reese, 2022), weak CD* (Pesaran & Xie, 2021) tests, and the weak CD_{w+} test with power enhancement approach by Fan et al. (2015). The selection of these techniques was based on their efficiency and

TABLE 1 Data sources and description statistics.

Unit of measurement	Notation	Series	Source
Employment in agriculture (% of total employment, modeled ILO estimate)	asemp	Employment in agriculture	WDI
Employment in industry (% of total employment, modeled ILO estimate)	isemp	Employment in industry	WDI
Employment in services (% of total employment, modeled ILO estimate)	ssemp	Employment in services	WDI
GDP per capita constant 2015 US$	gdpc	Economic growth	WDI
Renewable energy consumption of total final energy consumption	ren	Renewable energy	WDI
Self-employed total (% of total employment, modeled ILO estimate)	selfemp	Self-employed	WDI
Wage and salaried workers total (% of total employment, modeled ILO estimate)	wsw	Wage and salaries	WDI
Total natural resource rents (% of GDP)	nrr	Natural resource rents	WDI

Abbreviation: WDI, World Development Indicators.

reliability in determining whether to accept or reject the null hypothesis of cross-sectional dependency (CD). While the traditional CD test (Pesaran, 2004) proposed the null hypothesis of cross-sectional error independency, which can result in excessive rejections, the enhanced techniques hypothesized the null of weak CD and the alternative of strong CD. The results of the CD tests were used to decide whether to employ first-generation panel procedures or second- and third-generation panel procedures. If the null hypothesis of cross-sectional error independence was rejected, it means that first-generation panel procedures were not applicable.

$$CD = \sqrt{\frac{2}{B(B-B)}} \sum_{n-1}^{B-1} \sum_{m=n+1}^{B} A_{nm} B_{nm}^2 \to B(0,1) \tag{2a}$$

where B_{nm}^2 represents the statistical measure associated with the residuals, while "A" and "B" represent the dimensions of time and cross-section, respectively.

$$CD_w = \sqrt{\frac{2}{T_n(n-1)}} \sum_{t=1}^{T} \sum_{i=2}^{n} \sum_{j=1}^{t-1} (w_n \varepsilon_{it})(w_i \varepsilon_{it}) \tag{2b}$$

$$CD_{w+} = CD_w + \Delta_{nT} \tag{2c}$$

Equations (2a)–(2c) correspond to the functional formulations suggested by Pesaran (2004) for the average correlation coefficient CD test, $\mathrm{CD_w}$, and Fan et al.'s (2015) weak $\mathrm{CD_{w+}}$ tests, respectively. Xie and Pesaran (2022) established the bias-corrected CD test to address the shortcomings of CD, $\mathrm{CD_w}$, and $\mathrm{CD_{w+}}$. The bias-corrected CD test (CD*) is expected to follow a normal distribution in theory, with the ability to handle both weak and strong latent components (Xie & Pesaran, 2022). CD* specifically targets the inherent asymptotic bias found in regular CD tests. Therefore, Equation (2d) defines the mathematical structure of CD.

$$CD^* = \frac{CD + \sqrt{\frac{T}{2}\theta_n}}{1-\theta_n} \tag{2d}$$

where $\theta_n = 1 - \frac{1}{n}\sum_{i}^{n} \varphi_{i,n}^2$ represents the function that guarantees the existence of CD^* in the functional scheme equation (2d).

3.3.2 | Slope heterogeneity tests

The study utilizes the slope heterogeneity (SLH) technique proposed by Pesaran and Yamagata (2008) to address the issue of varying slopes. The typical SLH framework is illustrated by Equations (3) and (4).

$$\widehat{\Delta}_{SH} = (N)^{\frac{1}{2}} (2k)^{-\frac{1}{2}} \left(\frac{1}{N}\bar{S} - k\right) \tag{3}$$

$$\widehat{\Delta}_{ASH} = (N)^{\frac{1}{2}} \left(\frac{2k(T-k-1}{T+1}\right)^{-\frac{1}{2}} \left(\frac{1}{N}\bar{S} - 2k\right) \tag{4}$$

The null and alternative hypotheses are the delta $\widehat{\Delta}_{SH}$ and modified delta $\widehat{\Delta}_{ASH}$ that is in tandem with the homogeneous and heterogeneous slope coefficients.

3.3.3 | Panel unit-root tests

The study employed a range of panel unit-root methodologies, including the second-generation cross-sectional IPS method (Pesaran, 2007), along with a modified version known as truncated CIPS (CIPS-TR), which incorporates specific adjustments to the original CIPS test. Furthermore, the research utilized a third-generation panel unit-root approach pioneered by Karavias and Tzavalis (2016), which accounts for structural shifts within the panel. Below is the equation representing the CIPS test.

$$\Delta Y_{it} = \omega_i + \rho_i^* Y_{i,t-1} + d_0 \bar{Y}_{t-1} + \sum_{j=0}^{p} d_{ij} \Delta \bar{Y}_{t-j} + \sum_{j=1}^{p} c_{ij} \Delta Y_{i,t-j} + \varepsilon_{it} \tag{5}$$

The symbol Δ is used to represent the difference operator. The variable of interest is denoted as Y, and the index i ranges from 1 to n, representing the countries being considered. Similarly, the index t ranges from 1 to T, representing the time periods. The stochastic error term is denoted as ε_{it}. The CIPS statistics are derived from Equation (5). The equation for the CIPS test can be expressed as follows:

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} CADF_i \tag{6}$$

In addition, as was previously indicated, we offer a reduced version of the CIPS statistics, called CIPS-TR. Modifications to the original CIPS test are included in the CIPS-TR and shown as follows:

$$CIPS - TR = \frac{1}{N} \sum_{i=1}^{N} CADF_i^* \tag{7}$$

This study employed CIPS panel unit-root tests in our research to ascertain the presence of cross-sectional dependence in the data. The Westerlund (2007) cointegration test of the second generation is employed for analyzing panels that possess both variation and dependency over several time periods. This examination enables us to assess the presence of cointegration among the variables inside the panels, indicating the existence of a long-term association. If cointegration is seen, it becomes possible to reject the null hypothesis positing the absence of any such link. Furthermore, the investigation employed a third-generation unit root devised by Karavias and Tzavalis (2016) for data analysis. This strategy accounts for any modifications that may have taken place within the cohort of subjects under investigation.

$$CIPS(N,T) = \frac{\sum_{i=1}^{N} t_i(N,T)}{N} \tag{8}$$

$$X_{it} = D_{it} + \lambda_t' F_t + \lambda_t' \tag{9}$$

In Equation (9), the variables X_{it}, D_{it}, F_t, λ_t', and λ_t' are utilized to denote distinct components. X_{it} is a mathematical expression that encompasses various components, including a deterministic component of D_{it}, a common component $\lambda_t' F_t$, a polynomial trend function, a vector of $r \times 1$ common factors, a vector of factor loadings, and the idiosyncratic error term. A more recent technique (Ditzen et al., 2021) was employed to perform a confirmatory test. This updated method considers the possibility of multiple breaks occurring at unknown breakpoints. It assists in determining whether to accept or reject the relevant null hypotheses. As domiciled in the Ditzen et al. (2021) approach, the null hypothesis assumes the absence of structural break(s), while the alternative hypothesis assumes the existence of a certain number of breaks. Equation (10) illustrates a standard panel unit-root procedure that incorporates multiple breakpoints.

$$\gamma_{i,t} = x_{i,t}'\beta + \omega_{i,t}'\partial_j + f_i'\gamma_i + \varepsilon_{i,t} \tag{10}$$

where f_i' denotes an $m \times 1$ vector of factors, while γ_i depicts the applicable vector of factor loadings.

3.3.4 | Econometric strategy

The study used the instrumental variable generalized method of moments (IV-GMM) methodology, which is preferred above ordinary least squares because of its ability to handle endogeneity, omitted variable bias, and autocorrelation concerns (Dimnwobi, Okere, et al., 2022; Dimnwobi, Okere, Azolibe, & Onyenwife, 2023; Okere et al., 2023b). IV-GMM is highly effective when the number of cross-sectional units is greater than the number of time periods ($N > T$). The IV-GMM technique can effectively address bias caused by variable omission, provide consistent estimates, and generate efficient results even when unknown heteroscedasticity is present, surpassing the need for orthogonality (Baum et al., 2003). The reliability and validation of this approach are evaluated using a one-step estimate process (Cameron & Trivedi, 2005). The IV-GMM approach[1] in this study provides just the mean effect of explanatory variables on the dependent variable. Therefore, it may provide just a small amount of real-world evidence to help policy analysis, especially when the data's distribution greatly differs from a normal (symmetrical) distribution. To overcome this constraint, we also employed a panel quantile regression method. This approach is capable of considering the impact of distributional effects when the data significantly deviate from a symmetric distribution, as recommended by Machado and Silva (2019). The comprehensive specification is utilized to modify the equation as follows:

$$Q_y(\tau|X_{it}) = (\beta_i + \delta_i qi) + X_{it}'\beta + Z_{it}'\gamma q(\tau) \tag{11}$$

where $Q_y(\tau|X_{it})$ depicts the quantile distribution of the dependent variable lnY_{it}, conditional on the location and scale of the explanatory variable (X_{it}'). X_{it}' is a vector of explanatory variables. $\alpha_i(\tau) = \alpha_i + \delta_i q(\tau)$ represents the distributional effect at τ or the scalar coefficient of the quantile τ fixed effect for individual i. $q(\tau)$ is the τth quantile estimated through the optimization function as follows:

$$\min_q \sum_i \sum_t \rho_\tau \left(\widehat{R}_{it} - \left(\widehat{\delta}_i + Z_{it}'\widehat{\gamma} \right) q \right) \tag{12}$$

Accordingly, the threshold $\rho_\tau(A) = (\tau - 1)AI\{A \le 0\} + \tau AI\{A > 0\}$ offers a check function. Drawing from Equation (12), we present the final modified baseline model stated in Equations (1) and (2) for panel quantile calculation as follows:

$$Q_{Y_{it},}(\tau|\beta_i, \varepsilon_{it}, X_{it}) = \beta_0 + \beta X_{it} + \gamma Z_{it} + \delta_{it} + \varepsilon_{it} \tag{13}$$

The quantile model presented in Equation (13) considers the distributional effects of explanatory variables on the explained variable and also accounts for the impact of natural resource rent and employment on renewable energy in Africa.

4 | RESULTS AND DISCUSSION

4.1 | Preliminary analysis

The correlation matrix and summary statistics data in Table 2 provide an empirical summary of the panel series under examination. Table 2 is divided into two panels: Panel A displays the correlation matrix, while Panel B presents the summary statistics that highlight important features of the series. The predicted values of all the series fall within the range of their minimum and maximum values, suggesting a potential for convergence. Among the series, *ln*asemp exhibits the highest dispersion, followed by *ln*ren, while *ln*wsw is the least scattered. Except for *ln*gdpc, which measures divergence from a normal distribution, all variables display left-skewness indicated by their negative coefficients. This implies that traditional linear econometric techniques may not produce consistent estimates, and nonlinear methods capable of capturing the effects of such irregular distributions should be employed. The correlation matrix in Panel A provides initial insights into the degree of correlation between the series. It reveals that *ln*ren is negatively associated with explanatory variables (*ln*gdpc, *ln*wsw, *ln*isemp, and *ln*ssemp), while *ln*selfemp, *ln*asemp, and *ln*nrr are potential positive predictors. Importantly, all correlation coefficients are below 60%, indicating that multicollinearity is not a concern.

To enhance knowledge of the attributes of the variable under investigation and the possible associations among various parts, the research employed CD and SH tests. Table 3 displays the outcomes of these examinations. The estimates derived from the CD and SH tests (Table 3) validate the presence of cross-sectional dependence in the

TABLE 2 Correlation matrix and descriptive statistics.

Panel A: Correlation matrix								
Variables	lnren	lngdpc	lnselfemp	lnwsw	lnasemp	lnisemp	lnssemp	lnnrr
lnren	1.0000							
lngdpc	−.6817	1.0000						
lnselfemp	.5556	−.6836	1.0000					
lnwsw	−.5085	.7003	−.8711	1.0000				
lnasemp	.5438	−.6179	.6075	−.6270	1.0000			
lnisemp	−.4496	.6041	−.6017	.6817	−.3939	1.0000		
lnssemp	−.5118	.7370	−.6155	.7239	−.7805	.6664	1.0000	
lnnrr	.2057	−.1887	.3509	−.3701	.4425	−.1750	−.3173	1.0000

Panel B: Descriptive statistics									
	Mean	Median	Max	Min	SD	Skewness	Kurtosis	JB	P-value
lnren	1.8081	1.8969	1.9927	0.5658	0.2244	−2.5240	10.4088	4567.875***	.0000
lngdpc	3.0241	2.9508	4.1530	2.2796	0.3746	0.6578	2.7643	101.515***	.0000
lnselfemp	1.8402	1.8974	1.9807	1.2946	0.1515	−1.6913	5.0280	884.046***	.0000
lnwsw	1.3288	1.3231	1.9047	0.6393	0.3093	−0.0152	2.2172	34.8799***	.0000
lnasemp	1.6756	1.7535	1.9661	0.0826	0.2866	−2.8664	13.8809	8596.631***	.0000
lnisemp	0.9877	0.9817	1.5415	0.3139	0.2574	−0.3489	2.8855	28.4172***	.0000
lnssemp	1.4788	1.4939	1.9704	0.7254	0.2300	−0.4919	3.2902	59.7832***	.0000
lnnrr	0.8766	0.9053	2.0638	−3.3344	0.4835	−1.3712	10.2684	3429.876***	.0000

Note: This information is based on calculations performed by the authors.
*Statistically significant correlations at the 10% level.
**Statistically significant correlations at the 5% level.
***Statistically significant correlations at the 1% level.

panel series since the traditional CD technique may tend to be misleading (Pesaran, 2004). The SH test (Panel B) presents compelling evidence of heterogeneity among the relevant panel series, indicating that the null hypothesis of a uniform slope across sections is likewise disproven. The study utilizes two second-generation unit-root approaches and a third-generation panel unit-root procedure, based on the findings of the CD and SH tests. The outcomes of these tests are summarized in Table 4. The chosen panel techniques are very suitable for addressing the issues presented by variances between different sections and structural disruptions.

The results of the second-generation panel unit-root analyses, as shown in Table 4, suggest that the relevant variables display a combination of integration features. This indicates that certain variables possess intrinsic stationarity, while others attain stationarity via undergoing first-order differencing. This pattern is uniform in both applied processes. In addition, the panel unit-root analyses of the third generation indicate that the variables have experienced structural fractures at several points in time, specifically in 1994, 2003, and 2021. These breaks align with the occurrence of the recent global financial and COVID-19 epidemic. Based on this outcome, the paper examines the long-term coevolution of the variables using the Westerlund cointegration testing methodologies. The findings of this panel cointegration analysis are concisely reported in Table 5.

Table 5 presents the estimations derived from the Westerlund cointegration techniques applied in this research across all models. The findings emphasize the long-term coevolution of the panel series included in the two models representing ($lnREN_{it} = \beta_0 + \beta_1$ $_{lnGDPC} + \beta_2 lnGDPCSQ_{it} + \beta_3 lnNRR_{it} + \beta_4 lnEMP_{it} + \varepsilon_{it}$), indicating evidence of cointegration among these panel series according to the Westerlund cointegration procedure. Given the compelling evidence from other identified attributes of the panel variables, the study opted for several enhanced panel estimators known for yielding robust outcomes for the final empirical inferences. The results of these panel estimators are summarized in Tables 6 and 7. Therefore, the utilization of IV-GMM, MMQR, and IV-MMQR techniques is crucial due to their capacity to generate reliable results that carry significant implications for the green energy transition in SSA nations. Tables 6 and 7 present the outcomes of the IV-GMM, MMQR, and IV-MMQR methods, illustrating the effects of distinct explanatory variables on the response variable, both conditionally and unconditionally.

4.2 | Regression result

Aligned with the previously outlined study objectives and the eventual findings of pertinent preliminary assessments, the selection and

TABLE 3 Cross-sectional dependency (CD) and slope heterogeneity (SH) tests.

Panel A: Cross-sectional independence											
Variable	Pesaran (2004) CD test	Pesaran (2015) CD test	Juodis and Reese (2022) CDw	Fan et al. (2015) CDw+	Pesaran and Xie (2021) CD*	**Variables**	Pesaran (2004) CD test	**CD**	**CDw**	**CDw**	**CD***
ren	57.949***	57.95***	−2.31***	2861.21***	0.56	ren	57.949***	57.95***	−1.69***	2861.83***	0.56***
gdpc	55.216***	55.22***	−2.74***	3132.38***	2.82	gdpc	55.216***	55.22***	−2.04***	3133.07***	2.82***
gdpcsq	55.467***	55.47***	−2.72***	3125.62***	2.9	gdpcsq	55.467***	55.47***	−2.05***	3126.29***	2.9***
nrr	27.295***	27.29***	0.17***	1675.64***	3.59	nrr	27.295***	27.29***	−0.49***	1674.98***	3.59***
selfemp	62.351***	62.35***	−2.3***	3371.02***	2.38	asemp	126.359***	126.36***	−0.42***	4315.26***	0.86***
wsw	61.478***	61.48***	−2.54***	3388.81***	1.76	isemp	28.594***	28.59***	−7.27***	3242.93***	0.3***
						ssemp	130.631***	130.63***	−2.07**	4421.35***	4.09***

Panel B: Slope heterogeneity					
		***p* value**			***p* value**
Delta	35.739***	.000	Delta	32.81***	.000
Adj.	40.434***	.000		37.885***	.000

Note: This information is based on calculations performed by the authors.
*Statistically significant correlations at the 10% level.
**Statistically significant correlations at the 5% level.
***Statistically significant correlations at the 1% level.

TABLE 4 Stationarity test.

	CD-adjusted (second-generation) panel unit-root tests				Karavias and Tzavalis (2016)		Ditzen et al. (2021)		
Series	CIPS (level)	ΔCIPS	TCIPS (level)	ΔTCIPS	Min *Z* stat	Break point	Coff.	*t* stat	Break date
ren	−2.086	−2.284**	−2.008	−3.228***	−12.7134***	1997	*F*(1/0)	3.98***	1994
gdpc	−2.086	−3.299**	−1.612	−2.715***	−16.4189***	1997	*F*(2/1)	4.79***	2003
gdpcsq	−1.803	−5.346**	−1.631	2.532***	−15.8545***	1997	*F*(3/2)	5.02***	2021
selfemp	−1.692	−3.144**	−2.604	2.748***	−1.1048***	n/a	*F*(4/3)	2.78	n/a
wsw	−1.923*	−2.947**	−2.436**	−2.747***	−8.0051***	1997	*F*(5/4)	2.22	n/a
asemp	−1.301	−5.571**	−1.989	−2.628***	−21.1129***	1997			
isemp	−2.328*	−3.228**	−1.732	−2.395***	−6.5300*	1997			
ssemp	−1.733	−3.144**	−1.943**	−3.134***	−22.6264***	1997			
nrr	−1.523	−3.596**	−2.106	−2.785***	−13.9546***	1997			

Note: This information is based on calculations performed by the authors.
*Statistically significant correlations at the 10% level.
**Statistically significant correlations at the 5% level.
***Statistically significant correlations at the 1% level.

TABLE 5 Cointegration test.

	$lnREN_{it} = \beta_0 + \beta_1 lnGDPC_{it} + \beta_2 lnGDPCSQ_{it} + \beta_3 lnNRR_{it} + \beta_4 lnEMP_{it} + \varepsilon_{it}$			
Statistic	Value	Robust *p* value	Value	Robust *p* value
Gt	−2.848***	.0100	−3.1120***	.000
Ga	−11.212***	.0300	−12.023***	.000
Pt	−15.628***	.3400	−15.376***	.500
Pa	−9.064***	.3500	−10.588***	.140

Note: The findings presented in this table disprove the null hypothesis that there is no cointegration among the variables in both the panel model specifications (as indicated by the Pt and Pa statistics) and the cross-sectional units (as represented by the Gt and Ga statistics). Therefore, the existence of a lasting relationship is confirmed in all the models used.
*Statistically significant correlations at the 10% level.
**Statistically significant correlations at the 5% level.
***Statistically significant correlations at the 1% level.

implementation of the IV-GMM, MMQR, and IV-MMQR methodologies hold utmost importance. Specifically, the estimates presented in Table 6 delve into the influence of employment types (self-employed and wage and salaries) and natural resource rents on the transition towards green energy (renewable energy) within SSA. Meanwhile, the estimates in Table 7 elucidate the impact of employment across key economic sectors (employment in agriculture, industry, and services) and natural resource rents on the level of green energy transition in the region. In Table 6, the IV-GMM effects regression in column 1 elucidates the average effect of the explanatory variables, utilizing estimates resilient to various forms of cross-sectional dependence. Meanwhile, the estimates in columns 2–10 are derived from MMQR, aiming to uncover distributional disparities in the influence of natural resources and employment across the sampled countries. This method categorizes the data into three quantile groups: the lower quantile (10th, 25th, and 40th quantiles), the median quantile (50th quantile), and the upper quantile (60th, 75th, and 90th quantiles).

The research commences by analyzing the coefficient of "*ln*gdpc" and its quadratic counterpart, revealing a notable inverted-U relationship between per capita GDP and the shift towards green energy in SSA in Tables 6 and 7. This discovery lends credence to the environmental Kuznets curve (EKC) hypothesis. From a policy perspective, it is predicted that the contribution of economic growth to renewable energy will decline once gdpc reaches the turning point level. The intricate relationship between economic expansion and the utilization of clean energy in SSA shows a pattern of economic evolution entangled with clean energy dynamics. Initially, the expansion of income drives an increase in clean energy utilization, encouraged by enhanced prosperity and advancements in infrastructure. However, as economies progress, a tipping point emerges where the quadratic nature of growth yields diminishing returns or even hampers green energy integration. This shift could be attributed to factors like entrenched infrastructure, vested interests in conventional energy sources, and bureaucratic inertia. Moreover, as economies mature, the focus often pivots towards maintaining existing energy facilities rather than embracing renewable alternatives.

In pursuit of the study's objective, the influence of *ln*nrr on the transition to green energy exhibits a notably positive trend, as

TABLE 6 Results of panel estimators on employment types.

	1	2	3	4	5	6	7	8	9	10
Variables	**IV-GMM**	**q10**	**q20**	**q30**	**q40**	**q50**	**q60**	**q70**	**q80**	**q90**
*ln*nrr	0.269***	0.32	0.627	0.420***	0.329***	0.306***	0.296***	0.304***	0.300***	0.336***
	(0.037)	(1.316)	(1.283)	(0.157)	(0.127)	(0.045)	(0.027)	(0.013)	(0.011)	(0.014)
*ln*gdpc	2.890***	3.81	5.706*	4.461***	2.986**	1.717***	1.512***	1.634***	1.819***	1.950***
	(0.321)	(7.163)	(3.403)	(0.876)	(1.434)	(0.493)	(0.249)	(0.176)	(0.171)	(0.193)
*ln*gdpcsq	−0.521***	−0.709	−1.018*	−0.804***	−0.539**	−0.307***	−0.262***	−0.277***	−0.310***	−0.331***
	(0.054)	(1.186)	(0.610)	(0.148)	(0.245)	(0.088)	(0.043)	(0.029)	(0.028)	(0.032)
*ln*selfemp	−0.208**	−0.0646	−1.004	−0.387	−0.432	−0.216**	−0.0719**	−0.0452**	−0.183**	−0.210**
	(0.106)	(2.343)	(3.665)	(0.363)	(0.214)	(0.117)	(0.077)	(0.078)	(0.076)	(0.084)
*ln*wsw	−0.0168	−0.0149	−0.196	−0.0881	−0.107	−0.075***	−0.0516**	−0.0397**	−0.0521**	−0.0282**
	(0.034)	(0.109)	(0.711)	(0.061)	(0.030)	(0.028)	(0.024)	(0.025)	(0.024)	(0.033)
Constant	−1.922***	−3.495	−4.755**	−3.874***	−1.601	−0.275	−0.329	−0.589**	−0.543**	−0.721***
	(0.404)	(7.860)	(2.008)	(0.818)	(1.827)	(0.521)	(0.300)	(0.240)	(0.214)	(0.245)
Observations	1408	1408	1408	1408	1408	1408	1408	1408	1408	1408
R^2	.369									

*Statistically significant correlations at the 10% level.
**Statistically significant correlations at the 5% level.
***Statistically significant correlations at the 1% level.

TABLE 7 Results of panel estimators on employment across key economic sectors using instrumental MMQR.

		1	2	3	4	5	6	7	8	9
Variables	IV-GMM	q10	q20	q30	q40	q50	q60	q70	q80	q90
nrr	0.0683	0.189***	0.177**	0.00591***	0.136***	0.188***	0.187***	0.0539***	0.0505***	0.0764***
	(0.050)	(0.048)	(0.071)	(0.046)	(0.047)	(0.042)	(0.064)	(0.207)	(0.098)	(0.107)
gdpc	1.862***	4.021***	4.064***	2.506***	2.147***	1.878***	1.628***	0.237***	0.952***	0.0407***
	(0.358)	(0.421)	(0.531)	(0.395)	(0.324)	(0.278)	(0.324)	(1.449)	(0.840)	(0.868)
gdpcsq	−0.337***	−0.729***	−0.723***	−0.456***	−0.382***	−0.327***	−0.277***	−0.0486***	−0.144***	−0.0095***
	(0.058)	(0.066)	(0.086)	(0.069)	(0.054)	(0.049)	(0.058)	(0.229)	(0.135)	(0.139)
asemp	0.309***	0.00215	0.0428	0.251	0.102	0.0513	0.0645**	0.243**	0.347***	0.209*
	(0.056)	(0.112)	(0.131)	(0.102)	(0.050)	(0.041)	(0.057)	(0.210)	(0.110)	(0.116)
isemp	−0.212***	−0.163***	−0.174***	−0.169***	−0.103***	−0.109***	−0.0967***	−0.0519**	−0.0206**	−0.0073**
	(0.024)	(0.041)	(0.043)	(0.040)	(0.021)	(0.028)	(0.033)	(0.026)	(0.018)	(0.019)
ssemp	0.152***	0.0364	0.0376	0.0539	0.020	0.0758**	0.0802**	0.0876**	0.162*	0.0479**
	(0.054)	(0.030)	(0.039)	(0.031)	(0.035)	(0.039)	(0.065)	(0.141)	(0.086)	(0.095)
Constant	−1.165**	−3.686***	−3.878***	−1.934***	−1.306***	−0.838**	−0.548	1.092	2.704**	1.396
	(0.461)	(0.541)	(0.728)	(0.478)	(0.467)	(0.388)	(0.419)	(1.862)	(1.078)	(1.114)
Observations	1408	1408	1408	1408	1408	1408	1408	1408	1408	1408
R^2	.534									

Note: Wages and salaries were used as instrumental variable.
*Statistically significant correlations at the 10% level.
**Statistically significant correlations at the 5% level.
***Statistically significant correlations at the 1% level.

observed through both the conventional instrumental GMM approach and across the entire conditional quantile distribution in Tables 6 and 7, respectively. According to the IV-GMM results in column 1, a 1% increase in *ln*nrr corresponds to a 0.269% increase in *ln*ren. The MMQR estimations across columns 2–10 reveal that irrespective of a country's position within the distribution quantiles, a 1% rise in *ln*nrr leads to an increase in *ln*Ren, with the magnitude varying slightly across quantiles. Specifically, at the 10th quantile (column 2), the increase is approximately 0.32%, while at the 90th quintile (column 10), it is about 0.336%. This leads us to reject Hypothesis 1. These findings indicate that the incremental impacts are relatively more pronounced in the lower percentiles of green energy adoption within SSA, particularly around the 30th quantile. This observation suggests that the abundance of natural resources facilitates the production of renewable energy by providing crucial financial resources. When effectively managed and redirected into renewable energy initiatives, technology innovation, environmental conservation, and energy security endeavors, these funds can significantly contribute to the transition towards green energy in SSA. Theoretically, these findings support the growing empirical repositories and downplay the illustration of resource curse symptoms in SSA (Nwani et al., 2023) and also support SDGs 7, 8, and 13. This aligns with the findings of Ahmadov and van der Borg (2019), Olanrewaju et al. (2019), Han et al. (2023), and Ma et al. (2023), who argue that the utilization of natural resources incentivizes the adoption of renewable energy. However, contrasting perspectives are evident in the research of Shinwari et al. (2022), which reveals a negative association between natural resources and renewable energy investment in China.

When examining the effects of *ln*selfemp and *ln*wsw on the shift towards green energy, the empirical analyses yield the following findings. Both the variables "*ln*selfemp" and "*ln*wsw" had negligible impacts on the shift to green energy in the lower quartiles (10th–40th quantiles). However, the influence of their actions is statistically significant, especially in nations in the middle and upper quartiles (50th–90th quantiles). These employment types undermine the green transition drive, which could possibly be because these sets of workers may prioritize immediate financial security and economic stability over clean energy investments.

4.2.1 | Result of employment across key economic sectors

Table 7 provides the role of leveraging resources rent and employment in supporting the green transition in Africa using the instrumental MMQR. This technique furnishes decision-makers with an understanding of how resource rent and employment across the key sectors of the economy impact clean energy growth in the lower, middle, and upper quantiles. By utilizing the ivqregress algorithm, this technique efficiently tackles endogeneity concerns that could emerge owing to factors like variable omission, self-selection, and measurement error. The justification for utilizing this technique is driven by the concern that employment and natural resources are likely endogenous, as they may be shaped by unobserved factors like salaries and wages, which could also impact green energy as employed by Chernozhukov and Hansen (2004).

Natural resource rent is positive and significant across all quantiles of clean energy, aligning with the previously established results. A unit increase in natural resources strengthens the transition to renewable energy in this group of developing countries, with a more pronounced effect observed in countries at the lower end of the distribution (10th quantile). These results are consistent with the findings of Yuan et al. (2023), Liu and Lu (2023), and Zhang et al. (2024), indicating a positive association between natural resource rent and renewable energy. This is plausible given that resource rent can provide additional funds to the government that can be utilized to support sustainable energy initiatives. The revenue from these resources can also be employed to fund incentives or inducements for clean energy technologies, thereby making them more affordable and widely accessible. In addition, increased resource rent can propel policy adjustments towards sustainability as decision-makers strive to stabilize economic gains with enduring environmental objectives.

The significant positive coefficients of the agriculture and services sector indicate that employment in these sectors is striding towards a greener future in SSA, and the benefits of employment in these sectors are greater in high-energy transitioning countries (60th–90th quantiles). As a result, Hypothesis 2 is rejected. These outcomes, which align with Zhao and Luo (2017) and Karmaker et al. (2023), are not surprising given that these sectors appear to be considerably focused on sustainability and ecological protection. In agriculture, the desire for sustainable strategies can propel the uptake of green energy to lessen the dependence on traditional fuels, which are usually not pro-environment. Relatedly, in the service sector, there is an expanding attention on innovation and clean energy investment, which results in green energy use.

Finally, the study reveals that employment in the industrial sector undermines clean energy utilization. Numerous factors account for this outcome. First, the industrial sector relies considerably on unclean fuels because of their economic viability and perceived dependability. This increased reliance on non-renewable energy might deter industries from exploring sustainable energy sources. Besides, industrial processes usually entail considerable energy inputs, which are usually met using traditional fuels that are environmentally unfriendly. In developing economies, shifting towards clean energy might encounter obstacles like inadequate incentives and infrastructure, especially in regions with abundant fossil fuels (Dimnwobi, Onuoha, Uzoechina, et al., 2023). This outcome does not conform to the outcomes of Zhao and Luo (2017) and Karmaker et al. (2023).

5 | CONCLUSION AND POLICY IMPLICATIONS

In recent years, several economies across the globe have been faced with mounting ecological concerns propelled by the climate crisis and dependence on unclean fuels for their development trajectories. This global concern uniquely manifests across regions, with Africa being the most vulnerable. Consequently, countries within this region are shifting their power generation and distribution towards greener and more eco-friendly sources. This study delved into this transition within SSA, analyzing panel data spanning from 1991 to 2022 across 44 economies. Its primary aim was to explore how natural resource rent and employment dynamics influence the adoption of green energy in the region, employing the MMQR methodology. The study's key findings indicate a positive relationship between natural resource rent and the uptake of green energy. However, the impact of employment types shows that green energy consumption is undermined by self-employment and wages/salaried workers. Furthermore, the research highlights the role of employment across different economic sectors. Employment in the agriculture and services sectors is found to promote green energy utilization, while employment in the industrial sector impedes renewable energy consumption. Drawing from these findings, some policy suggestions are put forward to propel the widespread utilization of green energy in Africa.

- Our study finds that clean energy development in Africa is facilitated by natural resource rent. Therefore, decision-makers should designate some portion of the revenue generated from natural resources to fund sustainable energy initiatives, ensuring that these natural assets are directed towards sustainable development endeavors. Strategies can be established to offer inducements for private investments in clean energy, utilizing revenues from resource rents to subsidize initial expenses. Furthermore, accountable and transparent utilization of revenues from natural resource is essential to avoid misallocation and guarantee that resources are efficiently utilized to advance clean energy. Collectively, the extensive application of these suggestions will ensure that natural resource rent will continue to support clean energy utilization in Africa.
- We observe that while agriculture and service sector employment support clean energy transition, industrial sector employment impedes it. Hence, the priority of the decision-makers in this region should be on advancing clean energy initiatives within the agricultural and service sectors by providing tailored support and incentives to these sectors and harnessing their enhancing effect on green energy utilization. In contrast, strategies should be established to tackle the various impediments within the industrial sector undermining clean energy utilization like regulation revisions or offering transitional assistance to industries that are dependent on traditional energy sources. Encouraging these industries to embrace greener solutions via mandates or subsidies could aid in integrating industrial processes with sustainable energy goals. Moreover, the development of cross-sectoral tactics is essential to guarantee green energy transitions, incorporating the strengths of both the agricultural and service sectors while the impediments confronting the industrial sector are effectively addressed.
- Lastly, we discover the green energy reduction influence of both wages/salaried workers and self-employment, indicating that efforts in tackling the barriers hindering the drive to sustainable energy are critical. Decision-makers in Africa should establish actionable strategies to make clean energy less expensive and very accessible for these employment categories. These strategies could include low-interest credits, subsidies, and financial inducements for sustainable technologies. In addition, awareness programs should be widely enforced to expand the understanding of the gains derivable from clean energy utilization and enhance uptake among these categories. Governments in these economies should also consider incentivizing enterprises in these regions to embrace clean energy techniques, as this can indirectly benefit individuals in these categories through their work environments.

We recognize several limitations in this study that suggest avenues for further research. First, due to data limitations, not all nations in the SSA were included, and the focus remained solely on aggregate natural resource rent. Future studies should broaden the geographical scope to encompass more countries and include both aggregate and disaggregated natural resource data for a more thorough assessment. Additionally, this study employs panel data from SSA countries to assess the factors influencing their transition to green energy. However, the impact of the identified factors on the individual members of SSA's utilization levels for renewable energy remains uncertain. Conducting country-specific analyses is another area future studies can explore. Moreover, while this study provides valuable insights from the standpoint of developing or emerging nations, it overlooks the determinants of green energy adoption within the context of developed nations. Consequently, future research endeavors could incorporate a counterfactual analysis utilizing data from developed nations to ascertain the robustness and consistency of the findings across diverse samples encompassing both developing and developed nations. Lastly, our study faces a limitation related to our methodology. While the quantile regression model employed offers valuable insights into the conditional distribution effects of natural resource rent and employment dynamics on green energy transition, it does not provide clarity on the threshold levels of these variables required to attain specific outcomes in green energy transition. Exploring these thresholds would constitute a valuable direction for future research efforts.

DATA AVAILABILITY STATEMENT

The data supporting the findings of our study can be found at https://databank.worldbank.org/reports.aspx?source=2&country=PHL#.

ORCID

Kingsley I. Okere https://orcid.org/0000-0002-1845-4583
Stephen Kelechi Dimnwobi https://orcid.org/0000-0002-5964-9627
Ismail O. Fasanya https://orcid.org/0000-0001-5816-4815

ENDNOTES

[1] The use of natural logarithms in variables aids in estimating the parameters of the functional relationship as elasticities, thus aiding in the understanding and development of policies.

[2] The IV-GMM approach is justified for addressing endogeneity (Wang, 2015), handling weak instruments, dealing with complex causal effects (Bennett et al., 2019), errors-in-variables models, policy analysis, and panel data analysis (Almeida et al., 2015).

REFERENCES

Ahmadov, A. K., & van der Borg, C. (2019). Do natural resources impede renewable energy production in the EU? A mixed-methods analysis. *Energy Policy*, *126*, 361–369. https://doi.org/10.1016/j.enpol.2018.11.044

Almeida, H., Campello, M., & Galvao, A. F. (2015). Assessing the performance of estimators dealing with measurement errors. In *Handbook of financial econometrics and statistics* (pp. 1563–1617). Springer.

Arvanitopoulos, T., & Agnolucci, P. (2020). The long-term effect of renewable electricity on employment in the United Kingdom. *Renewable and Sustainable Energy Reviews*, *134*, 110322. https://doi.org/10.1016/j.rser.2020.110322

Baum, C. F., Schaffer, M. E., & Stillman, S. (2003). Instrumental variables and GMM: Estimation and testing. *The Stata Journal*, *3*(1), 1–31.

Bennett, A., Kallus, N., & Schnabel, T. (2019). Deep generalized method of moments for instrumental variable analysis. *Advances in Neural Information Processing Systems*, 32. Retrieved from https://proceedings.neurips.cc

Çakmak, T. K., Beşer, M. K., & Alola, A. A. (2024). Explaining employment and environmental degradation nexus with environmental employment curve (EEC): A sector-wide threshold estimation for China. *Journal of Cleaner Production*, *436*, 140264. https://doi.org/10.1016/j.jclepro.2023.140264

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: Methods and applications*. Cambridge University Press.

Çelik, O. (2021). Assessment of the relationship between renewable energy and employment of the United States of America: Empirical evidence from spectral Granger causality. *Environmental Science and Pollution Research*, *28*, 13047–13054. https://doi.org/10.1007/s11356-021-12414-x

Chen, Y. (2019). Renewable energy investment and employment in China. *International Review of Applied Economics*, *33*(3), 314–334. https://doi.org/10.1080/02692171.2018.1513458

Chernozhukov, V., & Hansen, C. (2004). The effects of 401(k) participation on the wealth distribution: An instrumental quantile regression analysis. *Review of Economics and Statistics*, *86*(3), 735–751.

Deng, Z., Song, S., Jiang, N., & Pang, R. (2023). Sustainable development in China? A nonparametric decomposition of economic growth. *China Economic Review*, *81*, 102041. https://doi.org/10.1016/j.chieco.2023.102041

Dimnwobi, S. K., Ekesiobi, C., Madichie, C. V., & Asongu, S. A. (2021). Population dynamics and environmental quality in Africa. *Science of the Total Environment*, *797*, 149172. https://doi.org/10.1016/j.scitotenv.2021.149172

Dimnwobi, S. K., Madichie, C. V., Ekesiobi, C., & Asongu, S. A. (2022). Financial development and renewable energy consumption in Nigeria. *Renewable Energy*, *192*, 668–677. https://doi.org/10.1016/j.renene.2022.04.150

Dimnwobi, S. K., Ikechukwu Okere, K., Azolibe, C. B., & Onyenwife, K. C. (2023). Towards a green future for sub-Saharan Africa: Do electricity access and public debt drive environmental progress? *Environmental Science and Pollution Research*, *30*(41), 94960–94975. https://doi.org/10.1007/s11356-023-29058-8

Dimnwobi, S. K., Okere, K. I., Onuoha, F. C., & Ekesiobi, C. (2022). Energy poverty, environmental degradation and agricultural productivity in sub-Saharan Africa. *International Journal of Sustainable Development & World Ecology*, *30*(4), 428–444. https://doi.org/10.1080/13504509.2022.2158957

Dimnwobi, S. K., Okere, K. I., Onuoha, F. C., Uzoechina, B. I., Ekesiobi, C., & Nwokoye, E. S. (2023). Energizing environmental sustainability in sub-Saharan Africa: The role of governance quality in mitigating the environmental impact of energy poverty. *Environmental Science and Pollution Research.*, *30*, 101761–101781. https://doi.org/10.1007/s11356-023-29541-2

Dimnwobi, S. K., Onuoha, F. C., Uzoechina, B. I., Ekesiobi, C. S., & Nwokoye, E. S. (2023). Does public capital expenditure reduce energy poverty? Evidence from Nigeria. *International Journal of Energy Sector Management*, *17*(4), 717–738. https://doi.org/10.1108/IJESM-03-2022-0008

Dingru, L., Onifade, S. T., Ramzan, M., & Al-Faryan, M. A. S. (2022). Environmental perspectives on the impacts of trade and natural resources on renewable energy utilization in sub-Sahara Africa: Accounting for FDI, income, and urbanization trends. *Resources Policy*, *80*, 103204. https://doi.org/10.1016/j.resourpol.2022.103204

Ditzen, J., Karavias, Y., & Westerlund, J. (2021). Testing and estimating structural breaks in time series and panel data in Stata. arXiv preprint arXiv:2110.14550.

Durani, F., Bhowmik, R., Sharif, A., Anwar, A., & Syed, Q. R. (2023). Role of economic uncertainty, financial development, natural resources, technology, and renewable energy in the environmental Phillips curve framework. *Journal of Cleaner Production*, *420*, 138334. https://doi.org/10.1016/j.jclepro.2023.138334

Ezenekwe, U. R., Okere, K. I., Dimnwobi, S. K., & Ekesiobi, C. (2024). Balancing the scales: Does public debt and energy poverty mitigate or exacerbate ecological distortions in Nigeria? *International Social Science Journal*, *74*(252), 451–475. https://doi.org/10.1111/issj.12465

Fan, J., Liao, Y., & Yao, J. (2015). Power enhancement in high-dimensional cross-sectional tests. *Econometrica*, *83*(4), 1497–1541.

Fanti, L., & Manfredi, P. (2009). Neoclassical production theory and growth with unemployment: The stability issue revisited. *Structural Change and Economic Dynamics*, *20*(2), 126–135. https://doi.org/10.1016/j.strueco.2008.12.002

Füllemann, Y., Moreau, V., Vielle, M., & Vuille, F. (2020). Hire fast, fire slow: The employment benefits of energy transitions. *Economic Systems Research*, *32*(2), 202–220. https://doi.org/10.1080/09535314.2019.1695584

Halkos, G., & Psarianos, I. (2016). Exploring the effect of including the environment in the neoclassical growth model. *Environmental Economics and Policy Studies*, *18*, 339–358. https://doi.org/10.1007/s10018-016-0146-5

Han, Z., Zakari, A., Youn, I. J., & Tawiah, V. (2023). The impact of natural resources on renewable energy consumption. *Resources Policy*, *83*, 103692. https://doi.org/10.1016/j.resourpol.2023.103692

Henriques, C. O., Coelho, D. H., & Cassidy, N. L. (2016). Employment impact assessment of renewable energy targets for electricity generation by 2020—An IO LCA approach. *Sustainable Cities and Society*, *26*, 519–530. https://doi.org/10.1016/j.scs.2016.05.013

Holdren, J. P., & Ehrlich, P. R. (1974). Human population and the global environment: Population growth, rising per capita material consumption, and disruptive technologies have made civilization a global ecological force. *American Scientist*, *62*(3), 282–292.

International Energy Agency. (2019). Africa Energy Outlook 2019. https://www.iea.org/reports/africa-energy-outlook-2019#renewables

International Energy Agency. (2020). World Energy Outlook 2020. https://iea.blob.core.windows.net/assets/a72d8abf-de08-4385-8711-b8a062d6124a/WEO2020.pdf

International Renewable Energy Agency. (2020). Global Renewables Outlook. https://www.irena.org//media/Files/IRENA/Agency/Publication/2020/Apr/IRENA_Global_Renewables_Outlook_2020.pdf

Jin, G., & Huang, Z. (2024). Resource curse or resource boon? Appraising the mediating role of fin-tech in realizing natural resources-green growth nexus in MENA region. *Resources Policy*, *89*, 104590. https://doi.org/10.1016/j.resourpol.2023.104590

Juodis, A., & Reese, S. (2022). The incidental parameters problem in testing for remaining cross-section correlation. *Journal of Business & Economic Statistics*, *40*(3), 1191–1203.

Karavias, Y., & Tzavalis, E. (2016). Local power of fixed-*T* panel unit root tests with serially correlated errors and incidental trends. *Journal of Time Series Analysis*, *37*(2), 222–239.

Karmaker, S. C., Barai, M. K., Sen, K. K., & Saha, B. B. (2023). Effects of remittances on renewable energy consumption: Evidence from instrumental variable estimation with panel data. *Utilities Policy*, *83*, 101614. https://doi.org/10.1016/j.jup.2023.101614

Khobai, H., Kolisi, N., Moyo, C., Anyikwa, I., & Dingela, S. (2020). Renewable energy consumption and unemployment in South Africa. *International Journal of Energy Economics and Policy*, *10*(2), 170–178.

Li, X., & Tong, X. (2024). Fostering green growth in Asian developing economies: The role of good governance in mitigating the resource curse. *Resources Policy*, *90*, 104724. https://doi.org/10.1016/j.resourpol.2024.1047

Liu, J., Ge, J., & He, H. (2023). The evolution of renewable energy and its impact on employment in China: Assessing the role of education. *Environmental Science and Pollution Research*, *30*, 79363–79375. https://doi.org/10.1007/s11356-023-27808-2

Liu, J., & Lu, S. (2023). Do natural resources ensure access to sustainable renewable energy in developing economies? The role of mineral resources in a resources-energy novel setting. *Resources Policy*, *85*, 104008. https://doi.org/10.1016/j.resourpol.2023.104008

Ma, Q., Li, S., Aslam, M., Ali, N., & Alamri, A. M. (2023). Extraction of natural resources and sustainable renewable energy: COP26 target in the context of financial inclusion. *Resources Policy*, *82*, 103466. https://doi.org/10.1016/j.resourpol.2023.103466

Machado, J. A., & Silva, J. S. (2019). Quantiles via moments. *Journal of Econometrics*, *213*(1), 145–173.

Muniyoor, K. (2020). Is there a trade-off between energy consumption and employment: Evidence from India. *Journal of Cleaner Production*, *255*, 120262. https://doi.org/10.1016/j.jclepro.2020.120262

Nwani, C. (2022). Global trade flows and the role of bank financing: Policy path for mitigating associated environmental impacts in import-oriented economies. *Journal of International Commerce, Economics and Policy*, *13*(03), 2250014. https://doi.org/10.1142/S1793993322500144

Nwani, C., Okezie, B. N., Nwali, A. C., Nwokeiwu, J., Duruzor, G. I., & Eze, O. N. (2023). Natural resources, financial development and structural transformation in sub-Saharan Africa. *Heliyon*, *9*(9), e19522. https://doi.org/10.1016/j.heliyon.2023.e19522

Okere, K. I., Dimnwobi, S. K., Ekesiobi, C., & Onuoha, F. C. (2024). Pollution, governance, and women's work: Examining African female labour force participation in the face of environmental pollution and governance quality puzzles. *Women's Studies International Forum*, *102*, 102851. https://doi.org/10.1016/j.wsif.2023.102851

Okere, K. I., Dimnwobi, S. K., Ekesiobi, C., & Onuoha, F. C. (2023b). Turning the tide on energy poverty in sub-Saharan Africa: Does public debt matter? *Energy*, *282*, 128365. https://doi.org/10.1016/j.energy.2023.128365

Olaniyi, C. O., & Odhiambo, N. M. (2024). Do natural resource rents aid renewable energy transition in resource-rich African countries? The roles of institutional quality and its threshold. *Natural Resources Forum*. https://doi.org/10.1111/1477-8947.12430

Olanrewaju, B. T., Olubusoye, O. E., Adenikinju, A., & Akintande, O. J. (2019). A panel data analysis of renewable energy consumption in Africa. *Renewable Energy*, *140*, 668–679. https://doi.org/10.1016/j.renene.2019.02.061

Omoju, O. E., Beyene, L. M., Ikhide, E. E., Dimnnwobi, S. K., & Ehimare, O. A. (2024). Being green and prudent: Economy-wide and environmental impacts of renewable energy production subsidy in Nigeria. *The Journal of Developing Areas*, *58*(3), 47–66.

Onuoha, F. C., Dimnwobi, S. K., Okere, K. I., & Ekesiobi, C. (2023a). Funding the green transition: Governance quality, public debt, and renewable energy consumption in sub-Saharan Africa. *Utilities Policy*, *82*, 101574. https://doi.org/10.1016/j.jup.2023.101574

Onuoha, F. C., Dimnwobi, S. K., Okere, K. I., & Ekesiobi, C. (2023b). Sustainability burden or boost? Examining the effect of public debt on renewable energy consumption in sub-Saharan Africa. *Energy Sources, Part B: Economics, Planning, and Policy*, *18*(1), 1–15. https://doi.org/10.1080/15567249.2023.2214917

Ortega, M., Río, P. D., Ruiz, P., Nijs, W., & Politis, S. (2020). Analysing the influence of trade, technology learning and policy on the employment prospects of wind and solar energy deployment: The EU case. *Renewable and Sustainable Energy Reviews*, *122*, 109657. https://doi.org/10.1016/j.rser.2019.109657

Osei, B., Kunawotor, M. E., & Kulu, E. (2022). Renewable energy production and employment: Comparative analysis on European and Asian countries. *International Journal of Energy Sector Management*, *17*(4), 761–778. https://doi.org/10.1108/IJESM-04-2022-0015

Pesaran, H. M. (2015). Testing weak cross-sectional dependence in large panels. *Econometric Reviews*, *34*, 1089–1117. https://doi.org/10.1080/07474938.2014.956623

Pesaran, M. H. (2004) General diagnostic tests for cross section dependence in panels. CESifo Working Paper Series No. 1229; IZA Discussion Paper No. 1240.

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, *22*(2), 265–312. https://doi.org/10.1002/jae.951

Pesaran, M. H., & Xie, Y. (2021). A bias-corrected CD test for error cross-sectional dependence in panel data models with latent factors. arXiv preprint arXiv:2109.00408.

Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics*, *142*(1), 50–93. https://doi.org/10.1016/j.jeconom.2007.05.010

Proença, S., & Fortes, P. (2020). The social face of renewables: Econometric analysis of the relationship between renewables and employment. *Energy Reports*, *6*, 581–586. https://doi.org/10.1016/j.egyr.2019.09.029

Przychodzen, W., & Przychodzen, J. (2020). Determinants of renewable energy production in transition economies: A panel data approach. *Energy*, *191*, 116583. https://doi.org/10.1016/j.energy.2019.116583

Saboori, B., Gholipour, H. F., Rasoulinezhad, E., & Ranjbar, O. (2022). Renewable energy sources and unemployment rate: Evidence from the US states. *Energy Policy*, *168*, 113155. https://doi.org/10.1016/j.enpol.2022.113155

Shinwari, R., Yangjie, W., Payab, A. H., Kubiczek, J., & Dördüncü, H. (2022). What drives investment in renewable energy resources? Evaluating the role of natural resources volatility and economic performance for China. *Resources Policy*, *77*, 102712. https://doi.org/10.1016/j.resourpol.2022.102712

Wang, C. J. (2015). Instrumental variables approach to correct for endogeneity in finance. In *Handbook of financial econometrics and statistics* (pp. 2577–2600). Springer USA.

Westerlund, J. (2007). Testing for error correction in panel data. *Oxford Bulletin of Economics and Statistics*, *69*(6), 709–748.

World Bank. (2023). World Development Indicators. https://databank.worldbank.org/source/world-development-indicators#

Xie, Y., & Pesaran, M. H. (2022). A bias-corrected cd test for error cross-sectional dependence in panel data models with latent factors (August 23, 2022). Available at SSRN: https://doi.org/10.2139/ssrn.4198155

York, R., Rosa, E. A., & Dietz, T. (2003). STIRPAT, IPAT and ImPACT: Analytic tools for unpacking the driving forces of environmental impacts. *Ecological Economics*, *46*(3), 351–365. https://doi.org/10.1016/S0921-8009(03)00188-5

Yuan, J., Yang, R., & Fu, Q. (2023). Aspects of renewable energy influenced by natural resources: How do the stock market and technology play a role? *Resources Policy*, *85*, 103820. https://doi.org/10.1016/j.resourpol.2023.103820

Zhang, J., Li, B., He, H., & Shen, Y. (2024). Natural resource dependence and renewable energy development: Does government policy support matter? *Journal of Cleaner Production*, *436*, 140466. https://doi.org/10.1016/j.jclepro.2023.140466

Zhang, Y., Danish, & Khan, S. U. D. (2023). The role of energy poverty in the linkage between natural resources and economic performance: Resource curse or resource blessing? *Resources Policy*, *85*, 103838. https://doi.org/10.1016/j.resourpol.2023.103838

Zhao, X., & Luo, D. (2017). Driving force of rising renewable energy in China: Environment, regulation and employment. *Renewable and Sustainable Energy Reviews*, *68*, 48–56. https://doi.org/10.1016/j.rser.2016.09.126

How to cite this article: Okere, K. I., Dimnwobi, S. K., & Fasanya, I. O. (2025). Striding towards a greener future: Unlocking the potential of natural resources and employment dynamics in green energy transition in sub-Saharan Africa. *Managerial and Decision Economics*, *46*(1), 329–346. https://doi.org/10.1002/mde.4377

APPENDIX A: COUNTRIES STUDIED

Angola	Ghana
Benin	Guinea
Botswana	Guinea-Bissau
Burkina Faso	Kenya
Burundi	Lesotho
Cabo Verde	Liberia
Cameroon	Madagascar
Central African Republic	Malawi
Chad	Mali
Comoros	Namibia
Congo, Democratic Republic	Niger
Congo, Republic	Nigeria
Côte d'Ivoire	São Tomé and Príncipe
Djibouti	Senegal
Equatorial Guinea	Sierra Leone
Eritrea	South Africa
Eswatini	Sudan
Ethiopia	Tanzania
Gabon	Togo
Gambia	Uganda
Mozambique	Zambia
Rwanda	Zimbabwe