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ARTICLE

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Finance and the environment: The eco-impact of market- and institution-driven development in Africa using land-use-adjusted metrics across sources of greenhouse gases

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Abstract

Africa must ensure that its development trajectories are sustainable. In pursuit of viable policy pathways, this study examines the eco-impact of the energy mix (Te) and financial development (FD) in selected African countries. The Te path is defined using the emission-intensity paradigm, where positive trends indicate a strong dependence on fossil fuels, while negative trends suggest a shift toward greener energy sources. The FD impact is disaggregated to recognize the separate effects of market-based (FM) and institution-based (FI) development. This study utilized land-use metrics across major greenhouse gas (GHG) sources, drawing data from a panel of 33 countries spanning from 1982 to 2021. It employs a novel instrumental-variables approach for fitting panel-data models, addressing cross-sectional dependence issues and incorporating heterogeneous slope coefficients using the mean-group estimator. Empirical findings reveal that positive trends in Te have a significant and positive impact on total GHG emissions (GHGe), whereas FM has a negative and significant effect on GHGe, suggesting its active role in mitigating climate impacts. The disaggregation of GHGe highlights the distinct impacts on CO_2 (CO_2e), nitrous oxide (N_2Oe) and methane (CH_4e) emissions. Economic affluence positively impacts CH4e, while positive trends in Te primarily increase CO_2e. FI significantly reduces N_2Oe, while FM notably decreases CO_2e. Furthermore, FI has a significant negative impact on the emission intensity of Te, indicating its role in promoting green energy transition. These findings underscore the necessity for nuanced policy interventions that integrate FD with environmental objectives, promote green energy transition and address land-use challenges.

KEYWORDS

energy-based carbon intensity, financial institutions, financial markets, greenhouse gases, land-use-adjusted emissions

1 | INTRODUCTION

The COP27 (27th United Nations Climate Change) Conference held in Egypt provided Africa with the opportunity to seek and advance climate-friendly measures that demonstrate a sustainable way to maintain the global temperature below 1.5°C. Despite being the least contributor to global greenhouse gases (GHGs), the continent has witnessed a massive increase in its territorial emissions in recent years, deepening sustainability concerns. From 1980 to 2021, Africa's GHG emissions increased by 108%, from 2,276,265,500 tons to 4,728,741,000 tons, with a significant contribution from fossil fuel-dependent industrializing countries such as South Africa, Algeria, Nigeria, Egypt and Morocco (see Jones et al., 2023). As energy demands continue to rise, keeping Africa's GHG emissions low while addressing issues of growth, poverty and insecurity remains a challenge. Technologically, these countries strongly rely on abundant fossil fuel-based energy sources, particularly oil and coal. This reliance is exacerbated by major industries related to energy and mineral extraction and processing, leading to carbon-intensive paths to growth. Additionally, the renewable energy sources in Africa are predominantly traditional biomass, such as wood and charcoal (Olabisi et al., 2023). Modern renewable technologies (e.g., wind, solar and hydropower) currently account for less than 10% of Africa's total energy use (BP, 2023). Transitioning to modern renewable energy sources provides a path to lowering the carbon intensity of the energy structure, which is critical for facilitating climate-resilient and low-carbon development (Kabeyi & Olanrewaju, 2022).

Policymakers anticipate that having a well-developed financial system will be crucial for overcoming technological constraints, inhibiting the transition to a low-carbon energy structure (Olabisi et al., 2023; Taghizadeh-Hesary et al., 2022). Hence, African countries have intensified policy efforts in the past four decades, primarily aimed at restructuring through liberalization, privatization and stabilization policies, accompanied by auxiliary financial development (FD) policies (Beck et al., 2011). However, the benefits continue to be debated among experts, particularly regarding the financial system's efficiency in traditional roles of pooling savings, allocating capital to productive investments, monitoring investments and risk diversification (Olaniyi et al., 2023). Structurally, the financial system is institution-based, with banks, insurance companies and pension funds playing dominant roles in resource mobilization and allocation. Remarkably, policy efforts have resulted in only marginal improvement in financial market development. Even with respect to developing regions' standards, Africa's financial system remains the least developed in

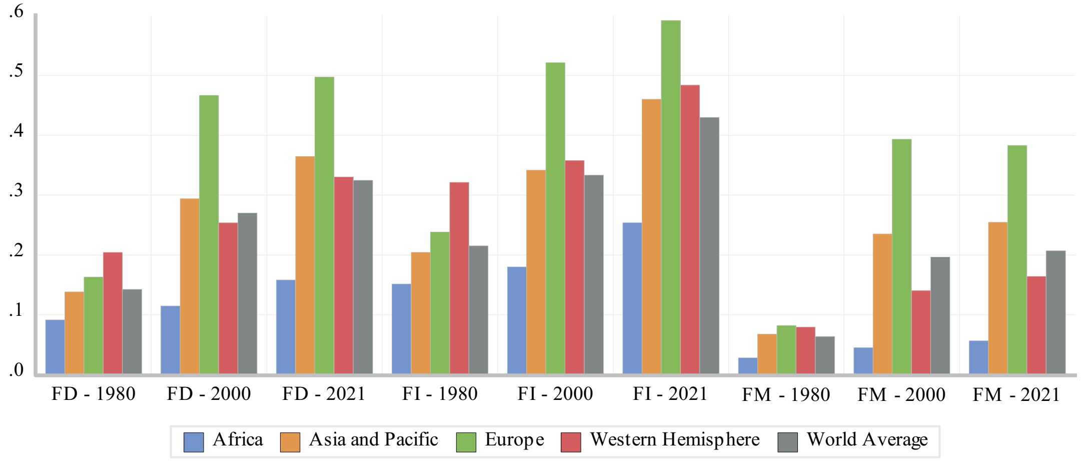


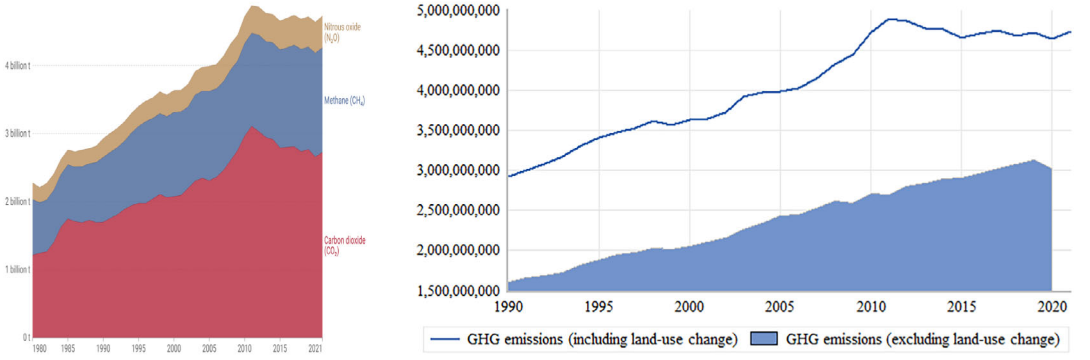
FIGURE 1 Financial development indices across regions. *Source*: IMF Dataset compiled by Svirydzenka (2016).

the world (see Figure 1). This underdevelopment suggests limited opportunities for Africa's integration into the global financial system and a low capacity to attract capital from international investors (Ibrahim & Alagidede, 2018; Ouedraogo & Sawadogo, 2022).

In light of the above discussion, this study examines the eco-impact of energy and financial system transformations in Africa. The empirical formulation is guided by the following specific objectives: to examine the role of innovations underlying the progress of the current energy transition in mitigating GHG emissions in Africa and to examine whether financial system development minimizes trade-offs and maximizes synergies between energy and climate targets. To achieve the first objective, this study models an impact equation relating GHG emissions to the environmental efficiency of the energy mix. Building on the work of Waggoner and Ausubel (2002), the energy-based innovations inducing environmental efficiency are defined using the carbon intensity metric, which quantifies the "greenness" of energy sources, indicating the degree to which economies shift away from fossil fuels toward sustainable sources, such as renewables (De La Peña et al., 2022; Lin et al., 2023). To understand how and whether financial system development constrains or strengthens the energy transition to a low-carbon path, the eco-impact equation is extended to account for the role of FD, with additional insight that financial markets and institutions may provide different policy considerations.

Several recent studies have explored pathways for scaling up climate action in Africa (Adedoyin et al., 2023; Chen et al., 2023; Emenekwe et al., 2022; Espoir & Sunge, 2021; Nwani, 2022; Shobande & Asongu, 2022). However, certain limitations affect the policy relevance of these findings. First, these studies have focused primarily on modelling carbon dioxide (CO_2) emissions, overlooking other significant GHGs, such as methane (CH_4) and nitrous oxide (N_2O), which also contribute significantly to the growth in GHG emissions in Africa (see Figure 2, Plot a). Second, these studies have focused mainly on emissions produced by burning fossil fuels and industrial production and have failed to account for the contributions of agricultural and land-use changes. Land-use activities, including deforestation, agricultural practices and soil degradation, release GHGs. As shown in Figure 2 (see plot b), land-use changes accounted for more than 35% of the total GHG emissions in Africa in recent years. Therefore, existing studies may have produced limited empirical findings to guide policy formulation in Africa without proper adjustment. Third, the eco-impact of FD in Africa has been studied using metrics describing mainly the institution-based dimension, with limited or no empirical evidence explaining the role of market-based development. This study adopts empirical steps to resolve these gaps.

The following contributions are made to the literature. First, to the best of our knowledge, this is one of the first studies to model drivers of GHG emissions in Africa across different gas sources. This study looks at total GHG



Plot (a) – Sources of GHG emissions; Plot (b) –Adjusted vs. unadjusted GHG emissions.

FIGURE 2 GHG emissions, Africa; *Source*: Jones et al. (2023) via OurWorldInData.org.

emissions and the breakdown of other major gases, including methane and nitrous oxide. Additionally, the emission estimates are adjusted for the contributions of land-use challenges in Africa. Second, this study adopts a different perspective on the energy-environment dilemma by using the low-carbon paradigm to define the technological efficiency of the energy mix. This study therefore brings to the fore the energy policy path to understanding the conditional and technological effects of FD in the carbon mitigation model. Third, this study uses the extended impact equation and tests to determine the impact of development trends in financial markets and institutions on the energy-based carbon intensity metric. Previous empirical tests have modelled mainly direct and unconditional effects by introducing FD indicators directly into the impact equation. Thus, this study provides one of the first empirical tests of the technological effects of FD on climate policy in Africa. From the perspective of empirical methodology, this study employs a large-T panel data model, which provides valid homogeneous and heterogeneous slope coefficients and offers several advantages relative to the small-T models used in previous studies. These empirical findings have policy implications for catalysing the broader development transformation required to strengthen the synergies between climate and energy transition targets in Africa.

The following section examines the literature to provide both empirical and theoretical context, while the subsequent section outlines the model, data and modelling techniques. The fourth section elucidates and discusses the results and the fifth section brings the study to a close, offering policy insights.

2 | REVIEW OF THE THEORETICAL AND EMPIRICAL LITERATURE

This review aims to explore key concepts, frameworks and empirical findings related to the interplay between the carbon intensity of energy sources, FD and the resultant impact on greenhouse gas (GHG) emissions.

2.1 | Theoretical framework

The eco-impact identity delineates a multiplicative function involving population, affluence and technology as the anthropogenic determinants of environmental changes (Ehrlich & Holdren, 1971; York et al., 2003). These factors exert direct influence on environmental indicators and are influenced by other variables. Subsequent discussions have expanded the analysis to a much more complex set of eco-impact frameworks. One such framework is the Kaya identity specification, which assumes that technology depends on the structure of the energy mix (Lin et al., 2015; Ma & Cai, 2018). The structure of the energy mix refers to the combination of various energy sources used to meet energy demands (Ali et al., 2023; Nwani et al., 2023; Sun et al., 2023). The composition encompasses fossil fuels (coal, oil and gas), nuclear materials, renewables (solar, wind and hydro) and biomass. The relative share of each source within the mix determines its overall carbon intensity (Ali et al., 2023; Nwani et al., 2023; Sun et al., 2023). Renewables are characterized by minimal greenhouse gas emissions and SDG 7.2 targets their scalability and integration into existing energy systems (De La Peña et al., 2022). Conversely, fossil fuels are known for their high carbon intensity, which releases significant amounts of greenhouse gases when burned (Ali et al., 2023). In an extended eco-impact framework, Waggoner and Ausubel (2002) used the carbon intensity metric as a proxy for efficiency, arguing that it quantifies the inherent "greenness" of energy sources in production.

In recent eco-impact modelling, the crucial role of financial systems in shaping the adoption and diffusion of low-carbon energy technologies and, consequently, their environmental impact has been recognized (Acheampong et al., 2020; Ali et al., 2023; Paramati et al., 2021; Sun et al., 2023; Tiwari et al., 2022; Wang & Yi, 2023). Insights from these studies present diverse perspectives on the anticipated effects of FD on eco-impact indicators, such as GHG emissions and ecological footprints. On the one hand, there is the income scale effect of FD, wherein FD enhances the operations of financial institutions (FI) and markets (FM), providing economic entities (firms, households and government agents) increased access to alternative funding sources. This has resulted in an increase in economic output, heightened energy consumption, and, consequently, increased GHG emissions (Mhadhbi et al., 2021). The alternative view holds that FD has technological and structural transformational effects and, as a result, can facilitate a low-carbon transition. For instance, De Haas and Popov (2019) argue that financial market development deepens the economic participation of local and foreign investors who take CO_2 emissions into account in the assessment of traded instruments so that market prices rationally discount future cash flows of carbon-intensive industries. In this process, firms are made to incorporate environmental concerns into their operations and increase their research and investment in technological development, all of which have the potential to facilitate the adoption of energy-conserving and green technologies (Tiwari et al., 2022). Similarly, Nwani (2022) illustrates how financial institutions reduce CO_2 emissions through credit policies that allocate more resources to environmentally friendly economic sectors.

2.2 | Related empirical literature

Empirical testing of the eco-impact of energy systems has attracted increased amounts of attention in recent literature (Jahanger, Yu, et al., 2022; Rafei et al., 2022). Among the most recent related studies are those conducted by Mhadhbi et al. (2021), Wang et al. (2021), Rahman et al. (2022), Zhang and Wang (2022) and Nwani et al. (2023). Some investigations concentrated on a single-country context, such as the works of Wang et al. (2021) and Zhang and Wang (2022), while others targeted a group of countries utilizing classification criteria spanning geographic, income, or economic blocs, as observed in studies by Namahoro et al. (2021), Rahman et al. (2022) and Nwani et al. (2023). Rahman et al. (2022) employed data spanning from 1990 to 2018, focusing on 25 major emerging economies, to empirically examine the impact equation. The results indicate that CO_2 emissions increase when economic output is energy intensive and decrease when the share of renewables increases to displace fossil fuels in the energy mix. Other recent investigations that corroborate these findings include Dong et al. (2019), Adebayo et al. (2023) and Adedoyin et al. (2023). Dong et al. (2019) used a dataset of 128 countries from 1990 to 2014. Adebayo et al. (2023) undertook a modelling analysis encompassing the BRICS countries from 1990 to 2019; Adedoyin et al. (2023) focused on the specific case of sub-Saharan African countries over the period from 2002 to 2019; and Nwani et al. (2023) examined a panel dataset of European economies from 1995 to 2019. The findings reveal that growth in affluence and carbon intensity of the energy mix contributes to the increasing trends in CO_2 emissions. From a policymaking perspective, the positive correlation between the carbon intensity of the consumption mix and CO_2 emissions underscores that enhancing the economic efficiency of energy use and the carbon efficiency of the energy structure are pivotal pathways for decoupling energy-related CO_2 emissions (Ali et al., 2023).

Several studies offer empirical assessments of the theoretical permutations concerning the impact of FD on GHG emissions (Chen et al., 2022; Chen et al., 2023; Jahanger, Usman, & Balsalobre-Lorente, 2022; Wang & Yi, 2023; Zafar et al., 2019). Zafar et al. (2019) utilized a panel dataset covering the G-7 and N-11 countries from 1990 to 2016 and revealed that the influence of FD on CO_2 emissions varies among countries. In the G-7 economies, FI decreases CO_2 emissions, while in the N-11 economies, it increases. Regarding FM, the study showed that FM development heightens CO_2 emissions in G-7 economies but supports mitigation strategies in N-11 countries. In a panel data study encompassing 83 countries from 1980 to 2015, Acheampong et al. (2020) demonstrated that FM reduces CO_2 emissions in developed and emerging economies but increases emissions in frontier economies. Mhadhbi et al. (2021) analysed the impacts of FM and energy intensity on CO_2 emissions using a panel dataset of 19 emerging markets from 1994 to 2014, revealing an increasing effect on CO_2 emissions. Paramati et al. (2021) reported similar findings in a panel dataset of OECD countries from 1991 to 2016 but noted that FI also increases CO_2 emissions. Sharma et al. (2021) approached the impact equation differently by modelling the drivers of carbon intensity using a panel dataset of South Asian countries from 1990 to 2016 and found that FM increases the carbon content of the energy consumption mix. Using an aggregated FD index, Emenekwe et al. (2022) analysed a panel dataset of Sub-Saharan African countries from 2000 to 2016 and found that FD reduces CO_2 emissions in the region. In a similar study using a dataset consisting of 34 countries, Chen et al. (2023) showed that FI increases CO_2 emissions in Africa. Wang and Yi (2023) used a Chinese provincial dataset to examine the eco-impact of FD. The results show that FD reconciles energy-climate conflicts by reducing the carbon intensity of the energy mix through its mediating role in deepening the market for technological development. In a related study, Sun et al. (2023) showed that the digitization of the financial system mitigates CO_2 emissions by improving the efficiency of the energy structure in China. Huang and Guo (2023) corroborate the positive effect of FD on energy-based carbon efficiency using a similar Chinese provincial dataset from 2000 to 2019.

2.3 | Literature gaps

Several gaps are apparent in the empirical works reviewed. First, these studies examined only CO_2 emissions, neglecting the growing contribution of methane and nitrous oxide to total GHG emissions in Africa. Second, these studies focused solely on emissions from the burning of fossil fuels and industrial production, overlooking the significant contributions of agricultural and land-use challenges, which are burgeoning environmental issues in Africa. Third, previous empirical formulations concentrated on understanding the direct effect of FD on CO_2 emissions, thereby disregarding possible indirect effects via energy transition paths. Modelling these indirect impact channels is crucial because it allows us to comprehend how FD shapes technological factors in the impact mitigation model. Additionally, the eco-impact of FD in Africa has been studied using metrics that predominantly describe institution-based dimensions of FD, with limited or no empirical evidence to elucidate the role of market-based development. To address these gaps, this study disaggregates FD into market-based and institution-based development and employs land-use-adjusted metrics across sources of greenhouse gases. These empirical steps are designed to inform the shaping of sustainable developmental policy targets in Africa.

3 | MODEL, DATA AND REGRESSION TECHNIQUES

3.1 | Construction of the empirical model

This study employs the stochastic impact by regression on population, affluence and technology (STIRPAT) model, a framework advocated by Dietz and Rosa (1994) for assessing the environmental impact of human activities. This framework is chosen for its capacity to incorporate the influence of diverse factors. In its foundational formulation, the STIRPAT model is stated as follows:

$$I_t = \alpha P_t^{\theta} A_t^{\varphi} T_t^{\delta} \tag{1}$$

In Equation (1), α represents the constant scaling factor; θ, φ, and δ are the exponents associated with population (P), affluence (A) and technology (T), respectively. The environmental impact indicator (I) can also be defined in per capita form by dividing both sides of the equation by P. Taking this step, Equation (1) can be adjusted as follows:

$$(I/P)_t = \alpha A_t^{\varphi} T_t^{\delta} \tag{2}$$

In accordance with Waggoner and Ausubel (2002) and York et al. (2003), T can be defined using the green or carbon intensity of the energy mix (Te). This metric quantifies the "greenness" of the energy mix. A decreasing Te implies a technological shift away from fossil fuels toward sustainable energy systems such as renewables. Similarly, a rising Te reflects a low technological capacity to diversify the energy system away from fossil fuels (Waggoner & Ausubel, 2002). This step extends Equation (2) to derive the following extendable equation for understanding the driving factors of environmental impacts:

$$(I/P)_t = \alpha A_t^{\varphi} Te_t^{\delta} \tag{3}$$

Applying both algebraic and natural logarithmic (ln) transformations to Equation (3) yields the following dynamic model for empirical inquiry:

$$\ln(I/P)_t = \alpha + \beta \ln(I/P)_{i(t-1)} + \varphi \ln A_{it} + \delta \ln Te_{it} + u_{it} \tag{4}$$

where $\ln(I/P)_{i(t-1)}$ represents the one-year lagged series of the dependent variable; the subscripts pertain to country *ith* in year *t*; *u* represents the stochastic error term; and φ and δ are the elasticity coefficients concerning the effects of changes in affluence (A) and the carbon intensity of the energy mix (Te), respectively. In theory, φ and δ are expected to be positive parameters. As a measure of decarbonisation intensity, Te decreases with an increase in the share of low-carbon energy sources such as renewable energy but increases with an increase in the share of fossil fuels in the total energy mix (De La Peña et al., 2022; Sun et al., 2023). As a result, economies will emit more GHGs as the Te of their energy structure increases. Following Chen et al. (2022) and Tao et al. (2023), Equation (4) can further be extended to account for the impact of FD and other variables:

$$\ln(I/P)_t = \alpha + \beta \ln(I/P)_{i(t-1)} + \varphi \ln A_{it} + \delta \ln \mathrm{Te}_{it} + \pi \ln \mathrm{FI}_{it} + \phi \ln \mathrm{FM}_{it} + g \ln \mathrm{GI}_{it} + u_{it} \tag{5}$$

For deeper empirical insight, Equation (5) defines FD using disaggregated indicators: institutions (FI) and markets (FM). The impact model also incorporates the role of globalization (GI), thus exposing economies to global economic, social and political shocks (Omoke et al., 2023). For robust empirical estimation, environmental impacts (I/P) are defined using greenhouse gas emissions in per capita form. These estimates are further disaggregated to explain the specific challenges associated with the mitigation of the following major sources of gas emissions: carbon dioxide, nitrous oxide and methane.

$$\ln \mathrm{GHGe}_t = \alpha + \beta_{ghg} \ln \mathrm{GHGe}_{i(t-1)} + \varphi_{ghg} \ln A_{it} + \delta_{ghg} \ln \mathrm{Te}_{it} + \pi_{ghg} \ln \mathrm{FI}_{it} + \phi_{ghg} \ln \mathrm{FM}_{it} + g_{ghg} \ln \mathrm{GI}_{it} + u_{it} \tag{6}$$

$$\ln \mathrm{CO}_2 e_t = \alpha + \beta_{co_2} \ln \ln \mathrm{CO}_2 e_{i(t-1)} + \varphi_{co_2} \ln A_{it} + \delta_{co_2} \ln \mathrm{Te}_{it} + \pi_{co_2} \ln \mathrm{FI}_{it} + \phi_{co_2} \ln \mathrm{FM}_{it} + g_{co_2} \ln \mathrm{GI}_{it} + u_{it} \tag{7}$$

$$\ln H_2Oe_t = \alpha + \beta_{H_2O} \ln \ln H_2Oe_{i(t-1)} + \varphi_{H_2O} \ln A_{it} + \delta_{H_2O} \ln Te_{it} + \pi_{H_2O} \ln FI_{it} + \phi_{H_2O} \ln FM_{it} + g_{H_2O} \ln GI_{it} + u_{it} \quad (8)$$

$$\ln CH_4e_t = \alpha + \beta_{CH_4} \ln \ln CH_4e_{i(t-1)} + \varphi_{CH_4} \ln A_{it} + \delta_{CH_4} \ln Te_{it} + \pi_{CH_4} \ln FI_{it} + \phi_{CH_4} \ln FM_{it} + g_{CH_4} \ln GI_{it} + u_{it} \quad (9)$$

GHGe in Equation (6) represents total greenhouse gas emissions. In the model specifications that follow, CO_2e represents carbon dioxide emissions (see Equation 7), H_2Oe represents nitrous oxide emissions (see Equation 8) and CH_4e represents methane emissions. These emission estimates are all defined in per capita form. The specifications in Equations (6)–(9) can test only the direct eco-impact of FD. Theoretically, it is expected that FD will adjust the carbon mitigation model through the Te channel, given its increasing role in defining production and consumption patterns (Sun et al., 2023). Taking this into consideration, the following additional empirical model is formulated:

$$Te_{it} = \eth + \ell Te_{i(t-1)} + \lambda \ln A_{it} + \vartheta \ln FI_{it} + \Omega \ln FM_{it} + g \ln GI_{it} + u_{it} \quad (10)$$

The variables in Equation (10) remain as previously defined. In theory, ϑ and Ω can be positive or negative coefficient estimates, respectively (Nwani, 2022; Shahbaz et al., 2022; Tiwari et al., 2022). A positive coefficient implies that FD reduces the environmental efficiency of the energy structure (Sun et al., 2023). On the other hand, a negative coefficient will suggest that FD enhances environmental efficiency and facilitates a clean energy transition (Sun et al., 2023).

3.2 | Variables and data sources overview

The dataset encompasses 33 African countries, primarily selected based on the availability of annual time series data spanning from 1982 to 2021 (40 years). The countries are listed in Figure 3. Table 1 provides a concise summary of the definitions of the variables, data sources and fundamental descriptive statistics. Additionally, the correlation matrix is available in Table A1 of Appendix A. Land-use-adjusted metrics are utilized across various greenhouse gas sources: total GHG emissions (GHGe), CO_2 emissions (CO_2e), nitrous oxide emissions (N_2Oe) and methane emissions (CH_4e). The technological structure of the energy mix (Te) is defined using the emission-intensity paradigm, where positive trends indicate a strong dependence on fossil fuels, while negative trends suggest a shift toward greener energy sources. To track the multidimensional structure of FD, we utilize the broad-based indices compiled by Svirydzenka (2016), specifically those based on banking and nonbanking financial institutions (FI) and another set that measures financial market development (FM). These indices are based on a set of depth, access and efficiency parameters. Both the FI and FM indices are normalized scores ranging from 0 (indicating the lowest level of development) to 1 (indicating the highest level of development). The utilization of these aggregated indices is necessitated by the unavailability of data for certain specific indicators, predominantly the access and efficiency components of the FM index.

3.3 | Instrumental variable (IV) estimation with heterogeneous coefficients

The panel data constructed for this study included a moderately large temporal dimension ($T = 40$) and cross-sectional dimension ($N = 33$). The presence of the lagged dependent variable in the model specifications (see Equations 6–10) is likely to correlate with specific country effects, thereby raising concerns about possible endogeneity bias (Nickell, 1981). This issue predominantly arises with least squares-type dynamic panel estimators (Norkutė et al., 2021). The instrumental variable (IV) estimator for dynamic linear panel data models with many time-series observations (IV-LT), developed by Norkutė et al. (2021), is used in this study to correct this bias. The IV-LT approach employs defactored instruments to control for multifactor error structures. Due to its structural properties, it addresses endogeneity bias (Norkutė et al., 2021). Considering the following autoregressive distributed lag panel-

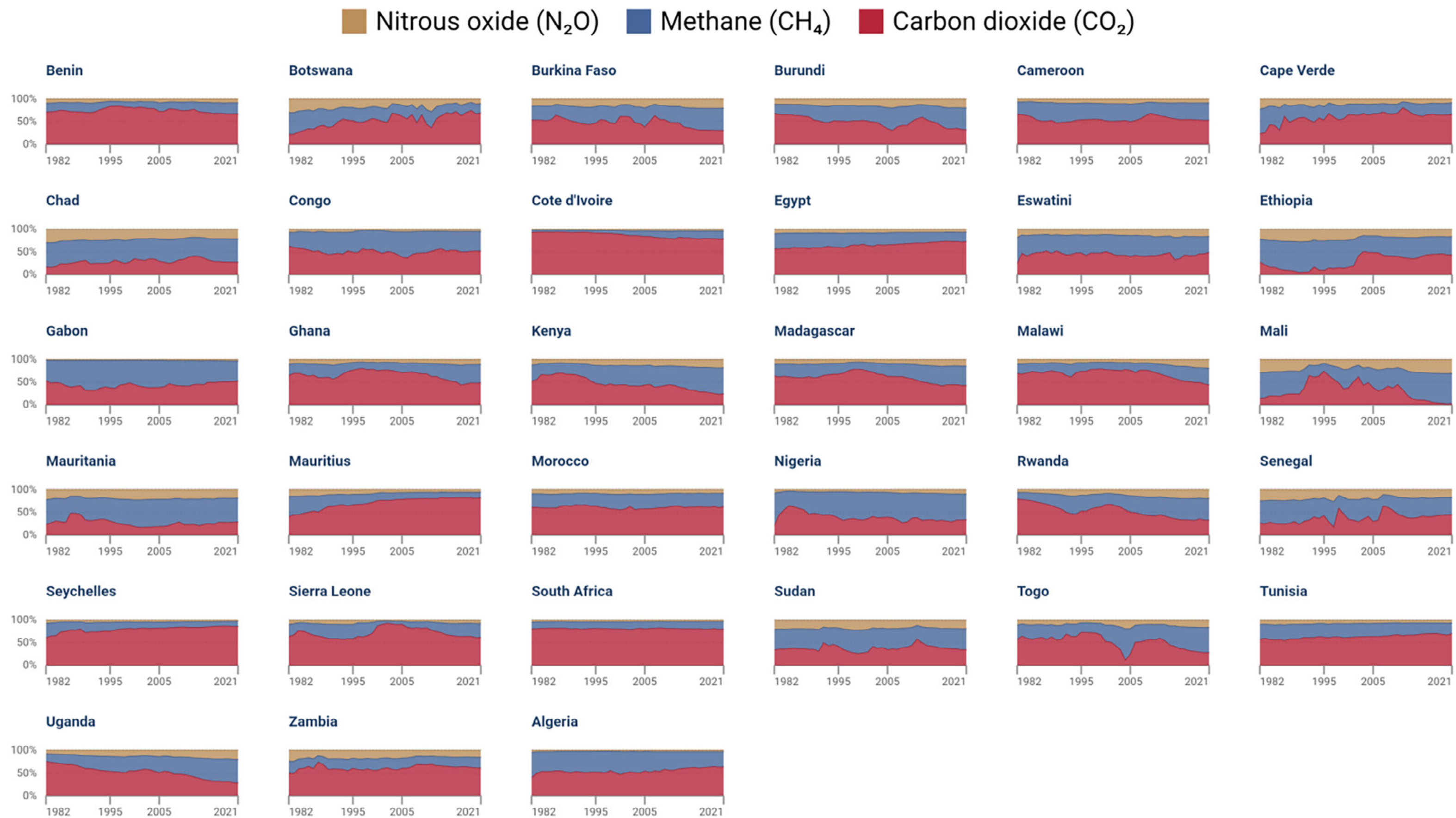


FIGURE 3 Greenhouse gas emissions across all gas sources (including land-use change in tonnes of CO_2 equivalents), Selected African Countrie. *Source*: Jones et al. (2023) via OurWorldInData.org.

TABLE 1 Definition of variables and data description.

Variables	Definition and measurement	Data sources	Web-links to data sources	Mean	Median	Maximum	Minimum	Std. dev.	Observ.
lnGHGe	Geenhouse gas emissions including land-use changes (in tonnes of CO_2 equivalents per patita)	OurWorldInData	https://ourworldindata.org/co2-and-greenhouse-gas-emissions	1.255	1.200	3.480	−0.807	0.704	1320
lnCO_2e	CO_2 emissions including land-use changes (tonnes per capita)	OurWorldInData	https://ourworldindata.org/co2-and-greenhouse-gas-emissions	0.568	0.550	2.727	−3.261	0.913	1320
lnN_2Oe	Nitrous oxide emissions including land-use changes (in tonnes of CO_2 equivalents per capita)	OurWorldInData	https://ourworldindata.org/co2-and-greenhouse-gas-emissions	−1.108	−1.243	1.528	−2.427	0.665	1320
lnCH_4e	Methane emissions including land-use changes (in tonnes of CO_2 equivalents per capita)	OurWorldInData	https://ourworldindata.org/co2-and-greenhouse-gas-emissions	0.078	−0.023	2.863	−1.401	0.759	1320
lnA	GDP per capita constant 2015 US$	WDI		7.225	7.192	9.726	5.249	0.961	1320
lnTe	Energy-based carbon intensity (CO_2 emissions per kilowatt-hour of primary energy use)	OurWorldInData	https://ourworldindata.org/grapher/kaya-identity-co2?country=~Africa	−1.588	−1.579	0.082	−2.947	0.418	1320
lnFI	Financial institutions development index	IMF dataset compiled by Svirydzenka (2016)	https://data.imf.org/	−1.618	−1.629	−0.449	−3.969	0.508	1320
lnFM	Financial markets development index	IMF dataset compiled by Svirydzenka (2016)	https://data.imf.org/	−4.325	−4.339	−0.541	−23.595	2.619	1320
lnGI	Overall globalization index	KOF, complied by Gygli et al. (2019)	https://kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-globalisation-index.html	3.750	3.781	4.276	2.907	0.266	1320

data model, where T observations for each i yield the functional relationship between the dependent (y) and explanatory (X) variables (Kripfganz & Sarafidis, 2021; Norkutė et al., 2021):

$$y_{it} = \alpha y_{i(t-1)} + \beta' X_{it} + u_{it};\ \ i = 1,2,\ldots,N;\ \ t = 1,2,\ldots,T \text{ and } u_{it} = \gamma'_{y,i} f_{y,t} + \varepsilon_{i,t} \tag{11}$$

where $u_{i,t} = \gamma'_{y,i} f_{y,t} + \varepsilon_{i,t}$ indicates that the error term is a composite, $\gamma'_{y,i}$ is a vector of true unobserved factors, $f_{y,t}$ is for factor loadings and $\varepsilon_{i,t}$ is for the idiosyncratic error. Taking $W_i = (y_{i(t-1)}, X_i)$ and $\theta = (\alpha, \beta')'$, Equation (11) can be written more succinctly as follows:

$$y_{it} = W_{it}\theta + u_{it} \tag{12}$$

The defactored IV estimator of θ is defined as

$$\widehat{\theta}_{\mathrm{IV},\ i} = \left(\tilde{A}'_{i,T} \tilde{B}^{-1}_{i,T} \tilde{A}_{i,T}\right)^{-1} \tilde{A}'_{i,T} \tilde{B}^{-1}_{i,T} \tilde{g}_{i,T} \tag{13}$$

The mean group (MG) estimator is used to adjust Equation (13) to produce cross-sectionally heterogeneous slope coefficients as follows:

$$\widehat{\theta}_{\mathrm{MGIV}} = \frac{1}{N}\sum_{i=1}^{N} \widehat{\theta}_{\mathrm{IV},\ i} \tag{14}$$

As $(N,T) \xrightarrow{j} \infty$ then $N/T \to c$ with $0 < c < \infty$, meaning that $\sqrt{N}\left(\widehat{\theta}_{\mathrm{MGIV}} - \theta\right) \xrightarrow{d} N\left(0, \Sigma_\eta\right)$ (Norkutė et al., 2021). Thus, Equation (14) provides a computationally robust estimator, the mean-group-type IV estimator (MGIV), for addressing potential cross-sectional dependence and slope heterogeneity concerns, and because of its computational properties, requires no bias correction (Norkutė et al., 2021).

4 | RESULTS AND DISCUSSION

The outcomes of the Pesaran (2021) cross-sectional dependence test (CD-test) are presented in Table 2. The test statistics, under the null hypothesis (H_0) of cross-sectional independence CD N(0,1), indicate correlated data series

TABLE 2 Pesaran (2021) cross-sectional dependence test.

Variable	CD-test	Average joint	Mean ρ	Mean abs(ρ)
lnGHGe	12.378***	40.00	0.09	0.46
$lnCO_2e$	8.527***	40.00	0.06	0.46
lnN_2Oe	11.95***	40.00	0.08	0.39
$lnCH_4e$	2.274**	40.00	0.02	0.43
lnA	56.806***	40.00	0.39	0.66
lnTe	−0.388	40.00	0.00	0.27
lnFI	42.336***	40.00	0.29	0.48
lnFM	5.025***	40.00	0.03	0.47
lnGI	136.388***	40.00	0.94	0.94

***p < .01; **p < .05 indicate rejection of cross-section independence.

TABLE 3 Pesaran and Yamagata (2008) slope homogeneity test.

Impact model	Delta tilde ($\tilde{\Delta}$)	Adjusted delta tilde ($\tilde{\Delta}_{Adj}$)
1. lnGHGe	37.051***	40.792***
2. $\ln CO_2e$	35.192***	38.745***
3. $\ln N_2Oe$	35.628***	39.225***
4. $\ln CH_4e$	38.161***	42.014***
5. lnTe	21.685***	23.520***

***$p < .01$ indicate rejection that slope coefficients are homogenous.

across panel groups for the lnGHGe, $\ln CO_2e$, $\ln N_2Oe$, $\ln CH_4e$, lnA, lnFI, lnFM and lnGI series. Therefore, the results confirm the presence of cross-sectional dependence in the data series of these variables. However, H_0 is not rejected for lnTe, signifying that the data series of lnTe are not correlated across panel groups. Table 3 displays the results of the slope homogeneity test conducted using the approach developed by Pesaran and Yamagata (2008). The test is carried out under the null hypothesis that the slope coefficients are homogeneous. The delta statistics, along with the adjusted version, suggest that H_0 is rejected, implying that the slope coefficients of the model specifications exhibit heterogeneity. Based on the variance inflation factor (VIF) tests (see Table A2 in Appendix A), the model specifications are relatively free from multicollinearity issues. In the following empirical step, the parameter estimates are computed using the MGIV estimator, which allows for homogeneity and heterogeneity in the slope coefficients. Therefore, the parameter estimates are robust and reliable for policy decisions.

In our examination of GHG emissions, including land-use changes as an adjustment, we observed intriguing empirical outcomes. Initially, parameter estimates were computed assuming homogeneity in the slope coefficients, which were then extended using the more robust MGIV estimator, accommodating heterogeneity in these coefficients. Table 4 lists the empirical results derived from the GHGe equation. Notably, with the incorporation of land-use adjustments, Te and FM emerge as the only variables exerting statistically significant impacts on total GHG emissions across the selected African countries. The positive coefficient estimates of Te suggest that a percentage increase in the carbon intensity of the energy mix correlates with a 0.074% to 0.093% increase in total GHG emissions. Conversely, this implies a potential 0.074% to 0.093% reduction in total GHG emissions with a percentage improvement in the green intensity of the energy consumption mix. This observation resonates with the aspirations of the UN Sustainable Development Goal (SDG) 7.2 target, underlining the imperative to bolster the share of renewable energy within the energy mix. Moreover, these findings echo the findings of Namahoro et al. (2021), Adebayo et al. (2023), Adedoyin et al. (2023) and Nwani et al. (2023). Considering the energy mix in African economies, there is a prevalent reliance on abundant fossil fuel primary sources, notably oil and coal (BP, 2023). Biomass constitutes a significant low-carbon alternative, as highlighted by Olabisi et al. (2023). However, the policy landscape underscores the necessity for a substantial energy transition, pivoting away from fossil fuels and toward environmentally sustainable renewable technologies, as emphasized by Kabeyi and Olanrewaju (2022). Integrating land-use adjustments into our analysis not only enhances the precision of our estimates but also underscores the complex interplay between energy consumption patterns and environmental sustainability in African contexts. Moving forward, policy interventions must prioritize renewable energy integration while navigating the intricate dynamics of land-use changes to effectively mitigate GHG emissions.

In our analysis, we accounted for the unconditional impact of FD on GHG emissions by introducing FI and FM directly into the impact equation. Leveraging the more robust heterogeneous slope coefficients, the statistical properties of the parameter estimates reveal noteworthy insights. Specifically, FI has a positive but statistically insignificant coefficient estimate. Conversely, the coefficient estimates of FM are negative and statistically significant at the 5% level. Notably, a percentage increase in FM corresponds to a reduction in total GHG emissions of approximately

TABLE 4 Impact of FD on GHGe-aggregated analysis.

Variables	(1) Homogeneous slope coefficients	(2) Heterogeneous slope coefficients	(3) AR(2)	(4) AR(3)
L.lnGHGe	0.318***	0.815***	0.734***	0.736***
	(0.072)	(0.061)	(0.050)	(0.044)
	[4.396]	[13.438]	[14.757]	[16.802]
lnA	0.233***	−0.031	0.030	0.032
	(0.059)	(0.064)	(0.066)	(0.068)
	[3.982]	[−0.493]	[0.458]	[0.470]
lnTe	0.098***	0.093***	0.090***	0.074***
	(0.020)	(0.025)	(0.025)	(0.027)
	[4.855]	[3.774]	[3.638]	[2.709]
lnFI	−0.023	0.035	0.009	0.026
	(0.017)	(0.034)	(0.035)	(0.036)
	[−1.336]	[1.051]	[0.262]	[0.711]
lnFM	−0.003	−0.036**	−0.034**	−0.033**
	(0.007)	(0.014)	(0.014)	(0.015)
	[−0.401]	[−2.564]	[−2.454]	[−2.234]
lnGI	−0.033	−0.143	0.050	0.096
	(0.078)	(0.180)	(0.118)	(0.132)
	[−0.426]	[−0.793]	[0.423]	[0.723]
Constant	−0.605	1.054	−0.098	−0.296
	(0.591)	(0.794)	(0.695)	(0.662)
	[−1.023]	[1.327]	[−0.141]	[−0.448]
Hansen test: χ^2	8.8210	-	-	-
Prob > χ^2	0.454	-	-	-
Number of Instruments	15	10	15	20
Observations	1254	1287	1254	1221
Number of ID	33	33	33	33

Note: Robust std. err. (); t-stat []. Hansen test for the overidentifying restrictions *H*0: overidentifying restrictions are valid; Stata command: xtivdfreg.
****p* < .01; ***p* < .05.

0.033% to 0.036%. This finding resonates with similar observations documented by Acheampong et al. (2020) across developed and emerging economies. From a policy perspective, the implications are profound. This finding suggests that FM provides a structural and technological pathway to deepen the expansion of economic output through sectors and technologies that actively mitigate GHG emissions. As underscored by De Haas and Popov (2019), financial markets play a pivotal role in amplifying the economic participation of both local and foreign investors, who increasingly factor climate impacts into their assessments of traded instruments. This market mechanism leads to rational price adjustments whereby future cash flows of carbon-intensive industries are discounted, rendering them less attractive to investors. Consequently, firms are incentivized to incorporate climate concerns into their operational

TABLE 5 Impact of FD on the GHGe-disaggregated analysis.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Homogeneous slope coefficients			Panel B: Heterogeneous slope coefficients		
	CO_2e	N_2Oe	CH_4e	CO_2e	N_2Oe	CH_4e
L.lnCO_2e	0.444***			0.752***		
	(0.064)			(0.049)		
	[6.911]			[15.394]		
L.lnNOe		0.636***			0.673***	
		(0.100)			(0.050)	
		[6.371]			[13.440]	
L.lnMe			−0.058			0.215***
			(0.103)			(0.074)
			[−0.557]			[2.892]
lnA	0.245**	0.077**	0.177***	−0.048	0.056	0.131**
	(0.101)	(0.031)	(0.039)	(0.138)	(0.044)	(0.054)
	[2.419]	[2.497]	[4.533]	[−0.345]	[1.291]	[2.403]
lnTe	0.229***	0.006	−0.008	0.135***	−0.018	−0.020
	(0.035)	(0.008)	(0.013)	(0.039)	(0.027)	(0.025)
	[6.558]	[0.721]	[−0.621]	[3.432]	[−0.651]	[−0.798]
lnFI	0.018	−0.020*	−0.054***	0.020	−0.060**	−0.032
	(0.038)	(0.011)	(0.013)	(0.067)	(0.028)	(0.039)
	[0.481]	[−1.779]	[−4.279]	[0.306]	[−2.189]	[−0.827]
lnFM	−0.009	0.010***	0.007	−0.059**	−0.003	0.009
	(0.013)	(0.004)	(0.004)	(0.028)	(0.018)	(0.023)
	[−0.723]	[2.593]	[1.570]	[−2.118]	[−0.169]	[0.394]
lnGI	−0.171	−0.045	0.106*	−0.092	0.036	0.069
	(0.185)	(0.051)	(0.056)	(0.219)	(0.077)	(0.065)
	[−0.924]	[−0.883]	[1.894]	[−0.418]	[0.468]	[1.065]
Constant	−0.461	−0.779*	−1.672***	0.715	−0.951**	−1.235**
	(0.992)	(0.473)	(0.470)	(1.109)	(0.481)	(0.526)
	[−0.465]	[−1.648]	[−3.555]	[0.645]	[−1.979]	[−2.347]
Hansen test: χ^2	6.271	13.318	6.402	-	-	-
Prob > χ^2	0.713	0.149	0.699	-	-	-
Number of Instruments	15	15	15	15	15	5
Observations	1254	1254	1254	1254	1254	1287
Number of ID	33	33	33	33	33	33

Note: Robust std. err. (); t-stat []. Hansen test for the overidentifying restrictions *H0*: overidentifying restrictions are valid; Stata command: xtivdfreg.
***$p < .01$; **$p < .05$; *$p < .1$.

strategies, leading to increased research and investment in technological development. These efforts, as highlighted by Tiwari et al. (2022), have the potential to facilitate the adoption of energy-conserving and green technologies, further contributing to the mitigation of GHG emissions.

In our continued analysis, further empirical steps disaggregate total GHG emissions into CO_2, N_2O and CH_4, yielding the intriguing insights presented in Table 5. Leveraging the more robust heterogeneous slope coefficient estimates in Panel B, we unravel distinct eco-impacts across different models. Affluence (A) exhibits significance solely in the CH4e model. The positive coefficient suggests that a 1% increase in per capita GDP is related to a 0.131% increase in CH_4 emissions. Notably, Chen et al. (2023) reported a similar positive eco-impact of affluence in Africa concerning CO_2 emissions, albeit using unadjusted emission estimates that omitted the contribution of land-use changes. Our findings, particularly the significant positive coefficient estimate in panel A (column 1), underscore the improvement afforded by the MGIV estimator, which accounts for heterogeneity in slope coefficients, providing more robust estimates crucial for policy formulation. The positive coefficient of per capita GDP in column (6) further indicates that economic growth tends to drive consumption patterns toward meat and dairy products, which are significant contributors to methane emissions through livestock-related activities.

The variable Te demonstrates significance solely in the CO_2e model, with both homogeneous and heterogeneous estimates proving positive and significant at the 1% level. This suggests that a 1% increase in energy-based carbon intensity amplifies land-use-adjusted CO_2 emissions by 0.135%, with no significant impact on N_2O and CH_4 emissions. These findings align with previous studies by Wang et al. (2021), Rahman et al. (2022), Zhang and Wang (2022) and Nwani et al. (2023), reinforcing the intuitive understanding that a more carbon-intensive energy mix significantly contributes to global warming. The adjustment for land-use changes underscores the critical role of addressing deforestation, agricultural expansion and land degradation, which notably contribute to CO_2 emissions in Africa. Therefore, integrating policies that address land-use issues alongside the promotion of cleaner energy sources such as modern renewables, wind and solar energy is imperative for achieving comprehensive GHG emission reduction in the region.

The analysis further dissects the direct impact of FD across the three primary sources of GHG emissions, separating the effects of FI and FM. Drawing upon the more robust heterogeneous slope coefficients, the statistical properties of the parameter estimates reveal intriguing patterns. First, FI has a significant negative impact on N_2Oe, while its effects on CO_2e and CH_4e are statistically insignificant. Notably, a percentage increase in FI is associated with a notable decrease in N2Oe of 0.060%. Most of those previous studies focused predominantly on CO_2e, yielding conflicting evidence. For example, while Emenekwe et al. (2022) suggested that FI mitigates CO_2e in Sub-Saharan Africa, Chen et al. (2023) presented contrasting findings indicating an increase in CO_2 emissions due to FI in Africa. On the other hand, FM has a significant negative impact solely on CO_2e, with its effects on N_2Oe and CH_4e deemed statistically insignificant. A percentage increase in FM is linked with a 0.059% reduction in CO_2e. Acheampong et al. (2020) reported similar findings for both developed and emerging economies.

The findings reported in Table 5 highlight the structural pathways offered by both FI and FM in mitigating land-use challenges and associated environmental impacts. This finding underscores the multifaceted nature of the influence of FD on GHG emissions and suggests avenues for targeted policy interventions. By recognizing the differential impacts of financial mechanisms on various GHG sources, policymakers can craft more nuanced strategies to address both financial and environmental objectives concurrently. These insights contribute to a more comprehensive understanding of the intricate relationships among FD, land-use dynamics and environmental sustainability, facilitating informed decision-making for achieving sustainable development goals.

In addition to examining the conditional effects of FD from the extended eco-impact equations, it is essential to recognize that FI and FM likely influence GHG emissions indirectly through the energy transition path Te, reflecting the role of financial systems in shaping production and consumption patterns (De Haas & Popov, 2019; Huang & Guo, 2023; Sun et al., 2023). Thus, this study models the impact of FI and FM on Te while controlling for economic affluence and globalization, enabling an assessment of FD's potential to adjust the impact of carbon intensity (CI) on GHG emissions in Africa, as reported in Table 6. The coefficients of FI, both homogeneous and heterogeneous, are negative and statistically significant. Specifically, a percentage increase in FI leads to a reduction of 0.090% in the carbon emission intensity of the energy structure. This indicates that FI facilitates carbon mitigation by steering the technological composition of African economies' energy mix toward greener sources. Similar findings in China, as reported by Huang and Guo (2023), Sun et al. (2023) and Wang and Yi (2023), underscore the eco-efficiency benefits of FD in reducing the carbon intensity of the energy mix. Conversely, the coefficients of FM are found to be insignificant. While Sharma et al. (2021) reported a positive relationship between FM and energy-based carbon intensity in South Asian countries, our findings suggest that FM's impact on Te in the selected African countries lacks statistical significance. Furthermore, the effect of globalization on Te is noteworthy, demonstrating a positive and significant impact. Specifically, a unit increase in globalization results in a considerable increase in Te, estimated to be 0.281% or more.

From a policy perspective, it becomes evident that FD can drive a shift away from fossil fuels toward low-carbon energy sources such as wind and solar renewables (Shahbaz et al., 2022). The eco-impact of FI and FM across model specifications highlights how liberalization, privatization and stabilization policies can channel more financing into the technological transition of the energy mix toward low-carbon development. However, compared to other developing regions, African financial markets still exhibit considerable underdevelopment, hindering full integration into global funding sources (Svirydzenka, 2016). Despite being well-capitalized and liquid, the financial institution sector has not yet been structured to play a defined role in climate change mitigation. Based on the insights gleaned from Table 6, it becomes apparent that a well-developed financial system will play a critical role in adjusting the technological composition of the energy mix toward more climate-friendly renewable energy sources (De Haas & Popov, 2019). Thus, fostering FD in Africa should be a priority for policymakers seeking to align economic growth with sustainable environmental practices, particularly in the context of energy transition and climate change mitigation efforts.

5 | CONCLUSION AND POLICY RECOMMENDATIONS

This study examines the environmental implications of energy and financial system development in selected African countries considering land-use-adjusted metrics across various greenhouse gas sources: total GHG emissions (GHGe), CO_2 emissions (CO_2e), nitrous oxide emissions (N_2Oe) and methane emissions (CH_4e). Utilizing data from a panel of 33 countries spanning from 1982 to 2021, the study employs a novel instrumental variables approach for panel data modelling. This method addresses cross-sectional dependence issues and incorporates heterogeneous slope coefficients using a mean-group (MG) estimator to ensure accurate parameter estimates. By adopting the carbon-intensity paradigm, this study examines the environmental efficiency of the energy mix (Te) to elucidate the role of energy policies in carbon mitigation strategies. Moreover, the study extends its analysis to explore how financial system development influences the transition to low-carbon pathways, recognizing the potential differences in policy implications between financial markets and institutions.

The empirical findings reveal that the energy mix and financial market development significantly influence total GHG emissions in Africa. Positive coefficients in the technology path indicate a correlation between a carbon-intensive energy structure and increases in GHG emissions. While financial institution development has a positive but statistically insignificant impact, financial market development has a negative and significant effect on GHG emissions, suggesting its active role in GHG mitigation. Disaggregation of GHG emissions has distinct impacts on CO_2e, N_2Oe and CH_4e. Economic affluence positively impacts CH_4e, while the carbon intensity of the energy mix primarily affects CO_2e. Financial institution development significantly reduces N_2Oe, but its effects on CO_2e and CH_4e are insignificant. Similarly, financial market development notably decreases CO_2e but has no significant effects on N_2Oe or CH_4e. Furthermore, financial institution development has a significant negative impact on energy-based carbon intensity, indicating its role in promoting greener energy sources. However, the impact of financial market development on the energy transition lacks statistical significance, suggesting a need for improvement in its role in the green energy transition. These findings underscore the pivotal role of FD in shaping environmental sustainability, particularly in GHG mitigation and the energy transition to low-carbon sources. They highlighted the necessity for nuanced

TABLE 6 Impact of FD on Te.

Variables	(1) Homogeneous slope coefficients	(2) Homogeneous slope coefficients AR(2)	(3) Heterogeneous slope coefficients	(4) Heterogeneous slope coefficients AR(2)
L.lnTe	−0.006	0.397**	0.527***	0.619***
	(0.411)	(0.160)	(0.096)	(0.052)
	[−0.015]	[2.484]	[5.478]	[11.962]
lnA	0.107	0.005	0.061	0.043
	(0.117)	(0.052)	(0.066)	(0.057)
	[0.911]	[0.100]	[0.935]	[0.753]
lnFI	−0.044*	−0.036*	−0.093*	−0.090**
	(0.024)	(0.022)	(0.055)	(0.043)
	[−1.817]	[−1.670]	[−1.705]	[−2.101]
lnFM	−0.009	−0.006	0.005	−0.002
	(0.010)	(0.009)	(0.029)	(0.025)
	[−0.940]	[−0.606]	[0.157]	[−0.074]
lnGI	0.346	0.234	0.390***	0.281**
	(0.288)	(0.161)	(0.150)	(0.143)
	[1.202]	[1.457]	[2.593]	[1.967]
Constant	−3.781	−1.960*	−2.839***	−2.209***
	(2.831)	(1.003)	(0.816)	(0.695)
	[−1.336]	[−1.953]	[−3.481]	[−3.178]
Observations	1287	1254	1287	1254
Number of ID	33	33	33	33

Note: Robust std. err. (); *t*-stat []. Hansen test for the overidentifying restrictions *H*0: overidentifying restrictions are valid; Stata command: xtivdfreg.
****p* < .01; ***p* < .05; **p* < .1.

policy interventions integrating financial systems with environmental objectives, promoting renewable energy adoption and addressing land-use challenges.

These findings underscore crucial policy implications for enhancing climate impact mitigation in Africa and other developing regions. First, prioritizing the improvement of the green intensity of the energy mix is necessary. Continued reliance on fossil fuels, notably oil, coal and traditional biomass, diminishes Africa's capacity for meaningful climate change mitigation. Urgent steps, such as phasing out consumption subsidies, are imperative to steer Africa toward climate neutrality. The vast renewable energy potential of wind, solar, hydro and geothermal sources in Africa must be fully tapped to effectively mitigate climate impacts across sectors. Second, the results highlight the significance of FD in shaping climate change mitigation policies. Despite marginal progress in financial market development over the past three decades, Africa has yet to integrate deeply into the global financial system. Addressing the thinness and illiquidity of financial markets requires enhanced regulatory transparency and regional cooperation to mobilize capital for effective climate change. Financial institutions, including banks, can play a pivotal role by aligning their strategies with green financing initiatives. Developing green credit packages tailored to support investments in renewable energy technologies can redirect financial flows away from fossil fuels toward sustainable alternatives. Third, policies must address land-use issues, including deforestation and agricultural expansion, while promoting cleaner energy sources. Integrating land-use adjustments into policy frameworks enhances environmental sustainability efforts and contributes to comprehensive GHG emission reduction. In conclusion, policymakers must prioritize initiatives that promote renewable energy adoption, enhance financial market development and address land-use challenges. By aligning financial incentives with environmental goals, policymakers can leverage the transformative potential of financial systems to combat climate change effectively. It is imperative to implement proactive measures that foster sustainable development and resilience in the face of climate challenges across Africa and other developing regions.

This study has certain limitations, yet it paves the way for future research. First, the study is limited by the use of a sample of African countries, which may lead to future investigations targeting diverse countries or regions. Second, the examination in this study delves into the technological implications of FD for CO_2 emissions through energy transition pathways. Consequently, the impact equations employed could prove valuable not only for comprehending ecological degradation in Africa but also for analysing environmental impacts in different regions for comparative insights. Third, examining specific land-use changes, such as deforestation, agricultural expansion and degradation, separately could provide deeper insights into their individual contributions and inform targeted mitigation strategies. The impact of land-use changes on emissions varies across Africa. For example, deforestation might be a greater contributor in regions with extensive forests, while agricultural expansion might play a more significant role in areas with limited forested land. Africa is a diverse continent with significant variations in energy sources, economic development and land use patterns. It is worth exploring whether the findings hold true across all countries or if there are regional or country-specific nuances.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available: GHG emissions dataset: https://ourworldindata.org/co2-and-greenhouse-gas-emissions IMF: IMF financial development index dataset, https://data.imf.org/KOF: KOF globalization index dataset, https://kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-globalisation-index.html.

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APPENDIX A

TABLE A1 Correlation matrix.

	lnGHGe	lnCO_2e	lnN_2Oe	lnCH_4e	lnA	lnTe	lnFI	lnFM	lnGI
lnGHGe	1.000								
lnCO_2e	0.880	1.000							
lnN_2Oe	0.482	0.194	1.000						
lnCH_4e	0.783	0.459	0.601	1.000					
lnA	0.531	0.543	0.014	0.378	1.000				
lnTe	0.243	0.148	0.071	0.327	0.132	1.000			
lnFI	−0.033	0.015	−0.043	−0.104	0.520	0.071	1.000		
lnFM	0.168	0.277	−0.007	−0.006	0.375	0.044	0.327	1.000	
lnGI	0.156	0.219	−0.099	0.070	0.626	0.095	0.459	0.331	1.000

TABLE A2 Variance inflation factor (VIF) tests.

	Model: lnGHGe		Model: lnCO_2e		Model: lnN_2Oe		Model: lnCH_4e	
Variable	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
lnA	1.92	0.520	1.92	0.520	1.92	0.520	1.92	0.520
lnTe	1.02	0.982	1.02	0.982	1.02	0.982	1.02	0.982
lnFI	1.46	0.686	1.46	0.686	1.46	0.686	1.46	0.686
lnFM	1.21	0.827	1.21	0.827	1.21	0.827	1.21	0.827
lnGI	1.73	0.577	1.73	0.577	1.73	0.577	1.73	0.577
Mean VIF	1.47		1.47		1.47		1.47	