Received: 19 February 2022 | Revised: 23 March 2023 | Accepted: 12 April 2023

DOI: 10.1002/sd.2584

RESEARCH ARTICLE

Sustainable Development WILEY

Achieving environmental sustainability in Africa: The role of financial institutions development on carbon emissions

George S. Chen[1] | Emmanuel Kwaku Manu[1] | Dennis Asante[2]

[1]UNE Business School, Faculty of Science, Agriculture, Business and Law, University of New England, Armidale, Australia

[2]College of Medicine & Public Health, Rural and Remote Health, Flinders University, Renmark, Australia

Correspondence
George S. Chen, UNE Business School, Faculty of Science, Agriculture, Business and Law, University of New England, Armidale, New South Wales, Australia.
Email: george.chen@une.edu.au

Abstract

We investigate the causal impact of the development of financial institutions on environmental sustainability in Africa. Drawing on a distinctive panel data set encompassing 34 countries from 1980 to 2017, with carbon emissions serving as an indicator of environmental sustainability, we discover that enhanced development of financial institutions leads to increased carbon emissions, especially in relation to the depth of these institutions. Furthermore, our study reveals support for the environmental Kuznets curve, heterogenous slopes, and shifts over time in the finance–emissions nexus. Our results remain robust to different model specifications. The conclusions we reach indicate that the development of financial institutions and the implementation of pro-growth policies are essential for attaining environmental sustainability on the African continent.

KEYWORDS

Africa, carbon emissions, environmental sustainability, financial development, pooled mean groups

1 | INTRODUCTION

The unveiling of the sustainable development goals (SDGs) by the United Nations in 2015 brought environmental sustainability to the center stage of public discourse (Allen et al., 2018). Over time, the SDG Progress Reports (https://sdgs.un.org/goals) have showcased numerous commendable efforts striving to harmonize the demand for affordable and clean energy (SDG-7), sustainable cities and communities (SDG-11), and climate action (SDG-13). Nevertheless, it is apparent that financing these endeavors poses a significant challenge for both private (Scheyvens et al., 2016) and public (Lagoarde-Segot, 2020) sectors. This obstacle appears insurmountable in Africa, where financial development has trailed other regions for an extended period (Kedir et al., 2017). Thus, one might ask, why is financial development so crucial in facilitating environmental sustainability in Africa?

Theoretically, financial development primarily influences environmental sustainability by altering energy demand. For instance, financial development can stimulate economic growth, which subsequently increases energy demand within the economy (Acheampong, 2019; Aluko & Obalade, 2020). Furthermore, financial development can augment the available pool of physical capital stock, leading to heightened energy demand from the private sector (Acheampong et al., 2020; Shahbaz et al., 2016). Nonetheless, the impact of financial development on the environment does not always have to be adverse. For example, research has demonstrated that financial development can promote responsible corporate behavior, fostering environmental preservation (Acheampong et al., 2020; Shahbaz et al., 2016). Financial development is also likely to support investments in eco-friendly innovation by both firms (Tamazian et al., 2009) and governments (Tamazian & Bhaskara Rao, 2010), particularly in developing nations. Lastly, financial development can draw high-quality foreign direct investment (FDI) that produces technological externalities, contributing to the mitigation of environmental degradation (Manu et al., 2022; Singhania & Saini, 2021).

In theory, financial development primarily impacts environmental sustainability by altering energy demand. For instance, financial development can enhance economic growth, which subsequently increases the demand for energy in the economy (Acheampong, 2019; Aluko & Obalade, 2020). Additionally, financial development can broaden the pool of physical capital stock, driving up energy demand from the private sector (Acheampong et al., 2020; Shahbaz et al., 2016). However, the influence of financial development on the environment need not always be detrimental. For example, it has been demonstrated that financial development can foster responsible corporate conduct, encouraging environmental conservation (Claessens & Feijen, 2007). Financial development is also likely to promote investment in eco-friendly innovation by companies (Tamazian et al., 2009) and governments (Tamazian & Bhaskara Rao, 2010), particularly in developing nations. Lastly, financial development can attract high-quality foreign direct investment (FDI) that produces technological externalities, reducing environmental degradation (Manu et al., 2022; Singhania & Saini, 2021).

From our prior discussion, the theoretical debate concerning the connection between finance and the environment remains unresolved. This tendency has also been observed in recent cross-country empirical studies. For example, Acheampong (2019), Acheampong et al. (2019), and Adedoyin et al. (2022) found that financial development harms the environment. In contrast, Abid (2017), Acheampong et al. (2020), Aluko and Obalade (2020), Emenekwe et al. (2022), Ahmed et al. (2022), and more recently, Adom et al. (2023) discovered that financial development enhances environmental quality. Finally, Omri et al. (2015), Adams and Klobodu (2018), and Charfeddine and Kahia (2019), among others, were unable to detect any statistically significant relationship between financial development and environmental sustainability. A brief examination of this vast literature reveals three possible explanations for these inconsistent findings. First, these studies employ various definitions for financial development, resulting in a finance-environment nexus sensitive to the scope of financial development, with a broader interpretation supporting a positive impact on the environment. Second, existing literature often utilizes different proxies for environmental sustainability. Among the competing proxies, carbon emissions appear to be the most common and reliable indicator of environmental sustainability. Finally, previous literature has frequently assumed a direct and linear finance–environment nexus, although nonlinearities in the effect of financial development on the environment should not be disregarded.

In this study, we contribute to the ongoing debate on the finance-environment nexus in Africa. Specifically, we focus on Africa not only because its environment has faced significant threats in recent years (Adekoya et al., 2022; Asongu & Odhiambo, 2019; Osuntuyi & Lean, 2023) but also because its financial system has undergone considerable transformation since the beginning of this century (Acheampong, 2019; Aluko & Obalade, 2020; Ehigiamusoe et al., 2022). This unique context provides us with a quasi-experimental setting to empirically explore the interactions, if any, between financial development and environmental sustainability. To that end, instead of examining financial development comprising both financial markets and financial institutions, we explicitly focus on the latter, especially in terms of access, depth, and efficiency (Svirydzenka, 2016). In doing so, we avoid the bias introduced by underdeveloped financial markets in many African countries and investigate how the intermediary functions of financial institutions induce behavioral changes in households and firms (Yartey, 2007). Moreover, we use carbon emissions as a measure of environmental sustainability. This is a deliberate choice because carbon emissions have been identified as the single largest pollutant threatening environmental sustainability on the continent (Emenekwe et al., 2022; Li et al., 2023). A comprehensive understanding of the determinants of carbon emissions will be crucial for environmental conservation. Finally, we capture the diversity in Africa by considering nonlinearity, mediation effects, and regional heterogeneity, all of which have not always been addressed in previous studies.

Using a strongly balanced panel data on financial institutions development published by the International Monetary Fund (IMF) for 33 African countries from 1980 to 2017, we find that financial institutions development exerts a positive causal effect on carbon emissions. Specifically, we attribute this effect to the dominance of financial institutions' depth. We also confirm regional heterogeneity in this effect in terms of physical geography and economic integration, as well as interactions through economic growth and foreign direct investment (FDI). Finally, we find support for the environmental Kuznets curve (EKC) but not for the pollution haven hypothesis (PHH).

In next section, we present the literature review, followed by data and methodology. We then discuss the results in Section 4 and offer policy recommendations in Section 5.

2 | LITERATURE REVIEW

2.1 | Financial institutions development and carbon emissions

In general, financial institutions development can impact carbon emissions through three main transmission mechanisms. First, financial institutions development can increase consumer credit intended for durable goods like automobiles, air conditioners, refrigerators, and washing machines (Sadorsky, 2011). However, without increasing the share of renewable sources in the energy mix, the surge in demand for durable goods can lead to higher consumption of non-renewable energy and more carbon emissions (Zhang & Razzaq, 2022). Second, financial institutions development can lower the cost of commercial loans by facilitating risk pooling and trading among lending institutions (Ramzan et al., 2022). These cheaper loans, in turn, encourage businesses to borrow and expand, raising energy consumption from additional workers, machinery, and logistic support (Çoban & Topcu, 2013). This expansion can contribute to carbon emissions without the support of an energy transition plan (Benlemlih et al., 2022). Despite these two negative mechanisms, the effect of financial institutions development on carbon emissions is not all negative. For instance, financial institutions development can provide platforms for buying and selling corporate green bonds affiliated with energy conservation initiatives (Leitao et al., 2021). In this regard, financial institutions development serves as a catalyst for reducing carbon emissions. In short, these three transmission mechanisms suggest that the nature of the finance–emissions nexus is far from conclusive and remains an open empirical question.

There is a substantial volume of studies on the finance–emissions nexus in the extant literature. Here, we selectively review those empirical studies that demonstrate the ongoing debate. Sadorsky (2010) provided the seminal paper on the interactions between financial institutions development and carbon emissions. Using deposit money bank assets as a proxy for financial institutions development and energy consumption in kilograms of oil equivalent per capita as a proxy for emissions level, he found no statistically significant finance–emissions nexus in 22 emerging countries for the 1990–2006 period. However, when Sadorsky (2011) considered different dimensions of financial institutions development, including financial system deposits, deposit money bank assets, and liquid liabilities to private credit in nine Central and Eastern European economies from 1996 to 2006, he found a positive and statistically significant relationship between each of these dimensions and energy consumption as a proxy for emissions level. To reconcile these mixed findings, he attributed the dominant effect of liquid liabilities on energy consumption to the short-term loans received by households for purchasing electronic appliances or scaling up their living quarters. In a similar vein, Gaies et al. (2019) found an inverted-U curve between the size and capacity of financial intermediation and carbon emissions in the Middle East and North Africa (MENA) region between 1996 and 2014. They ascribed this nonlinearity to the benefit of a matured banking sector in promoting energy-efficient projects. To capture the various facets of financial institutions development, Çoban and Topcu (2013) employed principal component analysis to construct a unique financial institutions development variable. Using the 1990–2011 data from the European Union (EU), they uncovered a positive and statistically significant finance–emissions nexus in the old EU members but an inverted-U nexus in the new EU members. In part, this heterogeneity reaffirms the need to carefully consider how financial institutions development is measured in the study.

Apart from the measurement problem on financial institutions development, the choice of emissions indicators poses another reason for the conflicting evidence on the finance–emissions nexus. This is because the preceding discussion only focused on those studies employing energy consumption per capita as a measure of emissions level (Trotta et al., 2022). However, it is argued that carbon emissions per capita provide a better and more direct indicator than energy consumption per capita. Following this line of reasoning, Omri et al. (2015) found no statistically significant nexus between financial institutions development measured by domestic private credit and carbon emissions in 12 MENA countries from 1990 to 2011. Meanwhile, Khan et al. (2021) found a negative and statistically significant relationship between domestic private credit and carbon emissions in 184 countries for the 1990–2017 period. They attributed their finding to the benefits of strong financial institutions development in encouraging green technologies, particularly in underdeveloped countries.

From the outset, the relationship between financial institutions development and carbon emissions can be endogenous to the level of economic development. Intuitively, this endogeneity stems from the fact that the economic institutions responsible for economic development are also conducive to the development of financial institutions (Hasan et al., 2009; Ho et al., 2018). To control for this endogeneity, Komal and Abbas (2015) used private credit as a proxy for financial institutions development and energy consumption as a proxy for carbon emissions, on the premise that economic institutions are similar within a country than between countries. Exploring the Pakistani data from 1972 to 2012, they identified a positive and statistically significant finance–emissions nexus, which worked through the indirect economic growth channel. Meanwhile, Hao et al. (2016) examined the same nexus in one of the world's largest carbon emitters, China, through financial institutions depth measured by the sum of loans and deposits and financial institutions efficiency by the loans-to-deposits ratio. Using provincial data spanning over the 1995–2012 period, they found that carbon emissions are positively associated with financial institutions depth but negatively associated with financial institutions efficiency. Similar to Komal and Abbas (2015), they established these effects to have indirectly transmitted via the economic growth channel and attributed this mixed effect to the misallocation of financial resources in backward provinces and inefficient state-owned enterprises and banks. Meanwhile, Zhou and Du (2021) investigated the effect of financial institution development on green technological innovation in 285 Chinese cities over the period 2003 to 2018. In general, they found that the volume of private loans, the sum of private deposits and private loans, and the transformation from private deposits to private loans have exerted a positive and statistically significant effect on emissions-reducing technology. Moreover, they constructed a multidimensional financial institutions development variable and found it to have promoted energy-biased technological progress in more developed cities.

2.2 | GDP, FDI, non-renewable energy consumption, and carbon emissions

One of the most recognized observations in environmental economics is the so-called Environmental Kuznets Curve (EKC). Grossman and Krueger (1996) propose that the relationship between economic growth and environmental quality follows an inverted-U curve, where the economy initially grows at the environment's expense before gaining enough capacity to tackle environmental issues in later stages. However, the EKC's precise shape depends on the chosen measure of environmental quality (Stern, 2004). For example, some studies identified an N-shaped EKC due to the rebound effect in energy consumption resulting from consecutive rounds of industrial upgrading, which harms the environment (Turner, 2013; Wei & Liu, 2017). To account for the effect of economic growth on carbon emissions, we include GDP per capita as a covariate in our study.

Two opposing views exist regarding the relationship between foreign direct investment (FDI) and carbon emissions. One perspective suggests that FDI negatively impacts the environment by increasing emissions levels, leading to the so-called pollution haven hypothesis (PHH) (Eskeland & Harrison, 2003; Singhania & Saini, 2021). The PHH posits that strict environmental regulations drive polluting firms to relocate from developed to developing countries, harming the environment in the latter (Ahmad et al., 2021; Cole, 2004). In contrast, the pollution halo hypothesis asserts that firms from developed countries generate positive technological spillovers that help protect the host-country environment, such as reducing emissions levels (Mert & Caglar, 2020; Millimet & List, 2004). To capture this ambiguous effect, we include FDI as a covariate in our study.

Non-renewable energy consumption significantly impacts carbon emissions in two ways. First, burning non-renewable energy directly raises emissions levels, contributing to global warming (Dogan & Seker, 2016; Jebli et al., 2016). Second, extracting non-renewable energy now depletes the environmental capital available for future generations and their capacity to emit carbon dioxide (Mufutau Opeyemi, 2021). To control for these effects, we include non-renewable energy consumption as a covariate in our study.

This brief literature review highlights that financial institutions development influences carbon emissions. However, the direction and magnitude of this effect depend on GDP, FDI, and non-renewable energy consumption. In the next section, we discuss the key theoretical issues that inform our empirical framework.

3 | METHODOLOGY AND DATA

3.1 | Model specification

Based on our review in Section 2, we propose the following log-linear model to examine the effect of financial institutions development on carbon emissions:

$$CO2_{it} = \alpha_i + \beta(OFI)_{it} + \mathbf{X}'_{\mathbf{it}}\boldsymbol{\theta} + \varepsilon_{it}, \tag{1}$$

where the subscript i corresponds to African countries, and t represents years. $CO2$ denotes carbon emissions per capita, while OFI signifies the overall financial institutions development index. To prevent aggregation bias in benchmarking financial development (Čihák et al., 2012), we also replace OFI with the sub-index of financial institutions development, specifically, financial institutions access (FIA), financial institutions depth (FID), and financial institutions efficiency (FIE) in Equation (1). $\mathbf{X}'_{\mathbf{it}}$ and ε_{it} represent a vector of covariates and stochastic error terms, respectively. As both carbon emissions and financial institutions development are expressed in natural logarithm terms, β serves as an elasticity, with its sign and statistical significance revealing the nature of the finance–emissions nexus in Africa.

3.2 | Econometric methodology

In our study, which follows a group of African countries over time, we could have estimated Equation (1) using standard panel data analysis methods such as pooled OLS, fixed effects, or random effects estimators. However, we have chosen not to use these approaches for several reasons. First, standard panel data analysis does not allow for the lagged dependent variable as a regressor in the model (Baltagi, 2008), which contradicts the evidence of strong path dependency in carbon emissions (Gasser et al., 2018). To include lagged carbon emissions in Equation (1), we need to transform it into a dynamic panel model. Second, standard panel data analysis assumes a homogenous slope across all cross-sectional units (Baltagi, 2008), which is a strong assumption given the diversity in economic development and political systems in Africa (Aluko et al., 2021). Third, standard panel data analysis requires all variables to be free of cross-sectional dependence and have the same order of integration (Baltagi, 2008). However, macroeconomic variables like carbon emissions (Lee & Lee, 2009) and financial development (Christopoulos & Tsionas, 2004) are prone to cross-sectional dependence and have mixed orders of integration. Ignoring these factors can lead to spurious results (Greene, 2019). Lastly, standard panel data analysis cannot effectively control for endogeneity (Semykina & Wooldridge, 2010), which can be problematic since financial development can be endogenous in certain situations (Arestis et al., 2015). Failing to address this concern could result in biased and inconsistent estimates in Equation (1).

The above discussion indicates the need to control for endogeneity, heterogeneous slopes, lagged dependent variables, cross-sectional dependence, and mixed orders of integration when estimating Equation (1). Consequently, we have chosen the panel ARDL model for theoretical and practical reasons. Theoretically, this model is more flexible than other linear estimators as it provides consistent and efficient estimates in the presence of cross-sectional dependence and mixed orders of integration (Bildirici, 2014). It also controls for endogeneity by using an optimal lag structure during estimation (Pesaran & Shin, 1999). Practically, the panel ARDL model offers valuable information to policymakers regarding the short-run effects and long-run dynamics of an innovation to the model (Pesaran et al., 1999). Since the panel ARDL model belongs to the ARDL(p, q) family, we can transform Equation (1) into a vector error-correction model (VECM) as follows:

$$\Delta CO2_{it} = \alpha_i + \theta_i\left(CO2_{it-1} - \varphi'_i \mathbf{X}_{it}\right) + \sum_{j=1}^{p-1} \mu'_{ij}\Delta CO2_{it-j} + \sum_{j=0}^{q-1} \delta'_{ij}\Delta \mathbf{X}_{it-j} + \varepsilon_{it}, \tag{2}$$

where Δ represents the first-difference operator. φ'_i and δ'_{ij} measure the long-run dynamics and short-run effects of the covariates, respectively. We pay particular attention to the magnitude and statistical significance of the error-correction term (ECT), θ_i. If θ_i lies between 0 and -1 and is statistically significant, it implies a cointegrating relationship between carbon emissions and the covariates.

To estimate Equation (2), we can use dynamic fixed-effects (DFE) (Beggs & Nerlove, 1988), mean group (MG) (Pesaran & Smith, 1995), or pooled mean group (PMG) (Pesaran et al., 1999) estimators. While DFE and MG estimators have their merits, neither is appropriate for our strongly balanced panel with mixed orders of integration. The PMG estimator, on the other hand, offers an ideal compromise, allowing for heterogeneity in short-run individual-specific coefficients while maintaining homogeneity in long-run dynamics for consistent results (Zribi & Boufateh, 2020). These characteristics are particularly relevant to our study, as long-run homogeneity may arise from improved financial institutions development (Attiaoui et al., 2017), among other factors. In addition to our verbal justification, we also perform the Hausman test to select the preferred estimator for Equation (2). Our test results do not reject the null hypothesis of no differences between the DFE and PMG estimators or between the MG and PMG estimators, suggesting that the maximum likelihood-based PMG estimator provides more consistent and efficient estimates than its DFE and MG counterparts (Qamruzzaman & Wei, 2020).[1]

By using the PMG estimator, we can effectively analyze the relationship between financial institutions development and carbon emissions in African countries, considering the complexities and nuances of this relationship. Our choice of the panel ARDL model and the PMG estimator allows us to address potential issues of endogeneity, heterogeneous slopes, lagged dependent variables, cross-sectional dependence, and mixed orders of integration that are inherent in this type of analysis. Moreover, this approach enables us to provide valuable insights to policymakers regarding the short-run effects and long-run dynamics of the finance-emissions nexus in Africa, which is crucial for designing effective policies to promote sustainable development while minimizing the environmental impact of economic growth. As a result, our study contributes to a better understanding of the complex relationship between financial institutions development and carbon emissions in the African context, providing a solid foundation for future research and policy recommendations.

3.3 | Data

In this study, we compile annual observations from 33 African countries for the period 1980–2017, creating a strongly balanced panel. Our selection process is guided by data availability and analytical requirements. We obtain carbon emissions per capita ($CO2$) from the World Development Indicators (WDI) published by the World Bank, and extract overall financial institutions development (OFI), financial institutions access (FIA), financial institutions depth (FID), and financial institutions efficiency (FIE) from the Financial Development Index compiled by the IMF. Lastly, we collect data on covariates such as GDP per capita (GDP), foreign direct investment as a share of GDP (FDI), and non-renewable energy consumption per capita (NRE).

Table A1 displays the summary statistics for the variables in Equation (1). All variables are transformed into natural logarithm. The table highlights several key points: noticeable differences in carbon emissions among countries with similar GDP and non-renewable energy consumption; a skewed distribution of *OFI* with few countries reporting high overall financial institutions development; and considerable variation in *FIA*, *FDI*, and *NRE* across Africa.

Table A2 presents the Pearson correlation matrix to address concerns of high correlation between variables in Equation (1). Generally, we observe a positive correlation between *CO2* and *GDP*, and moderate positive correlations between $CO2-OFI$, $CO2-FID$ and $CO2-FIE$ pairs. However, we find a weak negative correlation between *CO2* and *NRE*.

To further verify potential multicollinearity in Equation (1) and avoid spurious results, we calculate the variance inflation factor (VIF) and corresponding tolerance values for the regressors in Equation (1). Table A3 reveals that all VIFs and tolerance values fall below the threshold of 5 and above 0.2, respectively, indicating no multicollinearity in the model.

4 | RESULTS AND DISCUSSION

4.1 | Preliminary analysis

We commence our analysis by scrutinizing our variables and assessing the suitability of the panel ARDL PMG model. A crucial assumption in panel data analysis is the lack of correlation in the residuals among cross-sectional units (Baltagi, 2008). Nonetheless, phenomena such as trade liberalization, financial integration, and regional cooperation have led to groups of countries responding similarly to external shocks, resulting in correlated residuals within these groups. Failing to address this issue can yield biased and inconsistent estimates (De Hoyos & Sarafidis, 2006). To circumvent this, we perform the Breusch and Pagan (1980) Lagrange multiplier (LM) test for cross-sectional dependence. However, as the LM test may be unreliable in panels with a larger number of cross-sectional units (Qamruzzaman & Wei, 2020), we also conduct the Pesaran (2021) cross-sectional (CD) test, deemed superior in balanced panels. Panel (a) of Table A4 indicates that we reject the null hypothesis of no cross-sectional dependence for all variables at the 1% significance level. This can be partially attributed to geographical proximity (Glantz, 2019) and economic integration (Maruping, 2005) in Africa. For instance, the repercussions of an unexpected drought or recession in one country could rapidly spill over to its neighbors. These findings suggest that controlling for cross-sectional dependence is necessary when estimating Equation (1).

Subsequently, we investigate the order of integration for the variables in Equation (1), a vital step since some estimators perform better than others when the model contains mixed order of integration (Enders, 2008). Given the established cross-sectional dependence in our variables, we utilize second-generation panel unit tests such as the cross-sectionally augmented IPS (CIPS) and cross-sectionally

[1] We do not report the DFE or MG results here to conserve space. These results are available from the authors upon request.

augmented Dickey-Fuller (CADF) tests. These tests offer improved local power and stable results when cross-sectional dependence exists in the variable (Westerlund et al., 2016). Regarding the CIPS test, panel (b) of Table A2 reveals that only *FIE*, *FDI*, and *NRE* in the "with-intercept" and "with-intercept-and-trend" specifications reject the null hypothesis of panel unit roots, or that they are $I(0)$, at the 1% significance level. However, this inconsistency vanishes at first difference when all variables are stationary, or $I(1)$. For the CADF test, panel (c) of the same table demonstrates that, at the 5% significance level, *FIA*, *FIE*, and *FDI* are $I(0)$ in the "intercept-only" specification, while *OFI* and *FIA* are $I(0)$ in the "intercept-and-trend" specification. In line with the CIPS test, all variables at first difference are $I(1)$ at the 1% significance level, regardless of their specifications. These outcomes indicate the necessity to accommodate a mixed of $I(0)$ and $I(1)$ variables when estimating Equation (1).

The third preliminary analysis involves the slope of cross-sectional units. The PMG estimator is most suitable when there are heterogeneous slopes between cross-sectional units in the short run. While this seems consistent with the considerable diversity in economic development and political systems among African countries, we still perform the Pesaran and Yamagata (2008) slope homogeneity test to confirm our hypothesis. Panel (a) of Table A5 displays that we reject the null hypothesis of homogeneous slopes in cross-sectional units at the 1% significance level in all cases. From an econometric standpoint, this result offers additional support for our choice of the PMG estimator.

While our aim is to prevent multicollinearity by excluding highly correlated variable pairs from the model, it is essential to confirm that the remaining variables exhibit a long-run relationship to avoid model misspecification. As a result, we employ the Pedroni (1999) cointegration test, which accommodates heterogeneity in the panel for both short- and long-run slopes and intercepts. In this final preliminary test, we present four test statistics from two categories: (1) panel weighted statistics, which aggregate statistics along the within dimension (panel PP-statistics and panel ADF-statistics), and (2) group-mean statistics, which average the results of individual cross-sectional unit test statistics (group PP-statistics and group ADF-statistics). It is important to note that this test does not account for normalization or the precise number of cointegrating relationships. Rather, it offers a measure of evidence or the absence thereof for cointegration in the panel among two or more variables (Neal, 2014). Despite this limitation, we can later use the test result to compare against the ECT term in Equation (2). Based on panel (b) of Table A5, we observe that all test statistics reject the null hypothesis of no cointegration at the 5% significance level or better. This finding implies that, as specified in Equation (2), long-run fluctuations in carbon emissions are strongly associated with changes in financial institutions development, GDP, FDI, and non-renewable energy consumption.

4.2 | Benchmark PMG results

Our preliminary analysis demonstrates that the chosen estimator for Equation (1) must account for endogeneity, heterogeneous slopes, lagged dependent variables, cross-sectional dependence, and a mixed order of integration. As discussed in Section 3.2, the panel ARDL PMG estimator in Equation (2) fulfills these criteria. Additionally, the Hausman test supports our choice, determining that the maximum likelihood-based PMG estimator is more efficient than either the DFE or MG estimator. For simplicity, we assign columns (1)–(4) of Table A6 to the effects of *OFI*, *FIA*, *FID*, and *FIE* on *CO2*, respectively. We also divide the table into panel (a) for long-run dynamics and panel (b) for short-run effects.

We emphasize four key findings from Table A6. Firstly, the statistically significant *ECT* coefficient in each panel (b) column suggests cointegration and aligns with the Pedroni test in Section 4.1. As the range of these coefficients falls between 0 and -1, it indicates that the model is converging and structurally stable. Secondly, only the $\Delta(GDP)$ coefficient is positive and statistically significant in panel (b), with a 1% increase in $\Delta(GDP)$ raising *CO2* by 0.62%–0.64% in the short run. This suggests that changes in GDP drive convergence toward long-run equilibrium in each column. Thirdly, column (1) of panel (a) reveals that the OFI coefficient is statistically significant, with a 1% increase in OFI raising CO2 by 0.21 in the long run. Lastly, while the coefficient on the financial institutions development sub-index in columns (2)–(4) of panel (a) is positive and statistically significant, its magnitude is largest for *FID* (1.96), followed by *FIA* (1.65) and *FIE* (0.39). Remember that private-sector credit and the number of bank branches per 100,000 adults are key indicators for *FID* and *FIA*, respectively (Svirydzenka, 2016). In light of this, an increase in private-sector credit and bank branches is expected to enhance access to credit for purchasing durable goods and expanding operational scale, both contributing to carbon emissions. According to Sadorsky (2011), these behavioral changes align with the direct and business effects in the finance–emissions nexus. Conversely, the small coefficient magnitude for *FIE* reflects the high net interest margin and lending-deposit spread, which have maintained elevated borrowing costs, deterring potential borrowers (Chen, 2009).

4.3 | Robustness tests

In Section 4.2, we identified a positive effect of financial institutions development on carbon emissions. However, our analysis implicitly assumed a linear finance–emissions nexus, overlooking potential nonlinear effects of financial development on the economy (Levine, 2005). To address this, we include the squared term of the overall financial institutions development index as an additional regressor in Equation (1) below:

$$CO2_{it} = \alpha_i + \beta(OFI)_{it} + \eta(OFI)^2_{it} + \mathbf{X}'_{it}\boldsymbol{\theta} + \varepsilon_{it}. \tag{3}$$

For thoroughness, we also consider the squared term of the sub-index of financial institutions development, namely, $(FIA)^2$, $(FID)^2$, and $(FIE)^2$. Theoretically, the sign and statistical significance of the squared term's coefficient indicate the presence or absence of nonlinearity (Gujarati, 2022) in the finance-emissions nexus. Panel (b) of

Table A7 reveals that the *ECT* coefficients in columns (1)–(4) are negative and statistically significant at the 1% level, suggesting that including the squared term did not change the model's cointegration. Furthermore, these coefficients signify a convergence toward long-run equilibrium at a rate of 14%–16% per year. In fact, the positive and statistically significant coefficients on $\Delta(GDP)$ indicate that this equilibrium adjustment primarily results from changes in GDP, with a 1% increase in $\Delta(GDP)$ raising $CO2$ by 0.61–0.66% in the short run. Examining columns (1)–(4) of panel (a), none of the long-run coefficients on $(OFI)^2$, $(FIA)^2$, $(FID)^2$, and $(FIE)^2$ are statistically significant, implying a lack of nonlinear finance-emissions nexus.

Although we have dismissed nonlinearity in the finance–emissions nexus, we cannot be sure that no other sources of nonlinearity exist in Equation (1). To test this, we explore two popular conjectures in environmental economics: the EKC (Dinda, 2004) and PHH (Eskeland & Harrison, 2003). We investigate these conjectures econometrically by including the squared term of *GDP* and *FDI* in Equation (1) as follows:

$$CO2_{it} = \alpha_i + \beta(OFI)_{it} + \eta GDP_{it} + \delta(GDP)^2_{it} + \rho FDI_{it} + \upsilon(FDI)^2_{it} + \mathbf{X}'_{\mathbf{it}}\boldsymbol{\theta} + \varepsilon_{it}. \quad (4)$$

Intuitively, if $\eta > 0$, $\delta < 0$ and statistically significant, it implies an inverted U-shaped relationship between GDP and carbon emissions, confirming the EKC. Similarly, if $\rho > 0$, $\nu < 0$ and statistically significant, it suggests an inverted U-shaped relationship between FDI and carbon emissions, supporting the PHH. Column (5) of Table A7 shows that the *ECT* coefficient is negative and statistically significant, indicating cointegration and convergence in the model. In the same column, panel (a) displays that the OFI coefficient is positive and statistically significant, with a 1% increase in *OFI* raising $CO2$ by 0.17%. In the same panel, the coefficient on *GDP* is positive and statistically significant, while the coefficient on $(GDP)^2$ is negative and statistically significant. These results, similar to Acheampong et al. (2020), jointly support the EKC hypothesis in Africa. However, we find no evidence for the PHH.

So far, we have shown that financial institutions development directly impacts carbon emissions in Africa. However, this development might indirectly influence emissions levels through feedback loops between financial institutions and GDP (Beck & Levine, 2004; Levine & Zervos, 1998) or between financial institutions and FDI (Poelhekke, 2015; Yao et al., 2021). To account for these mediation effects, we modify Equation (1) to include an interaction term as follows:

$$CO2_{it} = \alpha_i + \beta(OFI)_{it} + \psi(OFI \times GDP)_{it} + \mathbf{X}'_{\mathbf{it}}\boldsymbol{\theta} + \varepsilon_{it}, \quad (5)$$

$$CO2_{it} = \alpha_i + \beta(OFI)_{it} + \psi(OFI \times FDI)_{it} + \mathbf{X}'_{\mathbf{it}}\boldsymbol{\theta} + \varepsilon_{it}, \quad (6)$$

where $(OFI \times GDP)$ and $(OFI \times FDI)$ represent the mediation effects between financial institutions and GDP and between financial institutions and FDI, respectively. Theoretically, a statistically significant coefficient on the interaction term would support the mediation effect. Panel (b) of Table A7 shows that the *ECT* coefficients are negative and statistically significant in columns (6)–(7), indicating cointegration. In the same table, panel (a) reveals that the OFI coefficients are positive and statistically significant in both columns, emphasizing the direct and positive long-run effect of financial institutions development on carbon emissions. However, the negative and statistically significant coefficient on $(OFI \times GDP)$ in panel (a) of column (6) confirms the long-run mediation effect from financial institutions development to carbon emissions via GDP. This negative effect aligns with Manu et al. (2022), who find that increased income enhances the capacity to adopt renewable energy in Africa. In the same panel of column (7), the coefficient on $(OFI \times FDI)$ is positive and statistically significant, implying the mediation effect from financial institutions to carbon emissions via FDI. This result partially supports the PHH facilitated by financial development (Gyamfi et al., 2021).

It is possible that our positive finance–emission nexus is influenced by a few large African economies. However, there are reasons to suspect that this nexus might vary between regions (Espoir & Sunge, 2021; Manu et al., 2022). To investigate this conjecture, we divide the sample according to natural geography and regional economic integration. Panel (b) of Table A8 reveals that the *ECT* coefficients indicate cointegration in columns (1)–(3), with western Africa displaying the fastest convergence to its long-run equilibrium, followed by its southern and eastern counterparts. This is consistent with rapid economic transformation in western (Assane & Chiang, 2014) and southern Africa (Manwa & Wijeweera, 2016). Specifically, apart from $\Delta(GDP)$, the adjustment in western and southern Africa has been primarily driven by $\Delta(OFI)$ in column (1) and $\Delta(FDI)$ in column (3), respectively. This heterogeneity extends to the long-run drivers of carbon emissions. For instance, the positive and statistically significant coefficient on *OFI* in columns (1) and (3) may reflect extensive financial reform in western and southern Africa since the 1990s (Ogbeide & Adeboje, 2020). Meanwhile, the positive and statistically significant coefficient on *NRE* in column (1) could be attributed to improved energy efficiency in western Africa (Adom, 2019). Finally, the positive and statistically significant coefficient on *FDI* in column (2) could result from FDI in natural resource extraction in eastern Africa (Gyamfi, 2022).

In addition to cardinal directions, another potential source of regional heterogeneity in Africa could be related to coastal proximity (Andrew & Luke, 2000). To explore this hypothesis, we divide our sample into coastal and landlocked groups and present their results in columns (4)–(5) of Table A8, respectively. Initially, panel (b) shows that the *ECT* coefficients confirm cointegration in both columns. However, there is a substantial difference in the *OFI* coefficient between these two columns. For instance, a 1% increase in *OFI* reduces $CO2$ by 0.17% in column (4) but raises $CO2$ by 0.23% in column (5). To provide context, the negative finance–emissions nexus may reflect better access to credit for installing green technology in the coastal group (Emenekwe et al., 2022). Conversely, the positive finance–emissions nexus may be attributed to weak absorptive capacity for green technology in the landlocked group (Edziah et al., 2022).

The formation of regional economic blocs could be an artificial source of regional heterogeneity. To test this assertion, we examine the finance–emissions nexus separately for, first, the Common Market for Eastern and Southern Africa (COMESA) membership, and second, the Southern African Development Community (SADC) membership. Generally, panel (b) of Table A8 reveals that the *ECT* coefficients confirm cointegration in columns (6)–(9). In these columns, the $\Delta(GDP)$ coefficients indicate that much of the long-run equilibrium adjustment is driven by changes in GDP in the short run. However, the Δ(OFI) coefficients show that short-run changes in financial institutional development only matter for the long-run equilibrium adjustment in COMESA (column (6)) and SADC (column (8)) members. Perhaps the most striking result is the mixed signs of the OFI coefficients in these columns. Specifically, the finance-emissions nexus seems to be positive for COMESA and SADC members but negative for non-COMESA and non-SADC members. This, along with the statistically significant *GDP* and *FDI* coefficients, aligns with the view that economic integration not only stimulates economic growth and FDI but also enhances the effect of financial institutions development on carbon emissions in COMESA and SADC members.

Lastly, the nature of the finance-emissions nexus may have changed over time (Dogan, 2016). The announcement of the Millennium Development Goals by the United Nations in 2000 has been considered by many as a turning point for Africa (Easterly, 2009). For example, this nexus could have changed due to economic and social initiatives implemented following the announcement. To test this hypothesis, we use the year 2000 as the demarcation point and present the pre- and post-2000 results in columns (10)–(11) of Table A8, respectively. A glance at panel (b) reveals that the *ECT* coefficients confirm cointegration in both columns. Notably, the magnitude of the OFI coefficient in panel (a) is larger for the 1980–1999 period than the 2000–2017 period. In other words, although financial institutions development contributed to carbon emissions in both periods, its effect had diminished significantly in the latter. In fact, given that the *GDP* and *NRE* coefficients are positive and statistically significant in column (11), this weakened finance-emissions nexus could reflect the rising popularity of green finance in Africa (Schwerhoff & Sy, 2017).

4.4 | Causality tests

To ensure a comprehensive analysis, we conclude our assessment by examining the direction of the causal effect, if any, in Equation (1). Taking into account cross-sectional dependence and heterogeneous panels, we opt for the Dumitrescu and Hurlin (2012) Granger non-causality test. The linear model of the test based on Equation (1) is given by:

$$CO2_{it} = \alpha_i + \sum\nolimits_{k=1}^{K} \beta_i^{(k)} CO2_{it-k} + \sum\nolimits_{k=1}^{K} \theta_i^{(k)} x_{it-k} + \varepsilon_{it}, \tag{7}$$

$$x_{it} = \alpha_i + \sum\nolimits_{k=1}^{K} \beta_i^{(k)} x_{it-k} + \sum\nolimits_{k=1}^{K} \theta_i^{(k)} CO2_{it-k} + \varepsilon_{it}, \tag{8}$$

where $\beta_i^{(k)}$ and $\theta_i^{(k)}$ represent the autoregressive parameter and the covariate with lag order k, respectively. Table A9 presents the test results for the null hypothesis of homogeneous non-causality. Generally, a bidirectional causality exists between financial institutions development and carbon emissions, as well as between GDP and carbon emissions. In context, the bidirectional causality supports the direct and business effects of financial institutions development and the existence of the EKC. Furthermore, a unidirectional causality runs from non-renewable energy consumption to carbon emissions, suggesting the technological effect in energy consumption (Apergis & Payne, 2012).

In addition to carbon emissions, Table A9 highlights other notable causalities. For example, bidirectional causality implies endogeneity in the following pairs: financial institutions development and GDP; financial institutions development and FDI; GDP and FDI, and GDP and non-renewable energy consumption. These results align with the positive feedback loops in the finance-growth (Levine et al., 2000) and finance–FDI (Desbordes & Wei, 2017) literature, as well as in the growth–FDI (Alfaro et al., 2004) and growth–energy (Song Zan et al., 2008) literature. Lastly, a unidirectional causality runs from financial institutions development to non-renewable energy consumption, suggesting that financial institutions development, as part of economic complexity, increases the demand for non-renewable energy (Can & Ahmed, 2023). Overall, these results are largely consistent with our panel ARDL PMG results and the existing literature in general.

5 | CONCLUSION

In this study, we explore the relationship between finance and carbon emissions in Africa during the 1980–2017 period. By accounting for endogeneity, heterogeneous slopes, lagged dependent variables, cross-sectional dependence, and mixed orders of integration, we discover a positive causal effect of financial institutions development on carbon emissions. This causal effect is corroborated by the cointegration Granger non-causality tests and remains robust across various model specifications. Generally, we attribute our findings to the direct and business effects of financial institutions development. Concurrently, we uncover evidence of the EKC and the mediating role of GDP, suggesting that economic growth can help reduce carbon emissions. Furthermore, we find that strong economic activity within regional economic integration may have amplified the causal effect, while the adoption of green technology since 2000 has weakened it.

Our findings yield several policy recommendations. First, to prevent short-term increases in carbon emissions resulting from financial institutions development, governments should offer incentives such as cash rebates or tax breaks to encourage households and businesses to adopt green technology. Second, the presence of the EKC indicates that promoting economic growth can serve as an effective long-term strategy for enhancing environmental sustainability. Lastly, in connection with the previous point, regional economic blocs should implement emissions trading schemes to counterbalance any additional carbon emissions generated by their member states.

ACKNOWLEDGMENTS

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. Open access publishing facilitated by University of New England, as part of the Wiley - University of New England agreement via the Council of Australian University Librarians.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available World Bank Group (2020) World Development Indicators 2019, Washington DC: World Bank.

ORCID

George S. Chen https://orcid.org/0000-0002-8519-9340
Emmanuel Kwaku Manu https://orcid.org/0000-0002-6233-3981

REFERENCES

Abid, M. (2017). Does economic, financial and institutional developments matter for environmental quality? A comparative analysis of EU and MEA countries. *Journal of Environmental Management*, *188*, 183–194.

Acheampong, A. O. (2019). Modelling for insight: Does financial development improve environmental quality? *Energy Economics*, *83*, 156–179.

Acheampong, A. O., Adams, S., & Boateng, E. (2019). Do globalization and renewable energy contribute to carbon emissions mitigation in sub-Saharan Africa? *Science of the Total Environment*, *677*, 436–446.

Acheampong, A. O., Amponsah, M., & Boateng, E. (2020). Does financial development mitigate carbon emissions? Evidence from heterogeneous financial economies. *Energy Economics*, *88*, 104768.

Adams, S., & Klobodu, E. K. M. (2018). Financial development and environmental degradation: Does political regime matter? *Journal of Cleaner Production*, *197*, 1472–1479.

Adedoyin, F. F., Bekun, F. V., Eluwole, K. K., & Adams, S. (2022). Modelling the nexus between financial development, FDI, and CO2 emission: Does institutional quality matter? *Energies*, *15*, 7464.

Adekoya, O. B., Ajayi, G. E., Suhrab, M., & Oliyide, J. A. (2022). How critical are resource rents, agriculture, growth, and renewable energy to environmental degradation in the resource-rich African countries? The role of institutional quality. *Energy Policy*, *164*, 112888.

Adom, P. K. (2019). An evaluation of energy efficiency performances in Africa under heterogeneous technologies. *Journal of Cleaner Production*, *209*, 1170–1181.

Adom, P. K., Amuakwa-Mensah, F., & Akorli, C. D. (2023). Energy efficiency as a sustainability concern in Africa and financial development: How much bias is involved? *Energy Economics*, *120*, 106577.

Ahmad, M., Jabeen, G., & Wu, Y. (2021). Heterogeneity of pollution haven/halo hypothesis and environmental Kuznets curve hypothesis across development levels of Chinese provinces. *Journal of Cleaner Production*, *285*, 124898.

Ahmed, F., Kousar, S., Pervaiz, A., & Shabbir, A. (2022). Do institutional quality and financial development affect sustainable economic growth? Evidence from south Asian countries. *Borsa Istanbul Review*, *22*, 189–196.

Alfaro, L., Chanda, A., Kalemli-Ozcan, S., & Sayek, S. (2004). FDI and economic growth: The role of local financial markets. *Journal of International Economics*, *64*, 89–112.

Allen, C., Metternicht, G., & Wiedmann, T. (2018). Initial progress in implementing the Sustainable Development Goals (SDGs): A review of evidence from countries. *Sustainability Science 13*, 1453–1467.

Aluko, O. A., Chen, G. S., & Opoku, E. E. O. (2021). Is foreign direct investment globalization-induced or a myth? A tale of Africa. *International Journal of Finance & Economics*, *20*, 1–13.

Aluko, O. A., & Obalade, A. A. (2020). Financial development and environmental quality in sub-Saharan Africa: Is there a technology effect? *Science of the Total Environment*, *747*, 141515.

Andrew, M., & Luke, G. J. (2000). Climate, coastal proximity, and development. In G. L. Clark, M. P. Feldman, & M. S. Gertler (Eds.), *The Oxford handbook of economic geography*. Oxford University Press.

Apergis, N., & Payne, J. E. (2012). Renewable and non-renewable energy consumption-growth nexus: Evidence from a panel error correction model. *Energy Economics*, *34*, 733–738.

Arestis, P., Chortareas, G., & Magkonis, G. (2015). The financial development and growth nexus: A meta-analysis. *Journal of Economic Surveys*, *29*, 549–565.

Asongu, S. A., & Odhiambo, N. M. (2019). Environmental degradation and inclusive human development in sub-Saharan Africa. *Sustainable Development*, *27*, 25–34.

Assane, D., & Chiang, E. P. (2014). Trade, structural reform, and institutions in sub-Saharan Africa. *Contemporary Economic Policy*, *32*, 20–29.

Attiaoui, I., Toumi, H., Ammouri, B., & Gargouri, I. (2017). Causality links among renewable energy consumption, CO2 emissions, and economic growth in Africa: Evidence from a panel ARDL-PMG approach. *Environmental Science and Pollution Research*, *24*, 13036–13048.

Baltagi, B. (2008). *Econometric analysis of panel data*. John Wiley & Sons.

Beck, T., & Levine, R. (2004). Stock markets, banks, and growth: Panel evidence. *Journal of Banking & Finance*, *28*, 423–442.

Beggs, J. J., & Nerlove, M. (1988). Biases in dynamic models with fixed effects. *Economics Letters*, *26*, 29–31.

Benlemlih, M., Jaballah, J., & Kermiche, L. (2022). Does financing strategy accelerate corporate energy transition? Evidence from green bonds. *Business Strategy and the Environment*, *32*, 878–889.

Bildirici, M. E. (2014). Relationship between biomass energy and economic growth in transition countries: Panel ARDL approach. *GCB Bioenergy*, *6*, 717–726.

Breusch, T. S., & Pagan, A. R. (1980). The Lagrange multiplier test and its applications to model specification in econometrics. *The Review of Economic Studies*, *47*, 239–253.

Can, M., & Ahmed, Z. (2023). Towards sustainable development in the European Union countries: Does economic complexity affect renewable and non-renewable energy consumption? *Sustainable Development*, *31*, 439–451.

Charfeddine, L., & Kahia, M. (2019). Impact of renewable energy consumption and financial development on CO2 emissions and economic growth in the MENA region: A panel vector autoregressive (PVAR) analysis. *Renewable Energy*, *139*, 198–213.

Chen, C. (2009). Bank efficiency in sub-Saharan African middle income countries. IMF Working Papers, 2009.

Christopoulos, D. K., & Tsionas, E. G. (2004). Financial development and economic growth: Evidence from panel unit root and cointegration tests. *Journal of Development Economics*, *73*, 55–74.

Čihák, M., Demirgüç-Kunt, A., Feyen, E., & Levine, R. (2012). Benchmarking financial development around the world. *World Bank Policy Research Working Paper*, *6175*, 1813–9450.

Claessens, S., & Feijen, E. (2007). *Financial sector development and the millennium development goals*. The World Bank.

Çoban, S., & Topcu, M. (2013). The nexus between financial development and energy consumption in the EU: A dynamic panel data analysis. *Energy Economics*, *39*, 81–88.

Cole, M. A. (2004). Trade, the pollution haven hypothesis and the environmental Kuznets curve: Examining the linkages. *Ecological Economics*, *48*, 71–81.

De Hoyos, R. E., & Sarafidis, V. (2006). Testing for cross-sectional dependence in panel-data models. *Stata Journal*, *6*, 482–496.

Desbordes, R., & Wei, S.-J. (2017). The effects of financial development on foreign direct investment. *Journal of Development Economics*, *127*, 153–168.
Dinda, S. (2004). Environmental Kuznets curve hypothesis: A survey. *Ecological Economics*, *49*, 431–455.
Dogan, E. (2016). Analyzing the linkage between renewable and non-renewable energy consumption and economic growth by considering structural break in time-series data. *Renewable Energy*, *99*, 1126–1136.
Dogan, E., & Seker, F. (2016). Determinants of CO2 emissions in the European Union: The role of renewable and non-renewable energy. *Renewable Energy*, *94*, 429–439.
Dumitrescu, E.-I., & Hurlin, C. (2012). Testing for granger non-causality in heterogeneous panels. *Economic Modelling*, *29*, 1450–1460.
Easterly, W. (2009). How the millennium development goals are unfair to Africa. *World Development*, *37*, 26–35.
Edziah, B. K., Sun, H., Adom, P. K., Wang, F., & Agyemang, A. O. (2022). The role of exogenous technological factors and renewable energy in carbon dioxide emission reduction in sub-Saharan Africa. *Renewable Energy*, *196*, 1418–1428.
Ehigiamusoe, K. U., Lean, H. H., Babalola, S. J., & Poon, W. C. (2022). The roles of financial development and urbanization in degrading environment in Africa: Unravelling non-linear and moderating impacts. *Energy Reports*, *8*, 1665–1677.
Emenekwe, C. C., Onyeneke, R. U., & Nwajiuba, C. U. (2022). Financial development and carbon emissions in sub-Saharan Africa. *Environmental Science and Pollution Research*, *29*, 19624–19641.
Enders, W. (2008). *Applied econometric time series*. John Wiley & Sons.
Eskeland, G. S., & Harrison, A. E. (2003). Moving to greener pastures? Multinationals and the pollution haven hypothesis. *Journal of Development Economics*, *70*, 1–23.
Espoir, D. K., & Sunge, R. (2021). CO2 emissions and economic development in Africa: Evidence from a dynamic spatial panel model. *Journal of Environmental Management*, *300*, 113617.
Gaies, B., Kaabia, O., Ayadi, R., Guesmi, K., & Abid, I. (2019). Financial development and energy consumption: Is the MENA region different? *Energy Policy*, *135*, 111000.
Gasser, T., Kechiar, M., Ciais, P., Burke, E. J., Kleinen, T., Zhu, D., Huang, Y., Ekici, A., & Obersteiner, M. (2018). Path-dependent reductions in CO2 emission budgets caused by permafrost carbon release. *Nature Geoscience*, *11*, 830–835.
Glantz, M. H. (2019). Drought, famine, and the seasons in sub-Saharan Africa. In *African food systems in crisis*. Routledge.
Greene, W. H. (2019). *Econometric analysis*. Prentice Hall.
Grossman, G. M., & Krueger, A. B. (1996). The inverted-U: What does it mean? *Environment and Development Economics*, *1*, 119–122.
Gujarati, D. N. (2022). *Basic econometrics*. Prentice Hall.
Gyamfi, B. A. (2022). Consumption-based carbon emission and foreign direct investment in oil-producing sub-Sahara African countries: The role of natural resources and urbanization. *Environmental Science and Pollution Research*, *29*, 13154–13166.
Gyamfi, B. A., Bein, M. A., Udemba, E. N., & Bekun, F. V. (2021). Investigating the pollution haven hypothesis in oil and non-oil sub-Saharan Africa countries: Evidence from quantile regression technique. *Resources Policy*, *73*, 102119.
Hao, Y., Zhang, Z.-Y., Liao, H., Wei, Y.-M., & Wang, S. (2016). Is CO2 emission a side effect of financial development? An empirical analysis for China. *Environmental Science and Pollution Research*, *23*, 21041–21057.
Hasan, I., Wachtel, P., & Zhou, M. (2009). Institutional development, financial deepening and economic growth: Evidence from China. *Journal of Banking & Finance*, *33*, 157–170.
Ho, C.-Y., Huang, S., Shi, H., & Wu, J. (2018). Financial deepening and innovation: The role of political institutions. *World Development*, *109*, 1–13.
Jebli, B. M., Youssef, B. S., & Ozturk, I. (2016). Testing environmental Kuznets curve hypothesis: The role of renewable and non-renewable energy consumption and trade in OECD countries. *Ecological Indicators*, *60*, 824–831.
Kedir, A., Elhiraika, A., Chinzara, Z., & Sandjong, D. (2017). Growth and development finance required for achieving sustainable development goals (SDGs) in Africa. *African Development Review*, *29*, 15–26.
Khan, S., Khan, M. K., & Muhammad, B. (2021). Impact of financial development and energy consumption on environmental degradation in 184 countries using a dynamic panel model. *Environmental Science and Pollution Research*, *28*, 9542–9557.
Komal, R., & Abbas, F. (2015). Linking financial development, economic growth and energy consumption in Pakistan. *Renewable and Sustainable Energy Reviews*, *44*, 211–220.
Lagoarde-Segot, T. (2020). Financing the sustainable development goals. *Sustainability*, *12*, 2775.
Lee, C.-C., & Lee, J.-D. (2009). Income and CO2 emissions: Evidence from panel unit root and cointegration tests. *Energy Policy*, *37*, 413–423.
Leitao, J., Ferreira, J., & Santibanez-Gonzalez, E. (2021). Green bonds, sustainable development and environmental policy in the European Union carbon market. *Business Strategy and the Environment*, *30*, 2077–2090.
Levine, R. (2005). Finance and growth: Theory and evidence. In P. Aghion & S. N. Durlauf (Eds.), *Handbook of economic growth*. Elsevier.
Levine, R., Loayza, N., & Beck, T. (2000). Financial intermediation and growth: Causality and causes. *Journal of Monetary Economics*, *46*, 31–77.
Levine, R., & Zervos, S. (1998). Stock markets, banks, and economic growth. *The American Economic Review*, *88*, 537–558.
Li, D., Bae, J. H., & Rishi, M. (2023). Sustainable sevelopment and SDG-7 in sub-Saharan Africa: Balancing energy access, economic growth, and carbon emissions. *The European Journal of Development Research*, *35*, 112–137.
Manu, E. K., Chen, G. S., & Asante, D. (2022). Regional heterogeneities in the absorptive capacity of renewable energy deployment in Africa. *Renewable Energy*, *193*, 554–564.
Manwa, F., & Wijeweera, A. (2016). Trade liberalisation and economic growth link: The case of southern African custom union countries. *Economic Analysis and Policy*, *51*, 12–21.
Maruping, M. (2005). Challenges for regional integration in sub-Saharan Africa: Macroeconomic convergence and monetary coordination. *Africa in the World Economy*, *129*, 129–155.
Mert, M., & Caglar, A. E. (2020). Testing pollution haven and pollution halo hypotheses for Turkey: A new perspective. *Environmental Science and Pollution Research*, *27*, 32933–32943.
Millimet, D. L., & List, J. A. (2004). The case of the missing pollution haven hypothesis. *Journal of Regulatory Economics*, *26*, 239–262.
Mufutau Opeyemi, B. (2021). Path to sustainable energy consumption: The possibility of substituting renewable energy for non-renewable energy. *Energy*, *228*, 120519.
Neal, T. (2014). Panel cointegration analysis with xtpedroni. *The Stata Journal*, *14*, 684–692.
Ogbeide, F. I., & Adeboje, O. M. (2020). Effects of financial reform on business entry in sub-Saharan African countries: Do resource dependence and institutional quality matter? *African Development Review*, *32*, 188–199.
Omri, A., Daly, S., Rault, C., & Chaibi, A. (2015). Financial development, environmental quality, trade and economic growth: What causes what in MENA countries. *Energy Economics*, *48*, 242–252.
Osuntuyi, B. V., & Lean, H. H. (2023). *Environmental degradation, economic growth, and energy consumption: The role of education*. Sustainable Development.
Pedroni, P. (1999). Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxford Bulletin of Economics and Statistics*, *61*, 653–670.

Pesaran, M. H. (2021). General diagnostic tests for cross-sectional dependence in panels. *Empirical Economics*, *60*, 13–50.

Pesaran, M. H., & Shin, Y. (1999). An autoregressive distributed lag modelling approach to cointegration analysis. *Econometric Society Monograph*, *31*, 371–413.

Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association*, *94*, 621–634.

Pesaran, M. H., & Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, *68*, 79–113.

Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics*, *142*, 50–93.

Poelhekke, S. (2015). Do global banks facilitate foreign direct investment? *European Economic Review*, *76*, 25–46.

Qamruzzaman, M., & Wei, J. (2020). The asymmetric relationship between financial development, trade openness, foreign capital flows, and renewable energy consumption: Fresh evidence from panel NARDL investigation. *Renewable Energy*, *159*, 827–842.

Ramzan, M., Razi, U., Quddoos, M. U., & Adebayo, T. S. (2022). Do green innovation and financial globalization contribute to the ecological sustainability and energy transition in the United Kingdom? Policy insights from a bootstrap rolling window approach. *Sustainable Development*, *31*, 393–414.

Sadorsky, P. (2010). The impact of financial development on energy consumption in emerging economies. *Energy Policy*, *38*, 2528–2535.

Sadorsky, P. (2011). Financial development and energy consumption in central and eastern European frontier economies. *Energy Policy*, *39*, 999–1006.

Scheyvens, R., Banks, G., & Hughes, E. (2016). The private sector and the SDGs: The need to move beyond "business as usual". *Sustainable Development*, *24*, 371–382.

Schwerhoff, G., & Sy, M. (2017). Financing renewable energy in Africa—Key challenge of the sustainable development goals. *Renewable and Sustainable Energy Reviews*, *75*, 393–401.

Semykina, A., & Wooldridge, J. M. (2010). Estimating panel data models in the presence of endogeneity and selection. *Journal of Econometrics*, *157*, 375–380.

Shahbaz, M., Shahzad, S. J. H., Ahmad, N., & Alam, S. (2016). Financial development and environmental quality: The way forward. *Energy Policy*, *98*, 353–364.

Singhania, M., & Saini, N. (2021). Demystifying pollution haven hypothesis: Role of FDI. *Journal of Business Research*, *123*, 516–528.

Song Zan, C.-W., Chen, C.-F., & Zhu, Z. (2008). Economic growth and energy consumption revisited: Evidence from linear and nonlinear granger causality. *Energy Economics*, *30*, 3063–3076.

Stern, D. I. (2004). The rise and fall of the environmental Kuznets curve. *World Development*, *32*, 1419–1439.

Svirydzenka, K. (2016). *Introducing a new broad-based index of financial development*. International Monetary Fund.

Tamazian, A., & Bhaskara Rao, B. (2010). Do economic, financial and institutional developments matter for environmental degradation? Evidence from transitional economies. *Energy Economics*, *32*, 137–145.

Tamazian, A., Chousa, J. P., & Vadlamannati, K. C. (2009). Does higher economic and financial development lead to environmental degradation: Evidence from BRIC countries. *Energy Policy*, *37*, 246–253.

Trotta, G., Hansen, A. R., & Sommer, S. (2022). The price elasticity of residential district heating demand: New evidence from a dynamic panel approach. *Energy Economics*, *112*, 106163.

Turner, K. (2013). "rebound" effects from increased energy efficiency: A time to pause and reflect. *The Energy Journal*, *34*, 25–42.

Wei, T., & Liu, Y. (2017). Estimation of global rebound effect caused by energy efficiency improvement. *Energy Economics*, *66*, 27–34.

Westerlund, J., Hosseinkouchack, M., & Solberger, M. (2016). The local power of the CADF and CIPS panel unit root tests. *Econometric Reviews*, *35*, 845–870.

World Bank. (2020). World development indicators. World Bank Group. https://databank.worldbank.org/source/world-development-indicators

Yao, Y., Chen, G. S., & Zhang, L. (2021). Local financial intermediation and foreign direct investment: Evidence from China. *International Review of Economics & Finance*, *72*, 198–216.

Yartey, C. A. (2007). Well-developed financial intermediary sector promotes stock market development: Evidence from Africa. *Journal of Emerging Market Finance*, *6*, 269–289.

Zhang, R. J., & Razzaq, A. (2022). Influence of economic policy uncertainty and financial development on renewable energy consumption in the BRICST region. *Renewable Energy*, *201*, 526–533.

Zhou, X., & Du, J. (2021). Does environmental regulation induce improved financial development for green technological innovation in China? *Journal of Environmental Management*, *300*, 113685.

Zribi, W., & Boufateh, T. (2020). Asymmetric CEO confidence and CSR: A nonlinear panel ARDL-PMG approach. *The Journal of Economic Asymmetries*, *22*, e00176.

How to cite this article: Chen, G. S., Manu, E. K., & Asante, D. (2023). Achieving environmental sustainability in Africa: The role of financial institutions development on carbon emissions. *Sustainable Development*, *31*(5), 3272–3290. https://doi.org/10.1002/sd.2584

APPENDIX A

TABLE A1 Summary statistics, by variable

Variable	Measurement	Mean	S.D.	Min	Max	Skew.	Kurt.
CO2	Carbon emissions per capita	9.859	3.439	3.426	16.870	0.535	2.225
OFI	Overall financial institutions development	−1.543	0.499	−3.795	−0.303	−0.154	3.866
FIA	Financial institutions access	0.082	0.130	0.001	0.862	3.035	13.311
FID	Financial institutions depth	0.118	0.168	0.001	0.884	2.751	10.411
FIE	Financial institutions efficiency	0.552	0.173	0.040	1.398	0.003	3.637
GDP	Gross domestic product per capita	7.944	1.620	5.335	11.425	0.531	2.202
FDI	Foreign direct investment as a share of GDP	0.285	1.471	−8.927	3.740	−1.065	6.075
NRE	Non–renewable energy consumption per capita	2.505	0.728	−4.178	3.998	−2.242	14.056

Note: The financial institutions development indices are from the International Monetary Fund. The remaining variables are from the World Development Indicators. The panel data is comprised of 33 countries for the 1980–2017 period.

TABLE A2 The correlation coefficient matrix, by variable

Variables	CO2	OFI	FIA	FID	FIE	GDP	FDI	NRE
CO2	1.000							
OFI	0.072***	1.000						
	(0.010)							
FIA	−0.017	0.668***	1.000					
	(0.551)	(0.000)						
FID	0.062**	0.663***	0.450***	1.000				
	(0.028)	(0.000)	(0.000)					
FIE	0.099***	0.814***	0.369***	0.265***	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)				
GDP	0.480***	−0.001	−0.164***	0.078***	0.085***	1.000		
	(0.000)	(0.982)	(0.000)	(0.006)	(0.003)			
FDI	0.049	0.140***	0.139***	0.214***	0.079***	0.218***	1.000	
	(0.081)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)		
NRE	−0.137***	0.291***	0.322***	0.310***	0.053	−0.009	0.170***	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.062)	(0.753)	(0.000)	

Note: The Pearson pairwise correlation coefficient is reported in the table. *** and ** indicate statistical significance at the 1% and 5% level, respectively.

TABLE A3 Multicollinearity test, by financial institution development indicator

Model	(1)		(2)		(3)		(4)	
	VIF	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF	Tolerance
OFI	1.103	0.906						
FIA			1.170	0.855				
FID					0.143	0.875		
FIE							0.013	0.987
GDP	1.053	0.950	1.095	0.913	0.055	0.948	0.058	0.945
FDI	1.094	0.914	1.104	0.906	0.111	0.900	0.087	0.920
NRE	1.115	0.897	1.136	0.880	0.124	0.889	0.034	0.967

Note: The dependent variable is CO2. Since the VIF and tolerance values, respectively, are well below 5 and well above 0.2, it can be concluded that there is no multicollinearity.

TABLE A4 Cross-sectional dependence and panel unit root tests, by variable

	(a). Cross–sectional dependence test		(b). CIPS				(c). CADF			
			I(0)		I(1)		I(0)		I(1)	
Variable	Breusch–Pagan LM	Pesaran CD	Intercept	Intercept and trend	Intercept	Intercept and trend	Intercept	Intercept and trend	Intercept	Intercept and trend
CO2	10396.40***	67.22***	−2.185	−2.549	−5.699***	−5.838***	−1.796	−2.150	−2.615***	−2.891***
OFI	3941.22***	28.54***	−2.179	−3.057	−5.733***	−5.776***	−1.935	−2.622**	−3.140***	−3.149***
FIA	12893.60***	107.78***	−2.249***	−2.563	−4.934***	−5.085***	−2.106**	−2.612**	−2.797***	−2.926***
FID	5900.33***	30.73***	−1.745	−2.348	−5.376***	−5.691***	−1.935	−2.474	−2.409***	−2.572***
FIE	3606.47***	9.00***	−2.591***	−3.171***	−5.766***	−5.972***	−2.260***	−2.573	−3.183***	−3.257***
GDP	10797.32***	64.61***	−1.853	−2.453	−4.440***	−4.780***	−1.888	−2.346	−2.336***	−2.645***
FDI	3895.34***	45.67***	−3.438***	−3.562***	−6.102***	−6.268***	−2.072**	−2.163	−3.294***	−3.395***
NRE	2903.46***	20.11***	−2.558***	−2.877***	−5.629***	−5.780***	−1.796	−2.381	−3.112***	−3.252***

Note: In panel (a), *** rejects the null hypothesis of no cross–sectional dependence at the 1% level of significance. In panels (b) and (c), *** and ** rejects the null hypothesis of panel unit roots at the 1% and 5% level of significance, respectively. For the CIPS test, the maximum lag is set as 3 and the Breusch–Godfrey lag is set as 3. For the CADF test, the lag is set as 3.

TABLE A5 The slope homogeneity and panel Pedroni cointegration tests, by financial institution development indicator

Model	(1)	(2)	(3)	(4)
(a) Slope homogeneity test	**OFI**	**FIA**	**FID**	**FIE**
$\widetilde{\Delta}$	40.521***	40.934***	42.128***	40.894***
$\widetilde{\Delta}_{adj}$	44.156***	44.607***	45.908***	44.563***
(b) Pedroni cointegration test	OFI	FIA	FID	FIE
Panel PP–statistic (weighted)	−5.218***	−5.098***	−5.205***	−5.681***
Panel ADF–statistic (weighted)	−5.036***	−5.188***	−4.901***	−5.126***
Group PP–statistic	−3.353***	−4.014***	−4.757***	−3.751***
Group ADF–statistic	−2.447***	−1.695**	−3.589***	−2.477***

Note: In panel (a), *** rejects the null hypothesis that there is slope homogeneity in the model at the 1% level of significance. In panel (b), *** and ** reject the null hypothesis that there is no cointegration relationship at the 1% and 5% level of significance, respectively. We assume "no deterministic trend," use automatic lag length selection based on SIC with a max lag of 8 and employ Newey–West automatic bandwidth selection and Bartlett kernel.

TABLE A6 Panel PMG ARDL estimations, by financial institutions development indicator

Model	(1)	(2)	(3)	(4)
(a). Long-run dynamics				
OFI	0.213***			
	(0.0598)			
FIA		1.649***		
		(0.256)		
FID			1.962***	
			(0.356)	
FIE				0.385***
				(0.128)
GDP	0.152**	0.041	0.252***	0.245***
	(0.076)	(0.095)	(0.088)	(0.0833)
FDI	0.050***	0.047***	0.023	0.0453***
	(0.015)	(0.014)	(0.015)	(0.0157)
NRE	−0.027**	−0.028	−0.030	−0.0282
	(0.014)	(0.035)	(0.040)	(0.0403)
(b). Short-run effects				
ECT	−0.145***	−0.150***	−0.156***	−0.142***
	(0.030)	(0.033)	(0.030)	(0.0296)
Δ(OFI)	−0.046			
	(0.040)			
Δ(FIA)		0.622		
		(1.148)		
Δ(FID)			0.919	
			(0.835)	
Δ(FIE)				−0.0139
				(0.0651)
Δ(GDP)	0.638***	0.625***	0.616***	0.641***
	(0.177)	(0.170)	(0.179)	(0.167)
Δ(FDI)	−0.0002	−0.001	0.003	0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Δ(NRE)	−0.002	0.017	0.004	−0.006
	(0.025)	(0.021)	(0.027)	(0.027)
Constant	1.235***	1.301***	1.089***	1.023***
	(0.246)	(0.257)	(0.205)	(0.197)
Log likelihood	1541.29	1548.68	1559.66	1540.01
Observations	1221	1221	1221	1221

Note: The optimal lag selection was based on the iterated log likelihood ratio computed by the xtpmg command in Stata17. *** and ** indicate the 1% and 5% level of significance, respectively. Δ is the difference operator. ECT denotes the error correction term.

TABLE A7 Robustness tests

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(a). Long-run dynamics							
OFI	1.996***				0.171***	1.374***	0.152**
	(0.222)				(0.056)	(0.300)	(0.063)
OFI^2	0.478						
	(2.0650)						
FIA		−2.242***					
		(0.708)					
FIA^2		3.147					
		(1.643)					
FID			−0.776***				
			(0.513)				
FID^2			3.159				
			(0.463)				
FIE				−1.570***			
				(1.717)			
FIE^2				1.964			
				(0.659)			
GDP	0.124	0.186**	0.011	0.659**	3.646***		
	(0.070)	(0.086)	(0.079)	(0.080)	(0.361)		
GDP^2					−0.140***		
					(0.020)		
FDI	0.058***	−0.003	−0.005	0.064***	0.009		
	(0.012)	(0.009)	(0.011)	(0.015)	(0.015)		
FDI^2					−0.002		
					(0.004)		
NRE	−0.050	0.015	−0.006	−0.022	−0.411***		
	(0.034)	(0.029)	(0.021)	(0.036)	(0.074)		
OFI x GDP						−0.114***	
						(0308)	
OFI x FDI							0.064**
							(0.032)
(b). Short-run effects							
ECT	−0.164***	−0.154***	−0.150***	−0.144***	−0.140***	−0.156***	−0.145***
	(0.036)	(0.0405)	(0.0346)	(0.031)	(0.031)		
Δ(OFI)	1.261				−0.00002	−3.794	0.025
	(1.204)				(0.065)	(2.392)	(0.070)
$\Delta(OFI^2)$	0.540						
	(0.487)						
Δ(FIA)		−0.225					
		(5.781)					
$\Delta(FIA^2)$		−73.83					
		(202.7)					
Δ(FID)			−0.151				
			(2.109)				
$\Delta(FID^2)$			18.690				
			(21.720)				

(Continues)

TABLE A7 (Continued)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ(FIE)				0.389			
				(0.636)			
Δ(FIE^2)				−0.165			
				(0.590)			
Δ(GDP)	0.666***	0.607***	0.652***	0.654***	10.321	1.178***	0.667***
	(0.186)	(0.166)	(0.176)	(0.162)	(6.666)	(0.434)	(0.176)
Δ(GDP^2)					−0.461		
					(0.371)		
Δ(FDI)	−0.002	0.003	0.004	0.002	0.007	−0.0003	−0.034
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.037)
Δ(FDI^2)					−0.005**		
					(0.003)		
Δ(OFI x GDP)						0.420	
						(0.291)	
Δ(OFI x FDI)							−0.026
							(0.024)
Δ(NRE)	0.003	−0.004	0.006	0.007	0.022	−0.004	0.001
	(0.029)	(0.021)	(0.027)	(0.028)	(0.028)	(0.029)	(0.025)
Constant	1.592***	1.201***	1.363***	1.151***	−1.474***	1.560***	1.120***
	(0.342)	(0.316)	(0.325)	(0.231)	(0.358)	(0.277)	(0.207)
Log likelihood	1574.47	1581.05	1587.59	1563.99	1584.34	1568.72	1561.40
Observations	1221	1221	1221	1221	1221	1221	1221

Note: The optimal lag selection was based on the iterated log likelihood ratio computed by the xtpmg command in Stata17. *** and ** indicate the 1% and 5% level of significance, respectively. Δ is the difference operator. ECT denotes the error correction term.

TABLE A8 Panel PMG ARDL estimations, by subsample

Model	(1) Geography	(2)	(3)	(4)	(5)	(6) Regional economic blocs	(7)	(8)	(9)	(10) Time	(11)
	WA	EA	SA	Coast	Landlock	COMESA	Non–COMESA	SADC	Non–SADC	1980–1999	2000–2017
(a) Long-run dynamics											
OFI	0.177**	0.240	0.242***	−0.169***	0.229***	0.936***	−0.129**	0.942***	−0.137***	0.453***	0.135***
	(0.070)	(0.153)	(0.299)	(0.062)	(0.078)	(0.109)	(0.056)	(0.116)	(0.0512)	(0.072)	(0.033)
GDP	0.401***	−0.097	−0.037	0.044	−0.007	0.262**	0.035	0.276**	0.037	−0.264***	0.643***
	(0.121)	(0.144)	(0.183)	(0.104)	(0.104)	(0.119)	(0.097)	(0.138)	(0.083)	(0.055)	(0.038)
FDI	−0.007	0.098***	−0.079	0.002	0.081***	0.071***	−0.001	0.074***	0.002	0.049***	0.010
	(0.021)	(0.025)	(0.049)	(0.011)	(0.020)	(0.015)	(0.010)	(0.0153)	(0.010)	(0.009)	(0.007)
NRE	−0.208**	−0.016	−0.904	0.026	−0.030	−0.058	0.032	−0.286**	−0.009	−0.010	0.100***
	(0.097)	(0.052)	(0.523)	(0.070)	(0.043)	(0.054)	(0.066)	(0.135)	(0.024)	(0.006)	(0.029)
(b) Short-run effects											
ECT	−0.200**	−0.135***	−0.195***	−0.119**	−0.239***	−0.161***	−0.181***	−0.174**	−0.173***	−0.205***	−0.386***
	(0.081)	(0.052)	(0.068)	(0.047)	(0.081)	(0.051)	(0.059)	(0.075)	(0.049)	(0.051)	(0.050)
Δ(OFI)	0.103***	−0.023	−0.082	−0.043	0.020	−0.098**	−0.010	−0.111**	−0.006	−0.215	−0.024
	(0.028)	(0.032)	(0.072)	(0.087)	(0.033)	(0.041)	(0.108)	(0.050)	(0.089)	(0.123)	(0.1000)
Δ(GDP)	0.250***	0.498***	0.582***	0.568***	0.705	0.688***	0.529**	0.800***	0.523**	0.635***	0.788**
	(0.195)	(0.151)	(0.208)	(0.144)	(0.507)	(0.225)	(0.259)	(0.271)	(0.220)	(0.164)	(0.349)
Δ(FDI)	0.003	−0.006	0.026***	−0.001	0.005	0.001	0.001	0.002	0.0005	−132.0	−0.009
	(0.008)	(0.00470)	(0.009)	(0.004)	(0.010)	(0.006)	(0.005)	(0.009)	(0.004)	(132.0)	(0.008)
Δ(NRE)	−0.013	0.034	0.040	−0.008	0.019	0.033	−0.028	0.007	−0.001	−2.722	−0.046
	(0.072)	(0.027)	(0.037)	(0.027)	(0.028)	(0.031)	(0.031)	(0.057)	(0.024)	(2.753)	(0.089)
Constant	1.336***	1.185***	0.977	1.078**	2.238***	1.144***	1.667***	1.336***	1.591***	2.363***	1.647***
	(0.505)	(0.353)	(0.567)	(0.427)	(0.772)	(0.310)	(0.545)	(0.494)	(0.452)	(0.660)	(0.201)
Log likelihood	410.23	566.05	251.74	1152.19	399.12	789.22	766.59	563.13	997.70	937.11	915.94
Observations	370	370	185	851	370	518	703	370	851	627	594

Note: The optimal lag selection was based on the iterated log likelihood ratio computed by the xtpmg command in Stata17. *** and ** indicate the 1% and 5% level of significance, respectively. Δ is the difference operator. ECT denotes the error correction term. WA, EA, and SA refer to western Africa, eastern Africa, and southern Africa, respectively. Coast and Landlock refer to those countries with and without a coastline, respectively. COMESA and SADC refer to the Common Market for Eastern and Sothern Africa and Southern African Development Community, respectively.

TABLE A9 The Dumitrescu–Hurlin causality test, by pairwise variables

Null hypothesis	W–statistic	Z–bar tilde	Prob.	Conclusion
OFI does not homogenously cause CO2	2.9762	2.1020	0.0356**	Bidirectional causality exists
CO2 does not homogenously cause OFI	3.3018	2.9185	0.0035***	
GDP does not homogenously cause CO2	4.2696	5.3454	0.0000***	Bidirectional causality exists
CO2 does not homogenously cause GDP	3.0601	2.3125	0.0208**	
FDI does not homogenously cause CO2	3.1438	2.5223	0.7462	No bidirectional causality exists
CO2 does not homogenously cause FDI	2.1568	1.0473	0.9623	
NRE does not homogenously cause CO2	8.5864	16.1705	0.0000***	NRE does Granger cause CO2 but not vice versa
CO2 does not homogenously cause NRE	1.9625	−0.4399	0.6600	
OFI does not homogenously cause GDP	3.6668	9.4930	0.0000***	Bidirectional causality exists
GDP does not homogenously cause OFI	3.7613	9.8375	0.0000***	
OFI does not homogenously cause FDI	2.0946	3.7620	0.0002***	Bidirectional causality exists
FDI does not homogenously cause OFI	2.2346	4.2726	0.0000***	
OFI does not homogenously cause NRE	1.7126	2.3697	0.0178**	OFI does Granger cause NRE but not vice versa
NRE does not homogenously cause OFI	1.5047	1.6118	0.1070	
GDP does not homogenously cause FDI	3.8728	10.2441	0.0000***	Bidirectional causality exists
FDI does not homogenously cause GDP	3.7284	9.7175	0.0000***	
GDP does not homogenously cause NRE	2.9206	6.7730	0.0000***	Bidirectional causality exists
NRE does not homogenously cause GDP	5.1326	14.8361	0.0000***	
FDI does not homogenously cause NRE	1.5721	1.8576	0.0632	No bidirectional causality exists
NRE does not homogenously cause FDI	1.3464	1.0349	0.3007	

Note: *** and ** indicate that the null hypothesis is rejected at 1% and 5% level of significance, respectively.