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Analysis of the Responsiveness of Environmental Sustainability to Non-Performing Loans in Africa

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Abstract

This study draws on Sustainable Development Goal 12 to analyze the responsiveness of environmental sustainability to non-performing loans (NPLs) in Africa over the period 2000–2016. We explore (1) how environmental sustainability reacts to shocks from NPLs and (2) heterogeneous responses of environmental sustainability to NPLs. We employed Generalized Method of Moment (GMM) style panel Vector Autoregressive and panel quantile regression models to investigate the phenomenon. Our results revealed that conditioning on other sustainability determinants, environmental sustainability responds negatively to NPLs. The impulse response function revealed that the impact of one standard deviation shock in rising NPLs on environmental sustainability is

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negative from year 1 to year 6 and equal to zero from years 7 to 10. Besides, the quantile regression revealed heterogeneous responses indicating that compared with countries distributed along a high environmentally sustainable path, countries on a low environmentally sustainable path suffer more environmental issues resulting from rising NPLs.

Keywords: environmental sustainability, non-performing loans, GMM style panel VAR, panel quantile regression, Africa

JEL Classification: C31, C33, O11, O55, Q56

1. Introduction

In line with Sustainable Development Goal (SDG) 12 that advocates for environmental sustainability, Africa's environmental sustainability has become a major concern to researchers and policy makers. For a continent like Africa that relies primarily on natural resources to achieve growth, the challenge of environmental sustainability is daunting. The extraction patterns of non-renewable resources such as gold, diamonds, and crude oil currently have countless impacts on the environment. Africa's desire to achieve its development goals through its huge dependence on natural resources and the possible implications for the environment has the potential to leave detrimental footprints for future generations. Due to this, a new environmental macroeconomic model, which places the banking sector at the heart of future growth and sustainability, has been proposed (Dafermos, Galanis, & Nikolaidi, 2015; Nieto, 2017; Schmidt-Traub & Shah, 2015). Through environmental management systems and business strategies, banks play a key role in driving sustainable economic growth, greater environmental responsibility, climate resilience, low carbon, social inclusion, and sustainable economic growth (Ntarmah, Kong, & Gyan, 2019; Rakić, Mitić, & Anđelić, 2015; Saeed, Ramzan, & Hamid, 2020). Adequate and stable funding is essential for Africa's environmental sustainability (United Nations Environment Programme [UNEP], 2015).

While banks play an important role in this environmental transition, the industry has been faced with several challenges. The banking sector in some African countries continues to suffer from rising non-performing loans[1](NPLs). Several factors, including exhange rate, poor credit appraisal, high interest rates, excessive and improper lending, and economic growth influence

[1] A loan is considered non-performing when more than 90 days pass without the borrower paying the agreed instalments or interest. Non-performing loans are also called “bad debt” (European Central Bank, 2016).

NPLs in Africa (Amuakwa-Mensah, Marbuah, & Ani-Asamoah Marbuah, 2017; Mpofu & Nikoaidou, 2019). NPLs harms the functioning of the banking system, with repercussions on the environment as a whole (Enkvist, Dinkel, & Lin, 2010; Gertler & Kiyotaki, 2010; Vodová, 2003). For instance, in Morocco, NPLs as a ratio of total bank loans (NPLs) rose from 5.5% to 7.8% over the period 2009–2016, while the ecological footprint decreased from 1.83 to 1.70 global hectares in the same period. Similarly, NPLs for Nigeria rose from 7.2% to 12.8% over the period 2008–2016, while the ecological footprint decreased from 1.24 to 1.09 global hectares in the same period. Additionally, NPLs of Senegal rose from 17.5% to 19.5% over the period 2008–2016, while the ecological footprint decreased from 1.39 to 1.14 global hectares for the same period (World Bank, 2020).

Empirical works linking NPLs and environmental sustainability have been limited, with varied results. Many of these studies focused on the relationship between financial instability (usually indexed by NPLs) and carbon emissions or environmental degradation (Enkvist et al., 2010; Shahbaz, 2010, 2013; Yang, Ali, & Nazir, 2020). For instance, Shahbaz (2010) revealed that NPLs as an index of financial instability increase the environmental degradation of Pakistan. Enkvist et al. (2010) revealed financial instability has little or weak influence on energy pollutants. On the other hand, Yang et al. (2020) found financial instability to have a negative influence on carbon emissions of developing economies. Other studies (Moghadam & Dehbashi, 2018; Nasreen, Anwar, & Ozturk, 2017) focused on financial stability and carbon emissions or environmental degradation. Another group, including Kim and Park (2016), Tamazian and Rao (2010), and Tamazian, Chousa, and Vadlamannati (2009) concluded that NPLs negatively influence various aspects of the economy, as they restrict financing of green projects and growth-related activities.

Critical examination of these studies revealed two common limitations: (1) inconclusive results of the subjects and (2) little recognition of the role of NPLs or financial instability in environmental sustainability, especially within the African context, where NPLs are rising. This has led to a new area of research focusing on environmental determinism within the framework of financial instability or financial development (Nasreen et al., 2017; Omri, Euchi, Hasaballah, & Al-Tit, 2019). In line with the limitations found in earlier studies, this study seeks to examine the responsiveness of environmental sustainability to NPLs among selected African countries. This objective is divided into two sub-objectives. First, we analyze how environmental sustainability among the selected African countries responds to a shock from NPLs over the period 2000–2016.

Second, due to the disparities among the selected countries in Africa, we examined heterogeneous responses of environmental sustainability to the impacts of NPLs.

This study contributes to the literature in several ways. First, this study fills an earlier gap identified in the finance–environmental literature (Lata, 2014; Morakinyo & Sibanda, 2016; Nasreen et al., 2017; Zeng, 2012) by providing clear empirical evidence to clarify the mixed results found in the finance–environmental literature. Secondly, it brings to light how environmental sustainability changes to NPLs from the perspective of the African context. We provide evidence of heterogeneous responses of environmental sustainability to the impact of NPLs by conditioning on other sustainability determinants. Methodologically, we employed econometric frameworks of (1) Generalized Method of Moment (GMM) style panel Vector Autoregressive (panel VAR) to examine the reaction of environmental sustainability to a shock in NPLs and (2) recent panel quantile regression with fixed effect (MM-QR) implemented by Machado and Santos Silva (2019) to examine heterogeneity in responses of environmental sustainability to rising NPLs.

The rest of the paper is organized as follows: Section 2 presents a literature review, while Section 3 focuses on the materials and methods. Section 4 deals with results and discussions. It presents the results based on the objectives of the study. Finally, Section 5 presents the conclusion and potential policy recommendations.

2. Literature review

Globally, several studies point out that environmental sustainability [2] is generally determined by several factors, including gross domestic product (GDP), trade, human development, government spending, financial stability, NPLs, urbanization, and population (Balcilar, Ozdemir, Tunçsiper, Ozdemir, & Shahbaz, 2019; Galeotti, 2007; Khan, Su, Tao, & Hao, 2019; Shahbaz, 2010; Yang et al., 2020). Given that human survival through the activities production and consumption depends largely on the environment (Montt, Fraga, & Harsdorff, 2018), the theoretical arguments by environmental economists raise questions on how we can develop economic incentives to improve environmental sustainability. In line with this, discussions of various sustainable development agendas place the global financial sector at the heart of

[2] Environmental sustainability reflects a strong sustainability perspective that rejects the perfect substitutability of different capital but views sustainability as non-declining life chances (refer to Romero and Linares (2013) for extensive discussion on strong and weak sustainability).

humanity's attempt to accomplish the SDGs (Schmidt-Traub & Shah, 2015). Recent estimates point out that the SDGs will need an extra US$2.4 trillion of annual investment into the health, energy, agriculture, education, low-carbon infrastructure, and other sustainability sectors globally (Schmidt-Traub & Shah, 2015). Since the 2007/2008 global financial crises and their adverse impacts on the global economy, it is well established that a stable financial system is crucial for future sustainability (Nasreen et al., 2017; Schmidt-Traub & Shah, 2015). This has led to a new area of research focusing on environmental determinism within the framework of financial (in)stability or financial development (Nasreen et al., 2017; Omri et al., 2019).

Studies on the subject have focused on financial stability and carbon emissions or environmental degradation/quality (Caldeott & McDaniels, 2014; Jamel & Maktouf, 2017; Moghadam & Dehbashi, 2018; Nasreen et al., 2017; Nizam, Ng, Dewandaru, Nagayev, & Nkoba, 2019) and financial instability and environment (Chaffin, 2010; Enkvist et al., 2010; Richard, 2010; Shahbaz, 2010, 2013; Yang et al., 2020). With the former, Nasreen et al. (2017) found that financial stability improves environmental quality among South Asian countries, while Moghadam and Dehbashi (2018) revealed adverse effects of financial stability on environmental quality in Iran. On the contrary, Jamel and Maktouf (2017) could not reveal any relationship among the variables among European countries. This highlights mixed results regarding the relationship between financial stability and environment. In addition, these studies paid little attention to the influence of NPLs (which is critical in Africa) on the environment.

Using static and dynamic models, Richard (2010) revealed that financial instability increases environmental degradation in emerging and advanced economies. In Pakistan, Shahbaz (2010) used annual data from 1972–2009 and found that financial instability proxied by NPLs increases environmental degradation. Similarly, Shahbaz (2013) revealed that NPLs dampen the environment through high carbon emissions. A recent study by Yang et al. (2020) investigated the relationship between financial instability and environmental quality. The authors used annual data of 54 developing countries from 1980 to 2016. The results from the system GMM revealed a negative relationship between financial instability and carbon emissions. Other studies on the subject concluded that NPLs negatively influence various aspects of the economy, as they restrict financing of green projects and growth-related activities (Kim & Park, 2016; Tamazian et al., 2009; Tamazian & Rao, 2010). A related study by Ntarmah et al. (2019) established that NPLs have significantly negative impacts on the economic sustainability of Asian economies. Generally, the findings on this topic are diverse and inconclusive, with little focus on the African continent where NPLs are rising.

As explained earlier, the African financial sector suffers from NPLs (World Bank, 2020), which has several implications for the economies, including their sustainability. Given the contextual problem within the continent and the literature, this study extends the recent literature on the finance–environment framework (Moghadam & Dehbashi, 2018; Nasreen et al., 2017; Omri et al., 2019) to establish how NPLs influence environmental sustainability among selected African economies. This study proposes the following hypotheses:

H1: Environmental sustainability will respond negatively to rising NPLs among selected African economies.

H2: There will be heterogeneous responses of environmental sustainability to NPLs among the selected African economies.

3. Methods and data

3.1 Variables and data

The key variables of interest are environmental sustainability and NPLs. However, we controlled for other determinants of environmental sustainability to minimizing endogeneity problem. Table 1 summarizes the variables and sources of data.

Table 1: Variable description and data sources

Variable	Indicator	Description	Source
Environmental sustainability	Ecological footprint (EF)	EF is a technique of assessing humans' dependence on natural resources to compute sustainability of the environment. It gives a comprehensive measure of how much nature we have used and how much nature is left.	GFN 2019
Non-performing loans	Non-performing loans as percent of all bank loans (NPLs)	NPLs refer to loans on which the borrowers are not making any interest payments or repaying any principal.	WDI 2019
Government expenditure	General government final consumption expenditure (GFE)	GFE includes all current government expenditures for purchases of goods and services.	WDI 2019

Human development	School enrollment, secondary (SEC)	SEC is the total secondary education (enrollment) regardless of age (expressed as a percentage of the population of official secondary education age).	WDI 2019
Trade openness	Trade openness as a percentage of GDP (TRADE)	TRADE is the sum of exports and imports of goods and services measured as a share of gross domestic product.	WDI 2019

Note: GFN stands for Global footprint network. WDI stands for World Development Indicators.

The selection of potential control variables among the list of environmental sustainability determinants in the literature followed series of selection procedures, such as the forward and backward selection, multicollinearity test, and model fitness checks. Based on these estimation procedures, we retained trade openness, government expenditure, and human development as control variables to minimize their impacts within the model. Other potential control variables such as GDP, population, inflation, and foreign direct investment were not found to be jointly influencing the dependent variable and may lead to model uncertainties (Dufrenot, Mignon, & Tsangarides, 2009). In addition, we found that the variables highly correlated with other key variables, such as trade openness and government expenditure, and hence posed threats to the stability and convergence of the models used in the study. The control variables used in this study are similar to the variables controlled in studies by Arcand, Berkes, and Panizza (2012); Al-Moulani (2016); and Omri et al. (2019).

Our sample comprises annual data from eight selected African countries (Egypt, Ghana, Morocco, Mauritius, Nigeria, Senegal, South Africa, and Tunisia) from 2000 to 2016. The number of African countries excluded was due to data unavailability over the sample period. As a normal practice in econometrics to minimize heteroscedasticity in the data, we transformed the variables into their natural logs and used them in our analysis (Charfeddine & Khediri, 2016). Table 2 presents the mean and standard deviations as well as the correlation matrix. The results in Table 2 show that none of the regressors highly correlated with each other, and the variance inflation factor (VIF) value is less than 5, with a tolerance (Tol) value greater than 0.2, indicating that multi-collinearity is not a problem in our explanatory variables.

Table 2. Descriptive statistics

	Mean and standard deviation (SD)					Correlation matrix					Collinearity statistics	
Variable	Obs	Mean	SD	Min	Max	lnef	lnnpl	lntrade	lngfe	lnsec	Tol	VIF
lnef	136	0.638	0.367	0.085	1.352	1						
lnnpl	133	2.274	0.755	0.095	3.618	-0.653	1				0.782	1.279
lntrade	136	4.204	0.386	3.031	4.875	0.471	-0.067	1			0.796	1.256
lngfe	136	2.546	0.497	-0.051	3.035	0.484	-0.257	0.439	1		0.671	1.490
lnsec	135	4.095	0.456	2.749	4.632	0.791	-0.460	0.315	0.498	1	0.628	1.592

Note: Obs means observations; SD means standard deviations; Min and Max are minimum and maximum, respectively. The dependent variable for the collinearity diagnostics is environmental sustainability (lnef).

3.2 Test of Normality

As a preliminary analysis, choosing a model that is suitable for research requires checking data normality. We use the Shapiro–Wilk and Shapiro–Francia tests to check data normality. Both tests are correlation-based algorithms, which assume that the higher the normality of the data, the closer the value is to 1. The Shapiro–Wilk and Shapiro–Francia tests are the test statistics, which are very important in identifying deviations from normality in all sample sizes (Mbah & Paothong, 2015). Table 3 reports the results obtained from these two tests. Based on the p statistic, the results reject the null hypothesis at the 1% significance level, which indicates that the data are not normally distributed.

Table 3: Normality test

		Shapiro–Francia test		Shapiro–Wilk test	
Variable	Obs	Statistic	Sig	Statistic	Sig
lnef	136	0.935	0.000	0.929	0.000
lnnpl	133	0.927	0.000	0.925	0.000
lntrade	136	0.975	0.015	0.973	0.008
lngfe	136	0.742	0.000	0.747	0.000
lnsec	120	0.887	0.000	0.883	0.000

Even though the two tests are useful in checking the normality of the data, they also have their limitations. Therefore, in graphical terms, we employed the most widely used quantile–quantile (Q–Q) normality test to compare two probability distributions. Figs. 1–5 show the distribution of variables. The blue line shows the expected normal distribution. As can be observed in Figs. 1–5, the variable does not fall (roughly straight, especially the outliers) on the normally distributed line, confirming the data are not normally distributed. In this case, conditional mean-based models such as ordinary least square (OLS) regression may have an estimation bias, because OLS is valid when the variables are normally distributed. Panel data models that allow for heterogeneity become appropriate (Canova & Ciccarelli, 2013).

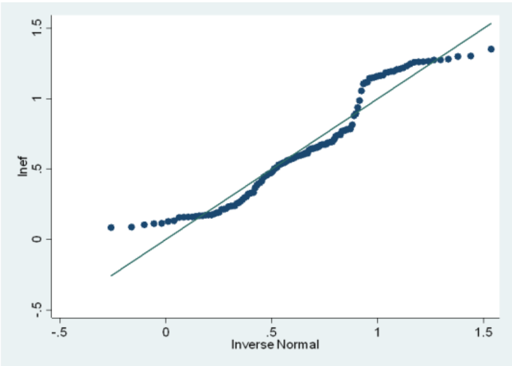

Figure 1: Q-Q plots of ecological footprint

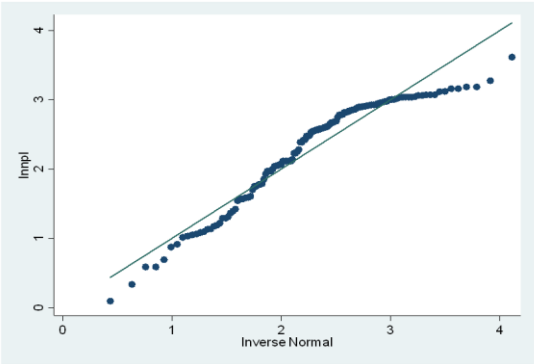

Figure 2: Q-Q plots of non-performing loans

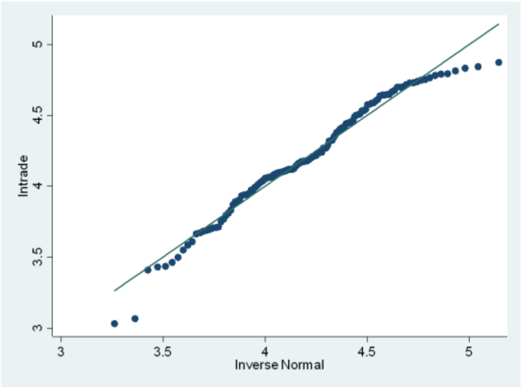

Figure 3: Q-Q plots of trade openness

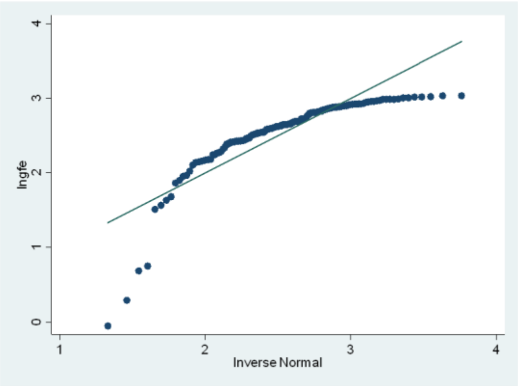

Figure 4: Q-Q plots of government expenditure

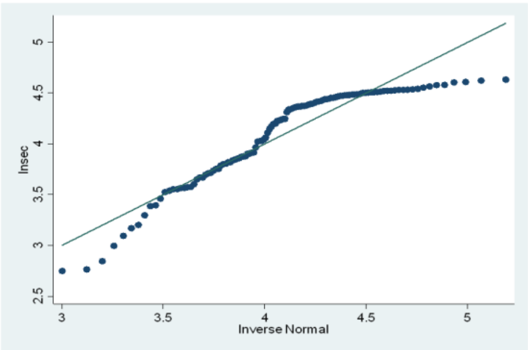

Figure 5: Q-Q plots of secondary education enrollment

3.3 Econometric Model

We employed the econometric frameworks of the panel VAR model in the GMM framework implemented by Love and Zicchino (2006) and recent panel quantile regression with fixed effects (MM-QR) by Machado and Santos Silva (2019). This study followed the studies by Abrigo and Love (2016), Charfeddine and Kahia (2019), and Rios-Avila (2020). Methodologically, we employed Pesaran (2004, 2007), Im, Pesaran, & Shin (IPS) (2003), and Fisher-type (Choi, 2001; Maddala & Wu, 1999) to test for cross-sectional dependence and unit roots in the dataset. In addition, we employed the Westerlund (2007) cointegration test to test for cointegration among the variables. Finally, we employed econometric frameworks of (1) GMM style Vector Autoregressive (VAR) and (2) recent panel quantile regression with fixed effect (MM-QR) implemented by Machado and Santos Silva (2019).

3.3.1 Panel Vector Autoregressive (Panel VAR) Model

This study employed a panel VAR approach. The panel VAR model accounts for the dynamic heterogeneity of cross-sections in our data by incorporating fixed effects that increase consistency and coherence measurement, especially where there is heterogeneity in environmental sustainability and NPLs among the selected African countries (Canova & Ciccarelli, 2013). Second, the panel VAR model is useful for studying exogenous and endogenous shocks, which are undoubtedly the most important source of dynamics in macroeconomics for open economies. Third, in line with the reality of interdependence, this panel VAR treats all variables in the model as endogenous and makes no distinction between endogenous and exogenous variables. In this case, each variable in the model depends on the historical realization of itself and other variables that show the actual simultaneity between the variables and their treatment. Finally, the panel VAR model does not limit itself to specific sustainability theories. As a result, this model follows contemporary movements from a series in its estimations (Charfeddine & Kahia, 2019; Kireyev, 2000).

The general formula for panel VAR implemented by Love and Zicchino (2006) is represented as:

$$Y_{it} = \mu_i + A(L)Y_{it} + \alpha_i + \delta_t + \varepsilon_{it} \qquad i=1, 2,\ldots,N \qquad t=1,2,\ldots,T \tag{1}$$

Where Y_{it} is the vector of endogenous stationary series variables of secondary education enrolment (lnsec), government final expenditure (lngfe), trade openness (lntrade), non-performing loans (lnnpl), and environmental sustainability (lnef). The country-specific fixed-effects matrix is represented as u_i, and the polynomial matrix in the lag operator with $A(L) = A_1L^1 + ... + A_{P-1}L^{P-1} + A_P L^P$ is represented as A(L). a_i captures individual heterogeneity or fixed effects between different cross-sectional units, δ_t represents the country-specific time dummy variables, and $\varepsilon_{i,t}$ denotes idiosyncratic errors, with $E(\varepsilon_{i,t}) = 0, E(\varepsilon_{i,t}^{'}\varepsilon_{i,t}) = \sum$ and $E(\varepsilon_{i,t}^{'}) = 0$ for t>j. Eq. 1 can be specified to reflect systems of equations involving the variables of the study as:

$$\begin{aligned}\Delta \ln \sec_{it} = \mu_{1i} &+ \sum_{j=1}^{p} \beta_{1j} \Delta \ln \sec_{it-j} + \sum_{j=1}^{p} \phi_{1j} \Delta \ln gfe_{it-j} + \sum_{j=1}^{p} \varphi_{1j} \Delta \ln trade_{it-j} \\ &+ \sum_{j=1}^{p} \eta_{1j} \Delta \ln npl_{it-j} + \sum_{j=1}^{p} \theta_{1j} \Delta \ln ef_{it-j} + \alpha_{1i} + \delta_{1t} + \varepsilon_{1it}\end{aligned} \tag{1.1}$$

$$\begin{aligned}\Delta \ln gfe_{it} = \mu_{2i} &+ \sum_{j=1}^{p} \beta_{2j} \Delta \ln \sec_{it-j} + \sum_{j=1}^{p} \phi_{2j} \Delta \ln gfe_{it-j} + \sum_{j=1}^{p} \varphi_{2j} \Delta \ln trade_{it-j} \\ &+ \sum_{j=1}^{p} \eta_{2j} \Delta \ln npl_{it-j} + \sum_{j=1}^{p} \theta_{2j} \Delta \ln ef_{it-j} + \alpha_{2i} + \delta_{2t} + \varepsilon_{2it}\end{aligned} \tag{1.2}$$

$$\begin{aligned}\Delta \ln trade_{it} = \mu_{3i} &+ \sum_{j=1}^{p} \beta_{3j} \Delta \ln \sec_{it-j} + \sum_{j=1}^{p} \phi_{3j} \Delta \ln gfe_{it-j} + \sum_{j=1}^{p} \varphi_{3j} \Delta \ln trade_{it-j} \\ &+ \sum_{j=1}^{p} \eta_{3j} \Delta \ln npl_{it-j} + \sum_{j=1}^{p} \theta_{3j} \Delta \ln ef_{it-j} + \alpha_{3i} + \delta_{3t} + \varepsilon_{3it}\end{aligned} \tag{1.3}$$

$$\begin{aligned}\Delta \ln npl_{it} = \mu_{4i} &+ \sum_{j=1}^{p} \beta_{4j} \Delta \ln \sec_{it-j} + \sum_{j=1}^{p} \phi_{4j} \Delta \ln gfe_{it-j} + \sum_{j=1}^{p} \varphi_{4j} \Delta \ln trade_{it-j} \\ &+ \sum_{j=1}^{p} \eta_{4j} \Delta \ln npl_{it-j} + \sum_{j=1}^{p} \theta_{4j} \Delta \ln ef_{it-j} + \alpha_{4i} + \delta_{4t} + \varepsilon_{4it}\end{aligned} \tag{1.4}$$

$$\begin{aligned}\Delta \ln ef_{it} = \mu_{5i} &+ \sum_{j=1}^{p} \beta_{5j} \Delta \ln \sec_{it-j} + \sum_{j=1}^{p} \phi_{5j} \Delta \ln gfe_{it-j} + \sum_{j=1}^{p} \varphi_{5j} \Delta \ln trade_{it-j} \\ &+ \sum_{j=1}^{p} \eta_{5j} \Delta \ln npl_{it-j} + \sum_{j=1}^{p} \theta_{5j} \Delta \ln ef_{it-j} + \alpha_{5i} + \delta_{5t} + \varepsilon_{5it}\end{aligned} \tag{1.5}$$

Even though our main equation is Eq. 1.5, it is important to estimate the equations for the other variables to establish their reactions within the estimation process. In the panel VAR model estimation process, the stationarity of the series and the selection of optimal autoregressive lag-length (j) are key.

In practice, there are limits on parameters in the panel VAR model. Therefore, the fixed effect (α_i) introduced into the model specification allows for individual heterogeneity at the level of the whole series to overcome these constraints. Similarly, country-specific fixed effects (μ_i) are added to the model to take into account all the time factors that are not observed at the country level. However, the presence of μ_i in the model causes estimation challenges, problems that occur in any specification including the lag of the dependent variable. We used Arellano and Bover's (1995) 'Helmert Procedure' or forward mean-differencing (superior to the usual average differentiation method) (Love & Zicchino, 2006), which allows the lagged independent variables to be used to consistently estimate coefficients using the GMM system. In addition, the inclusion of a common time effect, δ_i, in the regression captures any global macroeconomic shocks that might affect all countries simultaneously. To handle the time effect, we differentiate all variables before they are included in the model. These variables agree with the dummy settings in the system.

The panel VAR model evaluates the effects of orthogonal shocks and describes the impact of shocks from one variable to another while maintaining all other variables that are invariant. This is achieved by using the panel impulse response functions (IRFs), which describe the reaction of one variable in response to changes in other variables in the system over time while all other shocks are maintained at zero.

3.3.2 Panel Quantile Regression with Fixed Effects (MM-QR)

As indicated earlier, the normality test revealed the data are not normally distributed. In this case, models such as OLS built on the assumption of normal distribution may reveal biased estimates. To overcome this weakness, we apply quantile regression to estimate our results on various quintiles of the distribution and provide heterogeneous responses. Quantitative regression is noted for its robustness towards outliers and the ability to capture all-important relationships that failed to be handled by OLS and other classic econometric methods. We used the recent panel quantile regression method (MM-QR) developed by Machado and Santos Silva (2019). The model was initially developed in 2018 and modified in 2019. Unlike earlier quantile regression methods, MM-QR is used to estimate results through moment conditions that do not assume the presence of the moment function or make distribution assumptions (Machado & Santos Silva, 2019; Sherwood & Wang, 2016; Zhu, Duan, Guo, & Yu, 2016). Therefore, we consider estimating conditional quantiles $Q_Y(\tau \mid X)$ for location-scale in the form:

$$Y_{it} = \alpha_i + X'_{it}\beta + \left(\delta_i + Z'_{it}\gamma\right)U_{it} \qquad i=1,2,\ldots,n \qquad t=1,2,\ldots,T \tag{2}$$

with $P\{\delta_i + Z'_{i,t}\gamma > 0\} = 1.$ The individual fixed effects is represented as $\left(\alpha_i, \delta_i\right)$, and Z is a k-vector of recognized differentiable (with probability 1) transformations of the components of X. The statistically independent of $X_{i,t}$ which is $U_{i,t}$ is i.i.d. (across *i* and *t*). This is then normalized to satisfy the moment conditions. However, the model proposed in Eq. 2 suffers from incidental parameter problems and has no advantages over alternative approaches. To avoid this problem affecting the entire distribution, we introduce jackknife bias correction in the model and apply a bias-correction version of the model (as illustrated in Eq. 5) based on split panel jackknife (Dhaene & Jochmans, 2015).

$$Q_Y\left(\tau \mid X_{it}\right) = \left(\alpha_i + \delta_i q\left(\tau\right)\right) + X'_{it}\beta + Z'_{it}\gamma q\left(\tau\right) \tag{3}$$

where the scalar coefficient $\alpha_i\left(\tau\right) \equiv \alpha_i + \delta_i q\left(\tau\right)$ is a quantile-τ fixed effect for the distributional effect at τ or the individual *i.* The distribution effect is not the same as a usual fixed effect in that, in general, it is not a shift in location. That is, the effects of the distribution represent the effects of individual invariant-time features like other variables, which are permitted to have different effects on various regions of the conditional distribution of Y. $\int_0^1 q\left(\tau\right)d\tau = 0$ implies that α_i can be interpreted as the average effect for individual *i*. Thus, the jackknife correction introduced in Eq. 3 essentially eliminates the bias without a significant loss of precision (Machado & Santos Silva, 2019). In addition, the conditions established in Eq.3 do not imply strict exogeneity and, therefore, minimize endogeneity problems. Eq. 3 can be simplified to capture the specific variables as:

$$Q_\tau\left(\ln ef_{it}\right) = \alpha_\tau + \beta_{1\tau}\ln npl_{it-1} + \beta_{2\tau}\ln trade_{it-1} + \beta_{3\tau}\ln gfe_{it-1} + + \beta_{4\tau}\ln \sec_{it-1} + \varepsilon_{it} \tag{4}$$

where Q_τ denotes quantile regression parameters of the τth distributional point, and τ indicates the distributional point for the independent variables. Eq. 4 denotes the quantile regression equation of environmental sustainability being regressed on fixed effects (α_τ), initial values of NPLs, and a set of controlling variables (trade openness, government expenditure, and secondary education enrollment). As explained earlier, the impact of NPLs on environmental sustainability is dependent on the initial values of NPLs; hence, our estimated quantile equation used the initial value of NPLs. In addition, the lagged controlled variables in the equation minimize endogeneity problems (Al-Moulani, 2016; Arcand et al., 2012). To obtain detailed results from the quantile regression estimates, we estimate for nine different quantiles (15th, 25th, 35th, 45th, 55th, 65th, 75th, 85th, and 95th).

3.4 Test of Cross-Sectional Dependence

As part of examining the properties of the data, cross-sectional dependency testing in panel studies is very important. We used the modified Lagrange multiplier by the Pesaran (2004) test that is appropriate for testing cross-sectional dependence (Salahuddin, Gow, & Ozturk, 2015; Salim & Rafiq, 2012). Table 4 presents the results of the cross-sectional dependence.

Table 4: Results of Pesaran (2004) cross-sectional dependence (CD) test

Variable	CD test	p-value
lnef	6.75***	0.000
lnnpl	3.63***	0.000
lntrade	0.24	0.811
lngfe	4.97***	0.000
lnsec	12.77***	0.000

*** denotes the significance at 1% level.

The results in Table 4 reject the null hypothesis of cross-sectional independence at a 1% significance level for all the variables except trade openness. The results provide evidence of cross-sectional dependence among the variables, excluding trade openness.

3.5 Unit Root Tests

We conduct unit root tests to establish the stationarity of the variables, which is a precondition in panel VAR application. We used both first- and second-generation unit root tests. The first-generation tests assume cross-sectional independency and include Im et al. (IPS) (2003), Choi (2001), and Maddala and Wu (1999). The second-generation tests, which account for the cross-sectional dependency, include Pesaran (2007), Moon and Perron (2004), and Choi (2002). In the presence of CD, the second-generation tests fit. However, for the purposes of this study, we use the first and second generations to reveal the true stationarity of the variables, especially where one of the variables is cross-sectionally independent. Therefore, we used Pesaran (2007), IPS (2003), and Fisher-type (Maddala & Wu, 1999; Choi, 2001) tests to check the stationarity of the series. In addition, these tests are suitable for our dataset because they allow for heterogeneous panels. Table 5 presents the results of unit roots.

Table 5: Unit root tests

Variable	CIPS		MU		IPS		Fisher - ADF	
	At level	△	At level	△	At level	△	At level	△
lnsec	-0.038	-2.454***	14.566	76.585***	0.064	-3.070***	-1.575*	-9.197***
	[0.485]	[0.007]	[0.557]	[0.000]	[0.526]	[0.000]	[0.062]	[0.000]
lngfe	0.520	-4.814***	12.252	93.799***	0.609	-4.889***	1.258	-1.863***
	[0.698]	[0.000]	[0.726]	[0.000]	[0.729]	[0.000]	[0.893]	[0.034]
lntrade	0.974	-4.680***	15.065	108.363***	-0.267	-5.129***	0.728	-2.792***
	[0.835]	[0.000]	[0.520]	[0.000]	[0.395]	[0.000]	[0.765]	[0.003]
lnnpl	0.791	-2.314**	9.918	57.560***	0.464	-3.538***	-0.938	-2.665***
	[0.786]	[0.010]	[0.871]	[0.000]	[0.679]	[0.000]	[0.177]	[0.005]
lnef	-1.149*	-8.298***	24.944*	214.890***	-1.668**	-6.380***	-1.211	-2.685***
	[0.060]	[0.000]	[0.071]	[0.000]	[0.048]	[0.000]	[0.116]	[0.005]

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. △ represents first difference operator.

The panel unit roots results in Table 5 show that, at the level, the panel contains unit roots for all variables. However, at the first difference, the null unit root hypothesis is rejected at the 1% significance level, which indicates that all the variables are stationary at the first difference, establishing a pre-condition for panel VAR model estimations.

3.6 Westerlund (2007) ECM Panel Cointegration Tests

Because our variables are integrated of order one - I(1) and cross-sectionally dependent, it is normal to continue to test the cointegration between variables. Therefore, we use the cointegration procedure proposed by Westerlund (2007) using the bootstrap method. The test is superior to other tests such as Johansen and Pendroni's cointegration tests due to its ability to deal with cross-sectional dependencies in the data (Cialani, 2013; Persyn & Westerlund, 2008). Westerlund (2007) developed four-panel cointegration tests — Gt (intergroup), Ga (between groups), Pt (between panels), and Pa (between panels) — which are based on structural dynamics rather than residuals; therefore, they do not require general limiting factors. While the alternative hypothesis for Pt and Pa is that panel is cointegrated as a whole, the alternative hypothesis for Gt and Ga is that at least one panel is cointegrated. All tests are normally distributed and take into account specific short-term dynamics for unity, unit-specific trends, cross-sectional dependency, and slope parameters to recommend strong p-values to cross-sectional dependencies. The results are presented in Table 6. Under the null hypothesis of no cointegration, we could not reject the hypothesis of no cointegration in all four test statistics.

Table 6: Westerlund (2007) ECM panel cointegration tests

Statistic	Value	Robust P-value
Gt	-1.962	0.660
Ga	-4.026	0.210
Pt	-5.034	0.480
Pa	-4.372	0.180

The cointegration results provide further evidence to support the appropriateness of the panel VAR model (for all the variables in their first difference) to study the relationship among the variables. In addition to the usefulness and stationarity conditions met, we used panel VAR for the following reasons. First, the role of the banking system is to provide capital for eco-friendly projects. It is possible that the amount of bank credit allocated for these projects is expected to be given at the beginning of the year. Therefore, shocks in NPLs are likely to affect the banks' ability to finance environmentally sustainable projects in the future. It is better to estimate the model using variables' lag values. Second, the graphs generated by the IRF of the panel VAR model allow shocks to NPLs and their repercussions on environmental sustainability to be monitored throughout the observed period. This makes it possible to draw additional inferences from the behavior of variables in the model and help to understand whether certain policies and regulations, such as post-global financial crisis regulations and initiatives concerning NPLs, have been beneficial.

3.7 Optimal Lag Length

We proceed to select the optimal lag length. The three sequence selection criteria introduced by Andrews and Lu (2001) — Bayesian information criteria (MBIC), Akaike information criteria (MAIC), and Quinn information criteria (MQIC) — are used.

Table 7: Optimal lag

Lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	0.999978	25.62653	0.694049	-94.5935	-34.3735	-57.661
2	0.999887	11.86791	0.61691	-44.2348	-16.1321	-26.9996

Note: Based on the results in Table 7, first-order lag was chosen as the optimal lag length for the panel VAR model because the overall coefficient of determination (CD) is the highest with MBIC, MAIC, and MQIC, in that order.

4. Results and discussion

4.1 Panel VAR Estimates

Based on Equations. 1.1–1.5 and the optimal lag selected, we estimate the first-order lag panel VAR model through the GMM style. Table 8 presents the estimated first-order lag of the panel VAR equation.

Table 8: Panel VAR estimates

Variable	Dependent variables				
	SEC	GFE	TRADE	NPL	EF
$\Delta \ln sec_{(t-1)}$	-0.345***	0.945***	-0.232***	1.072***	-0.301***
	(0.099)	(0.206)	(0.086)	(0.220)	(0.112)
$\Delta \ln gfe_{(t-1)}$	0.089***	0.140*	0.100***	-0.224***	-0.141***
	(0.015)	(0.084)	(0.038)	(0.067)	(0.043)
$\Delta \ln trade_{(t-1)}$	-0.051*	0.374***	0.061	0.182**	-0.103***
	(0.027)	(0.044)	(0.038)	(0.092)	(0.014)
$\Delta \ln npl_{(t-1)}$	-0.024***	0.055***	0.036***	0.285***	-0.090***
	(0.006)	(0.012)	(0.012)	(0.028)	(0.005)
$\Delta \ln ef_{(t-1)}$	0.166***	-0.185*	-0.253***	1.190***	-0.585***
	(0.037)	(0.098)	(0.091)	(0.185)	(0.050)

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. Δ represents first difference operator.

For the secondary education enrollment equation, the result shows that the first-order lags of all the variables have a significant impact on secondary education enrollment at a 1% significance level except trade openness, which is significant at a 10% significance level. Concerning the government expenditure equation, lags of secondary school enrollment, trade openness, and NPLs positively influence current government expenditure at a 1% significance level, while its own lag is significant at a 10% significance level. However, environmental sustainability adversely influences government expenditure at a 10% significance level. This confirms the burden placed on the government by rising NPLs and declining environmental sustainability. Government is burdened in the sense that apart from the potential challenges associated with NPLs and environmental sustainability, the cost of setting up a unit and managing NPLs for environmental sustainability requires time and extra resources (Caprio & Klingebiel, 2002). The trade openness equation result shows that while the lags of secondary education enrollment and environmental sustainability adversely impact on current trade openness, government expenditure and NPLs positively impact on trade openness at a 1% significant level. The result confirms Africa's overreliance on natural resources and inappropriate link of the banking system to its trading activities with the rest of the world.

With the exception of government expenditure, which minimizes NPLs, all the other variables within the model increase NPLs, resulting from an increase in these variables. This implies that improving various sectors of these economies is associated with rising NPLs, except the government intervenes by increasing its spending. This brings to light banks' inappropriate assessment of viable and outcome-oriented projects before financing the projects through loans (UNEP, 2015). Finally, concerning our main equation, the results from the environmental sustainability equation show that the lags of all the variables within the equation adversely affect environmental sustainability at a 1% significant level. This finding supports hypothesis 1, which states that environmental sustainability will react negatively to NPLs. The finding corroborates with the study by Richard (2010), who revealed that financial instability worsens the environment by increasing environmental degradation. Similarly, the study supports the study by Nasreen et al. (2017), who revealed that financial stability improves environmental quality among South Asian countries, given that lower NPLs signify stability of the banking system. Despite conditioning on other sustainability determinants, the impacts of NPLs on sustainability are weak compared to other variables in the model. This weak link can partly be attributed to post-global financial crisis initiatives to minimize NPLs. This provides good bases for studying the trend of the impacts of NPLs on environmental sustainability over the period. The IRF that provides a detailed graphical analysis of the trend of a response of a variable to the other over a period is useful for this study. Generally, the results revealed that NPLs adversely affect the environmental sustainability and other macroeconomic variables within an economy. This study also supports the studies by Ghosh (2016) and Richard (2010), who found financial instability to affect the entire functioning of the economy.

4.2 Granger Causality Tests

Based on the Wald test by Abrigo and Love (2016), we proceed to estimate the Granger causality test. The null hypothesis states no causality. Table 9 presents the results from the Granger causality test.

Table 9: Granger Causality Test

Variable	△ lnsec	△ lngfe	△ lntrade	△ lnnpl	△ lnef
△ lnsec		21.037***	7.349***	23.739***	7.212***
△ lngfe	33.915***		6.994***	11.166***	10.868***
△ lntrade	3.529*	71.427***		3.901**	57.849***
△ lnnpl	13.487***	21.604***	8.958***		5.367***
△ lnef	19.782***	3.599*	7.770***	41.364***	
All	84.722***	131.393***	77.454***	298.514***	108.401***

Note: Chi-squared values and their respective probabilities are provided in the Table. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. △ represents first difference operator.

In Table 9, there is a bidirectional relationship among all the variables used in the equations. This implies that not only does one variable influence the other, but it is also influenced by the other variables within the model. For instance, secondary education enrollment influences government expenditure, and government expenditure also influences secondary education, indicating that an increase in secondary education increases government expenditure, while an increase in government expenditure also increases future secondary education enrollment. Similarly, the result shows a bi-directional causal links between environmental sustainability and NPLs suggesting that the variables affect each other. However, the feedback impacts of environmental sustainability on NPLs are stronger, indicating that environmental sustainability can worsen NPLs. The results depict interdependence among environmental sustainability and other macroeconomic variables in the model (Ghosh, 2016). Thus, a change in one variable — say, NPLs — can cause changes in the other variables.

4.3 Model Stability

It is appropriate to check the stability condition of the estimated panel VAR results as part of the robustness tests. As depicted in Fig. 6, the calculated modulus of each eigenvalue of the estimated model is strictly less than 1 (or lies inside the outer circle). This indicates that the model is stable (Lutkepohl, 2005). Therefore, we proceed to estimate IRF and forecast-error variance decomposition.

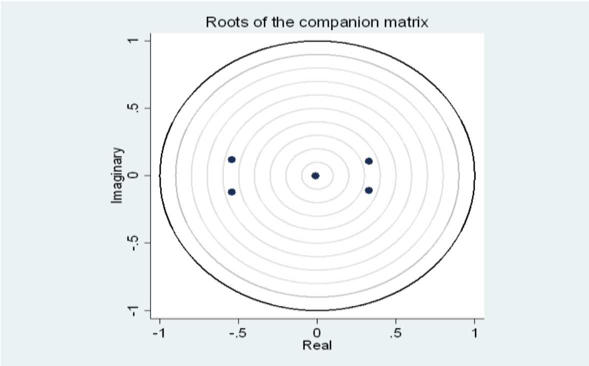

Figure 6: Module stability

4.4 Impulse Response

In order to perform the IRF of the panel VAR estimates, the order of the causal variables is important. As recommended by Sims (1980), the more exogenous variables appear earlier in the model and simultaneously affect the next variables (even with a lag), whereas the more endogenous variables appear later in the systems and affect the previous variable only with a lag. Based on the literature, we estimate the IRF by following the order of secondary education enrollment, government expenditure, trade openness, NPLs, and environmental sustainability. Secondary education enrollment is considered more exogenous, while environmental sustainability is more endogenous within the model. This order is similar to earlier studies (Charfeddine & Kahia, 2019; Tamazian et al., 2009). Following this order, we estimate the orthogonalized IRFs of shocks as suggested by Sims (1980) based on Cholesky decomposition. The examination of the IRFs requires their confidence intervals estimation that are generated using Gaussian approximation based on Monte Carlo simulations, with 500 replications with 5% error bands. Figure 7 illustrates the results of the IRFs.

The results show that the impact of one standard deviation shock in the rise of NPLs on environmental sustainability was negative from the first year up to about the sixth year and equal to zero from the seventh year to the tenth year. As expected, a period before the seventh year marks a period of high NPLs among the selected counties, and hence its impact is felt, while the period afterward marks the beginning of the inception of regulatory activities to curb NPLs, which might have helped minimize the impact of government expenditure on environmental sustainability. The result supports the studies by Hamadi and Bassil (2015) and Barajas, Chami, and Yousefi (2011), where the "resources curse" relating to the banking sector impedes banks' role to invest in green and eco-friendly projects, with repercussions on environmental sustainability.

Similarly, the impact of one standard deviation shock in the rise of government expenditure on environmental sustainability was negative up to the fifth year and equal to zero from the sixth year to the tenth year. However, the impact of one standard deviation shock in the rise of trade openness and secondary education enrollment on environmental sustainability was instantaneously positive as well as negative up to the seventh year and equal to zero from the eight year to the tenth year. These findings expose the ineffectiveness of the selected economies in addressing their environmental sustainability through other sectors within the economy.

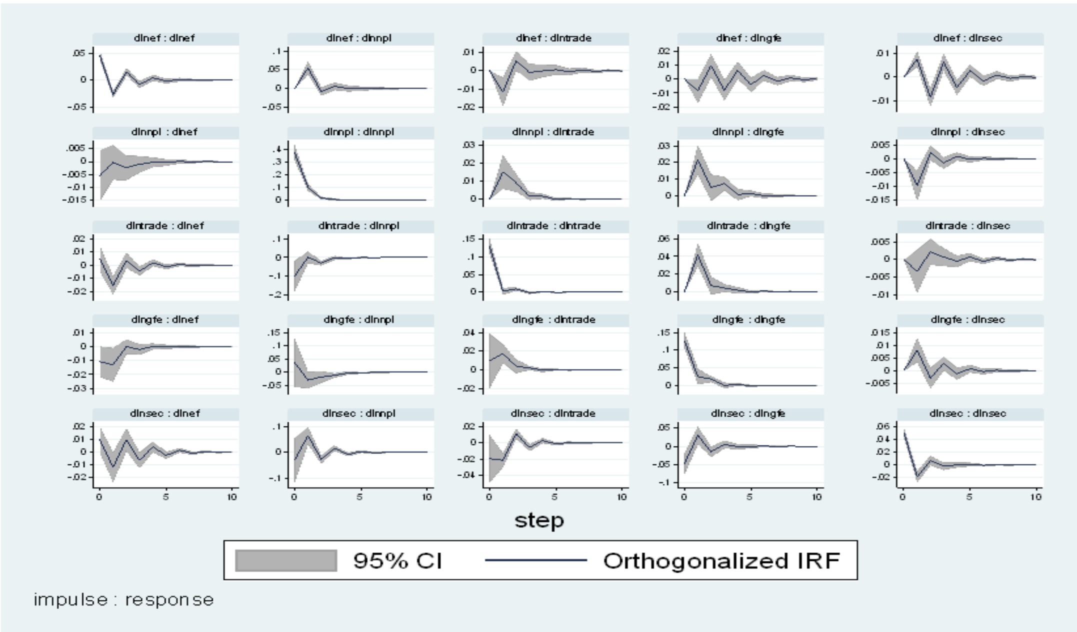

Figure 7: Impulse–response results. "d" means first difference of the variable.

4.5 Variance Decomposition

We estimate the variance decomposition technique to give details regarding the influence of variations and the magnitude in one variable on other variables, as well as the degree of these effects. Table 10 presents the results of variance decomposition obtained from the orthogonalized impulse–response coefficient matrices. For this study, we interpret the error variance decomposition by focusing on the tenth period, where most of the variables have the highest explaining power of the other.

Table 10: Error variance decomposition

Variable		Impulse				
Response		SEC	GFE	TRADE	NPL	EF
△lnsec						
	1	1.0000	0.0000	0.0000	0.0000	0.0000
	2	0.9256	0.0213	0.0037	0.0309	0.0186
	3	0.9008	0.0230	0.0050	0.0310	0.0403
	4	0.8872	0.0251	0.0051	0.0312	0.0515
	5	0.8816	0.0253	0.0051	0.0312	0.0568
	6	0.8793	0.0254	0.0053	0.0312	0.0589
	7	0.8786	0.0254	0.0053	0.0311	0.0596
	8	0.8783	0.0254	0.0053	0.0311	0.0598
	9	0.8782	0.0254	0.0054	0.0311	0.0599
	10	0.8782	0.0254	0.0054	0.0311	0.0599
△lngfe						
	1	0.1230	0.8770	0.0000	0.0000	0.0000
	2	0.1435	0.7542	0.0783	0.0208	0.0032
	3	0.1490	0.7450	0.0777	0.0211	0.0071
	4	0.1491	0.7399	0.0779	0.0233	0.0099
	5	0.1488	0.7386	0.0778	0.0233	0.0115
	6	0.1487	0.7381	0.0777	0.0233	0.0122
	7	0.1486	0.7378	0.0777	0.0233	0.0125
	8	0.1486	0.7377	0.0777	0.0233	0.0126
	9	0.1487	0.7377	0.0777	0.0233	0.0126
	10	0.1487	0.7377	0.0777	0.0233	0.0126
△lntrade						
	1	0.0215	0.0056	0.9730	0.0000	0.0000
	2	0.0448	0.0217	0.9138	0.0123	0.0074
	3	0.0510	0.0222	0.9015	0.0165	0.0088
	4	0.0527	0.0224	0.8995	0.0166	0.0089

	5	0.0531	0.0223	0.8990	0.0167	0.0089
	6	0.0531	0.0224	0.8989	0.0167	0.0089
	7	0.0532	0.0224	0.8989	0.0167	0.0089
	8	0.0532	0.0224	0.8988	0.0167	0.0089
	9	0.0532	0.0224	0.8988	0.0167	0.0089
	10	0.0532	0.0224	0.8988	0.0167	0.0089
△lnnpl						
	1	0.0054	0.0087	0.0642	0.9217	0.0000
	2	0.0293	0.0128	0.0574	0.8831	0.0174
	3	0.0329	0.0144	0.0620	0.8731	0.0176
	4	0.0345	0.0151	0.0618	0.8709	0.0177
	5	0.0347	0.0151	0.0620	0.8704	0.0177
	6	0.0348	0.0152	0.0620	0.8703	0.0177
	7	0.0348	0.0152	0.0620	0.8703	0.0177
	8	0.0348	0.0152	0.0620	0.8703	0.0177
	9	0.0348	0.0152	0.0620	0.8703	0.0177
	10	0.0348	0.0152	0.0620	0.8703	0.0177
△lnef						
	1	0.0400	0.0498	0.0096	0.0124	0.8882
	2	0.0653	0.0791	0.0699	0.0081	0.7776
	3	0.0837	0.0721	0.0672	0.0089	0.7681
	4	0.0913	0.0707	0.0697	0.0088	0.7595
	5	0.0945	0.0701	0.0700	0.0087	0.7566
	6	0.0957	0.0699	0.0701	0.0088	0.7555
	7	0.0961	0.0699	0.0702	0.0087	0.7551
	8	0.0962	0.0699	0.0702	0.0087	0.7550
	9	0.0963	0.0699	0.0702	0.0087	0.7549
	10	0.0963	0.0699	0.0702	0.0088	0.7549

Note: △ represents first difference operator.

The result shows that government expenditure, trade openness, NPLs, and environmental sustainability approximately explain 3%, 1%, 3%, and 6%, respectively, of the variance in secondary education. While secondary education enrollment explains approximately 15% of the variance in government expenditure, trade openness, NPLs, and environmental sustainability approximately explain only 7%, 2%, and 1%, respectively. Approximately 5% of the variations in trade openness is explained by secondary education enrollment, while government expenditure, NPLs, and environmental sustainability approximately explain 2%, 2%, and 1%, respectively. Secondary education enrollment and trade openness explain approximately 3% and 6%, respectively, of the variations in NPLs, while government expenditure and environmental sustainability each explains approximately 1% of the variations in NPLs.

The results show that secondary education enrollment explains approximately 10% of the variations in environmental sustainability, while government expenditure and trade openness each explains approximately 7% of the variations in environmental sustainability. However, NPLs explain approximately 1% of the variations in environmental sustainability, with the highest explaining power (1.2%) in the first year. It is clear that the bulk of the variations in environmental sustainability is explained by itself (approximately 75%). The results confirm that NPLs weakly explain environmental sustainability and even decrease further. These variations partly explain the effectiveness of post-global financial crisis initiatives to minimize the impacts of NPLs within the economy (Wyman, 2015).

4.6 Quantile Regression Results

Even though the panel VAR model allows for heterogeneity within the model, it does not provide evidence of heterogeneous responses. Therefore, we use panel quantile regression, which is known for its robustness to outliers and the ability to provide heterogeneous responses by conditioning countries to their environmental sustainability path to estimate our results. For comparison purposes, we estimate for OLS to provide a basis for making inferences of how different levels of environmental sustainability respond to the impact of NPLs. Table 11 presents the results of the quantile regression.

Table 11: OLS and panel regression results

Variables	OLS	Quantile levels								
		15th	25th	35th	45th	55th	65th	75th	85th	95th
	-0.188***	-0.075***	-0.070***	-0.060***	-0.054***	-0.043**	-0.037*	-0.030	-0.024	-0.013
llnnpl	(0.024)	(0.028)	(0.025)	(0.020)	(0.019)	(0.019)	(0.022)	(0.025)	(0.029)	(0.038)
	0.293***	0.144*	0.131*	0.108*	0.093*	0.067	0.052	0.036	0.021	-0.003
lnltrade	(0.048)	(0.085)	(0.074)	(0.060)	(0.055)	(0.057)	(0.064)	(0.075)	(0.087)	(0.112)
	-0.010	-0.113**	-0.105**	-0.091**	-0.082**	-0.066*	-0.057	-0.047	-0.037	-0.022
lnlgfe	(0.044)	(0.053)	(0.047)	(0.038)	(0.035)	(0.036)	(0.041)	(0.047)	(0.055)	(0.071)

	0.437***	0.093	0.091	0.087**	0.085**	0.081*	0.079	0.076	0.074	0.070
Inlsec	(0.046)	(0.064)	(0.056)	(0.040)	(0.041)	(0.043)	(0.048)	(0.057)	(0.066)	(0.084)
Obs.	113	113	113	113	113	113	113	113	113	113

Note: *Obs means observation.* ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

The results in Table 11 show that conditioning on other sustainability determinants, the NPLs have a significant and negative impact on environmental sustainability among the selected African countries. In the OLS results, a percentage increase in NPLs results in a 0.188% decrease in environmental sustainability. The quantile regression results show that the adverse impact of NPLs on environmental sustainability decreases from countries on the low environmental sustainability path to moderate environmental sustainability path and becomes insignificant for countries that lie above the 65th quantile (see Table 11). For instance, a percentage increase in NPLs will lead to 0.075% and 0.043% loss in environmental sustainability of countries on the 15th and 55th quantiles, respectively. This implies that countries on the low environmental sustainability path are relatively affected more by the impacts of NPLs than countries on the moderate or high environmental sustainability path. This finding supports hypothesis 2, which states that there will be heterogeneous responses of environmental sustainability to NPLs among the selected economies. This study disagrees with the study by Yang et al. (2020), who revealed that financial instability improves the environment but reduces carbon emissions in the developing world, yet it supports the study by Shahbaz (2010), who revealed that financial instability adversely affects the environment.

The results provide evidence of heterogeneous responses among countries distributed on different quantiles regarding how their environmental sustainability reacts to the impacts of NPLs. The main reason accounting for these variations may be attributed to the fact that (based on clear examination of the characteristics of the data used in this study) countries on the low environmental sustainability path are mostly countries whose NPLs are relatively high compared with those on the moderate and high environmental sustainability paths (World Bank, 2019). Generally, the finding corroborates with the multiple results revealed by finance–environment studies, such as those by Nasreen et al. (2017), Moghadam and Dehbashi (2018), and Jamel and Maktouf (2017).

Figure 8, which was generated from the quantile regression estimates, shows the graphical representation of quantile regression and OLS results of the impacts of NPLs on environmental sustainability. The coefficients of the OLS method (dash line) remain constant in the selected distributional points, while the quantile estimates (green line or in confidence interval term – gray area) around the coefficients vary significantly along with the distributional points of the environmental sustainability, providing further support for the appropriateness of choosing quantile regression over OLS.

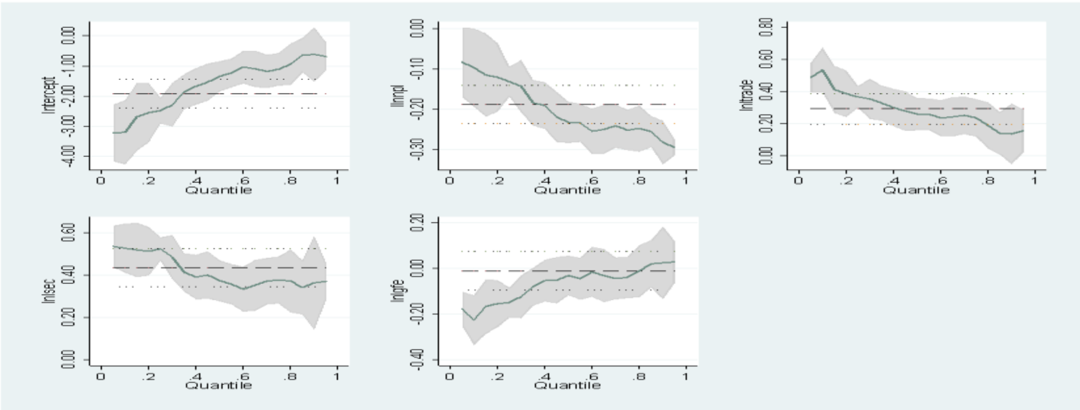

Figure 8: Quantile distributions of the impacts of non-performing loans on environmental sustainability

Notes: 1. Green line represents 95% confidence level for the quantile regression estimates.

2. Dash lines indicates the 95% confidence level of the OLS coefficient.

3. The gray area denotes the confidence interval for quantile estimates.

5. Conclusion and possible policy recommendations

This study examined the impacts of NPLs on environmental sustainability among selected African countries over the period 2000–2016. We explored how environmental sustainability reacts to one standard deviation shock in NPLs by applying the GMM style panel VAR approach while conditioning on other sustainability determinants. In addition, we provided evidence of heterogeneous responses of environmental sustainability to the impacts of NPLs by employing panel quantile regression with fixed effects. Overall, we concluded that conditioning on other sustainability determinants, NPLs have an adverse impact on environmental sustainability among the selected African countries. In addition, the impact of one standard deviation shock in the growth of NPLs on environmental sustainability is negative for the first six years and equal to zero from years 7 to 10. Secondly, there is strong evidence of heterogeneous responses of environmental sustainability to the adverse impact of NPLs. We established a decreasing trend of parameter heterogeneity from low environmentally sustainable countries to high environmentally sustainable countries, indicating that the marginal impact of NPLs on environmental sustainability is high among countries distributed on the low environmental sustainability path compared with countries on the high environmental sustainability path.

Based on the findings, the following potential policy recommendations are provided. First, we recommend that the selected countries should put in place mechanisms to minimize NPLs as a way of reducing their adverse impacts on the environment. In countries like Nigeria, Ghana, and Morocco, among others where NPLs are high and persistent, a unit or committee of experts should be set aside to investigate thoroughly the unique cause of NPLs in the banking sector and provide clear and specific recommendations to minimize and recover loans for these banks. However, the cost implications of setting up the unit/committee should be evaluated against economic outcomes before establishing it. In addition, these countries should ensure that the financial sector has comprehensive policy documents that will serve as guidelines for assessing economic viabilities of projects before granting loans to businesses and organizations. This could reduce excessive lending and minimize the threats its poses to the banking system. Furthermore, high interest rates should be reduced by reviewing existing interest rates packages in order not to make the borrowers worse off and encourage businesses and investors to be able to pay back loans within the specified period of time. Future research should focus on mechanisms to recover or minimize NPLs among African countries.

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