Acta Universitatis Danubius
ŒCONOMICA

Do Commercial Banks' Non-Performing Loans Respond to Environmental Financial and Economic Influences in the Sub-Saharan Region of Africa?

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Abstract: Recent global economic trends have resulted to financial reforms in many countries in the sub-Saharan Africa. Considering the vital roles played by the banking sub-sector in these fragile economies, the objective of the study is to assess the influences of internal and external environmental factors on non-performing loans in sub-Saharan Africa. Prior studies are myopic in scope of study or in analysis. Annual data for the period 2012 to 2021 that represents the influences of bank operations, bank quality, monetary policy and macroeconomic conditions were sourced. The preliminary data investigation results and subsequent empirical procedures resulted in using three estimators- Dynamic Generalized Method of Moments (GMM), System GMM (SYS-GMM) and system Seemingly Unsure Regression (SYS-SUR)- to analyze the data. The results confirm that bank quality; monetary policy and bank operations were significant determinants of the variations in non-performing loans in the region. The paper reveals that restricting money supply is detrimental as it would likely lead to an increased incidence of loan default. It then recommends that monetary authority should use monetary tools such as interest rates or required reserve ratio instead of the money supply since those tools do not have any impact on NPLs.

Keywords: SYS-GMM; Monetary Policy; Market Imperfection

JEL Classification: E58

1. Introduction

Undoubtedly, the banking subsector is the most vital financial subsector in fragile economies with underdeveloped financial systems akin to the dominant economies in sub-Saharan Africa. In these countries, banks play major roles in both the public

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(government) and private sectors of the economy. For the government, banks transmit the intentions of monetary policies, act as a means of cheap finance, and administer the payment system of an economy. For the private sector, banks perform the role of financial intermediation by gathering funds from savers and channelling them to the deficit units as collateralized loans.

As a business entity, the nature of the banking business is distinct from that of other businesses. Firstly, banks operate with sums of money relatively far larger than the investors' capital. This, therefore, gives the banks a distinct asset/liabilities combination. Again, while the liabilities of other businesses mature over some predictable term, a larger component of the liabilities of banks comprises deposits which are payable on demand and other short-term deposits while a significant portion of their assets comprises relatively longer termed maturity portfolios. This calls for a delicate balancing of asset/liability portfolios and creates a thin boundary between survival and bankruptcy for the banking business. These concerns are further heightened for bank management by several other constraints.

The first of these constraints is the mal-alignment between government policies and societal needs. In the course of executing the banking business, banks need to balance the execution of government policies which are usually based on faulty data, misguided information and political inclinations with the demand of the private sector, whose main purpose is to identify societal needs and fill up these needs. A case in point is the sub-prime housing loan policy of America that was linked to the global financial meltdown of 2008-2009 (Albanesi, De Giorgi & Nosal, 2017). Critics such as Stiglitz (2008) and Tamny (2011) emphasize that the root cause of the crisis is misguided government policy. It is important to note that many variations in the operational attitudes of the banking sector are the results of manipulations implied in monetary policy executions. The exercise of monetary policy is counter-cyclical. When the economy is overheated, monetary policy tries to bring it down and vice versa. Monetary policy may not have a direct impact on the real sector of the economy but policy success is gauged from the behaviour of some monetary policy targets such as the money supply, interest rate and in a broader perspective, the exchange rate.

A second constraint generally faced in the banking business is the business cycle. While banks are the major beneficiary of global business booms, they are also known to be worst hit during periods of recession. During periods of business booms, banks enjoy increased demand for loans, increased demand for banking services and a good supply of quality customers. On the other hand, during recessions, banks suffer from tightened policies of the government on one hand, and on the other hand, increasingly hostile operating environment, slouching bank earnings and impaired credit qualities associated with failing businesses in a slow economy (Lown and Morgan, 2001). During recessions, firms are prone to loan defaults thereby increasing the credit risks of banks.

As the value of loan defaults which eventually translates into non-performing loans becomes increasingly significant, this negatively impacts credit availability, credit quality, and interest revenue in the financial system. The dire consequence is extended to the economy in the form of reduced investment opportunities thereby resulting in downward spiralling economic growth and employment opportunities (Anita, Tasnova & Nawar, 2022). Given the adverse effects of non-performing loans, adequate research and policy attention are therefore required in all aspects of related issues. Over the years, there has been a proliferation of research on issues related to non-performing loans. A good number of these studies explore the determinants of non-performing loans while a fewer number is on effective forecasting methods.

In the same vein, various methods of analysis have also been employed. However, to the best of our knowledge, extant researches are rarely holistic. These researches can aptly be termed as myopic in their choice of variables or estimation techniques used.

They either focused on macroeconomic determinants of non-performing loans or focused on the effect of bank performance variables as possible indicators of non-performing loans or on the effects of monetary policies on non-performing loans. Secondly, conclusions were made using a single estimation technique. These researchers ignored the possibility of other techniques yielding better results. This, therefore, renders the results obtained in these researches subject to further examinations as they may be sub-optimal. This study deviates from existing studies by employing variables that reflect the effects of both the internal and external banking environment on non-performing loans.

Though the first population of this research comprises all countries in Sub-Saharan Africa, Sampling was constructed by excluding those countries lacking the required data for the period 2012-2021. This selection criterion eventually resulted in the selection of the 27 countries used in the study. The remainder of the study covers a review of some relevant literature, the methods of analysis, a presentation of the results, a discussion of findings and the conclusion of the study.

2. Literature Review

2.1. Conceptual Review

Financial systems exist and flourish mainly because of the needs of two major players-lenders and borrowers. Borrowers (deficit units) generally want to borrow on terms different from what lenders (surplus units) are willing to grant. For this reason, a clash of interests which requires the interventions of intermediaries normally exists in any financial system. By fulfilling their obligatory intermediation roles, banks automatically give their solvency to, and acquire the credit risk of lenders; thereby exposing them to the risk of default and the chances of acquiring Non-performing

loans (NPL). An NPL is a loan in which the borrower is in default and has not paid the monthly principal and interest repayments for a specified period (Gortsos, 2021). Though loans are part of normal banking business, the accumulation of NPLs to systemic proportions adversely affects the banks' solvency, lowers asset quality, reduces their lending capacity, impedes profitability eventually leads to bank failures and financial instability, Timely identification of NPLs is therefore very important. For this reason, policymakers set prudential guidelines (i.e. accounting standards and harmonized criteria) for assessing loan impairment across their jurisdictions (Baudino, Orlandi & Zamil, 2018; Syed, 2021). Identified NPLs are further classified under watch list, substandard, doubtful, very doubtful or Lost (for example, see CBN, 2010, pp. 63-68, CBK: pp. 130-145; Alhassan, Kyereboah-Coleman & Andoh, 2014). As stated by Alhassan and others (2014), NPLs are caused by poor loan underwriting, monitoring and control practices. Other reasons responsible for NPLs in sub-Saharan Africa as identified in Fofack (2005) are adverse economic shocks, high cost of capital and low-interest rate. Compared to other regions in the world, NPLs in SSA are high. According to IMF (2021) report, the average volatility and the medium NPL ratio in SSA (11.7%) as of 2018 was more than double the median figures of other regions, except South Asia (8%). The nominal total of NPLs for 25 countries for that year was $ 34.8 billion. Successful tackling of the NPL menace in Sub-Saharan Africa would be advantageous (Emmanuel, Musa & Polycarp, 2022).

2.2. Theoretical Review

The Arrow-Debreu General Equilibrium theory presents an economy composed of households and business firms who, by pursuing their self-interest, interact in such a manner that the utility functions of the households are maximized and the profit maximization objectives of the business firms are achieved, thereby producing an equilibrium position that potentially reconciles conflicting choices (Chen, 2022). Despite its eloquence, the model is broadly inconsistent with reality because its basic assumptions are hinged on market efficiency and symmetric information. In real life, information asymmetry prevails and markets are rarely efficient.

Attributing market imperfections to the flow of information, Stiglitz (1973) explained that to exploit some benefits in a market system, it is rational for custodians of information, acting in their self-interest, to hoard the information from those who could have made better market decisions if they had the information. In financial markets, asymmetric information increases the level of uncertainty and redirects capital flows from efficient uses (Karayalcin, McCollister & Mitra, 2002). To Rodoni and Yaman (2018), asymmetric information results in Moral hazards and adverse selection and agency problems. The moral hazard is associated with potential loan customers hoarding pertinent information that may hamper their chances of obtaining the loan thereby exposing banks to adverse selection. Adverse selection occurs

because of the lack of openness between the contracting parties and this makes banks extend loans to those who do not qualify (Rodoni et al., 2018).

Agency theory relates the contractual agreement between the shareholders of banks and the loan managers of the bank on one hand and the conflict of interest existing between both parties. According to the theory, shareholders delegate decision-making authorities to the loan managers believing that the managers are committed to the banks' solvency. However, the personal interest of the managers may conflict with the shareholders' interest and this results in agency problems. For example, as employees of the banks, managers are not fully exposed to the risk of business failures and are more attracted to the other inducements that are consequent on their positions rather than shareholders' objectives. Loan managers, therefore, are likely to neglect the precautionary principle and, either due to negligence or for selfish gains, will not pay prudent attention to loan assessment processes (Kennedy, 1973). Another agency problem is caused by differences in the levels of risk aversion between shareholders and management. While management might be reluctant to give out high-risk loans, shareholders' high-profit targets can coerce loan managers to approve high-risk loans that are likely to yield high interest; thereby exposing the banks to credit risk. In their bid to boost capital base, managers of undercapitalized banks are more prone to succumb to such coercion (Kennedy, 1973; Mitnick, 1973; Ross, 1973; Stiglitz & Weiss, 1981 &1983; Rodoni et. al., 2018).

A crucial issue that is lumped under macroeconomic determinants of non-performing loans is the role of monetary policy, especially in terms of bank restrictions that culminate in repressions. According to Fry (1995), monetary policy determines a good proportion of the various constraints in the environment of bank operations. In this respect are issues of selective sectorial policies that have no bearing on productivity and profitability and hence eventually, high levels of non-performing or credit risks. Other aspects include an interest rate ceiling policy that may be below the optimal level that encourages lending to otherwise unprofitable investments. While it is not very easy to measure with high accuracy the influence of monetary policy, policy tools in the form of money supply, interest rate and exchange rates are oftentimes adopted.

2.3. Empirical Literature

Recognition of the impact of monetary policy on non-performing bank loans has a long history. Morris (1985), Virmani (1985) and Tseng and Corker (1991) are in agreement in their respective findings for India, Korea in particular and Asian countries. Their findings show that excessive regulation has been a major source of NPLs. They agree that restrictive and repressive policies on banks in terms of interest rates, selective credit policies and credit allocation targets have been a major source of non-performing loans in banks. Mahrous, Samak and Abdelsalam (2020) investigated the impact of monetary policy on credit risk (non-performing loans in the

Middle East and North Africa (MENA) region countries. they used the Generalized Method of Moments (GMM) and Dynamic Panel threshold model. Their findings show, besides others, that monetary policy proxied by lending interest has a strong significant and positive effect on nonperforming loans. Guar and Mohapatra (2020) studied the nexus between non-performing loans and macroeconomic issues of economic growth and priority sector lending in the Indian banking sector. The findings show that if the level of non-performing loans is not to be adversely affected requires effective monitoring by policymakers in terms of supervision and control. Koju, Koju, & Wang (2018) investigated NPLs using 30 Nepalese Universal banks between 2003-2015 and established that low economic growth was the primary cause of high NPLs

Louzis, Angelos and Vasilios (2012) studied the macroeconomic and bank-specific determinants of non-performing loans in the Greek banking sector using panel data. Their findings include lending interest rates as significant determinants of non-performing loans. Kurti (2016) and Skarika (2014) found a positive and significant relationship between non-performing loans and inflation rate, while Messai and Jouini (2013) studied the case of sixteen European countries and found exchange rate increase (depreciation) and high level of inflation increase the level of non-performing loans.

For Africa, Ogbebor and Ighodaro (2017) studied the macroeconomic determinants of non-performing loans in commercial banks of selected African countries. By using the system GMM estimation technique, they found among others, that financial deepening ($\frac{M2}{GDP}$) and non-performing loans have a significant and positive relationship while that of inflation and non-performing loans is negative. Hanifah (2015) and Wairim and Gitundu (2017) who studied Uganda and Kenya respectively, arrived at the results that inflation rate, interest rate and exchange rate were not statistically significant determinants of non-performing loans in the two countries for the periods they studied. Adusei and Bannerman (2022) investigated the determinants of Ghana's Non-Performing Loans (NPLs) using annual data covering the period of 1998- 2019 Using the Seemingly Unrelated Regression model and Principal Component Analysis, the study found money supply, financial development, and macroeconomics variables to be significant determinants of NPL. Chege, Omagwa & Abdul (2019) assessed the relationship between prudential regulations and non-performing loans among commercial banks listed at Nairobi Securities Exchange, Kenya. Using nine commercial banks between the period 2012 to 2017 the panel regression results show that credit size, liquidity and inflation were significant while Bank size, lending rate and capital adequacy ratio were not significant.

3. Materials and Method

3.1. Variable Selection

A fully specified economic model requires that all significant determinants are included. Dogged application to this rule, however, often results in unmanageable estimation processes because of the inherent problems involved in pooling together, diverse and complex variables associated with the real-world phenomenon. Segregating and abstracting variables for estimation, therefore, has been an acceptable norm in empirical studies. Contemporary econometric modelling, therefore, has contained this problem in a general specification which may be expressed as:

$$Y = f(\alpha, \emptyset, \delta) + \varepsilon \quad 3.1$$

Where *Y* stands for the variable of interest, α is the autonomous component or constant or intercept; $\emptyset$ is the vector of regressors under consideration, δ is the vector of identified control variables that are reasonably expected to be other prime drivers the explanatory variable while Ɛ represents all other unobserved factors. In a well-specified model, Ɛ is random, unrelated to X, δ and its value should be closest to zero among other models.

Five sets of time-variant regressors were selected for this study. The first set recognizes the significance of autoregressive properties inherent in time series data. The second set of variables is the bank-related variables. Bank liquidity and Banks' credit to the private sector are indicators of the quality of bank operations while Banks' capital-to-asset ratio represents bank status. Monetary policy instrumental variables; particularly Money supply and interest rate, make up the third set. The fourth set comprises monetary policy target variables that consequently affect loan qualities. Indicators of macroeconomic conditions were used as control variables and these comprise the fifth set of regressors. Based on these sets of variables, equation 3.1 can be expressed more specifically as:

$$Y_{it} = \beta_0\alpha_{it} + + \beta_1\emptyset_{1it} + \beta_2\emptyset_{2it} + \beta_3\emptyset_{3it} + \beta_4\emptyset_{4it} + \mathrm{C}\delta_{it} + \varepsilon_{it} \quad 3.2$$

Where Y, $\alpha, \emptyset_{1,}\emptyset_{2,}\emptyset_{3,}\emptyset_4, \delta\ and\ \varepsilon$ are column-vectors of variables as previously explained, β_0 is the intercept, $\beta_{1,}\beta_2, \beta_3, \beta_3 and\ \mathrm{C}$ are slopes of the respective variables, *i* stands for cross-section dimension and *t* stands for the time series dimension. Table 1 describes the variables used in the study.

$$\begin{cases} Y_{it} = \alpha_0 + \delta_i Y_{it-1} + \varphi_i B_{it} + \omega_i L_{it} + \beta_i M_{it} + u_i + \varepsilon_{it} \\ i = 1,2,3,\dots,N; t = 1,2,3,\dots,T \end{cases}$$

The response variable (Y_{it}, which in this case is non-performing loan), is explained by its own lagged valueY_{t-1} as well as $B_{it,}$ L_{it} and M_{it}. B_{it} is the vector of Monetary Policy variables (Required Reserve, Money supply and interest rate); L_{it} is the vector of Bank-specific variables (credit to private sector and capital to asset ratio); M_{it} is the vector

of macroeconomic variables that are directly affected by monetary policies (inflation rate and exchange rate). $\delta_i, \varphi_i, \omega_i, \beta_i$ are vectors of coefficients to be estimated. u_i is the time-constant unobserved effects and $\mathcal{E}_{it}$ is a time-varying residual. u_i and $\mathcal{E}_{it}$ are assumed to meet the conditions expressed as E (u_i)≈0, E ($\mathcal{E}_{it}$)≈0 and E ($u_i \mathcal{E}_{it}$)≈0.

Table 1. Description of Variables

Indicator	Variables used	Acronym used	Description	Sign expectations
Dependent variable	Non-performing loan	NPL	Bank nonperforming loans to total gross loans (%)	+
Banking Sector Operations	Bank Liquidity	BL	Bank liquid reserves to bank assets ratio (%)	-
	Banks' Credit to Private Sector	CRPS	Domestic credit to private sector (% of GDP)	+
Bank Sector Quality	Banks' Capital to asset ratio	CAPA	Bank capital to assets ratio (%)	-
Macroeconomic Conditions	Inflation rate	INF	Inflation, consumer prices (annual %)	-
	Gross Domestic Product	GDP	GDP growth (annual %)	-
	Unemployment	UNEM	Unemployment, total (% of total labour force) (modelled ILO estimate)	+
Monetary Policy	Money Supply	Ms	Broad money (% of GDP)	-
	Lending rates	INT	Lending interest rate (%)	+
	Exchange rate	EXT	Real effective exchange rate index (2010 = 100)	+

Source: Authors' compilation. The authors acknowledge that there are no strict segmentations of the variables along the lines of the indicators used in this study. This segmentation is strictly for this study.

3.2. Data Sources and Description

To have an adequate degree of freedom and to avoid over-identification, Labra and Torrecilla (2018) recommended that the number of individual observations (n) should be significantly greater than the length of time (t) used. Annual data covering the period 2012 to 2021 (t=10) was sourced for 27 countries in the sub-Sahara region (N=27). The choice of 27 countries was primarily due to the availability of relevant data. The study sourced the data used from officially acceptable databanks. The bulk of the data used were sourced from the World Development Indicators (WDI) published by the World Bank. Where data gaps still existed, the study resorted to filling the gaps by sourcing data from the International Financial Statistics data of the International Monetary Fund (IMF) and the annual statistical bulletins published by the Central Banks of the respective countries; in that order. This hierarchy for sourcing data was adopted to ensure that these cross-country data have uniform measurements as much as possible. The reason for using low-frequency data is that most of the relevant in these international data banks are available on an annual frequency only.

3.3. Preliminary Data Investigations

The results of the Preliminary data investigations are presented in Table 2.

Table 2. Preliminary Data Investigation Results

Test Type	NPL	BL	MS	INT	EXT	INF	CRPS	CAPA	GDP	UNEM
Mean	11.05	28.19	23.62	16.57	99.17	5.77	12.71	9.36	2.94	9.44
Median	10.20	23.83	23.47	16.25	100.0	4.75	12.50	9.93	3.94	8.42
Std. Dev.	9.03	18.33	6.59	3.93	14.11	4.61	3.22	4.00	5.67	6.30
Skewness	1.90	1.90	0.61	-0.06	-0.11	0.99	0.46	-0.02	-3.41	0.87
Kurtosis	8.00	9.17	4.00	2.07	3.090	3.04	4.23	2.76	22.79	2.41
Jarque-Bera	181.09*	241.22*	11.39*	4.07**	0.25***	18.01*	10.87*	0.28***	2009.24*	15.63*
Correlation	1.00	-0.19	-0.31	0.29	0.16	-0.11	0.14	0.11	-0.40	-0.04
Unit Root Test (ii)	I (1)*	I (1)*	I (1)**	I (1)*	I (1)*	I (1)**	I (1)*	I (1)*	I (1)**	I (1)**
				t-Statistic			Prob.			
Co-integration Test (iii)	ADF			-3.1449			0.0008			
Note: (i) Degree of significance:*=1%; **=5%; ***= not significant (ii) Results of Unit Roots used: Levin, Lin & Chu t* for common unit root process Im Persaran &Shin W-stat; ADF Fisher-chi-square and PP Fisher-chi-square individual unit roots process (iii) The study employed the Kao (Engle-Granger) co-integration test										

Source: Authors' computation

Extracts of the normality tests, correlation tests, unit root tests and co-integration tests are contained in Table 2. The mean and median values of the respective variables indicate that the data distribution is essentially Gaussian. The standard deviation suggests that NPL, BL and INF have outliers, distributed either below or above twice

the value of the 95th percentile from the mean. The data for each of the explanatory variables are not related to NPL as shown by the correlation results from the signs associated with each variable in line with theoretical expectations. The unit root results show that the variables are stationary at first difference. The co-integration results confirm that the variables are co-integrated.

A combination of cross-sectional and time-series data can either be estimated as pooled or estimated as a panel. By employing the Breusch-Pagan Lagrangian Multiplier (LM) test, the study confirmed that the panel regression model is more appropriate. Based on this confirmation, the panel Generalized Method of Moments (GMM) model was adopted. Haussmann test confirmed the application of fixed effect modelling. As our way of addressing the problem of heterogeneity that may be present in the individual sets of country-wise data; the study employed the dynamic panel GMM as suggested in Labra and Torrecillas (2018).

3.3. Model Estimation and Results

When compared to other models, the Generalized Method of Moments (GMM) approach proposed by Hansen (1982) is known to produce more efficient estimators. The task of the GMM estimation method is to find the $\hat{\theta}_{\mathrm{GMM}}$ estimator that minimizes the errors such that E (u_i)≈0, E ($\mathcal{E}_{it}$)≈0 and E ($u_i\,\mathcal{E}_{it}$)≈0. Hansen (1982) shows that this GMM estimator may be derived as:

$$\hat{\theta}_{\mathrm{GMM}} = \underset{\theta\epsilon\Theta}{\arg\min}\left(\frac{1}{T}\sum_{t=1}^{T} g\,(x_t,\theta,\mathrm{Z_t})\right)' \widehat{W}\left(\frac{1}{T}\sum_{t=1}^{T} g\,(x_t,\theta,Z_t)\right)$$

By definition, $\left(\frac{1}{T}\sum_{t=1}^{T} g\,(x_t,\theta,Z_t)\right)^{-1} = \left(\frac{1}{T}\sum_{t=1}^{T} g\,(x_t,\theta,Z_t)\right)'\left(\frac{1}{T}\sum_{t=1}^{T} g\,(x_t,\theta,Z_t)\right)$ (Hwang & Sun, 2015)

The GMM estimator therefore is given as: $\hat{\theta}_{\mathrm{GMM}} = \arg\min \widehat{W}\left(\frac{1}{T}\sum_{t=1}^{T} g\,(x_t,\theta)\right)^{-1}$

Under general conditions, $\hat{\theta}_{\mathrm{GMM}}$ is efficient, consistent and asymptotically normal. $\widehat{W}$ is a suitable weight that ensures the consistency (but not necessarily the efficiency) properties of the GMM estimator. A detailed explanation of the procedure for estimating the model parameters using fixed-effect, random-effect and GMM methods for dynamic panel data can be found in Doornik and Hendry (2001). The variables selected are specified in an initial dynamic panel data model given:

$$\{NPL_{it} = \beta_0 + \beta_{1i}NPL_{it-1} + \beta_{2i}BL_{it} + \beta_{3i}MS_{it} + \beta_{4i}INT_{it} + \beta_{5i}INF_{it} + \beta_{6i}IEXT_{it} + \beta_{7i}CRPS_{it} + \beta_{8i}CAPA + \beta_{9i}GDP_{it} + \beta_{10i}UNEM + u_i + \varepsilon_{it}\}$$

$$i = 1,2,3,\dots,N; t = 1,2,3,\dots,T \qquad 3.2$$

The adverse effects of employing too many instrumental variables in dynamic panel data models are explained in Bun and Kiviet (2006) and Labra and Torrecillas (2018). Kiviet (2009) recommended the use of internal instrumental variables for overcoming several problems including weak variable and identification problems. Furthermore, a "restricted GMM" estimator that uses a subset of explanatory variables as instruments increase computational efficiency without significantly detracting from effectiveness (Judson and Owen, 1997). We, therefore, employed the first lag of the explanatory variables as the instrumental variables for this study and as such, the number of instrumental variables employed is equal to the number of regressors. This implies that the adopted GMM model is exactly identified and therefore it is assumed that the Sargan-Hansen value associated with the GMM estimator for this model is exactly zero (see Sato & Soderbom, 2013). The result of the dynamic panel GMM is presented in Table 3.

Table 3. Dynamic Panel GMM result

Variable	Coefficient	Std. Error	t-Statistic	Prob.
NPL (-1)	0.514046	0.035679	14.40743	0.0000
BL	-0.055824	0.023757	-2.349768	0.0197
MS	-0.083606	0.025195	-3.318374	0.0011
INT	-0.052055	0.151448	-0.343713	0.7314
INF	-0.004624	0.015161	-0.304980	0.7607
EXT	0.002603	0.002001	1.300822	0.1948
CRPS	0.037893	0.148821	0.254619	0.7993
CAPA	-0.544985	0.043633	-12.49027	0.0000
GDP	-0.022374	0.051873	-0.431326	0.6667
UNEM	-0.050626	0.191210	-0.264767	0.7915
	Effects Specification			
Cross-section fixed (first differences)				
Mean dependent var	0.385414	S.D. dependent var		3.051093
S.E. of regression	3.493666	Sum squared resid		2514.374
J-statistic	20.74405	Instrument rank		27
Prob (J-statistic)	0.237949			

Source: Authors' computation

The results presented in Table 3 suggest positive and significant autoregressive properties. The signs associated with the respective coefficients are in tandem with their theoretical expectations. However, only bank Liquidity (BL), money supply (MS) and capital-to-asset ratio (CAPA) were significant determinants. The results indicate that bank operations, monetary policy and the quality of the bank's asset composition are significant determinants of observed changes in non-performing loans. Judson *et al* (1997) cautioned that including the lagged value of the dependent variable may result in biased estimates. The model was therefore tested for bias. Table 4 shows an extract of the result of the bias test.

Table 4. Dynamic Panel Data Biasness Test

Lagged Variable	Coefficient using Pooled (κ)	Coefficient using Panel Least Square (ρ)	Coefficient using Dynamic Panel GMM (γ)	Remarks
NPL	0.914215	0.739537	0.514046	Downward Biased

The lagged value of the dependent variable can be taken as unbiased when the value of the computed coefficient of the dynamic panel model ($\widehat{NPL_{\gamma}}$) lies between the values of a computed pool regression ($\widehat{NPL_{\kappa}}$= upper bound) and a panel least square model ($\widehat{NPL_{\rho}}$=lower bound) (that is γ is unbiased when $\widehat{NPL_{\kappa}} \leq \widehat{NPL_{\gamma}} \leq \widehat{NPL_{\rho}}$) otherwise, the coefficient is biased. Table 4 shows that $\widehat{NPL_{\gamma}}$ is less than the lower bound $\widehat{NPL_{\rho}}$). The dynamic panel GMM estimator is therefore downward-biased. Based on this result, the study specified a system GMM as an alternative model. The specification for the Systems Generalized Method of Moments (S-GMM) is as follows:

The levels equation is specified as:

$$NPL_{it} = C_1 + C_2 NPL_{t-1} + C_3 RR_{it} + C_4 Ms_{it} + C_5 int_{it} + C_6 INF_{it} + C_7 EXT_{it} + \beta_8 CRPS_{it} + C_9 CAPA_{it} + C_{10} GDP_{it} + C_{11} UNEM_{it} @ NPL_{it-2},\ RR_{it-1},\ int_{it-1}, CRPS_{it-1,}\ CAPA_{it-1}, INF_{it-1}, EXT_{it-1} \quad 3.3$$

The differenced equation is then expressed as:

$$\Delta NPL_{it} = C_{12} + C_{13}\Delta NPL_{t-1} + C_{14}\Delta RR_{it} + C_{15}\Delta Ms_{it} + C_{16}\Delta int_{it} + C_{17}\Delta INF_{it} + C_{18}\Delta EXT_{it} + \beta_{19}\Delta CRPS_{it} + C_{20}\Delta CAPA_{it} + C_{21}\Delta GDP_{it} + C_{22}\Delta UNEM_{it} @ NPL_{it-2}, RR_{it-1,} MS_{it-1,}\ INT_{it-1,}\ INF_{it-1}, EXT_{it-1}, CRPS_{it-1}, CAPA_{it-1},\ GDP_{it-1}, UNEM_{it-1} \quad 3.4$$

The one-step option of system GMM is specified because the number of parameters is the same as the number of instruments for both equations (r=k). The instrumental variables are assumed to satisfy the condition for orthogonality which is expressed as:

$$E\left[\begin{pmatrix} z'_{i,1} & 0 & \cdots 0 \\ 0 & z'_{i,2} & \cdots 0 \\ \vdots & \vdots & \ddots \\ 0 & 0 & \cdots z'_{i,10} \end{pmatrix}\begin{pmatrix} \epsilon_{i,1} \\ \epsilon_{i,2} \\ \vdots \\ \epsilon_{i,10} \end{pmatrix}\right] = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

Or in a more precise form:

$$E\ (Z'\ \epsilon_i) = 0$$

Where Z is a 10x10 matrix of instruments and ϵ_i is a column vector of residuals (Sato & Soderbom, 2013). The results of the system GMM are presented in Table 5.

Table 5. Results of System GMM

Levels equation (NPL)	NPL = C (1) + C (2)*NPL (-1) + C (3)*BL + C (4)*MS +C (5)*INT + C (6)*INF + C (7)*EXT + C (8)*CRPS + 8.2608+ 0.7455 + 0.5667 - 0.2319 + 0.0657 + 0.0022 - 0.0009 - 0.2765 (0.861) (0.390) (0.821) (0.355) (0.938) (0.937) (0.892) (0.746) - C (9)*CAPA + C (10)*GDP + C (11)*UNEM 0.3793 - 0.0934 + 0.5617 (0.821) (0.908) + (0.471)
Difference equation (ΔNPL)	D (NPL) = C (12) + C (13)*D (NPL (-1)) +C (14)*D (BL) + C (15) *D (MS)+ C (16)*D (INT) + C (17)*D (INF) + 1.6312 + 0.0925 - 0.0784 + 0.1449 + 1.7805 - 0.0119 + (0.809) (0.975) (0.712) (0.811) (0.772) (0.892) C (18)*D (EXT) + C (19)*D (CRPS) + C (20)*D (CAPA) + C (21)*D (GDP) + C (22)*D (UNEM 0.0041 - 0.8065 + 1.3281 + 0.0541 - 4.5685 (0.744) (0.717) (0.788) (0.948) (0.783)

Levels equation (NPL)	Difference equation (ΔNPL)
R^2 = 0.433276	R^2 = -3.620
Adj. R^2 = 0.401437	Adj. R^2 = -3.845
D.W = 0.43525	D.W =2.121079

Source: Authors' computation Values in parenthesis = P-values J-statistics= $3.16X10^{-38}$ (3.16E-38)

The Durbin-Watson test result of 0.4 shown in Table 5 confirms positive autocorrelation in the model. This is expected due to the inclusion of the lagged dependent variable, (NPL_{t-1}) as one of the explanatory variables. The positive autocorrelation between NPL and its immediate lag value is also confirmed by the coefficients of NPLt-1 in both the levels and the differenced equations. This indicates that the observed increase in NPL in any year translates to an increase in the following

year's NPL. However, the p-square values reveal that none of the coefficients is significant despite the indication from the adjusted R-squared result that more than 40% of the variance in non-performing loans is explained by the independent variables used in the model. We further confirm joint significance by employing the Wald test based on the Null Hypothesis: C (1)=C (2)=C (3)=C (4)=C (5)=C (6)=C (7)=C (8)=C (9)=C (10)=C (11)=0. The result is presented in Table 6.

Table 6. Wald Test Result

Test Statistic	Value	df	Probability
F-statistic	486.9649	(11, 206)	0.0000
Chi-square	4382.684	11	0.0000

Source: Authors' computation

The Wald test result presented in Table 6 rejects the null hypothesis of no joint significance. Despite the confirmation of the joint significance of the variables used in the model, the non-significance of each independent variable necessitates further investigation using other estimation methods. Due to its relative ease of estimation and its application to a large class of modelling and testing problems, we find the Seemingly Unrelated Regressions (SUR) introduced by Zellner (1962) to be an attractive alternative model to explore. According to Mehrabani and Ullah (2020), SUR is an econometric development that is gaining wide application in applied work and particularly in a panel and pooled regression. However, unlike other panel models, the data used in SUR models are stacked in reverse order. That is, the stacking order in SUR models begins across time rather than across individuals. For this reason, the subscripts attached to each variable in the model are also reversed such that the time subscript (*t*) comes before the individual subscript (*i*).

A SUR model contains "m" number of multiple regression equations (m>1) and each equation has a single response variable and its own set of regressors (Greene, 2012 & Hayashi, 2000). Specifying the SUR model in its general form gives:

$$y_{ti} = \sum_{j=1}^{k_i} \beta_{ij} x_{tij} + \varepsilon_{ti} \qquad 3.5$$

Where β_{ij} is the coefficient associated with x_{tij} and $x_{tij}$is the t^{th} observation of j^{th} explanatory variable in the i^{th} equation. y_{ti} and ε_{ti} are the respective response variable and the error term for the t^{th} observation and the i^{th} equation. We employ the system SUR; specifying the levels and differenced models similar to models 3.3 and 3.4 but with reversed subscripts. The result of the estimated system SUR is presented in Table 7

Table 7. Results of the SUR model

Levels equation (NPL)	NPL = C (1) + C (2)*NPL (-1) + C (3)*BL + C (4)*MS +C (5)*INT + C (6)*INF + C (7)*EXT + C (8)*CRPS + 21.330+ 0.3480 + 0.0004 - 0.1140 - 0.0481 + 0.0058 - 0.0003 - 0.1362 (0.000) (0.000) (0.988) (0.005) (0.252) (0.426) (0.203) (0.000) - C (9)*CAPA + C (10)*GDP + C (11)*UNEM 0.7690 - 0.03633 - 0.1595 (0.000) (0.001) + (0.0103)
Difference equation (ΔNPL)	D (NPL) = C (12) + C (13)*D (NPL (-1)) +C (14)*D (BL) + C (15) *D (MS)+ C (16)*D (INT) + C (17)*D (INF) + 0.2625 - 0.424 - 0.0049 - 0.0677 + 0.0014 - 0.01 41 - (0.954) (0.000) (0.819) (0.035) (0.968) (0.036) C (18)*D (EXT) + C (19)*D (CRPS) + C (20)*D (CAPA) + C (21)*D (GDP) + C (22)*D (UNEM 0.0001 - 0.0023 - 0.2146 - 0.2080 - 0.2792 (0.471) (0.914) (0.023) (0.016) (0.000)

Levels equation (NPL) R^2 = 0.258975 Adj. R^2 = 0.227034 D.W = 2.557592	Difference equation (ΔNPL) R^2 = 0.476251 Adj. R^2 = 0.450702 D.W =2.514808

Source: Authors' computation P-values in Parenthesis

Based on the number of significant variables in Table 7, it is apt to infer that the system SUR model is relatively better than the system GMM model. The result confirms money supply, credit to the private sector, capital-to-asset ratio, GDP and unemployment rates to be significant determinants of variations observed in non-performing loans. These determinants also conformed to their theoretical sign expectations. The adjusted R-squared result shows that about 22.7% of the variance in non-performing loans is explained by the independent variables used in the model while 45% is explained in the short run. Interestingly, the difference equation indicates a negative autoregressive property which is weakly confirmed by the DW value (2.51). The joint significance is also confirmed by employing the Wald test. With the largest number of significant variables, it is apt to conclude that the SUR model is the best among the three models estimated. We however compared the relative efficiency of the three models based on certain criteria common to the three models using fundamental forecast evaluation methods and robustness tests. The results are presented in the following tables and figures.

Table 8. Forecast Evaluation Tests

test	Dynamic GMM	System GMM	System SUR	Preferred model
Standard Error of regression	3.493666	6.873166	7.239281	Dynamic GMM
Mean dependent variance	0.385414	11.64611	10.54251	Dynamic GMM
Standard Deviation dependent variance	3.051093	8.883866	8.234083	Dynamic GMM
Sum of squared Residual	2514.374	8408.792	12158.47	Dynamic GMM

Source: Authors' compilation

Coefficient robustness test using the confidence Ellipse:

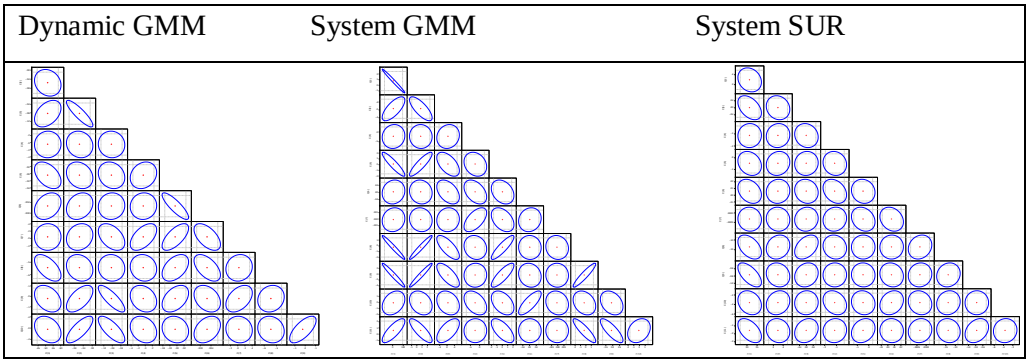

Figure 1. Confidence Ellipse for the Estimated Models at 95% Confidence Levels

The results shown in Table 8 consistently attest to the relatively superior forecast evaluation properties of the Dynamic GMM estimators. This implies that system GMM and system SUR models have less forecasting powers and contain higher residual errors. We also checked the robustness of the model by employing a coefficient diagnostic test using the confidence ellipse at 95% confidence levels. The output presented in Figure 1 depicts the respective confidence ellipses that result from pairwise tests implied by eleven coefficient restrictions (C (1)=0, C (2)=0, C (3)=0, …, C (11)=0).

Using the rule of thumb, a coefficient estimate is said to be independent when the ellipse is an exact circle. Otherwise, the coefficient is correlated. Based on this criterion, system GMM has the most numbers of correlated coefficients while the coefficients in the system SUR model are independent. Another indication of the ellipse is the consistency of coefficient estimates. The exact circles in system SUR at a 95% confidence level imply that there is a 95% level of certainty that the estimated values for the respective coefficient will be consistent. The study also tested the stochastic properties of the residuals for the three models using the residual unit root

test. This was found stationary at levels for all the models which implies that the residuals are *iid*.

4. Discussion of Findings

Using three estimation techniques, this study carried out a comparative investigation on the influences of bank policies, bank operations, financial factors and macroeconomic factors on NPLs in the sub-Saharan Africa region. Limited by data availability, data from twenty-seven sub-Saharan countries were eventually used for the analysis. The results reveal that despite the differences existing among the three estimators employed, similar results were obtained in the explanatory variables of essence to this study. The three estimators confirm that money supply is inversely related to NPLs. Money supply variation is a function of the state of the economy and the results obtained confirm the counter-factual nature of monetary policies in an overheated economy. As the economy becomes overheated, various forms of money supply are reduced and vice-versa. In the final analysis, an increase in money supply will significantly reduce NPLs. For the other two monetary indicators used in the study which are interest rate and exchange rate, the three estimators did not confirm their significance. These results confirm those of Hanifah (2015 and Gilundu (2017).

The estimators produced mixed results for the macroeconomic indicators. The estimators revealed that inflation rates do not significantly influence NPL. However, for GDP and UNEM, only systems SUR had results that were both significant and conformed to their theoretical expectations. Relying on the confidence ellipse, one can aptly say that in 95 out of 100 occurrences, GDP and unemployment will significantly affect NPLs in sub-Saharan Africa. As GDP increases, incidences of loan defaults reduce. Unemployment, which is a sign of a hailing economy, also testifies to economic buoyancy as an antidote for NPL. This shows that the economic environment significantly affects NPL.

The estimators also produced mixed results for bank liquidity (BL) and credit to private sector (CRPS) which were the variables employed to test the efficiency of bank operations. While dynamic GMM confirms the significance of BR and meets the sign expectations, system SUR confirmed that credit to the private sector has a significant influence on NPL variations. However, the result does not conform to expectations. We conclude that bank operations significantly influence NPL variations. The results confirm that the status of the banks represented by their capital-to-asset ratio (CAPA) influences NPL variations. The signs were as expected in all cases, though significant in dynamic GMM and system SUR results. This implies that the status of the banks and their capital base has a significant influence on their loan portfolio, giving credence to the agency theory. The high level of NPL points to the low capita-asset

base of a significant number of banks in sub-Saharan Africa and may be indicative of desperate efforts of managers to meet certain targets.

5. Policy Implications

Compared to other regions, the medium NPL ratio for sub-Saharan Africa is high and this can exert strong pressure on banks' balance sheets, adversely affect banks' lending operations and have dire consequences on other sectors of the respective economies in the region. This calls for policy attention from all stakeholders. The results support the present policy practice of relaxed policies during booms and tightened policies during recessions. However, caution is advised during periods of recession as to what policy tools should be employed. From the results, it is clear that restricting money supply is detrimental as it would likely lead to an increased incidence of loan default. In times when restrictive monetary policies are required, policymakers should consider other monetary policy options. Manipulating interest rates and other monetary policy tools may be better options as the results confirm that they do not have any significant effect on NPLs. Strict monitoring of banks is also recommended, given the significant effect of banking operations on NPLs. The results also confirm the need for shareholders to closely monitor the activities of loan managers through external inspection and auditing firms. Proper training of loan administrators to help them appreciate the benefits of proper loan assessment is also recommended.

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