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Linkages between Inflation, Exchange Rates, Finance and Non-Performing Loans: Evidence from Low-and Middle-Income Countries

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Abstract

This study explored the linkages between inflation, exchange rates, finance and non-performing loans in low- and middle-income countries from 2000 to 2022. Indicators such as non-performing loans (% GDP) was used to measure non-performing loan, while other variables are inflation rate, interest rate, digital financial measures such as automated teller machines, point of sale, mobile banking, mobile money, and electronic banking were used to measure finance, while we control for financial deepening and interest rate. These variables were estimated using the panel autoregressive distributed lag (ARDL) model as the baseline, and panel fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS) as the robustness checks. Findings from the ARDL results that inflation rate has significant impacts on the non-performing loans in low- and middle-income countries, while the exchange rate and finance have significant positive impacts on non-performing loans in low- and middle-income countries and these findings are similar to the results findings from the robustness checks models FMOLS and DOLS models. Thus, we recommend that to albeit non-performing loans (NPL) in low- and middle-income countries can be effectively reduced if the authorities improve the macroeconomic conditions of the countries monetary policy tools such as inflation rate, interest rate and exchange rate. This would aid in achieving economic stabilization, aid in reviving the overall well-being of households and other economic agents, improve per capita income since the economies would be very productive and lead to reduction in the non-performing loans (NPL).

1. Introduction

Nonperforming loans have far-reaching implications for financial institutions, borrowers, and the economy. Nonperforming loans (NPLs), are loans in which borrowers have failed to make required payments for a specified period, typically 90 days or more (Berger & De Young 1997). It has significant implications for the economy. These implications can affect financial institutions, borrowers, and the broader economic environment (Naili & Lahnchi 2022). Furthermore, high levels of NPLs can create liquidity problems for banks, as they may face difficulties in generating enough cash flow to meet their financial obligations and this can lead to a tighter lending environment and increase borrowing costs, which would make it more difficult for borrowers to get required credits for their businesses (Lee et al. 2019), and this can lead to a credit crunch, where banks become more risk-averse and restrict lending. A high volume of NPLs can threaten the stability of the financial system, particularly if a significant number of banks are affected. This can lead to a loss of confidence among depositors and investors, potentially triggering bank runs and broader financial crises. However, amidst these issues surrounding non-performing loans, factors such as inflation rate and its shocks, exchange rate and its movements, nature of digital financial services, level of financial literacy, and standard of living have been observed as factors that determine nonperforming loans, especially in poor countries like low and middle-income countries.

The relationship between inflation and non-performing loans is complex and multifaceted. High inflation generally increases the risk of NPLs through reduced repayment capacity, higher borrowing costs, economic uncertainty, and potential declines in asset values (Piatti & Cincinelli 2019). High inflation erodes the purchasing power of consumers, leading to reduced real income. As living costs rise, borrowers may struggle to meet their debt obligations, increasing the likelihood of loan defaults and NPLs (Mustafa & Jeffery 2020). Furthermore, for businesses, high inflation can lead to increased costs of raw materials, wages, and other operational expenses and this makes businesses inefficient in catering for these high costs of production as it attacks their profit margins and may shrink, impairing their ability to service debts (Norden & Stoin, 2014). Inflation can erode the real value of assets used as collateral for loans. If the real value of collateral declines significantly, the risk to lenders increases. In the event of a default, the lower collateral value may not cover the outstanding loan amount, resulting in higher losses. Persistent inflation might require structural economic adjustments, including reforms in the financial sector to enhance resilience. Strengthening regulatory frameworks and risk management practices can help banks better manage and mitigate the risk of NPLs in an inflationary environment.

Furthermore, the exchange rate can have significant impacts on non-performing loans (NPLs) through various mechanisms that influence both borrowers' repayment capacities and the financial health of lending institutions (Lee et al. 2019). It attacks borrowers' repayment capacity and income since it is volatile. Exchange rate fluctuations have a profound impact on non-performing loans through multiple channels, including borrower repayment capacity, economic stability, banking sector health, and policy responses. Depreciation of the domestic currency can increase the debt burden for borrowers with foreign currency loans, raise the cost of imports, and create economic uncertainty, all of which contribute to higher NPLs (Huljak et al. 2020). Conversely, improved export competitiveness can have a positive effect, though this is often outweighed by the negative impacts (Betz et al. 2017). Effective risk management, prudent regulatory oversight, and sound monetary policies are crucial in mitigating the adverse effects of exchange rate volatility on NPLs. Poor risk assessment and management practices can lead to higher NPLs if exchange

rate fluctuations are not adequately hedged or mitigated (Ozili 2019). Banks may need to increase provisions for loan losses if a significant portion of their loan portfolio becomes non-performing due to adverse exchange rate movements and this reduces their profitability and capital reserves (Ozili 2019).
Additionally, digital financial services (DFS) contribute to the management and potential reduction of nonperforming loans (NPLs) through various mechanisms that enhance efficiency, transparency, and accessibility in the financial sector (Chen et al. 2022). Digital financial services leverage big data and alternative data sources, such as social media activity, mobile phone usage, and transaction history, to assess creditworthiness more accurately and allow lenders to make better-informed lending decisions, reducing the likelihood of loan defaults (Buchak et al. 2018). It also enables real-time monitoring of borrowers' financial behaviours and economic conditions, through early warning systems to detect signs of financial distress and take proactive measures to prevent defaults (Hau et al. 2019). Moreover, automation of credit decision-making processes through digital platforms speeds up loan approvals and disbursements while maintaining robust risk assessment protocols and this efficiency helps in accurately identifying credit risks and reducing NPLs (Balyuk et al. 2020).

However, given the essence of nonperforming loans (NPLs) in the financial systems of the economy in shaping their performance in terms of efficiency, stability and profitability, it has become essential to investigate nonperforming loans (NPLs) effectively and this has drawn the conscientious interests of scholars around the globe (Wood & Skinner 2018, Lauzis et al. 2010, Norden & Stoin, 2014) among others in various degrees. Even with their insightful contributions, NPLs are high in most countries of the world (Wood & Skinner, 2018). To this end, this study centred on investigating the linkages between inflation, exchange rates, finance and non-performing loans in low and middle-income countries. Given the prominence of non-performing loans (NPLs), this study therefore departs from the existing studies in the following ways; firstly, we examined the linkages between inflation rate and non-performing loans (NPLs) in low- and middle-income countries since inflation cause incremental effects on NPLs. High inflation erodes the purchasing power of consumers, leading to reduced real income. It increases borrowing costs for both individuals and businesses and as the cost of servicing debt rises, borrowers with variable-rate loans or new loans may find it more challenging to make repayments, leading to higher NPLs and this can push previously manageable loans into non-performing status. Inflation-induced uncertainty can disrupt cash flows for businesses, particularly small and medium-sized enterprises (SMEs), making it harder for them to predict and manage their financial obligations. High and volatile inflation can create economic uncertainty, discouraging investment and spending and businesses may face reduced demand for their products and services, impacting their revenue streams and ability to repay loans. Hence, given the effects of inflation on the growth of non-performing loans (NPLs), we imperatively studied the role of inflation rate on NPLs in this study. Secondly, this study investigated the influence of exchange rates on non-performing loans (NPLs) in low- and middle-income countries due to special role exchange rates plays in shaping the amount of NPLs in the economy. Shocks in the exchange rate status significantly contribute to increase in non-performing loans in any country. It creates uncertainty ruin investment confidence and cause operational challenges. Volatile exchange rates create economic uncertainty, which can deter investment and business expansion which can lead to reduced economic activity and lower income for businesses, increasing the likelihood of loan defaults and higher NPLs. Businesses

operating in an uncertain exchange rate environment may face challenges in financial planning and forecasting, leading to operational inefficiencies and increased risk of defaults. In addition, banks with assets and liabilities in different currencies are exposed to exchange rate risks. Depreciation of the domestic currency can increase the value of foreign currency liabilities, impacting the bank's balance sheet and financial stability. Also, banks may need to increase provisions for loan losses if a significant portion of their loan portfolio becomes non-performing due to adverse exchange rate movements.

Thirdly, in this study, we explore the linkages between digital finance and non-performing loans (NPLs) in low- and middle-income countries since digital finance contribute to the management and potential reduction of nonperforming loans (NPLs). Digital financial services can provide borrowers with timely reminders and notifications about upcoming payments, reducing the chances of missed payments and consequent loan defaults. Online customer support through chatbots and digital assistants can help borrowers manage their loans more effectively by providing quick access to information and assistance. Also, digital finance often includes financial literacy programs and tools that educate borrowers on managing their finances, understanding loan terms, and maintaining healthy credit behaviors. Digital platforms allow lenders to offer personalized and flexible repayment plans based on borrowers' financial situations. Tailored solutions can help borrowers manage their repayments more effectively, reducing the risk of NPLs.
Fourthly, we estimated the linkages between inflation, exchange rates, finance and non-performing loans using the panel system generalized method of moment (GMM) and robustly checked the findings using the panel fully modified ordinary least squares (FMOLS) and panel dynamic ordinary least squares (DOLS). The essence of combining the models stems from the fact that while the GMM takes care of endogeneity and specification problems, the FMOLS and DOLS accounts for cross-sectional dependency problems, country-specific effects, and country-heterogeneity which may arise due to spatial effects and unobserved shocks and spikes in the model. However, the remaining sections of the paper was organized in the following way. Section 2 discussed review of related literature, section 3 discussed methodology and model specifications, section 4 contain the empirical results and discussion of findings, while section 5 contain the conclusion of the study and policy recommendations.

2. Review of Related Literature

2.1 Theoretical Review

Bad Management hypothesis, proposed by Berger and De Young (1997), postulates that poor management in the banking institutions brings about bad-quality loans and lower incomes, leading to an increase in the level of nonperforming loans. This implies that if due diligence is carried out in loan administration, the value of bad loans will reduce, and profitability will increase. According to this hypothesis, in a bid to mitigate rising NPLs, poor managers usually allocate more resources to underwriting and monitoring bad loans. This causes an increase in the operating expenses over interest income, which in the long run, leads to a higher cost-to-income ratio (low-cost efficiency). A good number of empirical studies are founded on this hypothesis. For instance, Norden and Stoian (2014) and Louzis et al. (2010) noted that bank-specific variables like performance and efficiency indicators influenced the level of NPLs significantly, thus, supporting the hypothesis. Based on this premise, a negative relationship between non-performing loans and Return on Asset (ROA) or Return on Equity (ROE) - as a proxy for profitability, is expected in the study.

The alternative hypothesis, also known as the "skimping" hypothesis, posits that a positive relationship exists between cost efficiency and non-performing loans. It suggests that the number of resources that banks invest in monitoring loans affects both NPLs and productivity. Banks are saddled with the decision of a trade-off between short-term operating costs and future loan performance problems. Therefore, banks that focus on long-run profit would be rationally motivated towards reducing short-term operating costs by skimping on the resources allocated to loan underwriting and monitoring. This, in the future, leads to a greater volume of non-performing loans and increases the costs of solving the problem in the future. Skimping behaviour, thus, makes banks appear cost-efficient in the short term because fewer operating expenses (inputs) can sustain the same quantity of loans or other outputs. Wood and Skinner (2018) explained further that "the link between cost efficiency and non-performing loans is opposed to the bad management hypothesis, that is, skimping implies that cost efficiency has a positive influence on bad loans".

2.2 Empirical Review

Ozili (2019) analyzed the effect of economic development on NPL using a sample of 134 countries from 2003 to 2014. Their conclusions indicate that economic development, measured by the presence of foreign financial institutions and the quality of financial intermediation, is related to NPL because low levels of supervision by regulators lead to lower-quality profiles of credit. In another study, Lee and Rosenkranz (2019) used panel data from 165 commercial banks from 17 emerging economies in Asia and found that both macroeconomic and bank-level variables are key to explaining the evolution of banks' NPL ratios in Asia, which themselves have strong negative feedback effects on the economy. Likewise, Syed and Aidyngul (2022) carried out an analysis for the period 1995–2019 based on the Generalized Method. Using a sample of developed and developing countries, they determined that the main macroeconomic factors affecting NPL are economic growth, inflation, and interest rates. Chowdhury et al. (2023) analyzed the specific macroeconomic factors affecting NPL in Bangladesh from 2007 to 2018. They concluded that credit growth, leverage, and interest margin reduce the NPL ratio. In contrast, inflation and GDP growth are the macroeconomic factors with influence.

In their study, Zainol, et al. (2018) studied the Macroeconomic Determinants of NPLs in Malaysia using the ARDL Approach. The study incorporates Gross Domestic Product, Base Lending Rate, Inflation and Household Income Distribution (Zainol, et al., 2018). The study found that inflation is insignificantly negative towards NPL. Both of these studies, while similar, possess different periods of economic observation. Barra and Ruggiero (2023) delve into the influence of factors unique to individual banks on the NPL ratio within Italy from 1994 to 2015. The findings from the analysis indicate that the critical determinants of NPL are regulatory credit policies, capital reserves, the amount of credit extended, and the level of intermediation costs. Kartal et al. (2023) analyzes the synchronized movement between NPL and economic growth in Turkey. This investigation utilizes quarterly data from the first quarter of 2005 to the fourth quarter of 2019 and employs the wavelet coherence method. The results demonstrate that there is a noteworthy susceptibility of NPL and economic growth during the specified period at various time intervals. Second, in the long run, economic growth in Turkey significantly influences NPL. Third, economic growth is a short-term factor causing NPL in Turkey, particularly between 2007 and 2010. Hassan et al. (2023) focus on Islamic banking within the context of Bangladesh. Their findings emphasize the need for future research to carefully consider this sector. This includes investigating areas such

as green banking, the integration of Islamic microfinance with Islamic banking, the efficiency of Islamic banking, governance concerns, and risk management within the Islamic banking framework.

Staehr and Uuskula (2020) show that many macroeconomic and macro-financial variables are leading indicators for non-performing loans in the EU countries, even years ahead, and higher GDP growth, lower inflation and lower debt are robust leading indicators of a lower ratio of non-performing loans in the future. Ozili (2020) finds that more profitable banks witness higher NPLs regardless of their being systemic or non-systemic and secondly, systemic banks (GSIBs) have fewer NPLs during economic booms and periods of increased lending, while non-GSIBs experience higher NPLs during periods of increased lending. Piatti and Cincinelli (2019) find that, first, when the NPLs ratio remains below the threshold value estimated endogenously, an increase in the quality of monitoring has a positive impact on the NPLs ratio, and second, if the NPLs ratio exceeds the estimated threshold, the relationship between the NPLs ratio and quality of monitoring assumes a positive value and is statistically significant. Betz et al (2017) show that the default resolution time (DRT) can be of great importance in direct and indirect ways, while it immediately impacts the liquidity of financial institutions it also plays an important role in credit costs, such as discounting costs and lower non-discounted rate of returns due to longer resolution processes and the analysis of DRT helps us in better understanding the occurrence of credit losses and, thus, improves risk assessments.

Naili and Lahrichi (2022) found a negative relationship between inflation and NPL explaining that inflation increases NPLs, especially in floating rate loans indicating high inflation reduces household's revenues and real value, constraining their ability to reimburse debts which finally reduces loan quality of the bank. Ogundipe, Akintola, and Olaoye (2020) investigated the interest rates and loan performance of DMB in Nigeria for the period 2010 to 2015. The study found a substantial association between interest rates and loan repayment, as measured by credit quality (through the use of the NPL ratio). This means that a rise in interest rates would almost certainly result in an increase or decrease in credit quality. It also demonstrated that any small improvement in the lending rate would result in a rise in NPLs. The study discovered a positive but insignificant correlation between bank CAR and NPLs. In a study by Mustafa and Jeffery (2020) on NPLs and loans and advances of commercial banks in Nigeria. From the analysis, the variable NPLs, capital adequacy, and GDP positively signed, indicating that there is a direct relationship between NPLs and banks' loans and advances while the variable interest rate has a negative sign which means that the relationship between interest rate and bank loan and advances is inverse and it is statistically significant. Furthermore, the result shows that total deposits have a positive but insignificant statistical effect on bank loans and advances.

Lee et al (2019) examine the determinants of NPL among EU banks after taking into account the existing macroeconomic factors, country governance factors and bank-specific characteristics. They examined 1,053 EU banks from 2007 to 2016 and found that NPL has a positive relationship with cost efficiency. They also find that NPL is negatively related to the state of the business cycle, which implies that NPL is lower during the economic boom and higher during a recession. Huljak et al (2020) estimate the impact of exogenous shocks to the change in NPL ratio across twelve (12)

euro area countries using a panel Bayesian VAR model. They find that an exogenous increase in the change in NPL ratio depresses the volume of bank lending, widens bank lending spreads and leads to a fall in real GDP growth and residential real estate prices. Ozili (2019a) compare the non-performing loans of systemic and non-systemic banks in Europe and finds that systemic banks have fewer NPLs during economic booms while non-systemic banks experience higher NPLs when they increase lending and exceed regulatory capital requirements. Kuzucu and Kuzucu (2019) compare the determinants of NPL in emerging countries compared to advanced countries during pre- and post-global financial crises. They find that real GDP growth, exchange rate and foreign direct investment are determinants of NPL in the two-country group.

Other scholars revealed that digital financial services influence NPLs. For instance, Chen et al. (2022) found that financial technology can stimulate innovative R&D activities by alleviating firms' innovation financing constraints, which indirectly affects the quality of economic growth through a mediating effect model. In addition, digital finance, through technology-driven and technology-enabled, can comprehensively and effectively present the business status and credit standing of enterprises, reduce adverse selection, and help banks reduce information search and risk control costs. Zeng (2022) examined the Impact of Digital Finance on the Non-Performing Loan Rate of Chinese Commercial Banks and found that modern technology can effectively suppress the credit risk of China's commercial banks. In addition, due to the existence of financial exclusion and development differences between the East and West, there is a heterogeneity of fintech in different dimensions and power points in different regions. Balyuk et al (2020) show that Fintech loans are risky and tend to replace loans offered by large banks. This is because Fintech lenders have efficiency advantages in the processing of large data. Pierri and Timmer (2020) analyse the behaviour of NPL among banks that adopted information technology (IT) for assessing bank loans during the 2008 global financial crisis. They found that banks with high-intensity IT adoption had fewer NPLs during the global financial crisis. Buchak et al (2018) find that Fintech lenders serve more creditworthy borrowers, are more active in the refinancing market, charge a premium of 14 to 16 basis points and provide convenience rather than cost savings to borrowers. Hau et al (2019) show that Fintech credit providers in China's credit market enjoy a competitive advantage over traditional banks because of their cheaper distribution channels and information advantage. Ozili (2021a) show that banks manage their reported earnings by smoothing out abnormal fluctuations in income in response to competitive pressure from Fintech lenders.

3. Methodology

3.1 Data and Sources

This study investigates the linkages between inflation, exchange rates, finance and non-performing loans in Low- and Middle-Income countries from 2000 to 2022. After conducting an extensive literature review, we carefully selected the following variables Bank nonperforming loans to total gross loans (%) was used to measure non-performing loans (NPL). In contrast, macroeconomic variables are the inflation rate (INFL) and exchange rate (EXR). We measured finance with digital financial measures such as automated teller machines (ATM), the point of sale (POS), mobile banking (MB), mobile money (MM) and electronic banking (Ebanking). At the same time, the control variables are financial deepening – a ratio of broad money (M2) and gross domestic product (GDP). However, the choices of the study area, the study period and variables are greatly

influenced by data availability. Thus, below in Table 1, we further define each variable and its sources to understand the reader better.

Acronym	Definition	Source
Dependent Variable		
NPL	Non-performing loans	https://data.worldbank.org/indicator/FB.AST.NPER.ZS
Explanatory Variables		
INFL	Inflation rate	https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG
EXR	Exchange rate	https://data.worldbank.org/indicator/PA.NUS.FCRF?locations=ZQ
ATM	Automated teller machines	https://data.worldbank.org/indicator/FB.ATM.TOTL.P5
POS	Point of sale	https://databank.worldbank.org/metadataglossary/g20-financial-inclusion-indicators/series/GPSS_4
MB	Mobile banking	https://www.worldbank.org/en/publication/globalfindex/Data
MM	Mobile money	https://www.worldbank.org/en/publication/globalfindex/Data
EBANKING	Electronic banking	https://www.worldbank.org/en/publication/globalfindex/Data
Control Variable		
M2/GDP	Financial deepening	https://data.worldbank.org/indicator/FM.LBL.BMNY.GD.ZS?locations=1W and https://data.worldbank.org/indicator/NY.GDP.MKTP.CD
INTR	Interest rate	https://data.worldbank.org/indicator/FR.INR.RINR?locations=NG

3.2 Model Specifications

3.2.1 Baseline General Method of Moment (GMM) Model

To examine the linkages between inflation, exchange rate, finance and non-performing loans, the Panel generalized method of moment (GMM) – a well-known econometric estimation approach was utilized as the baseline model. However, the GMM model was seen as the best estimator because it can measure the long-run relationship and deal with estimation problems such as endogeneity, overidentification of instruments and simultaneity restriction problems. The panel model for the estimation of linkages between inflation, exchange rate, finance and non-performing loans is specified as follows.

$$X_{i,t} = \alpha + \pi X_{i,t-1} + \vartheta R_{i,t-1} + \theta_i + \varepsilon_{i,t} \quad ---------- (1)$$

Where X is dependent variables, and R stands for a vector of explanatory variables, θ_i is the time-invariant country-specific fixed effect, ε is the disturbance term which follows N (0, δ_2) and the subscripts "i" and "t" represent country and time, respectively.

The justification for panel dynamic system GMM is that there must be a large cross-section (N) i.e. N must be large and a small number of periods (T) i.e. (the period). Thus, in this study, N=59, while T=22 i.e. 26 low-income countries and 33 middle-income countries. This estimation technique proves quite insightful, robust and enormously suitable based on its important features identified by Blundell and Bond (1998) as follows. First, the GMM approach is quite appropriate in addressing the problem of endogeneity triggered by the inclusion of the initial value of non-performing loans (NPLS) and other endogenous variables in the model using the instrumentation process of the corresponding lags of independent variables. Second, it corrects for unobserved country-specific heterogeneity, which is an inherent phenomenon across low-income and middle-income countries and the non-performing loans (NPLS) is dynamics across time. Third, it addresses the misspecification problem that usually occurs in a static model. The inclusion of a lagged dependent variable in GMM usually omitted in static models is important because of its robust influence in predicting the contemporaneous response of the dependent variable. Furthermore, it has been explained by Blundell and Bond (1998) that the system GMM estimator

is more efficient than the differenced GMM estimator given that the instruments become weak after estimating the first differenced GMM. Lastly, the system GMM robust estimator makes the standard error consistent even in the presence of persistent series and heteroscedasticity (Blundell and Bond 1998; Bond et al. 2001).

Thus, to estimate equation (1), the dependent variable would need to be lagged to override the country-specific effects and endogeneity problems (Hao 2020). Also, Levine and Zervos (1998) used the initial values of the explanatory variables as instruments to remove the simultaneity problem in the econometric model, but it resulted in information loss as well as potential consistency loss rendering the estimation inefficient (Beck and Levine, 2004). However, for the model to be efficient and consistent, proper instruments should be used in place of the initial values of the explanatory variables. In this stance, Blundell and Bond (1998) proposed an alternative estimator – system GMM since they discovered that instruments become weak after the first estimation and this is expressed as follows.

$$X_{i,t} - X_{i,t-1} = \pi\left(X_{i,t-1} - X_{i,t-2}\right) + \vartheta\left(R_{i,t} - R_{i,t-1}\right) + \left(\varepsilon_{i,t} - \varepsilon_{i,t-1}\right) - - - - - (2)$$

In equation (2), first-differencing eliminates the intercept and the country-specific effects (η). However, the estimation of equation (2) will be biased and inconsistent, as the lagged dependent variable $\left(X_{i,t-1} - X_{i,t-2}\right)$ and the error term $\left(\varepsilon_{i,t} - \varepsilon_{i,t-1}\right)$ will be correlated and would render the explanatory variables to be endogenous (Hao, 2006). Therefore, Arellano and Bond (1991) posit that the model must pass the following moment conditions.

$E\left[X_{i,t-n}\left(\varepsilon_{i,t} - \varepsilon_{i,t-1}\right)\right] = 0$ for $n \geq 2, t = 3, \ldots \ldots \ldots . . T$

$E\left[X_{i,t-n}\left(\varepsilon_{i,t} - \varepsilon_{i,t-1}\right)\right] = 0$ for $n \geq 2, t = 3, \ldots \ldots \ldots . . T$

Thus, to ensure that some estimation issues like identification, simultaneity and restrictions are treated, it is pertinent to shed light on how they are going to be resolved by the model. The statistical test to validate the selected variables is assessed using the Hansen J test of identifications and the null hypothesis of the underlying Sargan Overidentifying Restrictions Test should not be rejected for the strictly exogenous variables to explain the dependent variable exclusively via the channel of predetermined or suspected endogenous variables (Beck et al. 2003). Also, we estimated the Arellona-Bond serial correlations which have both AR1 and AR2 to ensure that there is no presence of AR2 in the estimated results (Arellano & Bond 1991).

3.2.2 Robustness Check Model – FMOLS and DOLS

Pertinently, this study further robustly checked the results of the GMM model using another cointegration technique – fully modified ordinary least squares (FMOLS) and dynamic ordinary least square (DOLS) model with the sole aim of eliminating the influence of the cross-sectional dependence problem and the possibility of the error terms being contemporaneously associated which GMM could not address. The FMOLS and DOLS have been widely used by McCoskey and Kao (1998) Chiang (2000), Phillips & Moon (1999), and Pedroni (2000). However, while Phillips and Hansen (1990) proposed a semi-parametric model for the correction of the problem of long-run correlation among cointegrating equations and stochastic regressors innovations resulting in FMOLS estimators, Saikkonen (1992) and Stock and Watson (1993) advanced asymptotically efficient estimator which eliminates the feedback in the cointegrating system by augmenting the cointegrating regression with lags and leads of independent variables which is the DOLS estimator on the other hand. The FMOLS and DOLS are specified as follows:

$$\beta FMOLS = \left[N^{-1}\sum_{i=1}^{N}\left(\sum_{t=1}^{T}(P_{i,t}-P_{i,t})^2\right)\right]X\left[\left(\sum_{t=1}^{T}(P_{i,t}-P_{i,t})\right)\right]S_{i,t} - T\Delta_{\varepsilon u} - - - - - - - - -(3)$$

$$\beta DOLS = \left[N^{-1}\sum_{i=1}^{N}\left(\sum_{t=1}^{T}(W_{i,t}+P_{i,t})^{-1}\right)\left(\sum_{t=1}^{T}(P_{i,t}-P_{i,t})\right)\right]S_{i,t} - T\Delta_{\varepsilon u} - - - - - - - - - - - -(4)$$

Where p represents explanatory variables, S denotes a dependent variable, and Z shows the regressor's vector (W=P – P) respectively. Thus, emphasis has been laid on the problem of heterogeneity with differences in means among the individuals and differences in individual responses to short-run disturbances from cointegrating equilibrium as the main reasons for concern in estimating dynamic cointegrated panels (Pedroni, 2001) and the FMOLS (equ. 4) is consistent in addressing the problems. Worthy to note, the DOLS outperforms the OLS, ARDL and FMOLS estimators in finite samples in terms of unbiased estimation based on Monte Carlo simulations. It equally takes care of endogeneity in a model thereby providing a robust correction for endogeneity in the explanatory variables.

4. Empirical Results and Discussion of Findings

Solely, to measure the linkages between inflation, exchange rates, finance and non-performing loans in low- and middle-income countries remain the aim of this study. As such, annual time series data from 2000 to 2022 were utilized for the analysis. To estimate these relationships, we employed the autoregressive distributed lag model (ARDL) which is consistent in measuring both long-run and short-run impacts simultaneously. We also robustly checked the findings from the ARDL model using the FMOLS and DOLS estimation techniques. However, basic econometric tests like descriptive statistics, normality test, serial correlation test, Ramsey Reset test, White Heteroscedasticity test, correlation test, and cointegration tests to ascertain the basic characteristics of the model variables, which would aid in making decisions on each of the model variables, the specified models and the overall findings of the study.

4.1 Data Description

Using the descriptive statistics which measures the basic summary of the model variables using the measures of central tendencies such as mean, median, standard deviation, Skewness and Kurtosis, was utilized to describe the data. We first investigate if the variables are consistent and would be suitable for the analysis of the relationships that is being tested. Findings therefore from the results of the descriptive statistics shows that the values of the mean, median, standard deviation, Skewness and Kurtosis for all the variables did not drift so much from each other. In addition, the total variations in the series which represents the least and highest values in the series on average are -6.350 and 7.683 and the probability values of the Jarque-Bera statistics for all the variables are less than 0.05 which implied that the errors of the variables are normally distributed. Thus, sequel to these findings, one can conclude that the variables are consistent and suitable for the analysis based on their characteristics.

Table 2: Results of Descriptive Statistics

	NPL	INFL	EXR	ATM	POS	MB	MM	EBANKING	M2/GDP	INTR
Mean	3.640	2.732	-0.071	3.273	0.783	5.273	0.612	2.099	3.314	4.135
Median	3.712	2.584	-0.080	3.209	0.986	5.256	0.808	2.415	3.253	4.310
Maximum	4.225	6.879	2.287	4.650	2.620	7.683	3.045	6.571	4.650	5.405
Minimum	2.920	-0.134	-3.368	1.650	-6.350	2.027	-3.177	-5.162	1.650	3.067
Std. Dev.	0.304	1.322	0.970	0.527	1.084	1.256	0.991	2.358	0.534	0.641
Skewness	-0.306	0.958	0.163	0.425	-2.416	-0.184	-0.969	-0.863	0.242	0.037
Kurtosis	2.279	4.191	2.998	3.852	14.62	2.636	5.029	3.796	3.811	1.743
Jarque-Bera	7.835	44.55	0.807	12.46	1042.	1.685	56.76	31.64	7.178	13.86
Probability	0.019	0.000	0.027	0.001	0.000	0.030	0.000	0.000	0.027	0.000
Observations	1295	1295	1295	1295	1295	1295	1295	1295	1295	1295

Source: Conceived by the Author.

To further our investigations, we also described the data by employing Spearman's correlation test to measures the degree of strength of association between inflation, exchange rates, finance and non-performing loans in low- and middle-income countries. Findings revealed that the inflation rate (INFL) strong positive correlations on non-performing loans, and this is similar to exchange rate which has moderate correlations with the NPL. Contrary to this, we found that the automated teller machines (ATM) have strong negative correlations with the NPL in low- and middle-income countries. We also found that the point of ale (POS), mobile banking (MB), mobile money (MM) and electronic banking (Ebanking) have strong positive correlations with the non-performing loans (NPL) in low- and middle-income countries. Similarly, positive but weak correlations were found between the financial deepening and non-performing loans (NPL) in low- and middle-income countries, while the interest rate (INTR) has negative and moderate correlations with the non-performing loans in low- and middle-income countries.

Table 3: Results of Spearman's Correlation Tests

NPL	1									
INFL	0.926	1								
EXR	0.483	-0.986	1							
ATM	-0.945	-0.831	0.897	1						
POS	0.970	-0.849	-0.826	-0.444	1					
MB	0.693	-0.081	0.332	-0.403	-0.675	1				
MM	0.613	-0.868	0.443	0.555	0.452	-0.305	1			
EBANKING	0.890	-0.325	-0.975	-0.813	0.426	0.595	-0.108	1		
M2/GDP	0.369	-0.117	0.910	0.786	0.282	-0.142	-0.671	0.178	1	
INTR	-0.568	-0.355	-0.568	0.921	0.684	0.581	0.182	0.638	-0.130	1

Source: Compiled by the Autor

4.2 Testing for Unit Root

Haven described the variables above; the researcher furthered her investigations by testing each of the model variables to ascertain if there is existence of unit root in the variables or not as well as their integration order. For this purpose, four-unit root tests which include Levin, Lin and Chu – LLC (2002), Im, Pesaran and Shin – IPS (2003), Fisher-ADF and Fisher-PP as proposed by Madala and Wu (1999) were employed. Note worthily, these tests are guided by null hypothesis "unit root" and alternative hypothesis "not unit root" and the decision rule for the test states that "we reject the null hypothesis if the probability value is less than 0.05 other wise do not reject. Thus, as seen in the results of the unit root tests presented in table 4 below, we reject the null hypothesis "unit root" and accept the alternative hypothesis "no unit root" since the probability values of the tests for each of the variables are less than 0.05 and therefore, we conclude that there is no unit root in the series. Also, the variables were found to the integrated at level (I(0)) and first difference (I(1)) integration order and none was integrated of second difference (I(2)) and above. Thus, these

qualities make the variables very suitable for the estimation of the relationships that is being tested using the ARDL model which accepts variables in model irrespective of their order of integration.

Table 4: Results of Unit Root Tests

Variable	LLC	IPS	Fisher-ADF	Fisher-PP	Integration Order	
					Level	First Diff.
NPL	-13.1616*** (0.0000)	-10.7213*** (0.0000)	127.290*** (0.0000)	133.327*** (0.0000)	_	I(1)
INFL	-10.4991*** (0.0000)	-9.10659*** (0.0000)	107.525*** (0.0000)	119.164*** (0.0000)	_	I(1)
EXR	-23.7489*** (0.0000)	-14.5295*** (0.0000)	92.4951*** (0.0000)	105.110*** (0.0000)	_	I(1)
ATM	-16.1349*** (0.0000)	-12.1472*** (0.0000)	188.242*** (0.0000)	198.936*** (0.0000)	_	I(1)
POS	-7.55645*** (0.0000)	-7.00275*** (0.0000)	84.9461*** (0.0000)	84.2693*** (0.0000)	I(1)	_
MB	-3.97735*** (0.0000)	-5.47181*** (0.0000)	73.6250*** (0.0000)	320.165*** (0.0000)	_	I(1)
MM	-9.31580*** (0.0000)	-6.96819*** (0.0000)	92.0352*** (0.0000)	94.3689*** (0.0000)	_	I(1)
EBANKING	-6.32730*** (0.0000)	-8.22927*** (0.0000)	100.075*** (0.0000)	112.302*** (0.0000)	I(0)	_
M2/GDP	-9.22093*** (0.0000)	-7.05912*** (0.0000)	82.1001*** (0.0000)	94.8221*** (0.0000)	_	I(1)
INTR	-3.71093*** (0.0001)	-2.98715*** (0.0014)	40.6142*** (0.0042)	38.8664** (0.0069)	I(0)	_

Source: Conceptualized by the Author. Note: ***, ** and * represent the 1%, 5% and 10% level of significance and (.) represent the probability value

4.3 Testing for Cointegration

Furthermore, after confirming that the variables have not evidence of unit root and are integrated of I(0) and I(1), we set to test for cointegration using the Pedroni (2004) cointegration test to test if there is existence of cointegergation between bank credit and investment growth in Africa. This test has a null hypothesis “no cointgeration” and alternative hypothesis “cointegration” and decision rule “reject the null if the probability values are less than 0.05”, otherwise do not reject. Worthy to note that Pedroni (2004) proposed seven (7) cointegration tests which include panel v-statistic, panel rho-statistic, panel pp-statistic, and panel ADF-statistic under “within dimension” as well as group rho-statistic, group pp-statistic and group ADF-statistic under “between dimension”. This test was proposed to measure the existence of cointegration relationships between econometric model variables. However, we present the results of the cointegration tests in table 5 below.

Results findings from Pedroni cointegration test in table 5 shows that there is existence of cointegration between inflation, exchange rates, finance and non-performing loans in low- and middle-income countries since the probability values of most of the tests across models 1-5 are less than 0.05 leading to rejection of the null hypothesis and acceptance of the alternative hypothesis. Therefore, we conclude that there is existence of cointegration between inflation, exchange rates, finance and non-performing loans in low- and middle-income countries. These findings were robustly checked by re-testing the cointegration of the models using Kao (1999) cointegration test and the result outcomes also revealed that there is existence of cointegration between inflation, exchange rates, finance and non-performing loans in low- and middle-income countries since the probability values of the ADF-statistic for all the models are less than 0.05.

Table 5: Results for Cointegration Tests

PEDRONI (2004) COINTEGRATION TEST					
Within Dimension					
TESTS	Model 1	Model 2	Model 3	Model 4	Model 5
Panel v-Statistic	1.686896 (0.0458)	-7.070776 (0.0000)	2.134181 (0.0284)	-7.790173 (0.0000)	6.103626 (0.0000)
Panel rho-Statistic	-6.215349 (0.0000)	0.504397 (0.6930)	4.256502 (0.0012)	6.930675 (0.0000)	12.48727 (0.0000)
Panel PP-Statistic	-4.098097 (0.0000)	-9.369468 (0.0000)	-3.027239 (0.0012)	-0.256725 (0.3987)	-1.991960 (0.0232)
Panel ADF-Statistic	-0.573009 (0.2833)	5.356233 (0.0000)	-7.356328 (0.0000)	3.203072 (0.0008)	-6.307389 (0.0000)
Between Dimension					
Group rho-Statistic	-4.355052 (0.0000)	5.003464 (0.0000)	8.041863 (0.0000)	4.310677 (0.0000)	3.010117 (0.0050)
Group PP-Statistic	-4.291360 (0.0000)	-11.37999 (0.0000)	-2.373415 (0.0088)	-5.504210 (0.0001)	-1.961463 (0.0249)
Group ADF- Statistic	-4.408671 (0.0000)	7.506813 (0.0000)	-15.38027 (0.0000)	2.153581 (0.0057)	-2.008874 (0.0165)
KAO (1999) COINTEGRATION TEST (ROBUSTNESS CHECK)					
ADF- Statistic	-3.540388 (0.0002)	-3.113109 (0.0009)	-3.275079 (0.0005)	-2.886087 (0.0020)	-4.240249 (0.0000)

Source: Conceptualized by the Author. Note: ***, ** and * represent the 1%, 5% and 10% level of significance and (.) represent the probability value

4.4 Estimation of the ARDL Long-Run Impact

To further our investigations, we employed panel autoregressive distributed lag model (ARDL) to estimate the long-run relationship between inflation, exchange rates, finance and non-performing loans in low- and middle-income countries. However, as proposed by Pesaran et al. (1999), ARDL was chosen over other estimation techniques because it is well-known for its ability in estimating both long-run and short-run impact, acceptance of variables irrespective of their order of integration, and gives consistent results. However, the models were taken through basic econometric tests such as – Normality, Breusch-Godfrey Serial Correlation LM Test, Ramsey Reset test for specifications and White Heteroscedasticity test to ensure that the basic assumptions of econometrics were fulfilled. However, from the result findings, it was discovered that the error terms of the models are normally distributed, serially uncorrelated, and homoscedastic, while the results of the Ramsey test for the models (1-3) shows that the models are correctly specified (see table 6). In addition, we employed a likelihood test – the Hausman (1978) test to select the most suitable model for the analysis and result suggested that the models be estimated with random effects model (RE) except for model 2 & 3 which would be suitably estimated using the fixed effects (FE).

From the estimated results, it was discovered that across the models, the past values of non-performing loans (NPL) positively contributed effectively with the present values of non-performing loans in low- and middle-income countries. We also found that the inflation rate (INFL) has significant negative effects on non-performing loans (NPL) in low- and middle-income countries across the models except in model 4, where it portrayed positive and significant effect on NPL in low- and middle-income countries. In addition, the exchange rate (EXR) showed significant positive impacts on the non-performing loans (NPL) in low- and middle-income countries. Closer look at the measures of finance revealed that automated teller machines (ATM) have significant positive impacts on non-performing loans (NPL) in low- and middle-income countries, while the point of sale (POS) has significant negative impacts on the non-performing loans in low- and middle-income countries. We further discovered that mobile banking (MB) has

insignificant but positive impacts on the non-performing loans in low- and middle-income countries, while the mobile money (MM) portrayed significant positive impacts on the non-performing loans (NPL) in low- and middle-income countries. Lastly, we found that the electronic banking has positive and significant impacts on non-performing loans in low- and middle-income countries. Furthermore, we found that financial deepening has significant positive impacts on non-performing loans (NPL) in low- and middle-income countries, but the interest rate (INTR) has significant positive impacts on the non-performing loans (NPL) in low- and middle-income countries except for models 2 & 3. Summarily, this study found that inflation rate has significant impacts on the non-performing loans in low- and middle-income countries, while the exchange rate and finance have significant positive impacts on non-performing loans in low- and middle-income countries. These findings are in line with the previous findings earlier made by scholars like (Berger & De Young 1997, Norden & Stoin 2014, Louzis et al. 2010, Wood & Skinner, 2018, Ozili 2019, Piatti & Cincine 2019, Betz et al. 2017, Mustafa & Jeffery, 2020, Lee et al. 2019, Huljak et al. 2020, Chen et al. 2022, Zeng 2020, Balyuk et al. 2020, Buchak et al. 2018, Hau et al. 2019, Ozili 2021a) among others.

Table 6: Estimated ARDL Results (1, 1, 1, 1, 1, 1, 1, 1)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
NPL (-1)	0.885*** (0.000)	-0.572*** (0.000)	0.882*** (0.000)	1.034*** (0.000)	0.922*** (0.000)
INFL	-0.818*** (0.000)	-0.95263*** (0.000)	-1.231*** (0.000)	8.894*** (0.009)	-0.918*** (0.000)
EXR	0.568*** (0.000)	0.849*** (0.000)	0.794*** (0.000)	-1.252*** (0.000)	0.013*** (0.006)
ATM	0.890*** (0.000)				
POS		-0.034*** (0.000)			
MB			1.448 (0.052)		
MM				0.018** (0.035)	
EBANKING					0.932*** (0.000)
M2/GDP	0.036*** (0.000)	-0.184*** (0.000)	0.531*** (0.000)	0.328*** (0.002)	0.013*** (0.006)
INTR	16.72*** (0.000)	-0.381*** (0.000)	-5.475*** (0.000)	9.697*** (0.000)	0.025*** (0.000)
No. of Obs.	1298	1295	1296	1297	1290
Normality	45.56 (0.000)	720.6867 (0.0000)	889.1985 (0.0000)	703.8722 (0.0000)	617.6062 (0.0000)
Serial Corr.	0.456050 (0.6346)	0.266108 (0.7667)	0.043320 (0.9576)	0.138801 (0.8705)	0.138801 (0.8705)
Ramsey	0.751766 (0.0000)	-0.068873 (0.0000)	-0.004927 (0.0199)	-0.179877 (0.0000)	0.014121 (0.0095)
Heteroscedasticity	0.971603 (0.5299)	0.982201 (0.5060)	1.314914 (0.1177)	0.625931 (0.9732)	1.263465 (0.1447)
Hausman	8.565612 (0.2854)	13.842855 (0.0166)	14.508381 (0.0244)	10.941369 (0.1412)	11.319414 (0.1842)

Source: Conceptualized by the Author. Note: ***, ** and * represent the 1%, 5% and 10% level of significance and (.) represent the probability value

4.5 Estimation of the ARDL Short-Run Impact

As proposed by Pesaran et al. (2001) "after estimating and confirming the existence of long-run relationships between the variables, the short-run impacts are estimated". However, the coefficient of error correction model (ECM) which represents the most critical point of analysis of the short-run ARDL result must possess negative sign and be statistically significant to be able to measure the speed of adjustment between long-run and short-run. Thus, the results of the ARDL short-run impacts were presented in table 7 below and it was discovered that for all the specified models 1 – 5, their coefficient values -0.961049, -0.753368, -1.233465, -0.676318 and -0.709305 possess negative signs respectively and are statistically significant at 5% level of significant. This implies that the speed of adjustments from the short-run to the long-run are measured at 96%, 75%, 12%, 67% and 70% magnitudes respectively to adjust from the short-run back to the long-run. These findings tallied with previous findings by (Berger & De Young 1997, Norden & Stoin 2014, Louzis et al. 2010, Wood & Skinner, 2018, Ozili 2019, Piatti & Cincine 2019, Betz et al. 2017, Mustafa & Jeffery, 2020, Lee et al. 2019, Huljak et al. 2020, Chen et al. 2022, Zeng 2020, Balyuk et al. 2020, Buchak et al. 2018, Hau et al. 2019, Ozili 2021a) among others.

Table 7: Results of the Short-Run Dynamics

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
ECM (-1)	-0.961** (0.031)	-0.753*** (0.000)	-1.233** (0.012)	-0.676*** (0.000)	-0.709*** (0.000)
ΔINFL	-0.341 (0.561)	0.025*** (0.003)	6.686 (0.447)	5.059 (0.676)	5.992 (0.539)
ΔEXR	0.132 (0.574)	1.506 (0.540)	0.050 (0.602)	1.123 (0.622)	1.260 (0.488)
ΔATM	0.506 (0.485)				
ΔPOS		0.834 (0.719)			
ΔMB			-1.130 (0.648)		
ΔMM				0.583 (0.965)	
ΔEBANKING					0.129 (0.086)
ΔM2/GDP	-0.039 (0.690)	0.298 (0.820)	-1.570 (0.162)	0.500 (0.715)	0.429 (0.738)
ΔINTR	-0.081 (0.815)	1.313 (0.103)	1.386*** (0.003)	1.328 (0.127)	1.320** (0.030)

Source: Conceptualized by the Author. Note: ***, ** and * represent the 1%, 5% and 10% level of significance and (.) represent the probability value

4.6 Robustness Check – FMOLS AND DOLS

We furthered our investigations by introducing another estimation technique – the fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS) which was used to re-estimate the specified models in order to take care of some estimation issues which the ARDL model did not handle such as endogeneity, heterogeneity and country-specific effects issues. The essence of employing the FMOLS and DOLS was to ensure we generated estimates devoid of inconsistency since the outcome of the study will be used for policy making in low- and middle-income countries. Findings from the estimated FMOLS results shows that the past values of the non-performing loans (NPL) have significant negative effects on the current values of non-performing loans (NPL) in low- and middle-income countries across the models. Also, it was discovered that inflation rate (INFL) has significant positive effects on nonperforming loans (NPL)

in low- and middle-income countries across the models but in model 2, inflation rate has significant negative effects on non-performing loans in low- and middle-income countries, and a similar result was found between the exchange rate and nonperforming loans in low- and middle-income countries. The automated teller machines (ATM) positively influenced that non-performing loans in low- and middle-income countries. In addition, the point of sale (POS) and mobile banking (MB) have significant positive influence on non-performing loans in low- and middle-income countries, which is different with the findings made from the result of mobile money (MM) which has significant negative effects on non-performing loans in low- and middle-income countries, but our result findings revealed that electronic banking (Ebanking) has significant positive effects on non-performing loans (NPL) in low- and middle-income countries. Across the models, financial deepening was found to show significant positive effects in models 1 – 3 on non-performing loans in low- and middle-income countries, but negative and significant effects on non-performing loans in low- and middle-income countries in models 4 and 5 respectively. Also, it was discovered that interest rate (INTR) has significant positive effects on non-performing loans (NPL) in low- and middle-income countries across the models. In addition, the results of the R-squared for each of the models reveled the total variations in the non-performing loans were greatly explained by the explanatory variables with over 50% magnitudes respectively. These findings corroborate with the previous findings made by (Berger & De Young 1997, Norden & Stoin 2014, Louzis et al. 2010, Wood & Skinner, 2018, Ozili 2019, Piatti & Cincine 2019, Betz et al. 2017, Mustafa & Jeffery, 2020, Lee et al. 2019, Huljak et al. 2020, Chen et al. 2022, Zeng 2020, Balyuk et al. 2020, Buchak et al. 2018, Hau et al. 2019, Ozili 2021a) among others.

From the DOLS perspective, we found that the values of the past effects of non-performing loans (NPL) contributed significantly on the current values of non-performing loans in low- and middle-income countries. Similarly, we discovered that the inflation rate (INFL) has significant positive effects on non-performing loans (NPL) in low- and middle-income countries, while the exchange rate has significant positive effects on non-performing loans in low- and middle-income countries except in model 2 where it portrayed significant negative effects on non-performing loans in low- and middle-income countries. Furthermore, we found that the automated teller machines have significant negative effects on the non-performing loans in low- and middle-income countries and similar findings were made from the point of sale which portrayed significant negative effects on non-performing loans in low- and middle-income countries. Contrary, we found that mobile banking (MB) has significant positive effects on non-performing in low- and middle-income countries, while the mobile money (MM) has significant and negative effects on non-performing loans (NPL) in low- and middle-income countries and a contrary finding were made from electronic banking (Ebanking) which has significant negative effects on non-performing loans (NPL) in low- and middle-income countries. In addition, we found that financial deepening (M2/GDP) and the exchange rate (EXR) have significant positive effects on the non-performing loans in low- and middle-income countries. Also, the results of the R-squared shows that variations in non-performing loans (NPL) were greatly explained by the explanatory variables with over 50% magnitudes across the models. Thus, these findings correspond with previous studies such as (Berger & De Young 1997, Norden & Stoin 2014, Louzis et al. 2010, Wood & Skinner, 2018, Ozili 2019, Piatti & Cincine 2019, Betz et al. 2017, Mustafa & Jeffery, 2020, Lee et al. 2019, Huljak et al. 2020, Chen et al. 2022, Zeng 2020, Balyuk et al. 2020, Buchak et al. 2018, Hau et al. 2019, Ozili 2021a) among others.

Table 9: Estimated Results of the FMOLS and DOLS Models

	FMOLS					DOLS				
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
NPL (-1)	0.023*** (0.000)	-0.573*** (0.000)	0.011*** (0.009)	-0.037*** (0.000)	-1.634*** (0.000)	0.464*** (0.000)	43.59*** (0.000)	82.77*** (0.000)	38.69*** (0.000)	0.313*** (0.000)
INFL	0.037*** (0.000)	-0.985*** (0.000)	0.494*** (0.000)	0.120** (0.030)	0.561*** (0.000)	0.351*** (0.003)	19.93*** (0.000)	56.29*** (0.000)	22.03*** (0.000)	-1.063*** (0.000)
EXR	0.235*** (0.000)	0.034*** (0.000)	0.295*** (0.000)	-0.642*** (0.000)	-0.473*** (0.000)	0.088*** (0.000)	-0.217*** (0.000)	0.459*** (0.000)	0.506*** (0.000)	0.988*** (0.000)
ATM	0.019*** (0.000)					-0.034*** (0.000)				
POS		0.822*** (0.000)					-0.105*** (0.000)			
MB			0.491*** (0.000)					0.349*** (0.000)		
MM				-0.211*** (0.000)					-1.920*** (0.000)	
EBANKING					0.036*** (0.000)					0.210*** (0.000)
M2/GDP	0.048*** (0.000)	0.045*** (0.000)	0.507*** (0.000)	-19.10*** (0.000)	-0.986*** (0.000)	0.463*** {0.000)	11.39*** (0.000)	130.9*** (0.000)	95.31*** (0.000)	1.828*** (0.000)
INTR	0.038*** (0.000)	0.013*** (0.000)	0.480*** (0.000)	0.143*** (0.000)	0.091*** (0.000)	0.344*** (0.000)	0.180*** (0.004)	78.76*** (0.000)	24.88*** {0.000)	0.247*** (0.0000)
No. of Obs.	1298	1295	1296	1297	1290	1298	1295	1296	1297	1290
R-squared	0.785	0.550	0.698	0.741	0.663	0.892	0.778	0.524	0.856	0.569

Source: Conceptualized by the Author. Note: ***, ** and * represent the 1%, 5% and 10% level of significance and (.) represent the probability value

4.7 Discussion of Findings

This study estimates the long-run relationship between inflation, exchange rates, finance and non-performing loans in low- and middle-income countries from 2000 to 2022 in a total of 59 countries made up of 26 low-income countries and 33 middle-income countries. However, after conducting an extensive literature review, we carefully selected the following variables Bank nonperforming loans to total gross loans (%) was used to measure non-performing loans (NPL). In contrast, macroeconomic variables are the inflation rate (INFL) and exchange rate (EXR). We measured finance with digital financial measures such as automated teller machines (ATM), the point of sale (POS), mobile banking (MB), mobile money (MM) and electronic banking (Ebanking). At the same time, the control variables are financial deepening – a ratio of broad money (M2) and gross domestic product (GDP). The unit root test results shows that there is no evidence of unit root and the variables were integrated of I(0) and I(1) and not I(2). The result of the cointegration tests – Pedroni (2004) and Kao (1999) shows that there is existence cointegration between inflation rate, exchange rate, finance and non-performing loans in low- and middle-income countries. We found from the ARDL results that inflation rate has significant impacts on the non-performing loans in low- and middle-income countries, while the exchange rate and finance have significant positive impacts on non-performing loans in low- and middle-income countries and these findings are similar to the results findings from the robustness checks models FMOLS and DOLS models. Our findings therefore are similar to some and contradict with previous studies (see: Berger & De Young 1997, Norden & Stoin 2014, Louzis et al. 2010, Wood & Skinner, 2018, Ozili 2019, Piatti & Cincine 2019, Betz et al. 2017, Mustafa & Jeffery, 2020, Lee et al. 2019, Huljak et al. 2020, Chen et al. 2022, Zeng 2020, Balyuk et al. 2020, Buchak et al. 2018, Hau et al. 2019, Ozili 2021a)

among others. This present study differentiate itself from the above studies by estimating both long-run and short-run impacts of inflation, exchange rates, and finance on non-performing loans in low- and middle-income countries. Also, unlike previous studies, this study was thorough in measuring finance with digital financial services indicators such as automated teller machines, point of sale, mobile banking, mobile money, and electronic banking which other studies reviewed neglected, thus, we found that finance has significant positive impacts on non-performing loans in low- and middle-income countries.

5. Conclusion and Policy Recommendations

Summarily, this study estimates the linkages between inflation, exchange rates, finance and non-performing loans in low- and middle-income countries from 2000 to 2022. After conducting an extensive literature review, we carefully selected the following variables Bank nonperforming loans to total gross loans (%) was used to measure non-performing loans (NPL). In contrast, macroeconomic variables are the inflation rate (INFL) and exchange rate (EXR). We measured finance with digital financial measures such as automated teller machines (ATM), the point of sale (POS), mobile banking (MB), mobile money (MM) and electronic banking (Ebanking). At the same time, the control variables are financial deepening – a ratio of broad money (M2) and gross domestic product (GDP). The unit root test results shows that there is no evidence of unit root and the variables were integrated of I(0) and I(1) and not I(2). The result of the cointegration tests – Pedroni (2004) and Kao (1999) shows that there is existence cointegration between inflation, exchange rates, finance and non-performing loans in low- and middle-income countries. Findings from the ARDL results that inflation rate has significant impacts on the non-performing loans in low- and middle-income countries, while the exchange rate and finance have significant positive impacts on non-performing loans in low- and middle-income countries and these findings are similar to the results findings from the robustness checks models FMOLS and DOLS models.

Based on the study findings, this study concludes that inflation rate has significant impacts on the non-performing loans in low- and middle-income countries, while the exchange rate and finance have significant positive impacts on non-performing loans in low- and middle-income countries. Thus, we recommend that to albeit non-performing loans (NPL) in low- and middle-income countries can be effectively reduced if the authorities improve the macroeconomic conditions of the countries monetary policy tools such as inflation rate, interest rate and exchange rate. This would aid in achieving economic stabilization, aid in reviving the overall well-being of households and other economic agents, improve per capita income since the economies would be very productive and lead to reduction in the non-performing loans (NPL). Furthermore, since digital finance brings about positive impacts on non-performing loans in low- and middle-income countries, it would be recommended that the authorities should uphold digital financial services in the countries to boost financial inclusion, ensuring that everyone have access to required financial services and this would aid in reducing the rate of non-performing loans in low- and middle-income countries.

Conflicts of Interest

The authors have disclosed no conflicts of interest.

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