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The effects of non-performing loans on bank stability and economic performance in Zimbabwe

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ABSTRACT

This study explores the impact of non-performing loans (NPLs) on the Zimbabwean banking industry's stability and economic performance during the dollarization era. The panel vector autoregressive (PVAR) model was applied using annual data from 2009 to 2017. The findings indicated that short-run NPL shocks negatively impact the risk-adjusted return, while the impact on risk-adjusted capitalization is positive but dies off in the long run. The findings from the paper further show that NPLs have a strong negative and significant effect on loan growth and economic performance in the short run but remain muted in the long run. The study results also show a bi-directional causality between banking industry stability and NPLs. In summary, NPLs affect banking industry stability, loan growth and economic performance in Zimbabwe. A possible implication is the formulation of a sound regulatory framework that curbs the increase in NPLs, promotes stability within the banking industry, and improves economic performance. The practical implication is that banks must get it right the first time regarding bank lending policies. Thus, the study recommends that Zimbabwean banks proactively manage their exposure to non-performing loans by implementing rigorous credit risk assessment processes.

Contribution/Originality: Several studies on non-performing loans and banking sector stability mainly employed a composite Z score as a proxy for stability. However, as a deviation from previous studies, this research uses decomposed Z scores, such as risk-adjusted return and capitalization, to illustrate how NPLs affect banking sector stability using different econometric models.

1. INTRODUCTION

The stability of the banking industry remains a key priority area for several central banks, and non-performing loans are among the variables that should be kept at minimal levels to achieve stability. The growth in NPLs leads to a build-up of toxic assets on banks' balance sheets, and as such, high NPLs might instigate banking industry instability and episodes of bank failures. Evidence shows that the evolution of NPLs causes fragility in the financial system, which induces a banking crisis (Foglia, 2022; Konstantakis, Michaelides, & Vouldis, 2016; Merhbene, 2021).

In addition, an upsurge in NPLs adversely impacts economic performance (Ahmad et al., 2016; Khairi, Bahri, & Artha, 2021; Morakinyo, Muller, & Sibanda, 2018; Serrano, 2021). Non-performing loans deter economic performance in several ways. To begin with, banks might strategically reduce lending to avoid further losses, which reduces the supply of loans to economic agents. A reduction in loans issued in the market slows economic activities, further negatively impacting the economic growth of a nation (Tölö & Virén, 2021). Furthermore, banks experiencing problem loans might divert their focus from creating new loans to improving asset quality, and such actions result in deteriorating economic performance (Balgova, Nies, & Plekhanov, 2018).

The complexity and connectivity of financial markets to the rest of the economy make it vital to understand the consequences of NPL accumulation, especially in developing economies (Bottazzi, De Sanctis, & Vanni, 2020; Krasniqi-Pervetica & Ahmeti, 2022). The impact of NPLs on banking industry stability and economic performance is explained by the financial accelerator theory suggested by Bernanke and Gertler (1989). The theory postulates that small credit market frictions induce large economic fluctuations. Based on this notion, the influence of credit market frictions (NPLs) splits into two inter-temporal relations. The first lag involves the adverse effect of NPLs on credit availability, where banks reduce credit availability in response to rising NPLs. In this regard, NPLs negatively affect loan growth. The other lag explains the effect of credit unavailability on economic performance. If banks curtail their lending activities, it will be difficult for firms and individuals to access credit for investment and consumption. This being so, the overall effect will be a reduction in gross domestic product (GDP). In this way, non-performing loans cause disruptions to credit supply and economic performance.

During Zimbabwe's dollarization, non-performing assets remained problematic. The co-existence of high NPL stock and economic catastrophes that prevailed during the dollarization era inspired the present study (Hanke & Kwok, 2009). Because NPLs are a barometer of the health of the banking industry, it is critical to look into the influence of NPLs on banking industry stability and economic performance. Globally, several studies attempted to examine the impact of NPLs on bank stability using a composite Z score (Atoi, 2018; Diaconu & Oanea, 2014; Koskei, 2020; Ozili, 2019). As a deviation from previous studies, this study examines the effect of NPLs on banking industry stability using decomposed Z scores and applying models that capture the possibility of second-round effects among variables. The analysis aims to shed light on whether NPLs destabilize the banking industry through risk-adjusted capitalization, risk-adjusted return, or both. Furthermore, non-performing loans (NPLs) are widely recognized to inhibit economic growth and undermine the stability of banks; however, this assertion has not yet been scientifically examined in the context of Zimbabwe.

The following section reviews the literature on the relationship between NPLs, the banking industry's stability, and economic growth; Section 3 presents the research methodology; Section 4 reports the findings; and Section 5 concludes the study.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

The dominance of NPLs can precipitate banking industry instability and poor economic performance. Moreover, if the repercussions associated with a surge in non-performing loans are not properly addressed, they can generate a new crisis and trigger a financial feedback loop within an economy. For example, NPLs increase the interest rates for bank loans, adversely affecting banks' profitability which induces instability (Merhbene, 2021). Moreover, if bank NPLs are high, confidence in the banking system could be damaged, resulting in bank runs that negatively affect banks and the economy.

Bernanke and Gertler (1989) documented that changes in the financial and credit market conditions propagate business cycles and termed the "financial accelerator theory". The theory stipulates that credit markets are procyclical and that information asymmetry between creditors (lenders) and debtors (borrowers), as well as the balance sheet effect, amplify and propagate credit market friction in the economy (Wairimu & Gitundu, 2017). The rationale behind the financial accelerator theory is that smaller shocks induce large cycles. Therefore, according to the theory, weak financial and credit market conditions, such as burgeoning NPLs, may force banks to be cautious about lending by adopting stricter policies that imply a reduction in credit availability leading to a contraction in economic performance (Serrano, 2021; Tölö & Virén, 2021).

In theory, financial markets are presumed to serve the real economy. However, in practice, Clementina and Isu (2014) discovered that NPLs stifle economic performance in Nigeria. Their study used time series data spanning from

1984 to 2012. A few years later, Atoi (2018) conducted a study on national and international banks to examine the impact of NPLs on the industry's stability. The study used the panel vector autoregressive (PVAR) model and quarterly data from 2014 to 2017. The composite Z score technique was adopted to construct a stability proxy for the Nigerian banking industry. The study results showed that international banks were more likely to withstand NPL shocks in the long run than national banks. Although the study analyzed banking industry stability using a composite Z score, the variable is less informative since it does not show channels through which NPLs destabilize the banking industry. Therefore, the present study applies decomposed Z score variables as a movement away from the approach used in earlier research. Instead of analyzing the banking industry from a generalized perspective, decomposed Z scores are essential in determining whether bank stability is influenced through capitalization or profitability channels.

In the same thread of research, Diaconu and Oanea (2014) researched Romanian banking system stability drivers spanning from 2008 to 2012 using the Z score as a banking system stability index. The ordinary least squares (OLS) regression technique was adopted to analyze several industry-specific and macroeconomic factors. Their research findings observed that banking system stability is positively driven by GDP growth and interbank offer rates. However, adopting the OLS regression technique failed to adequately capture both the magnitude and direction of each variable's influence in the short and long runs. Additionally, it did not identify if there was a one-way or two-way relationship, making it difficult to proffer appropriate policy interventions. A PVAR model could address this. Furthermore, the study only incorporated macroeconomic and industry-related variables, leaving out the possible influence of bank-level variables. The study could have considered the potential impact of bank-level variables, particularly NPLs, and investigated whether they significantly influence the Z score in the short and long runs.

Nkusu (2011) studied non-performing loans and macro-financial vulnerabilities in 26 advanced economies, utilizing data from 1998 to 2009. Using static, dynamic, and panel vector autoregressive models, the research uncovered that an increase in non-performing loans negatively affects economic performance. Moreover, it demonstrated that worsening macroeconomic conditions lead to debt servicing problems and higher non-performing loans. Furthermore, Jordan and Tucker (2017) carried out research in the Bahamas to explore how non-performing loans influence economic growth. By employing the OLS technique and vector error correction (VEC) model with quarterly data from 2002 to 2011, they discovered that economic growth is inversely related to NPLs in the short and long runs. The researchers also observed a minor yet significant feedback effect between non-performing loans and economic growth.

Using static and dynamic models, Beaton, Myrvoda, and Thompson (2016) investigated the determinants of non-performing loans in the Eastern Caribbean Central Union (ECCU). They further tested the impact of NPLs on economic activity using a panel VAR approach. The authors used a quarterly dataset of 34 banks (foreign and local) from six countries covering 1996 to 2015. They concluded that macroeconomic and bank-level factors cause deterioration in loan portfolio quality. In addition, Beaton et al. (2016) found that non-performing loans were higher in local banks than in foreign banks and that macro-financial feedback loops exist in the ECCU.

To the researcher's knowledge, no study has examined the interconnection between decomposed Z scores, economic performance, and NPLs in a single framework using Zimbabwean data. Furthermore, the identification of the literature gap is based on the inadequacy of using composite Z scores as a banking industry stability measure which the present study rendered less informative for policy formulation purposes. Therefore, there is a need to close the research gap by employing decomposed Z scores which will help policymakers understand the degree to which the banking industry is weakened through risk-adjusted capitalization and return, respectively.

To achieve the aims of the study, the paper proposes the following hypotheses:

Hypothesis 1: A negative correlation exists between NPLs and banking industry stability. An increase in NPLs indicates erosion of bank capital and profitability. Therefore, an increase in non-performing loans implies reduced capitalization, profitability, and banking industry instability (Foglia, 2022; Konstantakis et al., 2016).

Hypothesis 2: NPLs negatively affect loan growth. The evolution in non-performing loans is mainly accompanied by a reduction in lending activity by banks. This is explained by the fact that continuous growth in lending further induces deterioration in banks' asset quality (Alhassan, Brobbey, & Alhassan, 2013; Cucinelli, 2015).

Hypothesis 3: Loan growth has a positive impact on GDP. The general idea is that increased lending spurs economic growth by improving macroeconomic aggregates such as consumption and investment. Likewise, a reduction in credit availability induced by growth in NPLs is associated with declining economic performance (Banu, 2013; Roy et al., 2021).

3. METHODOLOGY

3.1. Data and Sources

This empirical study uses annual data from 2009 to 2017 to analyze the impact of NPLs on banking industry stability and economic performance. The sample consists of six locally-owned and seven foreign-owned banks, and the data used were sourced from banks' annual reports, the Bank Supervision Division (BSD) annual reports, and the World Bank. The variables are non-performing loans ratio, risk-adjusted return, risk-adjusted capitalization, loan growth rate and real GDP growth rate.

3.2. Model Specification

The estimated panel vector autoregressive (PVAR) model is derived from the study conducted by Atoi (2018). The PVAR is a technique for analyzing the dynamic correlations and interdependencies between several variables in a panel data structure. It further generalizes the time series VAR model by permitting heterogeneous coefficients across panels. The structural regression model with trivial modifications can be expressed as follows:

$$Y_{i,t} = \mu_i + \theta(L)y_{i,t} + \mathcal{E}_{i,t}\, , Y_{i,t} = [NPLS_{i,t}, ZSCORE_{1i,t}\, , ZSCORE_{2i,t}\, , LGR_{it}, GDP_t] \quad (1)$$

Since there are five variables to consider in this study, the final panel VAR model consists of the following five system equations:

$$NPLS_{i,t} = \sum_{\ell=1}^{L} A_{11\ell} NPLS_{i,t-1} + \sum_{l=1}^{L} A_{12\ell} ZSCORE_{1i,t-1} + \sum_{l=1}^{L} A_{13\ell} ZSCORE_{2i,t-1} + \sum_{\ell=1}^{L} A_{14\ell} LGR_{i,t-1} + \sum_{\ell=1}^{L} A_{15\ell} GDP_{t-1} + f_{1i} + f\mu_{1it} \quad (2)$$

$$ZSCORE_{1i,t} = \sum_{\ell=1}^{L} A_{11\ell} NPLS_{i,t-1} + \sum_{l=1}^{L} A_{12\ell} ZSCORE_{1i,t-1} + \sum_{l=1}^{L} A_{13\ell} ZSCORE_{2i,t-1} + \sum_{\ell=1}^{L} A_{14\ell} LGR_{i,t-1} + \sum_{\ell=1}^{L} A_{15\ell} GDP_{t-1} + f_{2i} + f\mu_{2it} \quad (3)$$

$$ZSCORE_{2i,t} = \sum_{\ell=1}^{L} A_{11\ell} NPLS_{i,t-1} + \sum_{l=1}^{L} A_{12\ell} ZSCORE_{1i,t-1} + \sum_{l=1}^{L} A_{13\ell} ZSCORE_{2i,t-1} + \sum_{\ell=1}^{L} A_{14\ell} LGR_{i,t-1} + \sum_{\ell=1}^{L} A_{15\ell} GDP_{t-1} + f_{3i} + f\mu_{3it} \quad (4)$$

$$LGR_{i,t} = \sum_{\ell=1}^{L} A_{11\ell} NPLS_{i,t-1} + \sum_{l=1}^{L} A_{12\ell} ZSCORE_{1i,t-1} + \sum_{l=1}^{L} A_{13\ell} ZSCORE_{2i,t-1} + \sum_{\ell=1}^{L} A_{14\ell} LGR_{i,t-1} + \sum_{\ell=1}^{L} A_{15\ell} GDP_{t-1} + f_{4i} + f\mu_{4it} \quad (5)$$

$$GDP_{t} = \sum_{\ell=1}^{L} A_{11\ell} NPLS_{i,t-1} + \sum_{l=1}^{L} A_{12\ell} ZSCORE_{1i,t-1} + \sum_{l=1}^{L} A_{13\ell} ZSCORE_{2i,t-1} + \sum_{\ell=1}^{L} A_{14\ell} LGR_{i,t-1} + \sum_{\ell=1}^{L} A_{15\ell} GDP_{t-1} + \mu_{5it} \quad (6)$$

Where:

$ZSCORE_{1i,t}$ is the risk-adjusted return that denotes banking industry stability. The variable is determined by dividing the return on assets ratio by its standard deviation (σROA).

$ZSCORE_{2i,t}$ is the risk-adjusted capitalization used as the second banking industry stability measure. It is obtained by dividing the equity-to-assets ratio by the standard deviation of return on assets (σROA).

$\mathrm{NPLS}_{i,t}$ is the ratio of non-performing loans to gross loans.

GDP_t measures economic performance by tracking changes in the real GDP growth rate.

$\theta(L)$ is the lag operator.

$LGR_{i,t}$ denotes changes in gross loans (credit availability) for bank i in period t.

$y_{i,t}$ is a vector of macroeconomic and bank-level variables defined in Equation 1.

$f_i(s)$ are bank-specific fixed effects, and $\mu_{i,t}s$ are disturbance errors.

The study performed several pre-estimation tests. Firstly, the study checked for contemporaneous dependencies among the study variables by constructing a correlation matrix under the guideline that all variables with a correlation coefficient below 0.8 were retained for further analysis (Shrestha, 2020). This was followed by unit root testing to determine whether the variables were stationary. The stationarity test was performed by employing the Pesaran cross-sectional augmented IPS (CIPS), a second-generation method that accounts for cross-sectional dependence. The optimal lag selection test was performed to identify the optimal number of lags to use in the analysis. The three information criteria considered were the modified Akaike information criterion (MAIC), the modified Bayesian information criterion (MBIC), and the modified quasi-information criterion (MQIC). The rule of thumb is to select the lag length with the lowest MBIC, MAIC, and MQIC. Finally, following Lütkepohl (2005), the study tested whether the estimated panel VAR model is stable. A panel VAR model is stable if all moduli of the companion matrix are strictly below one.[1] Following the tests mentioned above, the panel VAR model was estimated. The study employed the Granger causality test, impulse response, and forecast error variance decomposition analysis for robustness checking. The impulse response analysis was used to analyze the response of the study variables to orthogonal shocks. In addition, Cholesky's decomposition determined orthogonal shocks in the variables of interest while holding other shocks constant.

4. EMPIRICAL RESULTS AND ANALYSIS

4.1. Test for Multicollinearity

A correlation matrix was constructed to detect potential multicollinearity issues amongst study variables. The results presented in Table 1 indicate that the correlation coefficients for all study variables in the matrix are less than 0.8, thus confirming the absence of multicollinearity.

Table 1. Multicollinearity test results.

Variable	NPLS	$ZSCORE_1$	$ZSCORE_2$	LGR	GDP
$NPLS_{it}$	1				
$ZSCORE_{1it}$	-0.384	1			
$ZSCORE_{2it}$	-0.175	0.633	1		
LGR_{it}	-0.163	-0.003	-0.068	1	
GDP_{it}	-0.170	0.11	-0.095	0.619	1

Note: NPLS = Non-performing loans ratio; LGR = Loan growth rate; Z $Score_1$ = Risk-adjusted return; Z $Score_2$ = Risk-adjusted capitalization; GDP = GDP growth rate.

The findings in Table 1 suggest that NPLs negatively correlate with risk-adjusted capitalization, risk-adjusted return, loan growth rate and GDP growth. The negative correlation between NPLs and stability measures indicates that banking industry stability tends to weaken as NPLs rise. In the same way, the increase in NPLs stifles bank lending and economic performance. In addition, loan growth negatively correlates with both of the stability measures – risk-adjusted capitalization and risk-adjusted return. On the other hand, GDP growth positively correlates with risk-adjusted return but negatively associates with risk-adjusted capitalization. The correlation between GDP growth and loan growth is positive, and the magnitude is low. However, it is essential to note that correlation does not imply causation.

[1] The modulus of a complex number $h + iz$ is stated as:

$$|h + iz| = \sqrt{(h^2 + z^2)}$$

4.2. Test for Unit Root

The unit root test was conducted using CIPS criteria, and the results are shown in Table 2.

Table 2. Unit root test results.

Variable	5% Critical value	CIPS statistics
$NPLS_{it}$	-2.37	-2.746
$ZSCORE_{1it}$	-2.37	-2.649
$ZSCORE_{2it}$	-2.37	-2.704
LGR_{it}	-2.37	-3.523
GDP_{it}	-2.37	-2.61

Note: NPLS = Non-performing loans ratio; LGR = Loan growth rate; Z $Score_1$ = Risk-adjusted return; Z $score_2$ = Risk-adjusted capitalization; GDP = GDP growth rate.

The results indicate that NPLs, LGR, $ZSCORE_1$, $ZSCORE_2$ and GDP are integrated of order zero and that the CIPS statistics exceed the 5% critical values, indicating that all variables are stationary at level.

4.3. Optimal Lag Order Test

The optimal lag order test ensures that the correct number of lags is specified so that the model is not over fitted. Table 3 presents the optimal lag order test results.

Table 3. Panel VAR lag order selection.

Lag	Coefficient of determination (CD)	J	J p-value	MBIC	MAIC	MQIC
1	0.872	13.718	0.319	-30.244	-10.282	-17.44
2	0.935	7.310	0.504	-21.998	-8.690	-13.465
3	0.895	2.387	0.665	-12.267	-5.613	-8.000
4	-2.797	.	.	.	.	.

The results in Table 3 suggest that the first order panel VAR is the most appropriate model since it has lower MBIC, MAIC and MQIC values, based on the selection criteria specified by Andrews and Lu (2001).

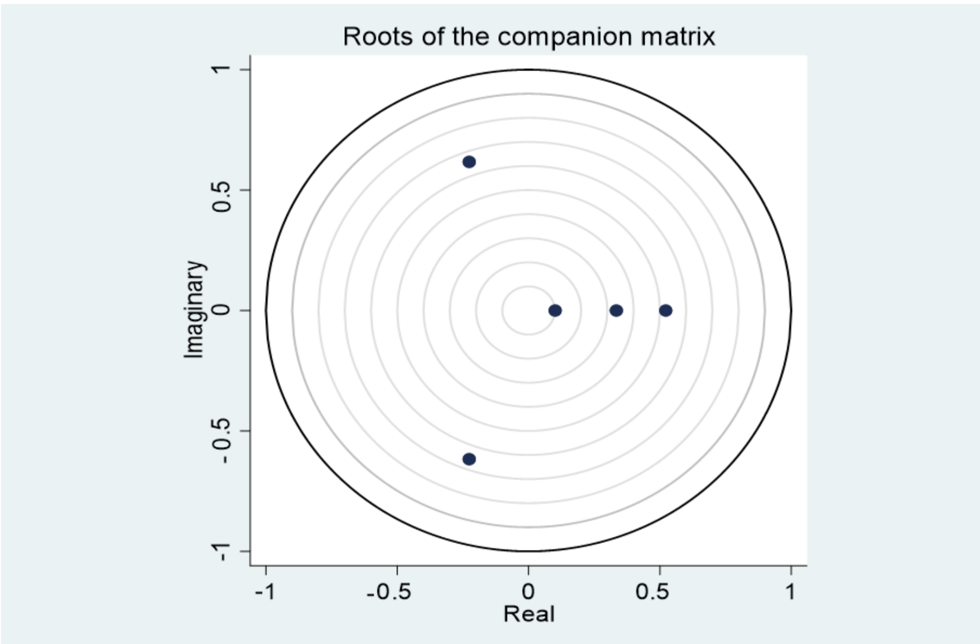

Figure 1. PVAR stability test.

4.4. Panel VAR Stability Test

In the panel VAR context, stability signifies that the panel VAR can be inverted and possesses an infinite-order vector moving average representation. This ensures a clear understanding of the estimated impulse response functions and forecast error variance decompositions (Abrigo & Love, 2016). Literature documents that a PVAR model is considered stable when the modulus for each eigenvalue is less than 1 (Hamilton, 1994). Figure 1 shows the roots of the companion matrix.

The panel VAR stability test indicates that the roots of the companion matrix are plotted within the unit circle, thus satisfying the stability condition.

4.5. Panel VAR Results

The study fitted the first order panel VAR model using the GMM-style estimation technique, and the results are reported in Table 4. The first row in Table 4 shows that previous period's NPLs have a negative but insignificant influence on current NPLs. In addition, the results suggest that previous non-performing loans negatively impact the current risk-adjusted return ($ZSCORE_1$). The coefficient for risk-adjusted return is statistically significant at 1%. The results imply that a percentage increase in the prior period's NPLs induces a 1.64% reduction in risk-adjusted return; thus, we can safely conclude that NPLs reduce banking industry stability through inferior risk-adjusted returns. These findings are in tandem with the hypothesized relationship. Foglia (2022) reported similar results, that growth in NPLs reduces banking industry stability.

In contrast, the impact of the previous period's NPLs on current risk-adjusted capitalization ($ZSCORE_2$) is positive and significant at 5%. According to the PVAR regression results, an increase in NPLs positively affect current risk-adjusted capitalization. These findings conform with Koskei (2020) in Kenya, whose main results were that NPLs positively affect bank stability. However, results on the impact of NPLs on risk-adjusted capitalization and return contradict the findings of Adusei (2015), who showed that NPLs in Ghana have a positive effect on risk-adjusted return and a negative impact on risk-adjusted capitalization.

Table 4. Panel VAR model estimates.

Response to	Response of				
	$NPLS_t$	$ZSCORE_{1t}$	$ZSCORE_{2t}$	LGR_t	GDP_t
$NPLS_{t-1}$	-0.144	-1.642***	12.419**	-4.048***	-0.337***
$ZSCORE_{1t-1}$	-0.031**	0.527***	0.668**	-0.049	0.002
$ZSCORE_{2t-1}$	-0.029***	-0.042	-0.124	-0.075	-0.007
LGR_{t-1}	-0.022	0.416***	0.598	0.092	0.012
GDP_{t-1}	0.073	-3.526*	-5.337	-0.255	0.154

Note: ***, ** and * denote 1%, 5% and 10% significance levels, respectively.

In addition, the present study observed that an increase in the previous period's non-performing loans leads to a reduction in the current loan growth rate in Zimbabwe. The coefficient for loan growth (LGR) is significant at 1%. The results imply that a percentage increase in the prior period's NPLs induces a 4.05% decrease in loan growth. These results are in line with hypothesis 2. Tölö and Virén (2021); Cucinelli (2015) and Serrano (2021) concluded similar results, that growth in NPLs reduces loan growth. Furthermore, study findings suggest that an increase in the previous period's non-performing loans causes deterioration in economic performance in Zimbabwe. The coefficient for economic performance (GDP) is negative and statistically significant at 1%. The results imply that a percentage increase in the prior period's NPLs induces a 0.33% reduction in economic performance (GDP). Ahmad et al. (2016); Khairi et al. (2021); Morakinyo et al. (2018) and Serrano (2021) concluded similar findings, that NPLs adversely impact economic performance.

The second row in Table 4 suggests that the prior period's risk-adjusted return negatively and significantly impacts current non-performing loans. According to the study outcomes, a percentage increase in the previous period's risk-adjusted return reduces the current NPLs by 0.03%, and the variable is statistically significant at 5%. These findings align with Khan, Siddique, and Sarwar (2020). Furthermore, the study revealed that a percentage increase in the previous period's risk-adjusted return leads to a 0.53% increase in the current risk-adjusted return. The variable is significant at 1%, and the finding implies that improving banking industry stability in one period will likely strengthen it further in the next period, suggesting a vicious cycle that reinforces itself through a feedback loop. The results also indicate that a percentage change in risk-adjusted return induces a 0.67% improvement in risk-adjusted capitalization. The variable is significant at 5%, and the results suggest that improving banking industry stability through risk-adjusted return induces further strengthening in stability through risk-adjusted capitalization. Yitayaw, Mogess, Feyisa, Mamo, and Abdulahi (2023) concluded similar findings, that historical bank stability has a positive and significant effect on the current level of bank financial stability. However, study outcomes have revealed that changes in the previous period's risk-adjusted returns do not influence current loan growth and economic performance.

Interestingly, the regression results in the third row indicate that a percentage increase in risk-adjusted capitalization induced a 0.029% reduction in NPLs. This suggests that banking industry stability puts downward pressure on non-performing loans, and the variable is significant at 1%. However, the results show that changes in risk-adjusted capitalization do not have a statistically significant influence on risk-adjusted return, loan growth or economic growth. Furthermore, the fourth row reveals that a percentage change in loan growth results in a 0.42% increase in risk-adjusted return, indicating that credit availability improves banking industry stability. Similar to Ozili (2019) and Ali and Puah (2018), the fifth row reveals that GDP negatively influences bank stability through risk-adjusted returns. However, the findings show that improvement in the previous period's economic performance does not affect current economic performance, NPLs, risk-adjusted capitalization or loan growth.

4.6. Impulse Responses

The impulse response analysis examined the reaction of endogenous variables when a shock is added to the error term. The orthogonalized impulse response functions presented in Figure 2 complement the PVAR model results. The analysis starts from the left-hand side of the last row, which is the response of GDP growth to one standard deviation shock in non-performing loans. The empirical results show that the GDP growth rate negatively responds to shocks in non-performing loans in the short run. This implies that it is crucial to maintain lower NPL ratios as they hinder economic performance in Zimbabwe. These findings are similar to the conclusions made by Nkusu (2011) and Rosenkranz and Lee (2019). However, GDP growth is less responsive to innovations in non-performing loans in the long run. This implies that deterioration in the quality of a bank's loan portfolio may have severe short-run implications, which Zimbabwean banks manage to absorb and correct in the short run, thus limiting its impact in the long term.

A one standard deviation innovation in NPLs reduces loan growth in the short run, ceteris paribus. The result implies that banks tend to lend less when NPLs are increasing. The finding partly satisfies the first lag of the financial accelerator theory, which assumes that growth in NPL stock (credit market frictions) negatively affects credit availability. Since bank lending is cyclical, banks tend to react abruptly to changes in non-performing loans by adjusting their lending standards in the short run, which may reduce credit availability. These results align with those reported by Rosenkranz and Lee (2019), whose main study indicated that rising NPLs reduce credit supply in Asia. Similar findings on the impact of NPLs on credit creation were also reported by Alhassan et al. (2013); Cucinelli (2015) and Tracey and Leon (2011). However, the response of bank lending (loan growth) to shocks in non-performing loans remains muted in the long run. This indicates that NPL shocks have little to no effect on bank lending in the long run, possibly due to periodic reviews of bank credit policies.

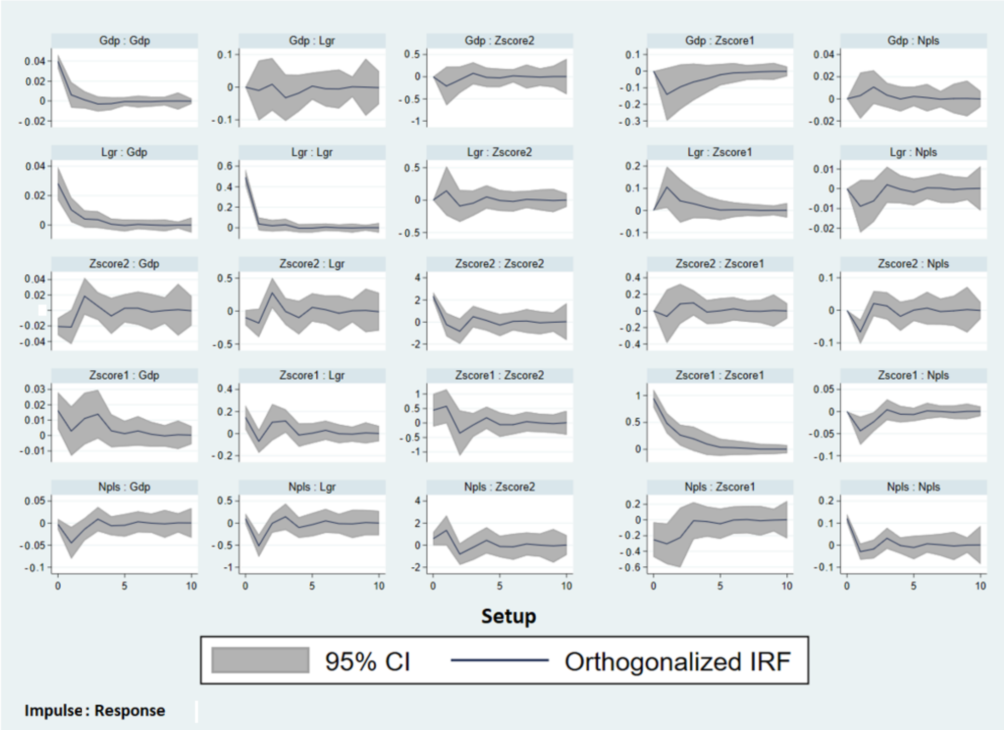

Figure 2. Impulse response functions.

Note: NPLS = Non-performing loans ratio; LGR = Loan growth rate; ZScore1 = Risk-adjusted return; ZScore2 = Risk-adjusted capitalization; GDP = GDP growth rate.

The short-run analysis indicates that both of the banking industry stability measures are responsive to shocks in non-performing loans in the short run but less responsive in the long run. Similar to the findings of the panel VAR model, the short-run results indicate that a shock in non-performing loans negatively affects the risk-adjusted return and positively influences risk-adjusted capitalization. However, these results diverge from the findings of Adusei (2015), whose study documented that NPLs positively impact risk-adjusted return and negatively affect risk-adjusted capitalization. Overall, the study observed that shocks in non-performing are more severe in the short run than in the long run in Zimbabwe.

In addition, the fourth row shows that innovations in loan growth induce deterioration in economic performance, and these findings are in line with those documented by Banu (2013) and Roy et al. (2021). Since the results established that innovations in loan growth adversely affect economic performance, the finding contradicts the final lag of the financial accelerator hypothesis (hypothesis 3). Thus, the study rejects the financial accelerator hypothesis in Zimbabwe.

4.7. *Granger Causality Results*

We performed the Granger causality Wald test to determine whether one variable could forecast another variable in a specific direction. The results for the Granger causality test are shown in Table 5, where the PVAR (1) dependent variables are in the first column, while the second column shows the excluded lagged variables.

The Granger causality test suggests that the previous period's non-performing loans predict future risk-adjusted return, loan growth, GDP, and risk-adjusted capitalization. Interestingly, both of the banking industry stability indicators also Granger-cause non-performing loans. The results evidenced bi-directional causality between non-performing loans and the banking industry stability indicators considered in this study. In the same vein, risk-adjusted return Granger-causes risk-adjusted capitalization. The results in Table 5 show that loan growth Granger-causes risk-adjusted return, which we noted had a positive relationship in the PVAR regressions. However, the latter does not Granger-cause the former, and such a scenario emphasizes the importance of bank lending in determining banking industry stability.

Table 5. Panel VAR Granger causality Wald test.

Equation	Excluded	χ^2	Df	$p > \chi^2$
$NPLS_t$	$ZSCORE1_{t-1}$	3.871	1	0.049
	$ZSCORE2_{t-1}$	9.884	1	0.002
	LGR_{t-1}	1.027	1	0.311
	GDP_{t-1}	0.075	1	0.784
	ALL_{t-1}	27.851	4	0.000
$ZSCORE_{1t}$	$NPLS_{t-1}$	8.116	1	0.004
	$ZSCORE2_{t-1}$	0.337	1	0.562
	LGR_{t-1}	10.785	1	0.001
	GDP_{t-1}	3.18	1	0.075
	ALL_{t-1}	18.334	4	0.001
$ZSCORE_{2t}$	$NPLS_{t-1}$	6.483	1	0.011
	$ZSCORE1_{t-1}$	5.669	1	0.017
	LGR_{t-1}	1.626	1	0.202
	GDP_{t-1}	0.73	1	0.393
	ALL_{t-1}	17.373	4	0.002
LGR_t	$NPLS_{t-1}$	26.254	1	0.000
	$ZSCORE1_{t-1}$	1.011	1	0.315
	$ZSCORE2_{t-1}$	1.831	1	0.176
	GDP_{t-1}	0.045	1	0.832
	ALL_{t-1}	33.558	4	0.000
GDP_t	$NPLS_{t-1}$	7.94	1	0.005
	$ZSCORE1_{t-1}$	0.055	1	0.814
	$ZSCORE2_{t-1}$	1.46	1	0.227
	LGR_{t-1}	1.09	1	0.296
	ALL_{t-1}	11.579	4	0.021
H_o: Excluded variable does not Granger-cause equation variable				
H_a: Excluded variable Granger-causes equation variable				

Note: NPLS = Non-performing loans ratio; LGR = Loan growth rate; $ZScore_1$ = Risk-adjusted return; $ZScore_2$ = Risk-adjusted capitalization; GDP = GDP growth rate.

4.8. Forecast Error Variance Decomposition Results

Table 6 reports the forecast error variance decomposition results based on a Cholesky decomposition of the residual covariance matrix of the estimated first-order PVAR model. The empirical study found that 11.79% of the variation in the risk-adjusted return is explained by non-performing loans in the short run, denoted by period 2. These findings imply low endogeneity. However, non-performing loans' contribution to risk-adjusted return fluctuations increases over time, as it accounts for 13.67% of the long-run variation (period 10). In addition, the findings suggest that risk-adjusted capitalization is affected more than risk-adjusted return in both the short and long runs. The results show that a shock in non-performing loans accounts for 26.02% and 29.46% of the fluctuations in risk-adjusted capitalization in the short and long runs, respectively.

Table 6. Forecast error variance decomposition results.

Response variable and forecast response horizon		Impulse variable				
		$NPLS_t$	$ZSCORE_{1t}$	$ZSCORE_{2t}$	LGR_t	GDP_t
$NPLS_t$	Period 2	0.709	0.087	0.200	0.004	0.000
	Period 10	0.674	0.101	0.214	0.005	0.005
$ZSCORE_{1t}$	Period 2	0.118	0.856	0.003	0.008	0.015
	Period 10	0.137	0.816	0.014	0.009	0.023
$ZSCORE_{2t}$	Period 2	0.260	0.064	0.667	0.003	0.005
	Period 10	0.295	0.067	0.629	0.003	0.006
LGR_t	Period 2	0.467	0.046	0.071	0.417	0.000
	Period 10	0.416	0.070	0.180	0.332	0.002
GDP_t	Period 2	0.353	0.048	0.157	0.159	0.283
	Period 10	0.343	0.088	0.194	0.137	0.237

Note: NPLS = Non-performing loans ratio; LGR = Loan growth rate; $ZScore_1$ = Risk-adjusted return; $ZScore_2$ = Risk-adjusted capitalization; GDP = GDP growth rate.

The findings also revealed that a shock in non-performing loans explains 35.33% of the variation in GDP growth in the short run. On the other hand, the long-run results indicated that innovations in non-performing loans explain 34.32% of the variations in real GDP, indicating that the impact marginally diminishes over time.

5. CONCLUSION AND RECOMMENDATIONS

The primary goal of this study was to investigate the impact of non-performing loans on banking industry stability and economic performance. The empirical study analyzed a sample of thirteen banks in Zimbabwe, with a dataset covering the entire dollarization period from 2009 to 2017. The study's novelty is predicated upon using decomposed Z scores instead of the composite Z score methodology applied in several previous studies. The results established that innovation in previous periods' non-performing loans induces short-run deterioration in risk-adjusted return, loan growth, and economic performance in Zimbabwe. Furthermore, the findings show that most variables are less responsive to innovations in NPLs in the long run.

Interestingly the Granger causality test results showed that NPLs Granger-cause both the risk-adjusted return and risk-adjusted capitalization, and both of the banking industry measures Granger-cause NPLs. The study, therefore, found a bi-directional causality between banking industry stability and non-performing loans. Furthermore, the study observed that NPLs negatively affect loan growth in the short run. Based on the PVAR and Granger causality tests, loan growth does not influence economic performance. Thus, the study rejected the financial accelerator hypothesis in Zimbabwe. The findings showed that non-performing loans account for approximately 35% and 34% of GDP growth fluctuations in the long and short runs, respectively. The forecast error variance decomposition results revealed that non-performing loans affect risk-adjusted capitalization more than the risk-adjusted return in the short and long runs.

In summary, the study showed that non-performing loans impact banking industry stability, loan growth, and economic performance. Therefore, monetary authorities should design policies to curb non-performing loans in the banking industry, especially in the short run. Policy options informed by this research propose that monetary authorities should periodically monitor the quality of bank loan portfolios. A possible implication is formulating a sound regulatory framework to curb growth in NPLs to ensure banking industry stability and improved economic performance. Based on the study findings, the practical implication is that banks must get it right the first time regarding lending policies. Data unavailability for periods beyond the entire formal dollarization period is the main limitation of this study. Even though the present study investigated the impact of NPLs on decomposed scores, future researchers can extend the focus to examine the effect of NPLs on other banking industry stability measures in the Sub-Saharan Africa region.

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