Assessing the Impact of Loan Restructuring on the Quality of Bank Assets in Rwanda

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Abstract

The main objective of this paper is to assess the impact of loan restructuring on the quality of bank assets in Rwanda. We use quarterly data covering the period 2012Q1 -2022Q1 in a sample of 14 banks and employ a Bias-Corrected Generalized Method of Moments to estimate this relationship. The major findings point to the fact that restructured loans, non-interest income, and return on equity are key factors that lower credit risk and improve the quality of banks' assets, while the ratio of total deposits to total assets, the ratio of loan loss provisions and bank size increase credit risk and diminish the quality of bank assets. The results are not robust to the inclusion of the dummy variable for 2020. However, other variables remain broadly in line with the main results. Given the results, we propose several policy recommendations, including a thorough assessment of the ability of borrowers to meet the restructured terms before the approval of the loan restructuring by focusing on the creditworthiness of borrowers, loan restructuring should target creditworthy borrowers facing transitory financial difficulties rather than those with unsustainable debt burdens, and strengthening monitoring mechanisms to track the performance of restructured loans post-approval through regular follow-up to identify early warning signs of deterioration and allows for timely intervention to mitigate losses.

Keywords: Loan Restructuring, Bank Asset Quality, BC-GMM

JEL Classification: G34,G38, C33

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1 Introduction

Since the 2008 global financial crisis, credit risk has emerged as one of the most key issues for policymakers and researchers. The issue has become even more pronounced in the recent past following the devastating effects of Covid-19 on many economies across the globe. Consequently, many borrowers have not been able to meet their loan obligations. Credit risk proxied by the level of non-performing loans (NPLs) has been considered the key determinant of bank failures, leading to banking crises (Reinhart & Rogoff, 2011). Banks that experience high levels of NPLs may threaten the stability of the banking sector and the entire financial system given that increasing NPLs affect the bank's asset quality, which in turn impacts the stability of the banking system.

As a coping mechanism, many banks have had to restructure loans to help borrowers manage debt and minimize default thereby ensuring business survival, which in turn helps financial institutions to recover their funds. Generally, the key factors that trigger bank loan restructuring include bank failures, low profits (Hoggarth, Reidhill, & Sinclair, 2004) high levels of non-performing loans, depressed assets, sharp increases in real interest rates and mergers and acquisitions (Claessens, Herring, Schoenmaker, & Summe, 2010). The impact of loan restructuring on credit risk depends on the type of restructuring being employed. Financial institutions, especially commercial banks, have employed various loan restructuring techniques, with the most prominent being debt rescheduling. In essence, loan restructuring involves changing the characteristics of the initial loan contract in terms of interest rate and maturity pertaining to borrowers who have difficulties in repaying the loan in a bid to help borrowers meet their debt repayment obligation. Applying loan restructuring measures banks follow their internal rules and the applicant's conditions and characteristics. If loan restructuring is done in a correct manner by considering the borrower's capacity to repay the loan and modifying the loan terms to make it more feasible for the borrower to repay, credit risk can be reduced.

Indeed, effective measures and regulations have been implemented to enable financially distressed firms to restructure and trade their NPLs rather than go into liquidation. The government of Rwanda through the National Bank of Rwanda (NBR) established the Economic Recovery Fund (ERF) to help sectors such as hotels and transport that were hard hit by COVID-19 to recover. Under ERF, the government paid 35 per cent of the outstanding loans on behalf of the hotels that had performing loans and adhered to the ERF guidelines, and this was to be repaid after recovery at an interest rate of 5 per cent. For this reason, there is a need to assess the impact of loan restructuring on the quality of bank assets in Rwanda. Despite the relevance of this topic, no study has been conducted in the case of Rwanda.

Most of the previous empirical work has focused on emerging and developed economies. (G. De Nicolo, 2001),(Imbierowicz & Rauch, 2014) for the United States of America.(Chortareas, Girardone, & Ventouri, 2012),(Kim, 2015), (Thorsten, Heiko, Thomas, & Natalja, 2009) for Europe and (Tan, 2016),(Zolkifli, Hamid, & Janor, 2015) for the Asian Economies. This paper, therefore, extends the existing stock of literature by focusing on Rwanda. The novelty of this research lies in the fact that this study has never been conducted before in the case of Rwanda, resulting in a lack of empirical evidence. Bias-corrected panel estimators are adopted to empirically assess the impact of bank loan restructuring on the quality of bank assets, estimators that are suitable for small macro-panels. The main results indicate that restructured loans, non-interest income, and return on equity are important factors that lower credit risk and improve the quality of banks' assets, while the ratio of total deposits to total assets, the ratio of loan loss provisions and bank size increase credit risk and diminish the quality of bank assets.

The rest of the paper is structured as follows. Section 2 presents an overview of loan restructuring in Rwanda. Section 3 reviews the empirical literature on the impact of loan restructuring on the quality of bank assets. Section 4 elaborates on the empirical models used in the study. Section 5 reports the estimation results. Section 6 provides conclusions and policy recommendations.

2 Stylized Facts of Loan Restructuring in Rwanda

Generally, the restructuring of loans involves altering the characteristics of the initial credit contract, in terms of interest rate, maturity or grace period relating to borrowers who have difficulties reimbursing debt, to help them meet their timely payment obligations. As a result of the restructuring measures, the debtor must return to the normal repayment parameters. In Rwanda, banks restructure credit facilities in accordance with Regulation nř12/2017 of 23/11/2017 on credit classification and provisioning. According to this regulation, a restructured credit facility is a facility which has been refinanced, rescheduled, rolled over, or otherwise modified because of weaknesses in the borrower's financial position or the non-payment of the debt as arranged.

Prior to COVID-19, the outstanding restructured stood at 31.6 percent at the end of December 2019 from 30.4 percent in December 2018, 28.8 percent in December 2017 and averaged 23.2 percent between December 2015 and December 2019. The restructured loans substantially increased during the COVID-19 period. To navigate through the pandemic, the NBR took a wide range of measures aimed at supporting financial intermediation and maintaining the stability of the financial sector. The measures that were taken by the NBR included for example easing the loan repayment conditions to borrowers affected by COVID-19 pandemic. The NBR allowed banks to exceptionally restructure outstanding loans of borrowers affected by the COVID-19 pandemic.

Normally, banks are allowed to restructure loan facilities to a maximum of 2 times. In such difficult times, where business is affected, banks agreed to assess case by case borrowers requests and restructure their loan facilities if its determined that their cash flows were affected by the COVID-19 shock. Subsequently, the demand for credit restructuring increased significantly and banks responded to the pandemic by offering loan repayment deferrals for customers affected by the crisis through loan restructuring. As at end December 2020, total outstanding restructured loans amounted to FRW 1,215 billion (51.1 percent of total banks loans) out of which the biggest portion worth FRW 799.9 billion (31.7 percent of total loans) were COVID-19 related (Figure 1). The resumption of economic activities in 2021 supported the improvement of businesses and normalization of loan payment. The credit relief measures, which had been in place for eighteen months from April 2020, expired in September 2021. The phasing out of the credit payment moratorium was made on basis of the economic recovery and aimed at preventing the forbearance to be in place for too long and causing moral hazard risks. In fact, 88.9 percent of loans that were restructured due to COVID-19 had resumed as at end December 2021.

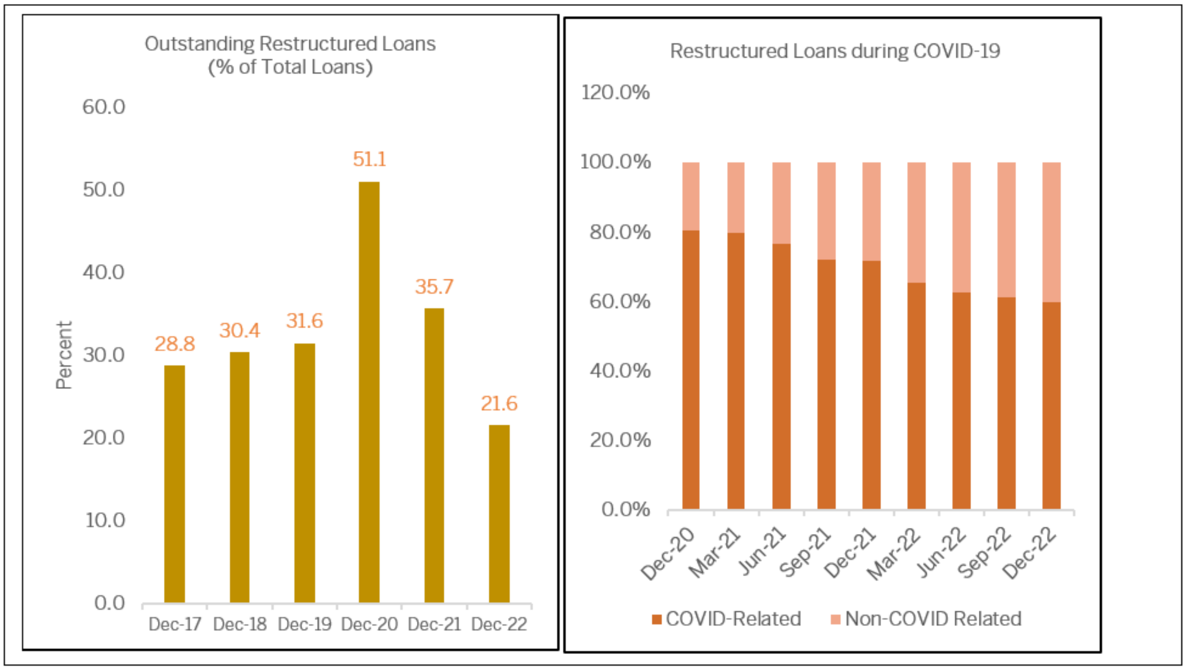

Figure 1: **Trend of Outstanding Restructured Loans in Banking Sector**
Source:NBR, Financial Stability

The decision by the NBR to grant exceptional permission to restructure loans of distressed borrowers due to COVID-19 prevented a one-off increase of non-performing loans (Figure 2) due to the shock and allowed banks to determine and classify assets based on the long-term impact of the pandemic. The quality of assets relatively remained and abrupt increase in provisional expenses was avoided. This in turn had a positive impact on the profitability of banks. Historical trends depict that NPL ratio and restructure loans somehow move in opposite direction which implies that the increase of restructured loans plays a role in containing credit defaults. In contrast, the profitability of banks measured by the Return on Equity (ROE) is negatively correlated with non-performing loans. The higher the NPL ratio, the lower the ROE and vice versa (Figure 2).

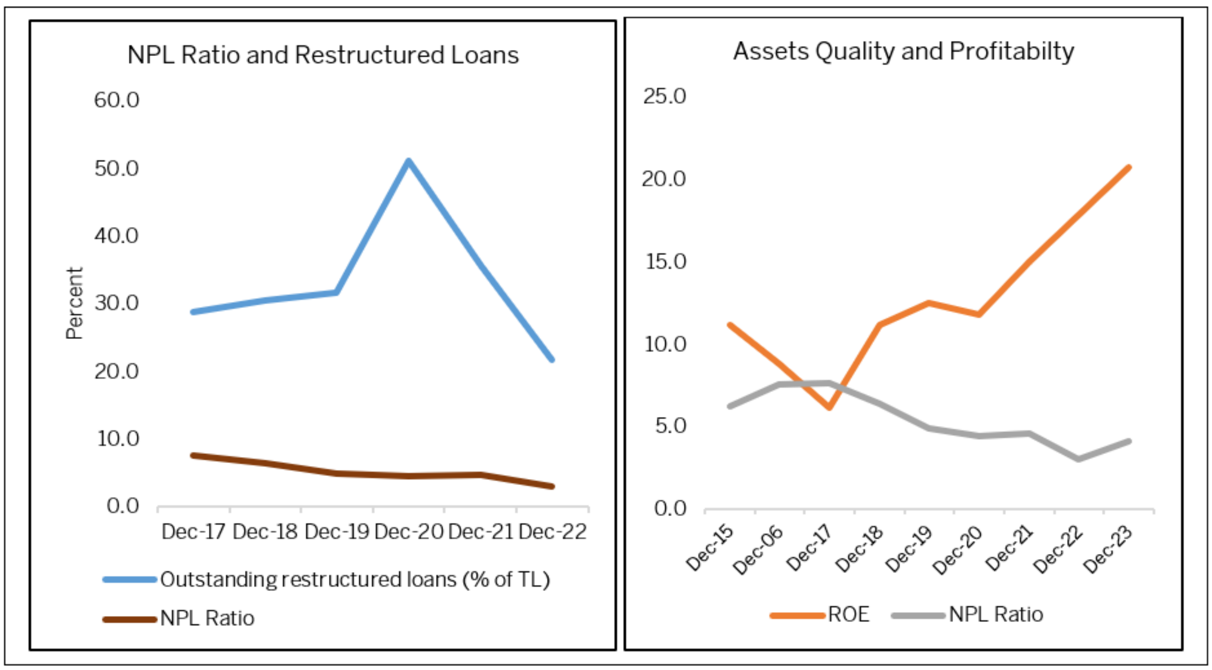

Figure 2: **Assets Quality, Restructured Loans and Profitability of the Banking Sector**
Source:NBR, Financial Stability

3 Literature Review

3.1 Theoretical literature

Theoretically, loan restructuring is defined as transforming a loan with different terms from its original terms (Nugroho & Trinugroho, 2023). Generally, this is done to help borrowers who have financial difficulties in paying off their loans. They further indicated that loan restructuring can affect credit risk, depending on the type of restructuring being done. When loan restructuring is done appropriately by reflecting the borrower's capacity to pay back the loan and revising the loan terms to make it more realistic for the borrower to pay off, credit risk can be diminished. This is because loan restructuring can help borrowers avoid late payments or defaults.

Different researchers such as Nugroho and Trinugroho (2023) and Rachmadi and Suyono (2021) distinguished various types of loan restructuring that can be done, among others:(1) Extension of the loan term (tenor): this restructuring is realized by widening the loan term in order to reduce the monthly instalment. However, extending the loan term will expand the amount of interest that must be paid back in the end.(2) Deferral of principal and interest payments: this form of restructuring offers flexibility to borrowers by deferring the payment of principal and interest for a certain period. However, this deferral is mostly followed by higher interest rates in the future. (3) Conversion of interest type: This restructuring is done by modifying the fixed interest charged on the loan, for example, to floating interest or vice versa. This is used to adjust the installment payment to the borrower's financial ability. (4) Partial debt forgiveness: This sort of restructuring is done by forgiving some of the borrower's debt so that the amount of debt to be paid becomes smaller and is usually given to borrowers who are facing severe financial difficulties. Combination of several types of restructuring: This category of restructuring is performed by combining two or more forms of restructuring to provide the best resolution for borrowers who are undergoing financial difficulties.

Nugroho and Trinugroho (2023) further contend that loan restructuring can affect non-performing loans (NPLs) both positively and negatively, depending on how the restructuring process is implemented. Loan restructuring can decrease the number of NPLs of banks by extending the repayment period of loans that were initially due and offering other opportunities to debtors to pay off their loans, thus recovering their financial performance. However, loan restructuring can also have a negative impact on NPLs if it is not followed by a careful evaluation of creditworthiness resulting to the rise in NPLs.

3.2 Empirical Literature

Broadly speaking, the empirical literature on the impact of loan restructuring on the quality of bank assets is premised on the financial intermediation theory and is mixed at best. Several studies have suggested that financing risky projects leads to an increase in non-performing loans that diminish bank liquidity, resulting in the banks' inability to meet depositors' demand for funds (Laeven, 2011; Gorton & Metrick, 2012; He & Xiong, 2012). In banking literature, several measures have been used as a proxy for credit risk. However, the conventional and the most used indicator is the NPLs ratio .

As a matter of fact, Previous studies have used NPLs as a proxy for credit risk (M. G. De Nicolo, Boyd, & Jalal, 2006; González, 2005; Horiuchi & Shimizu, 2001; Jiménez, Lopez, & Saurina, 2013; Jiménez, Ongena, Peydró, & Saurina, 2014). The NPLs are an ex-post measure of credit risk, and credit risk is one of the major risks faced by a bank. A bank's credit risk-taking affects not only its operational ability but also its profitability and liquidity. Previous studies have systematically explored the determinants that affect a bank's risk.

In a sample of 488 Italian banks over the period of 20072013, Cucinelli (2015) found that credit risk exerts a negative impact on bank lending behaviour. In this study, NPLs and loan loss provision ratio are used as measures of credit risk. In the same vein, Athanasoglou, Brissimis, and Delis (2008), using panel data analysis on Greek banks for the period 19852001, show that credit risk significantly decreases bank profitability. The authors explained this result by the risk-averse strategy adopted by Greek banks so as to maximize their profits. Berríos (2013) used a sample of 40 banks observed during the period of 20052009 to analyze the linkage between credit risk and profitability and liquidity. Empirical findings show a negative association between less prudent lending and net interest margin. Noman, Pervin, Chowdhury, Hossain, and Banna (2015), in a sample of 18 banks over the period 2003-2013, investigated the impact of credit risk on profitability in Bangladesh, and the results indicate that credit risk significantly depresses bank profitability. Laryea, Ntow-Gyamfi, and Alu (2016), in a sample of 22 Ghanaian banks covering the period of 20052010 investigated the effect of NPLs on bank profitability and confirmed the negative relationship. To minimize future losses, Teresienė, Keliuotytė-Staniulėnienė, and Kanapickienė (2021) suggest loan restructuring is crucial for the banking system to prevent future losses and emphasize that it is key to remember that loan restructuring should be done carefully and after carefully considering the borrower's financial ability because restructuring done carelessly can have adverse impact in the long run.

In their study, Nugroho and Trinugroho (2023) analyzed the effect of loan restructuring on credit risk in rural banks and Islamic microfinance banks in Indonesia, using Panel data and cross-sectional observations spanning the period 2020 - 2022. They used NPLs as the dependent variable; the explanatory variables are the number of banks that restructured their loans, the amount of restructured financing, the financing amount, and the capital adequacy ratio (CAR). Their findings revealed that the loan restructuring decreases the NPLs for rural banks. The increased financing amount deteriorates NPLs while the rise in CAR reduces them. On the other hand, the study did not find a significant impact of restructuring on Sharia rural banks, which are Islamic microfinance banks. Hence, it is imperative for banks to conduct a careful evaluation of creditworthiness before loan out and to actively monitor asset quality and possible credit risks that occur over time.

Ahamed and Mallick (2017) examined how the amount of restructured assets at the bank level affected the asset quality of Indian banks over the period 20032012. Their results suggested that higher levels of restructured assets substantially lowered risk-taking, especially for banks that had lower loan loss provisions. In addition, by restructuring distressed assets, public sector banks gained more in improving their stability than private sector domestic and foreign banks. As a policy implication, the authors proposed that similar regulatory support in the absence of a strong legal system is crucial to prevent bank fragility in other emerging market economies.

(Rachmadi & Suyono, 2021) analyzed the credit restructuring phenomenon of MSMEs in Indonesia and its effect on banking financial performance during the Covid-19 pandemic. This research used a comparative descriptive study which is a type of descriptive research. Their results revealed that credit restructuring reduced loan loss provisioning, which can improve bank profitability. Loan restructuring can also shrink NPLs which are an indicator of the soundness of a banking sector. Other researchers also found that loan restructuring affects positively profitability and NPLs of the banking sector in Indonesia and Uganda. This result of literature is line with Ahamed and Mallick (2017); Disemadi and Shaleh (2020) and Aketch and Musoke (2021). However, loan restructuring can also have a negative impact on NPLs if it is not followed by a careful evaluation of creditworthiness, resulting in a rise in NPLs. Mamatzakis, Matousek, and Vu (2016) incorporate the issues of loan restructuring in Japan and find that higher restructured loans are associated with a decline in bank efficiency and asset quality. Chiorazzo, D'Apice, Morelli, and Puopolo (2017) based on a panel of 1,116 observations from 2006-2014 for 124 banks from 21 European countries using dynamic panel data to investigate the link between real economy and credit markets, focusing on bank-specific factors such as total gross loans to total assets and credit risk show that bank-specific variables are found to have only a limited impact on NPLs, whilst the country-specific factors are shown to have a statistically significant impact.

4 Methodology

4.1 Empirical Model

This paper follows a dynamic panel data approach, where the behaviour of cross-sectional units is observed over time, providing a solution to accommodating the joint occurrence of dynamics and unobserved individual heterogeneity in assessing the impact of loan restructuring on the quality of the bank assets in Rwanda. Considering a homogeneous dynamic panel data model of order ρ

$$y_{it} = \alpha_i + \sum_{s}^{\rho} \gamma_{is} y_{it-s} + x_{it}\beta + \epsilon_{it} \tag{1}$$

where $t = 1, .., T$ are the cross-section and time-series dimension, respectively and y_{it} is the dependent variable, x_{it} is a $(1 \times (k - \rho)$ vector of strictly exogenous explanatory variables, where k is the total number of time-varying regressors, and is an unobserved individual effect that may be correlated with x_{it} and ϵ_{it} is the error term, assuming that it is serially uncorrelated, both within and over cross-sections. To simplify the notation, we assume that the initial values $(y - (\rho - 1), ..., y_{i0}$ are observed such that T is the actual time series dimension available for estimation. Several dynamic panel data estimators, such as the Generalized Methods of Moments (GMM) estimator by Holtz-Eakin, Newey, and Rosen (1988) and Arellano and Bond (1991) suffer from the problem of weak instruments when there is strong persistence in data as demonstrated by Blundell and Bond (1998). To address this issue, the system GMM was developed, and it has been the most frequently used method albeit the fact that (Bun & Windmeijer, 2010) show that it also suffers from weak instruments problem when the variance of the fixed effects is larger than that of the idiosyncratic errors. In addition, GMM estimators are not appropriate for small macro-panels. Due to this weakness, a group of bias-corrected within estimators have been proposed. Kiviet (1995), and Judson and Owen (1999) suggest bias-corrected estimators as suitable alternatives. However, they also appear to correct the bias on the basis of the unknown parameters and to correct this (Bun & Carree, 2005) proposed an alternative bias-corrected estimator which iteratively solves the non-linear equation with regard to unknown parameters. The adjusted profile score is transformed into non-linear methods and the underlying equations are similar to those of Dhaene and Jochmans (2016) estimator when fixed effects assumption for the exogenous regressors is considered. In line with the BC-LSDV of Bun and Carree (2005), we employ a recently developed bias-corrected method of moments (BC-GMM) estimator for linear dynamic panel data models by Breitung, Kripfganz, and Hayakawa (2022). It directly corrects the dynamic panel data bias, known in the literature as the Nickel bias of the conventional fixed effects estimator by retaining a small variance of the FE estimator compared to GMM estimators and analytically corrects the first-order condition of the FE estimator, leading to a set of non-linear moment conditions that can be optimized with conventional numerical methods such as Gauss-Newton, supports higher order autoregressive models, the associated standard errors are robust to cross-section dependence and does not necessitate a consistent estimator for initialization for bias approximation like in (Kiviet, 1995). From equation (1), we Stack the observations over time and cross-sections and obtain:

$$y = W\delta + D\alpha + \epsilon \tag{2}$$

where y is the $(NT \times 1)$ vector stacking the observations, $y_{it,w} = (y-1, \ldots.., y-\rho, X)$ is the $(NT \times 1)$ is the matrix stacking observations on the lags of the dependent variable $y_{it-1}, y_{it-\rho}$ and the exogenous explanatory variables $X_{it}\delta = (\gamma', \beta')'$ is the $K \times 1$ parameter vector of interest, and D is a $NT \times N$ dummy variable matrix calculated as $D = I_N \bigotimes \iota_T$ with a $T \times 1$ vector of ones. The variance-covariance matrix ϵ is denoted as Σ. Let $M_D D = I_N \bigotimes (I_T - D(D'D)^{-1}D')$ implies the symmetric and idempotent matrix that transforms the data into deviations from individual specific sample means $M_D D = 0$, the individual effect α can be eliminated from the model by multiplying equation (2) by M_D.

$M_D y = M_D W\delta + M_D D\alpha + M_D\epsilon$,

$$\tilde{y} = W\delta + \tilde{\epsilon} \tag{3}$$

$\tilde{y} = M_{Dy}$ indicates the centered dependent variable and similarly for the other variables. The least squares estimator δ in equation (3) defines the FE estimator:

$$\tilde{\delta} = (\tilde{W}'\tilde{W})^{-1}\tilde{W}'y' = (W'M_D W)^{-1}W'M_D y \tag{4}$$

We further need the bootstrap algorithm to correct the bias of the FE estimator is an extended version of the approach presented in (Everaert & Pozzi, 2007). The underlying idea is that the FE estimator δ is biased but still an unknown function of the true parameter vector, which implies that:

$$E(\hat{\delta}|\delta, \sum, T) = \int_{-\infty}^{+\infty} \hat{\delta} f(\hat{\delta}|\delta, \sum, T) d\hat{\delta} \neq \delta \tag{5}$$

with E being the expected value and f the probability distribution of $\hat{\delta}$ for given population parameter vector δ, the covariance matrix of the error terms $\sum$, and sample size T. If we can generate a sequence $(\hat{\delta}_1 \ldots. \hat{\delta}_j|\delta, \bar{\sum}, T)$ of J biased FE estimates $\hat{\delta}\delta$, the integral in equation (5) can be written as

$$\sum(\hat{\delta}|\delta, \sum, T) = \lim_{j\to\infty} \frac{1}{J} \lim \sum_{j=1}^{J} \hat{\delta}_j|\delta, \sum, T \tag{6}$$

Equation (6) suggests that an unbiased estimator δ can be obtained as the value δ^{bc} that yields the FE to have a mean of $\hat{\delta}$ over the J repeated samples. Formally,δ^{bc} is an unbiased estimator for δ if it satisfies

$$\hat{\delta} = \lim_{j\to\infty} \frac{1}{J} \lim \sum_{j=1}^{J} \hat{\delta}_j|\hat{\delta}^{bc}, \sum, T \tag{7}$$

The proposition in (Everaert & Pozzi, 2007) is that for any specific value of δ^*, the condition in equation (7) can be evaluated by generating J bootstrap samples from the data-generating process in equation (2) and applying FE to each of the samples to obtain the sequence $(\hat{\delta_1}, ..., \hat{\delta^*}, \sum, T)$ The bias-corrected $\hat{\delta^{bc}}$ can then be obtained by searching over different parameter values δ^* until equation (7) is satisfied. Everaert and Pozzi further suggest that the search $\hat{\delta^{bc}}$ can be performed well in iteration to update the parameter vector δ^* used for the creation of bootstrap samples, taking the original biased FE estimate as the initial best guess $(\delta_0^* = \hat{\delta})$. To hold various distributional assumptions about the error term ϵ_{it}, the bootstrap algorithm includes several parametric error sampling and non-parametric error resampling options. All of which rely in some way on the rescaled error terms ϵ_{it}^r

$$\epsilon_{it}^r = \epsilon_{it} = \sqrt{\frac{NT}{NT - k - N}} \tag{8}$$

where rescaling is necessary to correct for the fact that the estimated error terms $\hat{\epsilon_{it}}$, obtained in the bootstrap algorithm, have a lower variance than the population error terms $\hat{\epsilon_{it}}$.

4.2 Estimation Strategy

To investigate the impact of bank loan restructuring on the quality of bank assets in Rwanda, we utilize the bias-corrected generalized method of moments (BC-GMM) estimator for linear dynamic panel models by Breitung et al. (2022) which is appropriate for correcting the dynamic panel bias. The model is thus specified as:

$$asset\_qual_{it} = \alpha_0 + \beta_1 asset\_qual_{it-1} + \phi_2 rl_{it} + \theta fin\_stab_{it} + \gamma X_{it} + \epsilon_{it} \tag{9}$$

Where the dependent variable $asset\_qual_{it}$ is proxied by the non-performing loans ratio. The ratio of non-performing loans (NPLs), Z_score. the ratio of restructured loans to total loans (RL) is the main explanatory variable; fin_stab represents financial stability indicators that reflect bank profitability, and these include three measures, which are return on assets and return on equity used in this study as explanatory variables. X_{it} represents control variables. $\alpha, \beta, \phi, \theta$ and γ are parameters to be estimated while ϵ_{it} is the error term. The subscripts $i = 1, ...N$ and $t = 1, ...N$ refer to the cross-section and time series dimensions of the data, respectively.

The ratio of NPLs used as a proxy of credit risk/asset quality, shows the extent to which a bank is prone to variations in the repayment behaviour of its borrowers. Higher non-performing loans to total loans signify high borrower default and a higher likelihood of bank insolvency.

The bank Z-scores is used as a proxy of bank insolvency and captures the probability of default of a countrys banking system. The Z-score relates a firms capital level to the variability in its return on assets (ROA), indicating how much variability in returns can be absorbed by capital without the firm becoming insolvent. A higher value of the z-score means lower bank risk (Moreno, Parrado-Martínez, & Trujillo-Ponce, 2022; Pham, Dao, & Nguyen, 2021). The computation of the Z-score is a kin to Lepetit and Strobel (2013); Yusgiantoro, Soedarmono, and Tarazi (2019)

$$z\_score = \frac{ROA + \frac{Equity}{Assets}}{\sigma ROA} \tag{10}$$

Return on Assets and Return on Equity are used as proxies for bank profitability and capitalization, respectively. Higher ROA signifies higher bank profitability and higher ROE implies lower leverage risk and thus higher bank capitalization.

As for the control variables, we incorporate some that are bank-specific and those that reflect macroeconomic stability. Bank funding liquidity matters in affecting bank riskiness (Rokhim & Min, 2020) and thus, we control for bank liquidity by including the ratio of total deposits to total assets (DTA). Because financial intermediation is the main activity of banks, the ratio of total loans to total deposits (LDR) is also included. We incorporate the ratio of loan loss provisions to total loans (LLP) as a control variable given that bank loan loss provisioning is expected to affect bank riskiness, the ratio of total loans to total assets (RLTA). Bank asset size (SIZE) measured by the logarithm of bank total assets is included to control for the too big to fail hypothesis in which larger banks tend to undertake higher risk (Beck & De Jonghe, 2013). Finally, bank non-interest income activities measured by the ratio of non-interest income to total income (NIN) is incoporated to control for bank income diversification, which may affect bank riskiness either positively or negatively (Hidayat, Kakinaka, & Miyamoto, 2012; Meslier, Risfandy, & Tarazi, 2017). In addition to bank-level control variables, we also include a macroeconomic indicator that may affect bank riskiness. Specifically, we include the real gross domestic product (RGDP) growth rate. Soedarmono, Machrouh, and Tarazi (2011) indicate that the role of banking reforms in strengthening financial stability might also depend on the degree of economic development. We also explore the impact of inflationary pressures on the quality of bank assets by controlling for inflation. The effect is expected to be negative because higher inflation induces higher non-performing loans and lowers the quality of bank assets, given that higher inflation erodes the purchasing power of money, making it difficult for borrowers to repay the acquired bank loans (Sufian, Kamarudin, & Noor, 2012).

4.3 Definition of Variables and Data Sources

We use bank-level quarterly data covering the period 2012Q1 -2022Q1 in a sample of fourteen commercial banks. The choice of data is informed by the availability, uniformity, and consistency of the cross-sectional units. We restricted our sample to 2022Q2 to consider the period before some banks' recent mergers. Variable definitions, measurements, and data sources are provided in the table below.

Table 1:Definition of variables and sources

Variable	**Description**	**source**
credit risks	measured by non-performing loans to total loans	Balance Sheets and profit and loss accounts of commercial banks
ROA	Return on Assets, measured as a ratio of net income to total assets. It's a measure of bank Profitability.	Balance Sheets and profit and loss accounts of commercial banks
ROE	Return on Equity, measured as a ratio of net income to total shareholder's equity. It's a measure of bank profitability	Balance Sheets and profit and loss accounts of commercial banks

RL	A ratio of restructured loans (RL) to total loans (TL), akin to (Fukuyama & Matousek, 2017)	Balance Sheets and profit and loss accounts of commercial banks
RLTA	A ratio of total loans to total assets	Balance Sheets and profit and loss accounts of commercial banks
DTA	A ratio of total deposit to total assets	Balance Sheets and profit and loss accounts of commercial banks
LDR	A ratio of total loans to total deposits as a measure of financial intermediation	Balance Sheets and profit and loss accounts of commercial
LLP	A ratio of loan loss provision to total loans	Balance Sheets and profit and loss accounts of commercial
NIN	Non-interest payments are measured by the ratio of non-interest income to total income	Balance Sheets and profit and loss accounts of commercial
Bank size	Measured by the value of total assets in the banking system	Balance Sheets and profit and loss accounts of commercial
Z-score	The bank Z-score captures the probability of defaults in a country's banking system. It is computed $z\_score = \frac{ROA+\frac{Equity}{Assets}}{\sigma ROA}$	Computed based on data from Balance Sheets and profit and loss accounts of commercial banks
Inflation	Log of Consumer Price Index	NISR and NBR
RGDP growth	Growth in Real Gross Domestic Product	National Institute statistic of Rwanda (NISR)

Source:Authors' computation

5 Empirical Results

Table 2 reports the results of the BC-GMM estimator from five models, presented in columns 2-6. The first model represents the full model, which includes all the explanatory variables in the model specification. In models 2 and 3, we include profitability measures, especially return on equity and return on assets, one at a time. Models 4 and 5 exclude insignificant variables in the preceding 3 models. The coefficients of lagged dependent variables are positive and statistically significant, suggesting that lagged values of non-performing loans ratio are key in influencing the current values of NPLs. Assessing these models in terms of the expected signs and levels of significance, model 5 provides more plausible results thus, we focus our interpretation on the parameter estimates of model 5. Turning to the main variable of interest, the coefficient of restructured loans is negative and statistically significant, implying that loan restructuring reduces credit risk, thereby boosting the quality of bank assets. This finding is consistent with Ahamed and Mallick (2017); Nugroho and Trinugroho (2023) However, where loan restructuring is not followed by a careful evaluation of creditworthiness, it could lead to high credit riskiness (Mamatzakis et al., 2016).

The coefficient of return on equity as a measure of bank profitability is negative but only marginally significant, implying that if a bank is profitable and well-capitalized, the quality of bank assets improves, leading to a stable financial system. This result is in line with Poghosyan and Čihak (2011) who indicate that European banks that have good earnings profiles are less likely to experience distress in future. The coefficient of total deposit to total assets is positively and statistically significant; this implies that an increase in this ratio suggests increased liquidity risk for banks, which could potentially lead to liquidity problems if depositors withdraw their funds en masse, rendering the banks unable to meet their obligations. This increases the risk of loan default, which diminishes the quality of bank assets. Similarly, an increase in the deposit-to-assets ratio might trigger an increase in lending if the banks choose to deploy excess deposits by issuing more loans. However, if these loans are of lower quality or riskier, it could negatively impact asset quality should borrowers default on payments. The coefficient of non-interest income is negative and statistically significant, suggesting that income earned by banks from other sources of investment other than lending activities leads to bank income diversification and contributes to banks' profitability and strengthens the banks' overall ability to absorb potential credit risk, thereby boosting the quality of bank assets.

The coefficient of loan loss provisioning[1] is positive and statistically significant, implying that provisioning for bad loans decreases the quality of bank assets, a result that corroborates Bushman and Williams (2012). The parameter estimates for the ratio of total loans to total deposits and the ratio of total loans to total assets emerge as statistically insignificant in models 1,2 and 3, a justification for dropping them in models 4 and 5. The coefficient of bank size, which is measured by the total assets of the banking system, is positive but only marginally significant, implying that when banks have high liquidity, they tend to take more risks given that their loss absorption capacity increase, leading to high credit risk and low asset quality. The inflation coefficient is positive and significant, meaning that higher inflation erodes the purchasing power of money, making it difficult for the borrowers to repay the loan, which increases the likelihood of loans becoming non-performing, thereby diminishing the quality of bank assets. This result is in line with Msomi (2022); Kjosevski, Petkovski, and Naumovska (2019)

[1] we use data that were compiled before the introduction of IFRS9 where loan provisioning was done when loans had already become non-performing

Table 2: Bias-corrected Generalized Methods of Moments Estimation Results

VARIABLES	(1) Model1	(2) Model2	(3) Model3	(4) Model4	(5) Model5
Lagged Depend Variable	0.7890***	0.7882***	0.7888***	0.7878***	0.78772***
	(0.0374)	(0.0380)	(0.0375)	(0.0379)	(0.03761)
Restructured_Loans	-0.0004**	-0.0004**	-0.0004**	-0.0004**	-0.00042**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.00021)
Return on Equity	-0.0935	-0.0739*		-0.0739*	-0.07488*
	(0.1071)	(0.0418)		(0.0417)	(0.04235)
Return on Asset	0.1172		-0.3472*		
	(0.5189)		(0.1935)		
$\frac{TotalDeposits}{TotalAssets}$	0.0288*	0.0290*	0.0297*	0.0299**	0.03229**
	(0.0160)	(0.0158)	(0.0153)	(0.0142)	(0.01436)
Non Interest Income	-0.0308**	-0.0310**	-0.0310**	-0.0310**	-0.03277**
	(0.0144)	(0.0143)	(0.0140)	(0.0143)	(0.01401)
Loan_Loss Prov	0.0100***	0.0100***	0.0099***	0.0100***	0.00982***
	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.00249)
$\frac{TotalLoans}{TotalDeposits}$	-0.0008	-0.0008	-0.0006		
	(0.0032)	(0.0032)	(0.0032)		
$\frac{TotalLoans}{TotalAssets}$	0.0058	0.0056	0.0052	0.0047	
	(0.0205)	(0.0210)	(0.0207)	(0.0197)	
Bank_size	0.0101*	0.0101*	0.0103*	0.0101*	0.01037*
	(0.0053)	(0.0052)	(0.0053)	(0.0052)	(0.00613)
Inflation	0.0912*	0.0916*	0.0925*	0.0912*	0.09325*
	(0.0500)	(0.0491)	(0.0498)	(0.0492)	(0.05223)
Z_score	0.0035	0.0035	0.0034	0.0035	0.00371*
	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.00195)
GDP_Growth	-0.0090	-0.0089	-0.0092	-0.0092	-0.00873
	(0.0131)	(0.0130)	(0.0130)	(0.0132)	(0.01295)
Constant	0.0472**	0.0475**	0.0477**	0.0466*	0.04729*
	(0.0234)	(0.0235)	(0.0241)	(0.0238)	(0.02573)
Observations	520	520	520	520	520

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' Computation

5.1 Robustness Check

We conducted a sensitivity analysis to check whether our main results are robust to the relief measures that were implemented by the government through the central bank to ensure that banks continued to lend to firms and businesses during the COVID-19 pandemic period. We created a dummy for 2020, a year when the pandemic broke out and that is when relief measures were initiated. The dummy is then incorporated into our regression. The estimated coefficient of the dummy is statistically insignificant because the effects of the shock on credit risk were insulated by the credit relief measures. Generally, other explanatory variables remain broadly in line with our main results.

VARIABLES	(1) **dumm_model1**	(2) **dumm_Model2**	(3) **dumm_Model3**	(4) **dumm_model4**
Lagged Depend Variable	0.7834***	0.7826***	0.7831***	0.78202***
	(0.0369)	(0.0376)	(0.0369)	(0.03704)
Restructured Loans	-0.0004**	-0.0004**	-0.0004**	-0.00046**
	(0.0002)	(0.0002)	(0.0002)	(0.00021)
Return on Equity	-0.0930	-0.0726*		-0.07334*
	(0.1052)	(0.0415)		(0.04216)
Return on Assets	0.1223		-0.3394*	
	(0.5120)		(0.1937)	
$\frac{TotalDeposits}{TotalAssets}$	0.0250*	0.0252*	0.0259*	0.02789**
	(0.0144)	(0.0142)	(0.0137)	(0.01315)
Non Interest Income	-0.0322**	-0.0323**	-0.0323**	-0.03392**
	(0.0146)	(0.0145)	(0.0142)	(0.01417)
Loan Loss_Prov	0.0103***	0.0103***	0.0103***	0.01021***
	(0.0030)	(0.0030)	(0.0030)	(0.00256)
$\frac{TotalLoans}{TotalDeposit}$	-0.0006	-0.0006	-0.0005	
	(0.0033)	(0.0033)	(0.0033)	
$\frac{TotalLoans}{TotalAssets}$	0.0050	0.0048	0.0044	
	(0.0208)	(0.0213)	(0.0209)	
Bank_Size	0.0096*	0.0097*	0.0098*	0.00986*
	(0.0051)	(0.0050)	(0.0051)	(0.00587)
Inflation	0.0808*	0.0812*	0.0820*	0.08230
	(0.0486)	(0.0477)	(0.0488)	(0.05074)
Z_score	0.0033	0.0033	0.0032	0.00350*
	(0.0023)	(0.0023)	(0.0023)	(0.00195)
GDP_Growth	-0.0073	-0.0073	-0.0075	-0.00699
	(0.0137)	(0.0136)	(0.0135)	(0.01349)
dumm_20	-0.0028	-0.0028	-0.0028	-0.00285
	(0.0021)	(0.0021)	(0.0021)	(0.00198)
Constant	0.0518**	0.0521**	0.0524**	0.05223**
	(0.0236)	(0.0237)	(0.0242)	(0.02633)
Observations	520	520	520	520

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source:Authors' Computation

6 Conclusion and Policy Recommendations

It has become increasingly evident that a strong and healthy banking system is a precondition for sustainable economic growth. In the recent past, the banking sector in Rwanda recorded enormous growth, albeit operating in a challenging dynamic environment and one of the key challenges has been credit risk. As a coping mechanism, many banks have had to restructure loans to help borrowers manage debt and minimize default, thereby ensuring business survival, which in turn helps financial institutions to recover their funds.

The study, therefore, assesses the effects of loan restructuring on the quality of bank assets in Rwanda. This is an important issue, especially for emerging markets and developing economies (EMDEs), given its potential to prevent financial crises resulting from rapid deterioration in asset quality. The study uses quarterly data covering the period 2012Q1 -2022Q1 in a sample of 14 banks and employs a Bias-Corrected Generalized Method of Moments proposed by Breitung et al. (2022). The study established that restructured loans, non-interest income, and return on equity are key factors that lower credit risk and improve the quality of banks' assets, while the ratio of total deposits to total assets, the ratio of loan loss provisions and bank size increase credit risk and diminish the quality of bank assets. The significant impact of loan restructuring on the quality of bank assets points to the fact that credit relief measures are crucial in averting financial crises during times of unexpected shocks that could hit the economy.

We also conducted a robustness check by including a dummy in our model to capture the impact of the credit relief measures implemented to ease loan repayment by borrowers affected by the COVID-19 pandemic. The results are not robust to the inclusion of the dummy. However, other variables remain broadly in line with the main results.

The results point to important policy recommendations, including a thorough assessment of the ability of borrowers to meet the restructured terms before the approval of the loan restructuring by focusing on the creditworthiness of borrowers, loan restructuring should target creditworthy borrowers facing transitory financial difficulties rather than those with unsustainable debt burdens, and strengthening the existing monitoring mechanisms to track the performance of restructured loans post-approval through regular follow-up to identify early warning signs of deterioration and allows for timely intervention to mitigate losses.

References

Ahamed, M. M., & Mallick, S. K. (2017). House of restructured assets: How do they affect bank risk in an emerging market? *Journal of International Financial Markets, Institutions and Money*, *47*, 1–14.

Aketch, I., & Musoke, H. B. (2021). The influence of restructuring of loan recovery on profitability of commercial banks in uganda.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The review of economic studies*, *58*(2), 277–297.

Athanasoglou, P. P., Brissimis, S. N., & Delis, M. D. (2008). Bank-specific, industry-specific and macroeconomic determinants of bank profitability. *Journal of international financial Markets, Institutions and Money*, *18*(2), 121–136.

Beck, T., & De Jonghe, O. (2013). Lending concentration, bank performance and systemic risk: exploring cross-country variation. *World Bank Policy Research Working Paper*(6604).

Berríos, M. R. (2013). The relationship between bank credit risk and profitability and liquidity. *The International Journal of Business and Finance Research*, *7*(3), 105–118.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics*, *87*(1), 115–143.

Breitung, J., Kripfganz, S., & Hayakawa, K. (2022). Bias-corrected method of moments estimators for dynamic panel data models. *Econometrics and Statistics*, *24*, 116–132.

Bun, M. J., & Carree, M. A. (2005). Bias-corrected estimation in dynamic panel data models. *Journal of business & economic statistics*, *23*(2), 200–210.

Bun, M. J., & Windmeijer, F. (2010). The weak instrument problem of the system gmm estimator in dynamic panel data models. *The Econometrics Journal*, *13*(1), 95–126.

Bushman, R. M., & Williams, C. D. (2012). Accounting discretion, loan loss provisioning, and discipline of banks risk-taking. *Journal of accounting and economics*, *54*(1), 1–18.

Chiorazzo, V., D'Apice, V., Morelli, P., & Puopolo, G. W. (2017). Economic activity and credit market linkages: New evidence from italy. *Economic Notes: Review of Banking, Finance and Monetary Economics*, *46*(3), 491–526.

Chortareas, G. E., Girardone, C., & Ventouri, A. (2012). Bank supervision, regulation, and efficiency: Evidence from the european union. *Journal of financial stability*, *8*(4), 292–302.

Claessens, S., Herring, R., Schoenmaker, D., & Summe, K. A. (2010). *A safer world financial system: Improving the resolution of systemic institutions.* International Center for Monetary and Banking Studies Geneva.

Cucinelli, D. (2015). The impact of non-performing loans on bank lending behavior: Evidence from the italian banking sector. *Eurasian Journal of Business and Economics*, *8*(16), 59–71.

De Nicolo, G. (2001). Size, charter value and risk in banking: An international perspective. *Available at SSRN 255465*.

De Nicolo, M. G., Boyd, J. H., & Jalal, A. M. (2006). *Bank risk-taking and competition revisited: New theory and new evidence.* International Monetary Fund.

Dhaene, G., & Jochmans, K. (2016). Likelihood inference in an autoregression with fixed effects. *Econometric Theory*, *32*(5), 1178–1215.

Disemadi, H. S., & Shaleh, A. I. (2020). Banking credit restructuring policy amid covid-19 pandemic in indonesia. *Jurnal Inovasi Ekonomi*, *5*(02).

Everaert, G., & Pozzi, L. (2007). Bootstrap-based bias correction for dynamic panels. *Journal of Economic Dynamics and Control*, *31*(4), 1160–1184.

Fukuyama, H., & Matousek, R. (2017). Modelling bank performance: A network dea approach. *European Journal of Operational Research*, *259*(2), 721–732.
González, F. (2005). Bank regulation and risk-taking incentives: An international comparison of bank risk. *Journal of Banking & Finance*, *29*(5), 1153–1184.
Gorton, G., & Metrick, A. (2012). Securitized banking and the run on repo. *Journal of Financial economics*, *104*(3), 425–451.
He, Z., & Xiong, W. (2012). Dynamic debt runs. *The Review of Financial Studies*, *25*(6), 1799–1843.
Hidayat, W. Y., Kakinaka, M., & Miyamoto, H. (2012). Bank risk and non-interest income activities in the indonesian banking industry. *Journal of Asian Economics*, *23*(4), 335–343.
Hoggarth, G., Reidhill, J., & Sinclair, P. J. (2004). On the resolution of banking crises: theory and evidence.
Holtz-Eakin, D., Newey, W., & Rosen, H. S. (1988). Estimating vector autoregressions with panel data. *Econometrica: Journal of the econometric society*, 1371–1395.
Horiuchi, A., & Shimizu, K. (2001). Did amakudari undermine the effectiveness of regulator monitoring in japan? *Journal of Banking & Finance*, *25*(3), 573–596.
Imbierowicz, B., & Rauch, C. (2014). The relationship between liquidity risk and credit risk in banks. *Journal of Banking & Finance*, *40*, 242–256.
Jiménez, G., Lopez, J. A., & Saurina, J. (2013). How does competition affect bank risk-taking? *Journal of Financial stability*, *9*(2), 185–195.
Jiménez, G., Ongena, S., Peydró, J.-L., & Saurina, J. (2014). Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking? *Econometrica*, *82*(2), 463–505.
Judson, R. A., & Owen, A. L. (1999). Estimating dynamic panel data models: a guide for macroeconomists. *Economics letters*, *65*(1), 9–15.
Kim, C. (2015). Liquidity risk regulation and bank performance. evidence from european bank. *Global Economy and Finance Journal*, *8*(1), 11–33.
Kiviet, J. F. (1995). On bias, inconsistency, and efficiency of various estimators in dynamic panel data models. *Journal of econometrics*, *68*(1), 53–78.
Kjosevski, J., Petkovski, M., & Naumovska, E. (2019). Bank-specific and macroeconomic determinants of non-performing loans in the republic of macedonia: Comparative analysis of enterprise and household npls. *Economic research-Ekonomska istraživanja*, *32*(1), 1185–1203.
Laeven, L. (2011). Banking crises: A review. *Annu. Rev. Financ. Econ.*, *3*(1), 17–40.
Laryea, E., Ntow-Gyamfi, M., & Alu, A. A. (2016). Nonperforming loans and bank profitability: evidence from an emerging market. *African Journal of Economic and Management Studies*, *7*(4), 462–481.
Lepetit, L., & Strobel, F. (2013). Bank insolvency risk and time-varying z-score measures. *Journal of International Financial Markets, Institutions and Money*, *25*, 73–87.
Mamatzakis, E., Matousek, R., & Vu, A. N. (2016). What is the impact of bankrupt and restructured loans on japanese bank efficiency? *Journal of Banking & finance*, *72*, S187–S202.
Meslier, C., Risfandy, T., & Tarazi, A. (2017). Dual market competition and deposit rate setting in islamic and conventional banks. *Economic Modelling*, *63*, 318–333.
Moreno, I., Parrado-Martínez, P., & Trujillo-Ponce, A. (2022). Using the z-score to analyze the financial soundness of insurance firms. *European journal of management and business economics*, *31*(1), 22–39.
Msomi, T. S. (2022). Factors affecting non-performing loans in commercial banks of selected west african countries. *Banks and Bank Systems*, *17*(1), 1.
Noman, A. H. M., Pervin, S., Chowdhury, N. J., Hossain, M. A., & Banna, H. (2015). Comparative performance analysis between conventional and islamic banks in bangladesh-an application of binary

logistic regression. *Asian Social Science*, *11*(21), 248.

Nugroho, S. P., & Trinugroho, I. (2023). Does loan restructuring play a role in increasing credit risk of rural banks during covid-19 pandemic? In *International students conference on accounting and business (iscoab)* (Vol. 2).

Pham, T. T., Dao, L. K. O., & Nguyen, V. C. (2021). The determinants of banks stability: a system gmm panel analysis. *Cogent Business & Management*, *8*(1), 1963390.

Poghosyan, T., & Čihak, M. (2011). Determinants of bank distress in europe: Evidence from a new data set. *Journal of Financial Services Research*, *40*, 163–184.

Rachmadi, F., & Suyono, E. (2021). The credit restructuring phenomenon of the msmes and its effect on banking financial performance during the pandemic of covid-19. *Agregat*, *5*(1), 37–55.

Reinhart, C. M., & Rogoff, K. S. (2011). From financial crash to debt crisis. *American economic review*, *101*(5), 1676–1706.

Rokhim, R., & Min, I. (2020). Funding liquidity and risk taking behavior in southeast asian banks. *Emerging Markets Finance and Trade*, *56*(2), 305–313.

Soedarmono, W., Machrouh, F., & Tarazi, A. (2011). Bank competition, risk and capital ratios: Evidence from asia. *Journal of Asian Economics*, *22*(6), 460–470.

Sufian, F., Kamarudin, F., & Noor, N. H. H. M. (2012). Determinants of revenue efficiency in the malaysian islamic banking sector. *Journal Of King Abdulaziz University: Islamic Economics*, *25*(2).

Tan, Y. (2016). The impacts of risk and competition on bank profitability in china. *Journal of International Financial Markets, Institutions and Money*, *40*, 85–110.

Teresienė, D., Keliuotytė-Staniulėnienė, G., & Kanapickienė, R. (2021). Sustainable economic growth support through credit transmission channel and financial stability: in the context of the covid-19 pandemic. *Sustainability*, *13*(5), 2692.

Thorsten, B., Heiko, H., Thomas, K., & Natalja, V. (2009). *Bank ownership and stability: Evidence from germany* (Tech. Rep.). IMF Working Paper 09/200). Washington, DC: IMF.

Yusgiantoro, I., Soedarmono, W., & Tarazi, A. (2019). Bank consolidation and financial stability in indonesia. *International Economics*, *159*, 94–104.

Zolkifli, N. A., Hamid, M. A., & Janor, H. (2015). Liquidity risk and performance: The case of bahrain and malaysian banks. *Global Economy and Finance Journal*, *8*(2), 95–111.