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The criticality of credit recovery in banking system stability: A GMM estimation

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ABSTRACT

This study examines the criticality of credit recovery on banking system stability in Nigeria using data from 2007 to 2020. The system generalized method of moments (SYS-GMM) was used to analyze the data and determine the presence of cointegrating relationships among the variables. The findings revealed that credit recovery positively and significantly influences banking system stability. It was discovered that the recovery rate positively and significantly impacts the banking system stability in the short and long terms. In contrast, recovery expense only negatively and significantly affects the banking system in the short term. This implies that credit recovery is critical in business endeavors and operations for banks. Hence, the longer the delay in recovering bad debts, the more banks lose the opportunity to earn income from substitute investments, and collateral may lose value. Therefore, this study recommends that banks' management aggressively pursue the repayment of bad loans and maintain favorable and minimal recovery expenses, particularly with external debt recovery agents, to ensure that the cost of recovery is not higher than the amount recovered.

Contribution/Originality: Through its empirical findings, this study discovered that credit recovery is beneficial to banks as a tool toward achieving the desired banking system stability because the negative effect of loan defaults is neutralized in the long run when recovery is achieved.

1. INTRODUCTION

The procedure for disbursing loans by banks is less cumbersome than recovering them when they are classified as bad loans. Banks often recover much less than the main principal granted to the borrower. The problem is not giving credit facilities to prospective borrowers but recovering the same facility when the borrower defaults on payment terms. Natufe and Evbayiro-Osagie (2023) opined that lending to customers is much easier than recovering the funds, which can be challenging when a default event occurs. Banks lend to as many borrowers as possible, mainly to increase their asset level. Regardless of the reasons and the number and quality of the borrowers at the point of granting the facility, the bank will become bankrupt if it fails to practice proper credit management or take prompt recovery action against borrowers at the earliest event of a default (Amadi, Adetiloye, Babajide, & Amadi, 2021; Baselga-Pascual, Trujillo-Ponce, & Cardone-Riportella, 2015).

The distress and failure of the banking system caused by bad debts are not restricted to developing countries alone; similar crises and challenges have been reported in other countries. For instance, between 1928 and 1932, 9,000 out of 27,000 banks in the United States collapsed, and up to two-thirds of their aggregate deposits were lost, which caused severe bank runs. Britain experienced a similar banking crisis in the early 1820s, when 73 of the country's key banks failed and went into liquidation. In 1884, the Bank of England made the tough decision to avert the failure of Johnson Mathey Bank (Bongini, Cucinelli, Di Battista, & Nieri, 2019; Thobias, 2019; Wang, Forbes, Fenech, & Vaz, 2020). The bank failure situation caused by defaults in loan repayments, which leads to the growth of banks' non-performing loan portfolio, is no different in developing economies. What is different, though, is the quality of reforms, strategies and policies that followed the banking crises and how effective and efficient these policies were in stabilizing the banking system.

According to Muthama and Warui (2021), reforms, policies and strategies for promptly recovering delinquent and bad loans remain the best action toward solving banking crises in most countries. Piskorski and Seru (2021) opined that the problems associated with the recovery of bad loans do not only affect the banks' specific internal factors, such as deposits, interest rate spread, loan, capital, and liquidity asset size, or weaken the assets rating, its impact has begun to have adverse effects on the banking system's macroeconomic factors. A high percentage of bad loans not recovered by banks reflects inaction, fraudulent practices, a lack of prompt strategic action toward recovery activities, and the mismanagement of individual banks' structure. The inability of banks to request valid and critical documents at the time of processing loans has caused excessive losses, as most of these documents and information are essential to prompt repayment. Inadequate databases and a lack of proper record-keeping have prevented banks from tracing defaulting customers to recover the loans. This causes a continuous rise in the default rate and the non-performing loan portfolios of banks. The consistent increase in loan defaults without having a sustainable solution has remained a complex issue (Muthama & Warui, 2021; Pradhan, Akter, & Al Marouf, 2020).

Previous literature, such as Wang et al. (2020); Thobias (2019) and Matenda, Sibanda, Chikodza, and Gumbo (2022), has focused on the value of loan recovery efficiency on bank performance, determinants of bank loan recovery rates in both prosperous and difficult times, and the possibility of default and credit risk management. However, the impact of recovery and its obvious inverse relationship with banking system stability has been neglected. Consequently, there is a lack of literature on credit recovery and banking system stability in Nigeria, and studies that link credit recovery and the extent of its impact on banking system stability in deposit money banks (DMBs) in Nigeria are particularly scarce despite its importance and critical contribution to the development of a stable financial system. This noticeable gap has been filled by this study as it establishes a correlation between the key variables, credit recovery and the banking system. It also highlights the degree of significance in this relationship and aids regulatory authorities and bank managers in making decisions to solve the lingering instability in the banking system caused by an increase in DMBs' non-performing portfolios. This study will also help to reduce the level of losses of assets experienced by banks which are caused by an increase in loan default rates.

Based on the above, this study has two objectives. First, it analyzes the relationship between credit recovery and the stability of DMBs in Nigeria from 2007 to 2020 using the system generalized method of moments (SYS-GMM). Second, the study investigates the extent of the impact of credit recovery on the banking system stability in DMBs.

The rest of the article is organized as follows: the literature review in the next section explains the theoretical framework and the hypothesis development; Section 3 describes the model, the data, and the econometric method used; Section 4 presents the empirical results; Section 5 discusses the study's findings; Section 6 offers conclusion and recommendation; Section 7 details the limitations of the study; and Section 8 provides direction for future studies.

2. LITERATURE REVIEW

Debt recovery is an essential component of banking operations. It improves a bank's liquidity and profitability because funds recovered are credited into its revenue accounts, especially if the recovery is made on accounts classified as a loss/written off by banks. This is because, before classification, a certain percentage of provisioning was made for such accounts. Non-performing loans classified as losses (where a 100% provision has been made) by the prudential guidelines are often difficult to recover. Some accounts under this category are often called hardcore bad loans or irrecoverable/uncollectable (Natufe & Evbayiro-Osagie, 2023; Rocci, Carleo, & Staffa, 2022). Studies such as Ivan (2022) and Fenech, Yap, and Shafik (2016) explain that debt recovery involves engaging the services of a third party who acts as the bank's agent to recover bad debts. In the credit recovery process, the bank's recovery officers first try to recover bad loans, and failing this, the bank may seek the services of a debt recovery agent to help recover the debts from the recalcitrant customer. If the debtor forwards a reasonable repayment proposal to the bank for consideration, the bank may agree to the debtor's request by compounding.

2.1. Management of Loan Defaults and Debt Recovery

Managing risky assets, particularly loans and advances, is an ongoing source of concern for financial market participants, bank regulators, researchers, government authorities, scholars, and financial analysts. According to Ajao and Oseyomon (2019), market conditions and risk factors are not the only causes for concern when lending to borrowers. Gaining insight into how these factors change over time is increasingly regarded as critical when making lending decisions. Specifically, it is crucial to be mindful of the likelihood of default (Li, Chen, & Yang, 2022; Rocci et al., 2022; Wang et al., 2020).

Figure 1 explains the interaction between credit recovery and banking system stability in deposit money banks (DMBs). It highlights how the recovery of bad debts improves a bank's liquidity, profitability, and performance, leading to banking system stability, solvency, and sustainability.

Legal concerns in debt recovery are vital for banks to consider. Banks' recovery teams must be aware of the inherent legal implications of all the available loan recovery techniques, and particularly the methods that the banks wish to adopt. If not, the recovery efforts could be counter-productive, leading to further losses and damage to the bank's reputation (Ivan, 2022).

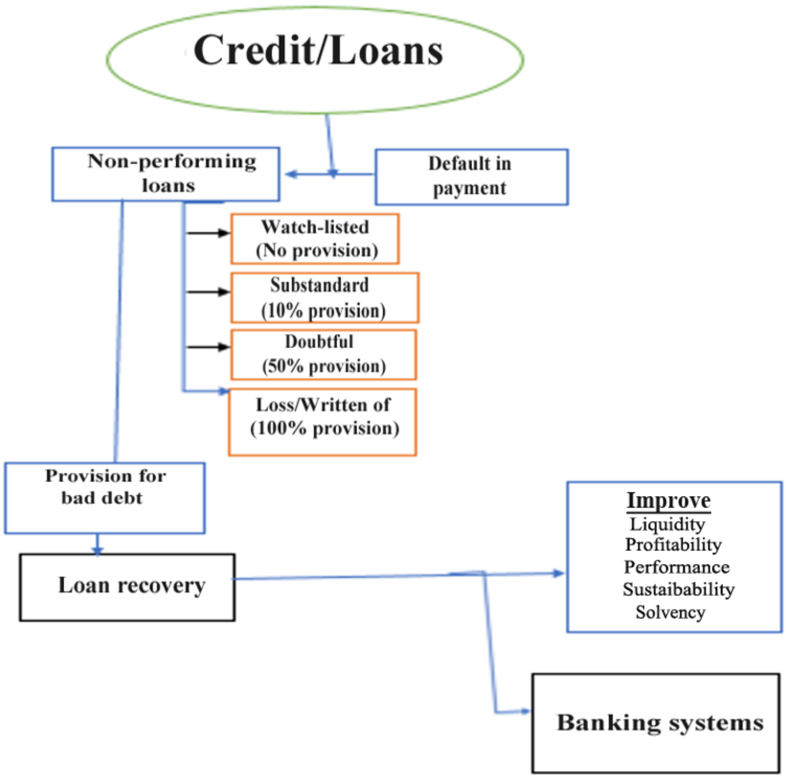

Figure 1. Credit recovery variables' interaction with the banking system.

Ironically, while few DMBs adopt orthodox debt recovery techniques, several others use unconventional techniques that contradict the rules and regulations. Nonetheless, these unconventional methods are used by banks because many debtors are poor, do not know their legal rights, or are afraid to pursue their legal rights. The danger, therefore, lies in the fact that if banks deal with debtors who know their legal rights and know the implications of the recovery actions that banks employ outside the established laws, the debtors can pursue their legal right to a substantial degree. Thus recovery officers need to be conversant with these laws and their implications, and avoid using unconventional processes of debt collection in order to avoid the banks being culpable (Bongini et al., 2019; Foglia, 2022; Koetter, Noth, & Rehbein, 2020).

2.2. Empirical Review

Li et al. (2022) extended the knowledge on the recovery of bad loans by examining commercial banks' recovery patterns concerning non-performing loans (NPLs) under centralized management in China. The empirical findings revealed that centralized management can significantly improve the collection efficiency of non-performing loans. Also, centralized management has a heterogeneous impact on contracts with different characteristics or client groups. The study further shows that the centralized management model performs better by eliminating the distance from the head office to the branch, promoting the efficient utilization of information and reducing the marginal cost of managing non-performing loans. In addition, studies such as Jayakumar, Pradhan, Dash, Maradana, and Gaurav (2018), examined the link between banking competition, banking stability and economic growth. The study adopted a panel vector error correction model (VECM) to analyze data collected for a panel of 32 European countries between 1996 and 2014. The empirical findings revealed that bank competition and stability are determinants of economic growth for European countries.

Altman, Brady, Resti, and Sironi (2005) focused on the connection between aggregated loan defaults and recovery rates on credit assets, using econometric multivariate and univariate models to analyze data from 1982 to 2002. The findings suggest that aggregated recovery rates are mainly a function of supply and demand for the securities, while default rates play a focal role. The results further revealed that low recovery rates amplify the cyclical effects when defaults are high. Wang et al. (2020) analyzed how to effectively improve the understanding of the recovery processes of corporate loans by defining the recovery rates of banks. They discovered that the factors causing variations in banks' recovery rates depend on the state of the whole credit cycle.

Matenda et al. (2022) estimated the workout recovery rates for defaulted bank loans using various amalgamations of firm features, loan characteristics and macroeconomic variables for private non-financial corporates in Zimbabwe under downturn conditions. The stepwise ordinary least squares technique was used to analyze the data, and the study's primary objective was to identify and interpret the determinants of recovery rates for private firms that defaulted in their repayment of bank loans. The study used a unique, real-life data set of defaulted bank loans for private non-financial firms for efficacy and suitability purposes. The empirical results show that collateral value, firm size, earnings before interest, tax/total assets ratio, exposure at default, total debt/total assets ratio, length of the workout process, ratio of (current assets–current liabilities)/total assets, interest rate, real GDP growth rate, and inflation rate are the significant determinants of the recovery rate of bank loans from private, Zimbabwean, non-financial firms. The study further indicates that accounting information is useful in examining the recovery rates for defaulted bank loans under distressed economic and financial conditions for private corporations. Moreover, it was discovered that the prediction results of recovery rate models increase by combining loan characteristics and firm features with macroeconomic factors.

Bellotti, Brigo, Gambetti, and Vrins (2021) employed a broad set of machine-learning algorithms and regression techniques to predict the recovery rates on non-performing loans using the private database from a European debt collection agency. The results showed that rule-based algorithms, such as boosted trees, random forests and Cubist, perform significantly better than other methods. Similarly, Ye and Bellotti (2019) focused on future recovery rates as a tool toward improving poor debt management, capital requirement calculations, risk assessment using default data, loan characteristics, previous part repayments by debtors, and data collection. The study used sets of quantitative performance methods under k-fold cross-validation to compare the factors. The results revealed that the recommended two-stage beta mixture model performed best.

Natufe and Evbayiro-Osagie (2023) focused on the credit risk management and return on equity (ROE) of Nigerian DMBs. The study adopted twelve years of data, from 2010–2021, which includes the post-adoption of the typical accounting year-end, authorized by the Central Bank of Nigeria (2009). The data set comprised the ROE, which is the dependent variable, and the independent variables include liquidity ratio (LQR), capital adequacy ratio (CAR), loan-to-deposit ratio (LDR), non-performing loans ratio (NPLR), risk asset ratio (RAR), size (SZ), and loan loss provision ratio (LLP). The study used a dynamic panel regression method, and the results show that NPLR, SZ, RAR and CAR are the significant determinants of ROE. The empirical findings revealed that Nigerian DMBs recently relied more on offshore borrowings in Eurobonds to create risk assets to overcome the Central Bank of Nigeria's (CBN's) constriction on using local depositors' funds to create risk assets. Furthermore, the outcome shows that within the study period, the shareholders of DMBs with international banking licenses were not compensated enough for their risk exposure than investors in risk-free assets (treasury bills). Therefore, it is suggested that the CBN should strengthen its regulatory roles and carry out regular reviews to improve the banks' credit risk management systems and mitigate the likely failure of the credit life cycle of granted loans. Additionally, a review of the regulatory cash reserve ratio of 37.5% will primarily reduce banks' dependence on offshore funding and its associated foreign exchange risk.

Bongini et al. (2019) investigated the key drivers of bank profitability/recovery shock, which allow banks to regain their loss of profit and avoid further severe crises. Their results suggest that half of the banks in the sample were more severely affected by the adverse macroeconomic context than the other banks. Also, banks that recovered from the profitability shock adopted stricter conservative loaning policies and managed their credit risk more effectively. Wang et al. (2020) analyzed the role of a complete set of recovery determinants using a two-state Markov switching apparatus to proxy the latent credit cycle. The study discovered that factors determining bank loan recovery rates differ and depend on the country's economic cycle.

3. METHODOLOGY

This study is underpinned by the asymmetry theory, developed in the 1970s, to emphasize the theoretical basis for the direct relationship between credit recovery and banking system stability. The theory was established to comprehend and distinguish good borrowers from bad borrowers as a complex problem that may generate moral hazard and adverse selection issues. Asymmetry theory explains further that in transactions such as lending and borrowing, the party that possesses more significant information about the market is in a superior position to negotiate better terms of the transaction than the other party.

The system generalized method of moments (SYS-GMM) technique was used to analyze the data for this study. This technique is a dynamic panel data estimator that regulates or controls for endogeneity of the lagged dependent variable when the explanatory variables correlate with the error term in the model. The reason for choosing a dynamic panel approach for this study is due to the fact that this study pools several quarterly data from the annual reports of 14 DMBs in Nigeria. Moreover, the panel is dynamic because of the divergence of risks that affect the banking system, especially credit risk and its multiple dynamic effects on the stability and survival of banks. The SYS-GMM estimator substantially improves the estimate of the effect of credit recovery on banking system stability relative to other models and makes it possible to include the lag of the dependent variable as an explanatory variable in the model to determine the dynamic nature of this study.

3.1. Model Specification

The methodical framework used for this study follows the banking system stability framework adapted from Sere-Ejembi, Udom, Salihu, Atoi, and Yaaba (2014). The framework is the composite index measure derived from a weighted mean and standardized procedure of three notable indices: banking soundness, banking vulnerability, and economic climate. These indicators are established in the framework prescribed by the International Monetary Fund's Financial Stability Indicators as follows:

$$BSSI_{\mathrm{it}} = \omega_1 BSI_t + \omega_2 BVI_t + \omega_3 ECI_t \qquad (1)$$

In Equation 1, BSSI represents the banking system stability index, w1 indicates the weight of the banking soundness index (BSI), w2 depicts the weight of the banking vulnerability index (BVI), w3 represents the weight of the economic climate index (ECI), and *t* signifies the period. However, for this study, only two out of the three banking system stability indexes (BSI and BVI) were adopted. Therefore, the model for this study is stated as follows:

$$Z\_score_{it} = \alpha_0 + \beta_1 \mathrm{LRR}_{it} + \beta_2 \mathrm{RER}_{it} + \beta_3 \mathrm{PBD}_{it} + \beta_4 \mathrm{LEV}_{it} + \beta_5 \mathrm{OPE}_{it} + \beta_6 \mathrm{BS}_{it} + \mathcal{E}_{it} \qquad (2)$$

$$EATA_{it} = \alpha_0 + \beta_1 \mathrm{LRR}_{it} + \beta_2 \mathrm{RER}_{it} + \beta_3 \mathrm{PBD}_{it} + \beta_4 \mathrm{LEV}_{it} + \beta_5 \mathrm{OPE}_{it} + \beta_6 \mathrm{BS}_{it} + \mathcal{E}_{it} \qquad (3)$$

In Equation 1, $BSSI_{it}$ signifies the vector of banking system stability during the period of study, which is proxied with the Z-score and the ratio of external assets to total assets (EATA) as dependent variables. The independent variables are loan recovery rate (LRR), recovery expense ratio (RER), and provision for bad debt (PBD), which signify the vectors of credit recovery. Leverage (LEV), operating expense (OPE), and bank size (BS) represent the control variables in the model because of their significant contribution to determining the stability of banks. α presents the intercept, β signifies the coefficient, ε represents the white noise error term, and *it* is bank one at time *t*.

Therefore, based on the theoretical framework, and following the works of Atoi (2018) and Dwumfour (2017), the study specifies the modified empirical models as follows:

$$\Delta Z\_score^1_{i,t} = \alpha \Delta Z\_score^1_{i,t-1} + \Delta\beta^1_{1,k}\Delta \mathrm{LRR}_{i,t} + \Delta\beta^1_{2,k}\Delta \mathrm{RER}_{it_{i,t}} + \Delta\beta^1_{3,k}\Delta \mathrm{PBD}_{i,t} + \Delta\beta^1_{4,k}\Delta \mathrm{LEV}_{i,t} + \Delta\beta^1_{5,k}\Delta \mathrm{OPE}_{i,t} + \Delta\beta^1_{6,k}\Delta \mathrm{BS}_{i,t} + \Delta\mathcal{E}^1_{i,t} \qquad (4)$$

$$\Delta \mathrm{EATA}^1_{i,t} = \alpha \Delta \mathrm{EATA}^1_{i,t-1} + \Delta\beta^1_{1,k}\Delta \mathrm{LRR}_{i,t} + \Delta\beta^1_{2,k}\Delta \mathrm{RER}_{it_{i,t}} + \Delta\beta^1_{3,k}\Delta \mathrm{PBD}_{i,t} + \Delta\beta^1_{4,k}\Delta \mathrm{LEV}_{i,t} + \Delta\beta^1_{5,k}\Delta \mathrm{OPE}_{i,t} + \Delta\beta^1_{6,k}\Delta \mathrm{BS}_{i,t} + \Delta\mathcal{E}^1_{i,t} \qquad (5)$$

Equations 4 and 5 represent the cross-sectional and the panel time dimension of the category of banks listed on the Nigerian Exchange. $\mathcal{E}_t$ indicates the stochastic error term, *t* is the time period measured, and α represents the intercept that describes the banking system stability when the independent variables are equivalent to zero.

The Sargan test and standard errors are usually downward biased whenever the instrument lists are equal to or more than the cross-sectional units (Arellano & Bond, 1991).

$$\Delta Z\_score^1_{i,t} = \alpha \Delta Z\_score^1_{i,t-1} + \Delta\beta^1_{1,k}\Delta \mathrm{LRR}_{i,t} + \Delta\beta^1_{2,k}\Delta \mathrm{RER}_{it_{i,t}} + \Delta\beta^1_{3,k}\Delta \mathrm{PBD}_{i,t} + \Delta\beta^1_{4,k}\Delta \mathrm{LEV}_{i,t} + \Delta\beta^1_{5,k}\Delta \mathrm{OPE}_{i,t} + \Delta\beta^1_{6,k}\Delta \mathrm{BS}_{i,t} + \beta^1_{6,k}\mathrm{X}^1_{6,k} + \Delta\mathcal{E}^1_{i,t} \qquad (6)$$

$$\Delta \mathrm{EATA}^1_{i,t} = \alpha \Delta \mathrm{EATA}^1_{i,t-1} + \Delta\beta^1_{1,k}\Delta \mathrm{LRR}_{i,t} + \Delta\beta^1_{2,k}\Delta \mathrm{RER}_{it_{i,t}} + \Delta\beta^1_{3,k}\Delta \mathrm{PBD}_{i,t} + \Delta\beta^1_{4,k}\Delta \mathrm{LEV}_{i,t} + \Delta\beta^1_{5,k}\Delta \mathrm{OPE}_{i,t} + \Delta\beta^1_{6,k}\Delta \mathrm{BS}_{i,t} + \beta^1_{6,k}\mathrm{X}^1_{6,k} + \Delta\mathcal{E}^1_{i,t} \qquad (7)$$

Equations 6 and 7 represent the "restricted" GMM model where bank-specific variables are included in the baseline techniques, one after another. $\mathbb{X}^l_{i,t-k}$ are the *ith* cross-sectional bank specific variables at time *t*. The other explanatory variables are as defined earlier. The general validity of the instruments is tested using the Sargan specification test propounded by Arellano and Bond (1991) and Blundell, Bond, and Windmeijer (2000).

3.2. Data Sources and Operationalization

The variables employed in this study are built on numerous existing works and the theoretical viewpoints of studies such as Wang et al. (2020); Sere-Ejembi et al. (2014); Altman et al. (2005) and Offiong and Egbuka (2017).

Data were sourced from the banks' audited annual accounts, the World Development Indicators, and the Central Bank of Nigeria's Statistical Bulletin from 2007 to 2020. This period was chosen due to the availability of complete data and to capture the effect of recovery on the change over the years on the banking system during the global financial crises and domestic financial reforms. The system generalized method of moments (SYS-GMM) technique has always been superior and more efficient than other methods, such as Modigliani–Miller (MM) and ordinary least squares (OLS), because the GMM is seen to be more advanced.

4. EMPIRICAL RESULTS

The descriptive statistics test, pairwise correlation test, and correlation tests were conducted to determine the likelihood of the presence of multicollinearity among the variables. The correlation test also indicates if the linear relationship in the sample data set is solid and robust enough to be used for modelling the relationship of the regressors in the sample.

Table 1. Variable identification, measurement, and A priori.

Variable	Measurement	Literature support	Data source	A priori
Z-score	Return on assets (ROA), Equity/Asset ratio, (R/E), and (σ(ROA))	Atoi (2018)	The CBN's Annual Statistical Bulletin	> 0
EATA	External assets to total assets	Sere-Ejembi et al. (2014)	The CBN's Annual Statistical Bulletin	> 0
Loan recovery rate (LRR)	Loan recovery (LR) or collectables/NPL + written-off loans {(LRR) = LR/NPL + WL)}	Altman et al. (2005)	DMBs' annual audited accounts	> 0
Recovery expense ratio (RER)	Total amount recovered divided by its total expenses multiplied by 100	Sopitpongstorn, Silvapulle, Gao, and Fenech (2021)	DMBs' annual audited accounts	< 0
Provision for bad debt (PBD)	Total bad debt over total accounts receivable divided by 100	Offiong and Egbuka (2017) and Umoh (1994)	DMBs' annual audited accounts	< 0
Leverage (LEV)	Total assets over total equity	Gabriel, Victor, and Innocent (2019)	DMBs' annual audited accounts	< 0
Operating expense (OPE)	Expenses over revenue	Ugoani (2016)	DMBs' annual audited accounts	< 0
Bank size (BS)	The natural logarithm of the value of total assets in dollars	Kingu, Macha, and Gwahula (2018)	DMBs' annual audited accounts	> 0

Table 1 contains the descriptive statistics. The results show that PBD has the lowest standard deviation among the variables. This means that the decrease or increase of PBD by deposit money banks concerning the bank's stability is inelastic. The implication is that an increase in the level of provision for bad debt if the credit is not recovered in a timely manner can affect bank performance, liquidity and profitability and could lead to instability. This is dependent on the risk culture and risk appetite of that bank. The LRR has the highest maximum standard deviation value, which signifies that the deficits or shortfall in the loan recovery rate is unpredictable and could be high or low. Table 1 also shows that the LRR has a high mean, which indicates payment challenges for customers.

Table 2 reveals that OPE has a minimum value of 11% and a maximum value of 41%. The results further reveal that EATA and PBD mirror a normal distribution since their skewed values are 0.200 and -0.425, respectively, while their kurtosis values are 2.867 and 3.20. For the data to be normally distributed, the kurtosis value must be 3, and the skewness value must be 0. Therefore, it can be concluded that EATA and PBD are mesokurtic. This implies that their distribution is symmetric around the mean. The skewed figures for LRR and LEV are 0.608 and 1.166, meaning that they have a long right tail (positively skewed). The kurtosis values for LRR and LEV are 4.077 and 4.874, meaning that they are leptokurtic. Leptokurtic is a measure of the peakedness or flatness of a curve that reveals the distribution of the series. Since 4.077 and 4.874 are higher than 3, which is the normal distribution figure, the individual curves for LRR and LEV are peaked rather than flat, as with EATA or PBD.

Table 2. Summary statistics of the regressors.

Variable	Mean	Std. dev.	Min.	Max.	Skewness	Kurtosis
ZSCORE	3.937	0.372	3.19	4.907	0.884	2.976
EATA	28.236	7.755	10.9	47.39	0.2	2.867
LRR	73.494	21.828	23.1	166.8	0.608	4.077
PBD	9.742	0.319	7.976	10.882	-0.425	3.20
RER	1.669	0.733	0.39	3.59	0.502	2.609
LEV	10.975	0.914	9.495	13.815	1.166	4.874
OPE	14.438	8.333	0.11	40.76	-0.182	2.899
BS	3.995	0.647	1.946	5.283	-0.537	2.897

The Z-score calculates the degree of a bank's soundness, and its distance from insolvency (Sopitpongstorn et al., 2021). The popularity of the Z-score is derived from the established inverse relationship that it has with the probability of the insolvency of financial institutions. It is computed with three essential soundness indicators: return on assets (ROA), equity/assets ratio (R/E), and the standard deviation of return on assets (σ(ROA)). LnZSCORE represents the lag of the Z-score, LnEATA is the lag of external assets to total assets, LnRER signifies the lag of recovery expense ratio, LnPBD is the lag of provision for bad debt, LnLEV represents the lag of leverage, LnOPE signifies the lag of operating expense, LnBS represents the lag of bank size, and LnLRR is the lag of the loan recovery rate.

Table 3. Correlation matrix of regressors.

Variable	ZSCORE	EATA	LRR	PBD	RER	LEV	OPE	BS
ZSCORE	1.000							
EATA	0.474	1.000						
LRR	0.342	0.426	1.000					
PBD	0.097	0.140	0.095	1.000				
RER	0.088	0.277	0.129	0.708	1.000			
LEV	0.254	0.129	-0.063	0.163	0.154	1.000		
OPE	-0.268	-0.082	-0.326	-0.304	-0.309	-0.019	1.000	
BS	0.184	0.311	-0.008	0.424	0.525	0.195	-0.197	1.000

Table 3 presents the correlation matrix, which calculates the presence of multicollinearity among the regressors. The correlation coefficient test is carried out to check the direction and strength of the linear association among the regressors used in the model. As presented in Table 2, the Z-score, the ratio of external assets to total assets, the loan recovery rate, the recovery expense ratio, the provision for bad debt, leverage, and operating expense do not have a strong correlation. The implication is that perfect multicollinearity does not exist between the regressors selected for the model, suggesting that the variables fit the model well. This agrees with the a priori expectation.

Table 4. Correlation significance matrix.

Variable	ZSCORE	EATA	LRR	PBD	RER	LEV	OPE	BS
ZSCORE	1.000							
EATA	0.4747* 0.000	1.000						
LRR	0.342*** 0.000	0.426* 0.000	1.000					
PBD	0.097 0.160	0.140* 0.042	0.095 0.170	1.000				
RER	0.088 0.204	0.277* 0.000	0.129 0.062	0.707* 0.000	1.000			
LEV	0.254* 0.000	0.129 0.061	-0.063 0.365	0.163* 0.018	0.154* 0.026	1.000		
OPE	-0.268* 0.000	-0.082 0.234	-0.326* 0.000	-0.304* 0.000	-0.309** 0.000	-0.019 0.783	1.000	
BS	0.186* 0.008	0.311* 0.000	-0.008 0.911	0.424* 0.000	0.525** 0.000	0.196* 0.005	-0.197* 0.004	1.000

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

The coefficient values of the variables in Table 4 indicate that the data is a good fit, and the model is suitable for analysis. Furthermore, the coefficient values reveal that although the regressors do not have a strong linear association with each other, a level of significance exists in their relationship with each other.

Table 5 indicates the pooled OLS and fixed effects results for Model 1. The result shows that the parameter value of the lagged dependent variable (Φ) is 0.9257 for the pooled OLS and 0.5800 for the fixed effects. According to Bond (2002), the pooled OLS value should be recognized as the upper bound estimate, and the fixed effects value should be recognized as the lower bound estimate. Table 5 further reveals that the number of observations is 150, and the number of groups is 15. The R-squared values for both estimations are 0.8517 and 0.7952, respectively.

Table 5. Pooled OLS and fixed effects estimation for Model 1 (Z-score).

Dependent var. (Z-score)	**Pooled OLS**	**Fixed effects**
Variable	**Coefficient**	**Coefficient**
ZSCORE L1	0.924***(0.0570)	0.580***(0.066)
RER	-0.007(0.042)	0.033 (0.033
PBD	-0.053 (0.059)	0.061 (0.054)
LEV	0.032* (0.018)	0.014 (0.018)
OPE	-0.002 (0.002)	-0.004*(0.002)
BS	0.044 (0.047)	0.0322(0.035)
LRR	0.008 (0.042)	0.003 (0.073)
R-squared	0.852	0.795
Number of observations	150	150
Number of groups	15	15

Note: **Standard errors in parentheses, * p < 10%, *** p < 1%.

Table 6 shows the pooled OLS and fixed effects results for Model 2. The results indicate that the parameter value of the lagged dependent variable (Φ) for the pooled OLS test is 0.3045, and the fixed effects is 0.0672. The R-squared values for both estimations are 0.5934 and 0.5626, respectively.

Table 6. Pooled OLS and fixed effects estimations for Model 2.

Dependent var. (EATA)	**Pooled OLS**	**Fixed effects**
Variable	**Coefficient**	**Coefficient**
EATA L1	0.305*** (0.113)	0.607 (0.112)
RER	3.165* (1.705)	5.500*** (1.493)
PBD	-3.771 (3.115)	-5.443 (2.226)
LEV	0.831 (0.521)	-0.752 (0.438)
OPE	0.201*** (0.073)	0.208* (0.115)
BS	-1.158 (.955)	1.791* (0.875)
LRR	10.989*** (2.200)	11.298*** (2.160)
R-squared	0.593	0.563
Number of observations	150	150
Number of groups	15	15

Note: Standard errors are in parentheses; * p < 10%, *** p < 1%.

Table 7 shows the one-step and two-step difference GMM results for Models 1 and 2. The results indicate that the parameter values of the lagged dependent variable (Φ) for the one-step are 0.4904 and -0.2866, and the parameter values of the lagged dependent variable for the two-step are -0.0773 and 0.47645 for Models 1 and 2. The parameter values of the lagged dependent variables for the difference GMM results for both models are compared with the parameter values of the lagged dependent variable for the fixed effects test result to determine whether the difference GMM result is downward biased due to a weak instrument (Bond, 2002) and decide whether to adopt system GMM for the models. Table 7 shows that the number of groups is 15, and the number of instruments is 12 for the one-step difference GMM and 11 for the two-step difference GMM. The number of instruments is smaller than the number of groups; therefore, the number of groups should exceed the number of instruments (N > T) fulfilled for each model. Hence, the data series can be used for regression.

Table 7. Dynamic One-step and Two-step difference GMM panel-data estimations.

Variable	One-step difference GMM		Two-step difference GMM	
	Model 1: LnZSCORE	Model 2: LnEATA	Model 1: LnZSCORE	Model 2: LnEATA
	Coefficient/ Std. error.	Coefficient/ Std. error.	Coefficient/ Std. error.	Coefficient/ Std. error.
LnZSCORE L1/LnEATA L1	0.490***(0.119)	-0.077 (0.357)	-0.287 (1.063)	0.476 (0.531)
LnRER	-0.128 (0.118)	12.139*** (5.772)	0.209 (0.473)	10.337 (29.328)
LnPBD	0.069 (0.146)	-11.212 (5.771	-0.190 (0.518)	0.117 (12.442)
LnLEV	0.029 (0.029)	-1.259 (1.031)	0.002 (0.061)	-1.877 (2.037)
LnOPE	-0.002 (0.003)	0.129 (0.136)	-0.004(0.006)	0.065 (2.037)
LnBS	0.241 (0.179)	16.577 (14.466)	0.554 (0.664)	5.743 (0.200)
LnLRR	0-.067 (0.078)	14.363*** (3.361)	-0.040 (0.090)	15.291**(7.220)
Year dummies	Yes	Yes	Yes	Yes
No. of obs.	150	150	150	150
AR(2)	0.397	0.248	0.448	0.162
Hansen statistics	0.384	0.362	0.426	0.410
Sargan test	0.22	0.18	0.20	0.18
No. of instruments	12	12	11	11
No. of groups	15	15	15	15

Note: Standard errors are in parentheses. ** and *** indicate significance at the 10% and 5% levels, respectively. LnZSCORE L1 = The logarithm of the lagged dependent variable, LnEATA L1 = The logarithm of the lagged dependent variable, LnRER = The logarithm recovery expense ratio, LnPBD = The logarithm of provision for bad debt, LnLEV = The logarithm of leverage, LnOPE = The logarithm of operating expense, LnBS = The logarithm of bank size, LnLRR = The logarithm of the loan recovery rate.

The serial correlation AR(2) values shown in Table 7 are 0.397, 0.248, 0.448 and 0.162 for the two models. The AR(2) values confirm the non-existence of serial autocorrelation in both models. Table 6 reveals that the Hansen statistic test values for the one-step and two-step difference GMMs are 0.384, 0.426, 0.362 and 0.410, respectively, while the Sargan values for both models are 0.22 and 0.20 for Model 1 and 0.18 for Model 2. The Sargan test checks for the over-restriction of the instruments, and the values confirm that the instruments in the model are not over-restricted (Bond, 2002).

Table 8. Lagged values of the dependent variables.

Estimator	LnZSCORE L1	LnEATA L1
	Coefficient	Coefficient
Pooled OLS	0.926	0.305
Fixed effects	0.580	0.607
One-step difference GMM	0.490	-0.077
Two-step difference GMM	-0.287	0.477
One-step system GMM	0.781	0.246
Two-step system GMM	0.763	0.318

Table 8 contains the parameter values of the lagged dependent variable (Φ) for the pooled OLS estimation, fixed effects test, and the one-step and two-step system GMMs for Models 1 and 2. The results show that 0.9257 and 0.3045 are the parameter values of the lagged dependent variable for the pooled OLS, and the parameter values of the lagged dependent variable for the fixed effects are 0.5800 and 0.6072. The parameter values of the lagged dependent variable for pooled OLS are the upper bound estimate values, and the parameter values of the lagged dependent variable for the fixed effects are the lower bound estimate values (Bond, 2002).

Table 8 further reveals that the one-step difference GMM values are 0.4904 and -0.0773, and the two-step difference GMM values are -0.2866 and 0.4765, respectively. The parameter values of the lagged dependent variable (Φ) for the one-step and two-step system GMM for Model 1 are 0.7817 and 0.2462, and the values for Model 2 are 0.7634 and 0.3181, respectively. Following the study of Bond (2002), which states that when the estimated parameter values of the lagged dependent variable for the difference GMM are less than or close to the lower bound estimate value (parameter value of the lagged dependent variable of fixed effect), the result of the difference GMM is downward biased due to weak instruments, so the system GMM is preferred. The lower bound estimate values for both models (0.5800 and 0.6072) are higher than the parameter values of the lagged dependent variable for the one-step and two-step difference GMM values (0.4904 and -0.0773 for Model 1, and -0.2866 and 0.4765 for Model 2). Based on the results in Table 8, the system GMM technique is preferred and is adopted for analysis.

4.1. Short-Run System GMM Estimation

Table 9 shows the short-run system GMM results for Models 1 and 2. The parameter values of the lagged dependent variable for the one-step SYS-GMM for both models are positive and significant at the 0.01% and 0.05% levels. At the same time, the results of the two-step version indicate that only Model 1 has a positive and significant lagged dependent value at 0.01%. Table 9 also indicates that under the one-system GMM, business size is positive and significant (0.094%) for Model 1. On the other hand, in Model 2, recovery expense ratio and operating expense are negative and significant at 0.021% and 0.085%, respectively, while business size is positive and significant at 0.0001%. The results of the two-step SYS-GMM in Table 8 shows that recovery rate and business size are statistically significant at 0.019% and 0.088%, while recovery expense ratio and provision for bad debt are negative and significant at the 0.030% and 0.018% significance levels. Also, Table 8 indicates that the number of groups is 15 and the number of instruments is nine for both models. As the number of instruments is smaller than the number of groups for both models, this implies that the requirement that the number of groups must be greater than the number of instruments (N > T) is fulfilled for each model in this data series.

The AR(2) values in Table 9 for the one-step SYS-GMM are 0.216 and 0.226, and the values are 0.410 and 0.522 for the two-step SYS-GMM. The AR(2) values confirm the non-existence of second-order autocorrelation in the models. The Hansen statistic values for both models are moderately high, with values of 0.312, 0.332, 0.238 and 0.179 for the one-step and two-step SYS-GMM.

The Hansen statistic results are used to check the instrument validity, and the lower the values in a data set, the better. The values must be insignificant, and values between 0.1 and 0.3 are appropriate (Arellano & Bond, 1991; Bond, 2002). The values in Table 8 show that the instruments used in these models are valid.

Furthermore, the Sargan test values in Table 9 are 0.13 and 0.23 for Model 1, and 0.12 and 0.18 for Model 2. The Sargan test checks for over-identifying restrictions in a model and ensures that more exogenous than endogenous instruments are included. However, Roodman (2006) suggested that the p-value of the Sargan test should not exceed 0.25. The Sargan values displayed in Table 8 for both models are lower than 0.25, which confirms that there are no over-identifying restrictions in the model. The F-statistic p-values further confirm the double significance of the explanatory variables.

4.2. Long-Run System GMM Estimation

Tables 10 and 11 display the long-run SYS-GMM estimation results. A long-run estimation was only carried out on the regressors that have significant coefficient values in the short run, as shown in Table 8, for both models.

Mathematically, the equation for estimating the long-run GMM technique is: Long-run = $\beta_k \div [1 - \Phi]$.

Tables 10 and 11 indicate the long-run estimations computed only for the variables that have significant coefficient p-values for both models. The results of the one-step SYS-GMM in Table 9 show that recovery expense and the recovery rate are the only variables that have positive and significant long-term relationships with banking system stability, at 10% and 1%, respectively. However, the results of the two-step SYS-GMM in Table 11 indicate that recovery expense, recovery rate, and provision for bad debt are statistically significant at 1% for banking system stability in the long term, which makes the results in Table 10 more robust. The comparison of the results in Tables 10 and 11 agree with Arellano and Bond (1991) and Blundell et al. (2000), who confirmed that two-step GMM results are more robust and solve heteroscedasticity and serial autocorrelation problems better than one-stem system GMM.

Table 9. One-step and two-step system GMM results for Models 1 and 2.

Variable	Model 1: LnZSCORE		Model 2: LnEATA		Model 1: LnZSCORE		Model 2: LnEATA	
LnZSCORE/LnEATA L1	0.782*** (0.71)	0.000	0.246 (0.24)	0.032	0.763*** (0.16)	0.000	0.318 (0.36)	0.390
LnRER	-0.021 (0.15)	0.892	-12.153**(5.12)	0.021	-0.547**(0.24)	0.040	-35.387** (14.61)	0.030
LnPBD	-0.148 (0.22)	0.521	-20.837**(8.02)	0.557	-0.603* 0.16)	0.072	-42.917** (15.95)	0.018
LnLEV	0.047 (0.03)	0.138	0.598 (0.99)	0.937	0.041 (0.31)	0.286	0.803 (0.36)	0.603
LnOPE	-0.005 (0.00)	0.132	-0.017 (0.21)	0.085	-0.002 (0.16)	0.595	0.065 (1.18)	0.837
LnBS	0.344*(0.19)	0.094	21.927* (11.83)	0.000	-0.221 (0.00)	0.444	24.660* (13.43)	0.088
LnLRR	0.106 (0.07)	0.166	17.181 *** (3.53)	0.328	0.113 (0.01)	0.217	53.464** (20.08)	0.019
Are year dummies included?	Yes		Yes		Yes		Yes	
No. of observations	150		150		150		150	
AR(2) values	0.216		0.226		0.410		0.522	
Hansen statistic values	0.312		0.332		0.238		0.179	
Sargan test values	0.13		0.23		0.12		0.18	
F statistic values	F (13, 14) = 34285.59 Prob > F =0.000		F (13, 14)= 178.20 Prob > F=0.000		F (14, 14) = 123.22 Prob > F 0.000		F (14, 14) = 123.22 Prob > F 0.000	
No. of instruments	9		9		9		9	
No. of groups	15		15		15		15	

Note: Standard errors are in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels. LnZSCORE L1 = The logarithm of the lagged dependent variable, LnEATA L1 = The logarithm of the lagged dependent variable, LnRER = The logarithm of the recovery expense ratio, LnPBD = The logarithm of provision for bad debt, LnLEV = The logarithm of leverage, LnOPE = The logarithm of operating expense, LnBS = The logarithm of bank size, LnLRR = The logarithm of the loan recovery rate.

Table 10. One-step system GMM long-run estimation.

	One-step SYS-GMM					
	Model 1: LnZSCORE			Model 2: LnEATA		
Variable	Coefficient	Std. error	P-value	Coefficient	Std. error	P-value
LnRER	N/A	N/A	N/A	16.122	8.687	0.063
LnPBD	N/A	N/A	N/A	-27.641	17.476	0.114
LnLRR	N/A	N/A	N/A	22.791	7.029	0.001
LnBS	1.577	1.253	0.208	29.087	22.694	0.200

Table 11. Two-step system GMM long-run estimation.

	Two-step SYS-GMM					
	Model 1: LnZSCORE			Model 2: LnEATA		
Variable	Coefficient	Std. error	P-value	Coefficient	Std. error	P-value
LnRER	-0.095	0.663	0.886	26.847	7.730	0.001
LnPBD	-0.677	1.179	0.566	-32.560	13.325	0.015
LnLRR	N/A	N/A	N/A	40.562	14.949	0.007
LnBS	N/A	N/A	N/A	18.709	12.559	0.136

5. DISCUSSION OF THE REGRESSION RESULTS

Table 9 shows that the recovery expense ratio has a negative and significant link with banking system stability at a 5% significance level for Models 1 and 2. This means that a change in recovery expense ratio is associated with 0.547% and 35.387% decreases in banking system stability in the short run at a 5% significance level, all things being equal. Table 11 reveals that the recovery expense ratio has a positive and significant association with banking system stability at 1% in the long term in Model 2. Hence, a percentage change in the recovery expense ratio is associated with a 26.8473% increase in banking system stability in the long run at a 1% significance level, *ceteris paribus*. This is understandable because recovery expenses are primarily paid to pursue recovery activities, e.g., money spent on external debt recovery agents or legal matters for litigation and other expenses arising from the recovery of defaulted loans. This means that funds spent on debt recovery can affect banks negatively in the short run. However, once recovery is achieved, the amount recovered cancels every expense incurred in the short run, thus increasing profitability and improving bank performance, thus enhancing banking system stability in the long run. The short-run negative association of the recovery expense ratio on banking system stability agrees with the a priori expectation. However, the long-run outcome is not in agreement with some a priori expectations. Therefore, failing to recover loans can exacerbate instability in the banking system.

The empirical evidence in Table 9 indicates that provision for bad debt significantly retards banking system stability at a 10% significance level for Model 1 of the two-step SYS-GMM and the 1% significance level for Model 2. The calculated coefficients specify that a percentage change in provision for bad debt results in the retardation of banking system stability in the short term, with values of 0.6025 and 42.917, respectively, for both models in the short term at the 10% and 1% significance levels. Similarly, Table 11 indicates that provision for bad debt has a negative and significant link with banking system stability at 1% in the long term in Model 2. Hence, a percentage change in provision for bad debt is associated with a 32.56% decrease in banking system stability in the long term at a 1% significance level on average, *ceteris paribus*. The implication is that an increase in the provision for bad debt further reduces banks' profits. This affects banks' ability to grant more credit to customers for productive activities. The results in Tables 10 and 11 signify that provision for bad debt has a lower adverse effect on banking system stability in the long run (32.560) than in the short run (42.917) for Model 2. This result is in tandem with the a priori expectation because banks provide for bad debts from their earnings. Therefore, bad debt provision reduces banks' earnings, profitability, and loanable funds.

Furthermore, the estimated short-run results in Table 9 show that the recovery rate has a positive significant link with banking system stability at the 1% significance level for Model 2. This means that a change in recovery rate is associated with a 53.464% increase in banking system stability in the short run at a 1% significance level. Similarly, Table 11 shows that the recovery rate has a positive and significant association with banking system stability at 1% in the long run in Model 2. Hence, a percentage change in recovery rate is associated with a 53.464% increase in banking system stability in the long term at a 1% significance level, *ceteris paribus*. This implies that as the loan recovery rate increases, it impacts the profitability and liquidity of the banks, thus enhancing banking system stability. The short- and long-term results of the positive association of credit recovery rate with banking system stability agree with the a priori expectations of this study.

The results in Table 9 reveal that bank size is positive and statistically significant for banking system stability at a 10% significance level in Model 2 of the two-step SYS-GMM. This means that a percentage change in bank size is associated with a 24.66% increase in banking system stability in the short run at a 10% significance level. However, bank size has no significant relationship with banking system stability in the long run, as displayed in Table 11. This implies that bank size plays a significant role in the issue of credit recovery and banking system stability only in the short run. Hence, big banks should utilize the size advantage to limit or stop loan defaults to improve banking system stability. This result does not agree with the a priori expectation.

The above results are in consonant with the findings of Offiong and Egbuka (2017), who discovered that a negative and significant relationship exists between the loan recovery rate and bank performance, while Bongini et al. (2019) found that credit recovery impacts positively on banks' profit shock. Furthermore, this result is in agreement with the findings of Dey (2018) and Atoi (2018), who found that credit recovery has a positive and significant link with banks' stability. Similarly, Li et al. (2022) confirmed that centralized credit risk management can significantly improve the efficiency of recovery and collection of non-performing loans in commercial banks.

6. CONCLUSION AND RECOMMENDATIONS

The main objective of this study was to examine the criticality of credit recovery in banking system stability in Nigeria using the GMM estimation technique. The study employed two banking system indicators: banking soundness and banking vulnerability. The Z-score was used to proxy the banking soundness index, while the ratio of external assets to total assets (EATA) was used to proxy the banking vulnerability index. In addition, the loan recovery rate and the recovery expense ratio were used to proxy credit recovery, while provision for bad debt, leverage operating expense, and bank size were the control variables. The analysis was conducted using firm-level data from 2007 to 2020. The panel data collected for this study was estimated using the system generalized method of moments (SYS-GMM) technique, which provides stable results in the presence of diverse sources of endogeneity, namely simultaneity, dynamic endogeneity, and unobserved heterogeneity (Wintoki, Linck, & Netter, 2012). The results revealed that recovery expense ratio has a negative and significant impact on banking system stability in the short run and a positive and significant effect in the long term, while the recovery rate has a positive and significant link with banking system stability in the short and long terms. However, provision for bad debt significantly retards the banking system's stability in the short and long terms.

The overall findings show that credit recovery positively and significantly impacts banking system stability in both the short and long terms. Through its empirical findings, the study confirmed that credit recovery is beneficial to banks as a tool toward achieving banking system stability because the negative effects of loan defaults are neutralized in the long run when recovery is achieved. Hence, an increase in credit recovery will increase banking system stability in deposit money banks. Previous studies have failed to discover this through their analyses.

Based on the results, this study recommends the following: (i) the management of banks must aggressively pursue the recovery of bad loans and maintain favorable and minimal recovery expenses, particularly with their external debt recovery agents, to ensure that the recovery expense is not higher than the actual amount recovered. The recovery of bad loans will automatically neutralize the negative effects of the default on banks' stability in the long run; (ii) banks should periodically employ internal loss given default estimation techniques to determine the degree of losses incurred as a result of defaulted loans and the impact on profitability and performance. This action will help the banks to work toward reducing the losses to meet projected risk and regulatory requirements; (iii) the management of banks should establish credit policy standards that not only conform with the banks' overall objectives and regulatory requirements but also include strategies and actions that are geared toward the prompt recovery of defaulted loans to minimize the degree of exposure to credit risk; (iv) banks should have recovery databases where credit files, information and documentation for every defaulting loan customer is stored once the first default in repayment occurs.

7. LIMITATIONS OF STUDY

One limitation of this study is that it is likely that other associations may exist among the studied variables with regard to the disparity of strategic actions taken on the non-payment of debts and credit recovery. For example, although the recovery expense ratio significantly retards the banking system, it is a significant factor to consider if recovery is to be achieved promptly in order to resolve the problem of loan evasion and achieve banking system stability in Nigeria.

Data availability is another major limitation of this study. The lack of availability of data restricted the period covered in this study to when data for all the variables can be found in the public domain.

8. SUGGESTIONS FOR FURTHER STUDIES

Despite this study's various contributions to the existing literature, several other extensions could be applied to enhance its robustness. For example, a study could be carried out that adopts the three banking system stability indicators—Banking Soundness Index (BSI), Banking Vulnerability Index (BVI) and Economic Climate Index (ECI)—simultaneously. This will increase the comparability of the factors adopted in this study for more robust findings.

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