EARLY WARNING INDICATORS AND FINANCIAL CRISIS IN NIGERIAN ECONOMY (1994-2023)

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ABSTRACT

This study applied two distinct methods of analyses to evaluate and compare the predictive ability of certain EWIs of financial crisis when gaps are generated using the Hodrick – Prescott filter method. First, the logistic regression encompassing the estimates for individual indicator parameters, the model Expectation-Prediction Evaluation and the Hosmer-Lemeshow (HL) and Andrews Tests for goodness-of-fit and 2, the receiver operating characteristics curve where the area under the receiver operating characteristic (AU-ROC) curve and distance to corner were the basis of evaluation. On the basis of the Logit regression, it leads to the conclusion that none of the EWIs tested (Credit-to-GDP gap, Nonperforming loans, Loan-to-Deposit ratio and asset prices) could predict financial crisis at the 5% level of significance although credit-to-GDP gap could at 10%. On the other hand, the AU-ROC and Distance to Corner concludes that credit-to-GDP gap is a predictor of financial crisis in Nigeria. Nevertheless, both the AU-ROC and Logit regression, suggest that credit-to-GDP gap outperforms non-performing loans, Loan to deposit ratio and asset prices as EWIs of financial crisis in Nigeria. It is hoped that regulatory authorities apply the EWIs of financial crisis with care, explore the different methodologies available and identify which EWI, filter method as well as the analytical model suitable for their jurisdiction.

Keywords: *Credit-to-GDP gap, Nonperforming loans, Loan-to-Deposit ratio, asset prices, financial crisis, early warning indicators.*

INTRODUCTION

Financial crises are one of the challenges affecting nations. Such crises could be currency crisis as well as debt crisis related (Oluremi & Olutomilola, 2018). Financial crisis is a bad egg that affects an entire economy and if not properly managed can result in a total economic downturn. Since the global financial crisis of 2007-2008, regulatory authorities have been working tirelessly to avoid the re-occurrence of such global phenomenon. Doing a regular financial stability check, assessment and identification of early warning indicators (EWIs) signalling a potential risk to the banking system some of which if not managed could cause huge financial crisis in the economy is the duty of supervisory and regulatory authorities (Kehinde & Devi, 2024).

Financial crisis early warning also known as early warning indicators (EWIs) is generally agreed by definition from both domestic and foreign scholars is that "Financial crisis early warning refers to the creation and testing of financial early warning indicator during economic cyclical movements using of particular statistical measurement methods (Qingyu, 2021).The reason is to forecast the possibility of a financial crisis in a certain country or region within a certain period of time before the occurrence of a financial crisis and to provide decision-makers with a background for monitoring and preventing financial crises, so as to avoid the disruptive effect of the financial crisis on the country or region's economic development (Padhan & Prabheesh, 2019). To keep an eye on the financial fragility or build-up of system-wide risk, the Basel Committee on Banking Supervision recommends a "common reference guide based on the aggregate private sector credit-to-GDP gap. The credit-GDP gap and the ratio of core to noncore liabilities, among other indicators, can show signs of financial cycle period, therefore serving as useful direction for macro prudential policies.

The financial markets early warning system seeks to see signs of vulnerability in stock market, bond market, and loan market. Periods of financial market instability are associated by unusual attitude in stock price, corporate bond yield, and the rate of dishonoured bill. In addition, the trading volumes in stock and bond markets, the volatility of stock price and bond yield, term spread and default spread are also used to determine the periods of financial instability. Asset price relates to the cost an asset is bought and sold, it can be shares or stock.

Ironically, banks took on too many risks because they relied on government protection in the event of failure or on the tendency of government to pursue accommodative monetary and fiscal policies following crises (Claessens & Kose 2023; Calomiris 2021). Government safety nets also led to poor market discipline, it removed depositor's incentives to monitor or discipline banks when they were taking such excessive risks because they believe they would not suffer any loss if a bank failed; they also increased the risk of fraud and embezzlement, thereby producing systemic vulnerabilities.

Statement of the Problem

Studies relating to the subject matter were not exactly on the topic because of geographical differences, indicators differences, and years of coverage. To start with, Qingyu (2021) used different variables like stock price index change rate, industrial added value growth rate, domestic and foreign real deposit interest rate differential, and foreign direct investment as a percentage of GDP to predict financial crisis in China using the traditional static Logit line and the dynamic Logit models, and found that there is a little probability of a systemic financial crisis in China in 2020 which means all the variables were useful in financial crisis prediction. Also, Drehmann and Juselius (2014) used the evaluation criteria method to investigate early warning indicators. The evaluation criteria were applied on a group of possible Early Warning Indicators and found that the credit-to GDP gap and a new indicator, the debt service ratio (DSR) consistently outperform other measures. The credit-to-GDP gap is the best indicator at longer scope, but not at shorter scope. but in the case of Nigeria, Ihejirika and Peter, (2025) applied the signal approach and the area under the receiver operating characteristic (AU-ROC) curve and also the graphical analysis for visualization for the period 1981 to 2019 to predict financial crisis in Nigeria and found that Credit-to-GDP Gap performs poorly in Nigeria as an early warning indicator for financial crisis. Similar to Ihejirika's result, Drehmann and Yetman (2024) used a different method called horse race and expanding samples based on quarterly data from the period 1970 to 2017 for 41 economies and the result showed that credit gaps based on linear projections in real time perform poorly when based on country-by-country estimation, and are subject to their own end-point problem. Contrary to the report by Ihejirika, Geršl, and Jašová (2018) evaluated the importance of credit-based variables as early warning indicators (EWIs) of banking crises for emerging economies using the signalling performance by using the area under the receiver operating characteristics (AUROC) curve. The results showed that small credit growth and change in the credit-to-GDP ratio have the best signalling properties and significantly outperform the credit-to-GDP gap in almost all specifications.

In Nigeria, there are not many studies to confirm the efficacy of credit-to-GDP gap as a predictor of financial crisis. Again, the few that are, differ in their findings.

Research Objectives

The broad research objective is to examine early warning indicators and financial crisis in Nigerian economy (1994-2023). The specific objectives are to:

1. examine the predictive strength of asset prices on financial crisis;
2. investigate the predictive power of nonperforming loan of deposit money banks on financial crisis;
3. ascertain the strength of credit to GDP gap in predicting financial crisis in Nigeria, and
4. investigate the predictive power of loan to deposit ratio on financial crisis in Nigeria.

Research Questions

The following research questions are answered in the course of this study

1. What is the strength of asset prices in predicting financial crisis in Nigeria?
2. What is the predictive strength of nonperforming loan in signalling a potential financial crisis in Nigeria?
3. To what extent do credit to GDP gap predict financial crisis in Nigeria?
4. To what extent do loan to deposit ratio predict financial crisis in Nigeria?

Research Hypotheses

The following hypotheses are stated in null (Ho) forms and are tested for accuracy in this study;

Ho_1: Asset prices do not significantly predict financial crisis in Nigeria

Ho2: Non performing loans does not significantly signal a potential financial crisis

Ho3: Credit to GDP gap does not significantly predict financial crisis in Nigeria

H04: Loan to deposit ratio does not predict financial crisis in Nigeria

Scope of the study

This study provides elaborate discussion on early warning indicators and financial crisis in Nigerian spanning the period of 1994-2023. It relies on secondary data from the central bank statistical bulletin 2023 and the National Bureau of Statistics 2024. The variables used as predictors of financial crisis are non-performing loans of deposit money banks in Nigeria, asset prices represented by the stock market index, credit to GDP gap and loan to deposit ratio while banking crisis in Nigeria is measured as a binary outcome (1= financial crisis and 0 = no financial crisis) for the years under review. The events of the crisis were extracted from the Harvard Business school financial crisis data bank.

REVIEW OF RELATED LITERATURE

This section covered the conceptual review, theoretical and empirical reviews related to this study.

Early warning indicators (EWIs)

Financial crisis early warning refers to the construction and analysis of financial early warning indicator system around economic cyclical movements through the application of certain statistical measurement methods (Ihejirika, & Peters, 2025). The reason is to forecast the possibility of a financial crisis in a certain country or region within a certain period of time before the occurrence of a financial crisis and to provide decision-makers with a base for monitoring and preventing financial crises, so as to avoid the destructive effect of the financial crisis on the country or region's economic development (Padhan & Prabheesh, 2019).

Predicting banking crises sometimes does not always give what is expected. The good indicator would signal all incoming crises and it will not signal crises that did not happen. All known Early Warning Indicators fall short of this good quality, and hence they must be appraised on the basis of how they trade off the rate of missed crises against the rate of false positives (i.e., the crisis that was not predicted but happened (Ihejirika, & Peters, 2025). This assessment depends on policymakers' choice concerning these two types of error. Early Warning Indicators must fulfil a number of additional requirements that go beyond statistical accuracy. Drehmann and Juselius (2014) propose three such requirements as it pertains to macro prudential policymaking. The first one is timing: EWIs must give signals early enough so that policy measures to take effect.

Macro prudential leading early warning indicators

a. Macroeconomic Variables

Higher asset and property price growth can be associated with the boom phase in the business cycle that might imply a build-up of financial imbalances and has the potential to result in banking system instability (Sally & Katsiaryna, 2025). For asset price indicators, it is pertinent to differentiate between property and equity prices, as they reflect distinct transmission ways of exogenous shocks to the real economy. Asset price is used as an indicator for internationally important real estate markets as they played an important role in the financial crisis.

b. Financial Variables

Moving to financial variables, the study examined indicators for giving loans to the private sector, financial market indicators and monetary indicators (Kehinde & Devi, 2024). Lending booms may precede banking system instability as they imply increased risk- taking in the financial system that has the potential to result in financial disturbance if the economy is strike by a negative, adverse shock. Therefore, the national private credit-to-GDP ratio is included as part of the financial variables. With respect to financial market indicators, the study takes into account the role of the interbank market, which has become especially important during the financial crisis of 2008/2009. As a result of the above deductions, there is possibility that the pre-crisis periods will be characterized by: rapid domestic credit growth, low GDP growth, low bank liquidity, profitability and capitalisation, runs on bank deposits, high rates of non-performing loans, high real interest rates, high inflation rates, falling asset prices, fiscal budget and current account imbalances etc.

c. Sovereign Debt Crisis Indicators

There are numbers of significant indicators that could act as explanatory variables for debt crises. For Sally and Katsiaryna (2025) the role of external debt ratios (short-term debt to reserves, debt service to reserves or to exports, and total debt to GDP) that measure the solvency and the debt sustainability of an economy, the growth in international reserves and export earnings which reflect the ability to service debt, the current account deficit plus short-term debt as a measure of illiquidity risk, and some macroeconomic indicators, namely real GDP growth, FDI flows, volatility of export growth, and inflation rate.

Financial crisis

When many banks in a country are in serious solvency or liquidity problems at the same time, this is called systemic banking crisis (The World Bank 2020). For Goldstein, Kaminsky, & Reinhart (2020), financial crisis means (i) the ratio of non-performing loans to total loans in the banking system exceeded ten percent; (ii) the cost of the bank rescue operation was a least two percent of GDP; (iii) the rescue episode involved either a large-scale nationalization of banks. For Drehmann and Yetman (2024) there is banking crisis if you see huge bank runs, closure of banks, mergers, or large public-sector takeovers of banks.

Causes of financial crisis

i. **Leverage**. Too much leverage is at the middle of all banking crises, by definition. Leverage goes beyond balance sheets. Leverage is rooted in off-balance-sheet instruments such as derivatives. And harmful unseen leverage is embedded in structured securities. We have no open and efficient accounting for leverage, so reducing it is complicated and beyond the skill of legislators to efficiently write into law, and beyond the ability of regulators to manage as we have learned.

ii. **Liquidity**. Just like leverage, liquidity mismatches (lending long, borrowing short) must be dramatically curtailed. That Lehman was giving loans to real estate holdings in the Repo and commercial paper markets was total madness. There is no ground for an investment bank to be speculating on buildings with the implicit backing of investor. The Basel III liquidity ratios are a crucial battle to observe.

iii. **Too Big to Fail.** There is now an industry filled with firms that are too big, sophisticated, and "systemically important" to manage, govern, or we allow it to fail. This needs an adjusted system structure. The academic studies discussing economies of scale and scope are faulty and a distraction from the important issue.

iv. **Conflicts of Interest**. There is no other profession where such blatant conflicts of interest endured. Many "old school" bankers are amazed, Even the asset management industry within finance.

v. **Taxes and Subsidies**. Tax policy has a significant effect on the cost and flow of capital and the current tax code as it affects finance needs a rebuild. There is need for taxes such as a Financial Transaction Tax to discourage short-term speculation and at the margin encourage longer term investment. There is also need for a much more progressive capital gains tax that has the impact of promoting real long-term investment over short-term speculation.

vi. **Governance.** It is important to note that the financial system has become really big and interlinked to the point that it is now effectively a general thing that impacts all citizens. Democratic governance becomes essential or there will be a bigger problem for the citizen. The end point of this perspective run wide and deep as exemplified by the case of the stock exchanges.

Factors That Can Turn Asset Volatility into Instability

Incentive Structures: Herding and short-termism among institutional investors leading to amplified or self-perpetuating price movements is usually encouraged by Peer-group performance measures or index- tracking. The heat to meet short-term profit targets, for example, or structures that reward staff at intermediaries according to volume of business rather than risk- adjusted return can lead to underestimation of long-term risk and imprudent leveraging. Insufficient disclosure of risks to investors can also be attributed to Conflicts of interest at intermediaries. Sudden changes in group sentiment, raised by any increase in leverage, could then create instability through contagious price falls and difficulty in re-pricing risks.

Lack of strong risk management: Leverage increases the sensitivity of financial institutions and the system as a whole to economic downturns and to asset price declines more generally. Unusual events and regime changes that may not be allowed into risk measurement models or stress tests may be sources of unappreciated risk. Currency inconsistency can lead to systemic risks, especially under fixed exchange rate regimes where the possibility of a regime change may not be fully taken into account in risk management. Feedback mechanisms that amplify price movements is caused by Certain hedging strategies (delta hedging or "portfolio insurance"). Volatility is often increased by the unwinding of a concentration of leveraged positions (relating perhaps to a popular "carry trade" or asset bubble) similarly. Heavy losses at key institutions and disruptions to market pricing could be as a result of a combination of extreme price movements and sudden realization of previously unappreciated market and credit risks.

Lack of Transparency: Lack of revelation by individual firms makes risk management by others under volatile conditions more difficult. When there is Inadequate initial disclosure of the true scale of positions or financial condition can lead to sudden changes in market sentiment when the existence of large exposures or weaknesses becomes known and to extreme price reactions as market participants try to discern the facts and assess the implications amid partial information and rumours. Market unreliability over the financial position of individual firms, and concerns (whether justified or not) about others that share some of the same characteristics, can impair the allocation of credit and functioning of payment systems.

Weaknesses in Market Infrastructure: Payment, clearing, or settlement systems may not be adequate to allow participants to cope with large margin calls, doubts over counterparty risk, or heavy volumes of business. This could lead to illiquidity problems and difficulties in payments to spread rapidly through the system.

The concept of non-performing loans (NPLs**)**

The ratio of non-performing loan is obtained by dividing the NPLs by the gross loans and advances in a given time (Amediku, 2006). By definition, a loan or credit facility refers to a contractual agreement between two parties in which one party, the creditor, agrees to provide a sum of money to a debtor, who promises to return the said amount to the creditor either in one lump sum or in many instalments over a specified period of time (Authur & Sheffrin 2023). Central Bank of Nigeria's loans classification indicates that loans that are performing are those for which the borrowers/beneficiaries are up to date in respect of payments of both principal and interest (CBN, 2010).

Low levels of NPLs portray a relatively stable financial system whereas high levels of NPLs points to the existence of financial stress which calls for deep concern from bank management and regulatory authorities. A low ratio points to low losses while increasing ratio signifies increasing write off of bad assets. The issue of loan default is closely related with non-recovery or non-repayment of loans. This occurs whenever a loan beneficiary in a particular sector such as agriculture or manufacturing industry cannot repay the interest and or principal after it has become due hence it can be described as defaulted loan or non-performing loan (Hou & Dickson 2017).

Theoretical Review

Financial instability hypothesis

Minsky (2020) started the financial instability hypothesis or "financial theory", which provided indicative explanation of the characteristics of monetary crisis. He asserted that during times of economic wellness and wealth, increasing wealth of economic agents (individual/corporate) generated fortunes above what was needed to pay off liabilities and, therefore, caused speculative tendencies. Rising speculative behaviour would cause excessive financial advantages, which might soon generate debts that exceeded what debtors could pay and eventually caused financial crisis.

Loan pricing theory

Deposit money banks should afford to line moderate rate of interest to avert the issues of adverse credit selection among borrowers (Stiglitz & Weiss, 2021). The problem of adverse credit selection existed when deposit money banks set high interest rate in other to improve their balance sheet position; risky borrowers will still be attracted to such rate of interest and once they receive such credit facilities, they develop problems of doubtful and bad debts to the banks. The theory also believed that interest rate is the price that determines the forces of demand and supply of credit in the market. The price increases when the demand for credit is more than the supply for such credits and vice versa.

Empirical Review

A number of empirical studies related to the study were carried out.

Sally and Katsiaryna (2025) predicted upcoming financial crisis using different financial variables which can serve as early warning indicators of banking crises. They used data from 59 developed and developing economies; the result showed that financial overheating are often detected in real time. GDP gap and Stock prices are the most common leading indicators in developed markets; in developing markets, the simplest are equity and property prices and credit gap. Moreover, aggregating this information flags financial crisis a few years before the crisis. Lastly, they called into question the longer frequency widely utilized in the estimation of countercyclical capital buffers because they found that the length of financial cycles is of medium-term frequency.

Ihejirika, and Peters (2025) in his work analysing the power of credit to GDP gap as an early warning indicator to predict financial crisis in Nigeria. The signal approach and the area under the receiver operating characteristic (AU-ROC) curve as well as graphical analysis for visualization were used. Annual data on domestic credit to the private sector as a ratio of gross domestic product for the amount 1981 to 2019 was used for the analysis. The area under the receiver operating characteristic (AU-ROC) curve is 63.68% which shows that Credit-to-GDP Gap performs poorly in Nigeria.

Drehmann and Yetman (2024) employed a race and expanding samples on quarterly data from 1970 to 2017 for 41 economies. The study acknowledged that credit gaps supported linear projections in real time execute badly when build on country-by-country evaluation, and are open to their own end-point problem. But once they estimated as a panel, and use an equivalent coefficient on all economies, linear projections perform marginally better than the baseline credit-to-GDP gap, with somehow larger improvements focused in the post-2000 period and for emerging market economies.

Kehinde and Devi (2024) used an Early Warning System model for predicting the financial crisis in four developing African economies employing a multinomial logit model and a knowledge set covering the period of January 1980 to December 2017. The results of the study suggest that emerging African economies are more likely to face financial crisis as debts still rise without a corresponding capacity to face up to capital flow reversal also as excessive exchange risk thanks to currency exposure. The result further indicates that rising debt exposure raises the likelihood of the economies remaining during a state of crisis. This result confirms the importance of a financial stability framework that addresses the problems confronting Africa's emerging economies like rising debt profile, liquidity and currency risk exposure.

Dawood, Horsewood, and Strobel, (2024) investigated the predictive power of the econometric model in predicting the sovereign debt crisis using an early alarm model for both developed and emerging economies. The findings of the study, which was found to be more precise as compared to previous studies, show that in constructing an efficient EWS model for the sovereign debt crisis, it is important to incorporate variables that capture and account for the likelihood of a spill over from the financial system.

Giordani and Simon (2023) estimated the performance of credit-to- GDP gap when it is de-trended using the HP filter compared to using a moving average and what they called the local level filter. Though the present study is not about methodology, the take away from their study is that credit-to- GDP is a veritable tool for managing financial fragility.

Other research by Bakhuashvili (2019) tested the predicting power of the credit to GDP gap as proposed by the Basel committee using the Kalman filter and Hodrick-Prescott (HP) filter. In comparing the credit to GDP gaps calculated using different filters; the Kalman filter outperformed the HP filter in Georgia between the years 2000 and 2016 as the paper shows. In the financial crisis of 2007-2008 case, the HP filter could only signal that a crisis was occurring after the fact, while the Kalman filter could work as an early warning indicator, giving information about an upcoming crisis in the beginning of 2006. The second instance is the 2016 first half, when the HP filter advised setting the Counter Cyclical Buffer while there was no financial crisis, which was correctly indicated by the Kalman filter.

Barrell, Karim, and Macchiarell (2017) considered the calculation of the credit-to-GDP gap by examining several ways of extracting the cyclical indicator for excess credit. The study compared various smoothing parameters for the credit gap, and it was evident that some countries require an AR (2) process while others do not. They arrived at this conclusion by using Logit models of financial crises, and further state that the AR (2) cycle is a much better contributor to their explanation than is the HP filter suggested by the BIS. Their study covered Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Spain, Sweden, UK and US with data that ranged from 1978 – 2016.

Gap in Literature

From the empirical studies reviewed, it is evident that there is a gap in Nigeria on this particular area of research which creates a curious question in the mind of the researcher, is this area of research not important to Nigeria as it is to other countries both developing and developed alike.

METHODOLOGY

Research Design

The study made use of the quasi-longitudinal experimental research design. The independent variables are non-performing loans of deposit money banks in Nigeria, asset prices represented by the stock market index, total credit, GDP and loan to deposit ratio while series of financial crisis in Nigeria is used as the dependent variable. The financial crisis is used as a binary variable.

Sources of Data

The research relies on secondary data from the Central Bank statistical bulletin 2024, and the National Bureau of statistics 2024. The events of the crisis were extracted from Harvard business school data bank.

Data Analysis Techniques

Logit Analysis

The study adopted the logit model as used by Ihejirika & Nwakanma (2012). This tool of analysis was used to estimate the predictive power of some early warning indicators of financial crisis in Nigeria. The model proceeds as follows:

Let y* denote banking crisis possibility,

Let y denote crisis result, then we can establish duality dependent variables model

$$y_i^* = x_i^{'}\beta + u_i$$

$$y = \begin{cases} 1 & y^*>0 \\ 0 & \text{other} \end{cases}$$

y* is latent variable, which cannot be observed in its concrete volume. X_i denotes the influence factor vector of banking crisis. U_i is residual error.

From the model, we get that expectation value of y is the probability of y equal to 1, namely:

$$E(y_i|x_i,\beta) = 1 \cdot \Pr(y=1|x_i,\beta) + 0 \cdot \Pr(y=0|x_i,\beta) = \Pr(y=1|x_i,\beta$$

The probability of y equal to 1 is the probability of y* >0, thus:

$$\Pr(y_i = 1|x_i, \beta) = \Pr(y_i^* > 0) = \Pr\left(x_i'\beta + u_i > 0\right) = 1 - F_u(-x_i'\beta)$$

F_U is the cumulated distribution function of u, and it follow Probit or Logit distribution, this study adopt Logit distribution namely:

$$\Pr(y_i = 1|x_i, \beta) = 1 - F_u\left(-x_i'\beta\right) = F_u\left(x_i'\beta\right) = \frac{1}{1 + \exp\,(-x_i'\beta)}$$

According to this model, the probability of a financial crisis is decided by influenced factors of financial crisis probability, we can get marginal impact of influenced factors on financial crisis probability and its influence on the probability of financial crisis from this model, and can estimate the extent of financial crisis probability by a group of factor vector X_1, therefore can forecast and evaluate the choice results of financial crisis.

There are studies that capture periods of crisis for several countries with a binary variable and explain the latter with macroeconomic factors applying either logit/probit. Applying a multivariate logit approach, the authors link a set of explanatory variables to the probability of occurrence of a binary crisis variable. The benefit of the technique is that it allows one to assess the relative importance of variables jointly, but this approach also makes it difficult to consider a large number of indicators at the same time. The Logit regression will show at different level of significance the variables that have predicting power and also if the constant in the model have statistically significant relationship with financial crisis. For this study, the level of significance is 5%. If any of the indicator variables has a t-statistics probability less than 0.05, it is said to have a predictive power or predicts financial crisis in Nigeria.

Expectation-Prediction (Classification) Table

"Correct" classifications are obtained when the predicted probability is less than or equal to the cut off and the observed y=o, or when the predicted probability is greater than the cut off and the observed y=1. The fraction of y= 1observations that are correctly predicted is termed the sensitivity, while the fraction of y=0 observations that are correctly predicted is known as specificity. The gain in the number of correct predictions provides a measure of the predictive ability of our model. The gain measures are reported in both absolute percentage increases (Total Gain), and as a percentage of the incorrect classifications in the constant probability model (Percent Gain). The implication of this prediction is either predicting crisis that failed to materialize (type 2 error) or not predicting crisis that will likely occur (type 1 error).

Test of the Validity of the Model

Hosmer-Lemeshow statistic and Andrews Statistic will be used to interpret the goodness of fit test. If the p-value is less than the Hosmer-Lemeshow statistic and Andrews Statistic, it shows that the logit model is a good fit and that the estimates of the variables' parameters in the model are meaningful.

Testing for Heteroskedasticity

The LM test for heteroskedasticity as described in Davidson and MacKinnon (1993, section 15.4) was estimated. The null hypothesis of homoskedasticity against the alternative of heteroskedasticity was specified. If the p-value is less than 0.05, the null hypothesis of homoscedasticity is rejected.

Area under the Receiver Operating Characteristics Curve (AUC-ROC) and Empirical Receiver Operating Characteristics Curve (E-ROC)

This is a popular measure of the accuracy of a warning indicator. Generally, higher AUC values indicate better performance (Drehmann & Juselius, 2014) for benefits of the AUC). The values of AUC range from 0.5 (no prediction ability), 0.7 - 0.8 (acceptable), 0.81 – 0.9 (excellent) and above 0.9 is considered outstanding (Mandrekar, 2010)

The Empirical ROC Curve is a graph showing the plots of the true positive rate (TPR) or sensitivity on the Y-axis against the false positive rate (FPR) or (1 – specificity) on the X-axis. TPR and FPR are derived from the counts of True Positives, False Positives, False Negatives and True Negatives for all possible threshold values.

Model Specification

Functionally:

Financial crisis (FC) = f (NPL, SMI, CG, LDR) ……………………………………….. (1)

Econometric Specification

$FC = \beta o + \beta_1\ NPL + \beta_2\ SMI + \beta_3\ CG + \beta_4 LDR + U_i$.. (2);

Where

NPL =non-performing loan

SMI = asset prices

CG = credit-GDP gap

LDR = loan to deposit ratio

β0… β4 are parameters to be estimated

U_i is the error term.

The derivation of the Credit to GDP gap followed the recommendation of the Basel Committee on Banking Supervision (BCBS). To derive the credit-to-GDP gap the Basel Committee on Banking Supervision (BCBS) (2010a) calculate the credit to GDP gap in period t as the actual credit-to-GDP ratio minus its long-term trend calculated using the one-sided Hodrick-Prescott filter. The Hodrick-Prescott filter divides the Credit to GDP Ratio (ratio) into two components: the trend (trend) and the gap (gap).

$$\boldsymbol{ratio_t = trend_t + gap_t} \qquad (3)$$

While the Credit-to-GDP ratio is calculated by dividing credit to the economy at time t with gross domestic product at time t. this is expressed

$$\boldsymbol{ratio_t = \frac{credit_t}{GDP_t}} \qquad (4)$$

The Credit to GDP Gap results from the difference between the ratio and the trend. Thus

$$gap_t = ratio_t - trend_t \quad (5)$$

The trend was calculated using the one-sided Hodrick-Prescott (HP) filter with lamda at 1600 (usually used for annual data BCBS 2010).

DATA PRESENTATION AND ANALYSIS

This chapter investigated the predictive power of different early warning indicators (non-performing loans of deposit money banks in Nigeria, asset prices represented by the all share index, credit to GDP gap and loan to deposit ratio) to financial crisis.

Table 1: Crisis episodes, Gap, Non-Performing Loans to Total Credit Ratio, Loan to Deposit Ratio and All Share Index for the year 1994-2023

YEAR	CRISIS EPISODES	GAP	NPL-TC ratio	LD Ratio	ASI
1994	1	0.016444	0.39	0.598	783
1995	1	0.006715	0.45	0.552	1107.6
1996	1	0.039869	0.41	0.429	1543.8
1997	1	0.016007	0.43	0.609	2205
1998	1	-0.01091	0.329	0.733	5092.2
1999	0	-0.01459	0.339	0.729	6992.1
2000	1	-0.00559	0.2581	0.766	6440.5
2001	1	-0.00827	0.1935	0.744	5672.7
2002	0	-0.00744	0.101	0.546	5266.4
2003	1	-0.01581	0.215	0.51	8111
2004	0	-0.0031	0.169	0.65625	10963.1
2005	0	-0.02045	0.213	0.62775	12137.7
2006	0	-0.02611	0.216	0.6185	20128.94
2007	0	-0.03448	0.2308	0.68625	23844.5
2008	0	-0.03959	0.181	0.708	24085.8
2009	1	-0.05008	0.088	0.96817	33189.3
2010	0	-0.02624	0.083	0.832557	57990.2
2011	0	0.059076	0.063	0.869118	31450.78
2012	1	0.082392	0.373	0.843001	20827.17
2013	1	0.038079	0.201	0.522869	24770.52
2014	1	-0.00708	0.0577	0.447737	20730.63
2015	1	0.019304	0.0371	0.423129	28078.81
2016	1	0.008843	0.0339	0.375595	41329.19
2017	1	0.010497	0.0296	0.63607	34657.15
2018	1	0.015458	0.0486	0.695777	28642.25
2019	1	0.018693	0.1282	0.7995	26874.62
2020	1	0.003922	0.1481	0.728413	38243.19
2021	1	-0.0213	0.114	0.601626	31430.5
2022	0	-0.02557	0.0606	0.587257	26842.07
2023	0	-0.01867	0.0602	0.583489	40270.72

SOURCE: National Bureau of statistics/Central Bank statistical bulletin, Harvard business school data bank and researcher's desk

Logit Analysis

Table 2: Logistic regression results

Dependent Variable: Crisis Episodes				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
NPL_TC	0.034830	0.057399	0.606802	0.5440
Asset prices	6.54E-06	4.39E-05	0.148854	0.8817
Credit-to-GDP	34.44803	19.87324	1.733388	0.0830
LDR	-0.023675	0.036603	-0.646801	0.5178
C	1.468931	2.452244	0.599015	0.5492

McFadden R-squared 0.154639; LR statistic 6.097339, Prob (LR statistic) 0.191996

The result of the logistic regression shown in table 2 above show the extent nonperforming loans, asset prices, credit-to-GDP and loan-to-deposit ratio can predict financial crisis in Nigeria. From the results, none of the EWIs showed enough strength at 5% level of significance to be able to predict financial crisis. However, credit-to-GDP out performs other EWIs with the likelihood of predicting financial crisis at the 10% level of significance.

Expectation-Prediction (Classification) Table

Turning to the model accuracy, the Expectation-Prediction (Classification) Table presented in table 3 below indicates that out of nineteen crisis episodes, seventeen were correctly predicted while six out of eleven non crises periods were correctly classified. This gives a sensitivity of 89.47 and specificity of 54.555 respectively. Overall, the estimated model correctly predicts 76.67% of the observations (54.55% of the Dep=0 and 89.47% of the Dep=1 observations).We report that the estimated equation is better than the constant probability model with 13.33 percentage points as indicated by the total gain and represents a 36.36% improvement over the 63.33 percent correct prediction of the default model shown in table 3 below.

Table 3: Expectation-Prediction Evaluation for Binary Specification

Success cutoff: C = 0.5						
	Estimated Equation			**Constant Probability**		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	6	2	8	0	0	0
P(Dep=1)>C	5	17	22	11	19	30
Total	11	19	30	11	19	30
Correct	6	17	23	0	19	19
% Correct	54.55	89.47	76.67	0.00	100.00	63.33
% Incorrect	45.45	10.53	23.33	100.00	0.00	36.67
Total Gain*	54.55	-10.53	13.33			
Percent Gain**	54.55	NA	36.36			

Test of the Validity of the Model

To test the validity of the estimated Logit regression model, the Goodness-of-Fit Evaluation for Binary Specification Andrews and Hosmer-Lemeshow Tests was used. The results are presented in table 4 below.

Table 4: Goodness-of-Fit Evaluation for Binary Specification Andrews and Hosmer-Lemeshow Tests

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.1166	0.3235	2	2.24622	1	0.75378	3	0.10741
2	0.3975	0.4784	2	1.71883	1	1.28117	3	0.10770
3	0.4793	0.5248	3	1.49858	0	1.50142	3	3.00568
4	0.5334	0.5996	1	1.29105	2	1.70895	3	0.11518
5	0.6146	0.6228	2	1.14748	1	1.85252	3	1.02571
6	0.6268	0.6560	0	1.08614	3	1.91386	3	1.70253
7	0.6580	0.6990	0	0.97249	3	2.02751	3	1.43895
8	0.7812	0.8666	1	0.54295	2	2.45705	3	0.46975
9	0.8774	0.8900	0	0.35360	3	2.64640	3	0.40085
10	0.9172	0.9769	0	0.14266	3	2.85734	3	0.14978
		Total	11	11.0000	19	19.0000	30	8.52354
H-L Statistic			8.5235		Prob. Chi-Sq(8)		0.3841	
Andrews Statistic			19.1143		Prob. Chi-Sq(10)		0.0388	

The results of the Hosmer-Lemeshow (HL) and Andrews Tests for goodness-of-fit show a p-value for the HL test that is large while the value for the Andrews test statistic is small. Thus, the model could not be adjudged to have a good or bad fit given the discrepancies between the Hosmer-Lemeshow (HL) and Andrews Tests statistics.

Area under the Receiver Operating Characteristics Curve (AUC-ROC) and Empirical Receiver Operating Characteristics Curve (E-ROC)

Presented in figure 1 below is the Receiver operating characteristics' curve for EWIs. The legends (source of the curve) identify the graphs for credit-to-GDP gap, non-performing loans, asset prices and loan-to-deposit ratio respectively. The nearer the curve to the corner indicated by the arrow the better the EWI. From the figure, we find that credit-to-GDP gap has the shortest distance to corner followed by non-performing loans, asset prices and lastly loan to deposit ratio in that order. Therefore, the Empirical ROC Curve employing the distance to corner statistic, indicates that credit-to-GDP gap outperforms non-performing loans, asset prices and loan-to-deposit ratio as a predictor of financial crisis in Nigeria.

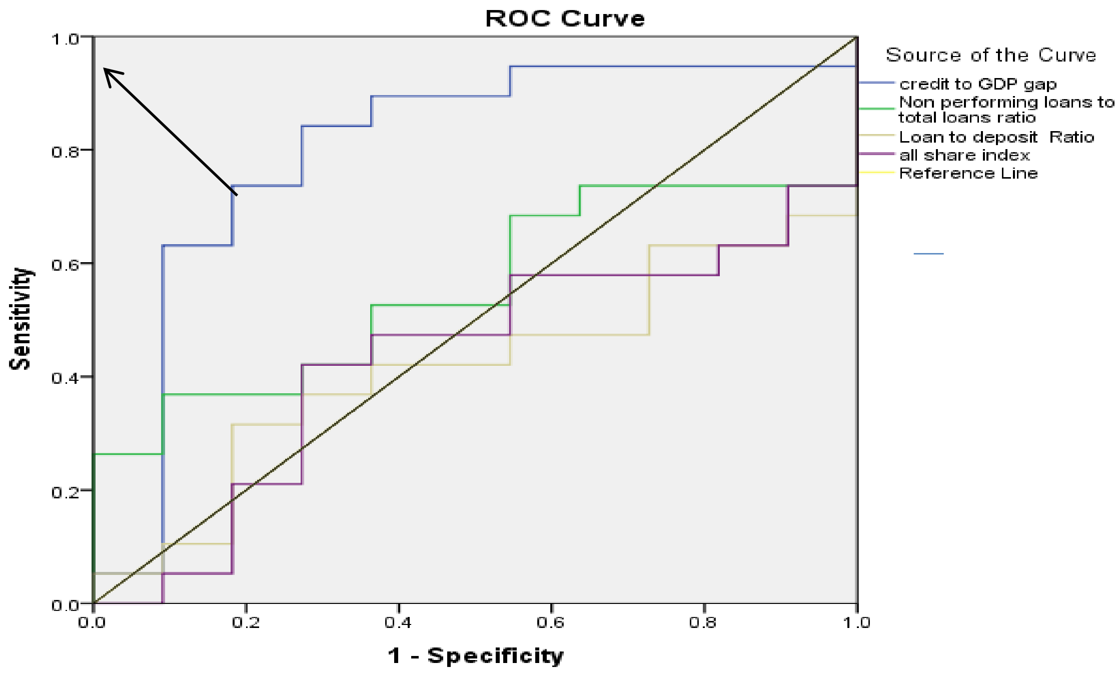

Figure 1: Receiver operating characteristics' curve for EWIs

Area under the ROC Curve (AUC)

The question of how good, efficient and effective the EWIs are in predicting financial crisis was addressed by the Area under the ROC Curve (AUC).

Table 5: Area under the result

Test Result Variable(s)	Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
credit to GDP gap	.799	.094	.007	.615	.983
Nonperforming loans to total loans ratio	.555	.105	.621	.350	.761
Loan to deposit Ratio	.416	.104	.451	.212	.621
Asset prices	.431	.107	.533	.220	.641

a. Under the nonparametric assumption; b. Null hypothesis: true area = 0.5

Source: Researchers' Desk, SPSS 23 output 2024

From table 5 above, credit to GDP gap has area 0.799 with an asymptotic significance value of 0.007. Following the AUC criteria above, the credit-to-GDP gap AUC of 0.799 falls in the acceptable category and thus is capable of predicting financial crisis in Nigeria. On the other hand, non-performing loans, Loan to deposit ratio and asset prices with AUC's 0.555, 0.416 and 0.431 respectively fall in the category of EWIs with no prediction ability.

Discussion of Findings

Using the AUC and distance to corner, the results indicate that credit-to-GDP gap is a predictor of financial crisis in Nigeria. Comparably, the AUC and distance to corner also show that credit-to-GDP gap outperforms Non performing loans, Loan to deposit ratio and asset prices as EWIs of financial crisis. This result supports several earlier studies including

Qingyu (2021), Sally and Katsiaryna (2025) for advanced economies, Drehmann and Yetman (2024), Beutel, List and Schweinitz (2019), Giordani and Simon (2023), Geršl, and Jašová (2018) among others. However, the result of the present study is at variant with Sally and Katsiaryna (2025) whose study indicated that asset prices do better for emerging economies and Ihejirika and Peters (2025) whose findings show that Credit-to-GDP Gap performs poorly in Nigeria. Similarly, the results from the Logit regression show that none of the EWIs tested (Credit-to-GDP gap, Nonperforming loans, Loan-to-Deposit ratio and asset prices) could predict financial crisis at the 5% level of significance although credit-to-GDP gap could at 10%. Furthermore, several studies argue that the method and specifications adopted by researchers affect the results (Qingyu, 2021; Drehmann &Yetman, 2024; Bakhuashvili 2019)

Using the AUC and distance to corner, the results indicate that credit-to-GDP gap is a predictor of financial crisis in Nigeria. Comparably, the AUC and distance to corner also show that credit-to-GDP gap outperforms Non performing loans, Loan to deposit ratio and asset prices as EWIs of financial crisis. And also, the study found out from the Logit regression that none of the EWIs tested (Credit-to-GDP gap, Nonperforming loans, Loan-to-Deposit ratio and asset prices) could predict financial crisis at the 5% level of significance although credit-to-GDP gap could at 10%.

CONCLUSIONS

From the findings, the study established that credit-to-GDP gap is a predictor of financial crisis in Nigeria using AUC and distance to corner. And that credit-to-GDP gap outperforms non-performing loans, Loan to deposit ratio and asset prices as EWIs of financial crisis. It also established that using Logit regression, none of the EWIs tested (Credit-to-GDP gap, Nonperforming loans, Loan-to-Deposit ratio and asset prices) could predict financial crisis. This shows that the method and specifications adopted by a researcher can affect the results

Therefore, the study recommends that:

1. Beyond the scope of this research, further research is needed to develop indicators that adequately map increased cross-border exposures of financial institutions. And also consider other forward-looking variables that can capture self-fulfilling crises.
2. When constructing a EWS for any type of financial crisis, policy makers are advised to consider the economic and financial conditions of the regional economies, as well as in countries with close trade and financial links to allow for the possibility of contagion.
3. The estimation of the likelihood of an approaching crisis should be updated at least once every six months for currency and banking crises, and once every year for sovereign debt crises, as the probability of such crises depends on the build-up of new vulnerabilities, as well as the corrective actions undertaken by policy makers.
4. Countries with high Credit-to-Deposit ratios and/or Current account deficits should make extra efforts in monitoring the performance of the private sector credit.

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