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Risk and Banks' Performance: Macrofinametric Evidences From Deposit Money Banks In Nigeria

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Abstract: *This study employed macroeconometric tools to investigate the impacts of risk factors on performance of deposit money banks in Nigeria with aggregated time series data from Nigeria Deposit Insurance Commission. It was found among others that bank performance proxied by return on assets is autoregressive, hence reinforces itself, non-performing loans (credit risks) exert negative and significant impact on bank performance within the period of the study, while average liquidity ratio (liquidity risk) insignificantly on bank performance within same period. This study found that bank performance proxied by return on assets respond to shocks of risk factors in both positive and negative direction. Therefore, suggested banks should demand insured collateral from customers on loan facility request in order to protect depositors' money as well as mitigating against risk on banks' performance.*

Keywords: Non-performing Loans, Liquidity risk, ROA, ARDL, VAR.

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I. Introduction

A good and sound performing bank is indispensible in an economy due to its role of intermediation, facilitating payments flow, maturity transformation, credit allocation, maintenance of financial discipline and other vital roles among borrowers. Bank, mostly deposit money banks make play important and positive task as mobilizing savings, allocation of financial resources, payment services and provision of liquidity.

In developed and highly sophisticated economies, banks remain the fulcrum and oscillating point of economic and financial activities and stand apart from other institutions as primary providers of payments services as a centre for monetary policy transmission. Even in emerging and developing financial markets, deposit money banks and other banks provides information readily needed for intermediation, provision of portfolio diversification used for maturity transformation and risk amelioration among others roles (Lindgren, Garcia and Saal, 1996).

Ogbeni and Oseni (2018), a pivotal role of banking sector in economic growth and development in developed and developing economies has been acknowledged by scholars, economists, accountants, researchers, and professionals. Banking sector contributes to the real productivity of the economy and the overall standard of living, since banks can simultaneously satisfy the needs and preferences of both surplus and deficit units. The failure or success of these banks will to a large extent affect the financial sector and the economy at large. This implies that banks are the major determinant of financial inclusion because they allocate funds from savers to borrowers in an efficient manner, Ogbeni and Oseni (2018) added.

Nwankwo (1991) said risk is inherent in banking business as seen in its maturity transformation (borrowing short and lending long). The foundation of doing this according to Nwankwo (1991) is the probability that it will not be called upon at any one time to redeem all its obligations, provided it manages their affairs prudently. Nwude and Okeke (2018) in the same vein added, banks use customers deposit to generate credit for their borrowers which in fact is a revenue generating activities for banks. This credit creation process exposes the banks to high default risk which might lead to financial distress including bankruptcy.

Perhaps the most vital aspect of bank's market interaction is their ultimate role in payment system. Operating within the central role of payments system exposes the participants to variants of risks. The most pervasive of the risks are credit risk and liquidity risk. Credit risk is the risk that one party in a transaction may not be able to meet up its obligation because of insolvency; liquidity risk is probability that the counterparty will not be able to settle on time (Lindgren, Garcia and Saal, 1996). No wonder Njoku, Ezeudu and Ekemezie (2017) were of the opinion that, the important of credit management to banks cannot be overemphasis and it also forms an integral part of the loan process. Njoku, Ezeudu and Ekemezie (2017) went further to argue that Credit risk management maximizes bank risk adjusted risk rate return by maintaining credit risk exposure with view to shielding the bank from the adverse effect of credit risk.

Researchers and theorists have made frantic efforts to unravel the linkage between risks and banks performance. As result, a good number of researchers recently have been able to come out with findings that could be reliable, though is still undecided and unending. Okeke, Isiaka and Ogunlowore (2018) examined the extent to which banks risk management affect banks' performance, with emphasis on credit and liquidity risks and impact on the performance of deposit money banks in Nigeria. Okeke et'al (2018) came out boldly to state that a positive relationship exist between risk management and banks' performance of Nigerian deposit money banks. Almekhlafia, Almekhlafia, Kargbo and Hu(2016) investigated the relationship between credit risk and commercial bank performance in Yemen and were able to found a negative relationship existing non-performing loan (credit risk) and performance of banks in Yemen. In this same way, Zhongming, Mpeqa,Mensah, Ding and Musah(2019) conducted the same research on credit risk and commercial bank performance in China and found that non-performing loan has a mitigating impact on bank performance.

On insulating the risk inherent in the banking business, signaling hypothesis was propounded. As cited by Kajola, Adedeji, Olabisi and Bbatolu (2018), the signaling hypothesis opined that banks demand collateral from reputable customers who request for loan facility. This is necessary according to Kajola et'al (208) in order to protect customers' deposit and at the same time send a signal to the banks that they (reputable companies) belong to the risky class of customers. In furtherance of the argument, Kojola et'al as cited advocated that high risk customers are also requested to provide huge collateral for loan facility and banks do change high interest rates to cover for the high risk of the customer request.

Meanwhile, this study was borne out of the concern of the researchers on the incessant cases of delinquent loans and under performance of deposit money banks in Nigeria. Its resultant effects have led to acquisition and takeover of perceived reputable banks and other contagion effects on the economy as whole. This is notwithstanding the immeasurable mitigating policies and regulations from the Central Bank of Nigeria (CBN) and the Nigerian Deposit Insurance Commission (NDIC). In seeking answers to the researchers concern, this study will empirically investigate the relationship and impact of Nigerian deposit banks' performance and the most pervasive of the risks (credit risk and liquidity risk).

The remaining sections of this study are organized as follows; section two will take care of review of related literature; section three addresses the materials and methods of analysis adopted; section four analyses the data, results and interpretation while section five handles conclusion and recommendations for policy making.

II. Review of Related Literature

2.1 Theoretical Review

***Signaling Hypothesis*:** The signaling hypothesis opined that banks demand collateral from reputable customers who request for loan facility. This is necessary in order to protect customers' deposit and at the same time send a signal to the banks that they (reputable companies) belong to the risky class of customers. In furtherance of the argument, that high risk customers are also requested to provide huge collateral for loan facility and banks do change high interest rates to cover for the high risk of the customer request (Kajola, Adedeji, Olabisi and Bbatolu, 2018).

***Information Asymmetry Theory*:** This study anchors on information asymmetry theory, because the theory is very relevant to this study. Information asymmetry theory elucidates on basic information to be known by both lenders and business owners in terms of potential risks and returns associated with investment projects for which the funds are earmarked. It is note that perceived information asymmetry poses two problems for the banks; moral hazard (monitoring entrepreneurial behavior) and adverse selection (making errors in lending decisions). This implies that before credit can be granted, the "5cs" (character, capacity, capital, collateral and conditions) must be adequately evaluated. This is because data needed to screen credit applications and to monitor borrowers are not freely available to banks. Bankers face a situation of information asymmetry when assessing lending applications. It is argued that information asymmetry arises when a borrower who takes a loan usually has better information about the potential risks and returns associated with investment projects for which the funds are earmarked. The banker on the other hand does not have sufficient information concerning the entrepreneurs. In the same vein, it is also noted that information asymmetry is the extents to which banks' managers know more about the firm than investors as a group (Ogbeni and Oseni, 2018).

2.2 Empirical Review

Scholars around the world have done impressive research to unveil the relationship between risk and banks performance. Among the reviewed papers some tilted towards positive relationship between risks components while others on the other extreme revealed negative relationship.

Outside Africa, Zhongming, Mpeqa, Mensah, Ding and Musah (2019) established the nexus of credit risk management and bank performance, employing variants of panel data analysis techniques. The results among others disclosed that non-performing loans has a mitigating impact on bank performance in China.

In the same vein, Almekhlafia, Almekhlafia, Kargbo and Hu(2016) examined credit risk and commercial banks' performance in Yemen using panel model analysis techniques. After a thorough analysis, it was found that non-performing loans negatively affects the bank performance of banks in Yemen. It was also established that credit risk management and its effect on banks performance are similar across banks in Yemen.

In Iran, Ahmadyan (2018) looked at measuring credit risk management and its impact on bank performance using panel data analysis method on financial statements of banks for the period of 2005 to 2016 inclusive. The result of the study showed that there was a significant relationship between risk management and profitability and bank survivability implying risk management impact significantly on banks' performance.

Wood and McConney (2018) examined the impact of risk factors on the performance of the commercial banking sector in Barbados using a quarterly data for period of 2000 to 2015. The study employed multiple regression models which includes a number of risk variables and other factors which might influence the banks financial performance. The study revealed among others that credit risk exerted a negative impact on the performance, thus added that banks must ensure they adopt appropriate measures to minimize the impact of this credit risk.

In Kenya, Makokha, Namusonge and Sakwa (2016) investigation the effect of risk management practices on commercial banks performance. The study employed Ordinary Least Square (OLS) technique and found that a positive statistically significant relationship exist between risk management practices and financial performance.

In Nigeria, Okere, Isiaka and Ogunlowore (2018) examined the degree to which banks' risk management (credit and liquidity risks) have impacted performance of Nigeria deposit money banks. The used panel data analysis techniques and descriptive statistics to reveal that there is a positive relationship between risk management financial performances of Nigerian deposit money banks.

Again, Olamide, Uwuigbe and Uwuigbe (2015) investigated the effects of risk management on the performance of financial institution in Nigeria employing OLS. After estimating the models Olamide et'al (2015) found negative and non-significant relationship between risk management proxies and banks' performance. The study noted that performance cannot be explained away by compliance or non-compliance to Basel's regulation by financial Institutions, but could be as a result of the accumulation of minor difficulties and inconsequential malfunction of the individual actors resulting in a massive breakdown.

Kajola, Adedeji, Olabisi and Bbatolu (2018) empirically explored the relationship between credit risk management practices of Nigeria listed deposit money banks and financial performance. The used Random effects Generalized Least Square (GLS) regression to disclose that all the three credit risk parameter have a significant relationship with Return on Assets and Return on Equity at 5% significance level.

In the same manner, Adeusi, Akeke, Obawele and Oladunjoye (2013) examined the effect of risks management on the financial performance of Nigeria banks using panel data estimation technique. The study unraveled relationship between financial performances of banks and doubt loans, and capital asset ratio is positive and significant. Therefore concludes a significant relationship exist between bank performance and risk management.

Njoku, Ezeudu and Ekemezie (2017) x-rayed whether credit risk management impact the performance of commercial banks in Nigeria with panel regression model. The study found that credit risk management has a significant impact on the performance of commercial banks in Nigeria.

Also, Nwude and Okeke (2018) investigated the impact of credit risk management on the performance of deposit money banks in Nigeria using five banks that had highest asset base. The study employed OLS regression model to disclose that credit management had a positive and significant impact on total loans and advances, the return on assets and return on equity of the deposit money banks. From the results of the study, it means that credit risk management exerts positive and significant impact on banks' performance in Nigeria according Nwude and Okeke (2018).

Still in Nigeria, Kolapo, Ayeni and Oke (2012) made an enquiry into the effect of credit risk on the performance of commercial banks over the period of eleven years (2000-2010) employing panel data estimation technique for analysis. The result showed that effect of credit risk and bank performance measured by th return on assets of banks is cross sectional invariants.

Ogunlade and Oseni (2018) specifically made an investigation on the effect of credit management practices on the performance of First Bank of Nigeria. Data was collected using purposive sampling technique from thirty (30) respondents as a sample size used to collect data from respondents. Descriptive statistics and multiple regressions were employed to discover that credit management practices have a significant positive influence on the financial performance of First Bank.

III. Methodology

3.1. Sources of data and Tools for analysis

The study employed aggregated data collected from Nigeria Deposit Insurance Commision (NDIC) for credit risk (CRR) (non –performing loans) and liquidity risk (LQR) (average liquidity ratio) and return on assets (a proxy of bank performance) from 2010 to 2017. In this study, Microfinametic tools are employed in the analysis and estimation; Descriptive Statistics is employed to describe the variables. In testing for multicollinearity, the correlation matrix is engaged. Ordinary Least Square (OLS) is employed to examine the global utility of the model. Augmented Dickey Fuller (ADF) unit root test is used to check the stationarity of the variables. Autoregressive Distributive Lag and Vector Autoregressive (VAR) models are employed to estimate the model.

3.2. Model Specification

The function model is as follows;

Bank Performance = f (Risk Factor) (1)

Bank Performance = f (Credit Risk, Liquidity Risk) (2)

ROA = f (CRR, LQR) (3)

While the explicit form in first difference is;

For ARDL Specification;

$$ROA = b_0 + b_1ROA_{t-1} + b_2CRR + b_3CRR_{t-1} + b_4LQR + b_5LQR_{t-1} + e_{t-1} \quad (4)$$

For VAR Specification;

$$ROA_t = \alpha_{01} + \alpha_{11}ROA_{t-1} + \alpha_{21}CRR_{t-1} + \alpha_{31}LQR_{t-1} + U_1 \quad (5)$$

$$CRR_t = \beta_{02} + \beta_{12}ROA_{t-1} + \beta_{22}CRR_{t-1} + \beta_{32}LQR_{t-1} + U_2 \quad (6)$$

$$LQR_t = \Upsilon_{03} + \Upsilon_{13}ROA_{t-1} + \Upsilon_{23}CRR_{t-1} + \Upsilon_{33}LQR_{t-1} + U_3 \quad (7)$$

Where, ROA = Bank Performance
CRR = Credit Risk
LQR = Liquidity Risk
e_t = Stochastic Elements

3.3. Apriori Expectation

The operation definition is; Bank Performance = f (Credit Risk, Liquidity Risk), $b_1, b_2 < 0$. The researchers expect risk factors to have negative influence on Bank Performance

IV. Data Analysis and Results

The researchers decided to commence the analysis by examining the trend of the variables as shown in figures 1a and 1b below.

Figure 1a: Trend of Variables

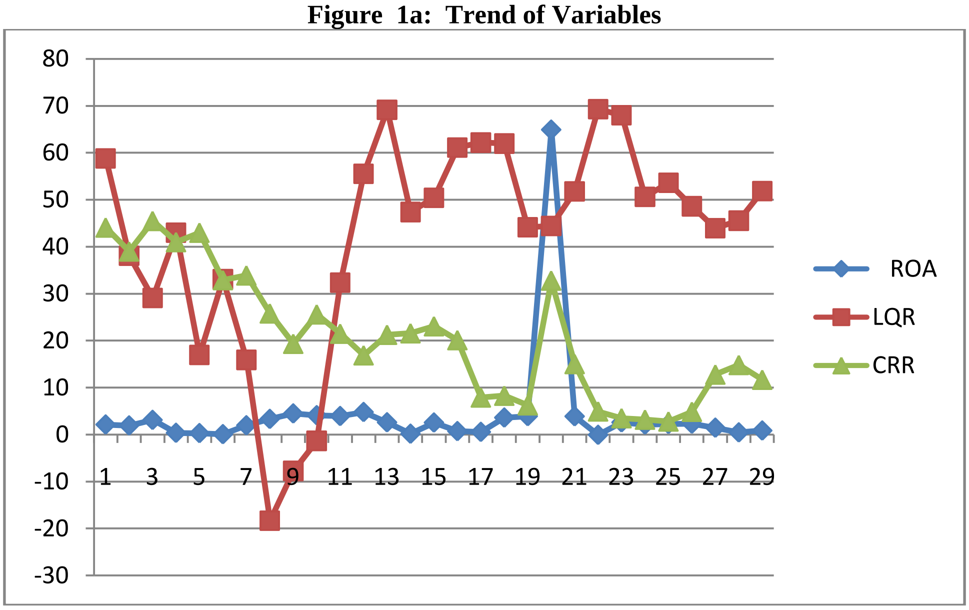
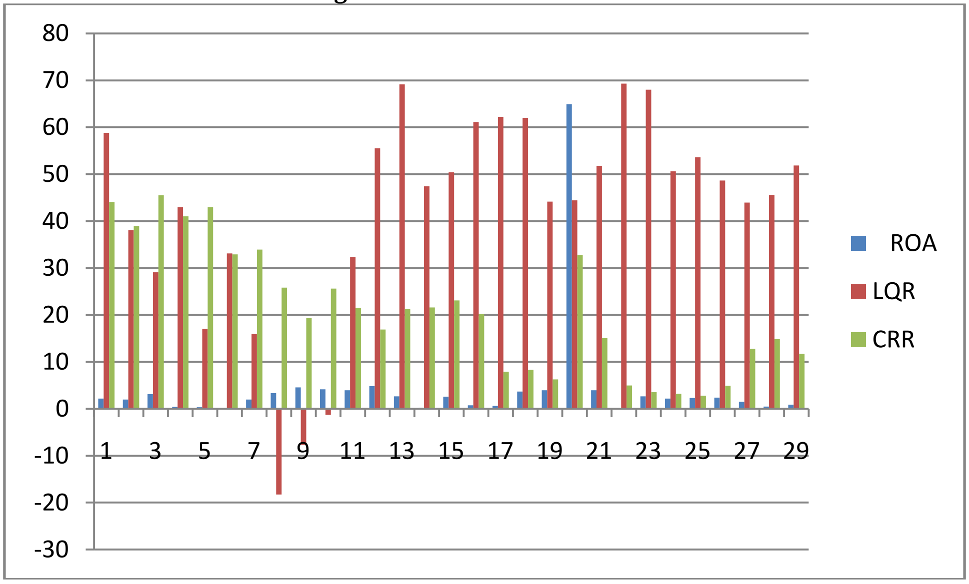


Figure 1b: Trend of Variables



From figures 1a and 1b, there was upward and downward trend for all the component of risk. Liquidity risk topped the list by making positive trend and some points made negative movements. This is followed by credit risk that trended from a higher level to lower level. At some point peaked up with the return on asset, though was below.

Next is description of the variables as depicted in Table 1 below;

Table 1: Descriptive Statistics

	ROA	CRR	LQR
Mean	4.352069	20.81517	42.06517
Median	2.290000	20.13000	47.40000
Maximum	64.92000	45.50000	69.29000
Minimum	-0.040000	2.810000	-18.30000
Std. Dev.	11.74056	13.50399	22.37126
Skewness	4.975258	0.373935	-1.199978
Kurtosis	26.20461	1.985547	3.842100
Jarque-Bera	770.2721	1.919346	7.816619
Probability	0.000000	0.383018	0.020074
Sum	126.2100	603.6400	1219.890
Sum Sq. Dev.	3859.542	5106.014	14013.25
Observations	29	29	29

Source: Authors' computation with E-view 10

Table 1 above shows a summary of statistics where ROA has standard deviation (SD) of 11.74056, Jarque Bera Statistic (JBS) of 770.2721 with associated probability Value (P-value) of 0.000000. LQR has SD of 22.37126, JBS of 7.816619 with P-value of 0.020074, which shows that ROA and LQR are abnormally distributed, while CRR has SD of 13.50399, JBS of 1.919346with P-value of 0.383018, announcing a normal distribution.

The researchers then proceeded to testing the presence of multicolinearity among the variables using Correlation Matrix as shown in Table 2 below;

Table 2: Correlation Matrix

Variables	ROA	CRR	LQR
ROA	1.000000	0.154845	-0.016174
CRR	0.154845	1.000000	-0.413891

LQR	-0.016174	-0.413891	1.000000

Source: Authors' computation with E-view 10

Table 2 above reveals the correlation of the variables. The correlations between CRR, LQR and ROA are 0.154845 and -0.016174 respectively, between CRR and LQR is -0.413891. The highest value here is 0.15 which informs that the variables are not linearly correlated. Therefore, the researchers have sufficient evidence to say no presence of multicollinearity in the model.

The researchers now proceeded to checking the global usefulness of our model by using Ordinary Least Square (OLS) method as shown in Table 3 below;

Table 3: Ordinary Least Square (OLS) method

Dependent Variable: ROA
Method: Least Squares
Date: 11/30/19 Time: 18:01
Sample: 1990 2018
Included observations: 29

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CRR	0.155431	0.184780	0.841165	0.4079
LQR	0.030344	0.111539	0.272047	0.7877
C	-0.159669	7.531783	-0.021199	0.9832

R-squared	0.026747	Mean dependent var	4.352069
Adjusted R-squared	-0.048118	S.D. dependent var	11.74056
S.E. of regression	12.01971	Akaike info criterion	7.908670
Sum squared resid	3756.309	Schwarz criterion	8.050114
Log likelihood	-111.6757	Hannan-Quinn criter.	7.952969
F-statistic	0.357274	Durbin-Watson stat	1.794842
Prob(F-statistic)	0.702962		

Source: Authors' computation with E-view 10

Table 3 reveals the Ordinary Least Square (OLS) estimated model for the relationship between risk factors and bank performance. From the table, the adjusted R-squared (R^2) is -0.48118 and F-statistics is 0.357274 with probability value of 0.702962 which shows the model is insignificant. This is unreliable and cannot be used for further analysis and policy formulation.

The researchers resorted to checking the stationarity of the variables. This procedure is normal in macroeconomic time series analysis to know the most suitable technique for estimating the model. Here, the researchers employed Augumented Dickey Fuller (ADF) unit root test as depicted below;

Table 4: Augmented Dickey-Fuller (ADF) Unit Root Test

Variables	Lag SCI	ADF Statistic	Probability	Remarks
ROA	0	-4.969551	0.0004	@1(0)
CRR	0	-6.482592	0.0000	@1(1)
LQR	0	-4.865181	0.0006	@1(1)

Source: Authors' computation with E-view 10

Table 4 presents the ADF unit root test. The result shows that the ROA variable is stationary at level while CRR and LQR are integrated at order one.

The researchers however have sufficient evidence to adopt Autoregressive Distributive Lag (ARDL) to estimating the model. The researchers proceed to model selection using Akaike Information Criterion(AIC) as shown below in Fig 2.

Figure: 2 Akaike Information Criterion (AIC)

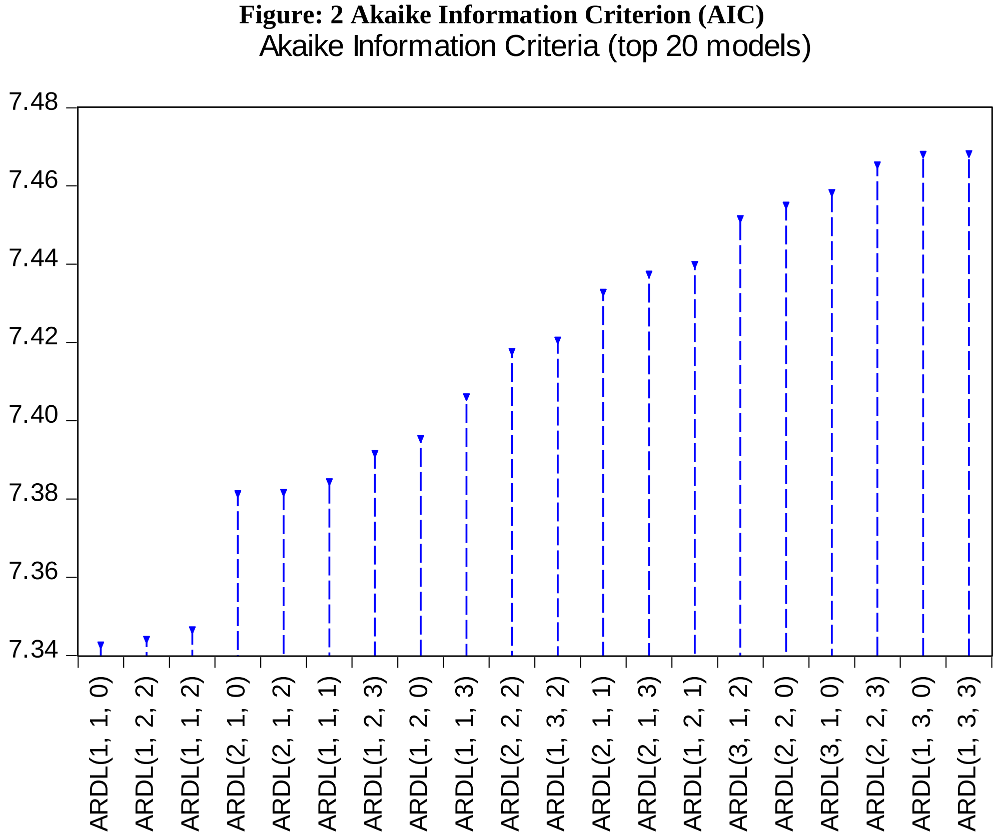


Figure 2 shows the ARDL model selection based on Akaike Information Criterion (AIC). Information criteria select models that minimize their values. From figure 2 above, the best model, according to AIC, is an ARDL (1, 1, 0). This implies that a model that includes on lagged value of the dependent variables as an additional regressor is the best description of researchers' data.

The researchers therefore move to estimating the models with ARDL as shown in table 5 below.

Table 5: Autoregressive Distributive Lag (ARDL) Model

Dependent Variable: ROA
Method: ARDL
Date: 11/30/19 Time: 15:00
Sample (adjusted): 1991 2018
Included observations: 28 after adjustments
Maximum dependent lags: 3 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (3 lags, automatic): CRR LQR
Fixed regressors: C
Number of models evalulated: 48
Selected Model: ARDL(1, 1, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
ROA(-1)	0.329947	0.151828	2.173158	0.0403
CRR	1.209532	0.244984	4.937195	0.0001
CRR(-1)	-1.188998	0.232233	-5.119844	0.0000
LQR	-0.002028	0.085931	-0.023600	0.9814
C	4.003087	5.997250	0.667487	0.5111

R-squared	0.551408	Mean dependent var	4.430357
Adjusted R-squared	0.473391	S.D. dependent var	11.94829
S.E. of regression	8.670612	Akaike info criterion	7.318188

Sum squared resid	1729.129	Schwarz criterion	7.556082
Log likelihood	-97.45464	Hannan-Quinn criter.	7.390915
F-statistic	7.067871	Durbin-Watson stat	1.975555
Prob(F-statistic)	0.000728		

*Note: p-values and any subsequent tests do not account for model selection.

Source: Authors' computation with E-view 10

From Table 5 shows the estimation results for the preferred model; ROA is autoregressive. CRR at lag one is negative and significant while LQR is insignificant. With R- square, it is a good fit, while Adjusted R-square shows reasonable explanation of variation. The results also indicate a significant F- statistics validating the model, and Durbin-Watson Statistics (Dw) shows no autocorrelation.

Having estimated the model, the researchers then proceeded to checking if long run relationship exist between the dependent and independent variables using Bound Cointegration Test and the speed of adjustment using Error Correction Model Regression as depicted below in Table 6 and 7 respectively;

Table 6: Bound Cointegration Test

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	5.211543	10%	2.63	3.35
K	2	5%	3.1	3.87
		2.5%	3.55	4.38
		1%	4.13	5

Source: Authors' computation with E-view 10

Table 6 above reveals ARDL Bound ciointegration Test examining if there is long run relationship in the model. From the bound test, it can be seen that the F-Statistics is 5.211543 and is greater than all the critical values at 1(0) and 1(1) bounds. This reject the null hypothesis of no cointegration, meaning there is long run relationship between credit risk, liquidity risk and bank performance proxied by Return on Asset (specified model).

Table 7: Error Correction Model Regression

ECM Regression

Case 2: Restricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CRR)	1.210727	0.214641	5.640698	0.0000
D(LQR)	0.105155	0.105021	1.001275	0.3287
D(LQR(-1))	-0.132238	0.100019	-1.322122	0.2011
CointEq(-1)*	-0.673750	0.140481	-4.796033	0.0001

Source: Authors' computation with E-view 10

As shown in the result in Table 7 above, error correction equation, CointEq(-1) has expected the negative sign and statistically significant. It can also be adduced that 67.3% of errors from the equilibrium can be corrected in the next period, and speed of adjustment is 67.3%.

Having concluded and satisfied with estimation of the model, the researchers decided to run some residual diagnostic test as seen table 8 and 9 below;

Table 8: Heteroskedasticity Test

Heteroskedasticity Test: ARCH

F-statistic	0.661010	Prob. F(1,24)	0.4242
Obs*R-squared	0.696900	Prob. Chi-Square(1)	0.4038

Source: Authors' computation with E-view 10

In table 8, F-Statistc is 0.661010 with P-value of 0.4242, meaning non rejection of the null hypothesis. The model is homoskedastic.

Next is checking if the model has serial correlation as shown below.

Table 9: Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.385256	Prob. F(2,18)	0.6858
Obs*R-squared	1.108323	Prob. Chi-Square(2)	0.5746

Source: Authors' computation with E-view 10

In table 9, F-Statistic is 0.385256 with P-value of 0.6858, implying non rejection of the null hypothesis. Hence, the model has no serial correlation.

The researchers then proceeded to validating the findings by employing Vector Autoregressive (VAR) Model. Starting from VAR lag length selection, this is to enable the researchers to make use of appropriate lag in the VAR estimations. It is shown in Table 10 below;

Table 10: VAR Lag Order Selection

VAR Lag Order Selection Criteria
Endogenous variables: ROA CRR LQR
Exogenous variables: C
Date: 11/30/19 Time: 15:06
Sample: 1990 2018
Included observations: 27

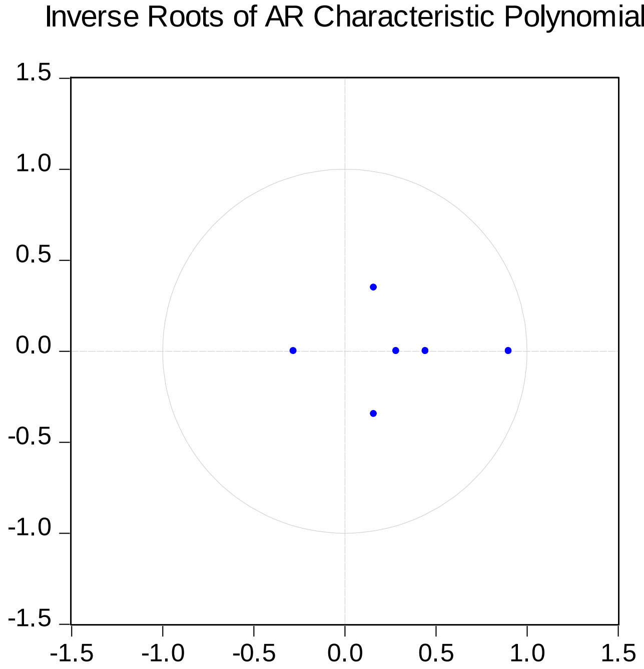
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-329.3275	NA	9853385.	24.61686	24.76084	24.65967
1	-293.3579	61.28165*	1345211.*	22.61910*	23.19503*	22.79036*
2	-288.9117	6.586914	1941791.	22.95642	23.96430	23.25612

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Source: Authors' computation with E-view 10

The VAR lag order selection criteria on table 10 above shows that lag length of 1 is selected at 5% level based on sequential modified LR test statistic, Final prediction error (FPE), Akaike information criterion (AIC), and Hannan-Quinn information criterion (HQ). Then move to evaluating the stationarity for policy making by employing Inverse Roots of AR Characteristics Polynomial Test as shown below.

Figure 3: Inverse Roots of AR Characteristics Polynomial Test



Source: Authors' computation with E-view 10

Figure 3 above shows that all np roots of the characteristics polynomial are in circle or lie within the unit imaginery circle (modulus). Hence, all are stationary.

Next is checking if the model is heteroscedastic as shown below.

Table 11: VAR Residual Heteroskedasticity Test

VAR Residual Heteroskedasticity Tests (Levels and Squares)
Date: 11/30/19 Time: 15:07
Sample: 1990 2018
Joint test:

Chi-sq	df	Prob.
69.07046	72	0.5760

In the same vein shows that Chi-sq is 69.07046 with P-value of 0.5760, therefore the researchers do not reject the null hypothesis. Hence, the model is homoskedastic.

Next is checking if the model has serial correlation as shown below.

Table 12: VAR Residual Serial Correlation LM Tests

VAR Residual Serial Correlation LM Tests
Date: 11/30/19 Time: 15:08
Sample: 1990 2018
Included observations: 27

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	3.830202	9	0.9222	0.407616	(9, 36.7)	0.9229

Source: Authors' computation with E-view 10

The result on table 12 indicates that there is absence of serial correlation in the model.

The researchers then proceed to checking the responses of bank performance to the shocks from variables risk. Starting from the response of bank performance proxied by ROA to the shock of CRR as shown in Fig 4

Figure 5: Response ROA to CRR

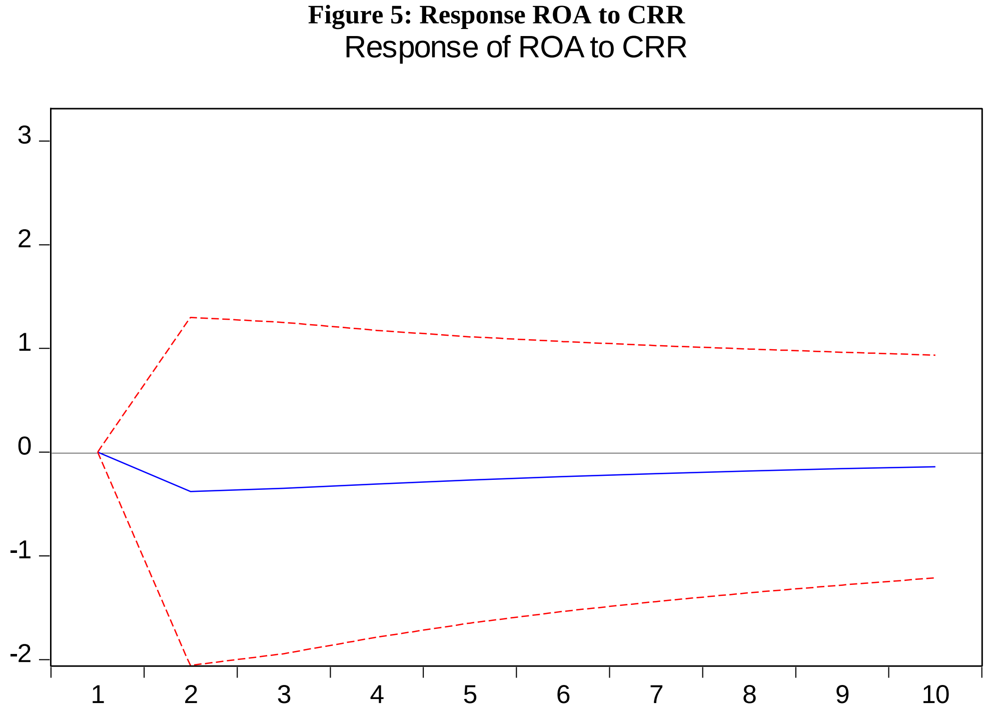


Fig.4 shows that ROA responds negatively from the first year until the tenth year. That means shock CRR engenders negative effects to the ROA.

Figure 4: Response ROA to CRR

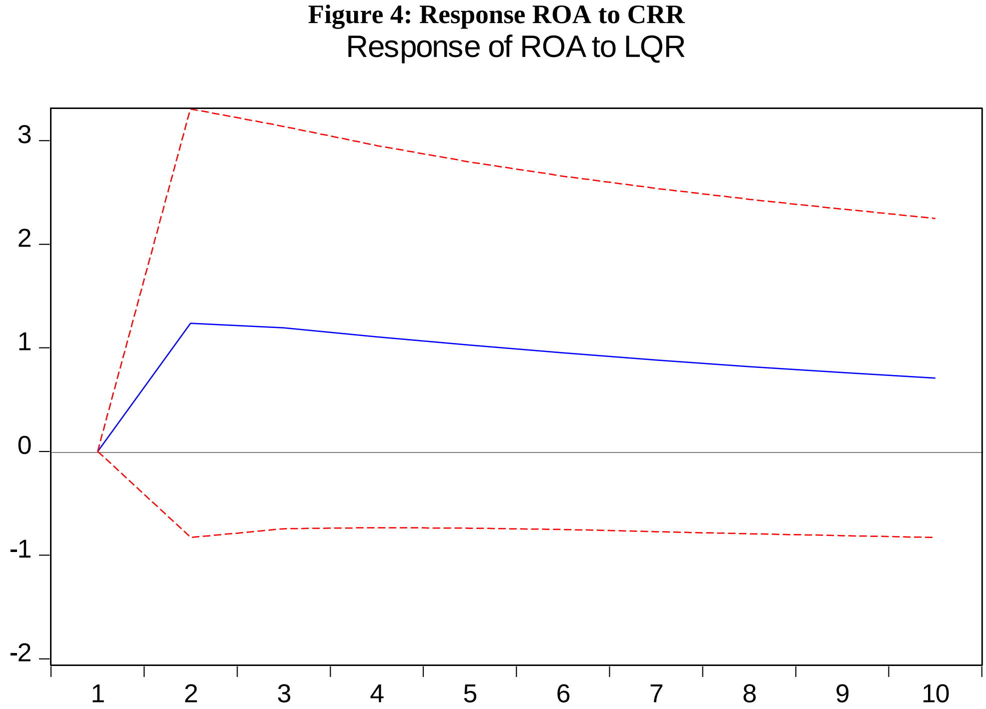


Fig. 5 shows that ROA responds positively from the first year until the tenth year. That means shock LQR engenders positive effects to the ROA.

The researchers proceed to Variance Decomposition as shown in Table 13 below;

Table 13: Variance Decomposition

Period	S.E.	ROA	CRR	LQR
1	12.63265	100.0000	0.000000	0.000000
2	12.72627	98.96647	0.088546	0.944982
3	12.79148	98.03178	0.161686	1.806538
4	12.84659	97.24923	0.217189	2.533585
5	12.89350	96.59300	0.259189	3.147814
6	12.93356	96.04020	0.290983	3.668820
7	12.96785	95.57256	0.315051	4.112391
8	12.99728	95.17545	0.333261	4.491290
9	13.02261	94.83706	0.347024	4.815915
10	13.04444	94.54780	0.357410	5.094793

Cholesky Ordering: ROA CRR LQR

Source: Authors' computation with E-view 10

From Table 13 above, ROA explains 100 percent of its variations in the first period and diminishes gently to 94.54% percent in the tenth period. In other words, "the own shock" started from 100 percent and decreased to 94.5% percent. CRR increased from zero percent of the variation in the first period 0.357410 in the tenth year. LQR also increased from zero percent in the first period to 5.094793 in the tenth period.

Finally, the researchers proceeded to know if deviations in the current period can be corrected in the next period and also the speed of adjustment using Vector Error Correction Estimates as shown in Table 14 below;

Table 14: Vector Error Correction Estimates

Error Correction:	D(ROA)	D(CRR)	D(LQR)
CointEq1	-0.845185	-0.366571	0.553106
	(0.27783)	(0.16736)	(0.34121)
	[-3.04211]	[-2.19033]	[1.62101]

Source: Authors' computation with E-view 10

The analysis in table 14 above shows that error correction equation (CointEq1) satisfied the condition, hence, significant.

V. Conclusions and Recommendation

In conclusion, this study revealed as follows; that bank performance proxied by return on assets is autoregressive, hence reinforces itself, non-performing loans (credit risks) exert negative and significant impact on bank performance within the period of the study, while average liquidity ratio (liquidity risk) insignificantly impact bank performance within same period. These results agree with the findings of Wood and McConney (2018). These results suggest the adoption of signaling hypothesis in order to ameliorating the adverse effect of credit risk on bank performance, corroborating the results of Nwude and Okeke (2018); Makokha, Namusonye and Sakawa (2016); Okere, Isiaka and Ogunlowore (2018); Njoku, Ezeudu and Ekemezie (2017); Ogunlade and Oseni (2018) that credit risk management exerts positive impact on the performance of banks and other financial institution. This study found that bank performance proxied by return on assets respond shocks of risk factors in both positive and negative direction. Therefore, suggested banks should demand insured collateral from customers on loan facility request in order to protect depositors' money as well as mitigating against risk on banks' performance. Again, adequate credit analysis should conduct before extending loans to customers.

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