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Bank Attributes and Financial Performance in Nigeria New Insights From Adopting Machine Learning Programming Approach

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Abstract
This paper examined the influence of bank attributes on financial performance of deposit money banks in Nigeria, using base data from annual reports and accounts of 13 purposively selected deposit banks in Nigeria for 8 years, culminating into 104 data set. The study adopted Python 3 to run the predictive models in order to evaluate their performance from the Jupyter Notebook and PyCharm (IDE). The exploratory data analysis (EDA) was deployed to uncover hidden insights for a better preparation to better assumptions that would satisfy the choice of best analytical tool. The results from analysis provide empirical evidence that credit risk and capital ratio are effective determinants of commercial banks' performance in Nigeria. Nevertheless, this behavioural pattern should take cognizance of requirement of Basel III especially the required minimum capital, leverage ratio, liquidity coverage ratio and net stable funding ratio (NSER).

Keywords: *Credit risk, capital to assets ratio, liquidity risk, risk-adjusted return on asset, Nigeria*

Introduction

One factor that has been conspicuous in the accounts of various financial crisis that engrossed world markets especially in 2007-09 is that capital ratios, liquidity ratio and default risk in developed and developing countries and once the scale of the losses arising from sub-prime lending and associated structured credit products became clear, markets confidence is reduced in many large banks' because of their ability to absorb losses and remain going concerns as a result of inadequate capital required, liquidity and high credit defaults (Milne, 2009; FSA, 2009). Bank capital can be view from the perceptive of capital structure that is the amount of equity capital and other securities which a bank holds as reserves against risky assets in order to avoid possibility of bank failure or distress. Liquidity generally can be view from the context of securities that can be easily converted to cash within shortest period of time at minimum cost. liquidity crisis significantly affected banks' operational environment because there is always of a dilemma of balancing between liquidity and profitability that is as liquidity increases profitability decreases and vice versa while on the other hand, there is a direct relationship between higher risk and higher return. Credit risk usually occurred as a result of non-fulfillment of financial obligation by customers, this has always been a major threat to stability of the banking industry and the whole financial system as the main courses of bank failures or distress.

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In a bid to reduced bank distress or failure that may arise as a result of inadequate capital, low level of liquidity asset and high level of default risk which has been the causes of various global financial distress. Bank of International Settlements (BIS) established a framework used as a benchmark for active management of bank capital, liquidity and credit risk for banks in the Group of Ten industrialized countries at a meeting in the city of Basle in Switzerland. This has come to be referred to as the Basle Capital Accord I II, III regulation (BCBS 2014; BCBS 2013; BCBS 2014). Intently, several authors like; Haneef, Archer, and Karim (2018); Ozili (2017); Chiaramonte and Casu (2017); Deyoung, Distinguin, and Tarazi (2017); DeYoung and Jang (2016); Diamond and Kashyap (2016); Tran, Lin, and Nguyen (2016) ; Beltratti and Paladino (2015) ; Beltratti and Paladino (2015); Beltratti and Paladino (2015) had examined the connection among bank capital, risk, liquidity, profitability and efficiency. However, their findings still remains controversial in respect to what should be the level of bank capital, liquidity and credit risk management that can adequately provide for profitability. Nevertheless, banks are to give returns back to the shareholders and other stakeholders. Intently, BCBS regulators (Basel III) recommended that financial institutions should maintain a higher proportion of capital and liquid assets that can served as shock absorber against run on a bank. In response to these regulations, financial institutions and economies have to bear a heavy cost in terms of lower profitability and slower economic activities. This tends examines impact of bank capital, credit risk and liquidity on the performance of deposit money banks in developing economies like Nigeria.

Literature Review

Saleh and Afifa (2020) examined effect of credit risk, liquidity risk and bank capital on bank profitability: Evidence from an USA and Asian banks using bank profit as dependent variable while credit risk, liquidity risk and bank capital are independent variables with the aid of generalized methods of moment and simultaneous equation. The findings revealed that liquidity influences profitability more intensively than capital whereas bank capital and credit risk significantly influence profitability in Asian and USA. However, liquidity is negatively insignificant in USA banks while it is positively significant in Asian. This study should have also considered the pre-crisis period in order to establish impact of policy framework. The study ignored some variables identified in Basel III especially the new liquidity coverage ratio and net stable funding ratio.

Abdelaziz, Rim and Helmi (2020) evaluated interactional relationships between credit risk, Liquidity Risk and Bank Profitability in MENA Region using Seemingly Unrelated Regression (SUR) and ordinary lease square (OLS) where dependent variables are profitability, credit and liquidity risks, X is the matrix of bank-specific variables (PROF, CRISK, LIQR, SIZE and CAP), Y is the matrix of financial environment and macroeconomic variables (international financial crisis, inflation and GDP growth) and Z is the matrix of institutional variables (government stability and law and order). Their findings revealed banks in this region should intensify more effort to enhance capital adequacy ratios and likewise reduced misallocation of depositors' fund. This study was limited only to conventional banks without taking cognizance of peculiarity of other traditional Islamic banks in the region.

Bougatef and Mgadmi (2016) examined the impact of prudential regulation on bank capital and risk-taking in MENA countries. The study used panel data estimation techniques. Dependent variables are risk and capital while the independent variables are bank size, return on asset, liquidity and regulatory pressure. Their findings revealed that prudential regulations could not reduce banks' risk-taking incentives and likewise increase capital sue to institutional and regulatory framework in MENA countries. However, larger banks are able to better manage their risk better than smaller banks as a result of their larger size. The sample size was too small for this study because basically there are twenty-four countries that comprises of MENA. This study ignored other variables such as bank growth, banks size and asset growth that would have enriched the model and likewise use RAROA to proxy performance.

Chalermchatvichiena, Jumreornvongb, and Jiraporn (2014) examined Basel III, capital stability, risk-taking, ownership in Asia using ordinary least square. The findings revealed that higher ownership concentration promotes risk-taking. However, there are no significant interaction effects between ownership and regulation on risk-taking. They further revealed that crisis does not change the fundamental relationships among risk-taking, ownership structure, and regulation. Ordinary least square is biased and it may not the sufficient to take decisions. The sample size is too small in relation to the numbers of the countries. The theoretical background was not enriched with corporate governance. Furthermore, Bougatef and Mgadmi (2016) explored the influence of prudential regulations on the correlation between the capitalization level and the credit risk using small sample of commercial banks operating in the MENA region. Their discoveries disclosed bank capital and credit risk are not significantly related and therefore prudential regulations have no impact in reducing banks' risk-taking incentives and in increasing capital. Daher., Masih., and Ibrahim (2015) examined the factors explaining capital buffers using sample of Islamic and conventional banks between 2005–2012 using twostep dynamic Generalized Method of Moments

(GMM). Their findings affirmed application of dynamic panel model and proposed that higher credit risk leads to significantly lower capital buffer. Conversely, the study of Ghosh (2017) examined the determinants of capital buffer of Islamic and conventional banks operating in the MENA region between 2001 and 2012. His provides evidence that banks tend to increase their capital buffers following an increase in credit risk. Basher, Kessler and Munkin (2017) applied Markov Chain Monte Carlo using data set of twenty-two (22) Islamic banks. There finding revealed that an increase in total capital can leads to an increase in the levels of asset risks.

In addition, Lee and Hsieh (2013) examine the impact of the bank capital on risk and profitability using bank-data level from 42 countries in Asia and the Middle East between 1994 to 2008. Their finding revealed that an increase in the capital ratio will have a positive effect on the performance of banks and whereas a negative effect on the bank risk. The authors further identify the level of magnitude of this increase subject to the geographical location and the status of the bank either investment bank or commercial. Specifically, Middle Eastern banks have the highest effect on capital efficiency and Asian banks have the highest effect of capital risk. This outcome may be due to the provisions of Islamic percepts that prohibit banks to give or receive interest and invest in speculative or risky activities. Mongid, Tahir & Haron (2012) examined the relationship between inefficiency, risk, and capital in a sample of commercial banks operating using eight countries of ASEAN between the period of 2003 to 2008 via the 3SLS method. Their findings revealed that capital and inefficiency have a negative effect on the level of risk. This further revealed that well-capitalized banks tend to manage their risk level because their ability to generate income from non-risky activities such as cash management and front office operations. In other way, it is imperative for inefficient banks to reduce their level of risk.

Methodology

The *ex post facto* research design was adopted. Data for this study were computed using base information from 13 purposively selected annual reports and accounts of selected deposit banks in Nigeria for 8 years, culminating into 104 data set. The model for this study is as specified in equation (1). It is stated thus:

$$\mathrm{RROA}_{it} = \beta_0 + \beta_1 \mathrm{CRDR}_{it} + \beta_2 CARA_{it} + \beta_3 LIQR_{it} + \beta_4 LODR_{it} + \beta_5 ASSG_{it} + \beta_6 BSIZ_{it} + \mu_{it} \quad --------(1)$$

Where: RROA = risk-adjusted return on assets

CRDR = credit risk

CARA = capital to assets ratio

LIQR = liquidity ratio

LODR = loan to deposit ratio

ASSG = asset growth

BSIZ = bank size

Table 1 describes variables as used in this study, alongside their measurement and their sources taken from extant literature.

Table 1: Variables Description and Measurement

Variables	Symbol	Description	Measurement	Source(s)
Dependent Variables				
Risk Adjusted Return on Asset	RROA	It is measured by return on asset divided by the standard deviation of the return of asset	$\frac{ROA_{it}}{SDROA_{it}}$	Baek, et al, (2018)
Independent Variables				
Credit risk	CRDR	It measures the exposure of DMBs to insolvency. It is measured by return on asset plus capital adequacy ratio divided by standard deviation of return on asset	$Z - Score_{it} = \frac{ROA_{it} + CAR_{it}}{SDROA_{it}}$	Ha and Quyen (2018); Majumder and Li (2018).
Capital to Assets Ratio	CARA	Capital is measured using total equity divided by total asset.	$Total\ Equity \div Total\ Asset$	Abbas et al, (2019); Majumder and Li (2018)
Liquidity Ratio	LIQR	Liquidity is measured by loan to total asset as used in the prior studies		Obim et al, (2020); Ha and Quyen (2018)
Control Variables				
Loan-to-Deposit Ratio	LODR	Loan-to-deposit is measure using customers loan divided by customers deposit		Hapsari, (2018); Rengasamy (2014).
Asset Growth	ASSG	Asset growth is measured using current year asset minus previous year asset divided by the previous year asset		Isshaq et al, (2019)
Bank Size	BSIZ	Bank size is measured using the natural logarithm of bank asset as used by past researchers		Abbas et al, (2019); Charles (2017); Andrés and Ingmar (2017); Bougatef and Mgadmi (2016)

In achieving the objective of this study, data gathered were used to train a model that would predict ROROA with greater accuracy using the independent variables described in table 1. Python has been discussed and accepted by data scientists as the best data science and machine learning programming language owing to its capability, flexibility, and readily available many packages and modules, as well as its accuracy performance over other statistical data science programming languages. Consequently, the study adopted Python 3 to run the predictive models in order to evaluate their performance from the Jupyter Notebook and PyCharm (IDE). The exploratory data analysis (EDA) was deployed to uncover hidden insights for a better preparation to better assumptions that would satisfy the choice of best analytical tool to conduct the analysis, as well as, the initial EDA checks for potential assumptions, including linearity, exogeneity, homoscedasticity, non-autocorrelation, and multicollinearity. Specifically, Kfold sampler approach was arrayed to perform linear model machine learning to measure performance of predictions.

Results and Discussion

This section presents results of data analyses and estimation of model specified for this study using machine learning technique.

Descriptive Statistics

Table 2 shows summarised descriptive statistics of all variables used in this study. Among the descriptive statistics are mean, standard deviation, as well as minimum and maximum values.

Table 2: Descriptive Statistics

	Mean	Std. dev.	Min.	Max.
RROA	0.7256	1.0000	-3.6495	7.6007
CRDR	6.2152	11.7782	-62.8997	44.6297
CARA	0.1434	0.2924	-1.5475	0.9730
LIQR	0.4129	0.1267	0.0002	0.5719
LODR	0.6416	0.1267	0.0000	1.0635
ASSG	0.0960	0.1706	-0.9199	0.5904
BSIZ	12.1412	0.3954	11.1945	12.9151

Correlation Analysis

The correlation matrix among variables as used in the study is as shown in table 3.

Table 3: Pearson Correlation Matrix

	RROA	CRDR	CARA	LIQR	LODR	ASSG	BSIZ
RROA	1.000						
CRDR	0.612	1.000					
CARA	0.554	0.998	1.000				
LIQR	-0.178	-0.142	-0.134	1.000			
LODR	-0.099	-0.049	-0.042	0.903	1.000		
ASSG	0.102	-0.096	-0.110	0.314	0.312	1.000	
BSIZ	0.149	0.056	0.045	0.344	0.340	0.309	1.000

From table 3, there is a strong correlation between CRDR and CARA (0.998), while LIQR has a negative average correlation with the dependent variable. As a result, these indicate the possibility of multi-collinearity between the explanatory variables, particularly the CRDR and the CARA. Furthermore, while all other variables are held constant, changes in the CARA and CRDR may significantly induce a positive high change in the RROA, while changes in the LODR may induce a non-significant negative change in the RROA.

With evidence of regressors multi-collinearity in our data, it is necessary to perform a multi-collinearity test to be fully assured of the contribution and the extent of such collinearity.

Table 4: Multicollinearity Test

Features	VIF
CRDR	280.8992235
CARA	271.9814173
LIQR	68.80463758
Average VIF Average VIF	207.228
LODR	56.38329844
ASSG	1.564957829
BSIZ	15.11202627
Average VIF (Controlled Variables)	24.353

Table 4 shows that the independent variables CRDR and CARA have high multi-collinearity, with 207.228 as the average VIF for the independent variables and 24.353 as the average VIF for the controlled variables. As a result, we have an average overall IVF of 115.791, which is a very high VIF because the average accommodated VIF should be less than or equal to 10.

Regression Analysis

This section presents output of regression model to further investigate the linearity characteristics. Table 5 depicts estimates of regression outputs.

Table 5: Regression Analysis

```
       OLS Regression Results
==============================================================================
Dep. Variable:                  RAROA   R-squared:                       1.000
Model:                            OLS   Adj. R-squared:                  1.000
Method:                 Least Squares   F-statistic:                 9.883e+27
Date:                Mon, 26 Dec 2022   Prob (F-statistic):               0.00
Time:                        14:45:24   Log-Likelihood:                 3060.2
No. Observations:                 104   AIC:                            -6106.
Df Residuals:                      97   BIC:                            -6088.
Df Model:                           6
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept   -5.862e-14   1.36e-13     -0.432      0.667   -3.28e-13    2.11e-13
CRISK           1.0000    5.2e-15   1.92e+14      0.000       1.000       1.000
CAR           -38.2878   2.09e-13  -1.83e+14      0.000     -38.288     -38.288
LR            1.91e-14   7.87e-14      0.243      0.809   -1.37e-13    1.75e-13
LDR         -5.884e-15   4.54e-14     -0.130      0.897    -9.6e-14    8.42e-14
ASSETGROWTH   1.11e-16   2.68e-14      0.004      0.997   -5.31e-14    5.33e-14
SIZE         2.859e-15   1.16e-14      0.247      0.806   -2.01e-14    2.59e-14
==============================================================================
Omnibus:                       83.667   Durbin-Watson:                   0.704
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1309.575
Skew:                           2.268   Prob(JB):                    4.26e-285
Kurtosis:                      19.782   Cond. No.                         799.
==============================================================================
```

Table 6a: Homoscedasticity Test

Bresuch-Pagan test	Values
statistic	7.431411e+01
p-value	5.312671e-14
f-value	4.047080e+01
f-p-value	2.538101e-24

Table 6b: Homoscedasticity Test

White's test	Values
Test Statistic	37.02784184
Test Statistic p-value	0.094548955
F-Statistic	1.556266375
F-Test p-value	0.068889122

It demonstrates the existence of a perfect relationship predicting power by the value of the R-square, which gave us 1.0. Furthermore, the significance of only the CRISK and the CAR, both with p-values equal to 0.0000 among both the independent and control variables, indicated that multicollinearity would influence the possible model we might learn from data. Furthermore, we saw in table 4 that the two tests for homoscedasticity violated the assumption, in that the pagan test gave a P-value less than 0.05 and the white test gave a value 0.0688 higher than the 0.05 confidence interval, indicating that heteroscedasticity exists.
Furthermore, the value of the Durbin Watson in the regression indicates that there is positive autocorrelation in the data, indicating that the effect of one year is interfering with the outcome of another. Because the Durbin Watson figure was 0.7, which was less than 2.0, this indicated the presence of positive autocorrelation. All the above tests indicated that our data, regardless of the linearity and correlation among the variables, violated almost all the assumptions. We then went on to investigate alternative prediction possibilities for the data using machine learning, even though our OLS above indicated that we would have a perfect prediction because R-squared equals 1.

Machine Learning Algorithm

We chose a liner model machine learner to train our model to uncover its behaviour and power in predicting the RAROA using the available predictors due to the strong linearity among the variables and the fact that the response variable is a continuous type of data. The Linear-Model Machine Learning module from the sklearn package was then used because it was most appropriate. In this situation and made use of Jupyter notebook as our IDE (Integrated development environment).

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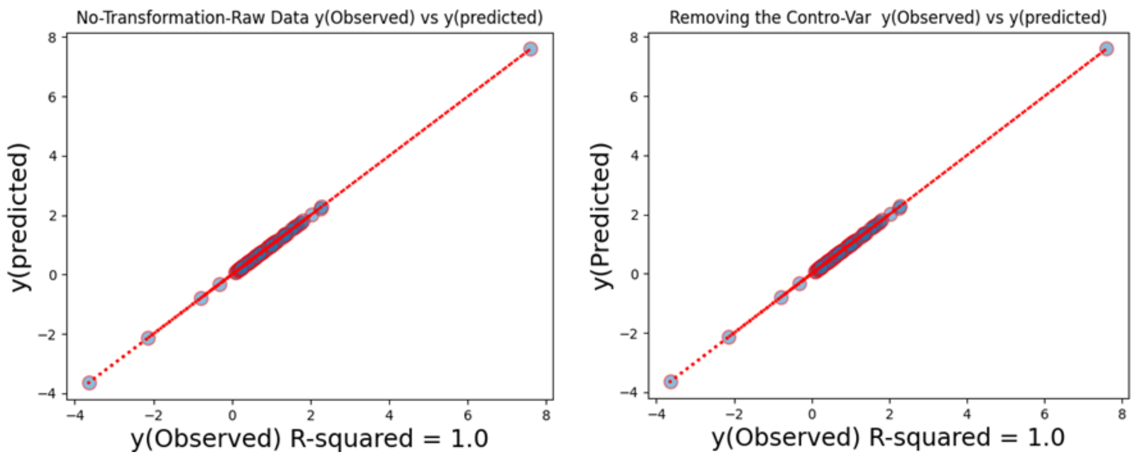

Figure 1 Scattered plot and best line of fit for the predicted and the observed test

The model was created by randomly dividing the data into two categories: test and train samples. And, based on knowledge discovery on the use of a small sample size data for prediction, (Nisha 2022) reported and discussed its argument that the best sampler method in machine learning is to use cross validation of K-fold where k equals 10 for efficient use of the data points, especially when the data set is small. The predictive algorithm demonstrates that the observed and predicted response variables had the same values across each element of the test sample.

This clearly demonstrated that the perfect prediction seen in Figure 1 was never due to fitting limitations or resampling, but rather to the presence of contributing highly correlated variables. As a result, it was proposed that the effect of multicollinearity affects the predicting accuracy of the RAROA using the independent variables. When the control variables were removed from the model, the learner's outcome remained unchanged, implying that the three-control variables had no impact on the model's predicting power and thus had little or no contribution to the possibility of predicting the response variable.

We proceeded by controlling multicollinearity, either by taking the log-transformation of the CRISK and CAR, two independent variables that were perfectly correlated, or by removing one of the two variables from the data modelling. We re-run the model to obtain the results.

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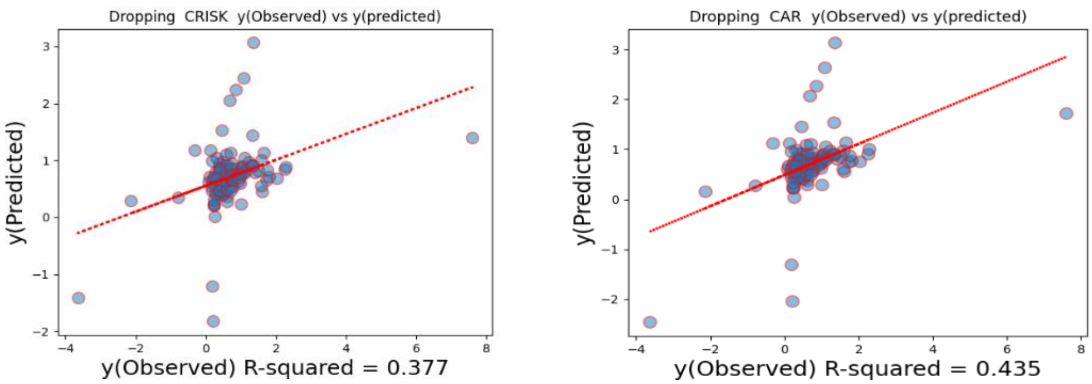

Figure 2 Machine learning performances when each of highly correlated independent variables was removed

When the log-transformation of the most correlated independent variables, that is the log (CRISK), and the log (CAR), we therefore obtained the following models. According to figure 2, the R-Squared of the linear machine learning models at different transformations of the independent variables revealed that the model performed best in predicting RAROA when log-transformation is performed on all the independent variables, with an R-Squared value of (0.536), implying that the regression model accounts for approximately 54% of the variability observed in the target variable (RAROA). As a result, reducing multicollinearity among the independent variables would result in an above-average predictive model.

We then tested whether removing the heteroscedasticity would improve the model by transforming the response variable and modelling it with the transformation of the independent variables, yielding the model performance shown below.

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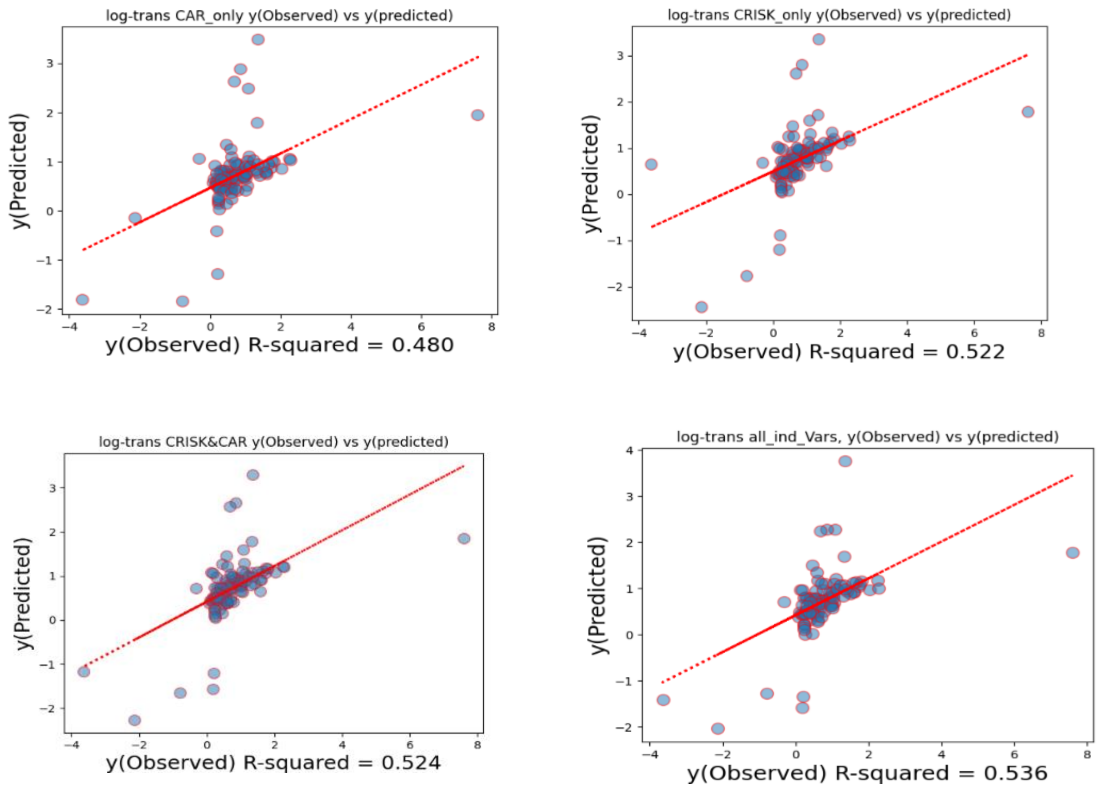

In addition, the effect of heteroscedasticity was removed using the log transformation of the dependent variable, and we have two scenarios of model fitting, by fitting the log transformation of the dependent variable with the raw observed independent variables, and by fitting the transformed dependent variable with the transformed independent variables, and the results of the model are shown below.

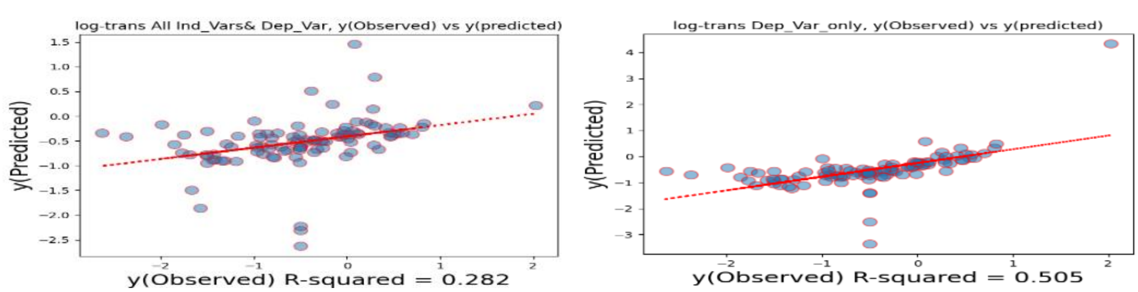

Figure 4 clearly demonstrated that the presence of heteroscedasticity in the data reduced the model's performance; when the effect was removed from the data, the R-Squared of the model was 0.505 as opposed to 0.282 when the effect was removed with a reduction in the linearity strength of the independent variables.

We then rerun our test for the multicollinearity on the transformed data, and observed the table for the multicollinearity as follows:

Figure 3 the new multicollinearity test post transformation of Predictors.

Features	VIF
CRDR	15.85382281
CARA	15.41890224
LIQR	5.948553047
Average VIF (Independent Variables)	12.407
LODR	25.1334004
ASSG	1.654982651
BSIZ	50.08861655
Average VIF (Controlled Variables)	25.626

The table 5 above showed that the VIF among the independent variables was significantly reduced to around 12, indicating that there is still collinearity, but it is now on a minima level, so our model developed based on the transformed independent variables may be sustained. The above VIF of 25.626 indicated that the presence of the controlled variables may interfere with the model's performance even when the dependencies within the independent variables are reduced.

Discussion of Findings

This paper main goal is to investigate the effects of bank attributes on the performance of deposit money banks in Nigeria using base information from 13 purposively selected annual reports and accounts of selected deposit banks in Nigeria for 8 years, culminating into 104 data set.The correlation matrix shows that the selected banks have strong credit risk management, total equity and total asset in relations to their performance. Maditinos., Zopounidis and Tsairidis (2018) findings indicated that effective credit risk management positively influences bank performance, as measured by return on assets (ROA) and return on equity (ROE). Almubarak., Khediri., and Chazi (2017) showed that higher levels of capital were associated with lower credit risk and higher bank performance. Arslan-Ayaydin., Küçükkocaoğlu and Arslan (2016). The study found that banks with higher equity ratios and effective credit risk management exhibited better performance in terms of profitability. Elmawazini., Ntim and Abdou, (2019) their results suggested that strong credit risk management practices positively influenced bank profitability.

However, contrary to the general consensus, Kolapo, Ayeni and Oke (2012) findings indicated that while credit risk had a negative effect on bank performance, this relationship was not significant in the short run, suggesting a more nuanced relationship between credit risk and performance. Becchetti., Ciciretti and Hasan (2019) findings indicated that higher credit risk was associated with higher profitability, suggesting a more complex relationship between credit risk management and performance. Kariuki., Ngugi, and Munyao (2019) findings suggested that credit risk management practices had a negative impact on bank performance, specifically in terms of return on assets.

However, their increase will surely enhance performance of the banks to certain extent. This is an evidence that the three banks are aligning with bank regulations and best practices in risk management.

Furthermore, the three banks should properly manage their liquidity level because it has reached the highest level and therefore banks should balance their liquidity taking cognizance of the liquidity requirement of Basel II such as financial soundness and incentives to enhance risk measurement and management capabilities without under estimating returns to shareholders. In addition, the outcome had shown that there is always one year interference effect with the outcome of another which had always been the behavioural pattern of Nigeria banks. Nevertheless, this behavioural pattern should take cognizance of requirement of Basel III especially the required minimum capital, leverage ratio, liquidity coverage ratio and net stable funding ratio (NSER).

Conclusion

The work presented here has demonstrated that when there is a relationship and interdependence among the independent variables (CRISK, CAR, LR), a linear model machine learning would provide a perfect prediction of a RAROA, and that if the relationship among the independent variables is reduced, the capability of the prediction may also reduce. Also, when linear dependency is reduced among the independent variables, it must be done on the control variables as well in order for the model not to be inferred by the control variables; thus, the linearity of the When the relationship between the independent variables is maintained, removing any effect of heteroscedasticity on RAROA has little or no effect on the predicting power of the linear model. As a result, to accurately predict the outcome variable RAROA, there must be a positive linear relationship between the CRISK and CAR. We can then conclude that the possibility of a perfect RAROA prediction is dependent on the linear relationship between these two major independent variables. The work went on to investigate the inter-year dependency of the data by obtaining the Durbin Watson statistic and confirming that there is a year-year relationship in the data, which means that a future investigation on RAROA prediction may need to be done by capturing the random effect of variables, using a deep learning approach such as RNN (recurrent neural network) or LSTM (Long short-term memory), to check the behaviour of the linearity and the predictive power considering the effect of the autocorrelation.

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