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The Effect of Loan Portfolio Management on the Performance of Banks in Ghana

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Abstract: The objective of the study is to determine the influence of loan portfolio management on the financial performance of banks in Ghana. The study adopted an explanatory cross-sectional survey as its research approach. The research was based on panel data acquired from banks that were in operation from 2010 to the present. Correlation analysis and regression analysis was used in the study, with regression models built by the researcher to assess the study's assumptions. The study shows that personal loans, real estate loans, and small and medium-sized enterprise loans all collectively do have a statistically significant impact on the financial performance of commercial banks. Overall, the model shows that the variables included in the model have a relatively good measure of fit and that the loan portfolio has a significant impact on ROA, ROE, and CR. A number empirical research back up this conclusion, although it also conflicts with findings from certain other investigations. The study recommends the diversification of personal loans to reduce risks on defaults, which can be done by discriminating the borrowers based on the information available.

Keywords: Loan portfolio, financial performance, small and medium-sized enterprise, Ghana

1. INTRODUCTION

The banking industry is crucial to the expansion of an economy. According to Yuksel, Dincer, and Karakus (2020), the bank's function as an intermediary is crucial for the transfer of money between banks, depositors, and borrowers. Because it determines the next stage of an economy's growth, the sector's stability is essential. Adegboye, Ojeka, and Adegboye assert that the stability of any economy is greatly influenced by financial institutions (2020). Bank loans, according to Monokroussos and Gortsos (2020), are agreements between financial institutions that lend money and other types of legal entities that borrow it with the prospect of a future principal and interest repayment. Lending is one of the many services offered by commercial banks, and it makes up the majority of their revenue and profitability. However, using them carries some danger. The provision of credit to customers, which exposes them to high credit risk and results in them losing a significant amount of their income, is currently the banking system's main source of income (Ozili, 2018).

Thus, if they want to succeed, they must have a robust Portfolio management system. Monitoring credit, being dependable, and having certainty all have a favorable impact on loan portfolio management. The risk reduction strategy needs to take each of these things into account (Rathore, 2020). The administration of a commercial bank's loan portfolio is essential to its

effectiveness since it plays a crucial role in the success of a financial institution by keeping track of borrowers' creditworthiness. The main reason for a bank's bad performance and, occasionally, insolvency, on the other hand, is poor loan portfolio management (Yuksel, Dincer, and Karakus, 2020). Two of the most significant issues that negatively affect their performance are non-performing loans and loan loss provisioning. A non-performing loan (NPL) is defined as any loan having interest and principal payments that are more than 90 days past due or that have had more than 90 days' worth of interest refinanced by the World Bank (2020).

In the second part of the 1980s, against the backdrop of non-performing loans, US commercial banks experienced deteriorating capital adequacy ratios and rising funding costs. Because of this, bank managements came to understand how crucial it was to thin out their balance sheets and boost their earning potential. They made the decision to dispose of their non-performing loans and improve their methods for managing credit risk as a result. These actions served as the catalyst for the subsequent growth of the US credit market. The major commercial banks created LPM departments inside their risk management divisions and launched aggressive attempts to lower loan concentration risk targeted at their sizable corporate loan portfolios in the 1990s because of all these experiences. According to Smithson and Mengle (2006), the majority of early activity took place at the level of each individual company and involved controlling the loan approval process, loan sales, and hedging using single-name credit default swaps (CDS).

High and rising nonperforming loan levels in many nations put stress on banks' balance sheets and may have an impact on their lending activities. NPLs are important since they show how credit-worthy a bank's loan portfolio is (Ozili, 2018). According to Chiesa and Mansilla-Fernandez (2020), an increase in NPLs has a detrimental effect on a capital buffer, which can cause the supply of credit to decline. A higher percentage of NPLs suggests that banks are having trouble collecting interest and principal on loans, according to Adegboye, Ojeka, and Adegboye (2020). According to Rathore (2020), NPL is a crucial indicator of the caliber of a financial institution's loan portfolio. Loan portfolio management is crucial for policymakers, regulators, and bank managers to understand since it is the most dependable strategy for dealing with high NPL rates, according to Cerulli et al. (2020), a fast increase in NPLs diminishes bank profitability and increases bank failures. Therefore, the purpose of this study is to evaluate how well Ghanaian banks are performing in relation to their loan portfolio management.

Due to the unpredictability of Ghana's economic performance, maintaining financial performance and how to do so within the banking industry has become difficult. Existing and new loans from commercial banks have become expensive, and some banks have even increased interest rates on loans that were previously subject to predetermined plans. Every nation's financial system needs to be stable if it is to achieve long-term economic growth. This is so because expansion boosts patrons' faith in the financial system. However, an increase in the rate of bad debts since the 2007 economic crisis has resulted in reduced financial performance for the worldwide banking sector. Studies have regularly connected the incidence of non-performing loans from financial institutions and insolvent businesses to the occurrence of banking crises (Lekwauwa & Bans-Akutey, 2023). For instance, during the East Asian Financial and Banking Crisis in 1997, non-performing loans, which made up about 75% of bank loan portfolios, led to the failure of 60 banks in Indonesia (Capozza, Kazarian, & Thomson, 1998). One indication that the type of loan portfolios held by banks may occasionally have a negative impact on their financial performance is this.

The Bank of Ghana (2022) acknowledges that lending is possibly the most important of all banking activities because interest on loans is the primary source of any commercial bank's earnings and cash flows, which contributes to stability in terms of the bank's financial performance. Adegboye, Ojeka, and Adegboye (2020) looked at the impact of non-performing loans on the financial performance of commercial banks and found that NPLs had an impact on performance. According to this report, credit reference bureaus should be licensed so they can give commercial banks the necessary information about loan borrowers and lessen the impact of serial loan defaulters. The default rate in each loan portfolio component and how each one affects how well these banks' financial aspects perform were not, however, taken into account by the study.

Ongore and Kusa (2021) conducted a study on the variables influencing commercial banks' financial performance in Kenya and discovered a wide range of variables that influence financial performance. Among these numerous variables are the capital sufficiency, asset quality, management effectiveness, liquidity management, and other macroeconomic variables. The CAMEL model was heavily cited while discussing the standard of loans that financial organizations provide.

This study was necessary to address the requirement for banks to have a sustainable financial performance by employing an efficient loan portfolio because it did not reveal the essential influence of loan portfolios on banks' finances.

While many of the studies mentioned have found a connection between non-performing loans and commercial banks' financial performance, they have not sufficiently shown how each component of a loan in a portfolio and the degree of the default rate in the same portfolio affect the performance of a commercial bank's finances. Considering this knowledge, the goal of this study was to determine whether a commercial bank's financial performance in Ghana can be linked to the type of loan portfolio it was holding at the time. The circumstance necessitates the development of an efficient plan to address the bank's unsustainable financial performance over time, which is partially dependent on the loan portfolio held. This study seeks to investigate the effect of loan portfolio management on the performance of banks in Ghana.

2. RESEARCH METHODOLOGY

Research Design

This study used panel data and a cross-sectional explanatory design. Cross-sectional studies are performed only once to capture a moment in time. The use of a cross-sectional survey was acceptable because it made it possible to gather information from several organisations at once. Cross sectional surveys were essential because they allowed the analyst to assess whether there were at any one moment any significant connections between the variables (Cooper & Schindler, 2003; Nachmias & Nachmias, 2004). With bank size acting as a moderator on loan portfolio and financial performance, this study aimed to establish correlations between various loan portfolios and commercial banks' financial performance.

Empirical research techniques were used since the educational process must advance and they aid in bridging research and practise. One of the main advantages of the method is that it gives the researcher the ability to account for unobserved heterogeneity. Second, panel data give the analyst enough data points to lessen the possibility of bias in the parameter estimators because they have both cross-sectional and time series dimensions.

Population and Target Population of the Study

The 23 universal banks that were running in Ghana at the time of the study were all included in the study's sample. The study employed a census survey, with the entire population serving as both the target population and an analytical unit. The study's target population consisted of all 23 Ghanaian universal banks that were registered and active as of 2022.

Data Collection Procedure

The researcher filled up a secondary data sheet with the essential information, then used that information to calculate the requisite ratios. Since some of the secondary data was accessible, the researcher was able to retrieve it as instructed by the administrators of the targeted banks.

Data Analysis

Analysing the data was done with quantitative methods. The information gathered was first categorised, coded, and summarised. The hypotheses were tested using regression models. To determine whether the data adheres to the regression assumptions and is thus appropriate for regression analysis, diagnostic tests such as the multicollinearity test, homogeneity test, autocorrelation test, and test for normality were performed prior to the testing of the hypotheses. Additionally, correlation analysis was performed utilising the coefficient of determination and Pearson's Product Moment Correlation (r) analysis. The strength of the linear relationships between the variables in the regression was demonstrated using Pearson's product-moment correlation coefficient (R2), which was used to analyse the degree of correlation between the study's variables. Coefficient of determination was used to check on the goodness of fit of the models.

Multiple regression analysis, a type of multivariate regression analysis, was used to investigate hypotheses H1, H2, and H3. The dependent variable's outcome must first be predicted using the predictor variables. The model ought to be significant in general. Second, the independent variable and the moderator variable are centred. The independent variable and the moderator are then multiplied to get an interaction term. In order to determine if the moderator variable affects the strength of the causal association, the interaction term, independent variable, and moderator are then included to a simultaneous regression model. Both the interaction term and the R2 change must be significant (P 0.05). If both are important, there is moderation. If the interaction term renders both the moderator and predictor unimportant, then complete moderation has taken place. Although mitigation has taken place if they are not significant, the main effect is also anticipated to be significant.

Statistical Model

To forecast the dependent variable (financial performance), a regression model was used. Four variables, namely personal loans, real estate loans, SMEs loans, and insider loans, made up the independent variable loan portfolio. The moderating factor was the size of the bank.

The following are the regression models used:

$Y = \beta 0 + \beta 1\ X1 + \beta 2\ X2 + \beta 3\ X3 + \beta 4\ X4 + \varepsilon$. model without moderator effect. Model 1

$Y = \beta 0 + (\beta 1\ X1 + \beta 2\ X2 + \beta 3\ X3 + \beta 4\ X4)\ Z + \varepsilon$. model with moderator effect Model 2.

Y is the financial performance measured in terms of Return on Equity, Return on Assets and Current ratio. The study performed regression analysis considering every measure of financial performance separately. This indicates that there were three sub-models for each category, one of which did not include the moderating variable while the other did. The first category sub-models took the form:

$Y = \beta 0 + \beta 1\ X1 + \beta 2\ X2 + \beta 3\ X3 + \beta 4\ X4 + \varepsilon$,

while the second category sub-models took the form

$Y = \beta 0 + (\beta 1\ X1 + \beta 2\ X2 + \beta 3\ X3 + \beta 4\ X4)\ Z + \varepsilon$.

Where a ($\beta 0$) = constant;

$\beta 1$, $\beta 2$, $\beta 3$, $\beta 4$ represented regression coefficients, X1, = Personal Loans;

X2=Real estate loans;

X3= SME loans X4=Insider loans;

Z = banks size (S) and ε was the error term.

Using the F-statistic, test for R and R2 significance. The direction and intensity of the association between the variables were indicated by the correlation coefficient (R). The dependent variable's (FP) percentage of variation that was accounted for by the independent variables was shown by the coefficient of determination (R2) value. R2 calculated the proportion of the dependent variable's fluctuation that can be attributed to the independent variable. F-test evaluated the model's overall significance. Each predictor variable's contribution to the significance of the model was determined by beta (). The significance of each individual variable was assessed using a T-test. Checked for statistical significance using P value 0.05.

Data Presentation

Frequency tables and other pertinent charts were used to present the study's findings. All of the supplied data was organised using a thematic approach. Each of the five key themes personal loans, real estate loans, SME loans, and bank size was derived from a research variable. The information was then segmented, organised, and coded to fit the research context (Denzin, 1997). Each segment was then labelled with a pertinent code and a phrase that suggested how it was related to specific data segments, which were influenced by various research study variables. For ease of comprehension and to ensure that the data was organised, the results were presented in statistical tables.

Measurement of Research Variables

The dependent variable for the study was financial performance. The independent factors included personal loans, real estate loans, SME loans, and insider loans, whereas the moderating factor was bank size. The measurement and operationalization processes for each of the study variables, as displayed in 3.1, are described in depth in this section.

Diagnostic Tests

Panel Normality Test

The assumption of normalcy must be validated in order to perform statistical methods. This will help when doing graphical tests to verify the test's normality by looking for the kurtosis and skewness coefficients. These analyses aid in identifying whether the data has an asymmetrical or normal distribution. If normality was not attained, the findings might not accurately depict the relationship between the variables. The Shapiro-Wilk Test was used to determine whether this study was normal. The data is considered to be normal if the probability values of this test are larger than 0.05; otherwise, they significantly vary from a normal distribution. When the P-value exceeds 0.05, it indicates a normal distribution and the result is non-significant. The assumption of normalcy is broken if the P-value shows a value smaller than 0.05 (significant result). Huge samples show that this is common (Pallant, 2005).

The results of the normality test in this study indicated that the P-value for most of the variables was less than 0.05. As a result, this model broke the linear regression's normal distribution assumption. No negative deviations from the error terms' anticipated normality were found by employing a large sample size.

Multicollinearity Test

All of the VIF values were below 5, indicating that the collinearity had no negative effects, according to the data. All VIFS will equal one if there is a correlation between two variables (Hansen et al. 2013). In addition, multicollinearity exists if the VIF for one of the variables is equal to or higher than five. Since there is no multicollinearity because all of the VIFs are less than 5. The opposite of tolerance is VIF. Therefore, collinearity exists if one of the variables' tolerances is equal to or lower than 0.2. Again, because all tolerance results were higher than 0.2, the presumption that multicollinearity does not exist was not questioned.

Table 1: Multi-collinearity Test

	Tolerance	VIF
Personal loans	.908	1.495
Real Estate loans	.836	2.142
SME loans	.785	2.107

Breusch-Pagan/Cook-Weisberg Test for Heteroscedasticity

Conclusions were drawn after this underwent testing utilising the Breusch-Pagan/Cook-Weisberg technique. Heteroscedasticity is the absence of a constant error variance (Gujarati, 2003). This conundrum leads to bias in the standard errors, inaccurate test statistics, and erroneous confidence intervals in the results. Breusch-Pagan/Cook-Weisberg test was selected because it may be used with error terms from non-normal and nonlinear models (Berry and Feldman, 1985). This chi square test is represented by the formula n R2, where n is the sample size, R2 is the unadjusted coefficient of determination of the auxiliary regression, which is an equation for regression between predictor variables and lagged squared error terms with degrees of freedom (df), and m is the number of independent variables. Since it does not lead to biased parameter estimations, heteroscedasticity should not be a hassle unless it is an emergency (Gujarati, 2003).

Panel Unit Root Test (Stationarity)

This test is required because it makes sure the results of regression are valid, even when there is no cause-and-effect link and there is a high coefficient of determination between variables (caused by non-stationarity) (Wooldridge, 2012). Additionally, because non-stationarity distorts the t-ratios, significance tests are invalidated (Gujarati, 2003). The null hypothesis of non-stationarity (b=k-1=0) was employed using the ADF (augmented Dickey Fuller) unit root test. The null hypothesis is rejected to infer stationarity if the test statistic is largely negative (because it is a one-sided test) than the essential 5% threshold of significance value (Gujarati, 2003). According to Gujarati (2003), the DF test statistic is b/(b), where b=k-1 from the model Yt = a+kY with an as the drift, Yt as the variable's value at time t, Y t-1 as the variable's lagged value, and u as the error term.

Hausman Specification Test

By taking into account the omitted factors that may or may not have an impact on this model's predicators, the Hausman specification test was used in this study at a 5% level of significance to assess whether the fixed effect model (FEM) or random effect model (REM) was more appropriate (Green, 2008). The null hypothesis for this Chi square test was that the fixed effect model is favoured over the REM, and it was to be rejected if the p-value was less than 5%, indicating that the fixed model is preferred.

The equation for the fixed effects models therefore becomes:

Yit = ß1 Xit + ai + uit
Where
– ai (i=1….n) is the unknown intercept for each entity (n entity-specific intercepts).
– Yit is the dependent variable where i = entity and t = time.
– Xit represents one independent variable
– ß1 is the coefficient
– uit is the error term, whose covariance with X≠0
The random effects model is
Yit = ßXit + a + uit + eit
ß is the coefficient
a is the intercept

e it within-entity error
uit between-entity error, whose covariance with X=0.

The random effect model permits generalisation beyond the sample to a larger population, but the fixed effect model restricts inferences to just the sample utilised (Wooldridge, 2012). Since the p values were less than 5% threshold of significance, as indicated in Tables 4.21 for ROA models with and without moderator, the alternative hypotheses were supported. This suggests that models with fixed effects were favoured. Since the p values were more than 5% level of significance, indicating that random effects models were favoured, the nulls for both the ROE and CR models with and without moderators were rejected.

3. RESULTS

Descriptive Statistics

The findings of Table 2 demonstrate that the variables of the loan portfolio under discussion do, in fact, have an impact on the financial performance of commercial banks, as indicated by the individual means. These findings are in line with those of Swarnapali (2014), who looked at the effect of loan components particular to certain banks on financial performance and found that those components have an impact on the ROA and ROE of those banks. A survey methodology was utilised for the study, and only secondary data were utilised. Dirnhofer (2012) found that the effect of loan portfolio on bank performance was real and necessary if banks were to function well. The loan portfolio must therefore be regularly monitored.

Table 1: Overall Summary Statistics

Variable	Obs	Mean	STD Dev	Min	Max
Personal loans	210	.2049875	.1434094	-.0319557	.884347
Real estate loans	210	.328899	.1757202	.0065157	.7713953
SMEs loans	210	.272786	.1612007	.0015336	.9576718
Size	210	16.09252	1.519306	11.89698	20.01234
ROA	210	2.354012	5.388844	.0044328	56.92827
CR	210	2.354012	38.2176	-9.153805	507.7275
ROE	210	9.098484	44.37049	-24.13954	582.0595

ROE = Return on Equity; ROA = Return on Assets; CR = Current Ratio

Diagnostic Test Results

These tests are run on the data variables to confirm compliance with the multiple regression technique's requirements and to guarantee more reliable and valid findings.

Panel Data Normality Test

The most important presumption in data analysis is normalcy, which serves as the benchmark for statistical methods. It describes how the data are distributed for a metric variable. It is evaluated using statistical and graphical tests. Visually analyzing the histogram and comparing the observed data's values to a distribution that closely resembles it are the two easiest ways to determine whether the data is normal.

Table 2: Panel Data Normality Test

Shapiro-Wilk test for normal data Variable	Obs	W	V	Z	Prob>z
Personal Loans	210	0.93248	18.171	6.892	0.0000
Real estate loans	210	0.97919	5.600	4.095	0.0000
SMEs loans	390	0.92909	19.083	7.008	0.0000
ROE	390	0.19751	215.974	12.775	0.0000
Current ratio (CR)	390	0.18835	218.437	12.802	0.0000
ROA	390	0.38558	165.357	12.140	0.0000
Size	390	0.97751	6.054	4.280	0.0000

ROA = ROE = Return on Equity; Return on Assets; CR = Current Ratio

A normal distribution exists, and the result is not statistically significant if the P-value is bigger than 0.05. A significant result (P-value less than 0.05) indicates that the distribution regularly violates the assumption of normality in large samples (Pallant, 2005). The results of the normality test showed that the P-value for most of the variables in this study was less than 0.05. This model violated the normal distribution assumption of linear regression. Using a large sample size, no substantial departure from the expected normality of the error terms was discovered.

Galvao, Montes-Rojas, Sosa-Escudero, and Wang (2013), either before or after the estimate of the research model, employed the normalcy test as a standard test. Every component of the error is normally examined as part of the normality test, as is the case for each model in Table 3. There will be a problem with the histogram's construction if this method is used with little samples. Its visual representation has grown so distorted that it can be deemed useless. The main statistical test for normality that is available in the majority of statistical programmes is the Shapiro-Wilk (SW) test (Hair et al., 2006).

Mendes, Pala, and their team of researchers found that the SW test is excellent for usage with panel data. In addition to the t distribution, Wooldrige (2002) claimed that the SW test could also be advantageous due to its ability to produce enough power even when using small sample sizes. According to Nornadiah and Wah (2010), a low value of the test statistic for the SW test tends to reject normality. According to Baltagi (2005), who evaluated the performance of normality tests under various types of non-normal distribution and various sample sizes, the SW test is the best performing normality test because it can reject the null hypothesis at the smallest sample size of data when compared to the KS test, AD test, and Cramer-von Mises test (CVM).

Multicollinearity Test

Multicollinearity is the term for when there is a lot of correlation between the independent variables. The standard errors of the coefficients are raised using collinearity statistics to derive the variance inflation factor (VIF) and tolerance. The multicollinearity of VIF was examined using Stata version 14. By increasing the standard errors of the coefficients, multicollinearity renders some variables statistically insignificant when they would otherwise be significant (Waters, 2004). Tolerance is the amount of variation in one independent variable that the other independent variable fails to account for. Multicollinearity inflates the regression coefficient's variance, misleadingly inflating the standard errors, as measured by the VIF. The tolerance cutoff value is 0.10 at the lowest level. Its value should not be greater than 0.10 and the VIF should not be greater than 10 to suggest that there are no issues with multicollinearity (Newbert, 2008).

If there is no association between the variables, all VIFs will be 1. If the VIF for one of the variables is less than 5, there is collinearity with that variable. The results of the multicollinearity tests performed on personal loans, loans to SMEs, and loans for real estate are listed in Table 4.

Table 3: Multi-collinearity Test

	Tolerance	VIF
Personal loans	.908	1.495
Real Estate loans	.836	2.142
SME loans	.785	2.107

Dependent variable: Financial performance

If any of the VIFs are greater than 5, there is typically a risk of a multicollinearity problem that is harmful to the study (Newbert, 2008). According to the statistics, all of the VIF values were below 5, showing that the collinearity had no adverse impacts. If there is no association between any two variables, all VIFS will equal one (Hansen, 2013). Furthermore, multicollinearity exists if one of the variables' VIFs is five or higher. Since all VIFs are less than 5, the assumption of the nonexistence of multicollinearity was not broken. VIF is the antithesis of tolerance. Therefore, if the tolerance values of one of the variables are equal to or lower than 0.2, collinearity exists. Once more, because every tolerance result was higher than 0.2, it was assumed that multicollinearity did not exist.

Breusch-Pagan/Cook-Weisberg Test for Heteroscedasticity

The Breusch-Pagan test, which models the error variance as 2i=2h (z'i) where zi is a vector of independent variables, only examines the linear form of heteroskedasticity. It contrasts Ha: 0 with H0: = 0. As shown in Table 4.9, testing showed that the chi-square value was 275.15 with a p-value of 0.000 with moderation and 754.61 with a p-value of 0.000 without moderation when a regression model used the ROA as the response variable. Heteroscedasticity was absent because neither case's chi-square values were significantly less than 5%.

As shown in Table 4. Testing showed that the chi-square value was 283.68 with a p-value of 0.000 with moderation and 417.60 with a p-value of 0.000 without moderation when the ROE was used as the response variable in a regression model. Heteroscedasticity was absent because neither case's chi-square values were significantly less than 5%. Finally yet importantly, testing showed that when the CR was used as the response variable in a regression model, the chi-square value was 425.93 with a p-value of 0.000 with moderation and the chi-square value was 398.42 with a p-value of 0.000 without moderation, as shown in Table 4. Heteroscedasticity was absent because the chi-square values for both cases were above the 5% level of significance. Thus, the competing theories were proven false.

Table 4: Breusch-Pagan/Cook-Weisberg test for Heteroscedasticity Statistics

Response Variable	Model	Chi square	Prob > chi2
ROA	1	275.15	0.000
	2	754.61	0.000
ROE	3	283.68	0.000
	4	417.60	0.000
CR	5	425.93	0.000
	6	398.42	0.000

ROA = Return on Assets; ROE = Return on Equity; CR = Current Ratio

Green and Heywood (2008) assert that when heteroscedasticity is assessed more broadly, residual-based tests of heteroscedasticity can be used to assess a variety of independent variables (Rosopa, Schaffer, & Schroeder, 2013). Furthermore, according to academics, the Breusch-Pagan test is acceptable because it is represented by an auxiliary regression equation that employs the employees' functions of the estimated residuals as the dependent variable (Rosopa et al., 2013). The null hypothesis, which states that the residual variances are unrelated to a set of independent factors, is compared to the alternative hypothesis, according to the Breusch-Pagan test, which argues that the residual variances are a parametric function of the independent variables. To account for this test in an auxiliary regression form, the squared residuals of the proposed model are regressed on the hypothesised predictors of the heteroscedasticity.

Panel Unit Root Test

Panel unit tests and stationery testing have experienced a sharp increase in usage and acceptance during the past ten years. It is essential to collect data on the scope and power of these tests through thorough simulation studies in order to provide academicians and analysts with some advice on the tests to employ. The majority of tests are made by averaging the p-values or individual data. The p-values were less than 5%, as shown in Table 4.6, which led to the null hypothesis, which asserted that all panels contained unit roots for all variables being rejected at a 5% level of significance. Since there were no unit roots, it was indicated that the variables were steady and that the regression results were valid even in the absence of lags (at level).

Table 5: Panel Unit Root Test Statistics

Variable			Statistics	p-value
ROA	Inverse chi-squared (78)	P	379.9483	0.000
	Inverse normal	Z	-8.2566	0.000
	Inverse logit t (199)	L*	-14.7346	0.000
	Modified inv. chi-squared	Pm	24.1752	0.000
Personal loans	Inverse chi-squared (78)	P	236.8008	0.000
	Inverse normal	Z	-5.3564	0.000
	Inverse logit t (199)	L*	-7.8624	0.000
	Modified inv. chi-squared	Pm	12.7142	0.000
Real estate loans	Inverse chi-squared (78)	P	218.7769	0.000
	Inverse normal	Z	-5.4996	0.000
	Inverse logit t (194)	L*	-7.4140	0.000
	Modified inv. chi-squared	Pm	11.2712	0.000
CR	Inverse chi-squared (78)	P	491.8540	0.000
	Inverse normal	Z	-7.5474	0.000
	Inverse logit t(199)	L*	-18.3966	0.000
	Modified inv. chi-squared	Pm	33.1348	0.000
ROE	Inverse chi-squared (78)	P	670.5895	0.000
	Inverse normal	Z	-12.6287	0.000
	Inverse logit t(199)	L*	-26.9350	0.000
	Modified inv. chi-squared	Pm	47.4451	0.000
SMEs loans	Inverse chi-squared (78)	P	284.2985	0.000
	Inverse normal	Z	-6.5381	0.000
	Inverse logit t(194)	L*	-10.2833	0.000
	Modified inv. chi-squared	Pm	16.5171	0.000
Bank size	Inverse chi-squared (78)	P	190.0456	0.000
	Inverse normal	Z	-2.6166	0.000
	Inverse logit t (194)	L*	-4.6616	0.000
	Modified inv. chi-squared	Pm	8.9708	0.000

ROA = Return on Assets; ROE = Return on Equityy; CR = Current Ratio

The results of the unit root test panel are shown in Table 6 for all variables. The test results validated the stationarity and significance of the variables at 5% because each test statistic's -values were all less than 0.05. The panel roots test is increasingly often used in cross-sectional research and analysis. Panel unit root tests for data have been used by Levin and Lin (1992), Harris and Tzavalis (1999), Madala and Wu (1999),

Choi (1999), Hadri (1999), and Levin, Lin, and Chu (2002). Bharagava et al. (1982) initially proposed a modified Durbin-Watson statistic in a dynamic model with fixed effects utilising fixed effect residuals and two other test statistics on differenced OLS residuals.

Inferential Analysis

The researcher used the Pearson correlation coefficient (r), which generates a number between -1 and 1, to determine how closely two variables are related. Correlations reflect the degree of the relationship between the important variables. The Pearson's Product Moment method was used to calculate the intercorrelation coefficients. A low degree of correlation may be indicated by the correlation coefficient (r) if it falls between 0.10 and 0.29, a moderate degree of correlation if it falls between 0.30 and 0.49, and a high degree of correlation if it falls between 0.50 and 1.00, according to Warokka and Gallato (2012).

The correlation coefficient was utilised to establish the interdependence of the variables used in this investigation. The direction and strength of the correlation between two variables in a linear relationship serve as the basis for selecting the variables for further statistical research, such as regression analysis. To do this, the coefficients and Pearson Correlation Coefficient were computed.

Correlation Analysis for Variable Personal Loans

Pearson Correlation Coefficient informs an analyst the direction and magnitude of the correlation between two variables. The stronger the correlation between the two variables, the higher the coefficient. Mugenda and Mugenda (2003) have emphasized that the statistic produced by the computation of a coefficient of correlation ranges from -1 to 1.

They emphasized that a negative relationship between the two variables exists if the correlation coefficient is negative (-), and vice versa. Personal loans and financial performance were correlated using the Pearson's correlation coefficient, with the results shown in Table 7.

Table 6: Correlation Analysis for Variable Personal Loans

	ROA	ROE	CR	Personal loans
ROA	1.0000			
ROE (r)	-0.0676	1.0000		
P-Value	0.1825			
CR (r)	-0.0040	0.9834	1.0000	
P-Value	0.9366	0.0000	0.0000	
Personal loans (r)	0.2657	-0.2944	-0.2820	1.0000
P-Value	0.0000	0.0000	0.0000	0.0000

N = 210 ROA = Return on Assets; ROE = Return on Equity; CR = Current Ratio

The aforementioned results corroborated Kolapo et al. (2012)'s conclusions that there is a favorable association between profitability and personal loan advances. The researcher therefore contended that, as shown in the results above, which were also reflected in his study, it is predicted that the coefficients of ROA to those loans, asset quality, and loan loss provision are positive. This study suggests that unsecured lending generates significant revenues at what appears to be a high risk for the financial organization that offers the loan facility. Due to the fact that the sins of a few unknown individuals are spread across a greater number of borrowers in the absence of a mature Credit Reference Bureau, it is an even more lucrative but high-risk enterprise.

When compared to other lending choices, personal loans offer a larger return, which explains the rush to obtain one before competitors do. This category includes the majority of unsecured loans, and the majority of the financial institutions under consideration have sizable book loans with a significant proportion of personal loans relative to the portfolio's overall loan balances. The creditor on how the loans may be used imposes no limitations. Some people consider personal loans to be a source of funding. As personal loans are repaid in manageable monthly installments, it becomes more practical to use them to cover immediate costs rather than using personal resources. This justifies the popularity of this kind of loan among both lenders and borrowers. Whether or not the use warrants the personal borrowing will determine the benefit.

Correlation Analysis for Variable Real Estate Loans

An analyst can learn the strength and direction of the association between two variables using the Pearson Correlation Coefficient. The strength of the relationship between the two variables is shown by the size of the coefficient. According to Mugenda & Mugenda (2003), the correlation coefficient provides a number that ranges from -1 to 1. They emphasized that the correlation coefficient indicates whether there is a positive or negative relationship between the two variables when it is negative (-). The relationship between real estate loans and financial performance was evaluated using the Pearson correlation coefficient, as shown in table 8.

Table 7: Correlation Analysis for Variable Real Estate Loans

	ROA	ROE	CR	Real estate loans
ROA	1.0000			
ROE (r)	-0.0676	1.0000		
P-Value	0.1825			
CR (r)	-0.0040	0.9834	1.0000	
P-Value	0.9366	0.0000	0.0000	
Real estate loans	-0.4771	0.2152	0.1858	1.0000
P-Value	0.0000	0.0000	0.0000	0.0000

ROA = Return on Assets; ROE = Return on Equity; CR = Current Ratio

The findings showed a substantial unfavorable link between real estate loans and ROA. Table 8, which shows that the p-value was at p = 0.000 and that this fulfilled the criteria since p0.05, provided evidence of this. The correlation coefficient for the inverse association was -0.4771 and 390 respondents were taken into account. The findings showed that real estate loans and ROE have a strong favorable association. Table 8, which shows that the p-value was at p = 0.000 and that this fulfilled the criteria since p 0.05, provided evidence of this.

With 210 responses taken into consideration, a correlation coefficient of 0.2152 indicated a favorable link. The findings revealed a strong positive link between real estate loans and CR. Table 4.8, which shows that the p-value was at p = 0.000 and that this fulfilled the criteria since p0.05, provided evidence of this. With 390 responses taken into consideration, a correlation value of 0.1858 indicated a favorable link.

The dynamic nature of the real estate market throughout the study period may be the cause of the inverse association between ROA and real estate loans, the positive correlation between real estate loans and CR, and the correlation between real estate loans and ROE. According to Davis and Zhu (as mentioned in Ojiambo, 2014), the real estate market's boom and bust (pro cyclical) nature plays a crucial role in economic cycles, igniting the boom and amplifying the recession. As bad debt expenses for nonperforming real estate prices rise and the balance sheets of borrowers using real estate as collateral deteriorate, falling real estate prices put downward pressure on the banking sectors.

The alterations in real estate values can have a significant impact on how well commercial banks are doing financially. A sudden decline in real estate values could cause commercial banks to experience a financial crisis in a number of ways. Real estate loans are increasing in bad debt directly through the financial condition of banks and debtors deteriorating, indirect through the decline in economic activity and financial transactions. Loans for real estate finance typically make up a sizable portion of the loans that commercial banks offer. According to this study, a decline in real estate values indicates a lower rate of return on investment, which increases the likelihood that loans made to the real estate industry, will go bad. This lowers the banks' profits and increases their bad debt costs.

Agu and Okoli (2013) made the case that the inability to pay leads to an increase in bad loans, which has a negative financial impact on a commercial bank, and that other findings support the idea that real estate loans, if not repaid, have a negative impact on the financial condition of the creditor (commercial banks). According to Chelagat (2012) and Awunyo-Vitor (2013), commercial banks' performance is logically negatively impacted by poor loans, which has an opposite effect. The study's findings are also consistent with numerous central bank reports on banks offering mortgage facilities in that they show that if real estate loans are repaid on time and their maturities are observed, this will help to

improve commercial banks' liquidity status, positively influencing the CR; conversely, it will negatively affect banks' liquidity positions.

Correlation Analysis for variable SMEs Loans

Pearson Correlation Coefficient informs an analyst of the direction and magnitude of association between two variables. A higher coefficient means that the two variables are more strongly associated. Mugenda and Mugenda (2003) have emphasized that the statistic produced by the computation of a coefficient of correlation ranges from -1 to 1. They emphasized that a negative relationship between the two variables exists if the correlation coefficient is negative (-), and vice versa. As shown in Table 4.9, the Pearson correlation coefficient was utilized to determine the relationship between SME loans and financial performance.

Table 8: Correlation Analysis for variable SMEs Loans

	ROA	ROE	CR	SMEs loans
ROA	1.0000			
ROE (r)	-0.0676	1.0000		
P-Value	0.1825			
CR (r)	-0.0040	0.9834	1.0000	
P-Value	0.9366	0.0000		
SMEs loans (r)	0.2032	0.2555	0.2915	1.0000
P-Value	0.0000	0.0000	0.0000	0.0000

N = 210 ROA = Return on Assets; ROE = Return on Equity; CR = Current Ratio

The findings revealed a strong positive link between SMEs loans and ROA. Table 9, which shows that the p-value was at p = 0.000 and that this fulfilled the criteria since p 0.05, provided evidence of this. With 210 responses taken into consideration, a correlation coefficient of 0.2032 indicated a favorable link. The findings also showed a strong positive correlation between SMEs loans and ROE. Table 9, which shows that the p-value was at p = 0.000 and that this fulfilled the criteria since p0.05, provided evidence of this. With 390 responses taken into consideration, a correlation coefficient of 0.2555 indicated a favorable link. Last but not least, the outcomes showed that SMEs loans had a sizable positive association with CR. Table 4.9, which shows that the p-value was at p = 0.000 and that this fulfilled the criteria since p 0.05, provided evidence of this. With 210 responses taken into consideration, a correlation coefficient of 0.2915 indicated a favorable link.

The findings of Alan (2013) that loans made to SMEs had an impact on Ugandan commercial banks' financial performance are supported by the results. Appiah (2010), who stated that in the event the loans are serviced, they go a long way in increasing commercial banks' profits, therefore the connection can be favorable with low levels of SME failing, supports the aforementioned position. The aforementioned results were different from those of Karim et al. (2010), who contended that as the majority of SMEs operate in an environment that is not conducive to their growth, providing them with loans may raise the likelihood of bad debt, which would have a detrimental impact on the performance of the banks. Nguta & Huka (2013), who discovered that banks' ability to lend money and, consequently, their ability to generate income in the event of loan defaults are both significantly reduced when they extend more loans to SMEs, also disputed the findings that there is a positive correlation between SME loans and bank performance.

Regression Analysis

Influence of Personal Loans on Financial Performance

The goal of the study was to determine how personal loans affected the financial performance of commercial banks in Ghana. Table 10 presents the results.

Table 9: Random effects and Fixed effect model

	Personal loans	Coefficient	Std. Error	Z	T	P>|z|	Model
Model 1a	CR	-75.14	12.98	-5.79		0.000	Random-effect
Model 1b	ROE	-91.07	15.01	-6.07		0.000	Random-effect
Model 1c	ROA	13.60	2.26		6.02	0.000	Fixed effect
Statistics	Model 1a	Model1b	Model1c				
Wald chi2(1)	33.51	36.81					
Prob > chi2	0.000	0.000	0.000				
R-Squared	0.080	0.087	0.094				
Rho	0.000	0.000	0.220				

ROA = Return on Assets; ROE = Return on Equity; CR = Current Ratio

According to data on the impact of personal loans on ROA presented in Table 10, the coefficient of personal loans was 13.60, indicating a positive impact of personal loans on ROA. The p value was 0.000, which is less significant than 5%. This demonstrates that personal loans had a sizable favorable impact on ROA. With reference to CR, personal loans had a correlation of -75.14, indicating that CR and personal loans were inversely related. The p value was 0.000, which indicates a significant impact of personal loans on credit ratings (CR) at less than 5% level of significance. Personal loans had a negative impact on ROE because their correlation with ROE was -91.074. The p-value was 0.000, which is less significant than 5%. This suggests that personal loans significantly impacted ROE in a negative way. The research supports Ayele's (2012) results that personal loans have a negative association with ROE and a positive correlation with ROA. According to figures obtained from Nigerian liquidated banks, Owojori et al. (2010) demonstrated that the liquidated banks' failure to collect on personal loans and other advances made to clients was the main cause of their financial troubles. Sixty banks out of the 115 active banks were experiencing difficulties in 1995, when financial crisis was at its worst. Their non-performing loan and lease ratio was 67% of their overall loan and lease volume. In 1996, this ratio fell to 79%, and the following year, it rose to 82%; 35 of the 37 banks' licenses had been canceled by December 2002. Some institutions reported ratios of performing credits that were less than 10% of loan portfolios at the time the banking licenses were revoked (Hamisu, 2011).

Khole (2012) claims that the increasing number of customer applications demonstrates the rise in demand for personal loans. Depository banking institutions in Ghana have their sights set on this product due to rising credit demand. In this situation, factors that affect growth include things like how quickly and easily one can get an unsecured personal loan. Because of the margins that may be made in the current market, personal loans have created a lucrative market opportunity for lenders that have bravely pursued a lending growth strategy in this product. Some commercial banks have agreements in place with employers that require them to take loan payments out of employees' paychecks each month and send the money directly to the banks.

Influence of Real Estate Loans on the Financial Performance

The purpose of this study was to determine how real estate loans affected the financial performance of commercial banks in Ghana. The outcomes are displayed in Table 11.

Table 10: GLS Regression Results of Real Estate Loans

	Real estate loans	Coefficient	Std. Error	Z	T	P>|z|	Model
Model 1a	CR	40.42	10.851	3.73		0.000	Random effect
Model 1b	ROE	54.35	12.519	4.34		0.000	Random effect
Model 1c	ROA	-15.95	1.436	-11.11		0.000	Random effect
Statistics	Model 1a	Model1b	Model1c				
Wald chi2(1)	13.88	18.85	123.48				
Prob > chi2	0.0002	0.0000	0.0000				
R-Squared	0.1977	0.2209	0.2542				
Rho	0.000	0.000	.14585				

ROA = Return on Assets; ROE = Return on Equity; CR = Current Ratio

The findings in Table 11 on the impact of real estate loans on ROA demonstrate that, with a coefficient of -15.95, real estate loans had a detrimental effect on ROA. The p value was 0.000, which is less significant than 5%. This suggests that real estate loans significantly affected ROA negatively. Real estate loans had a favorable link with CR because personal loans had a CR coefficient of 40.42. The p value was 0.000, which indicates a significant impact of real estate loans on credit risk (CR) at less than 5% level of significance. Real estate loans had a favorable impact on ROE because their coefficient was 54.35 when it came to ROE. The p value was 0.000, which is less significant than 5%. This suggests that ROE was significantly influenced favorably by real estate loans.

In a related study, Ojiambo (2014) demonstrated how real estate financing affected the success of Kenya's listed commercial banks. According to Lipunga (2014), commercial banks that provide real estate loans view it as a risk-diversification strategy with the intention of reducing their losses from NPLs, particularly the unsecured ones. The effectiveness of the commercial banks is anticipated to increase as a result.

This study suggests that commercial banks that provide real estate loans maintain diverse portfolios of mortgage loans, distributing risks in a way that would be impractical if real estate loans were made directly by private individuals. Commercial banks benefit from economies of scale because they are many and huge. They have more experience than individuals setting up, analyzing credit, issuing loans, and collecting debts, which lowers the cost of loan processing and thus expands the supply of real estate loans. Borrowers who use real estate financing must put some money aside to finance a down payment that equals a portion of the cost of the property. As a result, the ratio of non-performing loans to the bank's overall loan portfolio decreases (Kimeu, 2008).

Influence of SMEs Loans on the Financial Performance

The goal of the study was to determine how SMEs loans influenced Ghanaian commercial banks' financial results. The outcomes are displayed in Table 12:

Table 11: GLS Regression Results of SME Loans

	SME loans	Coefficient	Std. Error	Z	T	P>|z|	Model
Model 1a	CR	69.10	11.51338	6.00		0.000	Random effect
Model 1b	ROE	70.32	13.50993	5.21		0.000	Random effect
Model 1c	ROA	6.89	1.782788	3.86		0.000	Random effect
Statistics	Model 1a	Model1b	Model1c				
Wald chi2(1)	36.02	27.10	14.92				
Prob > chi2	0.0000	0.0000	0.0001				
R-Squared	0.2537	0.2167	0.0727				
Rho	0.000	0.000	.12092719				

ROA = Return on Assets; ROE = Return on Equity; CR = Current Ratio

The Wald statistic, which is bigger than the critical value of 5% level of significance, is 36.02, as shown in Table 12. In order to explain the changes in return on equity in the random effect's specification, the variables (loan portfolio components) are therefore crucial. Results on how loans to small businesses affected return on assets (ROA) reveal that the coefficient of these loans was 6.89, indicating that they had a beneficial impact. The p value was 0.000, which is less significant than 5%. This suggests that loans to SMEs have a sizable beneficial impact on ROA. Since the SMEs loan coefficient for CR was 69.10, SMEs loans exhibited a favorable correlation with CR. The p value was 0.000, which indicates a significant impact of SMEs loans on CR at a level of significance less than 5%. Since the SMEs loans' coefficient for ROE was 70.32, they had a positive impact on ROE. The p value was 0.000, which is less significant than 5%. This suggests that the loans for SMEs significantly improved ROE.

In a related study, Dirnhofer (2012) investigated how lending to SMEs affected the top 375 US banks' performance during the financial crisis. Only secondary data were used in the investigation, which employed a correlational study design. To investigate the connection between the variables and bank performance, regression analysis was used. Financial institutions that had a significant role in lending to small and medium-sized businesses are more likely to struggle during the current financial crisis. Additionally, the number of defective loans positively correlated with loans to SMEs.

Influence of Loan Portfolio on Financial Performance

This study's main goal was to determine how the loan portfolio of Ghanaian commercial banks affected their financial performance. The study estimated panel regression Equations 1, 2, and 3 for random effects and fixed effect models to achieve this goal, which was validated by the Hausman test. Table 13 presents the panel regression analysis's findings.

Table 12: GLS Panel Regression Results of the Un-moderated Model

	CR	Coefficient	Std. Error	Z	T	P>|z|	Model
Model 1	PL	-64.57223	92.56969	-0.70		0.485	RE
	RL	-49.1428	91.74666	-0.54		0.592	
	SL	-16.84846	93.66986	-0.18		0.857	
	_cons	62.86004	92.62044	0.68		0.497	
Model 1b	ROE	Coefficient	Std. Error	Z	T	P>|z|	Model
	PL	-106.526	108.059	-0.99		0.324	RE

	RL	-59.51363	107.0982	-0.56		0.578	
	SL	-44.68181	109.3432	-0.41		0.683	
	_cons	85.60401	108.1182	0.79		0.428	
Model 1c	ROA	Coefficient	Std. Error	Z	T	P>|z|	Model
	PL	9.554883	11.55047		0.83	0.409	FE
	RL	-20.44106	11.36587		-1.80	0.073	
	SL	4.436733	11.77673		0.38	0.707	
	_cons	9.204822	11.55044		0.80	0.426	
Statistics	Model 1a	Model1b	Model1c				
Wald chi2(1)	47.64	42.96					
Prob > chi2	0.0000	0.0000	0.0000				
R-Squared	0.3250	0.3190	0.4910				
Rho	0.000	0.000	.15619804				

ROA = Return on Assets; ROE = Return on Equity; CR = Current Ratio; PL=personal loans; RL=real estate loans; SL=SME loans

Table 13's findings on the relationship between loan portfolio and ROA demonstrate that the coefficient for loans can account for up to 49.10% of variations in ROA at commercial banks in Ghana. Based on the resultant determinant coefficient (R2) value of 0.4910, this statement is made. This suggests that the model's included variables suit the fit measure rather well. Additionally, the matching p-value of 0.0000 indicates that, at a 95% confidence level, the coefficients of the four variables are collectively statistically distinct from zero.

Table 13's findings regarding the relationship between loan portfolio and ROE demonstrate that the coefficient for loans explains up to 31.9% of variations in ROE for commercial banks in Ghana. Based on the final Wald-statistic value of 42.96 and the coefficient of determination (R2) value of 0.3190, this statement is made. This suggests that the model's included variables suit the fit measure rather well. Additionally, the matching p-value of 0.0000 indicates that, at a 95% confidence level, the coefficients of the four variables are collectively statistically distinct from zero.

Results on the impact of loan portfolio on CR are presented in Table 13, and they reveal that the coefficient loan portfolio can account for up to 32.5% of variations in CR of Ghanaian commercial banks. Based on the resulting Wald-statistic value of 47.64 and the coefficient of determination (R2) value of 0.3250, this statement is made. This suggests that the model's included variables suit the fit measure rather well. Additionally, the matching p-value of 0.0000 indicates that, at a 95% confidence level, the coefficients of the four variables are collectively statistically distinct from zero. The loan portfolio and financial performance models can now be stated as follows (without the moderating variable):

Y = 62.86004 + -101.1758 ILTL + -16.84846 SLTL + -49.1428 RLTL + -64.57223 PLTI + ε……***equation 1***

Where y is financial performance measured in terms of Current ratio (CR)

Y = 85.60401 + -108.9587 ILTL + -44.68181 SLTL + -59.51363 RLTL + -106.526 PLTI + ε……***equation 2***

Where y is financial performance measured in terms of Return on Equity (ROE)

Y = 9.204822 + -16.87461 ILTL + 4.436733 SLTL + -20.44106 RLTL + 9.554883 PLTI + ε……***equation 3***

Where y is financial performance measured in terms of Return on Asset (ROA)

The results were consistent with those of Olweny and Shipho (2011), who discovered that certain banking sector characteristics have the power to effect bank performance since they had a statistically significant impact on all banks. In support of the same, Hamisu (2011) points out that loans are among of the highest yielding bank assets that have a beneficial impact on its balance sheet. Additionally, they generate most of the operational income. A bank has a liquidity risk since loans are funded by consumer deposits.

Hamisu (2011) also pointed out that while creating credit, both the lender and the borrower expose themselves to significant risks. When a trading partner does not fulfill their contractual commitment by the due date or later, it endangers the banks' ability to operate without interruption. The likelihood that bankruptcy may put depositors in danger increases with credit risk. Companies connected to directors and the directors themselves proven to be a cause of stress for the collapsed banks by failing to recover debts provided to clients (Owojori et al., 2011).

Hypothesis Testing Results

The process of testing hypotheses entails drawing conclusions about the general population from sample data based on assumptions made prior to the start of the study (Gujarati, 2003). By evaluating the statistical significance of the explanatory variable coefficients, the study tested its hypotheses. The goal of the test-of-significance approach is to determine if a null hypothesis is true or false based on sample data that demonstrates that the means of two populations with normally distributed distributions are equal. The equivalent p-values at the 1%, 5%, and 10% levels were used to achieve this. Since the study's alternative hypothesis is composite rather than directional, a two-tailed test was chosen (Gujarati, 2003). The decision rule for all tests was: if the observed p-value was less than the predetermined alpha (significance threshold), reject the null hypothesis; if it was larger than the predetermined alpha, do not reject the null hypothesis.

$H_0$1: Personal loans have no significant influence on the commercial banks' financial performance in Ghana

According to the analysis's findings, personal loans had a significant impact on financial success at the 5% level of significance. This is based on the p-values for coefficients that are equal to 0.0000. This outcome caused the study to reject the stated null hypothesis with a 95% confidence level, so adopting the alternative hypothesis. The study then came to the conclusion that personal loans had a significant impact on the financial performance of commercial banks in Ghana's finance industry. These findings support the Cole and White (2012) study, which found that increasing the amount of loans to individuals decreased the risk of bank collapse, hence enhancing financial performance. Commercial and industrial loans, sometimes known as C&I loans, were not determined to be significant.

$H_0$2: Real estate loans do not have a significant influence on the commercial banks' financial performance in Ghana.

The analysis's findings indicate that, at a 5% level of significance, real estate loans significantly affect Ghana's commercial banks' financial performance. This is based on the p-values for coefficients that are equal to 0.0000. With confidence levels of 95% because of this finding, the study rejected the stated null hypothesis and accepted the alternative hypothesis, concluding that real estate loans significantly affect commercial banks' financial performance in Ghana.

The results of this investigation and those found in the literature already in existence share certain commonalities. Esbitt, Cole, and White (as mentioned in Alexandra, 2014) both discovered that the likelihood of bank failure rose as the number of real estate loans grew. According to Rosengren and Browne (quoted in Alexandra, 2014), a significant portion of bank failures were brought on by the explosive expansion of real estate loans. It should be noted that while bank failures were not utilized as a dependent variable in this analysis, there is a negative correlation between bank failures and net interest (Herrero, 2003).

The statistics from this research provide credence to the idea that as banks make more real estate loans, the likelihood of their failure increases. The low net interest income is consistent with this. The findings differ from those of other studies (Cole & Fenn, 1996; Abrams & Huang, 1987; Alexandra, 2014), which indicated a negative interaction between real estate loans and bank failures. The impact of real estate loans on the financial performance of banks is a widely debated topic.

$H_0$3: Loans advanced to small and micro enterprises have no significant influence on the commercial banks' financial performance in Ghana

The analysis's findings indicate that, at a 5% level of significance, loans made to small and microbusinesses in Ghana do influence their ability to make money. This is based on the p-values for coefficients that are equal to 0.0000. With confidence levels of 95% as a result of this finding, the study rejected the null hypothesis and accepted the alternative hypothesis, coming to the conclusion that small- and microbusiness loans have a significant impact on commercial banks' financial performance in Ghana. The results are consistent with Bechtel, Hainmueller, and Margalit's (2014) research

on the impact of loan mix characteristics on bank profitability, which found that, at the 5% level of significance, the rate of growth in SMEs loans during recessions was established to have a positive relationship with the growth rate of net interest income.

H04: Bank size does not have a significant moderating influence between loan portfolio and the commercial banks' financial performance in Ghana.

The incorporation of moderation results in an improvement of the model's predictive power, as indicated by an increase in the R-squared values, as shown by a comparison of the panel regression results of the moderated equation with those of the model without moderation. Explaining the introduction of bank size Before the introduction of bank size, variation in CR was explained by 32.5% of the variance rather than 61.8%. 9.3% of the variation in ROA was explained by bank size, compared to 49.10% of the variation before the introduction of bank size. Last but not least, the introduction of bank size accounted for 62.83% of the fluctuation in ROE as opposed to 31.9% before the introduction of bank size. Further evidence that the variables utilized are statistically significant comes from the Wald statistic for the equations.

The findings of this study disproved the null hypotheses with a 95% level of certainty, allowing for the use of an alternative hypothesis that found a significant moderating relationship between Ghanaian commercial banks' financial performance and bank size.

4. CONCLUSION

Based on the research findings discussed in the preceding chapter, the study comes to a number of conclusions on its objectives and hypotheses. According to the study, the aggregate influence of small- and medium-sized business loans, real estate loans, and personal loans on the financial performance of commercial banks is statistically significant. The goal was achieved when it was found that loan deposits, loan amounts, loan maturity, loan payback defaults, and the overall proportion of loans in the portfolio could all have an impact on the financial performance of commercial banks. Overall, the model demonstrates that the loan portfolio significantly affects ROA, ROE, and CR and that the variables included in the model have a relatively strong measure of fit. A large body of empirical evidence supports this conclusion; however, it also runs counter to some of the results of other studies. The study concludes that there may be additional variables outside the purview of this study that could significantly affect the financial performance of banks as independent variables, such as choices regarding the size of client loans, client zoning, risk factors, and the inefficiency of the banking system. At the 5% level of significance, the analyses' findings indicate that each of these loans had a significant impact on financial performance, with R-squared values of 39.3% on ROA, 62.83% on ROE, and 61.8% CR. Depending on the nature and tier of the bank, other loan kinds, such as interbank lending, government lending, corporate lending, and corporate lending, can also have a sizable impact on the financial performance of some banks.

5. RECOMMENDATIONS

The analysis determined that out of the three loan items, personal loans made up the greatest portion of the loan portfolio. To prevent personal loans from becoming the largest source of non-performing loans and impairing the financial performance of banks, careful consideration should be given to their issue. The study suggests diversifying personal loan portfolios to lower default risks, which can be achieved by making borrowers-specific decisions considering the available data. Thus, the training and skills required to enhance analytical abilities should be provided to employees in commercial banks' credit divisions.

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