

ESTIMATING THE MARGINAL EFFECT OF INTERACTION BETWEEN INDUSTRY CONCENTRATION AND CAMELS INDICATORS ON FINANCIAL PERFORMANCE OF DEPOSIT MONEY BANKS IN NIGERIA

¹Dogarawa A. B. ²Maude F. A. and ³Ringim K. J.

¹Department of Accounting, Ahmadu Bello University, Zaria

²Department of Business Education, Federal College of Education, Zaria

³Department of Business Administration, Ahmadu Bello University, Zaria

Corresponding Author's email: abellodogarawa@gmail.com



Abstract

*This paper estimates the marginal effect of the interaction between industry concentration and CAMELS indicators on financial performance of deposit money banks in Nigeria. The paper used secondary data extracted from the financial statements of 15 out of 22 licensed banks over the period of nine years, 2010-2018 to first examine the moderating effect of industry concentration on the relationship between CAMELS indicators and financial performance before estimating the marginal effect of the interaction. The analysis carried out shows that unlike the result of the clustered robust random effects regression, which reveals that asset quality, management efficiency, liquidity and sensitivity to market risk have significant effect on financial performance of DMBs in Nigeria; the estimates of the marginal effect shows that only the marginal effect of the interaction between capital adequacy - CAR and industry concentration - INC (CAR*INC) and managerial efficiency - MGE and industry concentration - INC (MGE*INC) is statistically significant each at 1% level of significance based on their respective p-values of 0.004 and 0.000. This confirms the fear that focusing on moderation effect of an interaction variable rather than marginal effect in a cause-effect relationship could lead to the problem of overstating regression results that involve such interaction variables. In light of the above, the paper recommends that researchers who use moderator variables should always extend their analysis to cover estimation of marginal effect of the interaction variable(s).*

Keywords: CAMELS indicators; Deposit Money Banks (DMBs); Financial performance; Industry concentration; Marginal effect

Introduction

The interpretation of interaction terms in regression relationship is a topic of wide interest in the domain of management and social sciences that has been attracting the attention of researchers particularly from the late 1980s. Previous empirical studies in the field of Accounting and finance that used moderator variables however tend to ignore the importance of estimating the marginal effect of moderator variables on the primary variables that formed such interaction terms. Instead, most studies often limit their scope to analysis of regression results while very few extend to examining whether the moderation is supported or not. By so doing, many researchers place more emphasis on the sign and statistical significance of the interaction but give little emphasis to its marginal effect as well as the substantive and practical significance of the findings (Williams, 2018). According to Long and Freese (2006), results of interaction variables can often be made

more tangible by estimating its marginal effect to see how the adjusted predictive margins differ from the unadjusted predictive margins.

As Brambor, Clark and Golder (2006) and Pepinsky (2018) explained, it is not possible for a researcher to infer correctly whether a variable (X) has a meaningful conditional effect on another variable (Y) from the sign and statistical significance of the coefficient of the interaction term. Instead, there should be effort to estimate the predictive marginal effect of the moderator variable across substantively the primary variables of interest. Estimating marginal effect of interaction variables is necessary in order to avoid the problem of overstating regression results that involve such variables. According to Kingsley, Noordewier and Vanden-Bergh (2017) and Hainmueller, Mummolo and Xu (2019), overstating regression results can occur when the coefficient of the interaction terms are statistically significant but the marginal effect of some value(s) of the moderator variable is not significantly different from zero.

The implication of not extending regression analysis to cover margins effect estimation as Pepinsky (2018) opined is the possibility of falling into type-1 error, or the problem of false positives. This is because inspection of predictive marginal effect could reveal that interaction effect does not exist even though simply by looking at the significance of the coefficient in respect of the interaction term, it can be concluded that it exist. Thus, it is necessary to estimate the margins effect of an interaction rather than relying on only the magnitude and statistical significance of the coefficients.

In light of the foregoing and using the methodology and data contained in Maude (2019), this paper attempts to estimate the marginal effect of the interaction between industry concentration and CAMELS indicators on financial performance of deposit money banks in Nigeria. The paper tests the primary hypotheses that industry concentration does not significantly moderate the effect of CAMELS financial indicators, which represent capital adequacy, assets quality, management efficiency, earnings ability, liquidity and sensitivity to market risk on financial performance of the banks. Thereafter, the paper extends to estimation of the marginal effect of the interaction to determine whether the result of the regression is the same or different in the two scenarios.

The paper, which contributes to the pool of literature on the use of moderation and interaction variables particularly in Accounting and finance research, and in general management and social science research is organised in five sections. Section two explains the steps involved in estimating marginal effect. Section three highlights the methodology of the paper and the source of data used. Section four presents the results and interprets it. Section five concludes the paper.

Steps in Estimating Marginal Effect of Interaction Variable

Four steps are involved in estimating marginal effect of interaction variable. The steps are briefly explained hereunder:

Step 1

The first step involves determining whether to proceed with the inclusion of the interaction variable in the estimation of the regression relationship or not. As Kenny (2018) pointed out, ideally the moderator variable should be measured prior to interaction to determine whether it should be included in the final estimation or not. Conventionally, this is achieved by estimating the margin effect of the moderator variable on the variables of interest to determine whether a model should include an interaction term or not (Pepinsky, 2018).

A simpler method that researchers commonly used involves running two separate regression models whereby model 1 consists of ordinary least square (OLS) estimates of the relationship between the dependent variable and all other co-variables with the exception of the moderator variable while model 2 comprises OLS estimates of the relationship between the dependent variable and all other co-variables including the moderator (Sharma, Durand & Gur-Arie, 1981). In this case, the moderator variable is considered appropriate for inclusion in the estimation if the explanatory power, R-squared (R^2) of the model that included it is greater than that of the model without it (McClelland & Judd, 1993; Brambor, Clark & Golder, 2006). Moderation should also proceed if its coefficient is found to be statistically significant when included in the estimation (Aiken & West, 1991; Hayes & Matthes, 2009).

However, Sharma, Durand and Gur-Arie (1981) noted that some researchers emphasised the use of R^2 to determine the presence of moderator variable while others focused on the form of the relationship but concluded that the use of R^2 is not satisfactory. Baron and Kenny (1986) on their part noted that R^2 approach is not conceptually directly relevant to testing the moderator hypothesis but to help a researcher decide whether or not to include the moderator variable in the estimation of the final model. As Kenny (2018) noted, some scholars such as Aguinis, Beaty, Boik and Pierce (2005) have suggested that the average effect size in tests of predicting power of moderation is as low as 0.009; he however, argued that a more realistic standard for effect sizes might be 0.005, 0.01, and 0.025 for *small*, *medium*, and *large* sample sizes respectively.

Step 2

The second step involves estimating the relationship between the dependent and explanatory variables after the inclusion of the interaction variable. For both linear and non-linear relationship, several relevant pre and post estimation diagnostic and robustness tests are required to give effect stability to causal inference (Plumper & Neumayer, 2016). In a linear relationship that involves panel dataset that has no stationarity issue for example, the Breusch-Pagan test for heteroskedasticity, variance inflation factor (VIF) for multicollinearity and Hausman specification test are required (Víšek, 2015).

In Breusch-pagan/Cook-weigberg test for heteroskedasticity, the null hypothesis in the test assumes that the variance of the residuals is constant. This means, if the p-value is statistically significant, there will be a substantial evidence to reject the null hypothesis and conclusion could be arrived that there is the presence of heteroskedasticity. Multicollinearity is a situation whereby two of the covariate in a regression model are highly correlated (Hair, Black, Babin & Anderson, 2010). To test for the absence of harmful multicollinearity, the variance inflation factor (VIF) test and its corresponding tolerance values ($1/VIF$) are often computed. The rule of thumb is that VIF should be less than 10 and values of $1/VIF$ approaching 1 are evidence that a co-variate is not collinear with the other co-variables (Neter, Kutner, Nachtsheirn & Wasserman, 1996; Tobachnick & Fidell, 1996; Wooldridge, 2013).

Both fixed effect (FE) and random effect (RE) models are required to be estimated. Hausman specification test is used to decide between the two models. Generally, the null hypothesis in Hausman specification test is that the preferred model is the FE. The hypothesis states that the estimators of the FE and RE do not significantly differs. If the p-value of the Hausman χ^2 value is statistically significant, FE model is favoured otherwise RE model is considered as the most efficient model. Where the result of the Hausman specification test favours RE model to FE model, another test for panel effect using Breusch-Pagan Lagrange Multiplier (LM) is required to determine whether the entities are of the same or different characteristics. The rule is that if the entities are of the same characteristics, they would not have to be treated separately since there

would be no panel effect, and thus, pooled OLS regression would suffice. The null hypothesis in the LM test is that there is no panel effect across entities. If the result obtained from the LM test reveals a χ^2 value that has a probability that is statistically significant, the RE model will be used for analysis and interpretation otherwise pooled OLS is used. If the result favours FE, another test for heteroskedasticity in FE is required to ascertain whether heteroskedasticity still exist in the FE result or not.

Step 3

The third step involves testing the moderating effect of the moderator variable. An estimation model that contains interactive variable(s) need to be subjected to test of moderating effect in order to determine whether moderation is supported or not (Baron & Kenny, 1986; Aiken & West, 1991; Brambor, Clark & Golder, 2006; Hayes & Matthes, 2009). According to Baron and Kenny (1986) and Fairchild and MacKinnon (2009), moderation is supported for a hypothesis if the interaction between the moderator variable and another predictor (factor variable) is statistically significant. If the interaction variable is not statistically significant, the moderator is not considered as a moderator variable but just an independent variable in the model. In this second case, moderation is considered not supported (Sharma, Durand & Gur-Arie, 1981). Moderation is also said to have been supported if the direction of relationship between a predictor variable and dependent variable change from positive to negative and vice versa as a result of interaction with a moderator variable provided the change in direction is in line with what has been established by theory (Fairchild & MacKinnon, 2009).

In interpreting moderating effect generally, the focus is on the coefficient of the interaction because it captures the moderator effect. In a linear relationship like in this study, if on one hand, the coefficient is positive, it then indicates that the effect of the predictor (factor) variable on the dependent variable increases as the moderator variable increases. If on other hand, the coefficient is negative, it indicates that the effect of the predictor variable decreases as the moderator variable decreases (Kenny, 2018).

Based on the above, it can be concluded that moderation is supported if an interactive variable is statistically significant or if it changes the direction of association between a predictor/factor variable and a dependent variable in support of the theory. In addition, the traditional measures of effect size could be used in measuring moderator effects in terms of predicting power or Wald/F-test (Kenny, 2018). In this case, moderation is considered supported when the explanatory power and value of Wald/F-test of the model with interaction is higher than the one in the model without interaction.

Step 4

The fourth step involves the actual estimation of both the marginal effect and average marginal effect of the interaction variable. This step is necessary in order to avoid the problem of overstating regression results that involve interaction variables. According to Kingsley, Noordewier and Vanden-Bergh (2017) and Hainmueller, Mummolo and Xu (2019), this can occur when the coefficient of the interaction terms are statistically significant but the marginal effect of some value(s) of the moderating variable is not significantly different from zero.

Data and Variables

This paper adopts the methodology and dataset used in the study of Maude (2019). The study assessed the moderating effect of industry concentration on the relationship between CAMELS

financial indicators and financial performance of deposit money banks (DMBs) in Nigeria using secondary data extracted from the financial statements of 15 out of 22 licensed banks over the period of nine years (2010-2018). The secondary data were extracted from the annual reports and accounts of the banks to generate 132 unbalanced panel observations for each of the study variables.

The econometric relationship of the explanatory and outcome variables was given as:

$$ROA_{it} = \beta_0 + \beta_1 CAR_{it} + \beta_2 ATQ_{it} + \beta_3 MGE_{it} + \beta_4 ERA_{it} + \beta_5 LQT_{it} + \beta_6 SMR_{it} + \beta_7 INC_{it} + \beta_8 CAR*INC_{it} + \beta_9 ATQ*INC_{it} + \beta_{10} MGE*INC_{it} + \beta_{11} ERA*INC_{it} + \beta_{12} LQT*INC_{it} + \beta_{13} SMR*INC_{it} + \epsilon_{it}$$

Where ROA is a financial performance measure; CAR, ATQ, MGE, ERA, LQT, SMR are the vectors of CAMELS; INC is industry concentration; and CAR*INC, ATQ*INC, MGE*INC, ERA*INC, LQT*INC and SMR*INC represent interaction between industry concentration and each of the CAMELS variables. $\beta_0 - \beta_{13}$ represent the parameters of the model to be estimated, ϵ is the disturbance error term while subscripts i and t represent firm and year respectively.

ROA was measured in the study of Maude (2019) as profit before interest and tax divided by total assets; CAR as the ratio of risk weighted capital to total assets; ATQ as the ratio of non-performing loans to total assets; MGE as the ratio of non-interest expenses to non-interest income; ERA as the ratio of net interest income to total loans and advances; LQT measured as the ratio of total loans and advances to total deposits; and SMR as the ratio of net interest income to average total assets. The moderator variable, ICN was measured as bank (i)'s Herfindahl-Hirschman index (HHI) of market concentration.

Analysis and Interpretation

Four steps were followed in this paper to estimate the marginal effect of the interaction between industry concentration and CAMELS indicators on financial performance of the DMBs.

Test for Inclusion of Moderator Variable

In line with the explanation of Sharma, Durand and Gur-Arie (1981) on framework for identifying moderator variable, the first and second models were estimated. Table 1 contains the summary of results obtained from the estimation of two regression models; one without the moderator variable and the other after the inclusion of the moderator variable.

Table 2: OLS Results with and without Moderator Variable

Model 1				Model 2			
OLS without Moderating Variable				OLS with Moderating Variable			
Variable	Coef.	t-value	P-value	Variable	Coef.	t-value	P-value
CAR	0.129	2.100	0.037	CAR	0.119	1.960	0.052
ATQ	0.043	0.970	0.335	ATQ	0.095	1.790	0.076
MGE	-0.064	-3.360	0.001	MGE	-0.051	-2.550	0.012
ERA	0.029	0.480	0.633	ERA	0.053	0.880	0.381
LQT	-0.030	-0.900	0.370	LQT	-0.018	-0.530	0.595
SMR	-0.088	-1.640	0.104	SMR	-0.091	-1.710	0.091
				INC	0.241	1.770	0.079
_CONS	0.169	3.150	0.002	_CONS	0.120	2.000	0.047
F-Statistics	3.21			F-Statistics	3.25		
Prob> F	0.006			Prob> F	0.003		
R-squared	0.13			R-squared	0.15		
Adj R-squared	0.09			Adj R-squared	0.10		

Source: Extraction from STATA 13.0 Output

The result in Table 1 shows that both models are fitted based on their respective F-statistics of 3.21 and 3.25 that are statistically significant at 1% level of significance. With regard to model 1 where regression was run without the moderator variable, the R^2 is 13% while in model 2, which was run after including the moderator variable, the R^2 is 15%. The R^2 of model 2 indicates a 2% increase in the explanatory power of the variables in the model following the inclusion of the moderator variable, industry concentration (INC). Similarly, the adjusted R^2 slightly increased from 9% to 10%, which further corroborates the increase in explanatory power of the second model as a result of the presence of the moderator variable. The variable also records a coefficient value of 0.241 and t-value of 1.770. The p-value of 0.079, which is statistically significant at 10% level of significance indicates a strong relationship between the moderator variable, INC and the dependent variable, ROA. Based on the increase in the predicting power of the second model and the significant p-value of the moderator variable, the interaction term was included in the final model estimation.

Estimation of Regression Result

The second step involves running panel regression models in view of the fact that the data is in panel form. Both fixed effect (FE) and random effect (RE) models were run and Hausman Specification test was used to decide between the two models. The result of the Hausman test reveals a χ^2 value of 5.18 and p-value of 0.971 in favour of the random effect model result. The Breusch-Pagan Lagrange Multiplier (LM) was also conducted to select between the random effect model and pooled OLS regression. The LM test result turns in a χ^2 value of 50.74 and a p-value of 0.000, which is statistically significant at 1% level of significance. The result confirms the presence of panel effect in the dataset thereby making the random effect model the preferred

model. Clustered robust random effect option was then obtained to address the problem of heteroskedasticity of the dataset as presented in Table 3.

Table 2: Summary of Clustered Robust Random Effect Result

Variable	Robust Coefficient	z-value	p-value
CAR	-0.1319	-0.970	0.334
ATQ	0.3791	2.940	0.003***
MGE	0.1150	2.640	0.008***
ERA	0.1307	1.320	0.187
LQT	-0.1138	-1.970	0.049**
SMR	-0.1580	-1.620	0.105*
INC	2.3348	3.020	0.003***
CAR*INC	2.5256	1.460	0.146
ATQ*INC	-7.1204	-3.150	0.002***
MGE*INC	-2.5121	-3.340	0.001***
ERA*INC	-3.6160	-2.360	0.018**
LQT*INC	0.1578	0.390	0.699
SMR*INC	3.0785	0.970	0.333
_CONS	0.1218	1.490	0.138
Wald Chi ²	115.37		
Prob> Chi ²	0.000		
R-squared within	0.28		
R-squared overall	0.21		

Source: Extraction from STATA 13.0 Output

From Table 2, the Wald Chi² value, which indicates whether the model is fitted or not is 115.37. The p-value of the Wald is 0.000, which is statistically significant at 1% level of significance. This shows that on the overall, the model is fitted and the variables selected for the study are not misspecified. The predicting power of the model is 28%. This means that the combined effect of the explanatory variables explained changes in the dependent variable by 28% while the remaining 72% is explained by variables not included in the model.

The interaction variables have different levels and directions of relationship with the dependent variable. The interaction between industry concentration and capital adequacy (CAR*INC) reports a coefficient value of 2.5256 and a z-value of 1.460. The p-value of 0.146 indicates that the relationship is not statistically significant even though the direction of association between the interaction variable and dependent variable is positive and in line with theoretical expectation. The interaction between asset quality and industry concentration (ATQ*INC) reports a coefficient value, z-value and p-value of -7.1204, -3.150 and 0.002 respectively. The p-value indicates that

ATQ*INC has negative effect on ROA that is statistically significant. The direction of association between the two variables is in line with theoretical expectation.

The interaction between management efficiency and industry concentration, MGE*INC, reveals a coefficient value of -2.5121 and a z-value of -3.340. The relationship is statistically significant based on the p-value of 0.001. The relationship between earnings ability and industry concentration on one hand (ERA*INC) and ROA on other hand reports a coefficient value of -3.6160. The z-value is -2.360 while the p-value is 0.018. The result shows ERA*INC has significant negative effect on ROA. In addition, LQT*INC reports 0.1578, 0.390 and 0.699 as coefficient value, z-value and p-value respectively. The p-value of 0.699 indicates that the relationship between LQT*INC and ROA is not statistically significant. Furthermore, the interaction between sensitivity to market risk and industry concentration (SMR*INC) has an insignificant positive relationship with ROA. This is based on the coefficient, z-value and p-value of 3.0785, 0.970 and 0.333 respectively.

Overall, the result in Table 2 has provided evidence for the rejection of some of the primary hypotheses formulated by the paper and non-rejection of others. On one hand, the second, third and fourth hypotheses that represent the interaction between industry concentration and asset quality (ATQ*INC), management efficiency (MGE*INC) and earnings ability (ERA*INC) are rejected. On other hand, the paper could not reject the first, fifth and sixth hypotheses that represent interaction between industry concentration and capital adequacy (CAR*INC), liquidity (LQT*INC) and sensitivity to market risk (SMR*INC).

Test of Moderating Effect of Industry Concentration

In testing the moderating effect of industry concentration (ICN), the result of the clustered robust random effect model was used. Table 3 presents the summary of the moderating effect of INC after interaction with capital adequacy (CAR*INC), asset quality (ATQ*INC), management efficiency (MGE*INC), earnings ability (ERA*INC), liquidity (LQT*INC) and sensitivity to market risk (SMR*INC).

Table 3: Summary of Moderating Effect of Industry Concentration

Variable	Expected sign based on theory	Sign before interaction	Sign after interaction	Moderating effect	p-value before interaction	p-value after interaction	Moderating effect
CAR*INC	+	–	+	Moderation is supported	Not significant	Not significant	Moderation not supported
ATQ*INC	–	+	–	Moderation is supported	1%	1%	Moderation is supported
MGE*INC	–	+	–	Moderation is supported	1%	1%	Moderation is supported
ERA*INC	+	+	–	Moderation not supported	Not significant	5%	Moderation is supported
LQT*INC	–	–	+	Moderation not supported	5%	Not	Moderation not supported
SMR*INC	+	–	+	Moderation is supported	10%	Not	Moderation not supported

Source: Extraction based on STATA 13.0 output

Table 3 indicates that the interactive variables of ATQ*ICN, MGE*ICN and ERA*ICN all show causal relationship with financial performance of deposit money banks in Nigeria that is statistically significant. The causal effect of both ATQ*ICN and MGE*ICN is statistically significant at 1% level of significance while the causal effect of ERA*ICN reports a 5% level of statistical significance. Based on the result, it is concluded that moderation is supported for the interaction between industry concentration and asset quality, managerial efficiency and earnings ability. The moderating effect of these interactive variables is corroborated by the fact that earnings ability (ERA) which is statistically not significant when treated as an independent variable becomes statistically significant when treated as interactive variable. In addition to statistical significance, the direction of relationship in respect of both ATQ*ICN and MGE*ICN has changed from positive to negative after interaction in line with theoretical expectation.

Furthermore, moderation is supported in respect of the interactive variable of CAR*INC on ground of change in the direction of relationship with the dependent variable in line with theoretical expectation. Prior to interaction, CAR reported a negative relationship with financial performance contrary to theoretical expectation. Though the causal effect of the interaction is still not statistically significant, the change in the direction of relationship in line with the theory has provided evidence for the support of moderation. Similarly, moderation is supported in respect of SMR*INC as a result of change in the direction of association with the dependent variable in

line with theoretical expectation even though the relationship is statistically not significant after the interaction.

Estimating Marginal Effect of Industry Concentration

In line with Esarey and Sumner (2016), Medeiros (2017), Williams (2018) and Long (2019), the interaction marginal effect regression for the CAMELS financial indicator variables and industry concentration was run. Table 4 presents the summary of the regression result.

Table 4: Summary of Interaction Marginal Effect Result

Variable	Coefficient	t-value	p-value
c.car#c.inc	2.7676	2.930	0.004***
c.atq#c.inc	0.1158	0.110	0.909
c.mge#c.inc	-1.2146	-4.130	0.000***
c.era#c.inc	0.3089	0.310	0.754
c.lqt#c.inc	-0.2474	-0.670	0.506
c.smr#c.inc	-0.4227	-0.300	0.765
_cons	0.1395	14.430	0.000
F-Statistics	4.18		
Prob>F	0.000		
R ²	0.167		
Adjusted R ²	0.127		

Source: Extraction based on STATA 13.0 output

From Table 4, only the marginal effect of the interaction between CAR and INC (CAR*INC) and MGE and INC (MGE*INC) is statistically significant each at 1% level of significance based on their respective p-values of 0.004 and 0.000. However, in view of the fact that the overall model has an F-statistics value of 4.18 that is statistically significant at 1% level of significance based on its p-value of 0.000, industry concentration is said to have marginal effect (Kingsley, Noordewier & Vanden-Bergh, 2017).

Furthermore, the interaction average marginal effect is predicted to enable estimation of the marginal effect of the moderator variable on each of the CAMELS financial indicators as suggested by Esarey and Sumner (2016), Medeiros (2017) and Long (2019). Table 5 presents the summary of the STATA output for the test.

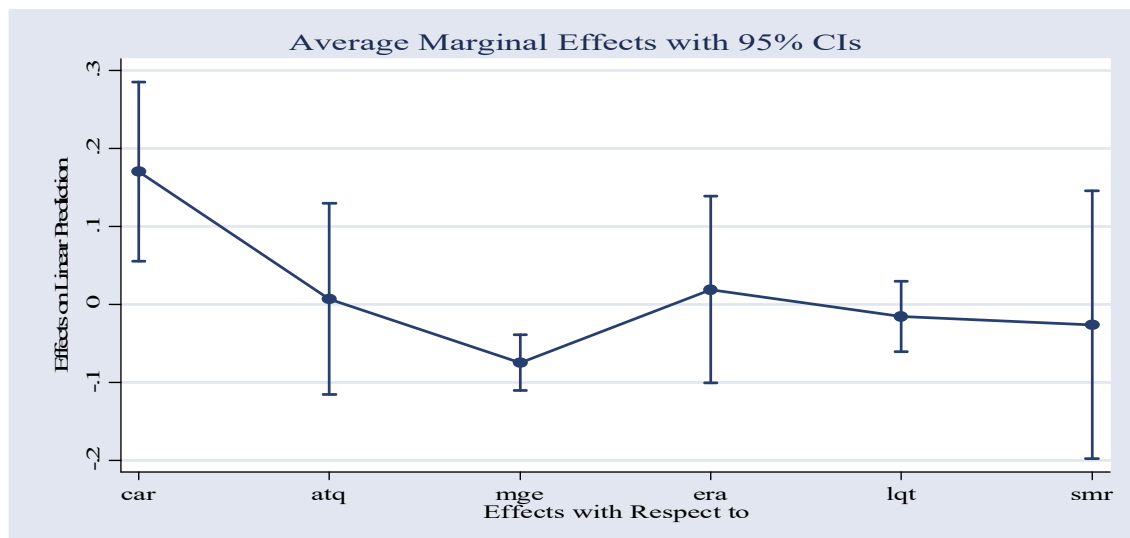
Table 5: Summary of Interaction Average Marginal Effect Prediction Result

Variable	dy/dx	t	P> t
CAR	0.170	2.930	0.004***
ATQ	0.007	0.110	0.909
MGE	-0.075	-4.130	0.000***
ERA	0.019	0.310	0.754
LQT	-0.015	-0.670	0.506
SMR	-0.026	-0.300	0.765

Source: Extraction based on STATA 13.0 output

Table 5 shows that the average marginal effect of INC on CAR, ATQ, MGE, ERA, LQT and SMR is 0.170, 0.007, -0.075, 0.019, -0.015 and -0.026 respectively. From the result, it can be concluded that though the average marginal effect of INC is very low for all the variables except CAR, the effect of the value(s) of the moderating variable is different from zero. To make the average marginal effect of INC on CAMELS financial indicators more visible, the prediction was plotted on a graph. Figure 1 presents the moderator graph of the interaction marginal effect.

Figure 1: Graph of Interaction Average Marginal Effect



Source: Extraction based on STATA 13.0 output

From figure 1, the average marginal effect of the interaction between INC and ATQ is very close to zero while the interaction between INC and CAR and MGE is significantly different from zero. The interaction between INC and each of ERA, LQT and SMR has an average marginal effect that is clearly different from zero but the difference is not significant. Based on the average marginal effect estimates, it can be concluded that the interaction marginal effect of INC on CAMELS financial indicators is significant.

Conclusion and Recommendations

The analysis carried out in this paper shows that industry concentration has a significant moderating effect on the relationship between most of the CAMELS indicators and financial performance of the DMBs during the period of the study on the basis of either statistical significance of the p-value or change in the direction of relationship after the interaction. However, the result of the marginal effect estimation confirms the fear that focusing on moderation effect of an interaction variable based on the magnitude and significance of its coefficient rather than marginal effect in a cause-effect relationship could lead to the problem of overstating regression results that involve such interaction variables. In light of the above, the paper recommends that researchers who use moderator variables should always extend their analysis to cover estimation of marginal effect of the interaction variable(s).

Reference

- Aguinis, H., Beaty, J. C., Boik, R. J. & Pierce, C. A. (2005). Effect size and power in assessing moderating effects of categorical variables using multiple regression: A 30-year review. *Journal of Applied Psychology*, 90: 94-107.
- Aiken, L. S. & West, S. G. (1991). *Multiple regression: Testing and interpreting interactions*. Newbury Park, CA: Sage.
- Baron, R. M. & Kenny, D. A. (1986). The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations. *Journal of Personality and Social Psychology*, 51(6): 1173-1182.
- Brambor, T., Clark, W. R. & Golder, M. (2006). Understanding Interaction Models: Improving Empirical Analyses. *Political Analysis*, 14: 63-82.
- Esarey, J. & Sumner, J. (2016). Marginal effects in interaction models: Determining and controlling the false positive rate. *Comparative Political Studies*, 51(9): 1144-1176
<https://journals.sagepub.com/doi/abs/10.1177/0010414017730080?journalCode=cpsa>.
- Fairchild, A. J. & MacKinnon, D. P. (2009). A General Model for Testing Mediation and Moderation Effects. *Prevention Science*, 10(2): 87-99.
- Hainmueller, J., Mummolo, J. & Xu, Y. (2019). How Much Should We Trust Estimates from Multiplicative Interaction Models? Simple Tools to Improve Empirical Practice. *Political Analysis*, 27(2): 163-192.
- Hair, J. F., Black, W. C., Babin, B. J. & Anderson, R. E. (2010). *Multivariate Data Analysis*. 7th Edition, Pearson, New York.
- Hayes, A. F. & Matthes, J. (2009). Computational procedures for probing interactions in OLS and logistic regression: SPSS and SAS implementations. *Behaviour Research Methods*, 41: 924-936.
- Kenny, D. A. (2018). Moderator Variables: Introduction. Available at <http://davidakenny.net/cm/moderation.htm>
- Kingsley, A. F., Noordewier, T. G. & Vanden-Bergh, R. G. (2017). Overstating and understating interaction results in international business research. *Journal of World Business*, 52(2): 286-295.
- Long, J. S. & Freese, J. (2006). *Regression Models for Categorical Dependent Variables Using Stata*. 2nd ed. College Station, TX: Stata Press.
- Long, J. (2019). Exploring interactions with continuous predictors in regression models. <https://cran.r-project.org/web/packages/interactions/vignettes/interactions.html>
- Maude, F. A. (2019). Moderating effect of industry concentration on the relationship between CAMELS financial indicators and financial performance of deposit money banks (DMBs) in Nigeria. Draft Thesis presented at the department of Accounting, Ahmadu Bello University in partial fulfilment of the requirements for the award of the degree of Doctor of Philosophy in Accounting and Finance.
- McClelland, G. H., & Judd, C. M. (1993). Statistical difficulties of detecting interactions and moderator effects. *Psychological Bulletin*, 114: 376-390.
- Medeiros, R. (2017). Linear Regression Models with Interaction/Moderation. StataCorp LLC. <https://www.stata.com/why-use-stata/easy-to-grow-with/linear.pdf>

- Neter, J., Kutner, M. H., Nachtsheim, C. J. & Wasserman, W. (1996). *Applied Linear Statistical Models*, 4th Edition, WCB McGraw-Hill, New York.
- Pepinsky, T. B. (2018). Visual heuristics for marginal effects plots. *Research and Politics*, 2018: 1-9.
- Plumper, T. & Neumayer, E. (2016). Robustness Tests and Statistical Inference. <http://www.lse.ac.uk/website-archive/GeographyAndEnvironment/neumayer/pdf/Robustness%20Tests%20and%20Statistical%20Inference%20.pdf>
- Sharma, S., Durand, R. M., & Gur-Arie, O. (1981). Identification and analysis of moderator variables. *Journal of Marketing Research*, 18(3): 291-300.
- Tobachnick, B. G. & Fidell, L. S. (1996). *Using Multivariate Statistics*. 3rd Edition, Harper Collins Publishers, New York.
- Víšek, J. A. (2015). Estimating the Model with Fixed and Random Effects by a Robust Method. *Methodology and Computing in Applied Probability*, 17(4): 999-1014.
- Williams, R. (2018). Using Stata's Margins Command to Estimate and Interpret Adjusted Predictions and Marginal Effects. *The Stata Journal*, 12(2): 308–331. Available at <http://www.stata-journal.com/article.html?article=st0260>
- Wooldridge, J. (2013). *Introductory Econometrics: A Modern Approach*, 5th Edition, Cengage Learning.

Appendices

. regress roa car atq mge era lqt smr

Source	SS	df	MS	Number of obs =	132
Model	.052224974	6	.008704162	F(6, 125) =	3.21
Residual	.338946088	125	.002711569	Prob > F =	0.0058
				R-squared =	0.1335
				Adj R-squared =	0.0919
Total	.391171062	131	.002986039	Root MSE =	.05207

roa	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
car	.1286974	.0611809	2.10	0.037	.0076128 .249782
atq	.0430816	.0445429	0.97	0.335	-.0450743 .1312375
mge	-.0638351	.0189966	-3.36	0.001	-.1014318 -.0262384
era	.0285539	.0596822	0.48	0.633	-.0895646 .1466725
lqt	-.030297	.0336386	-0.90	0.370	-.096872 .036278
smr	-.0879555	.0536331	-1.64	0.104	-.194102 .018191
_cons	.1686038	.0534589	3.15	0.002	.062802 .2744057

. regress roa car atq mge era lqt smr inc

Source	SS	df	MS	Number of obs =	132
Model	.060611755	7	.008658822	F(7, 124) =	3.25
Residual	.330559308	124	.002665801	Prob > F =	0.0034
				R-squared =	0.1549
				Adj R-squared =	0.1072
Total	.391171062	131	.002986039	Root MSE =	.05163

roa	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
car	.1193963	.0608886	1.96	0.052	-.0011193 .2399119
atq	.0945182	.0528351	1.79	0.076	-.0100572 .1990935
mge	-.0513409	.0201097	-2.55	0.012	-.0911437 -.0115382
era	.0534323	.0608159	0.88	0.381	-.0669395 .1738041
lqt	-.0181554	.0340487	-0.53	0.595	-.0855473 .0492366
smr	-.0907131	.0532012	-1.71	0.091	-.1960133 .014587
inc	.2409878	.1358662	1.77	0.079	-.0279294 .509905
_cons	.1197568	.059733	2.00	0.047	.0015284 .2379852

```
. xtreg roa car atq mge era lqt smr inc carinc atqinc mgeinc erainc lqtinc smrinc, fe
```

```
Fixed-effects (within) regression      Number of obs   =      132
Group variable: id                    Number of groups =      15

R-sq:  within = 0.2895                Obs per group:  min =       8
      between = 0.0498                      avg =      8.8
      overall  = 0.1352                      max =       9

                                         F(13,104)        =      3.26
corr(u_i, Xb) = -0.2373                Prob > F          =     0.0004
```

roa	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
car	-.1485551	.0805013	-1.85	0.068	-.3081921	.011082
atq	.3729752	.0793112	4.70	0.000	.215698	.5302523
mge	.1231252	.0360299	3.42	0.001	.0516765	.1945739
era	.1316334	.1021546	1.29	0.200	-.0709431	.3342098
lqt	-.1261347	.0486929	-2.59	0.011	-.2226945	-.0295748
smr	-.1382934	.1531221	-0.90	0.369	-.4419402	.1653535
inc	2.361618	1.17073	2.02	0.046	.0400164	4.683219
carinc	2.12361	1.889942	1.12	0.264	-1.624217	5.871436
atqinc	-6.931471	1.727227	-4.01	0.000	-10.35663	-3.506314
mgeinc	-2.544791	.7257698	-3.51	0.001	-3.984019	-1.105562
erainc	-3.469963	1.922687	-1.80	0.074	-7.282723	.3427979
lqtinc	.2420782	.5221688	0.46	0.644	-.7934021	1.277558
smrinc	2.298567	4.589392	0.50	0.618	-6.80237	11.3995
_cons	.1418924	.0799906	1.77	0.079	-.016732	.3005169
sigma_u	.04166912					
sigma_e	.03624663					
rho	.56925888	(fraction of variance due to u_i)				

```
F test that all u_i=0:      F(14, 104) =      7.37      Prob > F = 0.0000
```

```
. estimates store fe
```

```
. xtreg roa car atq mge era lqt smr inc carinc atqinc mgeinc erainc lqtinc smrinc, re
```

```
Random-effects GLS regression           Number of obs   =       132
Group variable: id                     Number of groups  =        15

R-sq:  within = 0.2843                  Obs per group: min =         8
      between = 0.1624                      avg =       8.8
      overall  = 0.2119                      max =         9

                                           Wald chi2(13)    =       44.43
corr(u_i, X)  = 0 (assumed)              Prob > chi2      =       0.0000
```

roa	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
car	-.131895	.0766851	-1.72	0.085	-.2821949	.018405
atq	.379145	.0756816	5.01	0.000	.2308117	.5274783
mge	.1150087	.0337751	3.41	0.001	.0488107	.1812067
era	.1306957	.0962587	1.36	0.175	-.0579678	.3193593
lqt	-.1138082	.0465095	-2.45	0.014	-.2049651	-.0226512
smr	-.1579827	.1400101	-1.13	0.259	-.4323975	.1164321
inc	2.334804	1.108744	2.11	0.035	.161705	4.507903
carinc	2.525616	1.632867	1.55	0.122	-.674745	5.725977
atqinc	-7.120418	1.617393	-4.40	0.000	-10.29045	-3.950386
mgeinc	-2.512131	.652817	-3.85	0.000	-3.791629	-1.232633
erainc	-3.616004	1.803451	-2.01	0.045	-7.150702	-.0813056
lqtinc	.1578427	.5057661	0.31	0.755	-.8334406	1.149126
smrinc	3.07853	4.165821	0.74	0.460	-5.086329	11.24339
_cons	.1217863	.0741479	1.64	0.100	-.0235409	.2671134
sigma_u	.04241901					
sigma_e	.03624663					
rho	.57798344	(fraction of variance due to u_i)				

```
. estimates store re
```

. hausman fe re

	—— Coefficients ——			
	(b) fe	(B) re	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
car	-.1485551	-.131895	-.0166601	.024492
atq	.3729752	.379145	-.0061699	.0237184
mge	.1231252	.1150087	.0081164	.0125458
era	.1316334	.1306957	.0009376	.0342028
lqt	-.1261347	-.1138082	-.0123265	.0144174
smr	-.1382934	-.1579827	.0196893	.0619963
inc	2.361618	2.334804	.0268133	.375891
carinc	2.12361	2.525616	-.4020062	.9516443
atqinc	-6.931471	-7.120418	.1889474	.6060972
mgeinc	-2.544791	-2.512131	-.0326598	.3171304
erainc	-3.469963	-3.616004	.146041	.6665521
lqtinc	.2420782	.1578427	.0842354	.1298494
smrinc	2.298567	3.07853	-.7799636	1.925735

b = consistent under Ho and Ha; obtained from xtreg
 B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(13) = (b-B)'[(V_b-V_B)^(-1)](b-B)
 = 5.18
 Prob>chi2 = 0.9711

. xttest0

Breusch and Pagan Lagrangian multiplier test for random effects

roa[id,t] = Xb + u[id] + e[id,t]

Estimated results:

	Var	sd = sqrt(Var)
roa	.002986	.0546447
e	.0013138	.0362466
u	.0017994	.042419

Test: Var(u) = 0

chibar2(01) = 50.74
 Prob > chibar2 = 0.0000

```
. xtreg roa car atq mge era lqt smr inc carinc atqinc mgeinc erainc lqtinc smrinc, re vce(cluster id)
```

```
Random-effects GLS regression           Number of obs   =       132
Group variable: id                     Number of groups  =        15

R-sq:  within = 0.2843                  Obs per group: min =         8
      between = 0.1624                                avg   =        8.8
      overall  = 0.2119                                max   =         9

                                           Wald chi2(13)    =    115.37
corr(u_i, X)  = 0 (assumed)              Prob > chi2      =     0.0000
```

(Std. Err. adjusted for 15 clusters in id)

roa	Robust		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
car	-.131895	.1365741	-0.97	0.334	-.3995753	.1357853
atq	.379145	.1287434	2.94	0.003	.1268127	.6314774
mge	.1150087	.0436421	2.64	0.008	.0294719	.2005456
era	.1306957	.0991526	1.32	0.187	-.0636399	.3250313
lqt	-.1138082	.0577318	-1.97	0.049	-.2269604	-.000656
smr	-.1579827	.0975359	-1.62	0.105	-.3491495	.0331841
inc	2.334804	.7734143	3.02	0.003	.8189401	3.850668
carinc	2.525616	1.735474	1.46	0.146	-.8758516	5.927083
atqinc	-7.120418	2.257	-3.15	0.002	-11.54406	-2.69678
mgeinc	-2.512131	.7518303	-3.34	0.001	-3.985691	-1.03857
erainc	-3.616004	1.534585	-2.36	0.018	-6.623735	-.6082723
lqtinc	.1578427	.4088067	0.39	0.699	-.6434038	.9590892
smrinc	3.07853	3.179767	0.97	0.333	-3.153698	9.310759
_cons	.1217863	.0820098	1.49	0.138	-.0389499	.2825225
sigma_u	.04241901					
sigma_e	.03624663					
rho	.57798344	(fraction of variance due to u_i)				

roa	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
c.car#c.inc	2.767594	.9444486	2.93	0.004	.8984134	4.636776
c.atq#c.inc	.1157805	1.007292	0.11	0.909	-1.877774	2.109335
c.mge#c.inc	-1.214635	.2944269	-4.13	0.000	-1.797342	-.6319273
c.era#c.inc	.308935	.9842779	0.31	0.754	-1.639073	2.256943
c.lqt#c.inc	-.2473837	.3708225	-0.67	0.506	-.9812874	.4865199
c.smr#c.inc	-.4226885	1.411195	-0.30	0.765	-3.217114	2.371737
_cons	.1395324	.0096669	14.43	0.000	.1204005	.1586644

	Delta-method					
	dy/dx	Std. Err.	t	P> t	[95% Conf. Interval]	
car	.1702322	.0580922	2.93	0.004	.0552606	.2852038
atq	.0071216	.0619576	0.11	0.909	-.1155002	.1297433
mge	-.0747111	.0181099	-4.13	0.000	-.1105529	-.0388693
era	.0190023	.060542	0.31	0.754	-.1008179	.1388225
lqt	-.0152163	.022809	-0.67	0.506	-.0603581	.0299254
smr	-.0259992	.0868478	-0.30	0.765	-.1978817	.1458834

```
. marginsplot  
Variables that uniquely identify margins: _deriv
```

