Product Market Competition and Market-Based Performance Extremeness of Quoted Non-Financial Firms in Nigeria

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DOI: 10.56201/ijmcs.v8.no2.2024.pg61.85

Abstract

This study investigates the relationship between product market competition and performance extremeness of listed non-financial firms in Nigeria. Secondarily sourced panel data over the period from 2007 to 2022 of 30 of those firms on the floor of the Nigerian Exchange Group (NXG) was used. The estimated generalized least squares (EGLS) results reveal that two of the variables (HHIA and LI3) are positively and statistically significant with performance extremeness; three variables (LI1, LI2 and BI) are negatively and statistically significant with it while HHIS, CRS and CRA are insignificant.

Keywords: P*roduct market competition; performance, EGLS, NXG, Non-financial firms.*

1.0 Introduction

Economic and finance research has demonstrated the value of product market competition (PMC) as a mechanism for allocating resources and for correcting managerial inefficiencies. It is well known that a variety of economic outcomes can be improved by competition in the product market, which is a crucial external corporate governance tool (Kartika et al., 2023). Businesses naturally face rivalry in the product market since it lowers profitability because of diminishing market dominance. The rivalry between businesses in the same industry to draw clients and increase market share is referred to as "product market competition." It entails rivalry on elements like cost, caliber, and uniqueness of offering. As a result, in order for firms to stay competitive, they must increase their operational effectiveness, responsiveness, and supervision of management decisions. Rapid globalization of the financial and product markets throughout the last 20 years has led to the creation of a number of innovation-driven economic development strategies that support market integration and fierce competition in the hopes of achieving a substantial economic rebound with corporate investment decisions being influenced by the increased competitiveness in the product market brought about by globalization (Ebenezer et al., 2023). Consequently, companies design tactics to counter this danger. In the product market, competition serves as a disciplinary mechanism that is explained and supported by current empirical research. Corporate governance specialists have long been interested in how competition affects the product market. Early financial

theories held that fierce competition in the product market puts companies in a fight for survival, which reduces agency problems by forcing managers to make decisions that maximize shareholder value. Research has shown that competition in the product market lowers managerial incentives to manipulate profitability and promotes conservative financial reporting when it comes to the disclosure of corporate information. According to Schmidt (1997), internal governance or external monitoring methods are not as successful as competition between enterprises as a disciplinary tool. The competitiveness in the product market will compel and discipline a company's management to employ methods for efficient monitoring, which will lessen the manager's attempt to conceal the accounting figure when it comes to external monitoring for corporate governance. According to Shleifer (2004), PMC is one of the most effective corporate governance instruments for inspiring managers to attain economic efficiency and optimize firm value. Numerous studies have looked into how PMC affects several aspects of accounting, finance, and corporate governance. According to earlier studies, PMC significantly affects business performance, the quality of financial reporting, including managerial disclosures, earnings quality, tax evasion, and the effectiveness of corporate tax planning (Huang et al., 2022). It also enhances cost stickiness, audit fees, financial statement comparability, and accounting conservatism. Consequently, PMC has been associated with variations in stock returns, volatility of idiosyncratic returns, corporate investments, cost of equity, cash holdings and marginal value, company decisions regarding capital structure, CEO compensation, chance of CEO turnover, diminution of CEO power, and so on(Laksmana & Yang, 2014). Moreover, Shleifer (2004) has shown that PMC may lead to "unethical problems". He said that managers in competitive businesses are under pressure to maintain organizations' performance because they fear severe career implications, even if PMC typically cuts compensation. When bad news reaches a tipping point and abruptly seeps into the stock market, managers of businesses in competitive industries often refuse or postpone disclosing it to the public, which increases the likelihood of unfavorable career consequences that will eventually make these companies' stock values to crash(Huang et al., 2022).
Several studies on how product market competition impacts corporate performance has attracted researchers' attention leading to a range of study designs and findings which found strong relationship between them. Although some of the previous results may have shown mixed outcomes, the ones reviewed in this study are all positively significant with firm performance.

This study differs from others in that it uses eight (8) different measurements of product market competition. While Tuyet and Ninh (2023) two measurements (Herfindahl Hirschman Index (HHI) and Boone Index (BI)); Ilhang and Hansol (2023) used two measurements (Herfindahl Hirschman Index (HHI) for sales and assets, but the others used only one measurement. This study uses a longer time span of 16 years from 2007 to 2022 which to the best of my knowledge none in the previous studies reviewed used.

We, therefore, hypothesized that all the various PMC measurements considered in this study have no significant relationship with performance extremism of quoted non-financial firms in Nigeria. Following this introduction, the rest of the paper is divided into five sections with the literature review in section two, methodology in section three, discuss of results in section four and the fifth section concludes this paper.

2.0 Review of Related Literature.

2.1 Theoretical Underpinning.

2.1.1 Contestable Market Theory.

The contestable market theory was introduced by the Economist William J. Baumol in 1982, when he published his book titled 'Contestable Markets and the Theory of Industrial Structure'(Liberto, 2022). According to Baumol, because there is always a risk of new entrants, contestable markets eventually lead to a competitive equilibrium. According to the contestable market idea, where there is equal access to technology and little to no barrier to entry, there is always a chance that new competitors will emerge and threaten the well-established, well-established enterprises. Companies in the market are always susceptible to contestability, which causes them to adjust how they operate and become cautious. In general, such an atmosphere maintains low pricing and discourages the emergence of monopolies. Thus, if entry barriers are low, even a monopoly may be forced to operate in a competitive market. A monopoly owner may come to the conclusion that if they are too profitable, a rival will simply enter the market, challenge them, and reduce their earnings. In a contestable market, an entry-level competitor might employ a hit-and-run strategy. The newcomers can "hit" the market, make a profit, and then "run" out of business without having to pay any exit costs because there are either none or very low obstacles to entry. These risks have an impact on executive management teams in the industry, which causes them to reconsider their business strategies and prioritize increasing sales over profits (Liberto, 2022). According to the theory, unlimited earnings would be reduced to regular profits in a highly competitive market.

2.2 Empirical Literature

Kartika et al. (2023) attempted an empirical study of how product market competition (PMC) represented by Herfindahl Hirschman Index (HHI) enhanced the performance of firms in Indonesia. The study used secondary panel data over the period from 2018 to 2020 obtained from listed manufacturing firms on the Indonesia Stock Exchange (IDX). The OLS regression results indicated that PMC and return on equity (ROE) had a positive and significant effect.

Ebenezer et al. (2023) attempted a study to ascertain if PMC represented by Lerner Index (LI) affects the performance of firms in four emerging countries of Brazil, Russia, India, China (BRIC). The researchers used annually sourced panel data collected over the period from 2009 to 2020 on 1971 listed firms from their various Stock Exchanges. The results of the generalized methods of moments (GMM) revealed that PMC had a negative impact on firm value in China while it had a positive impact on firms' values in Brazil, Russia and Indian.

Ilhang and Hansol (2023) carried out an empirical examination to ascertain the impact of product market competition represented by Herfindahl Hirschman Index (HHI) for both sales and assets on a firm's organization capital in Korea. Annual secondary panel data which covered the period 2001 to 2020 collected from the financial reports of listed Korean firms was used. The regression results of the OLS indicated that a positive and significant relationship existed between product market competition and organization capital.

Tuyet and Ninh (2023) empirically tested whether competition represented by Herfindahl Hirschman Index (HHI) and Boone Index (BI) has affected corporate performance of firms in Vietnam. The study used secondary panel data over the period from 2015 to 2019 obtained from 352 companies listed on the Vietnamese stock exchanges. The GMM regression results indicated that PMC was positively significant with ROE.

Ha and Tran (2022) undertook a research to determine if PMC represented by Herfindahl Hirschman Index (HHI) has had any relationship with firm performance in Vietnam. The samples consist of 180 firms listed on the Vietnamese stock exchanges between 2015 and 2019. The Structural Equation Model method results revealed that PMC positively and significantly affected performance.

Liu et al.(2022) studied whether there is any relationship between PMC represented by Herfindahl Hirschman Index (HHI) and the performance of firms in China. The researchers used annually sourced panel data collected over the period from 2016 to 2020 of A-share listing with China Stock Markets and Accounting Research (CSMAR) database. The results of the GMM regression revealed that there was a positively significant impact of PMC and firms' performance.

Fosu (2013) researched to ascertain the extent to which PMC represented by the Boone indicator (BI) impacted performance of firms in South Africa. Secondary data collected from annual reports of 257 firms listed on the Johannesburg Stock Exchange (JSE) Limited between 1998 and 2009 was used. The OLS regression results showed that revealed that there was a positive and significant impact of PMC on firms' performance.

Xu (2013) carried out an empirical examination to ascertain the impact of capital structure on product market competition represented by the m-Firms Concentration ratio in the Netherlands. Annual secondary panel data which covered the period 2003 to 2012 collected from the financial reports of listed firms in Orbis database was used. The regression results of the OLS indicated that a positive and significant relationship existed between concentration ratio and capital structure.

3.0 Methodology

3.1 Research Design

Using the ex-post facto research design, often referred to as the descriptive or correlational research design, the study investigates if there is any relationship between ownership structure and firm performance of companies in Nigeria. The sample of this study consists of 30 non-financial firms listed on the floor of the Nigerian Exchange Group (NXG). The secondarily sourced data of the sampled firms was obtained from their annual reports gathered over a period of sixteen (16) years, from 2007 to 2022, totaling 480 firm-year observations.

3.2 Measurement and Definitions of Variables.

Table1

S/N		Definitions	Variable Types	Measurements
1	MBPE	Market-based performance extremeness	Dependent	See 3.2.1 for Details
2	HHIS	Herfindahl-Hirschman Index (HHI) using firms and industry sales values	Independent	See 3.2.2 for Details
3	HHIA	Herfindahl-Hirschman Index (HHI) using firms and industry assets values	Independent	See 3.2.2 for Details
4	CRS	Concentration ratio using firms and industry sales values	Independent	See 3.2.2 for Details
5	CRA	Concentration ratio using firms and industry assets values	Independent	See 3.2.2 for Details
6	LI1	Lerner index 1	Independent	See 3.2.2 for Details
7	LI2	Lerner index 2	Independent	See 3.2.2 for Details
8	LI3	Lerner index 3	Independent	See 3.2.2 for Details
9	BI	Boone indicator	Independent	See 3.2.2 for Details
10	SGROWTH	Sales growth	Control	$Sales_t / Sales_{t-1} - 1$
11	RISK	Volatility of return on assets(ROA)	Control	Standard deviation of return on asset(ROA)
12	SIZE	Firm size	Control	Log of total assets
13	LEV	Leverage	Control	Total debts/ Total assets
14	BIG4	Deloitte & Touche; Ernst & Young; PriceWater Cooper and KPMG	Control	Dummy variable which equals "1" in year a firm is audited by one of the four biggest audit firms; "0" otherwise.

15	IDUM	Industry Sector Fixed Effect Dummy	Control	A dummy variable which takes the value '1' for each industry
16	YDUM	Year Fixed Effect Dummy	Control	A dummy variable which takes the value '1' for each year

Source: Researcher's Computations from Extant Literature.

3.2.1 Derivation of the Dependent Variable (Market-Based Performance Extremeness)

This study uses three market-based performance measurements to compute extreme performance. These are: a) Economic Value Added (EVA); b) Tobin'sQ and c) Earnings Per Share(EPS)

a) Economic Value Added (EVA): Economic value added is a performance measure of estimating the true economic profit of a firm not derived purely from accounting conventions (Stewart, 2018). EVA makes a firm to focus on value creation, capital structure policy, maximizing shareholders returns by maximizing the investment return while minimize the cost of capital (Ende, 2017)
EVA is calculated in based on the following formula:
EVA = NOPAT – A Capital Charge.

EVA = NOPAT – (WACC x Capital Employed)

EVA = NOPAT – Cost of Capital x Capital Employed
Where NOPAT = Net operating profit after tax = Net profit after tax plus fixed interest charges.

WACC = Weighted average cost of capital = Long-term debt / Long-term debt + Equity multiplied by cost of debt Plus Equity / Long-term debt + Equity multiplied by cost of equity.

b) TOBIN"S Q: Tobin'sQ measures market value instead of real performance, comparing a company's value to its replacement or book value. Consequently, it illustrates how the market evaluates a company's performance in relation to its replacement cost rather than being an accurate measure of a company's performance. Tobin's Q formula is an economic ratio that is used to compare an index or firm's market value to its book or replacement value. It can be used to determine the relative value of a company's shares or the market as a whole. The ratio is calculated by dividing a company's market value by its asset replacement value.

i)Tobin'sQ = $\frac{\text{Total market value of a company}}{\text{Total replacement value of the company's assets.}}$

Since estimating the replacement cost of all assets is difficult, analysts often utilize an alternate versions of the technique to estimate Tobin's Q ratio like:

ii)Tobin'sQ = Total market value of a company

Total company's assets value.

$$\text{iii) Tobin'sQ} = \frac{\text{Total market value of a company + total liabilities market value}}{\text{Total equity book value + total liabilities book values.}}$$

c) Earnings Per Share(EPS):A financial metric called earnings per share (EPS) is the net profits accessible to common shareholders. It is computed by dividing net earnings by the average number of outstanding shares during a certain time period. The EPS calculation shows a company's capacity to produce net profits for common shareholders.

$$\text{Earnings Per Share} = \frac{\text{Profits after tax less dividends to preferred shareholders}}{\text{Total number of equity shares outstanding and ranking for dividends.}}$$

Thus, the following steps are undertaken to obtain the value for performance extremeness, extreme performance or performance extremism as the case may be.
Step1: Calculate the value for each performance indicator (EVA, Tobin'sQ and EPS) for each firm and for the sampled period, that is, for the firm-year observations.
Step2: Normalize each indicator by subtracting the industry-year average/mean and then divide the outcome by the industry-year standard deviation.
Step3: Take the absolute value of the results in Step2 above.
Step3: Finally, take the average value of all the performance indicators (EVA, Tobin'sQ and EPS) to form a composite value for performance extremeness. That is, sum the three indicators (EVA, Tobin'sQ and EPS) and then divide by three. The larger the value, the greater the firm has deviated from the industry concentration or the mainstream trend.

3.2.2 Derivation of the Independent Variables

3.2.2.1. HHIS = Herfindahl-Hirschman Index (HHI) Using Firms and Industry Sales Values.
The Herfindahl Hirschman Index (HHI) is a statistical indicator that illustrates how market share is allocated among index companies and assesses the level of competition in a market or industry. The level of market competition can have a significant impact on pricing decisions for products and services that a company offers as well as for strategic planning. A higher HHI means a lower competition and vice versa, a lower HHI means a higher competition.

The HHI for sales can be calculated using the following steps below:
Step1: Add the values for each company's sales revenue for the sampled periods.
Step 2: Add the values for all companies' sales revenue within an industry for the sampled periods.
Step 3: Divide Step 1 by Step 2 above to obtain the market share of each company.
Step 4: Square the value obtained in Step 3 above. That is, square each company's market share.

Step 5: Sum or add up all the squared market share of each company in Step 4 above to obtain the Herfindahl-Hirschman Index (HHI).

3.2.2.2. HHIA = Herfindahl-Hirschman Index (HHI) Using Firms and Industry Assets Values.

The HHI for assets can be calculated using the following steps below:

Step1: Add the values for each company's total assets for the sampled periods.
Step 2: Add the values for all companies' total assets within an industry for the sampled periods.
Step 3: Divide Step 1 by Step 2 above to obtain the market share of each company.
Step 4: Square the value obtained in Step 3 above. That is, square each company's market share.
Step 5: Sum or add up all the squared market share of each company in Step 4 above to obtain the Herfindahl-Hirschman Index (HHI).

3.2.2.3. CRA = Concentration Ratio (CR) Using Firms and Industry Sales Values.
The concentration ratio shows how competitively the businesses that make up an industry are with one another. It is the proportion of company size to the size of the sector as a whole. Understanding the nature of the industry is made easier by the concentration ratio. There could be fierce competition in the sector, or a small number of dominant companies. A high concentration ratio that is closer to 100% suggests that there is either no competition for these businesses or that there is a monopoly in the industry. Increased competitiveness among industry firms is indicated by a lower concentration ratio.
The CR for sales can be calculated using the following steps below:

Step1: Add the values for each company's sales revenue for the sampled periods.
Step 2: Add the values for all companies' sales revenue within an industry for the sampled periods.
Step 3: Divide Step 1 by Step 2 above to obtain the market share of each company.
Step 4: Sum or add up all the market shares of the first four largest companies in Step 3 above to obtain the Concentration Ratio (CR).

3.2.2.4. CRA = Concentration Ratio (CR) Using Firms and Industry Assets Values.
The CR for assets can be calculated using the following steps below:
Step1: Add the values for each company's total assets for the sampled periods.
Step 2: Add the values for all companies' total assets within an industry for the sampled periods.
Step 3: Divide Step 1 by Step 2 above to obtain the market share of each company.
Step 4: Sum or add up all the market shares of the first four largest companies in Step 3 above to obtain the Concentration Ratio (CR).

3.2.2.5. LI1 = Lerner Index (LI).

The Lerner index is used to measure competition in the product market because it provides a scientific examination of market strength. In other words, it's a measurement of a company's price-to-cost margin, sometimes referred to as price elasticity of demand. The difference between the firm's pricing and its marginal cost at the output rate that optimizes profits was used to calculate the degree of monopoly using the Lerner index. Therefore, a higher degree of monopolistic power was represented by a larger difference between P and MC. It is a more direct measure of PMC since it considers the ability of enterprises to set prices higher than their marginal cost of production. Pricing power is exhibited by the difference between the cost and the marginal price. The range of values for the Lerner index is 0 to 1. Companies that have a large amount of market control are commonly referred to as monopolies. A pure monopoly business that controls the whole market for a good would be given a value of 1. A business that only participated in that market would have limited influence over price and a value that was closer to 0.

The Lerner Index is calculated as the difference between the price of an organization's output and the marginal cost of production divided by the price as shown in the formula below.

$$\text{Lerner Index} = \frac{Price_{it} - MC_{it}}{Price_{it}}$$ Where MC = marginal costs.

The above is also known as the price-costs margin(PCM)

3.2.2.6. LI1 = Lerner Index (L2).

$$\text{Lerner Index} = \text{Adjusted} \quad \frac{Price_{it} - MC_{it}}{Price_{it}}$$

The above is also known as the adjusted price-costs margin(IPCM) where the industry average is deducted from the PCM results.

3.2.2.7. LI1 = Lerner Index (L3).

$$\text{Lerner Index} = \frac{Sales_{it} - (COGS_{it} - SGA_{it})}{Sales_{it}}$$

OR

$$\frac{EBITDA_{it}}{Sales_{it}}$$

Where COGS = costs of goods sold; SGA = selling, general and administrative expenses; EBITDA = Earnings before interest, tax, depreciation, and amortization

3.2.2.8. Boone Indicator (BI): The Boone indicator is a relatively recent characteristic in a competitive industry. It determines how efficiency affects output in terms of profits. Put differently, the Boone indicator is a novel approach to measuring competitiveness, based on the premise that companies in more efficient or competitive industries suffer severe consequences for inefficiencies (Boone, 2004). Therefore, in a highly competitive business, it is expected that an increase in marginal costs will cause a dramatic fall in variable profits. The main tenet of the Boone indicator is that banks that operate more efficiently make more money. When the Boone indicator is more negative, market competition rises because reallocation has a greater impact (Focus, 2013).

The Boone indicator is calculated by estimating the regression equation below:
$V\ ROA_{it} = \beta o + \beta_1 LnMC_{it} + \varepsilon_{it}$
where $V\ ROA_{it}$ = Variable profit (Sales less cost of goods sold) divided by total assets; $LnMC_{it}$ = Natural logarithm of the marginal cost (Cost of goods sold divided by Sales less cost of goods sold) divided by total assets; β_1 = the coefficients of LnMC which is expected to be negative. The absolute value of β_1 is used to measures competition. The higher the absolute value of the coefficients is an indication that the level of competition in the industry is very high.

3.3 Model Specification

The functional equation of performance extremeness to test the eight (8) hypotheses specified is stated as in equation 1:

MBPE = f (HHIS, HHIA, CRS, CRA, LI1, LI2, LI3, BI) (Eq1)

3.3.1. Universal Usage of Control Variables in Published Scholarly Articles From High Quality Journals.

Traditionally, control variables (CVs) are used in research models that have causal relationship. The two main ways of controlling for variables are by experimental design (before gathering the data) where the samples are manipulated or by statistical control (after gathering the data) where the researcher just includes relevant variables in the model. Some of the reasons for controlling are to eliminate omitted variables biases thereby reducing the error term which in turn increase statistical power by improving the estimated coefficients precision (De Battisti & Siletti, 2018). Cinelli et al. (2022) was of the opinion that while some data analysts, students as well as empirical social scientists have discussed the problem of omitting certain relevant variables, they have not provided a means of deciding which variables could improve or worsen existing biases in a regression model. According to Becker (2005), CVs are just as important as the predictors (independent) variable and the criterion (dependent) variable because one author‘s CV could be another author‘s predictor‘s or criterion variable such that including improperly any CV can produce misleading results. Hunermund and Louw (2020) noted that over 47 percent of scholarly papers published the previous five years in top management journals made use of CVs. They pointed out that they were specifically as authors asked to hypothesized and interpret CV coefficients as though these CVs were focal main variables for as much as the CVs could give valuable information to other researchers.

Therefore, introducing the five firm-specific control variables give rise to equation 2 as:

MBPE = f (HHIS, HHIA, CRS, CRA, LI1, LI2, LI3, BI, SGROWTH, RISK, SIZE, LEV, BIG4) (Eq2)

Eq2 becomes Eq3 when the year dummy and industry sector dummy variables are introduced to control for specific fixed effect.

MBPE = f (HHIS, HHIA, CRS, CRA, LI1, LI2, LI3, BI, SGROWTH, RISK, SIZE, LEV, BIG4, IDUM, YDUM) (Eq3)

The functional testable model will be derived as:

$$MBPE = \beta o + \beta_1 HHIS + \beta_2 HHIA + \beta_3 CRS + \beta_4 CRA + \beta_5 LI1 + \beta_6 LI2 + \beta_7 LI3 + \beta_8 BI + \beta_9 SGROWTH + \beta_{10} RISK + \beta_{11} SIZE + \beta_{12} LEV + + \beta_{13} BIG4 + \beta_{14} IDUM + \beta_{15} YDUM + \varepsilon \quad (Eq4)$$

Since we are using panel data, the model will be specified in the appropriate form as:

$$MBPE_{it} = \beta o + \beta_1 HHIS_{it} + \beta_2 HHIA_{it} + \beta_3 CRS_{it} + \beta_4 CRA_{it} + \beta_5 LI1_{it} + \beta_6 LI2_{it} + \beta_7 LI3_{it} + \beta_8 BI_{it} + \beta_9 SGROWTH_{it} + \beta_{10} RISK_{it} + \beta_{11} SIZE_{it} + \beta_{12} LEV_{it} + \beta_{13} BIG4_{it} + \beta_{14} IDUM_{it} + \beta_{15} YDUM_{it} + \varepsilon_{it} \quad (Eq5)$$

3.4 Data Analysis using Static Estimated Generalized Least Squares (EGLS) Technique:

The ordinary least squares (OLS) has been an important method of prediction ever known to mankind since it was invented in 1795 by the mathematician Carl Friedrich Gauss, and later on rediscovered and popularized by another mathematician known as Adrien-Marie Legendre in 1805 (ClockBackward, 2009). The OLS regression model is built on certain assumptions such that if any of these assumptions are violated, then OLS estimator may no longer be Best Linear Unbiased Estimate (BLUE) and so the generalized least squares (GLS) was developed towards the mid-twentieth centuries by Alexander Aitken in 1936 (Virgantari et al., 2019). The GLS regression is an extension of the normal linear OLS estimation designed with some level of unequal error variances (heteroscedastic), not equal or constant variance (homoscedastic) and correlations between the residuals or error terms (serial correlation) in mind. The GLS and OLS estimators are the same in the absence of autocorrelation and heteroskedasticity and so they differ with respect to the error term assumptions which the GLS estimator was improvised to tackle. Thus, the GLS estimator is a generalization of the OLS estimator which transforms it to a new estimator that is more efficient, consistent, unbiased and asymptotically normal (Priya & Riya, 2017).

Where the definitions are as stated in Table2 above.

β_1 to β_{15} are the beta coefficients of the instrumental, independent and control variables. From this study, we expect β_1 to β_{15} to be greater than zero.

ε_{it} = Error term for year 'i' in year 't'

4.0. Method of Data Analysis

Data collected are analyzed using EViews 13 in the following order: univariate data analyses or descriptive statistics; bivariate data analysis or correlation analysis; estimation of the models; performance of some additional analysis and diagnostics tests.

4.1 Univariate Data Analyses (Descriptive Statistics)

The statistics in Table 2 below, which is based on equation1 above, show that the mean values of the variables as well as the maximum values. Since the mean values are lower than the maximum values, it confirms that there are no outliers in our data. The Jarque-Bera Statistics and its Probability of 0.000000 for all the variables show that the distribution is not normal. However, Ghasemi and Zahediasl (2012) noted that, in accordance with the central limit theorem (CLT), violating the normality assumption shouldn't be a significant problem once the observation is 100 and above. Our observation is 480, and so normality assumption does not matter here.

Table 2.

	HHIS	HHIA	CRS	CRA	LI1	LI2	LI3	BI	SGROWTH	RISK	SIZE	LEV	BIG4	IDUM	YDUM
Mean	0.500271	-0.494496	0.873836	0.894495	23.28081	-41.55475	-41.50629	1.725770	4.119697	0.070059	6.994558	6.857261	0.377880	4.642857	8.615207
Median	0.311947	-0.415300	0.954096	0.967505	0.110976	0.086326	0.084392	0.272880	0.040395	0.040149	7.006247	0.163105	0.000000	5.000000	9.000000
Maximum	0.973609	-0.197240	0.999885	1.000000	915.4609	1201.442	1201.181	87.36733	865.9743	1.021136	9.817402	1192.730	1.000000	9.000000	16.00000
Minimum	0.128101	-0.993480	0.624083	0.701822	-736.9090	-3352.798	-3351.131	0.000000	-2.607431	0.000000	0.000000	-28.01377	0.000000	0.000000	1.000000
Std. Dev.	0.345998	0.267776	0.152267	0.120572	136.3160	259.6137	259.5034	6.549000	47.86219	0.118847	1.343116	76.02634	0.485417	2.967741	4.575954
Skewness	0.343310	-0.323687	-0.922179	-0.822009	3.664526	-7.318491	-7.317488	7.832752	15.15030	5.764434	-2.321320	13.48598	0.503735	-0.042210	-0.028277
Kurtosis	1.306042	1.496850	2.040619	1.884987	26.51005	77.69054	77.67468	83.37320	255.1722	43.01754	14.43685	193.7421	1.253749	1.492444	1.820428
Jarque-Bera	60.41537	48.43720	78.15739	71.35773	10966.41	104755.3	104711.4	121253.5	1166537.	31362.26	2755.099	671072.8	73.49769	41.22730	25.21879
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000003
Sum	217.1177	-214.6113	379.2448	388.2109	10103.87	-18034.76	-18013.73	748.9843	1787.949	30.40554	3035.638	2976.051	164.0000	2015.000	3739.000
Sum Sq. Dev.	51.83633	31.04786	10.03927	6.294801	8046024.	29183891	29159097	18571.11	991911.9	6.115916	781.1153	2502742.	102.0276	3813.643	9066.740
Observations	480	480	480	480	480	480	480	480	480	480	480	480	480	480	480

Source: Researcher's Computations (2023) Using EViews13 Software.

4.2 Bivariate Data Analysis (Correlation Analysis)

The correlation analysis among the variables, which is based on equation1 above, are meant to first determine the association between each pair of the dependent and independent variables as well as among the explanatory variables. The degree of association may be weak (0.00 to 0.5), moderate (0.51 to 0.8) or high (0.81 and above). A very high association among the regressors poses a problem of multi-collinearity (Gujarati, 2003)

Table 3

Covariance Analysis: Ordinary
Date: 03/09/24 Time: 15:22
Sample: 1 464
Included observations: 434
Balanced sample (listwise missing value deletion)

Covariance Correlation	HHIS	HHIA	CRS	CRA	LI1	LI2	LI3	BI	SGROWTH	RISK	SIZE	LEV	BIG4	IDUM	YDUM
HHIS	0.119439														
	1.000000														
HHIA	-0.075740	0.071539													
	-0.819371	1.000000													
CRS	0.036473	-0.031195	0.023132												
	0.693896	-0.766842	1.000000												
CRA	0.027855	-0.023445	0.018073	0.014504											

	0.669243	-0.727831	0.986662	1.000000								
LI1	9.672820	0.560537	1.970826	2.356285	18539.23							
	0.205558	0.015392	0.095169	0.143693	1.000000							
LI2	-16.49829	6.792991	-4.155283	-3.480355	-18222.97	67243.99						
	-0.184094	0.097941	-0.105358	-0.111442	-0.516115	1.000000						
LI3	-16.49724	6.793029	-4.151832	-3.478242	-18217.96	67215.39	67186.86					
	-0.184161	0.097983	-0.105315	-0.111422	-0.516192	1.000000	1.000000					
BI	0.403228	-0.077827	0.094009	0.083615	243.9633	-1245.080	-1244.526	42.79058				
	0.178363	-0.044482	0.094491	0.106136	0.273908	-0.734000	-0.733986	1.000000				
SGROWTH	0.106100	-0.310077	0.397535	0.299737	-97.57250	168.8353	169.3363	-6.175884	2285.511			
	0.006422	-0.024250	0.054674	0.052060	-0.014990	0.013619	0.013665	-0.019748	1.000000			
RISK	0.002075	-0.001859	0.000770	0.000471	-1.437353	1.121776	1.120946	0.001982	0.339407	0.014092		
	0.050588	-0.058537	0.042638	0.032970	-0.088927	0.036441	0.036430	0.002552	0.059806	1.000000		
SIZE	-0.055140	0.050431	-0.028946	-0.025219	16.11463	20.59914	20.61756	-0.151852	3.042141	0.029204	1.799805	
	-0.118927	0.140546	-0.141865	-0.156088	0.088219	0.059212	0.059290	-0.017303	0.047432	0.183375	1.000000	
LEV	2.906117	-2.172541	0.774860	0.503796	-400.7626	-11027.25	-11021.95	329.2040	-25.84632	0.030432	-8.524140	5766.686
	0.110733	-	0.067089	0.055087	-	-	-	0.662717	-0.007119	0.003376	-	1.000000

		0.106963			0.038760	0.559986	0.559955				0.083671				
BIG4	-0.052277	0.045643	-0.010530	-0.007087	-8.891052	14.10476	14.11858	-0.300306	-1.251541	-0.005527	0.057280	-2.513915	0.235087		
	-0.311980	0.351955	-0.142789	-0.121369	-0.134677	0.112182	0.112340	-0.094684	-0.053993	-0.096029	0.088060	-0.068277	1.000000		
IDUM	-0.417400	0.468594	-0.184310	-0.110076	59.15437	12.84700	12.86046	0.489675	4.460995	-0.029140	0.044497	-17.86532	0.439105	8.787196	
	-0.407432	0.591018	-0.408807	-0.308335	0.146560	0.016713	0.016737	0.025253	0.031479	-0.082810	0.011189	-0.079364	0.305512	1.000000	
YDUM	0.049721	-0.036711	0.012134	0.007687	46.62721	-66.44638	-66.36941	2.071070	-18.55708	0.059777	1.226809	28.34913	0.232963	-0.317149	20.89111
	0.031476	-0.030029	0.017455	0.013965	0.074923	-0.056061	-0.056020	0.069269	-0.084925	0.110171	0.200071	0.081676	0.105122	-0.023408	1.000000

Source: Researcher's Computations (2024) Using EViews13 Software.

From Table 3 above, all the variables have weak associations and this attest to the fact that there is no problem of multicollinearity among the variables except those of HHIA to CRS (-0.819371); CRS to HHIS (0.693896) ; CRS to HHIS (0.693896) ; CRS to HHIA (-0.766842) ; CRA to HHIS (0.669243); CRA to HHIA (-0.727831) and CRA to CRS (0.986662) which are moderately and highly correlated.

4.2b Bivariate Data Analysis (Variance Inflation Factor)

Variance Inflation Factors (VIFs) is a statistical technique used for the detection of multicollinearity or collinearity among independent variables. A high VIFs reflect the fact there is collinearity among the independent variables meaning the standard errors and the variances of the regression coefficient estimates will increase leading to a very low *t*-statistics (Murray et al, 2012). Table 4 shows the results of the variance inflation factor(VIF) and the corresponding tolerance column. A VIF of any variable less than 10 with its tolerance level greater than 0.2 is free of multicollinearity for VIF that ranges between 5 to 10 is adjudged to have highly correlated variables (Shrestha, 2020). All the variables have a VIF less than 10 with a tolerance greater than 0.2 except few ones like those of CRS, CRA, LI2 and LI3. Thus, Table 3 and Table 4 show that our model has no issue with multicollinearity. There is no one single solution to eliminating multicollinearity in a model, and so what to consider is to either: do nothing; drop a redundant variable; transform the multicollinear variables or increase the sample size. Belsley et al. (1980) as cited in Murray et al.(2012) was of the opinion that researchers should take caution in treating VIFs threshold of 5 or 10 or 30 when taking decisions to eliminate or reduce collinearity since other factors like sample size which influence regression coefficients variability should also be considered.

Table 4

S/N	Variables	Variance Inflation Factor (VIF)	Tolerance
1	HHIS	4.063441	0.2457
2	HHIA	6.285241	0.158983
3	CRS	83.57345	0.011966
4	CRA	76.96605	0.012987
5	LI1	2.465920	0.4
6	LI2	1542447.	6.48E-07
7	LI3	1542502.	6.48E-07
8	BI	3.023871	0.331126
9	SGROWTH	1.036535	0.328947
10	RISK	1.091277	0.909091
11	SIZE	1.198160	0.833333
12	LEV	2.276249	0.434783
13	BIG4	1.373533	0.714286
14	IDUM	2.622840	0.384615
15	YDUM	1.104211	0.909091

Source: Researcher's Computations (2024) Using EViews13 Software.

4.4 Regression Models Estimation Results.

Table 5. Dependent Variable: MBPE
Method: Panel EGLS (Period SUR)
Date: 03/08/24 Time: 22:46
Sample: 2007 2022
Periods included: 16
Cross-sections included: 30
Total panel (unbalanced) observations: 480
Linear estimation after one-step weighting matrix
Period SUR (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HHIS	0.049816	0.027972	1.780915	0.0756
HHIA	0.073670	0.030181	2.440949	0.0150
CRS	0.008458	0.124112	0.068149	0.9457
CRA	-0.009257	0.152194	-0.060824	0.9515
LI1	-0.007876	0.002319	-3.395972	0.0007
LI2	-0.000803	9.80E-05	-8.187417	0.0000
LI3	0.000590	0.000165	3.576758	0.0004
BI	-0.000717	0.000250	-2.869967	0.0043
C	0.011621	0.039048	0.297605	0.7661

	Weighted Statistics		
R-squared	0.087808	Mean dependent var	0.021001
Adjusted R-squared	0.072282	S.D. dependent var	1.024684
S.E. of regression	0.986837	Sum squared resid	457.7086
F-statistic	5.655334	Durbin-Watson stat	2.012266
Prob(F-statistic)	0.000001		

	Unweighted Statistics		
R-squared	0.021694	Mean dependent var	0.000320
Sum squared resid	149.2565	Durbin-Watson stat	1.273430

Source: Researcher's Computations (2024) Using EViews13 Software.

4.5 Discussion of the Regression Estimation Results and Hypotheses Testing.

From Table 5 above for the MBPE model, both the R^2 (0.087808) and the Adj R2 = (0.072282) indicated that about 7% of systematic variations in performance extremeness is accounted for by HHIS, HHIA, CRS, CRA, LI1, LI2, LI3 and BI which is very, very low. The remaining 95% can be explained by other factors not captured by the model. The F-statistic (5.655334) and a Prob(F-stat.) of 0.000000 confirm that there is a joint statistical significant of a linear relationship between the variables (dependent and independent). With a Durbin-Watson stat of 2.012266, the model is freed from serial correlation.

Looking at the independent variables (HHIS, HHIA, CRS, CRA, LI1, LI2, LI3 and BI) reveal that five of the variables (HHIA, LI1, LI2, LI3 and BI) are statistically significant while three (HHIS, CRS and CRA) are statistically not significant.

Specifically, HHIA relationship with MBPE is positively significant with a coefficient of 0.073670 0.073670, a t-Statistic of 2.440949 and a p-value of 0.0150. This suggests that an increase in HHIA will increase MBPE. This means that the more competitive the industry is, the more profitable the firms' performance. The sign or direction as well as the size or magnitude is aligned with our expectations. We, therefore, reject the null hypothesis of no significant relationship and accept the alternative hypothesis that there is a significant relationship between HHIA and MBPE.

LI1 relationship with MBPE is negatively significant with a coefficient of -0.007876, a t-Statistic of -3.395972 and a p-value of 0.0007. This means that as LI1 decreases, MBPE increases. This means that the less competitive the industry is, the more profitable the firms' performance. The sign or direction is contrary to our expectations but the size or magnitude is in line with our expectations. We, therefore, reject the null hypothesis of no significant relationship and accept the alternative hypothesis that there is a significant relationship between HHIA and MBPE.

LI2 relationship with MBPE is negatively significant with a coefficient of -0.000803, a t-Statistic of -8.187417 and a p-value of 0.0000. This means that as LI2 decreases, MBPE increases. This means that the less competitive the industry is, the more profitable the firms' performance. The sign or direction is contrary to our expectations but the size or magnitude is in line with our expectations. We, therefore, reject the null hypothesis of no significant relationship and accept the alternative hypothesis that there is a significant relationship between HHIA and MBPE.

LI3 relationship with MBPE is positively significant with a coefficient of 0.000590, a t-Statistic of 3.576758 and a p-value of 0.0004. This suggests that an increase in LI3 will increase MBPE. This means that the more competitive the industry is, the more profitable the firms' performance. The sign or direction as well as the size or magnitude is aligned with our expectations. We, therefore, reject the null hypothesis of no significant relationship and accept the alternative hypothesis that there is a significant relationship between LI3 and MBPE.

BI relationship with MBPE is negatively significant with a coefficient of -0.000717, a t-Statistic of -2.869967 and a p-value of 0.0043. This means that as BI decreases, MBPE increases. This means that the less competitive the industry is, the more profitable the firms' performance. The sign or direction is contrary to our expectations but the size or magnitude is in line with our expectations.. We, therefore, reject the null hypothesis of no significant relationship and accept the alternative hypothesis that there is a significant relationship between HHIA and MBPE.

While HHIS and CRS are positively insignificant with MBPE; CRA is negatively insignificant with it.

4.6 Additional Analysis for Robustness Checks using Results from Table5a and Table 7

To test the robustness of our results, we include both the firm-specific control variables (SGROWTH, RISK, SIZE, LEV and BIG4) as well as the industry-year fixed effect control variables (YDUM and IDUM) as stated in equations 2 and 3.

Table 6. Dependent Variable: MBPE
Method: Panel EGLS (Period SUR)
Date: 03/08/24 Time: 22:58
Sample: 2007 2022
Periods included: 16
Cross-sections included: 30
Total panel (unbalanced) observations: 480
Linear estimation after one-step weighting matrix
Period SUR (PCSE) standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HHIS	0.032105	0.072926	0.440247	0.6600
HHIA	0.030102	0.081070	0.371306	0.7106
CRS	0.105358	0.468900	0.224692	0.8223
CRA	-0.026892	0.548683	-0.049013	0.9609
LI1	-0.010205	0.004298	-2.374377	0.0180
LI2	-0.000833	0.000198	-4.209627	0.0000
LI3	0.000456	0.000335	1.360969	0.1742
BI	-0.000814	0.000278	-2.925431	0.0036
SGROWTH	-8.28E-05	0.000113	-0.732237	0.4644
RISK	-0.325664	0.187902	-1.733163	0.0837
SIZE	0.037678	0.014565	2.586899	0.0100
LEV	0.074338	0.021099	3.523369	0.0005
BIG4	0.031657	0.022700	1.394536	0.1638
IDUM	0.009938	0.005862	1.695306	0.0907
YDUM	0.001912	0.006878	0.277949	0.7812
C	-0.414640	0.178530	-2.322522	0.0206

	Weighted Statistics		
R-squared	0.090638	Mean dependent var	-0.033068
Adjusted R-squared	0.060856	S.D. dependent var	1.026448
S.E. of regression	0.994124	Sum squared resid	452.6336
F-statistic	3.043329	Durbin-Watson stat	2.037348
Prob(F-statistic)	0.000105		

	Unweighted Statistics		
R-squared	0.051055	Mean dependent var	-0.003312
Sum squared resid	143.8416	Durbin-Watson stat	1.313003

Source: Researcher's Computations (2024) Using EViews13 Software.

Table 7

Comparative Analysis of the two Regression Models Estimation Results.

VARIABLES	P-Values of the Model without control variables	VARIABLES	P-Values of the Model with control variables
HHIS	0.0756	HHIS	0.6600
HHIA	0.0150	HHIA	0.7106
CRS	0.9457	CRS	0.8223
CRA	0.9515	CRA	0.9609
LI1	0.0007	LI1	0.0180
LI2	0.0000	LI2	0.0000
LI3	0.0004	LI3	0.1742
BI	0.0043	BI	0.0036
C	0.7661	SGROWTH	0.4644
		RISK	0.0837
		SIZE	0.0100
		LEV	0.0005
		BIG4	0.1638
		IDUM	0.0907
		YDUM	0.7812
		C	0.0206

Source: Researcher's Computations (2024) Using EViews13 Software.

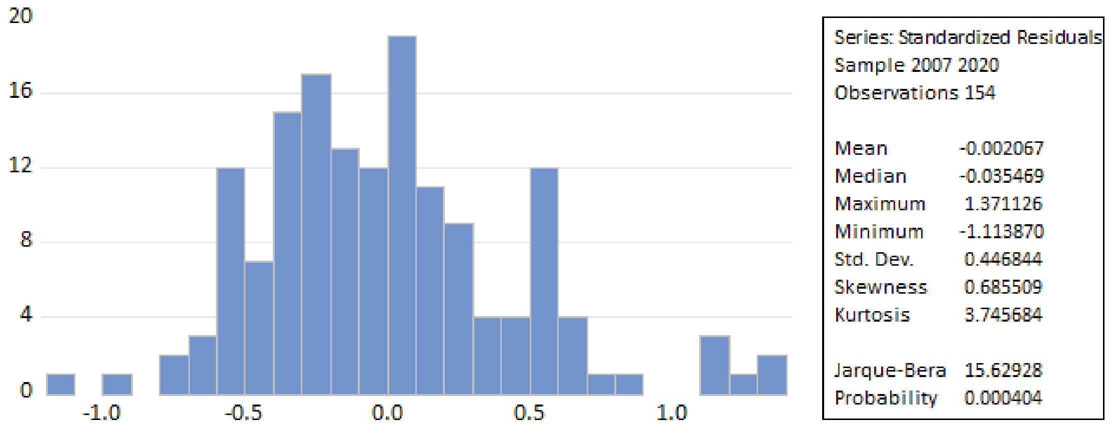
A comparative analysis of the two results shows that the following variables (LI1, LI2 and BI) are statistically significant for both models while HHIS, CRS and CRA are statistically insignificant for both models. HHIA and LI3 are statistically significant for the model without control variables but are statistically insignificant for the model with control variables. Also, they both have a very low R-squared and Adjusted R-squared and are both free of serial correlation. This shows that the results are robust in explaining the relationship between product market competition and performance extremeness in Nigeria.

4.7. Normality Test

The purpose of the normality test is to determine if the distribution of data within a group of data or variables is regularly distributed or not. Data that has been collected in a normal distribution or taken from a normal population can be identified using the normality test. In data analysis, normalcy assumptions are used by descriptive statistics, correlation, regression, ANOVA, t tests, etc. This normality assumption should be upheld despite the sample size because choosing the incorrect data set representation will result in an incorrect interpretation (Mishra et al., 2019). Again, it is essential to check for non-normal errors in regression models since the assumption of normality is crucial for the validation of inference techniques, forecasting, and model specification tests, both conceptually and methodologically (Alejo et al., 2015). However, Ghasemi and Zahediasl (2012) noted that, in accordance with the central limit theorem (CLT), violating the normality assumption shouldn't be a significant problem once the sample size is 100 and above. From the value of Jarque-Bera statistic and its probability value in Table 8 below, the data used in analyzing the regression model are not normally distributed since the p-value is less/lower than

0.05, that is, 5%. This is not a problem because the number of observation is large at 480 observations.

Table 8



Source: Researcher's Computations (2024) Using EViews13 Software.

Conclusion and Recommendations

This study investigates the relationship between product market competition and performance extremeness of listed non-financial firms in Nigeria. Secondarily sourced panel data over the period from 2007 to 2022 of 30 of those firms on the floor of the Nigerian Exchange Group (NXG) was used. The estimated generalized least squares (EGLS) results reveal that two of the variables (HHIA and LI3) are positively and statistically significant with performance extremeness; three variables (LI1, LI2 and BI) are negatively and statistically significant with it while HHIS, CRS and CRA are insignificant.

Based on the results above, the study recommends the followings:

- Management should to be aware of the danger posed by unrestricted competition in the industry they are into so as to be at alert for any eventualities. Thus, they should fully understand the Federal Competition and Consumer Protection Act ("FCCPA") of 2018 which is the primary legislation for the regulation of competition and protection of consumers in Nigeria.
- Policy makers like the Federal Competition and Consumer Protection Commission need to be abreast with the realities on the market situations so as to prohibit restrictive or unfair

business practices that prevent or restrict competition (as captured in Part VIII (Section 59-69) of the FCCPA).

- The government should work more aggressively to prevent monopolies and intense competition, such as by enhancing and amending the laws and rules governing competition. In order to revitalize existing businesses and encourage the entry of new ones, entry barriers must be lowered if market competition is not at its best. The government may impose more regulations when competition gets too intense in order to ensure that the market functions as intended and to drive out unproductive businesses.

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