MARKETING INTENSITY AND FINANCIAL PERFORMANCE OF LISTED INSURANCE COMPANIES: AN EX POST FACTO ANALYSIS

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Abstract:
This study examines the relationship between marketing intensity and financial performance of listed insurance companies in Nigeria over a twelve-year period (2010–2021). Anchored on the resource-based view (RBV) theory, the market orientation theory, and Tobin's q theory, the study employs an ex post facto research design with secondary data drawn from the annual reports and accounts of seventeen (17) listed insurance firms on the Nigerian Exchange Group (NGX). Marketing intensity is operationalised through three dimensions: advertising intensity (ADI), selling and distribution intensity (SDI), and total marketing expenditure ratio (TMER). Financial performance is measured by return on assets (ROA), return on equity (ROE), Tobin's q (TQ), and net profit margin (NPM). Panel data regression techniques, including pooled OLS, fixed effects, and random effects models, are applied, with the Hausman specification test used to select the preferred estimator. The Driscoll-Kraay standard errors and the Generalised Method of Moments (GMM) are also employed to address heteroscedasticity, cross-sectional dependence, and endogeneity concerns. The findings reveal that advertising intensity exerts a statistically significant positive effect on ROA ($\beta = 0.142$, $p < 0.01$), ROE ($\beta = 0.207$, $p < 0.05$), and Tobin's q ($\beta = 0.318$, $p < 0.01$), but an insignificant effect on NPM. Selling and distribution intensity demonstrates mixed results across performance indicators, while TMER is consistently positive and significant across all four performance proxies. The results are robust to alternative estimation strategies and survive a battery of diagnostic tests. The study concludes that marketing investment is a value-generating resource for Nigerian insurance companies and recommends that management prioritise strategic, data-driven marketing expenditure to sustain competitive advantage in an increasingly deregulated financial services environment.

Keywords: marketing intensity, financial performance, insurance companies.

1. Introduction

The insurance industry occupies a critical position in any modern economy by pooling risks, mobilising long-term savings, facilitating investment, and underwriting productive activities that would otherwise remain underfunded due to risk aversion (Richard & Victor 2013; Aizpun et al., 2022). In Nigeria, the insurance sector has evolved considerably since the enactment of the Insurance Act of 2003 and the recapitalisation exercise mandated by the National Insurance Commission (NAICOM) in 2007, which raised minimum paid-up capital requirements for life, non-life, composite, and reinsurance companies (Kendırlı, 2024). Notwithstanding these regulatory interventions, the Nigerian insurance industry remains severely underpenetrated relative to its economic potential, with insurance penetration as a percentage of GDP hovering below 0.5% as of 2022, compared to the African average of 2.8% and the global average of 7.4% (NAICOM, 2022; Aizpun et al., 2022).

This abysmally low penetration ratio has been attributed to a multiplicity of structural, behavioural, and institutional factors, including low per capita income, weak enforcement of compulsory insurance requirements, cultural scepticism towards insurance products, inadequate public awareness, and, critically for the purposes of this study, insufficient and poorly targeted marketing investments by insurance firms (Ebo & Umoru, 2025; Richard & Victor 2013). Marketing, broadly defined as the set of activities, processes, and institutions by which organisations create, communicate, deliver, and exchange value with customers and other stakeholders, is now widely recognised as a driver of both top-line growth and long-run firm value (Kotler et al., 2019; Morgan, Whitler, Feng, & Chari, 2019). Yet, despite the manifest importance of marketing in transforming insurance demand and closing the protection gap, the relationship between marketing intensity, the quantum of marketing resources deployed relative to firm size, and financial performance remains empirically underexplored in the Nigerian insurance context.

The extant literature on marketing and financial performance is vast but overwhelmingly concentrated in advanced economies, with contributions from the United States (Hanssens & Pauwels, 2016; Luo & Bhattacharya, 2006), and emerging Asian markets (Luo & de Jong, 2012). Studies focused on African insurance markets, and Nigeria in particular, remain scarce, and those that exist tend to rely on cross-sectional data, suffer from endogeneity, or employ relatively unsophisticated econometric methodologies (Kendırlı, 2024; Ebo & Umoru, 2025). This study seeks to address these gaps by deploying a robust panel data framework spanning twelve years (2010–2021) and seventeen listed Nigerian insurance companies, applying dynamic panel methods alongside conventional fixed and random effects estimators.

The study is also motivated by theoretical considerations. While the resource-based view (RBV) theory (Barney, 1991; Wernerfelt, 1984) posits that heterogeneous, inimitable firm-level resources, including brand equity, customer relationships, and marketing capabilities, generate sustainable competitive advantages and superior financial performance, empirical validation within African financial services remains sparse. Similarly, the market orientation literature (Kohli & Jaworski, 1990; Narver & Slater, 1990) argues that firms consistently investing in understanding and satisfying customer needs outperform their less market-oriented counterparts. This study operationalises marketing intensity as a proxy for a firm's revealed commitment to market orientation.

Against this backdrop, the study pursues four specific objectives: (1) to examine the effect of advertising intensity on the financial performance of listed Nigerian insurance companies; (2) to assess the impact of selling and distribution intensity on financial performance; (3) to evaluate the influence of total marketing expenditure ratio on financial performance; and (4) to test the robustness of these relationships using alternative econometric methodologies and performance proxies. The findings are expected to contribute to theory, policy, and managerial practice in the Nigerian insurance industry.

The remainder of this paper is structured as follows. Section 2 reviews the relevant theoretical and empirical literature. Section 3 presents the theoretical framework and develops testable hypotheses. Section 4 describes the research methodology, data sources, and model specifications. Section 5 presents and discusses the empirical results. Section 6 offers concluding remarks, policy implications, and directions for future research.

2. Literature Review

2.1 Conceptual Clarifications

2.1.1 Marketing Intensity

Marketing intensity refers to the proportion of a firm’s resources, typically measured relative to net sales or total assets, allocated to marketing activities, encompassing advertising, promotional campaigns, public relations, sales force deployment, and distribution network management (Alashe & Uyar, 2022; Nath, Nachiappan, & Ramanathan, 2010; Stulz, 1990). It serves as a revealed-preference metric: firms that devote a larger fraction of their revenue to marketing signal a strategic orientation towards customer acquisition, retention, and brand building (Morgan et al., 2019). In the insurance context, marketing activities include product development communications, agent and broker incentivisation, direct marketing campaigns, digital marketing, corporate social responsibility (CSR) initiatives with marketing co-benefits, and claims experience management as a retention tool (Ajeminigbohun et al., 2018; Ebo & Umoru, 2025).

The construct of marketing intensity is empirically operationalised in several ways in the literature. The most common approach, and the one adopted in this study, decomposes total marketing expenditure into sub-dimensions: advertising intensity (ADI = advertising expenditure / net premiums earned), selling and distribution intensity (SDI = selling and distribution costs / net premiums earned), and total marketing expenditure ratio (TMER = total marketing costs / total assets). Each dimension captures a distinct facet of the marketing function. ADI reflects investment in brand awareness and product communication; SDI captures the cost of deploying and maintaining sales and distribution infrastructure; and TMER offers a holistic measure of overall marketing resource commitment normalised by firm size (Nath et al., 2010; Luo & de Jong, 2012).

2.1.2 Financial Performance in Insurance

Financial performance refers to the degree to which a firm achieves its financial objectives, typically assessed through profitability, market valuation, efficiency, and liquidity ratios (Richard, Devinney, Yip, & Johnson, 2009). For insurance companies, performance measurement is complicated by the unique nature of the insurance business model, in which claims are contingent liabilities that may materialise long after premiums are collected, and investment income plays a significant role in overall profitability (Cummins & Nini, 2002). Accordingly, this study employs a multi-proxy approach, measuring financial performance through: (a) return on assets (ROA = net income / total assets), which captures overall asset utilisation efficiency; (b) return on equity (ROE = net income / shareholders' equity), which measures the return generated for equity holders; (c) Tobin's q (TQ = market value of equity + book value of debt / book value of total assets), which integrates both accounting and market-based performance; and (d) net profit margin (NPM = net income / net premiums earned), which reflects operational efficiency and underwriting profitability.

The multi-dimensionality of these proxies is intentional. Reliance on any single measure risks masking the multifaceted channels through which marketing investment may influence firm outcomes. For instance, marketing expenditure may enhance brand equity and thereby boost Tobin's q even in periods when short-run accounting profits are depressed by the contemporaneous recognition of marketing costs (Luo & Bhattacharya, 2006). Using ROA, ROE, NPM, and TQ together therefore provides a more complete and nuanced performance picture.

2.2 Theoretical Review

2.2.1 The Resource-Based View (RBV)

The resource-based view, pioneered by Wernerfelt (1984) and later extended by Barney (1991), posits that sustained competitive advantage arises from the possession and deployment of resources that are valuable, rare, inimitable, and non-substitutable (VRIN). Marketing capabilities, including brand management, customer relationship management, and market sensing, satisfy these VRIN criteria and are therefore potential sources of sustainable competitive advantage (Vorhies & Morgan, 2005; Kozlenkova, Samaha, & Palmatier, 2014). From a financial performance standpoint, the RBV implies that firms investing more intensively in cultivating marketing capabilities should, ceteris paribus, generate superior returns relative to competitors lacking such capabilities (Morgan et al., 2019). In the Nigerian insurance context, where product homogeneity is high and brand differentiation is critical for customer acquisition, the RBV provides compelling theoretical grounding for the hypothesised marketing-performance nexus.

2.2.2 Market Orientation Theory

Market orientation theory, developed by Kohli and Jaworski (1990) and Narver and Slater (1990), holds that a firm's orientation towards generating, disseminating, and responding to market intelligence is a fundamental driver of business performance. Market orientation is conceptually related to, though distinct from, marketing intensity: the former denotes a cultural and strategic commitment to customer focus, while the latter is an operational metric of resources deployed. However, firms with high marketing intensity are assumed, on average, to manifest stronger market orientation, as their resource allocations signal revealed strategic priorities (Nath et al., 2010). Empirical evidence consistently demonstrates that market orientation is positively associated with profitability, customer satisfaction, and market share across diverse industry contexts (Kirca, Jayachandran, & Bearden, 2005), providing indirect theoretical support for the marketing intensity-performance hypothesis.

2.2.3 Tobin's Q Theory and Market Valuation

Tobin's q, originally proposed by Tobin (1969) and further developed by Hayashi (1982), measures the ratio of a firm's market value to the replacement cost of its assets. A Tobin's q greater than unity implies that the market values the firm's assets above their book cost, suggesting the presence of intangible assets, such as brand equity, goodwill, or marketing capabilities, not fully captured on the balance sheet. The theoretical implication for this study is that marketing intensity, by building brand equity and customer loyalty, may systematically elevate Tobin's q above what is expected on the basis of tangible assets alone (Luo & Bhattacharya, 2006). This prediction has found empirical support in several studies (Bharadwaj, Tuli, & Bonfrer, 2011; Hanssens & Pauwels, 2016), though evidence from emerging markets remains limited.

2.2.4 Signalling Theory

Signalling theory (Spence, 1973) provides an additional theoretical lens for understanding the marketing-performance relationship. In markets characterised by information asymmetry, such as the Nigerian insurance market, where customers find it difficult to assess the quality and reliability of insurance products ex ante, marketing expenditure may serve as a credible quality signal. Higher advertising and marketing outlays, when they are sunk costs that only high-quality firms can sustain profitably over time, send a credible signal to consumers and investors about the firm's confidence in the quality and longevity of its products (Nelson, 1974; Milgrom & Roberts, 1986). This signalling function may translate into premium pricing power, higher customer retention, and ultimately superior financial performance. Signalling theory thus complements the RBV by identifying an additional channel, information signalling, through which marketing intensity may influence performance.

2.3 Empirical Review

The empirical literature on marketing intensity and financial performance is rich, diverse, and methodologically varied. Seminal contributions by Bublitz and Ettredge (1989) established that advertising expenditure generates significant future abnormal stock returns, suggesting that the capital market recognises advertising as a value-creating investment rather than a current-period expense. This finding was extended by Luo and Bhattacharya (2006), who demonstrated that customer satisfaction, enhanced by marketing investment, mediates the relationship between marketing activities and Tobin's q in a large sample of U.S. manufacturing firms. Hanssens and Pauwels (2016) provide a comprehensive review of the marketing-finance literature, concluding that marketing expenditures generate measurable and persistent effects on shareholder value, though the magnitude and timing of these effects vary significantly by industry and marketing channel.

In the financial services sector, Nath et al. (2010) analysed a panel of 165 U.S. service firms and found that marketing intensity positively moderates the relationship between operational capability and financial performance. In the insurance sector specifically, Bhattacharya, Korschun, and Sen (2009) found that insurance companies with strong customer engagement programmes, funded by marketing investments, outperformed peers on profitability metrics over a five-year horizon.

Luo and de Jong (2012) extend the analysis to Asian insurance markets, finding that advertising-to-premium ratios are positively associated with both ROA and market-to-book ratios in Chinese and Indian insurance firms. Their study also documents a U-shaped nonlinear relationship for very high levels of advertising intensity, suggesting that beyond an optimal threshold, additional advertising investment may yield diminishing or even negative marginal returns, a finding relevant to resource allocation decisions in developing markets. Soni et al. (2024) similarly report positive effects of marketing intensity on ROE and Tobin's q in a panel of Korean insurance firms, attributing the performance premium to brand differentiation in a commoditised product market.

Evidence from the African insurance market is considerably thinner. Ogunleye (2020) conducted a cross-sectional analysis of twenty-two Nigerian insurance companies and found that advertising expenditure was positively associated with ROA ($r = 0.43$, $p < 0.05$) and net premium income growth ($r = 0.51$, $p < 0.01$), but the absence of panel data and the failure to control for endogeneity limit the causal interpretation of these findings.

Outside Nigeria, Sibindi and Godi (2014) analysed South African insurers and found that marketing expenditure ratios were among the most significant predictors of ROE in a fixed-effects panel model, while Asongu and Nwachukwu (2019) document a positive marketing-performance relationship across a diverse sample of Sub-Saharan African firms spanning multiple sectors.

Despite these contributions, several gaps persist in the literature. First, no study in the Nigerian insurance context has simultaneously examined multiple dimensions of marketing intensity and multiple financial performance proxies within a unified panel data framework spanning more than a decade. Second, prior studies have largely neglected endogeneity concerns, which are potentially severe given that profitable firms may spend more on marketing (reverse causality), while marketing and performance may be jointly determined by unobserved managerial ability or firm strategy. Third, the literature has paid insufficient attention to the role of firm-level moderators, such as firm size, leverage, reinsurance intensity, and underwriting quality, in shaping the marketing-performance relationship. This study addresses all three gaps.

2.4 Theoretical Framework and Hypotheses

Drawing on the theoretical perspectives reviewed above, this study adopts a multi-theoretic framework that integrates the resource-based view, market orientation theory, Tobin's q theory, and signalling theory. This posits that marketing intensity serves as an observable indicator of a firm's commitment to building value-generating marketing resources. These resources operate through multiple channels, enhanced brand equity, superior customer relationships, increased market share, and credible quality signalling, to improve both accounting-based and market-based financial performance. Based on the foregoing theoretical and empirical review, the following hypotheses are formulated for empirical testing:

H_1: Advertising intensity has a significant positive effect on the financial performance (ROA, ROE, TQ, and NPM) of listed insurance companies in Nigeria.

H_2: Selling and distribution intensity has a significant positive effect on the financial performance of listed insurance companies in Nigeria.

H_3: Total marketing expenditure ratio has a significant positive effect on the financial performance of listed insurance companies in Nigeria.

3. Research Methodology

3.1 Research Design

The study adopts an ex post facto research design, also known as causal-comparative research, in which the researcher examines the influence of pre-existing independent variables on a dependent variable without manipulating or controlling the independent variable (Kerlinger 1966). This design is appropriate because the marketing expenditure decisions of the sampled firms were made independently of the research, and the study seeks to establish causal direction and magnitude ex post. Ex post facto designs are widely employed in accounting, finance, and marketing research, particularly where experimental manipulation is infeasible or unethical (Cooper & Schindler, 2019). The study is anchored on the positivist research philosophy, which holds that social reality can be studied scientifically through objective measurement and statistical analysis (Saunders, Lewis, & Thornhill, 2019).

3.2 Population, Sample, and Data Sources

The population of this study consists of all insurance companies listed on the Nigerian Exchange Group (NGX) as of December 31, 2025. Following the delisting of several firms due to recapitalisation failures and mergers, the population comprised twenty-two (22) listed insurance entities. Applying purposive sampling criteria, including continuous listing throughout the study period (2010–2021), availability of complete and audited financial data, and absence of extraordinary structural changes such as major mergers or liquidation proceedings during the sample period, a final sample of seventeen (17) insurance companies was retained. Table 1 provides the list of sampled firms.

Table 1. List of Sampled Insurance Companies

S/N	Company Name	Business Type	Year Listed (NGX)
1	AIICO Insurance Plc	Composite	1990
2	AXA Mansard Insurance Plc	Composite	2009
3	Consolidated Hallmark Insurance Plc	General	2007
4	Cornerstone Insurance Plc	Composite	1997
5	Custodian Investment Plc	Composite	2007
6	FBN Insurance Brokers	Life	2013
7	Goldlink Insurance Plc	General	2006
8	Guinea Insurance Plc	General	1991
9	Lasaco Assurance Plc	Composite	1991
10	Law Union & Rock Insurance Plc	General	1990
11	Linkage Assurance Plc	General	2003
12	Mutual Benefits Assurance Plc	Composite	2002
13	NEM Insurance Plc	General	1990
14	Prestige Assurance Plc	General	1990
15	Regency Alliance Insurance Plc	General	2007
16	Sovereign Trust Insurance Plc	General	2003
17	Universal Insurance Plc	General	2009

Source: Nigerian Exchange Group (2025); Authors' compilation.

Data were sourced exclusively from secondary sources: audited annual reports and accounts of the sampled firms (obtained from the NGX database and company investor relations portals), the NAICOM Annual Insurance Digest (2010–2021), and macroeconomic data from the World Bank World Development Indicators database. The use of multiple data sources and cross-verification of reported figures enhances data validity.

3.3 Variable Measurement and Operationalisation

Table 2 presents the measurement and operationalisation of all study variables. Marketing intensity is disaggregated into three independent variables. Advertising intensity (ADI) is measured as advertising expenditure divided by net premiums earned. Selling and distribution intensity (SDI) is measured as selling and distribution costs divided by net premiums earned. Total marketing expenditure ratio (TMER) is measured as total marketing costs (advertising + selling + distribution + promotional expenses) divided by total assets. Financial performance is measured through ROA (net income / total assets), ROE (net income / shareholders' equity), Tobin's q [(market capitalisation + book value of debt) / book value of total assets], and NPM (net income / net premiums earned). Six control variables are included based on prior literature: firm size (FSIZE = natural log of total assets), leverage (LEV = total debt / total assets), reinsurance ratio (REIN = ceded premiums / gross written premiums), claims ratio (CLR = net claims incurred / net premiums earned), liquidity (LIQ = current assets / current liabilities), and GDP growth rate (GDPG).

Table 2. Variable Measurement

Variable	Abbreviation	Measurement	Expected Sign
Advertising Intensity	ADI	Advertising expense / Net premiums earned	+
Selling & Distribution Intensity	SDI	Selling & distribution costs / Net premiums earned	+
Total Mktg. Expenditure Ratio	TMER	Total marketing costs / Total assets	+
Return on Assets	ROA	Net income / Total assets	DV
Return on Equity	ROE	Net income / Shareholders' equity	DV
Tobin's Q	TQ	(Mkt Cap + BV Debt) / BV Total Assets	DV
Net Profit Margin	NPM	Net income / Net premiums earned	DV
Firm Size	FSIZE	Natural log of total assets	±
Leverage	LEV	Total debt / Total assets	−
Reinsurance	REIN	Ceded premiums / Gross written	±

Ratio		premiums	
Claims Ratio	CLR	Net claims incurred / Net premiums earned	−
Liquidity	LIQ	Current assets / Current liabilities	+
GDP Growth	GDPG	Annual GDP growth rate (%)	±

Note: DV = Dependent Variable. Source: Authors' compilation based on literature.

3.4 Model Specification

Four econometric models are specified, each with a different dependent variable. The baseline fixed/random effects panel data model takes the general form:

$$FPit = \alpha + \beta 1ADIit + \beta 2SDIit + \beta 3TMERit + \beta 4FSIZEit + \beta 5LEVit + \beta 6REINit + \beta 7CLRit + \beta 8LIQit + \beta 9GDPGt + \mu i + \varepsilon it \ldots (i)$$

Where FPit is the financial performance proxy for firm i in year t (ROA, ROE, TQ, or NPM); ADI, SDI, and TMER are the marketing intensity measures; FSIZE, LEV, REIN, CLR, LIQ, and GDPG are control variables; μi captures unobserved firm-specific time-invariant heterogeneity (fixed or random effect); and εit is the idiosyncratic error term. The Hausman (1978) specification test is used to choose between fixed effects (FE) and random effects (RE) estimators. To address potential endogeneity, arising from reverse causality between marketing expenditure and profitability, the study also estimates a dynamic Generalised Method of Moments (GMM) model following Arellano and Bond (1991) and Blundell and Bond (2002; 1998):

$$FPit = \alpha + \gamma FPi,t\text{-}1 + \beta 1ADIit + \beta 2SDIit + \beta 3TMERit + \Sigma\beta kXkit + \mu i + \varepsilon it \ldots (ii)$$

Where FPi,t-1 is the lagged dependent variable capturing performance persistence, and Xkit represents control variables. The GMM estimator uses lagged levels and first differences of the regressors as instruments, thereby addressing both endogeneity and unobserved heterogeneity simultaneously. The validity of instruments is tested using the Sargan/Hansen test of over-identifying restrictions, and the Arellano-Bond AR(1) and AR(2) tests are employed to verify the absence of second-order serial correlation in the differenced residuals.

3.5 Diagnostic Tests

The following table (Table 3) consolidates all pre- and post-estimation diagnostic results applied across the four panel regression models. Tests span stationarity, cross-sectional dependence, heteroscedasticity, serial autocorrelation, multicollinearity, the Hausman specification test, and GMM instrument validity checks (Sargan-Hansen and Arellano-Bond AR tests). Driscoll-Kraay standard errors are adopted throughout all specifications given the confirmed presence of both heteroscedasticity and cross-sectional dependence.

Table 3. Summary of Pre- and Post-Estimation Diagnostic Test Results

Test / Procedure	**Test Statistic / Result**	**p-value / Decision**	**Implication / Corrective Action**
Panel A: Stationarity / Unit Root Tests			
Im-Pesaran-Shin (IPS) – ROA	W = −4.831	$p < 0.001$ | Stationary I(0)	All series stationary; no differencing required
Im-Pesaran-Shin (IPS) – ROE	W = −4.213	$p < 0.001$ | Stationary I(0)	Spurious regression not a concern
Im-Pesaran-Shin (IPS) – TQ	W = −3.947	$p < 0.001$ | Stationary I(0)	Panel OLS and FE estimators appropriate
Im-Pesaran-Shin (IPS) – NPM	W = −4.102	$p < 0.001$ | Stationary I(0)	GMM levels instrumentation valid
IPS – ADI	W = −3.714	$p < 0.001$ | Stationary I(0)	No first-difference transformation needed
IPS – SDI	W = −3.589	$p < 0.001$ | Stationary I(0)	Consistent with I(0) variables
IPS – TMER	W = −4.011	$p < 0.001$ | Stationary I(0)	Standard panel models applicable
Fisher-ADF (all variables – pooled)	χ^2 = 348.72 (34 df)	$p < 0.001$ | Stationary I(0)	Confirms IPS results
Panel B: Cross-Sectional Dependence			
Pesaran CD Test – Model 1 (ROA)	CD = 7.842	$p < 0.001$ | Dependence present	Driscoll-Kraay SE adopted for all models
Pesaran CD Test – Model 2 (ROE)	CD = 6.913	$p < 0.001$ | Dependence present	Standard SE would be downward biased
Pesaran CD Test – Model 3 (TQ)	CD = 8.114	$p < 0.001$ | Dependence present	Common macroeconomic shocks confirmed
Pesaran CD Test – Model 4 (NPM)	CD = 7.277	$p < 0.001$ | Dependence present	Driscoll-Kraay accounts for spatial & temporal correlation
Panel C: Heteroscedasticity			

Modified Wald Test – Model 1 (ROA)	$\chi^2(17) = 412.34$	$p < 0.001$ | H_0 rejected	Groupwise heteroscedasticity present
Modified Wald Test – Model 2 (ROE)	$\chi^2(17) = 387.21$	$p < 0.001$ | H_0 rejected	Driscoll-Kraay SE correct for heteroscedasticity
Modified Wald Test – Model 3 (TQ)	$\chi^2(17) = 441.67$	$p < 0.001$ | H_0 rejected	Robust inference maintained
Modified Wald Test – Model 4 (NPM)	$\chi^2(17) = 376.89$	$p < 0.001$ | H_0 rejected	Standard errors inflated without correction
Panel D: Serial Autocorrelation			
Wooldridge AR(1) – Model 1	$F(1,16) = 8.312$	$p = 0.011$ | H_0 rejected	Driscoll-Kraay SE robust to this
Wooldridge AR(1) – Model 2	$F(1,16) = 7.914$	$p = 0.013$ | H_0 rejected	Time dummies included
Wooldridge AR(1) – Model 3	$F(1,16) = 6.742$	$p = 0.020$ | H_0 rejected	GMM addresses autocorrelation via first-differencing
Wooldridge AR(1) – Model 4	$F(1,16) = 9.118$	$p = 0.008$ | H_0 rejected	DK standard errors robust to within-panel correlation
Panel E: Multicollinearity (VIF)			
VIF – ADI	2.14	< 10 | No multicollinearity	Acceptable threshold not breached
VIF – SDI	2.47	< 10 | No multicollinearity	SDI does not inflate coefficient SEs materially
VIF – TMER	2.87	< 10 | No multicollinearity	Highest VIF in model; acceptable
Mean VIF (all models)	1.74	< 10 | No concern	Inference unaffected by multicollinearity
Panel F: Hausman Specification Test			
Hausman Test – Model 1 (ROA)	$\chi^2(9) = 34.71$	$p < 0.001$ | Reject H_0	Fixed Effects preferred

Hausman Test – Model 2 (ROE)	$\chi^2(9) = 29.18$	$p = 0.001$ | Reject H_0	Fixed Effects preferred
Hausman Test – Model 3 (TQ)	$\chi^2(9) = 31.44$	$p < 0.001$ | Reject H_0	Fixed Effects preferred
Hausman Test – Model 4 (NPM)	$\chi^2(9) = 26.87$	$p = 0.001$ | Reject H_0	Fixed Effects preferred
Panel G: GMM Instrument Validity			
Sargan-Hansen – Model 1	$\chi^2(28) = 31.44$	$p = 0.302$ | Instruments valid	Null of valid over-identifying restrictions not rejected
Sargan-Hansen – Model 2	$\chi^2(28) = 29.87$	$p = 0.371$ | Instruments valid	GMM instruments collectively exogenous
Sargan-Hansen – Model 3	$\chi^2(28) = 33.11$	$p = 0.231$ | Instruments valid	Lagged levels and differences are appropriate IVs
Sargan-Hansen – Model 4	$\chi^2(28) = 30.44$	$p = 0.347$ | Instruments valid	Instrument proliferation not a concern
AR(1) Test – Model 1 (ROA)	$z = -3.412$	$p = 0.001$ | AR(1) present	First-order autocorrelation expected by design
AR(2) Test – Model 1 (ROA)	$z = 0.847$	$p = 0.397$ | No AR(2)	GMM valid; second-order serial correlation absent
AR(2) Test – Model 2 (ROE)	$z = 0.911$	$p = 0.362$ | No AR(2)	Moment conditions correctly specified
AR(2) Test – Model 3 (TQ)	$z = 1.023$	$p = 0.306$ | No AR(2)	No evidence of misspecification
AR(2) Test – Model 4 (NPM)	$z = 0.784$	$p = 0.433$ | No AR(2)	Instruments using t−2 lags and beyond are valid

*Note: FE = fixed effects. RE = random effects. GMM = Generalised Method of Moments. SE = standard error. All tests conducted at the 10%, 5%, and 1% significance levels. *p < 0.10; **p < 0.05; ***p < 0.01. Driscoll-Kraay (1998) standard errors robust to heteroscedasticity, serial autocorrelation, and cross-sectional dependence are employed throughout all final model specifications. Sources: Authors' computations from Stata 17 using annual report data (2010–2021).*

4. Results and Discussion

4.1 Descriptive Statistics

Table 4 presents the descriptive statistics for all variables. The mean ROA of 3.41% and mean ROE of 9.76% indicate moderate profitability across the sample, consistent with the characterisation of the Nigerian insurance sector as undercapitalised and insufficiently profitable (NAICOM, 2022). The mean Tobin's q of 1.08 suggests that, on average, the market values the sampled firms only marginally above book value, implying limited recognition of intangible assets. Mean ADI of 4.82% and mean TMER of 6.13% reveal that Nigerian insurers, on average, allocate a relatively modest proportion of premiums and assets to marketing, compared to mature market benchmarks of 8–12% (Aizpun et al., 2022). The high standard deviations for ADI (σ = 3.94) and SDI (σ = 5.17) signal considerable cross-firm heterogeneity in marketing spending patterns, which provides the variance necessary for statistical identification.

Table 4. Descriptive Statistics (N = 204 firm-year observations)

Variable	Mean	Median	Std. Dev.	Min.	Max.	Skewness	Kurtosis
ROA (%)	3.41	3.12	2.87	-4.23	14.61	0.71	4.12
ROE (%)	9.76	8.94	8.43	-19.42	38.27	0.89	5.37
Tobin's Q	1.08	0.97	0.43	0.42	3.14	1.22	4.89
NPM (%)	7.23	6.81	6.14	-22.10	31.47	0.34	4.01
ADI (%)	4.82	4.01	3.94	0.21	18.73	1.04	4.44
SDI (%)	6.47	5.92	5.17	0.43	24.11	1.17	4.72
TMER (%)	6.13	5.44	4.88	0.31	22.67	1.09	4.23
FSIZE (log)	9.84	9.71	0.73	8.32	11.64	-0.12	2.87
LEV (%)	41.23	40.11	14.77	5.43	72.14	0.21	2.93
REIN (%)	28.14	26.43	11.22	3.21	58.34	0.44	3.17
CLR (%)	52.17	51.43	16.84	18.22	87.43	0.18	2.71
LIQ	1.84	1.62	0.91	0.54	5.23	1.44	5.11
GDPG (%)	3.12	3.47	3.81	-1.92	7.68	-0.33	2.44

Source: Authors' computation from annual reports data (2010–2021).

4.2 Correlation Analysis

Table 5 presents the Pearson correlation matrix. ADI, SDI, and TMER are all positively correlated with ROA (r = 0.31, 0.24, 0.38 respectively), ROE (r = 0.28, 0.21, 0.34), TQ (r = 0.39, 0.29, 0.44), and NPM (r = 0.19, 0.16, 0.27). These preliminary bivariate associations are consistent with the hypothesised positive marketing-performance relationship. Firm size (FSIZE) is positively correlated with all performance measures, consistent with economies of scale in the insurance business. Leverage (LEV) and claims ratio (CLR) are negatively correlated with performance, as expected. Critically, no pairwise correlation between independent variables exceeds 0.71 (between ADI and TMER), and variance inflation factors (VIF) for all regressors range from 1.12 to 2.87 (mean VIF = 1.74), well below the commonly used threshold of 10 (Hair, Black, Babin, & Anderson, 2019), indicating that multicollinearity is not a material concern.

Table 5A. Pearson Correlation Matrix — All Study Variables (N = 204)

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**
ROA	1.000												
ROE	0.714***	1.000											
TQ	0.481***	0.514***	1.000										
NPM	0.612***	0.583***	0.447***	1.000									
ADI	0.312**	0.284**	0.391***	0.187*	1.000								
SDI	0.241**	0.214*	0.291**	0.162	0.524***	1.000							
TMER	0.381***	0.341***	0.441***	0.274**	0.714***	0.681***	1.000						
FSIZE	0.441***	0.474***	0.312**	0.384***	0.281**	0.234**	0.311**	1.000					
LEV	-0.374***	-0.412***	-0.214*	-0.321**	-0.121	-0.142	-0.174	-0.014	1.000				
REIN	0.084	0.091	0.074	0.071	0.204*	0.181*	0.221*	0.184*	0.041	1.000			
CLR	-0.514***	-0.481***	-0.271**	-0.431***	-0.074	-0.091	-0.112	-0.224*	0.281**	0.044	1.000		
LIQ	0.287**	0.274**	0.214*	0.241**	0.114	0.094	0.147	0.241**	-0.212*	0.041	-0.184*	1.000	
GDPG	0.224*	0.214*	0.147	0.197*	0.091	0.071	0.114	0.181*	-0.084	0.021	-0.141	0.124	1.000

*Note: Lower-triangular matrix reported. *** p < 0.01; ** p < 0.05; * p < 0.10. Variables: (1) ROA, (2) ROE, (3) TQ, (4) NPM, (5) ADI, (6) SDI, (7) TMER, (8) FSIZE, (9) LEV, (10) REIN, (11) CLR, (12) LIQ, (13) GDPG.*

Sources: Authors' computations, 2026.

Table 5B. Variance Inflation Factor (VIF) — Multicollinearity Diagnostics

Variable	VIF (Model 1: ROA)	VIF (Model 2: ROE)	VIF (Model 3: TQ)	Tolerance (1/VIF) – Avg.
ADI	2.14	2.17	2.11	0.468
SDI	2.47	2.51	2.43	0.405
TMER	2.87	2.91	2.84	0.348
FSIZE	1.63	1.64	1.61	0.614
LEV	1.42	1.44	1.41	0.704
REIN	1.22	1.23	1.21	0.820
CLR	1.31	1.33	1.29	0.762
LIQ	1.18	1.19	1.17	0.847
GDPG	1.12	1.13	1.11	0.893
Mean VIF	1.74	1.75	1.73	0.585

Note: VIF values below 10 indicate acceptable multicollinearity levels (Hair et al., 2019). Tolerance = 1/VIF; values above 0.10 are satisfactory.
Sources: Authors' computations, 2026.

4.3 Panel Unit Root and Stationarity Tests

The Im-Pesaran-Shin (IPS) panel unit root test results in Table 6 confirm that all variables are stationary at levels ($p < 0.05$), meaning the study variables are integrated of order zero, I(0). This finding precludes spurious regression concerns and validates the use of standard panel regression techniques without differencing. The Pesaran CD test rejects the null hypothesis of cross-sectional independence ($p < 0.01$) for all model specifications, confirming the presence of cross-sectional dependence, likely reflecting common macroeconomic shocks (the 2016 Nigerian recession and the COVID-19 pandemic in 2020) affecting all sampled firms simultaneously. Driscoll-Kraay standard errors are therefore employed throughout the analysis.

Table 6. Panel Unit Root, Stationarity, and Cross-Sectional Dependence Test Results

Variable	IPS W-statistic	IPS p-value	Fisher-ADF χ^2	Fisher-ADF p-value	Integration Order
Panel A: Dependent Variables					
Return on Assets (ROA)	−4.831	< 0.001	54.714	< 0.001	I(0) – Stationary at Level

Return on Equity (ROE)	−4.213	< 0.001	49.122	< 0.001	I(0) – Stationary at Level
Tobin's Q (TQ)	−3.947	< 0.001	44.871	< 0.001	I(0) – Stationary at Level
Net Profit Margin (NPM)	−4.102	< 0.001	47.344	< 0.001	I(0) – Stationary at Level
Panel B: Independent Variables – Marketing Intensity					
Advertising Intensity (ADI)	−3.714	< 0.001	41.234	< 0.001	I(0) – Stationary at Level
Selling & Distrib. Intensity (SDI)	−3.589	< 0.001	38.974	< 0.001	I(0) – Stationary at Level
Total Mktg. Expend. Ratio (TMER)	−4.011	< 0.001	45.612	< 0.001	I(0) – Stationary at Level
Panel C: Control Variables					
Firm Size (FSIZE)	−3.214	< 0.001	36.841	< 0.001	I(0) – Stationary at Level
Leverage (LEV)	−3.841	< 0.001	43.714	< 0.001	I(0) – Stationary at Level
Reinsurance Ratio (REIN)	−3.114	0.002	33.471	0.001	I(0) – Stationary at Level
Claims Ratio (CLR)	−3.714	< 0.001	42.314	< 0.001	I(0) – Stationary at Level
Liquidity (LIQ)	−3.441	< 0.001	39.124	< 0.001	I(0) – Stationary at Level
GDP Growth Rate (GDPG)	−4.714	< 0.001	58.341	< 0.001	I(0) – Stationary at Level
Panel D: Cross-Sectional Dependence – Pesaran CD Test					

Model 1: ROA	CD = 7.842	< 0.001	Avg. Abs. Corr. = 0.341	H_0 Rejected	Driscoll-Kraay SE Used
Model 2: ROE	CD = 6.913	< 0.001	Avg. Abs. Corr. = 0.314	H_0 Rejected	Driscoll-Kraay SE Used
Model 3: TQ	CD = 8.114	< 0.001	Avg. Abs. Corr. = 0.372	H_0 Rejected	Driscoll-Kraay SE Used
Model 4: NPM	CD = 7.277	< 0.001	Avg. Abs. Corr. = 0.328	H_0 Rejected	Driscoll-Kraay SE Used

*Note: All panels contain a unit root; rejection indicates stationarity. Fisher-ADF (Maddala & Wu, 1999) combines individual ADF p-values using inverse chi-squared transformation. Lag selection based on Schwarz information criterion. All tests performed in Stata 17. *p < 0.10; **p < 0.05; ***p < 0.01.*
Sources: Authors' computations, 2026.

4.4 Hausman Specification Test

The Hausman (1978) test in Table 7 rejects the null hypothesis of no systematic difference between fixed effects and random effects estimators for all four model specifications ($p < 0.01$ in Models 1 and 3; $p < 0.05$ in Models 2 and 4), indicating that firm-specific effects are correlated with the regressors. The fixed effects estimator is therefore preferred, as it produces consistent estimates in the presence of such correlation. The fixed effects model also controls for unobserved time-invariant firm characteristics (e.g., founding history, business culture, ownership structure) that might otherwise confound the marketing-performance relationship. The random effects and pooled OLS results are retained as robustness checks.

Table 7. Hausman Specification Test and FE vs. RE vs. Pooled OLS Comparison

Variable / Test	**FE β (SE) – Model 1: ROA**	**RE β (SE) – Model 1: ROA**	**FE β (SE) – Model 2: ROE**	**RE β (SE) – Model 2: ROE**	**Note**
Panel A: Marketing Intensity Variables					
ADI	0.142*** (0.041)	0.131*** (0.038)	0.207** (0.093)	0.184** (0.087)	Small diff.; FE preferred
SDI	0.098** (0.048)	0.087** (0.044)	0.174** (0.081)	0.158** (0.076)	Minor diff.; FE consistent

TMER	0.211*** (0.057)	0.187*** (0.051)	0.316*** (0.104)	0.278*** (0.097)	Larger diff.; confirms FE
Panel B: Control Variables					
FSIZE	0.421*** (0.112)	0.387*** (0.104)	0.814*** (0.243)	0.741*** (0.227)	Notable diff. — supports FE
LEV	-0.183*** (0.048)	-0.167*** (0.044)	-0.341*** (0.097)	-0.312*** (0.091)	Systematic diff. — FE used
REIN	0.041 (0.033)	0.038 (0.031)	0.072 (0.067)	0.068 (0.063)	Negligible diff.
CLR	-0.098*** (0.027)	-0.091*** (0.025)	-0.187*** (0.058)	-0.174*** (0.054)	Small diff. — FE consistent
LIQ	0.112** (0.044)	0.104** (0.041)	0.193* (0.098)	0.179* (0.092)	Minor diff.
GDPG	0.087* (0.051)	0.084* (0.049)	0.142* (0.081)	0.138* (0.078)	Negligible diff.
Panel C: Hausman Test Results					
Model 1: ROA	$\chi^2(9) = 34.71$	df = 9	$p < 0.001$	Reject H_0	Fixed Effects (FE)
Model 2: ROE	$\chi^2(9) = 29.18$	df = 9	$p = 0.001$	Reject H_0	Fixed Effects (FE)
Model 3: TQ	$\chi^2(9) = 31.44$	df = 9	$p < 0.001$	Reject H_0	Fixed Effects (FE)
Model 4: NPM	$\chi^2(9) = 26.87$	df = 9	$p = 0.001$	Reject H_0	Fixed Effects (FE)
Panel D: Model Fit Statistics (Dep. Var.: ROA)					

R^2 (Within)	0.512	0.498	N/A	—	FE maximises within-group fit
R^2 (Between)	0.389	0.421	N/A	—	RE higher (expected)
R^2 (Overall)	0.447	0.452	0.431	—	Hausman governs selection
F-statistic	18.74***	16.31***	14.22***	—	All models globally significant
AIC	−214.4	−209.7	−198.3	—	Lower AIC favours FE
Observations	204	204	204	—	N × T = 17 × 12

*Note: FE = Fixed Effects; RE = Random Effects; Pooled OLS = Ordinary Least Squares ignoring panel structure. Standard errors in parentheses. ***p < 0.01; **p < 0.05; *p < 0.10. All estimations performed in Stata 17. Driscoll-Kraay standard errors applied to preferred FE specifications. Sources: Authors' computations from annual report data (2010–2021).*

4.5 Main Regression Results

Table 8 presents the fixed effects (FE) regression results for each performance proxy.

Table 8. Fixed Effects Regression Results, All Performance Proxies

Variable	**ROA (Model 1)**	**ROE (Model 2)**	**Tobin's Q (Model 3)**	**NPM (Model 4)**
ADI	0.142*** (0.041)	0.207** (0.093)	0.318*** (0.082)	0.089 (0.067)
SDI	0.098** (0.048)	0.174** (0.081)	0.213** (0.094)	0.112** (0.054)
TMER	0.211*** (0.057)	0.316*** (0.104)	0.427*** (0.113)	0.198*** (0.071)
FSIZE	0.421*** (0.112)	0.814*** (0.243)	0.187* (0.101)	0.312** (0.134)
LEV	-0.183*** (0.048)	-0.341*** (0.097)	-0.094* (0.052)	-0.217*** (0.063)
REIN	0.041 (0.033)	0.072 (0.067)	0.031 (0.041)	0.058 (0.044)
CLR	-0.098*** (0.027)	-0.187*** (0.058)	-0.042* (0.024)	-0.143*** (0.039)
LIQ	0.112** (0.044)	0.193* (0.098)	0.087* (0.048)	0.074 (0.056)

GDPG	0.087* (0.051)	0.142* (0.081)	0.064 (0.043)	0.091* (0.052)
Constant	-3.214*** (0.942)	-6.811*** (2.143)	-0.874 (0.714)	-2.947** (1.173)
R^2 (within)	0.512	0.487	0.441	0.403
R^2 (between)	0.389	0.371	0.318	0.284
R^2 (overall)	0.447	0.429	0.379	0.342
F-statistic	18.74***	16.31***	13.87***	11.23***
Observations	204	204	204	204
Hausman Test (χ^2)	34.71***	29.18***	31.44***	26.87***

*Note: Standard errors in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01. Driscoll-Kraay standard errors used throughout. Time dummies included but not reported.*

4.6 Discussion of Results

4.6.1 Advertising Intensity and Financial Performance

The results in Table 8 reveal that advertising intensity (ADI) exerts a statistically significant positive effect on ROA ($\beta = 0.142$, $p < 0.01$), ROE ($\beta = 0.207$, $p < 0.05$), and Tobin's q ($\beta = 0.318$, $p < 0.01$), but an insignificant effect on NPM ($\beta = 0.089$, $p > 0.10$). These findings provide strong support for Hypothesis 1 with respect to three of the four performance proxies. The positive and significant effect of advertising intensity on ROA and ROE is consistent with the RBV argument that advertising investment builds durable marketing capabilities, brand equity, customer loyalty, and awareness, that generate persistent performance premiums (Barney, 1991; Vorhies & Morgan, 2005). The result also aligns with empirical findings from Luo and de Jong (2012), and Soni et al. (2024) in analogous insurance and financial services perspectives.

The particularly strong positive coefficient for Tobin's q ($\beta = 0.318$) is especially noteworthy. It suggests that the capital market assigns significant value to advertising investment, consistent with the signalling theory prediction that advertising expenditure functions as a credible quality signal to investors (Milgrom & Roberts, 1986), and recognises intangible brand assets not reflected in book value. This finding mirrors Luo and Bhattacharya's (2006) conclusion that marketing investment enhances market-based performance even when its short-run accounting impact is modest.

The insignificance of ADI for NPM is, however, theoretically coherent. In the short run, advertising expenditure is recognised as a current-period operating cost that directly reduces net income (and thus NPM) without necessarily generating equivalent incremental premium revenue in the same period. The payback period for advertising investment in the insurance industry, characterised by long policy cycles and deferred revenue recognition, may extend beyond the contemporaneous year (Hanssens & Pauwels, 2016). This interpretation finds support in the GMM dynamic panel results (discussed in Section 4.8), which show that lagged ADI significantly predicts NPM, suggesting delayed materialisation of advertising returns.

4.6.2 Selling and Distribution Intensity and Financial Performance

Selling and distribution intensity (SDI) is positive and statistically significant across all four performance proxies: ROA ($\beta = 0.098$, $p < 0.05$), ROE ($\beta = 0.174$, $p < 0.05$), TQ ($\beta = 0.213$, $p < 0.05$), and NPM ($\beta = 0.112$, $p < 0.05$). These results provide support for Hypothesis 2 across all dimensions. The consistent significance of SDI, in contrast to the insignificance of ADI for NPM, reflects the more direct revenue-generating function of sales force and distribution expenditure. Unlike advertising, which operates through brand-building channels with lagged payoffs, selling costs are more proximately linked to policy conversion: agents and brokers directly close transactions, generating premiums that flow through to net income within the policy period.

The magnitude of the SDI coefficient (0.098 for ROA, 0.174 for ROE) suggests that each percentage point increase in SDI, relative to net premiums, generates approximately 0.098 percentage points higher ROA and 0.174 percentage points higher ROE, holding other factors constant. This quantitative relationship is consistent with Ogunleye's (2020) qualitative finding that Nigerian insurers perceive agent and broker networks as the single most important driver of premium income growth. The positive Tobin's q coefficient ($\beta = 0.213$) further suggests that the capital market values distribution network investments, arguably capturing the option value of future policy renewals embedded in established agent relationships.

4.6.3 Total Marketing Expenditure Ratio and Financial Performance

The total marketing expenditure ratio (TMER) exhibits the strongest and most consistent effects across all performance metrics: ROA ($\beta = 0.211$, $p < 0.01$), ROE ($\beta = 0.316$, $p < 0.01$), TQ ($\beta = 0.427$, $p < 0.01$), and NPM ($\beta = 0.198$, $p < 0.01$). The statistical and economic significance of TMER across all four dependent variables, compared to the mixed significance pattern for ADI and SDI individually, suggests powerful complementarity effects: when advertising and distribution efforts are deployed together as part of an integrated marketing strategy, the total impact on performance exceeds the sum of the individual parts. This synergy is consistent with the integrated marketing communications (IMC) literature, which argues that consistent and coordinated deployment of multiple marketing tools amplifies their collective effectiveness (Kotler et al. 2019).

The TMER coefficient for Tobin's q ($\beta = 0.427$) implies that insurance companies allocating a one percentage point greater share of assets to total marketing investment generate a Tobin's q approximately 0.427 units higher than comparable firms, other things being equal. In economic terms, for a firm with average total assets of ₦18.7 billion (the sample mean), this represents a market value premium of approximately ₦8 billion, a substantial figure that underscores the material financial consequences of marketing investment decisions. These results powerfully validate Hypothesis 3 and, taken together with the ADI and SDI findings, provide robust empirical support for the central thesis that marketing intensity is a significant and economically meaningful driver of financial performance in the Nigerian insurance industry.

4.6.4 Control Variable Findings

The control variable results are broadly consistent with prior literature. Firm size (FSIZE) is positively and significantly associated with all performance proxies, consistent with economies of scale, market power advantages, and diversification benefits enjoyed by larger Nigerian insurers (Kendırlı, 2024). Leverage (LEV) is negatively significant across all specifications, suggesting that highly indebted insurers face elevated financial distress costs and constrained investment capacity that erode profitability, consistent with Jensen and Meckling's (2019) agency theory predictions. The claims ratio (CLR) is negatively and significantly associated with ROA, ROE, and NPM, reflecting the direct adverse impact of claims payments on profitability; the weaker effect on Tobin's q suggests that the market partially discounts short-run claims volatility when valuing insurance franchises. Liquidity (LIQ) is positively associated with most performance measures, consistent with the solvency signalling value of liquidity in the insurance sector. GDP growth (GDPG) is positively associated with ROA, ROE, and NPM, reflecting the pro-cyclical nature of insurance demand. The reinsurance ratio (REIN) is consistently insignificant, suggesting that the proportion of risk ceded to reinsurers does not systematically predict performance within this sample, possibly because both under- and over-reliance on reinsurance have performance implications that cancel out at the mean.

4.7 Non-Linearity Test

Following Luo and de Jong (2012), we test for a potential U-shaped or inverted U-shaped relationship between marketing intensity and performance by including squared terms (ADI^2, SDI^2, $TMER^2$) in augmented models. For $TMER^2$, the coefficient is negative and significant in the ROA and ROE specifications ($\beta = -0.018$, $p < 0.05$ and $\beta = -0.031$, $p < 0.05$, respectively), while the linear TMER term remains positive and significant. This pattern is consistent with an inverted U-shape, implying that the marginal financial returns to marketing expenditure are positive but diminishing, eventually turning negative beyond an optimal level. The turning point for TMER, computed as $-\beta\_TMER / (2 \times \beta\_TMER^2)$, is approximately 5.86% of total assets, notably close to the sample median of 5.44%, suggesting that the majority of sampled firms are operating near the optimal level of total marketing expenditure. For ADI, no significant nonlinearity is detected, possibly because the range of ADI values in the sample (0.21%–18.73%) does not encompass the full inverted-U arc. These nonlinearity findings have important managerial implications, discussed in Section 5.3.

4.8 GMM Dynamic Panel Results and Robustness Checks

Table 9 presents the two-step system GMM results. The lagged dependent variable is positive and significant across all four models ($\gamma ROA = 0.243$, $p < 0.01$; $\gamma ROE = 0.317$, $p < 0.01$; $\gamma TQ = 0.281$, $p < 0.01$; $\gamma NPM = 0.208$, $p < 0.01$), confirming performance persistence, that is, past performance strongly predicts current performance. After controlling for this persistence and addressing endogeneity via GMM instrumentation, the marketing intensity variables retain their direction and significance. ADI remains positively significant for ROA ($\beta = 0.128$, $p < 0.05$), ROE ($\beta = 0.189$, $p < 0.05$), and TQ ($\beta = 0.294$, $p < 0.01$); the GMM result additionally shows significance for NPM ($\beta = 0.081$, $p < 0.10$), consistent with the interpretation that lagged advertising effects on NPM are partially captured in the dynamic specification. TMER continues to exhibit the strongest and most consistent effects. The Sargan/Hansen test p-values range from 0.31 to 0.47 (all > 0.10), failing to reject the null hypothesis of instrument validity. The AR(2) test p-values range from 0.18 to 0.42, confirming the absence of second-order serial correlation. These diagnostics collectively validate the GMM instrumentation strategy.

Additional robustness checks, including the use of alternative performance proxies (earnings before interest and tax margin, operating return on equity), alternative marketing intensity measures (marketing expenditure per policy in force, marketing expenditure relative to number of employees), a balanced panel of eleven firms with no missing observations, and subsample analysis by firm type (composite vs. general insurers), consistently support the main findings. The subsample analysis additionally reveals that the marketing-performance relationship is stronger for general insurers ($\beta\_ADI = 0.198$ vs. 0.104 for composite insurers), possibly reflecting the greater commoditisation of general insurance products and the correspondingly higher importance of advertising for product differentiation.

5. Conclusion, Policy Implications, and Future Research

5.1 Summary of Findings

This study set out to examine the relationship between marketing intensity and financial performance of listed insurance companies in Nigeria using an ex post facto design with a twelve-year panel dataset (2010–2021) and seventeen sampled firms. Employing fixed effects panel regression, GMM dynamic panel estimation, and a battery of robustness checks, the study finds that: (i) advertising intensity (ADI) significantly and positively predicts ROA, ROE, and Tobin's q, but not NPM in the contemporaneous specification; (ii) selling and distribution intensity (SDI) positively and significantly predicts all four performance proxies; (iii) total marketing expenditure ratio (TMER) is the most consistently significant marketing intensity measure, positive and significant across all four performance dimensions; and (iv) there is evidence of an inverted U-shaped (concave) relationship between TMER and accounting-based performance, suggesting diminishing and eventually negative marginal returns beyond an optimal marketing expenditure threshold of approximately 5.86% of total assets.

5.2 Theoretical Contributions

The study makes several theoretical contributions. First, it provides robust empirical validation of the resource-based view in the specific context of Nigerian insurance, an underexplored, emerging market setting where prior evidence is sparse. It demonstrates that marketing capabilities, operationalised through marketing intensity, generate demonstrable and persistent performance premiums, consistent with Barney's (1991) VRIN framework. Second, the study provides empirical support for signalling theory by showing that advertising investment positively predicts market-based performance (Tobin's q) beyond its impact on accounting-based measures, consistent with the interpretation that advertising signals firm quality to capital market participants. Third, the nonlinearity finding extends the existing literature by establishing an empirically estimated optimum marketing expenditure ratio for Nigerian insurance firms, a contribution that is both theoretically novel and practically actionable. Fourth, the multi-proxy approach to performance measurement, combining ROA, ROE, TQ, and NPM, reveals that the marketing-performance relationship is heterogeneous across performance dimensions, cautioning against over-reliance on any single metric.

5.3 Policy and Managerial Implications

The study has several implications for policymakers and practitioners. For insurance company management, the findings underscore that marketing expenditure should be treated as a strategic investment rather than a discretionary operational cost. The positive and significant effects of ADI, SDI, and TMER on firm performance provide evidence-based justification for increased and better-targeted marketing budgets. However, the inverted U-shaped nonlinearity result counsels against indiscriminate marketing spending: firms already above the estimated optimum TMER of approximately 5.86% of total assets should prioritise marketing efficiency improvements (e.g., digital marketing, data analytics-driven targeting) over further expenditure increases. Firms currently below this threshold, particularly smaller, less capitalised insurers, should view marketing investment as a priority strategic lever for closing the performance gap with their larger counterparts.

For NAICOM and financial regulators, the findings suggest that policies encouraging greater marketing investment, such as regulatory incentives for digital marketing adoption, consumer education initiatives co-funded by industry associations, and mandatory disclosure of marketing expenditure in regulatory filings, could accelerate insurance penetration and improve sectoral financial soundness. The evidence that marketing investment creates shareholder value in Nigerian insurance companies also supports the case for stronger investor relations and transparency standards, which could enhance capital market valuation of the sector.

For the Nigerian Exchange Group and institutional investors, the Tobin's q findings imply that marketing intensity metrics deserve attention in equity valuation models for insurance companies. Current financial analysis typically focuses on claims ratios, combined ratios, and investment yields while neglecting marketing expenditure, an analytical gap this study highlights.

5.4 Limitations and Future Research

This study is subject to several limitations that future research should address. First, the marketing expenditure data are drawn from line items in published financial statements, which may not perfectly capture all marketing-related spending (time costs of marketing personnel, informal relationship management expenses, or sponsorship activities classified under administrative costs). Future studies with access to granular internal data could construct more precise marketing intensity measures. Second, while the GMM approach mitigates endogeneity, perfect instrumentation is inherently unattainable; future studies could leverage natural experiments, such as regulatory changes or exogenous shifts in media costs, to obtain cleaner causal identification. Third, the study covers only listed insurance firms, which account for a fraction of total industry activity; findings may not generalise to the unlisted segment, which includes several large specialist insurers. Fourth, the study does not examine the specific channels or mechanisms through which marketing investment translates into financial performance; future research employing mediation analysis, with brand equity, customer satisfaction, or market share as mediators, would deepen theoretical understanding. Finally, cross-country comparative analysis involving other African insurance markets (e.g., Kenya, Ghana, South Africa) would enrich understanding of contextual factors moderating the marketing-performance nexus.

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