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MARKET DEPTH AND SECURITIES MARKET VOLATILITY AT THE NAIROBI SECURITIES EXCHANGE

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ABSTRACT

Purpose: This paper examined the effect of market depth on securities market volatility at the Nairobi Securities Exchange (NSE), Kenya. The analysis isolated the price-impact dimension of liquidity to determine whether changes in the market's capacity to absorb order flow were associated with changes in GARCH-estimated volatility.

Methodology: The paper adopted a correlational quantitative design and used 2,334 daily market-level observations covering January 2017 to December 2025. Securities market volatility was generated from daily log returns of the NSE 20 Share Index using a GARCH(1,1) model. Market depth was operationalized through a daily price-impact measure based on Kyle's lambda. The inverse hyperbolic sine transformation was used to reduce skewness and accommodate very small observations. Descriptive statistics, Pearson correlation, analysis of variance and simple linear regression were estimated using Stata 18.

Findings: Market depth had a positive and statistically significant relationship with securities market volatility. The Pearson correlation was $r = 0.3550$ ($p < 0.001$). The regression model was statistically significant, $F(1, 2332) = 336.19$, $p < 0.001$, with R-squared = 0.1260 and adjusted R-squared = 0.1256. Market depth had a positive coefficient of 8.1940 (SE = 0.4469, $t = 18.34$, $p < 0.001$). The result implies that higher price impact, which represents weaker effective depth, was associated with higher conditional volatility.

Unique Contribution to Theory, Practice and Policy: The paper extends Market Microstructure Theory by demonstrating that the price-impact dimension of liquidity is statistically relevant to volatility in an African emerging market. The findings support policies that strengthen liquidity provision, order-book transparency, market-making capacity and surveillance of counters where modest trading pressure generates disproportionate price movements.

Keywords: *market depth; securities market volatility; Nairobi Securities Exchange; GARCH; Kyle's lambda; market microstructure*

INTRODUCTION

Securities markets are central to financial development because they mobilize long-term savings, allocate capital among competing investments, permit risk transfer and generate prices that guide economic decision-making. Their ability to perform these functions depends not only on the number of listed securities or the value of market capitalization, but also on the quality of trading. A market in which investors can enter and exit positions at predictable prices supports portfolio diversification, lowers the required return on capital and strengthens confidence in the financial system. Conversely, a market in which orders produce large and erratic price movements may discourage participation and raise the cost of financing for listed firms.

Liquidity is therefore a defining element of securities-market quality. It describes the ability to execute transactions quickly, in substantial quantities, at low cost and without materially disturbing prices. Liquidity is multidimensional: depth captures the volume that can be absorbed near prevailing prices; breadth reflects the distribution of trading across securities; immediacy captures execution speed and cost; and resilience concerns the restoration of orderly prices after shocks (Sarr & Lybek, 2002; Harris, 2003). These dimensions are related but not interchangeable. A market may record high turnover while still being shallow if a relatively small imbalance causes a large price response.

This paper concentrates on market depth because it is the dimension most directly connected to price impact. Market depth reflects the capacity of available buy and sell interest to accommodate order flow without causing a substantial movement in price. In a conventional order book, depth may be observed as the quantity available at successive bid and ask levels. Where complete order-book data are unavailable, price-impact measures provide a practical alternative by estimating the price movement associated with a unit of trading activity. Kyle's lambda is one of the most widely recognized measures of this relationship (Kyle, 1985). A high lambda indicates that a given quantity of order flow moves prices substantially and therefore represents weaker effective depth; a low lambda indicates stronger absorptive capacity.

The depth-volatility relationship is theoretically important because it links the trading mechanism to market risk. When depth is strong, buy and sell pressure can be accommodated through available liquidity, limiting temporary dislocations. When depth is weak, an imbalance may consume available quotations and force execution at progressively less favorable prices. The resulting price path may display larger returns, more frequent reversals and persistent volatility. Modern evidence confirms that order-book characteristics contain information about immediate price impact and future volatility, although the strength and direction of the relationship differ across markets and measurement choices (Pham et al., 2020; Będowska-Sójka & Echaust, 2020).

The relationship is especially relevant in emerging markets. Such markets often have fewer active securities, concentrated institutional ownership, uneven investor participation and comparatively limited market-making capacity. These features may cause liquidity to disappear more quickly during stress and may make volatility more responsive to order imbalances. Muzaffar and Malik (2024) demonstrate that the liquidity-volatility nexus in Asian emerging economies is sensitive to economic-policy uncertainty, underscoring the importance of examining market-specific institutions rather than assuming that evidence from developed exchanges applies uniformly.

The Nairobi Securities Exchange provides a suitable context for this analysis. It is Kenya's principal organized securities market and performs a major role in capital formation, investment and price discovery. Nevertheless, trading activity is concentrated in a limited number of counters and varies materially across market cycles. The CMA reported a weak equity-market environment in the fourth quarter of 2023, when turnover, volume and market capitalization declined. The subsequent recovery in 2024, when equity turnover and traded volumes increased, illustrates that market liquidity at the NSE can change substantially over relatively short periods (CMA, 2023; NSE, 2024).

These changes have direct implications for volatility. A recovery in turnover may reflect improved participation and confidence, but it may also intensify price movements if the order book is unable to absorb larger trades. Similarly, low turnover may coincide with calm conditions or may indicate a fragile market in which the few trades that occur have disproportionate effects. The empirical relationship between depth and volatility is therefore not self-evident and must be estimated using measures that capture both price impact and time-varying conditional risk.

Securities-market volatility is commonly understood as the degree of variation in returns over time. Financial returns typically exhibit volatility clustering, heavy tails and persistence, meaning that periods of high volatility tend to be followed by further high volatility. The ARCH and GARCH frameworks developed by Engle (1982) and Bollerslev (1986) are designed to model these properties. Recent Kenyan research continues to find GARCH-family models useful for describing NSE volatility (Rugut, 2021; Wanjuki et al., 2024). Accordingly, this paper uses GARCH(1,1)-estimated volatility rather than raw index changes or an unconditional standard deviation.

The paper contributes by isolating market depth from a broader liquidity framework and examining its standalone relationship with daily conditional volatility over the 2017–2025 period. The period covers election-related uncertainty, the COVID-19 shock, global monetary tightening and a subsequent recovery in equity-market activity. By combining a price-impact proxy with GARCH-estimated volatility, the study provides evidence that is directly relevant to liquidity management, trading strategy and market-stability policy at the NSE.

Problem Statement

Securities-market volatility is necessary for price discovery because prices must respond to new information. The policy problem arises when volatility is amplified by weak liquidity rather than by changes in fundamental value. In a shallow market, modest order imbalances can produce large price changes, increase execution risk and make quoted prices less reliable. This can discourage long-term investment, increase portfolio-risk estimates and raise the liquidity premium demanded by investors. For listed firms, a volatile and shallow secondary market may increase the cost of equity and weaken the attractiveness of new capital issues.

The NSE has experienced marked fluctuations in activity and valuation. In the fourth quarter of 2023, equity turnover declined to KShs. 11.80 billion from KShs. 17.22 billion in the preceding quarter, traded share volume declined to 812.07 million shares and market capitalization fell to approximately KShs. 1.439 trillion (CMA, 2023). The NSE 20 Share Index also recorded material weakness. These outcomes pointed to reduced market activity, weaker participation and heightened sensitivity to domestic and global uncertainty.

The market improved in 2024. NSE reports show that annual equity turnover rose to approximately KShs. 105.97 billion from KShs. 88.2 billion in 2023, while trading volume increased to about 4.93 billion shares (NSE, 2024). Although this recovery was positive, a rise in activity does not automatically imply that the market became deeper. Turnover can increase because of a limited number of large block transactions, information shocks or concentrated trading in highly capitalized counters. The relevant question is whether the market could absorb this activity without generating disproportionate price impact.

Existing Kenyan studies do not provide a complete answer. Research on the NSE has established volatility clustering, persistence and structural changes, but much of that literature concentrates on selecting or forecasting volatility models rather than explaining volatility through market-depth conditions (Ndei et al., 2019; Rugut, 2021; Wanjuki et al., 2024). Other local studies examine multidimensional liquidity in relation to firm performance, but firm performance and conditional market volatility are conceptually different outcomes (Alusa & Kalui, 2021). Consequently, the standalone role of market depth in explaining GARCH-estimated market volatility remains insufficiently documented.

The international evidence is also inconclusive. Pham et al. (2020) show that market-depth information materially improves predictions of immediate price impact, while Będowska-Sójka and Echaust (2020) demonstrate that liquidity proxies perform differently under extreme illiquidity. Muzaffar and Malik (2024) find that the liquidity-volatility relationship in emerging economies changes with economic-policy uncertainty. These studies establish the importance of depth but are based on market structures, data availability and institutional conditions that differ from those of the NSE.

A measurement gap further motivates the study. Trading volume alone cannot distinguish between high activity in a deep market and high activity that moves prices sharply in a shallow market. Similarly, raw changes in an index do not capture volatility persistence. The study therefore operationalizes depth through a price-impact measure based on Kyle's lambda and derives volatility from an NSE 20 Share Index GARCH(1,1) process. The use of daily observations provides sufficient frequency to capture changes in liquidity and volatility that may be hidden in monthly or annual data.

The problem is thus empirical, contextual, conceptual and methodological. Empirically, the direction and strength of the depth-volatility relationship remain mixed. Contextually, limited evidence isolates depth at the NSE. Conceptually, market depth must be distinguished from volume and other dimensions of liquidity. Methodologically, the relationship requires a price-impact proxy and a time-varying volatility measure. This paper addresses these gaps by estimating the effect of market depth on GARCH-estimated securities-market volatility using 2,334 daily observations from January 2017 to December 2025.

Objective of the Study

The objective of the study was to establish the effect of market depth on securities market volatility at the Nairobi Securities Exchange, Kenya.

Research Hypothesis

H01: Market depth has no statistically significant effect on securities market volatility at the Nairobi Securities Exchange, Kenya.

LITERATURE REVIEW

Theoretical Review

Market Microstructure Theory

Demsetz (1968) laid the foundational proposition of Market Microstructure Theory by explaining that the cost of trading arises from the organization of exchange and the provision of immediacy by market intermediaries. The theory was subsequently formalized through models of dealer inventory, asymmetric information and order flow, including Kyle's (1985) model of informed trading and price impact and O'Hara's (1995) comprehensive treatment of trading institutions. Unlike conventional asset-pricing models that assume frictionless exchange, market microstructure theory examines how orders are submitted, matched and executed and how these processes influence observed prices.

The theory rests on several central assumptions. First, market participants differ in information, trading motives and urgency. Some investors trade because of private information, while others trade for liquidity, portfolio rebalancing or cash-flow reasons. Second, liquidity providers bear inventory and adverse-selection risks when they stand ready to transact. Third, market design matters: the rules governing order priority, disclosure, tick size and trading continuity influence spreads, depth and price adjustment. Fourth, order flow conveys information, so a trade may move prices even before its fundamental content is fully known.

Kyle (1985) expresses these ideas through lambda, which measures the price change associated with a unit of net order flow. The inverse of lambda can be interpreted as market depth because it represents the amount of order flow required to generate a given price change. A higher lambda indicates greater price impact and weaker effective depth. In the present study, the independent variable follows this price-impact logic. The positive regression coefficient should therefore be understood as evidence that higher price impact rather than greater order-book thickness is associated with higher volatility.

The theory predicts several channels through which weak depth may increase volatility. Large orders may consume available quotations and force transactions at increasingly unfavorable prices. Liquidity providers may widen spreads or withdraw quotations when they face inventory risk or suspect informed trading. Thin order books may also generate temporary overshooting because the marginal trade exerts a large influence on the transaction price. These mechanisms make volatility partly endogenous to the structure of trading rather than solely to changes in fundamental information.

A major strength of Market Microstructure Theory is its explicit causal mechanism. It connects observable trading variables order size, depth, spreads, order imbalance and execution cost to price formation and volatility. It also explains why two markets receiving similar information may display different price responses when their trading structures differ. This makes it particularly useful for emerging markets, where the capacity of liquidity providers and the concentration of trading can differ substantially from developed exchanges (Foucault et al., 2013).

The theory also has strong measurement relevance. It supports the use of price-impact indicators when complete order-book data are unavailable. Pham et al. (2020) confirm that incorporating depth information improves the prediction of immediate price impact, while Fong et al. (2017) show that liquidity proxies capture different dimensions and must be selected according to the research question. A Kyle-type measure is therefore appropriate when the focus is the sensitivity of prices to trading rather than the displayed volume at the best quotes.

Nevertheless, the theory has limitations. Classical models often assume continuous trading, rational agents, a simplified information structure and stable behaviour by market makers. Actual emerging markets may experience trading interruptions, price limits, concentrated ownership, strategic order splitting and periods with few or no trades. A daily price-impact proxy also cannot observe the full depth available at multiple order-book levels. It may combine permanent information effects with temporary liquidity effects, creating potential simultaneity between volatility and measured depth.

Despite these limitations, Market Microstructure Theory remains the most suitable framework for the study. The NSE's combination of electronic trading, concentrated activity and episodic liquidity makes the absorptive capacity of the market a central issue. The theory allows the paper to interpret a positive coefficient not as evidence that genuine depth destabilizes the market, but as evidence that stronger measured price impact indicating weaker effective depth is associated with higher conditional volatility. The study thereby tests the theory in an African emerging-market context using daily data and a GARCH-based risk measure.

Empirical Review

Empirical studies report mixed relationships between depth and volatility because they differ in the definition of depth, trading frequency, market design and estimation method. Some studies use displayed quantity at the best bid and ask, while others use turnover, order-book slopes or price-impact ratios. Volatility is likewise measured through realized variance, absolute returns, high-low ranges or conditional GARCH estimates. These differences complicate direct comparison and support context-specific investigation.

Pham, Anderson, Duong and Lajbcygier (2020) examined the influence of trade size and market depth on immediate price impact in a limit-order-book market. Using transaction-level information and a dynamic price-impact model, they found that the inclusion of market-depth information materially reduced forecast errors. Their results demonstrate that the quantity available in the order book affects how strongly a trade moves price. The study provides direct support for the microstructure mechanism used in the present paper. However, it relied on detailed order-book data from a developed market and focused on immediate transaction-level price impact rather than daily GARCH volatility.

Będowska-Sójka and Echaust (2020) compared alternative liquidity proxies during episodes of extreme illiquidity. They found that proxy performance is state dependent and that measures that work well under normal conditions may behave differently during market stress. The study is important because it cautions against treating liquidity as a single construct and supports the use of a measure aligned to the research objective. Its focus was the relative performance of proxies rather than a direct regression of market depth on conditional volatility.

Muzaffar and Malik (2024) investigated market liquidity and volatility in China, India, Pakistan and South Korea and assessed the moderating influence of economic-policy uncertainty. They incorporated dimensions including depth, breadth and resilience and reported that the liquidity-volatility relationship was sensitive to uncertainty conditions. The study is relevant because it demonstrates that liquidity conditions can amplify or dampen volatility in emerging economies. Its cross-country Asian setting, composite liquidity measures and institutional differences limit direct generalization to the NSE.

Recent evidence from highly liquid government-securities markets also shows that depth and volatility interact dynamically. Meldrum and co-authors (2023) reported that rising volatility was associated with deteriorating liquidity and that periods of low depth were particularly vulnerable to high price impact. Although the institutional structure of the United States Treasury market differs from the NSE, the findings reinforce the argument that depth is not simply a static quantity; it can become fragile when traders depend on rapid quote replenishment.

At the level of volatility modelling, Wanjuki, Lumumba, Kimtai, Mbaluka and Njoroge (2024) compared GARCH-family models using Kenyan securities-market data. They found that GARCH-based specifications are useful for representing the time-varying and persistent nature of volatility in the NSE environment. Their study validates the methodological decision to derive the dependent variable using GARCH. It did not, however, examine depth or other liquidity determinants of the estimated volatility series.

Rugut (2021) compared asymmetric GARCH models and neural networks in forecasting volatility at the NSE. The work confirmed that NSE returns exhibit nonlinear and persistent risk dynamics that are not adequately represented by a constant-variance model. The study concentrated on forecasting performance and did not test the explanatory contribution of market depth. The present paper extends that strand by treating GARCH volatility as an outcome related to a specific microstructure variable.

Alusa and Kalui (2021) examined stock-market liquidity and performance among firms listed at the NSE, conceptualizing liquidity through depth, breadth, resilience and immediacy. Their findings indicate that liquidity dimensions matter in the Kenyan market. The study provides valuable local evidence but differs in its dependent variable and unit of analysis. Firm performance may respond to profitability, governance and capital structure, whereas the present paper focuses on daily market-level conditional volatility.

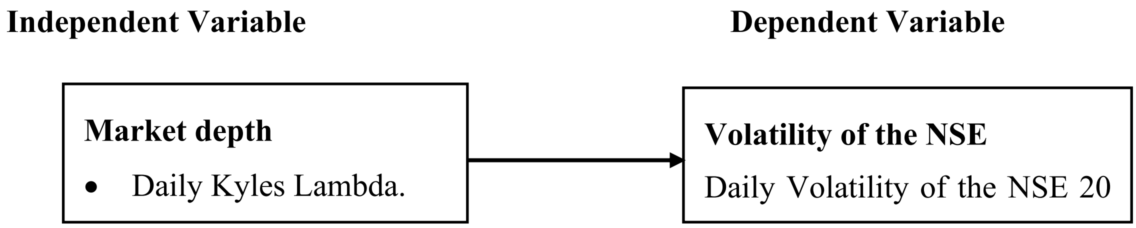
Ndei, Muchina and Waweru (2019) modelled NSE return volatility in the presence of structural breaks and documented volatility clustering and persistence. Although published before the primary 2020–2026 emphasis of this review, the study remains important local evidence that structural changes affect NSE volatility. It reinforces the need to use conditional variance rather than raw index levels but does not isolate the price-impact channel of liquidity.

The reviewed literature reveals four gaps. First, recent empirical evidence is concentrated in developed or Asian markets. Second, studies that measure depth using rich order-book data are difficult to replicate where such data are limited. Third, Kenyan volatility research emphasizes modelling and forecasting rather than microstructure determinants. Fourth, local liquidity studies generally use firm performance rather than market volatility. The present study addresses these gaps by combining a daily Kyle-type price-impact measure with GARCH-estimated NSE 20 Share Index volatility over an extended nine-year period.

Conceptual Framework

The conceptual framework specifies market depth as the independent variable and securities market volatility as the dependent variable. Market depth is represented by a daily Kyle-type price-impact measure. Because higher values of the proxy indicate stronger price impact, they represent weaker effective depth. Securities market volatility is represented by the conditional standard deviation generated from a GARCH(1,1) model of NSE 20 Share Index log returns.

Figure 1:Conceptual Framework



METHODOLOGY

Research Design

The study adopted a correlational quantitative research design. The design was appropriate because it examined the direction, magnitude and statistical significance of the association between two historical market variables without manipulating the trading environment. The design does not by itself establish definitive causality; accordingly, the results are interpreted as explanatory associations consistent with the proposed microstructure mechanism.

The study was conducted at the Nairobi Securities Exchange, Kenya. The unit of analysis was the daily market-level observation. A total of 2,334 trading-day observations covering January 2017 to December 2025 were used. Daily frequency was selected because liquidity and volatility adjust rapidly and annual or monthly data may conceal short-lived market stress, clustering and order-flow effects.

Secondary data were obtained from official NSE market records, index series and published reports. The NSE 20 Share Index provided the price series used to compute returns and conditional volatility, while daily trading information was used to construct the market-depth proxy. Data were organized in a structured collection sheet, checked for chronological consistency and analysed using Stata version 18.

Daily continuously compounded returns were calculated as:

$$R_t = \ln(P_t) - \ln(P_{t-1}) \text{ .... Equation (1)}$$

where R_t is the return on trading day t, P_t is the NSE 20 Share Index level on day t and P_{t-1} is the preceding trading-day index level. The return series was used to estimate a GARCH(1,1) conditional variance model:

$$h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1} \text{ .... Equation (2)}$$

where h_t is conditional variance, ω is the variance constant, ε^2_{t-1} is the lagged squared innovation and h_{t-1} is lagged conditional variance. The square root of h_t was used as the daily volatility measure. The GARCH(1,1) model was selected because it captures volatility clustering and persistence while remaining parsimonious.

Market depth was measured using a daily price-impact indicator based on Kyle's lambda. Conceptually, lambda expresses the price movement associated with trading activity. Higher values indicate that a unit of trading produces a larger price change and therefore signal weaker effective depth. Lower values indicate that trading is absorbed with less price disturbance. The direction of the proxy is important: a positive coefficient means that higher price impact, rather than stronger order-book depth, is associated with higher volatility.

The inverse hyperbolic sine transformation was used to reduce skewness and accommodate zero or very small values. It was defined as:

$$IHS(x) = \ln[x + \sqrt{(x^2 + 1)}] \text{ .... Equation (3)}$$

The empirical regression model was specified as:

$$VOL_t = \beta_0 + \beta_1 DEPTH_t + \varepsilon_t \text{ .... Equation (4)}$$

where VOL_t is GARCH-estimated securities-market volatility, $DEPTH_t$ is the IHS-transformed Kyle-type price-impact measure, β_0 is the intercept, β_1 is the market-depth coefficient and ε_t is the error term. The hypothesis was evaluated at the 5% significance level.

FINDINGS AND DISCUSSIONS

Descriptive Statistics

Table 1 presents the distribution of market depth and securities-market volatility. Both variables are daily financial-market measures and consequently have small numerical values. Market depth was positively skewed and leptokurtic, indicating that most days recorded relatively low price impact but a smaller number of trading days experienced unusually high price impact. The volatility series was also strongly right-skewed and heavy-tailed, which is consistent with volatility clustering and occasional market stress.

Variable	N	Mean	Median	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
IHS Market Depth	2,334	0.00000357	0.00000245	0.00000345	0.000000231	0.0000172	1.8829	6.5809
Securities Market Volatility	2,334	0.000410	0.0000125	0.00007964	0.000000	0.000557	4.0320	22.8168

The mean market-depth proxy was 0.00000357 and its standard deviation was 0.00000345. The maximum was substantially above the median, confirming that some days experienced a much larger price response to trading activity. Securities-market volatility had a mean of 0.000410 and a standard deviation of 0.00007964. Its high kurtosis indicates a greater frequency of extreme observations than would be expected under normality. These characteristics support the use of the IHS transformation and a GARCH-based volatility measure.

Correlation Analysis

Table 2 shows the bivariate relationship between market depth and volatility. The correlation coefficient was positive and statistically significant.

Correlation	IHS Market Depth	Securities Market Volatility
IHS Market Depth	1	
Securities Market Volatility	0.3550**	1
Sig. (2-tailed)	0.001	

The coefficient of 0.3550 indicates a positive, modest relationship. Because the variable is a price-impact measure, the result means that higher price impact equivalent to weaker effective depth was associated with higher volatility. The probability value was below 0.001, indicating that the observed correlation was unlikely to have arisen by sampling variation under the null hypothesis of no linear relationship.

Model Summary

Regression Statistic	Value
Multiple R	0.3550
R Square	0.1260
Adjusted R Square	0.1256
Root MSE	0.00007447
Observations	2,334

The R-squared value of 0.1260 indicates that market depth explained 12.60% of the observed variation in daily securities-market volatility. The adjusted R-squared of 0.1256 is only slightly lower because the model contains one predictor and a large number of observations. The remaining 87.40% reflects macroeconomic news, political events, investor sentiment, global risk, firm-specific information and other liquidity dimensions not included in this standalone model. An R-squared of 12.60% is economically meaningful for a single daily market microstructure variable, although it does not imply that depth is the only or dominant determinant of volatility.

Analysis of Variance (ANOVA)

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	0.0000018644	1	0.0000018644	336.19	0.001
Residual	0.0000129327	2,332	0.000000005546		
Total	0.0000147971	2,333			

The ANOVA results show that the regression model was statistically significant, $F(1, 2332) = 336.19$, $p = 0.001$. The regression sum of squares represents the variation explained by market depth, while the residual sum of squares represents unexplained variation. The ratio of the regression sum of squares to the total sum of squares is 0.1260, confirming agreement with the model-summary R-squared. The significant F-statistic leads to rejection of the proposition that the model has no explanatory power.

Regression Coefficient Results

Variable	B	Std. Error	Beta	t	p-value
Constant	0.00038075	0.00000222		171.63	0.001
IHS Market Depth	8.1940	0.4469	0.3550	18.34	0.001

The market-depth coefficient was positive and statistically significant. The unstandardized coefficient of 8.1940 means that a one-unit increase in the transformed price-impact measure was associated with an 8.1940-unit increase in the volatility measure. Because the market-depth values are very small, practical interpretation should focus on realistic incremental changes and on the standardized beta of 0.3550 rather than on a literal one-unit change. The t-statistic of 18.34 equals the square root of the model F-statistic, as expected in a simple regression with one predictor. The 95% confidence interval does not include zero.

The estimated model was:

$$VOL_t = 0.00038075 + 8.1940\ DEPTH_t$$

The null hypothesis that market depth has no statistically significant effect on securities-market volatility was rejected. The evidence supports a positive relationship between the price-impact proxy and conditional volatility.

Discussion of Findings

The finding is consistent with Market Microstructure Theory. A market in which order flow produces larger price changes is less able to absorb transactions without disturbing prices. Higher price impact can therefore increase the amplitude of daily returns and feed into the conditional variance process. The result does not mean that genuinely deeper markets are destabilizing. Rather, because the empirical variable is a Kyle-type lambda, a higher observed value signifies weaker depth.

The coefficient is also consistent with Pham et al. (2020), who show that market-depth information is important for explaining immediate price impact. Their work demonstrates that trade size becomes more consequential when it exceeds the quantity available in the order book. The NSE result extends that insight from transaction-level price impact to daily GARCH-estimated volatility in an emerging African market.

The finding also corresponds with Będowska-Sójka and Echaust (2020), who emphasize that liquidity proxies reveal different aspects of market conditions, especially in extreme illiquidity. The statistically significant result obtained from the price-impact proxy suggests that an aggregate volume measure might miss an important channel through which liquidity affects volatility at the NSE.

Muzaffar and Malik (2024) find that liquidity dimensions influence volatility in emerging economies and that the relationship is affected by policy uncertainty. The 2017–2025 Kenyan sample contains several uncertainty episodes, including elections, the COVID-19 pandemic and global monetary tightening. During such periods, liquidity suppliers may become more cautious, making market depth more sensitive to order flow and strengthening the relationship with volatility.

Market depth explained 12.60% of daily volatility, which is meaningful for a single predictor but leaves most volatility unexplained. Volatility also responds to macroeconomic announcements, exchange-rate movements, foreign-investor flows, interest rates, political news and global risk. The result therefore supports market depth as one relevant explanatory factor rather than a complete model of volatility.

CONCLUSION AND RECOMMENDATIONS

Conclusion

The paper concludes that market depth has a positive and statistically significant relationship with securities-market volatility at the Nairobi Securities Exchange. The model was statistically significant, $F(1, 2332) = 336.19$, $p < 0.001$, and market depth explained 12.60% of the variation in GARCH-estimated volatility. The positive coefficient means that higher price impact, indicating weaker effective market depth, was associated with higher volatility. The null hypothesis was therefore rejected.

The finding supports the Market Microstructure Theory proposition that trading arrangements and order-flow absorption influence price behaviour. It demonstrates that volatility at the NSE cannot be understood solely through public information or macroeconomic shocks; the capacity of the market to absorb transactions also matters. Nevertheless, the unexplained variation confirms that depth should be considered alongside other dimensions of liquidity and broader economic conditions.

Recommendations

The Nairobi Securities Exchange and the Capital Markets Authority should strengthen liquidity-provision mechanisms. Market-making arrangements, incentives for continuous two-sided quotation and closer monitoring of depth at different price levels can reduce the probability that modest order imbalances generate excessive price movements.

Order-book transparency should be improved within the limits necessary to prevent strategic exploitation. Regulators and market operators should monitor changes in quoted depth, replenishment speed and concentration of orders, especially during periods of political, macroeconomic or global-market stress.

Brokers, asset managers and institutional investors should incorporate price-impact estimates into pre-trade analysis. Large orders can be divided, timed or executed through strategies that reduce market impact. Execution decisions should consider not only headline trading volume but also the available depth and the sensitivity of price to order flow.

Listed firms should support timely and credible information disclosure. Better information flow reduces adverse-selection risk faced by liquidity providers and may encourage them to supply greater depth. Improved investor-relations practices can also broaden participation and reduce abrupt order imbalances triggered by uncertainty.

Suggested Areas for Further Studies

Future studies should estimate dynamic models using lagged depth and volatility, vector autoregression, Granger-causality tests or instrumental-variable methods to address simultaneity and clarify the temporal direction of the relationship.

Alternative depth measures should be tested, including turnover-adjusted price impact, Amihud illiquidity, order-book depth at multiple quote levels and the slope of the limit order book. Comparing measures would determine whether the result is robust to the specific proxy used.

Subperiod analysis should examine whether the relationship differs across pre-COVID, COVID and post-COVID periods, election cycles and episodes of global financial stress. Nonlinear or quantile regressions may reveal that depth matters more during extreme volatility than during normal trading conditions.

Comparative research should extend the model to other African exchanges, including Johannesburg, Ghana, Uganda, Rwanda and Dar es Salaam, to determine whether the observed relationship reflects a general emerging-market mechanism or characteristics specific to Kenya.

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