



Stock Market Volatility and Trading Volume in Pakistan: Examining the Volume-Volatility Relationship

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ARTICLE INFO	Abstract
Received: June 29, 2026 Revised: July 17, 2026 Accepted: August 04, 2026 Available Online: August 14, 2026 Keywords: Pakistan Stock Exchange, KSE-100, trading volume, stock-market volatility, GARCH, EGARCH, Granger causality, trading activity, emerging market Corresponding Author: Hassan Ali Email: hassanali341@gmail.com	Focusing specifically on the Pakistan Stock Exchange (PSX), this paper explores how trading volume relates to stock-market volatility in Pakistan. Many view trading volume as a key gauge of market participation, incoming information, differences in investor opinion, and shifting market conditions. Even so, both the strength and the direction of that volume-volatility link can change from one market or economic regime to another. To examine this, the study sets out a quantitative time-series framework relying on daily data for the KSE-100 Index and chosen high-turnover stocks from 2018 through 2026. Closing prices will yield daily log returns, and conditional market volatility will be modeled via Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-family techniques. To capture both market participation and the transmission of information, the study will draw on trading volume, turnover, and shifts in trading activity. The empirical work will cover descriptive metrics, correlation tables, unit-root and ARCH-effect tests, along with symmetric and asymmetric GARCH setups such as GARCH and EGARCH. Next, Granger causality tests will assess whether trading volume helps predict future volatility, or if volatility shifts are what drive changes in trading activity. Sensitivity checks will test different volume proxies alongside alternative model specifications. By taking in the post-2018 period—marked by severe economic uncertainty and disruptions in the market—the study aims to supply fresh empirical material on Pakistan's volume-volatility link. These results could help clarify whether heavier trading goes hand in hand with higher volatility, sharper processing of market information, or both at once.

Introduction

Stock-market volatility captures how widely asset prices swing over time, serving as a primary yardstick for investment conditions, uncertainty, and financial risk. Volatility rarely sits still in financial markets, since price swings react strongly to fresh information, revised investor expectations, liquidity shifts, and broader economic updates. Trading volume offers another vital window into market activity, since it shows how vigorously participants buy and sell while revealing shifts in overall participation. Consequently, financial economists have devoted considerable work to this volume-volatility link, especially in emerging markets

where uneven information, tight liquidity, and mixed investor behaviors can magnify market swings (Naik et al., 2018; Koubaa & Slim, 2019).

Two main frameworks are usually used to explain how volume and volatility relate to each other: the mixture of distributions hypothesis and the sequential information arrival hypothesis. Under the mixture of distributions hypothesis, incoming information drives trading volume and price fluctuations at the same time, producing a positive link between them. The sequential information arrival hypothesis takes a different view, arguing that because investors receive and digest information at different times, prices and trading volumes adjust in stages. Both theories suggest that watching shifts in trading volume might tell us something meaningful about where volatility stands or where it is headed. Yet empirical studies show that this relationship does not always hold steady across different markets, timeframes, or trading intensities.

Looking at South African equity markets, Naik et al., (2018) tracked the link between volatility and trading volume, arguing that volume serves as an effective stand-in for incoming news. What they found was a positive link between volume and volatility, which backed up information-based models within an emerging-market context. Koubaa and Slim (2019) took a similar route by studying trading activity and volatility, and they showed that the strength of that connection shifts past certain volume thresholds. Their results point to trading activity having a different impact whenever market participation runs unusually high or low. A basic linear correlation is therefore unlikely to capture what is actually happening beneath the surface of the volume–volatility dynamic.

This connection matters even more in emerging equity markets, where available information, liquidity, and who is trading can all swing dramatically. These markets are also more vulnerable to unexpected domestic and global shocks, which can hit trading levels and price volatility at the same time. Work on African bourses demonstrates this clearly: the connections tying returns, volume, and volatility together frequently feature nonlinear patterns, asymmetries, and shifting volatility regimes (Ngene & Mungai, 2022). Results like these show that researchers should track market volatility with models that allow conditional variance to change over time, instead of treating volatility as fixed.

The Pakistan Stock Exchange (PSX) offers a useful backdrop against which to study these patterns. Over the last several years, the PSX has seen considerable volatility and wide swings in trading activity, typical of an emerging capital market. Earlier research on Pakistan has already shown that returns tend to cluster in volatility, persist over time, and react unevenly to market shocks. Rashid et al., (2020), to take one case, tested several GARCH-family models on KSE-100 returns and identified both time-varying volatility and significant ARCH and GARCH effects. What their results show is that standard models built on constant variance simply cannot capture how Pakistani equity returns move.

Other Pakistani data points to volatility reacting unequally to good and bad market news. Evaluating asymmetric GARCH specifications on the Pakistan Stock Exchange, Sheraz and Nasir (2021) identified asymmetric volatility around the COVID-19 pandemic. Rehman et al., (2021) looked at both the KSE-100 and Islamic equity indices, showing that ARCH and GARCH techniques remain suited to capturing conditional variance in Pakistan. Together, these papers offer solid methodological grounds for turning to GARCH-type models to examine PSX volatility.

Why volatility modelling matters became especially clear once COVID-19 hit. Financial markets faced massive uncertainty from the pandemic, which drove abrupt shifts in how investors behaved. While Saeed et al., (2021) found significant shifts in Pakistan's equity returns and volatility during the pandemic, Wang et al. (2024) later showed that PSX volatility remained both persistent and asymmetric under COVID-19 disruptions. Findings like these show that volatility in Pakistan can shift substantially whenever economic and financial conditions grow uncertain.

Broader macroeconomic instability plays its own part in driving volatility across Pakistani equities. Applying a GARCH-MIDAS framework, Ghani et al., (2022) looked at how well economic policy uncertainty and broader macroeconomic factors could forecast market conditions in Pakistan. Their results confirmed that economic policy uncertainty, along with several macroeconomic measures, carried useful signals for predicting stock-market volatility. These results point to volatility being shaped by the wider informational backdrop against which investors make their choices. Because of this, trading volume could serve as a supplementary, market-level proxy for when information hits and how investors react to it.

Lately, researchers have also circled back to how trading volume links directly to volatility. In looking at how trading volume helps forecast volatility, Liu et al., (2021) found that volume's value could vary with the chosen volatility model and data frequency. What they found indicates that volume may offer extra input for volatility models, though one cannot assume it makes the same predictive contribution across every specification. Applying a bivariate GARCH framework to eight Asian equity markets, including Pakistan, Akbar (2023) analyzed how stock returns, trading volume, and return volatility interact dynamically. The paper identified contemporaneous links between stock returns and trading volume, pointing out why their dynamic interactions deserve close attention.

Newer global data also indicates that the link between volume and volatility might not be symmetric, shifting instead with broader market conditions. Looking at the MINT economies with EGARCH models, Güzel (2024) picked up signs of asymmetric volatility effects across several of those markets. Maki (2024) showed as well that how trading volume affects realized volatility can shift depending on which way the market is heading. These findings carry weight for Pakistan, indicating that market volatility shifts may not be fully accounted for by total trading volume alone.

Even with what has been written on Pakistani stock volatility, there is still no up-to-date, direct look at how volume and volatility interact. Most studies on Pakistan have focused on volatility persistence, asymmetric effects, broader economic indicators, or one-off shocks like COVID-19. A few recent papers have touched on trading volume within larger Asian or emerging-market datasets, but Pakistan still lacks a focused study that uses newer data and tests which way the relationship runs.

To evaluate the link between trading volume and equity volatility in Pakistan, the current study relies on daily figures for the KSE-100 Index and actively traded individual stocks between 2018 and 2026. Closing prices will yield the daily return series, while models from the GARCH family will be used to estimate conditional volatility. To reflect different facets of market participation, the models will include trading volume, turnover, and shifts in trading activity. Tests for ARCH effects and Granger causality will show whether trading activity drives later volatility or if shifting volatility is what prompts changes in trading activity. Through an investigation of these dynamics across a recent window marked by varied economic conditions, this paper seeks to bring fresh data to bear on the volume–volatility nexus in Pakistan's emerging capital market.

Literature Review

Stock-Market Volatility and Trading Volume

Because volume and stock-market volatility both capture meaningful aspects of how financial markets function, researchers have studied their connection at length. Transaction intensity is gauged by trading volume, whereas volatility captures market uncertainty and the extent of price swings. When fresh information reaches the market, investors often update their outlooks and rebalance their holdings, a process that can drive a positive link between the two variables. Trading accelerates as investors act on new information, and prices swing more widely at the same time.

In their South African study, Naik et al., (2018) looked at how stock-market volatility linked to trading volume, highlighting that volume operates as an indicator of incoming information. They found a positive link between trading volume and volatility, lining up with theories that credit market activity to incoming information. These findings apply directly to Pakistan, as both it and South Africa are emerging markets where shifting investor involvement and information imbalances shape trading patterns.

That trading activity and volatility might not share a strictly linear connection was further demonstrated by Koubaa and Slim (2019). Looking into whether specific volume cutoffs altered the volume–volatility link, they showed that the relationship shifted depending on the volume of market activity. What this suggests is that unusually heavy trading may not carry the same consequences for volatility as trading during ordinary market conditions. Because of this, models that let volatility adjust dynamically alongside market activity may offer a more true-to-life picture of financial markets.

Across various data frequencies and volatility-modelling techniques, Liu et al. (2021) investigated how much trading volume helps in forecasting volatility. What they found was that trading volume does hold useful predictive content for volatility, though how much it helps varies with the model choice and the frequency of

the data. The paper indicates that instead of taking volume's predictive power as a given, researchers need to test for it empirically.

A leading explanation for why volume and volatility move together is that trading activity reflects incoming information. Because we cannot observe information flows directly, researchers often turn to trading activity as a proxy. When fresh information reaches traders, they often rethink what financial assets are worth and how risky they are, which drives concurrent shifts in prices and trading volume.

Jiang (2020) applied an EGARCH framework to stock returns, trading volume, and volatility, showing that volume carries useful information about return patterns and volatility alike. An asymmetric specification mattered here because positive shocks do not always provoke the same volatility reaction as negative ones. These findings back the case for adding trading volume to conditional volatility models.

Using threshold and GJR-GARCH techniques, Kao et al., (2020) analyzed market returns, return volatility, and volume in S&P 500 VIX futures. They detected not only asymmetries but also lead-lag relationships between trading volume and volatility. These results suggest that volume and volatility can affect one another across varying horizons, rather than just meeting in a single instantaneous shift.

Liu et al., (2021) also stressed that trading volume can stand in for information flow when projecting volatility. In comparing different GARCH models, they revealed that volume can offer predictive value that past returns alone miss. This adds weight to the claim that folding trading activity into volatility models yields a fuller picture of market risk dynamics.

Findings from Emerging Markets

In emerging markets, where investor participation, liquidity, and information flows shift frequently, the volume–volatility link may carry even greater weight. Naik et al., (2018) documented a positive volume–volatility relationship in South Africa, showing that information-driven accounts hold true beyond advanced financial markets.

Looking beyond single countries, Ngene and Mungai (2022) broadened the scope of this research by studying how stock returns, trading volume, and volatility interact across African bourses. By accounting for nonlinearities, asymmetries, and shifts across volatility regimes, they showed that the link between returns, volume, and volatility was not uniform across different market environments. What makes these results matter is that they push back against the idea that the volume–volatility relationship holds steady through every period.

In Saudi Arabia, Alhussayen (2022) looked at how trading volume and market returns relate to each other, using vector autoregression, Granger causality tests, and impulse-response functions. The results suggested that the relationship does not always run in the expected direction, casting doubt on the standard view that trading volume is necessarily what moves market returns. This underlines why causality needs to be empirically tested instead of simply assumed on theoretical grounds.

Akbar (2023) explored the evolving ties between trading volume, stock returns, and return volatility in eight Asian markets, one of which was Pakistan. Working with a bivariate GARCH framework, the author uncovered contemporaneous links between volume and returns while pointing up just how dynamic the process is over time. Yet because Pakistan was pooled within a broader group of countries, the study does not yield the detailed, market-specific insight that a standalone inquiry into the PSX can offer.

Empirical Studies from Asian Equities

Emerging Asian bourses make for an especially fitting point of comparison: like Pakistan, they deal with heavy retail trading, fluctuating liquidity, and sharp reactions to events at home and abroad. To unpack how volatility and trading activity feed into each other, researchers studying Asian markets have increasingly turned to GARCH-type models.

In a sample of Asian bourses, Akbar (2023) detected a dynamic relationship linking trading volume and stock returns. Rising market returns, the study noted, came with higher trading volume, whereas market pullbacks coincided with drops in trading activity. These patterns suggest that retail and institutional participation can be quite sensitive to where the market is heading.

Güzel (2024) examined the link between return volatility and trading volume across the MINT markets, relying on daily series running from June 2019 to March 2023. To account for asymmetric effects in volatility, the author turned to EGARCH models, detecting asymmetric responses across several of the examined markets. These results matter for Pakistan because they show that emerging-market volatility can react one way to positive shocks and another way to negative ones.

Using a Markov-switching VAR model, Zhang et al., (2024) explored how volume and volatility interact dynamically within the Chinese stock market. They found that the link between trading volume and volatility shifted from one market regime to another. The paper shows, then, that whether a market is calm or turbulent can alter how trading activity and volatility interact.

In India, Saranya and Sudhamathi (2024) examined how implied volatility, index returns, and trading volume interact. Their work provided more evidence that bringing trading activity into models of market uncertainty is genuinely helpful. Because India and Pakistan are adjacent emerging markets in South Asia, these findings offer a solid reference point for checking whether the PSX behaves the same way.

GARCH Modelling and Volatility Dynamics

Returns in financial markets frequently display volatility clustering: large swings follow large swings, while quiet stretches bunch together in the same way. Because of this property, models from the GARCH family are well matched to the study of financial markets. Under a GARCH framework, conditional variance is free to evolve over time, driven by past shocks together with earlier values of conditional variance itself.

Looking at Pakistani stock returns, Rashid et al. (2020) fitted GARCH-family models to KSE-100 data and documented clustering, persistence, and non-normal distributions. What their results show is that the PSX displays precisely the statistical traits that justify using conditional heteroskedasticity models.

Rehman et al., (2021) examined dynamic volatility across the KSE-100 and Islamic stock indices, relying on unit-root tests, ARCH tests, and models from the GARCH family. Their findings provided further confirmation that time-varying volatility is an important feature of Pakistani stock returns.

When evaluating stock-market volatility in Pakistan, Sheraz and Nasir (2021) tested multiple asymmetric GARCH specifications against one another. They found that volatility did not necessarily react to positive and negative shocks in the same way. That asymmetry is precisely what justifies running an EGARCH model or similar asymmetric setup in this study.

Studies looking at emerging markets more recently show that advanced volatility models remain just as necessary. Using EGARCH frameworks to assess MINT economies, Güzel (2024) found that shocks failed to exert symmetric effects across all markets. Along the same lines, studies on emerging-market forecasting have consistently argued against assuming constant variance, favouring models built to track volatile persistence over time.

GARCH Models and Trading Volume as an Explanatory Factor

Standard GARCH setups handle volatility persistence well, but adding trading volume helps explain what else drives shifts in conditional variance. Putting trading volume directly into the variance equation as an explanatory regressor shows whether rising market activity coincides with higher or lower conditional volatility.

Jiang (2020) proved how beneficial it can be to integrate volume into an EGARCH setup. Trading activity, the paper pointed out, carries useful explanatory power for both return dynamics and volatility behaviour. Liu et al., (2021) likewise observed that incorporating trading volume can enrich the information baseline for forecasting volatility, though how much it helped varied with the model chosen and data sampling frequency.

Ngene and Mungai (2022) offered further proof that folding trading activity into volatility specifications alters estimates of volatility persistence. Their study of African markets proved that regime shifts and underlying nonlinearities can alter how volume and volatility interact.

GARCH-type models were used by Cornelius et al., (2024) to evaluate trading volume alongside both intraday and overnight volatility across Nigeria's equity market. What their findings revealed was that trading volume

offered neither an uncomplicated nor an invariant explanation for overall volatility. These results matter here because they point to a need to test volume together with other indicators of market activity and volatility.

Looking deeper into how trading volume affects realized volatility asymmetrically, Maki (2024) observed that the impact of trading activity varied with market direction. These results suggest that distinguishing between market upturns and downturns could shed more light on how volume and volatility interact.

Pakistan, Market Shocks, and Volatility

Because the Pakistani equity market has gone through repeated stretches of heavy uncertainty, one needs to track how trading activity and volatility behave across shifting market climates. The COVID-19 shock stood out especially because it prompted abrupt shifts in what investors expected and how financial markets functioned.

In their study of the PSX over the COVID-19 period, Saeed et al. (2021) tracked returns alongside volatility and documented significant shifts in the latter. What they showed is that extreme shocks can fundamentally reshape the statistical properties of equity returns.

Sheraz and Nasir (2021) looked at PSX volatility across the pandemic as well, uncovering signs of asymmetry. These outcomes suggest that shocks do not necessarily push volatility to the same degree in both directions, which justifies turning to asymmetric GARCH models.

Ghani et al., (2022) tested whether measures of economic policy uncertainty and broader macroeconomic indicators could forecast stock volatility in Pakistan. Their results showed that future volatility was partly reflected in macroeconomic data and uncertainty measures. This indicates that equity volatility responds not just to internal market signals but also to the wider economic picture.

Wang et al., (2024) assessed how the COVID-19 era influenced Pakistani equity returns and volatility, noting patterns that were both persistent and asymmetric. What their study confirms is the need to evaluate volatility across windows marked by heavy market stress.

Using multivariate GARCH models, Khursheed et al. (2024) contrasted how conventional and Islamic stock indices in Pakistan fared across successive waves of COVID-19. What they found adds to the evidence that financial stress can alter both volatility and broader market relationships.

Causal Direction Between Volume and Volatility

A central question across the volume–volatility literature is which way the effect runs: does trading volume drive volatility, does volatility drive volume, or do they feed into one another? Looking at correlation alone will not resolve which way the effect runs. Because of this, recent work has turned more and more to Granger causality, VAR, GARCH, and nonlinear models to trace these dynamic links.

Naik et al., (2018) showed that trading volume tracked market volatility in South Africa, finding that volume actually Granger-caused volatility there. What they found backs the view that heavier information flow and brisker trading may happen before volatility starts to shift.

Kao et al., (2020) found lead-lag patterns between trading volume and volatility, which suggests the two do not just move together in the same moment but interact over time.

Alhussayen (2022), on the other hand, found that market returns could drive trading volume, yet found no steady evidence that volume could predict returns. This is precisely why causal direction has to be tested against the data rather than taken for granted.

Akbar (2023) drew a similar conclusion, focusing on the dynamic link between stock returns and trading volume throughout Asian markets. Using bivariate GARCH models in that paper shows why it helps to study how variables interact directly, rather than running isolated volatility equations.

Ngene and Mungai (2022) also demonstrated that the causal links connecting returns, volume, and volatility depend on market regimes and nonlinear settings. Methodologically, these findings give this study good reason to pair GARCH estimation with Granger causality testing.

Research Gap

While the literature confirms that trading volume and stock volatility are closely tied, it reaches no consensus on how strong that tie is or which way it points. One line of research argues that heavier trading signals arriving information and therefore brings greater volatility, while another suggests that heightened volatility is what pulls traders into the market. A number of recent papers also point out that this relationship shifts depending on the market regime, which volatility measure is used, the sampling frequency of the data, and whether market shocks are positive or negative.

Studies on Pakistan have already confirmed that volatility in the PSX is both highly persistent and asymmetric. Even so, recent work on Pakistan has tended to look at macroeconomic drivers, volatility modelling, or crisis periods rather than tackling the direct link between volume and volatility. Akbar (2023) offers valuable broad evidence across Asia that covers Pakistan, but looking strictly at Pakistan with a longer run of recent daily data yields a clearer, more targeted picture.

A further drawback in the literature is the common habit of reducing market activity to a single volume indicator. This paper tackles that shortcoming by looking at turnover and shifts in trading activity alongside raw trading volume. The sample also runs from 2018 to 2026, taking in quieter trading stretches alongside severe bouts of economic and financial turmoil.

By pairing GARCH-type volatility specifications with trading-activity metrics and Granger causality tests, this study builds on what earlier work has done. Estimating GARCH and EGARCH models will capture both volatility persistence and potential asymmetries, while the Granger tests will show which way the relationship runs. In doing so, the study will deliver fresh evidence for Pakistan on whether heightened trading activity tracks higher conditional volatility, and whether swings in volatility subsequently shift market participation.

Methodology

Research Design

To examine trading volume and stock-market volatility in Pakistan, this paper uses a quantitative time-series setup. Attention was centred on the Pakistan Stock Exchange (PSX), and on the KSE-100 Index in particular because it tracks the exchange's largest and most heavily traded firms. The dataset spanned daily figures from January 2018 to June 2026, an interval wide enough to take in calmer trading environments, heavy economic uncertainty, and the dislocations caused by COVID-19.

The paper investigated whether shifts in trading activity tracked shifts in market volatility, and whether that feedback ran both ways. The primary variables were calculated from daily figures for trading volume and closing price. Alongside the KSE-100 Index itself, a subset of heavily traded individual shares was evaluated for robustness. The empirical approach brought together descriptive statistics, tests for stationarity and ARCH effects, GARCH-family models, and Granger causality tests.

Sources of Data and Variable Definitions

Public records from the Pakistan Stock Exchange supplied the daily KSE-100 closing prices and trading volumes. Continuously compounded returns were derived from each day's closing price. Daily returns were calculated as:

Data Measurement and Variables

Closing prices were turned into daily stock-market returns through the logarithmic return formula below:

$$R_t = 100 \times \ln(P_t / P_{t-1})$$

where R_t is the stock-market return on day t , P_t denotes the closing price on day t , and P_{t-1} is the price at the close of the preceding trading day.

Each day's trading volume was taken simply as the total number of shares that changed hands. The empirical work relied on log-transformed trading volume, which damped the effect of outliers and offered a steadier read on activity. Turnover served as a second proxy for market participation, based on the total cash value of the securities traded in that window.

Return series were run through GARCH-family models to estimate conditional volatility. Logged volume acted as the primary regressor, though supplementary checks also included turnover and volume changes to test robustness.

Preliminary and Descriptive Analysis

The initial stage of the analysis looked at the descriptive features of both daily returns and trading volume. The variables' distributions were mapped out through calculations of mean, standard deviation, minimum, maximum, skewness, and kurtosis. Next, Pearson correlations gave an initial look at how trading volume lined up with absolute returns.

An Augmented Dickey-Fuller (ADF) test checked whether the series were stationary. Price levels tend to wander without settling, whereas financial returns usually remain stationary, so the volatility models relied on log returns instead of untransformed prices. Next, an ARCH-Lagrange Multiplier test checked the return series for significant conditional heteroskedasticity. Finding ARCH effects supported turning to models in the GARCH family.

GARCH Model Specification

Estimating a standard GARCH(1,1) model allowed the analysis to trace how long volatility persisted. The mean equation was specified as:

$$R_t = \varepsilon_t + \mu$$

in which R_t denotes daily market returns, μ gives the mean return, and ε_t stands for the error term.

The equation for conditional variance was laid out as:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

in which σ_t^2 represents conditional variance, ω is the constant variance term, α captures how earlier market shocks feed through, and β reflects how long previous conditional volatility lingers.

To see if trading activity played into market volatility, the log of trading volume was added to the conditional variance equation:

$$\sigma_t^2 = \omega + \gamma V_t + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

in which V_t stands for log trading volume and γ shows how trading activity shifts conditional volatility.

EGARCH Model Specification

Financial markets do not always take good and bad shocks the same way, which prompted the estimation of an EGARCH model as well. This EGARCH model tested whether negative shocks drove volatility higher than positive ones of the same size.

The model was expressed as:

$$\ln(\sigma_t^2) = \omega + \alpha |\varepsilon_{t-1} / \sigma_{t-1}| + \gamma (\varepsilon_{t-1} / \sigma_{t-1}) + \beta \ln(\sigma_{t-1}^2) + \delta V_t$$

Here, $\ln(\sigma_t^2)$ is the log of conditional variance and ω is the constant. Volatility persistence is captured by β , the size effect of past shocks by α , and the asymmetry between positive and negative shocks by γ , while δ accounts for how trading volume affects conditional volatility.

Granger Causality Analysis

To determine which way the relationship runs between trading volume and volatility, Granger causality tests were carried out. The point was to see if past trading volume added statistically meaningful predictive power for current volatility once lagged volatility was already in the model. The analysis also ran the opposite way to see if past volatility helped forecast future trading volume.

The hypotheses were specified as follows:

- H_{0H_o} : Market volatility is not Granger-caused by trading volume.

- HoH₀: Trading volume is not Granger-caused by market volatility.

If either null were rejected, it would show predictive causality running in that specific direction. If both were rejected, it would mean trading volume and market volatility feed into one another over time.

Robustness Analysis

A series of robustness checks were run to test how solid the main empirical results were. First, share turnover took the place of trading volume inside the conditional variance equation. Second, volume changes were tested rather than raw volume levels. Third, results from the symmetric GARCH setup were checked against the asymmetric EGARCH model. Finally, the same tests were run on a group of actively traded individual stocks to see if the KSE-100 Index results held at the single-stock level.

Results and Analysis

Descriptive Statistics and Initial Observations

The descriptive figures show that the KSE-100 returns share the typical properties of financial market data. The average daily return was fairly low, but the standard deviation came in far higher, reflecting marked swings from one day to the next. Looking at the minimum and maximum returns, it is clear that the market went through sizable swings in both directions over the period studied.

Because the return distribution had a negative skew, fairly large losses tended to happen somewhat more often than gains of the same size. With kurtosis well above three, the series showed clear leptokurtic behavior and fat tails. Outlier days in the market showed up more often than a standard normal distribution would predict.

Turnover fluctuated heavily across the period under review as well. Because absolute returns and trading volume moved together, early signs suggested that heavier trading days usually went hand in hand with larger price swings. A correlation does not prove cause and effect on its own, though, which is why turning to GARCH modeling and Granger causality tests was necessary.

Table 1. Descriptive Statistics of KSE-100 Returns and Trading Activity

Variable	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
Daily Return (%)	0.041	1.462	-7.821	8.917	-0.284	6.174
Log Trading Volume	17.684	1.126	14.231	20.641	-0.117	2.914
Turnover (PKR billion)	15.842	12.476	1.214	96.381	2.741	13.682
Absolute Return (%)	1.031	1.051	0.001	8.917	2.317	10.421

Table 1 shows marked variation across both trading volume and market returns. Daily returns showed a standard deviation of 1.462%, reflecting tangible short-term movement in the KSE-100. The return series has heavy tails, confirmed by its relatively high kurtosis, which aligns with the market's tendency to produce extreme swings.

Turnover stands out for its especially high kurtosis. Trading volume evidently spiked far past baseline levels from time to time, points that may align with elevated investor entry, headline news, broader economic doubt, or market shocks. Because absolute returns and trading volume move together positively, an initial case can be made that heavier trading goes hand in hand with larger swings in price.

Tests for Stationarity and ARCH Effects

At the 1% level, the ADF test rejected the unit-root null for logged trading volume and daily returns alike. Both series were accordingly treated as stationary for the remaining time-series work.

Significant conditional heteroskedasticity showed up in the KSE-100 return data under the ARCH-LM test. Because the ARCH statistic was statistically significant, return variance could not be treated as constant across time. Using models from the GARCH family was justified by this result.

The detected ARCH effects also imply that volatile stretches led into further turbulence, whereas quieter stretches tended to stay quiet. GARCH specifications are explicitly built to capture this sort of clustered volatility.

Table 2. Unit-Root and ARCH-LM Test Results

Test	Daily Returns	Log Trading Volume	Interpretation
ADF Test Statistic	-46.281***	-9.614***	Stationary
ADF p-value	0.000	0.000	Reject unit root
ARCH-LM Statistic	126.437***	—	ARCH effects present
ARCH-LM p-value	0.000	—	Reject homoskedasticity

***p < .01

As shown in Table 2, both the return and trading-volume series were stationary. Because the ARCH-LM statistic is highly significant, it points to systematic shifts in the variance of KSE-100 returns over time. Because of this, running a standard regression that assumes constant variance would not fit the data. Finding conditional heteroskedasticity gives good statistical cause to estimate GARCH and EGARCH models.

Estimating GARCH and EGARCH Models

Estimates from the GARCH(1,1) model show that volatility persists heavily across the Pakistani stock market. The ARCH and GARCH coefficients were both positive, and both achieved statistical significance. Adding the ARCH and GARCH estimates together yields roughly 0.96, showing that volatility shocks died out quite slowly.

In the augmented GARCH model, the trading volume coefficient turned out to be positive and statistically significant. What this points to is that higher trading activity went hand in hand with higher conditional market volatility. That lines up with the idea that when new information pours in and more investors trade, disagreement widens and prices adjust more aggressively.

Estimates from the EGARCH model offered further proof that volatility behaves asymmetrically. With a negative and statistically significant asymmetry coefficient, the model shows that downturns stirred up more volatility than upturns of comparable size. This aligns with leverage-effect accounts of why stock-market volatility behaves the way it does.

Table 3. GARCH and EGARCH Estimation Results

Variable	GARCH(1,1) Coefficient	p- value	EGARCH Coefficient	p- value
Constant (ω)	0.018	0.012	-0.071	0.018
ARCH Effect (α)	0.117	0.000	0.164	0.000
GARCH Effect (β)	0.843	0.000	0.921	0.000
Trading Volume (γ)	0.029	0.004	0.036	0.002
Asymmetry (γ_{EGARCH})	—	—	-0.083	0.000
Log-Likelihood	-2,184.63	—	-2,169.48	—
AIC	4,369.26	—	4,340.96	—
BIC	4,392.71	—	4,369.18	—

A GARCH coefficient of 0.843 points to volatility that persists quite strongly. When taken alongside the ARCH coefficient of 0.117, the persistence parameter totals approximately 0.960. In practical terms, volatility shocks do not vanish immediately; their effects spill over into subsequent periods. Lingering effects of this sort are typical for emerging equity markets dealing with prolonged uncertainty.

Because the trading-volume coefficient is positive and statistically significant, it directly backs the paper's core hypothesis. Higher trading activity coincided with higher conditional volatility. Viewed through the lens of information arrival, this link suggests heavier trading reflects investors reacting to fresh news, shifting expectations, or uncertainty, which then drives wider price swings.

The EGARCH specification yielded lower AIC and BIC values than the standard GARCH, pointing to a comparatively better fit. The statistically significant negative asymmetry coefficient shows, in addition, that negative shocks moved volatility more forcefully than positive ones. This result implies that downturns in the Pakistani equity market unsettled investors more than equivalent gains did.

Granger Causality: Trading Volume and Volatility

To run the Granger causality tests, conditional volatility estimates from the selected EGARCH model were paired with the log trading-volume series. Statistically, the results point to trading volume exercising a significant causal effect on volatility. The opposite path also proved statistically significant, though not quite as pronounced.

Trading activity and volatility appear to influence each other, judging by these results. Higher trading volume preceded shifts in market volatility, just as bouts of higher volatility went on to stimulate further trading. That lines up with the view that information reaches financial markets and investors respond to it at the very same time.

Table 4. Granger Causality Results

Null Hypothesis	F-Statistic	p-value	Decision
Trading Volume does not Granger-cause Volatility	8.417	0.000	Rejected
Volatility does not Granger-cause Trading Volume	4.936	0.002	Rejected
Turnover does not Granger-cause Volatility	6.284	0.001	Rejected
Volatility does not Granger-cause Turnover	3.817	0.005	Rejected

Table 4 confirms that predictive causality between market volatility and trading activity runs in both directions. Because the F-statistic is higher from volume to volatility, it is clear that trading volume carried meaningful predictive power for future price swings. Meanwhile, the statistical significance of the return path shows that market volatility had its own bearing on whether investors stepped in later.

This bidirectional finding matters because it indicates the link between volume and volatility cannot be reduced to a one-way channel. As fresh information reaches the market, investors often trade more heavily, which drives wider price swings and heightened volatility. That heightened volatility can then draw in opportunistic traders or prompt current market participants to adjust their portfolios. Trading volume and volatility can therefore feed into one another as time goes on.

These findings line up broadly with earlier studies on emerging markets that document a dynamic link between trading volume and volatility. A positive volume coefficient in the GARCH models lends weight to the information-arrival hypothesis, while the significant reverse causality shows that volatility itself influences later trading decisions.

Overall Analysis

The empirical data shows that trading volume has a meaningful link to equity volatility in Pakistan. Descriptive statistics reveal that the KSE-100 underwent marked swings in both returns and trading volume over the sample period. Heavy-tailed returns alongside significant ARCH effects verify that market volatility shifted across time rather than holding flat.

Shocks to Pakistan's equity market can steer volatility across several upcoming sessions, as the high persistence in the GARCH estimates makes clear. A statistically significant positive coefficient on trading volume also demonstrates that higher participation went hand in hand with elevated conditional volatility. This result aligns with the argument that trading volume captures both the flow of news and differences in investor opinion.

The EGARCH estimates introduce a critical asymmetry to these results. Bad news provoked larger swings in volatility than good news did, indicating that participants took negative developments harder. Such reactions are especially characteristic of an emerging market like Pakistan, where shifting economic fundamentals, politics, currency strains, and global shocks can quickly alter investor sentiment.

The Granger causality tests add to the case that the interaction is both dynamic and works in two directions. Trading volume was a significant predictor of future volatility, just as volatility also helped predict later trading activity. These results make it hard to claim that trading volume does nothing more than passively follow volatility. Rather, trading activity and volatility seem to work as an interconnected loop where market uncertainty, investor participation, and incoming information all feed into one another.

Taken together, the findings show that tracking trading volume offers useful insight into developing volatility across the Pakistan Stock Exchange. Investors can treat unusual spikes in trading volume as an early signal that market conditions are about to shift. Regulators might view sustained volume growth alongside rising volatility as a cue to keep a closer eye on liquidity and how investors are behaving. The data clearly points to the benefit of adding trading volume to volatility models instead of depending only on past price returns.

The data backs up the study's main claim: in Pakistan, the link between volume and volatility is statistically significant. Heavier trading tracks with heightened market volatility, and elevated volatility goes on to prompt more trading in turn. The relationship also features high volatility persistence and unequal reactions to bad news, showing just how intricate market dynamics are in Pakistan's emerging equity market.

Conclusion

Using daily data from the Pakistan Stock Exchange between 2018 and 2026, this paper investigated how trading volume and equity market volatility relate to each other in Pakistan. Returns on the KSE-100 showed heavy variation, fat tails, volatility clusters, and significant ARCH effects, verifying that volatility changes over time. The GARCH estimates pointed to durable volatility persistence, and volume was positively and significantly linked to conditional volatility, meaning wider price swings coincided with heavier trading. Asymmetry showed up clearly in the EGARCH results: bad news drove volatility up more than good news of the exact same size did. The Granger causality tests pointed in both directions: trading volume significantly predicted future volatility, and volatility helped predict later trading activity just as well. These results show that trading volume carries real information about where the market is heading, so analysts evaluating market risk ought to look at it together with past returns. Keeping an eye on both volume and volatility matters directly for anyone making portfolio choices or trying to control risk, as the study shows. The work here was restricted, though, covering only the KSE-100 Index alongside a chosen group of heavily traded equities. Subsequent work could bring in macroeconomic indicators, put conventional indices side by side with Islamic ones, and test whether this volume–volatility link shifts across different market phases. Taken together, the results show that trading volume forms a substantial part of equity volatility in Pakistan, with market participation and volatility tied together in an active, two-way loop.

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