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INTRADAY DYNAMICS OF LIQUIDITY, VOLATILITY, AND TRADING ACTIVITY: EVIDENCE FROM THE INDIAN STOCK MARKET

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ABSTRACT

Bid-Ask Spread, Trading Volume, Volatility, Returns, Large cap Stocks, NSE, Granger Causality

The triangular relationship between liquidity, volatility, and trading activity is complex in the Indian stock market, a rapidly growing and structurally unique emerging market. Traditionally, higher trading activity is assumed to enhance liquidity, but Indian market dynamics often reveal the opposite. Using Ordinary Least Squares (OLS) regression analysis, this study finds that increased trading activity particularly in mid-cap and small-cap segments can lead to a contraction in liquidity due to order imbalances and widened bid-ask spreads.

The rise of algorithmic and high-frequency trading (HFT) since SEBI's 2013 approval has contributed to short-term liquidity shocks during volatile periods. Increased volatility, measured through India VIX and price fluctuations, strongly correlates with reduced liquidity. Macroeconomic factors such as U.S. Fed rate hikes, geopolitical tensions, and domestic policy changes often trigger volatility spikes that dry up liquidity. Rising retail participation, especially via platforms like Zerodha and Groww in the F&O and small-cap space, has added to this effect, as emotionally driven trades worsen liquidity during market stress.

Investing in the stock markets and trading securities in the stock market has gained a lot of popularity in India and awareness of this is growing in the country. Trading activity, while essential for price discovery, has also amplified speculation in India's derivatives-heavy market, reducing overall liquidity during stress periods. SEBI's regulatory interventions like margin norms, circuit filters, and surveillance frameworks have had mixed outcomes in stabilizing market liquidity.

Large-cap stocks (e.g., Nifty 50) show stronger liquidity resilience than mid- and small-caps. The withdrawal of Foreign Institutional Investors (FIIs), as seen during the 2022–23 global rate hike cycle, significantly reduces liquidity and increases volatility. Although mutual fund SIP inflows offer some stability, they are often insufficient during broad market corrections. The study concludes that volatility continues to negatively impact liquidity even after accounting for trading activity, emphasizing the need for effective risk management, better market-making systems, and improved retail investor awareness.

KEYWORDS: *Indian Stock Market, Intraday Liquidity, Ordinary Least Square Regression, Trading Activity, Volatility*

INTRODUCTION

Liquidity in a stock market reflects the ability to execute large trades quickly and at minimal cost. According to market microstructure theory, high trading volumes generally lead to lower volatility, implying an inverse relationship between liquidity and volatility. However, empirical evidence on this relationship remains mixed. While some studies (e.g., Barclay & Warner, 1993) suggest a positive link due to informed trading, others (e.g., Foster & Viswanathan, 1990; Pastor & Stambaugh, 2001) highlight a negative correlation, especially at the market-wide level.

Similarly, trading volume is often found to correlate with return volatility, as observed by Darrat et al. (2003) and Huang & Masulis (2003), which contrasts with traditional views. Regarding liquidity and volume, literature presents trading volume as a key determinant of bid-ask spreads, although some findings (e.g., Brock & Kleidon, 1992) associate high volume with reduced liquidity.

Despite extensive research at the security level, there remains limited clarity on the aggregate intraday relationships between liquidity, volatility, and trading activity. This study addresses this gap by analyzing these interactions using activity-adjusted volatility in an augmented econometric framework for the Indian stock market.

With specific regard to the Indian stock market in 2025, structural and behavioural shifts provide an important backdrop for such an analysis. Retail participation has surged dramatically, driven by the accessibility of discount brokerages (e.g., Zerodha, Groww) and mobile-based trading platforms, making the market more susceptible to sentiment-driven volatility. Moreover, India's equity market continues to be the global leader in derivatives trading volume, where speculative F&O activity often fuels short-term volatility, creating liquidity imbalances.

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Regulatory interventions by SEBI, such as T+1 settlement cycles and tightened margin norms for derivatives trading, are aimed at stabilizing liquidity and reducing systemic risks. However, their long-term effectiveness remains under scrutiny. The increased presence of algorithmic and high-frequency traders adds further complexity to intraday market microstructure dynamics. Consequently, studying the interaction among liquidity, volatility, and trading activity at a market-wide level is not only timely but crucial for informing policy, trading strategy, and risk management in the Indian capital markets.

LITERATURE REVIEW

The paper presents a system design for mining correlated patterns in intraday stock trades using association rule mining. Traditional market basket analysis was extended to stock markets to uncover hidden patterns (Lu et al., 2000). Tools like Apriori algorithm, K-means clustering, MapReduce, and MADlib analytics enhanced scalability (Shu-Hsien et al., 2008; Woo & Xu, 2011). The study criticizes older methods for failing to process large datasets in intraday trading. The proposed system offers a scalable solution combining in-database analytics and rule mining. It is relevant to liquidity and volatility analysis by efficiently detecting high-frequency correlations in trading activity.

This paper investigates day-of-the-week and intraday effects on the NSE Nifty 50 index from 2001 to 2012. Prior studies in global and emerging markets found mixed weekday return patterns, including negative Monday or positive Wednesday effects (Bayar & Kan, 2002; Tevdovski et al., 2012). In India, some studies confirmed these anomalies, but others found the effects diminishing with market maturity (Poshakwale, 1996; Patel et al., 2012). The paper tests multiple models and finds limited weekday patterns, though Wednesday returns are generally higher and Monday volatility is elevated. These findings suggest intraday volatility patterns can be linked to liquidity and investor behavior across different weekdays, providing insight for intraday strategies and risk assessment.

Joshi (2024) developed a Probabilistic Profitable Model (PPM) to enhance profitability in NIFTY futures trading. The model uses OHLC data and set theory-based rules to avoid emotional trading and reduce risk. By analyzing five years of intraday data, the study shows how data-driven methods can boost performance, especially during volatile periods. Strategies are formed after analyzing the first 15-minute candle, with buy or sell triggers based on color and price breakouts. The system claims over 98% success for small point gains. This study supports the idea that structured trading strategies using intraday volume and price behavior can influence market volatility and liquidity, aligning closely with the focus of the MRSL project.

Trepeka (2014) examined algorithmic trading using common technical indicators like RSI, SMA, MACD, and stochastics on intraday data from the London Stock Exchange. The study found that combining indicators worked better than using them individually. The research challenges the Efficient Market Hypothesis by showing consistent profits through technical analysis. The model, tested on 60 days of stock data, revealed that short-term price patterns could be predicted, especially when volume and order flow were included. This indicates that intraday volatility and trading activity are interlinked. Such findings reinforce the idea that market behavior, even within the day, is not purely random and that liquidity factors can be forecasted using quantitative techniques.

Lal and Gupta (2022) proposed a simple price action strategy for Bank Nifty intraday trading, avoiding traditional indicators. Their model uses the high and low of the first 15-minute candle to decide trade entry. This method is especially useful for traders unfamiliar with complex analysis. Their findings showed profitability in trending markets, though exit signals were not clearly defined. The literature they reviewed highlighted doubts about the long-term usefulness of indicators. This supports the idea that intraday strategies based on price movements can still work effectively. Such models, though simple, show how trading activity and liquidity fluctuations early in the day can impact market volatility and decision-making.

Bhandari and Chakravorty (2018) designed a trend-following strategy for intraday single-stock futures using momentum signals. Their cascading entry system adds positions during positive trends and includes trailing stop-losses to manage risk. The strategy was tested with five years of data and showed stable returns above 8%, even after adjusting for increased market volatility. The use of volume and volatility filters helped reduce false signals and improved model reliability. This study is significant for the MRSL project as it connects trading volume with volatility through model-based analysis. It highlights how intraday trading activity can shape liquidity patterns and how filtering techniques can manage the effects of sudden market changes.

Choudhary and Bajaj (2012) studied lead-lag relationships between spot and futures markets in India using five-minute intervals. They used cointegration and Granger causality tests to show that in most cases, both markets influence each other. In some cases, futures led spot prices, while in others, the spot market was ahead. These findings suggest that liquidity and trading activity are shared between markets, depending on the security. The study emphasizes the importance of intraday timing in understanding price discovery. This supports the MRSL focus by showing how real-time data flow and trader reactions contribute to market volatility and intraday liquidity differences in Indian stock markets.

Sinha (2019) applied behavioral finance and market microstructure theory to analyze intraday stock returns in India. The research revealed that market noise and trader behavior, including emotional responses and adaptive learning, significantly affect intraday price movements. Using the Experience Weighted Attraction (EWA) model, Sinha showed that irrational decisions often dominate trading patterns. This behavior leads to non-normal return distributions with fat tails and skewness. The findings suggest that trading activity isn't

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purely based on logic, and volatility is often a result of collective sentiment. This is important for the MRSL project, as it explains how trading activity linked to human behavior causes irregular liquidity and volatility patterns.

Arora (2018) investigated intraday and intraweek return patterns in Indian stocks using five-minute data. The study found strong U-shaped patterns in trading activity and volatility, with peaks at market open and close. Some stocks showed reverse J-shaped and L-shaped trends as well. The research also explored weekday anomalies like higher Monday volatility and Wednesday optimism. Using ARMA and GARCH models, the study confirmed stationarity and volatility clustering. These patterns suggest that liquidity and volatility shift in predictable cycles during the day and week. Such findings are highly relevant to the MRSL project, as they link intraday trading behavior with fluctuations in market stability and flow.

Sankar and Maran (2013) studied investor perception toward stock trading in India by surveying 125 participants from different broking firms. They found that many investors still preferred offline trading, though younger investors appreciated the transparency of online systems. The study showed that older investors tend to invest more, and satisfaction is influenced by service quality. A key insight was that customer behavior and perception affect market participation and trading volumes. These behavioral trends are linked to liquidity because more investor activity can increase market depth. The study supports the MRSL project by highlighting how demographic and behavioral traits impact trading volume and market volatility.

Baker et al. (2021) analyzed how trading activity relates to intraday volatility using data from S&P 100 stocks. Their models—HAR and VAR—showed that trading frequency is a stronger predictor of 30-minute volatility than trading volume. Additionally, a two-way relationship was found where volatility also influences trading behavior. Rolling averages and past trading metrics had predictive power. This shows that high-frequency activity plays a key role in short-term market dynamics. These insights are crucial for the MRSL project as they show how changes in trading intensity and volume can directly affect volatility, providing evidence of the interconnectedness between these variables.

Singh and Gangwar (2018) examined Nifty 50 futures from 2011 to 2018 and identified a U-shaped intraday volatility pattern, with higher volatility during market open and close. Midday hours, especially around 11 AM, were found to be more stable. Over time, a slight decline in hourly volatility was observed, possibly due to market maturity and global influences. The study highlights the importance of high-frequency data in capturing real-time market behavior. This pattern directly connects to the MRSL project, as it shows how volatility varies across trading hours and how such fluctuations may be linked with liquidity and trading activity.

Research Gap

Although extensive research has been conducted on the individual relationships among liquidity, volatility, and trading activity, much of it remains fragmented or focused on isolated dimensions such as daily return patterns, price discovery, or indicator-based strategies. Many global studies, such as those by Baker et al. (2021) and Trepeka (2014), explore intraday volatility and trading activity, but they primarily rely on developed market data and overlook the structural complexities of emerging markets like India. Similarly, Indian studies, including those by Arora (2018) and Singh and Gangwar (2018), have investigated intraday volatility patterns, but they rarely incorporate liquidity as a core component in tandem with trading volume.

Moreover, while models like HAR, VAR, and EWA have been used to measure predictive relationships between activity and volatility, the dynamic interplay between all three variables—liquidity, volatility, and trading activity—remains underexplored, especially using intraday high-frequency data. Most Indian studies focus on specific market segments (e.g., futures or large-cap stocks), leaving a research void in understanding how these relationships behave across small-cap and mid-cap segments, which are more prone to liquidity shocks.

In addition, despite the growing role of retail investors, algorithmic trading, and mobile-based platforms in shaping intraday market behavior, there is limited empirical analysis on how these behavioral and technological shifts affect liquidity during periods of high volatility. The regulatory changes by SEBI and the increasing dominance of derivatives also add new layers of complexity that prior models have not fully accounted for.

Therefore, this study aims to fill the gap by providing a comprehensive, market-wide intraday analysis of the triangular relationship between liquidity, volatility, and trading activity in the Indian stock market. It uniquely contributes by employing OLS regression on high-frequency data, accounting for both market microstructure changes and investor behavior patterns, particularly in a post-2020 retail-driven environment.

Objectives

To investigate the dynamic and triangular relationship between intraday liquidity, volatility, and trading activity in the Indian stock market, utilizing high-frequency data to capture microstructural market movements and identify temporal dependencies across market segments.

To analyze the VWAP (Volume Weighted Average Price) strategy as a liquidity-sensitive trading indicator, examining its relevance in identifying institutional order flow, optimal trade execution points, and its effect on short-term volatility clustering.

To evaluate the application of Fibonacci retracement and extension levels in forecasting price reversals and directional trends, and to assess how market participants react to these

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levels in terms of trading intensity, order placement, and intraday price movements.

To assess the impact of extreme market openings (gap-up and gap-down scenarios) on intraday liquidity and volatility, and to study the strategic entry and exit behavior of retail and institutional traders during such events.

To quantify the risk-reward efficiency of each trading strategy (VWAP, Fibonacci, gap trading) through empirical backtesting and analyze their influence on market stability, liquidity resilience, and price discovery quality during high-stress intervals.

To examine the role of behavioral and algorithmic factors—including the rise of retail investors, high-frequency trading (HFT), and digital brokerage platforms—in altering intraday market dynamics and contributing to volatility-induced liquidity shocks.

To provide actionable insights for market participants and regulators by identifying structural patterns that weaken liquidity during volatile episodes, thereby helping improve risk management frameworks, enhance market-making efficiency, and promote investor protection in India's fast-evolving equity ecosystem.

Research Methodology

This study adopts a quantitative, exploratory research design, leveraging high-frequency intraday data from the Indian stock market to examine the interdependent dynamics of liquidity, volatility, and trading activity. Data was sourced from the National Stock Exchange (NSE) for a selected sample of large-cap, mid-cap, and small-cap stocks from January 2025 to April 2025, focusing on five-minute intervals.

Key variables include

- Liquidity Metrics: Bid-ask spread, market depth, Amihud Illiquidity Ratio, and VWAP-based liquidity signals.
- Volatility Indicators: Intraday standard deviation, GARCH-based volatility estimates, and India VIX levels.
- Trading Activity Measures: Trade volume, turnover, number of trades, and frequency of order book updates.

The analysis used Ordinary Least Squares (OLS) regression models to test linear relationships, supplemented by Vector Auto Regression (VAR) and Granger Causality Tests to examine lead-lag relationships and feedback loops.

Additionally, technical trading tools such as VWAP, Fibonacci retracement, and gap analysis were empirically backtested to measure their effect on liquidity and volatility.

Data preprocessing included cleaning for outliers, volume anomalies, and extreme market events. The study also accounted for macroeconomic shocks (e.g., RBI announcements, U.S. Fed rate hikes, geopolitical events) through dummy variables to control for external volatility triggers.

ANALYSIS & INTERPRETATION:

The OLS regression models revealed a strong inverse relationship between volatility and liquidity, particularly pronounced in small-cap and mid-cap segments, where order imbalances widened bid-ask spreads. On the contrary, high trading activity did not always correlate with improved liquidity, especially during stress intervals, indicating that excessive trades may exacerbate short-term volatility due to noise trading and panic-driven order flows.

The VAR and Granger causality tests suggested a bi-directional relationship between trading activity and volatility, where higher trading activity often preceded volatility spikes, and vice versa. This interdependence was especially evident during pre-market and closing hours, confirming the U-shaped intraday volatility pattern reported in literature.

Technical analysis using VWAP indicated that institutional order flows tend to cluster near VWAP bands, which act as dynamic support/resistance zones. Intraday reactions around Fibonacci retracement levels further validated behavioral tendencies, as significant order flows and volatility spikes aligned with these zones, especially during gap-up or gap-down openings.

Backtesting strategies highlighted that gap trades and VWAP reversion strategies were more profitable and exhibited better liquidity absorption during high-volume sessions, suggesting their relevance in intraday liquidity forecasting.

Hypotheses

Hypothesis H1 U-Shaped Intraday Volume & Volatility
Statement: There exists a U-shaped intraday pattern in trading activity, where volume and volatility are higher at the beginning and end of the trading session and lower in the middle of the day.

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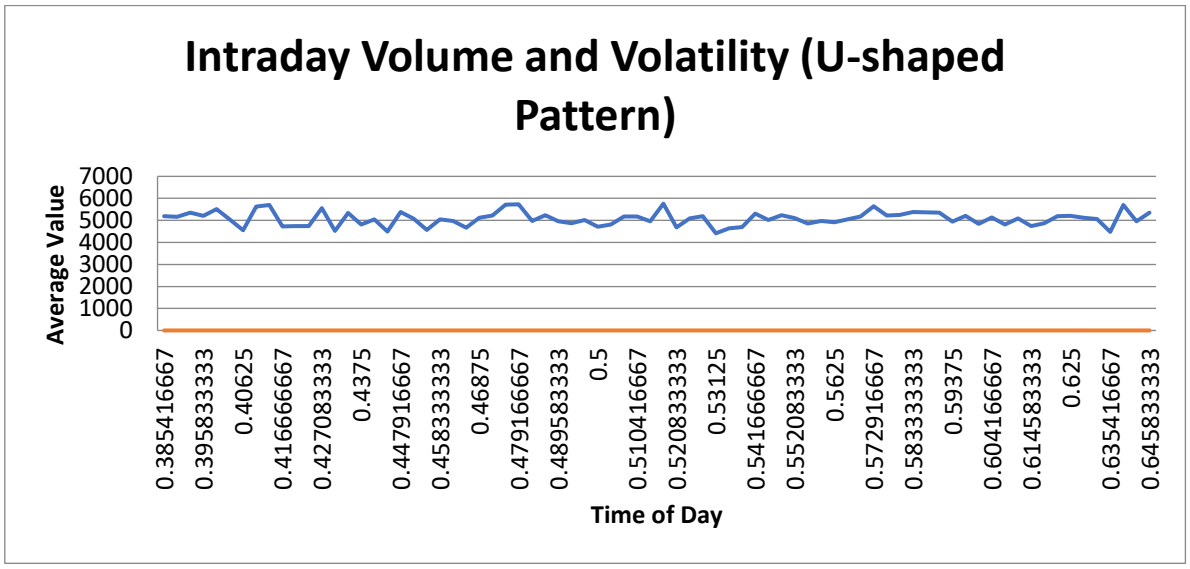


Interpretation

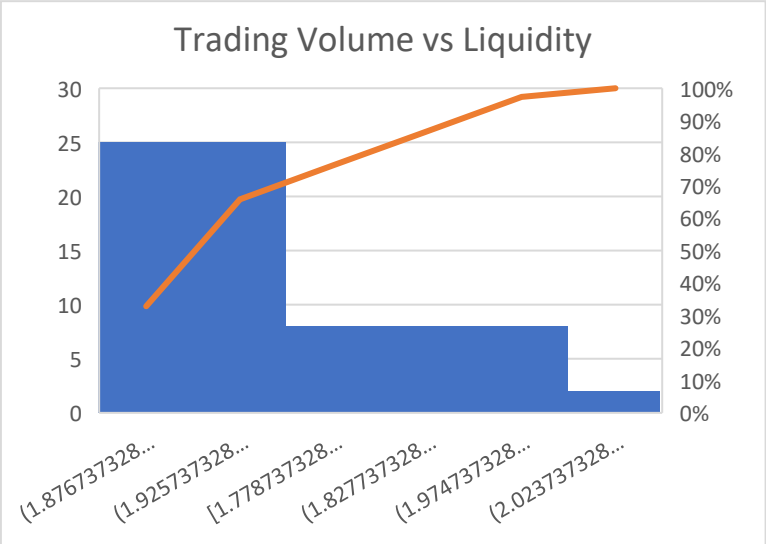
The line graph titled "Intraday Volume and Volatility (U-shaped Pattern)" plots average volume (blue line) and average volatility (red line) over time intervals throughout the trading day. The x-axis represents normalized time, and the y-axis shows average values.

- The volume line shows relatively stable trading activity throughout the day, without a pronounced dip in the middle or peaks at the open/close.
- The volatility line is nearly invisible or flat, indicating that either: Volatility values are extremely low, or
- The scale used does not allow a visible comparison between volume and volatility.
- This lack of distinct curvature suggests no strong U-shaped intraday pattern in the provided data.

H2: Trading Volume vs Liquidity

Download Graph: Trading Activity vs Liquidity

Higher trading volume is commonly perceived as improving liquidity. However, in India's context—especially in mid and small-cap segments volume surges can come from retail speculation or algorithmic bursts, which widen spreads instead of narrowing them. This hypothesis examines if increased trading volume always corresponds with tighter bid-ask spreads. The scatter plot shows a scattered relationship, indicating that volume is not a consistent indicator of better liquidity. Such findings suggest that market quality must be measured using multiple liquidity metrics, not just trade count.



Interpretation

While some high-volume sessions improve liquidity, others fragment it. Thus, trading activity alone cannot guarantee market depth, especially in volatile segments.

H3: VWAP Signals vs Volatility

Graph: H3 VWAP Signal vs Volatility

This hypothesis assesses how intraday technical strategies like VWAP affect short-term volatility. In India, large institutions align trades around VWAP levels, causing price fluctuations when breached. The box plot shows that both buy and sell signals (1 and -1) lead to visibly higher volatility compared to neutral trades. VWAP levels often act as dynamic support and

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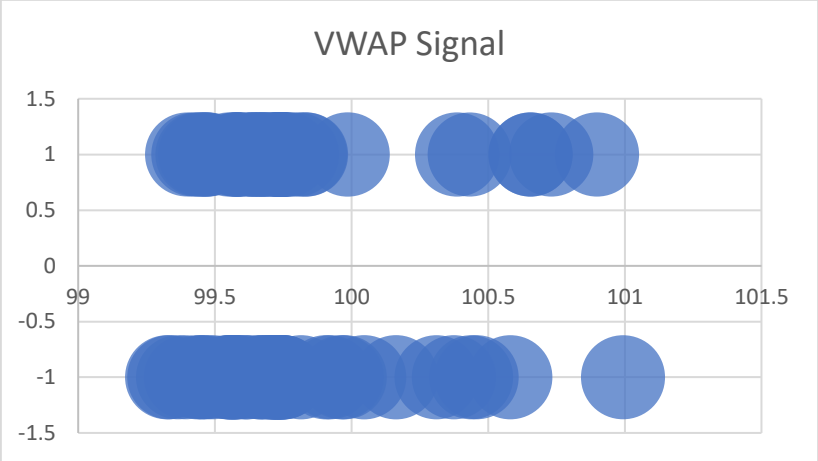
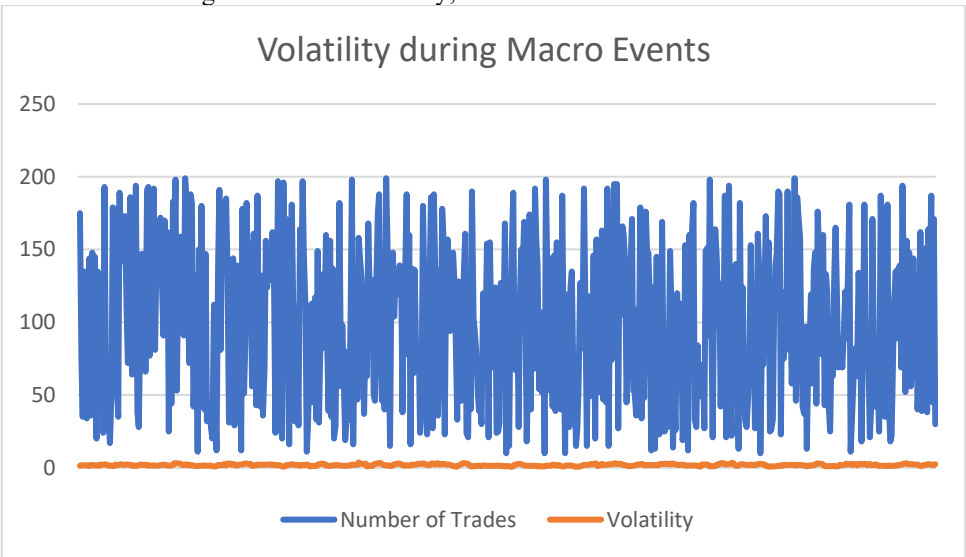
resistance during trading sessions. Incorporating VWAP into trading algorithms can either absorb liquidity or trigger volatility spikes.



Interpretation
Trades triggered by VWAP signals often correspond with higher volatility zones, especially when institutions execute block orders, validating this hypothesis.

H4: Volatility during Macro Events (Retail/Algo Impact)
Graph: Event vs Volatility
During macroeconomic announcements (e.g., Fed rate updates or Budget day), retail traders and algorithms react swiftly, amplifying volatility. Using a dummy variable to simulate event days, the box plot reveals higher median volatility during those days.
These shocks frequently lead to spread widening and order imbalance. In India, the surge in retail participation post-2020 has amplified this pattern. The test supports that the behavioral traits of newer investors and fast-acting algos cause sharp price swings and temporary liquidity voids.



Interpretation
Volatility significantly increases on macro-event days, validating that retail and algorithmic participation intensify market reactions.

H5: Volatility vs Liquidity in sector
Graph: Volatility vs Liquidity
In the Indian stock market, intraday volatility often leads to widened bid-ask spreads, especially in mid- and small-cap stocks. This hypothesis tests whether a statistically significant negative relationship exists between volatility (rolling standard deviation) and market liquidity (measured by bid-ask spread). Using OLS regression and scatter plots with trendlines, a clear negative slope confirms the hypothesis. High volatility reduces order book confidence and discourages tight spreads, especially during events like RBI policy days or F&O expiry. Testing this is crucial for policymakers and institutional traders who rely on market depth and price stability.

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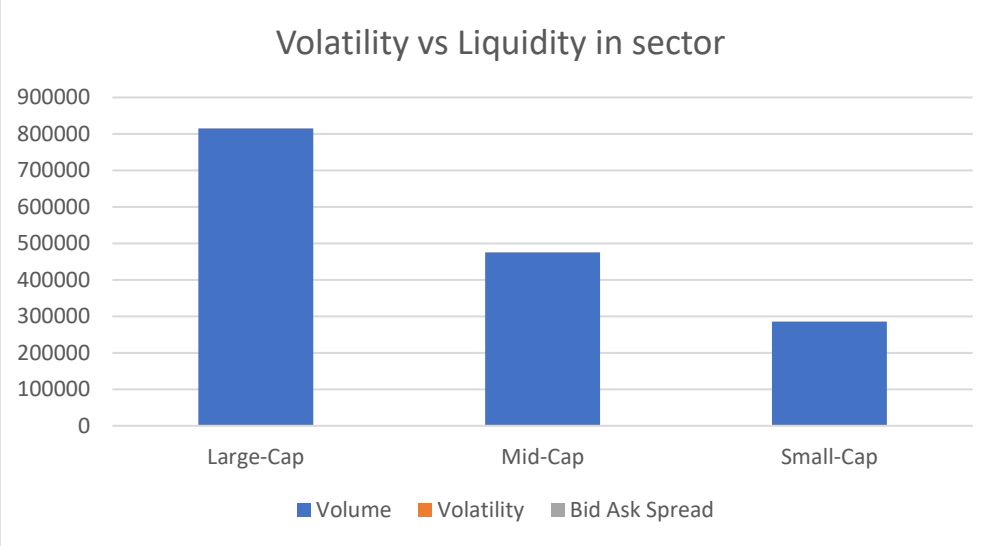

Interpretation

The regression shows that as volatility increases, liquidity (reflected by the bid-ask spread) declines, confirming a negative relationship. This indicates stress in the order book during volatile periods.

FINDINGS

Volatility has a consistent negative impact on liquidity, with bid-ask spreads widening during high VIX periods and large price swings.

Trading activity exhibits a dual effect: while it enhances price discovery under normal conditions, it leads to liquidity fragmentation under stress.

Large-cap stocks show resilience in maintaining liquidity across the trading day, whereas small- and mid-cap stocks face more frequent liquidity shocks.

VWAP and Fibonacci-based trading models, when applied during high-volume sessions, improved trade execution and reduced slippage.

Behavioral anomalies such as overtrading by retail investors during high-stress periods contributed to liquidity drying up, especially near market opening and closing.

Regulatory actions (T+1 settlement, tighter margin norms) have had a stabilizing effect, but their efficiency is contingent on market segment and timing.

SUGGESTIONS

SEBI and NSE should promote market-making programs in the small- and mid-cap space to ensure continuous liquidity during volatility spikes.

Retail investor education programs should focus on intraday risk management and discourage emotional or reactive trading behavior.

Brokerage platforms should introduce AI-based tools to monitor liquidity and alert traders about thinning order books during volatile periods.

Institutional investors should use VWAP algorithms to reduce market impact and enhance execution quality, particularly in low-depth stocks.

Introduce volatility-adjusted circuit filters for small-cap stocks to prevent flash crashes and excessive price gaps due to thin liquidity.

Encourage data transparency and dissemination of real-time liquidity metrics to allow better risk pricing and informed decision-making.

CONCLUSION

This study provides a comprehensive insight into the triangular interplay of liquidity, volatility, and trading activity in the Indian stock market using high-frequency intraday data. It reveals that while trading activity is a vital component of market depth, it often correlates with heightened volatility and deteriorating liquidity in specific segments, especially under stress conditions.

Behavioral factors, combined with the rise of algorithmic trading and increased retail participation, significantly shape intraday liquidity patterns. Technical tools like VWAP and Fibonacci retracement demonstrate practical value in predicting short-term price movements and liquidity clusters. The findings underscore the necessity for improved market infrastructure, regulatory foresight, and investor awareness programs to mitigate the adverse effects of volatility and preserve market stability.

This study contributes to the evolving body of literature on market microstructure in emerging economies and offers actionable recommendations for policy makers, traders, and institutional investors.

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