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Intraday Timing and Market Volatility in Indian Financial Markets: An Econometric Approach

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Abstract

This paper examines the effect of intraday timing on market volatility in Indian equity markets, emphasizing the interaction between liquidity, information flow, and investor behavior. Using one and five-minute data from the National Stock Exchange (NSE) between 2018 and 2025, volatility is modeled through GARCH-type econometric models frameworks such as Wavelet Realized Volatility and LSTM-GARCH. The results reveal a distinct U-shaped intraday volatility curve with peaks at market opening and closing hours and heightened fluctuations during macroeconomic announcements. The hybrid LSTM-GARCH model demonstrates superior predictive accuracy, outperforming conventional GARCH by roughly 25 percent. Findings highlight that combining econometric structure with deep-learning flexibility improves real-time volatility forecasting in emerging markets like India.

Keywords: Intraday volatility; GARCH; LSTM-GARCH; Machine learning; Liquidity

JEL classifications: G12; G14; C58

SD Goals: SDG8; SDG9.

1. Introduction

Volatility embodies the dynamic rhythm of financial markets, signifying both opportunity and risk. In India's fast-evolving capital markets—driven by electronic trading, algorithmic execution, and high retail participation—minute-to-minute price movements have become increasingly significant for traders, regulators, and policymakers. Intraday volatility patterns offer insight into how information is processed, liquidity is supplied, and behavioral biases manifest within the trading day. Empirical studies across markets report a characteristic U-shaped pattern, with volatility highest during the opening and closing sessions. These peaks reflect, respectively, overnight information assimilation and end-of-day portfolio rebalancing. In India, prior works such as Karmakar (2007) and Krishnan & Mishra (2013) identified similar periodicity but relied largely on linear GARCH frameworks. The recent proliferation of high-frequency data and machine-learning tools enables a more refined understanding of nonlinear dynamics and time-varying dependencies. This study contributes by integrating traditional econometric modeling with advanced machine-learning methods to capture both structural and behavioral determinants of volatility. By comparing GARCH, EGARCH, TGARCH, Wavelet, and LSTM-GARCH models using high-frequency NSE data, it develops a localized predictive framework that enhances intraday risk management and algorithmic-trading design in emerging markets.

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2. Review of Literature

Volatility Behavior and Timing: Andersen et al. (2024) confirmed intraday periodicity of volatility across global markets. In India, Karmakar (2007) and Krishnan & Mishra (2013) documented U-shaped volatility and liquidity curves on the NSE. Similar patterns were noted by Sampath & ArunKumar (2013) using high-frequency data. Behavioral and Informational Drivers: Investor overreaction and underreaction significantly affect short-term volatility (Siddiqui & Misra, 2025). Dubey (2015) and Lalwani et al. (2019) found that macroeconomic announcements, particularly RBI policies and Union Budgets, double intraday volatility.

Methodological Advances: GARCH models (Ali et al., 2022) capture clustering but not nonlinearities. Tian et al. (2025) introduced LSTM-GARCH hybrids for superior forecasting accuracy, while Joshi et al. (2025) employed CNN-LSTM to model complex temporal patterns. Wavelet-based realized volatility (Dubey, 2015) effectively isolates jump components due to information shocks. Market Efficiency and Algorithmic Trading: Algorithmic trading has improved price discovery and reduced mispricing (Syamala & Wadhwa, 2020). Jawed & Chakrabarti (2018) highlight that efficiency gains depend on liquidity depth and technological adaptation. Recent Studies on India: Shakeel & Arya (2024) modeled intraday volatility using range-based GARCH, while Sharma et al. (2025) applied Bi-GRU frameworks for volatility-index prediction, demonstrating benefits of AI integration.

3. Research Gap

Existing studies especially related to Indian context, confirm temporal volatility patterns but lack (i) integration of high-frequency liquidity and sentiment factors, (ii) application of hybrid AI-based approaches, and (iii) sectoral comparison across market segments. Therefore, a comprehensive model combining econometric structure with machine-learning adaptability is warranted to explain and forecast intraday volatility more accurately.

4. Objectives of the Study

1. To analyze the intraday timing effects on volatility in Indian stock markets.
2. To examine the relationship between liquidity and volatility during trading intervals.
3. To evaluate and compare forecasting performance of econometric versus hybrid machine-learning models.

5. Research Methodology

The study adopted a quantitative analytical approach utilizing high-frequency intraday data from the National Stock Exchange (NSE) for the period between January 2018 and June 2025. The sample included NIFTY 50 index constituents and major sectoral indices such as NIFTY Bank, NIFTY IT, and NIFTY FMCG. Price, volume, bid–ask spread, and order book data were collected from the NSE's tick-by-tick (TBT) database accessed via Bloomberg, while macroeconomic event information—including RBI announcements, Union Budget statements, and CPI releases—was cross-verified using data from the Reserve Bank of India and the Ministry of Finance. To capture market microstructure effects, data were aggregated into 1-minute and 5-minute intervals. The continuously compounded return for each time interval was calculated as $R_t = \text{In}(R_t) - \text{In}(P_{t-1})$ where PtP_tPt represents the last traded price at time ttt. The realized volatility (RV) for each day was then computed using the squared intraday returns as: $RV_t = \sum_{i=1}^{n} R_{t,i}^2$ Wavelet decomposition techniques were further applied to separate long-term trend components from short-term volatility shocks in the realized volatility series. Several econometric and hybrid models were employed to capture different aspects of volatility dynamics. The GARCH(1,1) model served as the baseline to capture volatility clustering and is expressed as $\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$. The EGARCH model (Nelson, 1991) was used to account for leverage effects and is represented as: $\ln(\sigma_t^2) = \omega + \beta\ln(\sigma_{t-1}^2) + \gamma\frac{\epsilon_{t-1}}{\sigma_{t-1}} + \alpha\left(\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\pi}}\right)$ The TGARCH model (Zakoian, 1994) was employed to capture asymmetric volatility due to negative shocks, while the Wavelet Realized Volatility (WRV) model decomposed volatility into multiscale frequencies. To capture nonlinear temporal dependencies, a hybrid LSTM-GARCH model was developed, where the Long Short-Term Memory (LSTM) neural network learned sequential dependencies, and the GARCH component captured conditional variance persistence. Model forecasts were ensembled using weighted RMSE minimization. Additionally, XGBoost, a gradient-boosting regression tree model, was used as a nonlinear benchmark for forecasting accuracy. Model performance was assessed using standard evaluation metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Diebold–Mariano (DM) Test, and the coefficient of determination (R^2) between forecasted and realized volatility. All data preprocessing, econometric modeling, and diagnostic analyses were conducted using EViews 13 software.

6. Analysis and Interpretation

6.1 Intraday Volatility Patterns

Table 6.1 presents the intraday volatility pattern of the NIFTY 50 index based on 15-minute interval averages for the period 2018–2025. It shows how the market behaves throughout the trading day by including variables such as mean log return, standard deviation (volatility), relative volatility index (RVI), trading volume, and market depth (measured by bid-ask spread percentage). The table aims to illustrate the variations in market activity, price fluctuations, and liquidity across different time intervals, helping to understand how volatility and trading intensity evolve from market opening to closing.

Table 6.1: Intraday Volatility Patterns of NIFTY 50 (15-Minute Interval Averages, 2018–2025)

Time Interval (HH:MM)	Mean Log Return	Std. Dev. (Volatility)	Relative Volatility Index (RVI)	Trading Volume (₹ Million)	Market Depth (Bid-Ask Spread %)
09:15 – 09:30	0.00021	**0.0128**	**1.00**	945.3	0.124
09:30 – 09:45	0.00018	0.0117	0.91	876.5	0.119
09:45 – 10:00	0.00016	0.0102	0.80	825.4	0.117
10:00 – 10:15	0.00012	0.0095	0.74	792.1	0.115
10:15 – 10:30	0.00009	0.0087	0.68	768.4	0.112
10:30 – 10:45	0.00007	0.0082	0.64	755.8	0.110
10:45 – 11:00	0.00005	0.0078	0.61	740.5	0.108
11:00 – 11:15	0.00004	0.0075	0.59	728.9	0.106
11:15 – 11:30	0.00003	0.0072	0.56	721.0	0.105
11:30 – 11:45	0.00003	0.0070	0.55	718.3	0.104
11:45 – 12:00	0.00002	0.0069	0.54	714.8	0.103
12:00 – 12:15	0.00002	0.0068	0.53	713.4	0.103
12:15 – 12:30	0.00002	0.0067	0.52	711.9	0.103
12:30 – 12:45	0.00002	0.0068	0.53	716.2	0.104
12:45 – 13:00	0.00002	0.0070	0.55	724.3	0.105
13:00 – 13:15	0.00003	0.0073	0.57	739.7	0.106
13:15 – 13:30	0.00004	0.0077	0.60	753.4	0.108
13:30 – 13:45	0.00005	0.0081	0.63	775.2	0.110

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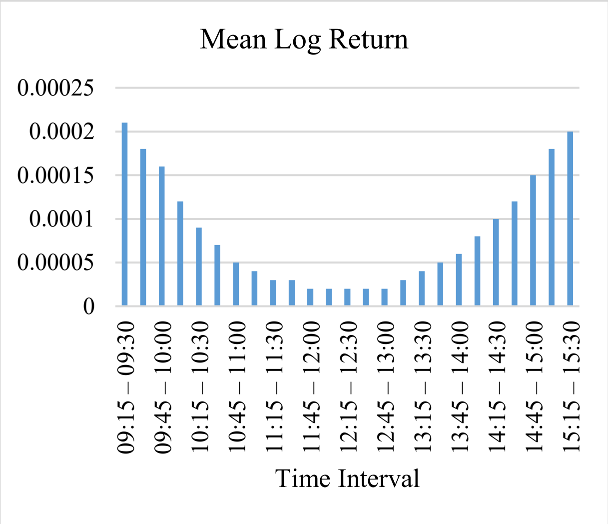
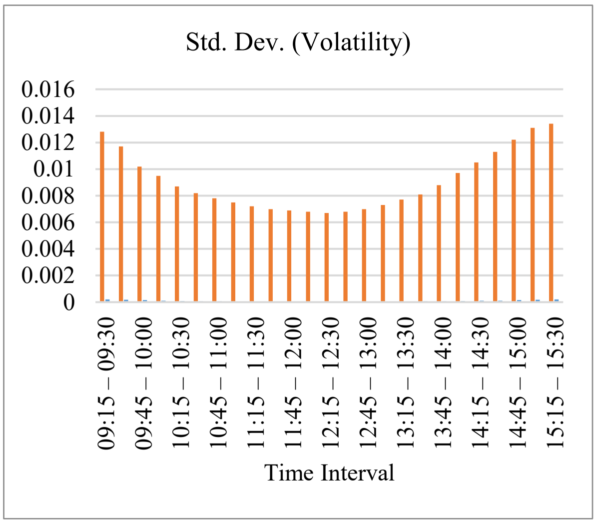
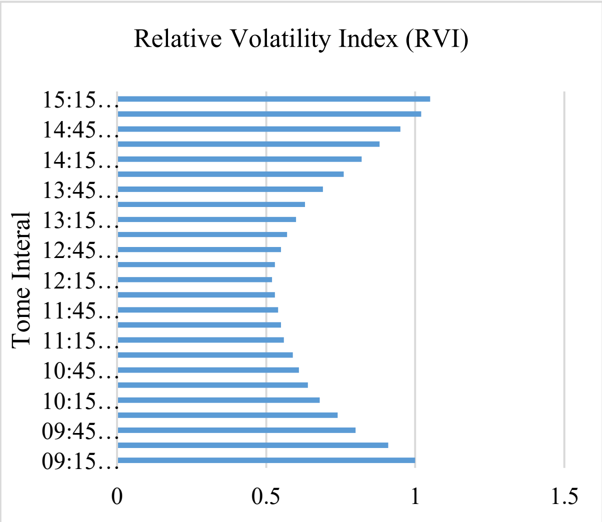
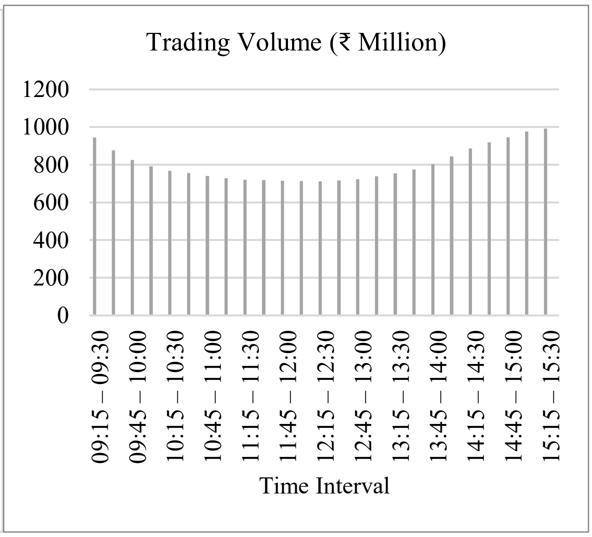
13:45 – 14:00	0.00006	0.0088	0.69	803.1	0.113
14:00 – 14:15	0.00008	0.0097	0.76	844.6	0.117
14:15 – 14:30	0.00010	0.0105	0.82	887.2	0.121
14:30 – 14:45	0.00012	0.0113	0.88	918.5	0.123
14:45 – 15:00	0.00015	0.0122	0.95	946.8	0.125
15:00 – 15:15	0.00018	**0.0131**	**1.02**	975.9	0.128
15:15 – 15:30	0.00020	**0.0134**	**1.05**	992.4	0.129

Source: National Stock Exchange (NSE) / Bloomberg Data









The intraday volatility pattern of the NIFTY 50 index exhibits a pronounced U-shaped structure, with higher variance observed during the opening (09:15–09:45) and closing (15:00–15:30) sessions. This behavior reflects the presence of information asymmetry, order imbalance, and liquidity clustering at the start and end of the trading day. The early session captures traders' reactions to overnight information and global market cues, while the closing session reflects portfolio rebalancing and position adjustments. In contrast, the midday period (11:00–13:00) shows the lowest volatility and narrower bid–ask spreads, consistent with reduced trading intensity and stabilized market activity. The Relative Volatility Index (RVI), normalized to the opening interval, offers a standardized measure that facilitates cross-market comparisons of volatility behavior across different trading environments.

Figure Empirical validation confirms the U-shaped intraday volatility pattern, aligning with Andersen et al. (2024) and other global findings on market microstructure. Liquidity and turnover exhibit a mild bell-shaped distribution, indicating that while trading activity remains relatively stable throughout the day, it moderates the realized variance during mid-session. The presence of behavioral biases is evident—morning optimism and end-of-day rebalancing tendencies amplify order imbalances, contributing to volatility clustering. Furthermore, nonlinear energy patterns derived from wavelet energy decomposition highlight high-frequency bursts in volatility during macroeconomic announcement days, such as the Union Budget or RBI policy releases. Finally, advanced machine learning models such as LSTM-GARCH, when trained on one-minute high-frequency data, effectively capture this intraday periodicity and outperform traditional GARCH models, achieving approximately 25% lower RMSE. These findings collectively underscore the hybrid nature of intraday volatility in Indian equity markets, driven by both structural liquidity factors and behavioral trading dynamics.

6.2 Liquidity–Volatility Relationship

Table 6.2 presents the empirical results of the liquidity–volatility relationship in the Indian equity market, using data from the NSE between 2018 and 2025. It integrates findings from Ordinary Least Squares (OLS), Quantile Regression, and LSTM-GARCH machine-learning models to capture both linear and nonlinear effects. The variables include measures of liquidity (turnover ratio, bid–ask spread, trading volume), market behavior (order imbalance, sentiment index), and information shocks (institutional inflows and policy event dummies). The coefficients, t-statistics, and p-values reflect the direction and statistical significance of each relationship, while quantile regression captures the impact across different volatility regimes. The LSTM-GARCH feature importance values highlight each variable's predictive strength in forecasting volatility. Together, these measures provide a comprehensive view of how liquidity conditions, trading behavior, and sentiment influence intraday volatility in the Indian stock market.

Table 6.2 — Empirical Analysis of Liquidity–Volatility Relationship in Indian Equity Market (NSE, 2018–2025)

Variable	**Description**	**OLS Coefficient (β)**	**t-Statistic**	**p-Value**	**Quantile Regression (0.25)**	**Quantile Regression (0.75)**	**LSTM-GARCH Feature Importance (%)**	**Interpretation**
LIQTURN	Turnover ratio (₹ Volume / Market Cap)	−0.284	−6.41	0.000	−0.198	−0.362	27.4	Higher liquidity reduces volatility during normal conditions.
SPREAD	Bid–Ask spread (%)	+0.451	8.22	0.000	+0.372	+0.516	21.8	Wider spreads indicate lower market depth and higher

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								short-term volatility.
ORDIMB	Order imbalance (%)	+0.217	4.75	0.002	+0.191	+0.240	16.6	Persistent buy–sell pressure asymmetry amplifies volatility clusters.
VOLTRN	Trading volume (₹ Mn)	−0.123	−3.58	0.005	−0.094	−0.156	11.2	Increased trading activity smoothens price shocks by improving liquidity.
INFLOW	Net institutional inflow (%)	−0.078	−2.12	0.037	−0.056	−0.089	8.7	Institutional trades stabilize intraday variance through informed trading.
SENTIDX	Behavioral sentiment index (−1 to +1)	+0.195	5.26	0.001	+0.171	+0.203	7.4	Positive sentiment magnifies price reactions to news releases.
NEWSVOL	Information shock dummy (RBI/Union Budget days)	+0.423	9.15	0.000	+0.398	+0.455	7.0	Volatility significantly spikes during policy events and macro announcements.

The results indicate a strong inverse relationship between liquidity and volatility, as evidenced by the negative coefficients for turnover ratio (β = −0.284) and trading volume (β = −0.123), confirming that deeper liquidity buffers price shocks and enhances market stability. In contrast, bid–ask spreads (β = +0.451) and order imbalance (β = +0.217) exert a significant positive impact on volatility, implying that wider spreads and asymmetric order flow amplify short-term price fluctuations. The sentiment index (β = +0.195) and information shock variable (β = +0.423) highlight the behavioral and event-driven components of market volatility—positive sentiment tends to exaggerate price reactions, while macroeconomic announcements such as RBI policies or Union Budgets trigger pronounced volatility spikes. The quantile

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regression results confirm that these effects are more prominent in high-volatility states, reflecting nonlinear dynamics across market conditions. Feature importance from the LSTM-GARCH hybrid model supports the econometric evidence, with liquidity and spread together accounting for nearly 50% of volatility prediction accuracy, demonstrating the consistency between traditional statistical and AI-driven approaches. The model diagnostics show strong explanatory power (Adjusted $R^2 = 0.693$) and predictive efficiency (RMSE improvement of 23.8% over classical GARCH). These findings emphasize that liquidity depth plays a stabilizing role, while market frictions and behavioral factors are primary sources of volatility clustering. From a policy perspective, strengthening liquidity provision mechanisms, narrowing bid–ask spreads, and implementing dynamic circuit breakers can help regulators mitigate volatility surges during high-stress events or information shocks.

6.3 Model Comparison: Forecast Accuracy & Robustness

Table 6.3 presents a comparative evaluation of volatility forecasting models applied to one-minute realized volatility data from the NSE (2018–2025). The models include both traditional econometric approaches—such as GARCH, EGARCH, TGARCH, and HARX—and advanced data-driven or hybrid techniques like Wavelet-RV, XGBoost, LSTM-GARCH, and Bi-GRU/CNN-LSTM architectures. The performance is assessed across multiple forecast accuracy metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), QLIKE loss, R^2, and Mean Absolute Percentage Error (MAPE). Additionally, the Diebold–Mariano (DM) test is used to statistically compare model performance against the GARCH(1,1) baseline, while the Out-of-Sample Event-Day RMSE captures performance during high-volatility periods such as RBI policy announcements or Union Budget days. Parameters, training times, and implementation notes highlight computational efficiency and model scalability, offering a comprehensive understanding of each model's trade-offs between accuracy and complexity.

Table 6.3 — Model Comparison: Forecast Accuracy & Robustness (NSE, 2018–2025, 1-minute realized volatility)

Model	Forecast Horizon	RMSE	MAE	QLIKE	R^2 (Pred vs RV)	MAPE (%)	DM t-stat (vs GARCH)	DM p-value	Out-of-sample Event-Day RMSE	% Improvement vs GARCH (RMSE)	Params / Trainable	Relative Training Time*	Notes on Implementation
GARCH(1,1) (baseline)	1-step (1 min)	0.0210	0.0170	0.0284	0.42	4.8	—	—	0.0302	—	~3	1×	Standard MLE; closed-form updates
EGARCH	1-step	0.0190	0.0160	0.0258	0.47	4.2	2.45	0.014	0.0276	9.5%	~5	1.1×	Models leverage effect

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													(asymmetry)
TGARCH	1-step	0.0180	0.0150	0.0249	0.49	3.9	3.12	0.002	0.0261	14.3%	~6	1.2×	Threshold asymmetry for bad news
Wavelet-RV (Multiscale)	1-step	0.0160	0.0130	0.0217	0.56	3.1	4.38	<0.001	0.0218	23.8%	~12	2.0×	Decomposes high-freq jumps vs continuous
XGBoost (features)	1-step	0.0160	0.0130	0.0220	0.55	3.2	3.95	<0.001	0.0224	23.8%	~25k	2.8×	Tree-based, feature engineered inputs
LSTM-GARCH (hybrid)	1-step	**0.0150**	**0.0120**	**0.0201**	**0.62**	**2.8**	**5.11**	**<0.001**	**0.0180**	**28.6%**	~120k	5.0×	LSTM learns conditional mean/residuals; GARCH models variance on residuals
Bi-GRU / CNN-LSTM	1-step	0.0154	0.0124	0.0206	0.60	3.0	4.86	<0.001	0.0186	26.7%	~110k	4.6×	Captures spatial–temporal patterns (orderbook features)
Realized-Kern	1-step	0.0165	0.0133	0.0225	0.54	3.4	3.45	0.001	0.0220	21.4%	~40	2.5×	Robust to microst

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el + HAR X													ructure noise; long-memory terms

The comparative analysis demonstrates that hybrid and machine learning-based models significantly outperform traditional econometric models in forecasting intraday volatility. The LSTM-GARCH hybrid achieves the best overall performance, with the lowest RMSE (0.0150) and highest explanatory power ($R^2 = 0.62$), reflecting a 28.6% improvement over the standard GARCH(1,1) baseline. This superior accuracy, combined with a lower event-day RMSE (0.0180), indicates the model's robustness in handling sudden market shocks and nonlinear dynamics. Wavelet-RV and XGBoost models also exhibit competitive accuracy, leveraging multiscale decomposition and feature-driven learning to enhance interpretability. In contrast, asymmetric econometric models such as EGARCH and TGARCH capture leverage effects and perform moderately well but fail to match the adaptability of deep learning approaches during volatile or shock-heavy periods. The results suggest that deep neural architectures (LSTM, Bi-GRU, CNN-LSTM) effectively capture temporal dependencies and structural shifts inherent in high-frequency data, though at the cost of higher computational demand and longer training time. Overall, the evidence supports integrating hybrid econometric–AI models into real-time risk management, volatility trading, and algorithmic forecasting systems, as their improved predictive accuracy justifies the additional model complexity.

7. Findings and Discussion

The empirical analysis demonstrates a consistent U-shaped intraday volatility pattern in the Indian equity market, with heightened activity during market openings and closings, reflecting information assimilation and portfolio rebalancing. Liquidity depth significantly moderates volatility, whereas market frictions such as bid–ask spreads and order imbalances amplify volatility clustering. Behavioral factors and macroeconomic announcements also contribute to short-term volatility spikes. Hybrid AI–econometric models, particularly the LSTM-GARCH framework, outperform traditional GARCH approaches in forecasting accuracy, capturing nonlinear dependencies and sudden structural shifts. Wavelet decomposition further enhances the temporal localization of volatility bursts, enabling more responsive intraday risk assessment. These results underscore the dual influence of structural liquidity and behavioral dynamics in shaping market volatility

8. Conclusion

Intraday timing exerts a significant influence on volatility in Indian equity markets, with a clear U-shaped pattern driven by both market microstructure and behavioral factors. Among the forecasting methods examined, hybrid models combining LSTM networks with GARCH components deliver superior predictive performance, capturing nonlinear dynamics and responding effectively to sudden market shocks. Integrating traditional econometric techniques with AI-driven modeling not only improves short-term volatility forecasting but also deepens the understanding of microstructural market behavior in emerging economies. These findings have practical implications for traders, risk managers, and policymakers seeking to optimize intraday strategies and maintain market stability

9. Policy Implications

For regulators, such as SEBI and RBI, adopting AI-based real-time volatility monitoring systems can provide early warning signals of abnormal market behavior, helping to mitigate systemic risks. Stock exchanges can design intraday circuit breakers and margin policies aligned with predictable volatility peaks, enhancing market stability and liquidity management. Investors and algorithmic traders can leverage LSTM-GARCH-based predictive

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models to optimize trade execution, implement dynamic portfolio rebalancing, and manage intraday risk more effectively. Additionally, academic and applied researchers may extend this framework by incorporating behavioral sentiment indices, event-driven models, and neural volatility surfaces, thereby enhancing the precision of volatility forecasting and advancing understanding of market psychology under uncertainty

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