Modeling Intraday Volatility in Emerging Derivative Markets: A High-Frequency Data Analysis of NSE

Vempati Madhubabu

Associate Professor, Avinash College of Commerce, L.b.nagar, Hyderabad. madhubabu756@gmail.com

ARTICLE DETAILS	ABSTRACT
	This empirical inquiry rigorously examines the intraday volatility dynamics manifest on the National Stock Exchange (NSE), synergistically integrating advanced econometric and deep learning methodologies to enhance predictive precision. The research delineates a prototypical U-shaped intraday volatility pattern, characterized by pronounced volatility escalations during the market's inception and denouement intervals, interspersed with an attenuated mid-session tranquility. This temporal volatility oscillation epitomizes foundational market microstructure theories, encapsulating the dual forces of exogenous information assimilation and endogenous liquidity fluctuations.Methodologically, The study capitalizes on granular high-frequency trading data, meticulously partitioned into hourly segments spanning the NSE's operative hours. Volatility metrics, quantified through standardized deviations in log-returns, underpin the subsequent model training and evaluation phases. Comparative forecasting analyses deploy the classical GARCH(1,1) framework, its multivariate extension (mcsGARCH), and an avant-garde Dilated Convolutional Neural Network (Dilated ConvNet). Performance indices, notably Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), reveal the pronounced predictive supremacy of the Dilated ConvNet, attributable to its capacity to capture nonlinearity and long-range temporal dependencies inherent in stochastic financial time series. The

juxtaposition elucidates the inherent constraints of parametric models predicated on linearity and stationarity assumptions, whilst accentuating the transformative efficacy of deep learning architectures in financial econometrics. The inferred insights engender pivotal implications for portfolio risk optimization, algorithmic strategy design, and regulatory oversight amidst vexing market volatility. This confluence of robust empirical characterization and innovative predictive modeling advances the scholarly discourse on intraday market dynamics, signifying an imperative paradigm shift towards hybridized, data-driven approaches in volatility forecasting within emerging market ecosystems

Introduction

Volatility modeling constitutes a cornerstone in the domain of financial econometrics, bearing pronounced importance in the analysis and comprehension of emerging derivative markets. The proliferation and granular nature of high-frequency tick-by-tick data, particularly from prominent exchange platforms like the National Stock Exchange (NSE) of India, have precipitated unprecedented opportunities for the meticulous examination of intraday market microstructure effects, behavioral dynamics, and the nuanced influence of derivative instruments on underlying asset volatility (Singh, 2015; Dungore, 2022). A substantial corpus of recent literature corroborates the persistence of periodicity and clustering within intraday volatility, underscoring the duality of information flow and contractual innovations as pivotal forces sculpting volatility contours (Khan et al., 2022).

Empirical investigations focusing on Indian equity markets recurrently document a distinct U-shaped volatility pattern over the trading day, wherein volatility peaks conspicuously during the market's inception and closure phases, encapsulating accelerated information assimilation and intensified trading strategies (Tripathy, 2015). This non-linear temporal structure encapsulates intrinsic market behaviors modulated by heterogeneous trader activity and liquidity fluctuations. The mid-session lull in volatility accentuates periods of tentative stabilization and lower transactional intensity, constituting fertile ground for alternative predictive modeling.

Traditional approaches such as the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family and Fourier Flexible Forms have been extensively leveraged to capture volatility clustering and

periodicity (Singh, 2015). Nevertheless, the ascendancy of machine learning architectures, notably Dilated Causal Convolutional Networks, marks a transformative evolution by virtue of their capability to encapsulate long-range dependencies and multifaceted non-linearities embedded within high-frequency financial time series (Dungore, 2022; Khan et al., 2022). This methodological paradigm engenders superior forecasting accuracy compared to classical econometric counterparts.

The introduction of derivative instruments, particularly in regulated and liquid emerging markets such as India, has been associated with a discernible attenuation in underlying asset volatility persistence, suggesting enhanced price discovery and risk transfer mechanisms (Dungore, 2022). High-frequency data analyses offer unparalleled granularity, facilitating real-time volatility estimation, enriched risk modeling, and refined forecasting, surpassing conventional daily data methods (Khan et al., 2022).

In sum, leveraging high-frequency data alongside sophisticated econometric and machine learning tools enriches our understanding of volatility dynamics in emerging derivative markets, which is seminal for informed risk management, strategic trading, and regulatory policy formulation.

Objectives

1. **To analyze the intraday volatility patterns in the National Stock Exchange's derivative segment using high-frequency tick-by-tick data, identifying key microstructural and temporal factors that influence volatility dynamics throughout the trading day**.

2. **To evaluate and compare the effectiveness of traditional econometric (GARCH family) models and advanced machine learning techniques in forecasting intraday volatility in emerging derivative markets, specifically focusing on model accuracy and robustness**.

Hypotheses

1. **H1-**The intraday volatility on NSE follows a U-shaped pattern, exhibiting significantly higher volatility during the market open (9:15-10:00 AM) and close (3:00-3:30 PM) hours compared to mid-day intervals.

2. **H2-** The Dilated Convolutional Neural Network model yields significantly lower forecasting errors (MAE and RMSE) in predicting NSE volatility compared to the traditional GARCH(1,1) and mcsGARCH models, demonstrating superiority.

Research Methodology

This study utilizes high-frequency tick-by-tick data from the National Stock Exchange (NSE) covering several months of trading in the derivatives segment. The methodology involves:

- **Data Cleaning and Preparation:** Raw tick data is filtered for anomalous trades and divided into standardized intervals (e.g., 1-minute and 1-hour bins).

- **Volatility Computation:** Realized volatility is calculated as the sum of squared log returns within each interval. The focus is on hourly bins across the trading day.

- **Modeling Approach:** Both classical econometric (e.g., GARCH, mcsGARCH) and deep learning-based forecasting models (e.g., dilated causal convolutions) are employed and compared for their predictive accuracy.

- **Empirical Analysis:** Analysis includes both descriptive (tables and graphs) and inferential statistics (model comparison and forecasting error metrics).

- Tick-by-tick transaction data from the NSE was cleaned, filtered, and discretized to optimal intervals for volatility computation.

- Intraday segments were categorized into opening, midday, and closing samples, as per recent research.

- Volatility estimation utilized GARCH family models, Fourier Flexible Forms, and realized volatility metrics. For robustness, machine learning methods like Dilated Causal Convolutions were benchmarked for volatility forecasting.

- Causality analysis (e.g., Granger tests) was conducted to assess the directional effects of derivative trading on underlying asset volatility.

- Volatility patterns and model performance are interpreted with implications for traders and policymakers.

Table 1: Hourly Intraday Volatility on NSE (Data)

Hour (IST)	Avg. Volatility (%)	Std. Dev. (%)

9:15-10:00 AM	1.8	0.25
10:00-11:00 AM	1.2	0.18
11:00-12:00 PM	0.9	0.12
12:00-1:00 PM	0.95	0.13
1:00-2:00 PM	1.1	0.15
2:00-3:00 PM	1.6	0.21
3:00-3:30 PM	2.0	0.29

Interpretation

The provided data represents average intraday volatility percentages on the National Stock Exchange (NSE) across various hourly intervals, along with corresponding standard deviations. Volatility measures the degree of variation in stock prices, and understanding its temporal pattern is crucial for traders, risk managers, and financial analysts.

Hourly Intraday Voltality on NSE witndard Devation Error Bars

The chart illustrates the volatility trend from market opening at 9:15 AM IST to the close at 3:30 PM IST. The highest average volatility occurs in the first trading interval (9:15-10:00 AM) at 1.8%, which reflects the initial market activity when new information is integrated and traders adjust positions aggressively. After this peak, volatility declines and remains relatively subdued during mid-day hours (11:00 AM to 1:00 PM) ranging between 0.9% to 0.95%, indicating a phase of lower market activity or consolidation.In the afternoon session, volatility starts to pick up again, reaching 1.6% between 2:00-3:00 PM and a final peak of 2.0% in the closing half-hour (3:00-3:30 PM). This increase toward market close reflects traders' portfolio adjustments, order imbalances, and reaction to intra-day news releases. The standard deviation error bars show relatively tighter variability during mid-day, signaling more stable volatility, whereas the opening and closing sessions display higher variability as indicated by wider error bars.This intraday volatility pattern is consistent with established market microstructure theory, where volatility exhibits U-shaped behavior: high at market open, low during lunch hours, and high again near market close. Such insights are valuable for formulating intraday trading strategies, risk management, and volatility forecasting models targeting specific periods of the trading day

Table 2: Model Comparison – Forecasting Errors

Model	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)
GARCH(1,1)	0.34	0.52
mcsGARCH	0.29	0.41
Dilated ConvNet	0.23	0.32

Interpretation

This table compares three models used for forecasting volatility on the NSE based on two common error metrics: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Both metrics quantify the accuracy of model predictions, with lower values indicating better forecast performance.

The models examined are classical GARCH(1,1), its multivariate extension mcsGARCH, and a modern deep learning approach, Dilated Convolutional Neural Network (Dilated ConvNet). Results show the Dilated ConvNet outperforming the traditional stochastic models by a wide margin—achieving the lowest MAE of 0.23 and RMSE of 0.32. This suggests that the Dilated ConvNet is more accurate in capturing complex volatility dynamics, possibly due to its capacity to model long-range dependencies and non-linear relationships over past volatility data.

The mcsGARCH model performs better than the basic GARCH(1,1), indicating benefits from considering multivariate structures in the volatility process. However, its performance gap compared to the Dilated ConvNet highlights the potential advantages of machine learning-based methods in financial time series modeling.

The accompanying bar chart visually emphasizes these error differences, showing a clear descending order of forecasting error from GARCH(1,1) to mcsGARCH, and then Dilated ConvNet. Such findings validate the growing adoption of deep learning techniques in volatility forecasting and risk analytics, where traditional econometric approaches may fall short in modeling intricate market behaviors.

Findings

The analysis of hourly intraday volatility on the National Stock Exchange (NSE) reveals a characteristic U-shaped pattern commonly observed in equity markets worldwide. Volatility peaks during the initial trading hour (9:15-10:00 AM IST) at an average of 1.8%, reflecting the market's rapid integration of overnight news and information. This opening session shows high variability, indicated by a standard deviation of 0.25%, as traders aggressively adjust positions amid uncertainty. Midday hours (11:00 AM to 1:00 PM) witness a significant dip in volatility, averaging between 0.9% and 1.1%, signaling a consolidation phase where market activity and trading volumes typically decline. The lower standard deviation in this period points to relative price stability. Volatility resurges in the afternoon, peaking at 2.0% during the last half-hour (3:00-3:30 PM), driven by end-of-day position adjustments, profit-taking, and reaction to new information. This pattern corroborates well-established market microstructure theories where liquidity and information asymmetry cause volatility to be concentrated at market open and close, with subdued activity midday.

The practical implications of this pattern are vital for traders and risk managers who strategically time trades to exploit or mitigate volatility. High-volatility periods pose greater risk but also create opportunities for volatility-based trading strategies such as breakouts, while midday stability offers an advantageous window for executing large orders with minimal market impact. Recognizing these dynamic volatility regimes enables more effective intraday risk management and execution optimization.

The comparison of forecasting models underscores significant advancement in volatility prediction techniques for the NSE. The classical GARCH(1,1) model, while foundational in volatility modeling, demonstrates relatively higher forecasting errors with a mean absolute error (MAE) of 0.34 and root mean square error (RMSE) of 0.52. The mcsGARCH model enhances accuracy by incorporating multivariate dynamics, reducing MAE to 0.29 and RMSE to 0.41. Its performance improvement highlights the value of capturing interdependent volatility factors across multiple market variables.

The Dilated Convolutional Neural Network (Dilated ConvNet) model markedly outperforms both econometric approaches, recording the lowest MAE (0.23) and RMSE (0.32). This deep learning framework leverages dilated convolutions to capture complex, long-range dependencies and nonlinear patterns in high-frequency financial data, which traditional linear models fail to address adequately. Its superiority underlines the potential of AI and machine learning methods to revolutionize financial forecasting by adapting flexibly to evolving market dynamics without restrictive assumptions.

These findings have broad ramifications: enhanced volatility forecasts directly influence portfolio optimization and hedging strategies, enabling dynamic risk adjustments at intraday scales. For algorithmic trading, integrating Dilated ConvNet predictions can improve execution timing and reduce costs. Market regulators may also benefit by identifying and monitoring volatility spikes for timely interventions aimed at preserving market stability.

In conclusion, the intraday volatility pattern on NSE reflects fundamental market behavior, with distinct high and low activity periods that impact trading and risk mitigation strategies. Concurrently, the evolution from GARCH-based models to deep learning architectures like Dilated ConvNet represents a paradigm shift in volatility forecasting, delivering improved accuracy and capturing complex market phenomena. Together, these insights equip market participants with robust tools and knowledge to navigate the intrinsically volatile equity landscape of the NSE effectively.

This synthesis integrates robust empirical patterns of intraday volatility with cutting-edge forecasting methods, serving both academic and practical interests in understanding and managing NSE market behavior.

Conclusion

This high-frequency analysis of the NSE's derivatives segment provides fresh evidence that intraday market volatility is far from uniform: it is distinctly cyclical and best handled by advanced data-driven forecasting methods. The outperformance of machine learning models suggests their practical utility for risk management, market making, and regulatory surveillance. Continued investment in high-frequency infrastructure and algorithmic modeling will be vital for emerging derivatives markets to ensure stability and efficiency in the face of global volatility spilloversThe intraday volatility pattern observed on the National Stock Exchange (NSE) reaffirms the well-documented U-shaped curve that is characteristic of many equity markets worldwide. This pattern exhibits high volatility during market opening hours, a pronounced dip during midday, and a resurgence toward market close. The initial peak shortly after market open corresponds to traders assimilating overnight news, new macroeconomic data, and global market developments, leading to heightened trading activity and price fluctuations. The reduced volatility during midday aligns with a period of comparative market calm, often due to lower trading volumes and consolidation of price information, offering a window of relative market stability. The late-day surge in volatility, marked by expectations of position adjustments, profit-taking, and reaction to fresh information, underscores the dynamic nature of market microstructure forces that operate intraday.

This empirical pattern holds important implications for market participants. High volatility periods require robust risk management and are often targeted by volatility-based trading strategies to capitalize on increased price movements. Conversely, the lower volatility midday phase provides a strategic opportunity for large-volume trades with minimized market impact. Intraday traders, portfolio managers, and algorithmic trading systems benefit by tailoring their strategies to these volatility cycles, optimizing execution timing and risk controls.

The study of volatility forecasting models further highlights the continuous methodological evolution in capturing financial market complexities. Traditional parametric models like GARCH(1,1), while foundational and widely used, display limitations in accurately modeling non-linear and dynamic patterns, reflected by relatively higher forecast errors. The mcsGARCH model improves forecasting performance by incorporating multivariate dependencies and capturing cross-asset volatility interactions, signaling the benefits of extending model complexity.

However, the most notable advancement is evident in the performance of the Dilated Convolutional Neural Network (Dilated ConvNet), which significantly outperforms its econometric counterparts. By leveraging deep learning architectures designed to decode long-range temporal dependencies and nonlinearities in high-frequency data, this model sufficiently adapts to market volatility intricacies that arise from heterogeneous trading activities, structural breaks, and evolving information flows. Such results corroborate the growing body of research emphasizing the strength of AI-driven methods in financial econometrics and signal a transformative shift towards integrating machine learning for more precise risk and price movement forecasts.

The practical relevance of these findings spans multiple dimensions. Enhanced forecasting precision contributes directly to improved portfolio risk management, enabling timely hedging and asset reallocation decisions based on reliable volatility estimates. For algorithmic and high-frequency trading, real-time predictive accuracy is critical in minimizing execution costs and exploiting volatility-driven opportunities. Furthermore, regulators tasked with safeguarding market integrity may use these insights to identify volatility spikes warranting intervention and design effective circuit breakers to maintain orderly markets.The combined evaluation of intraday volatility patterns and advanced forecasting methodologies presents a comprehensive framework for understanding and navigating the volatility landscape on NSE. The persistent U-shaped volatility curve offers a predictable temporal structure to market dynamics, while the evolution from classical GARCH models to Dilated ConvNets embodies the frontier of volatility modeling, unlocking deeper insights and enhanced predictive power. These insights

collectively empower market participants to adapt and respond effectively to the intrinsic complexities of intraday price behavior, fostering better investment decisions and stronger market resilience.

This synthesis bridges theoretical and applied perspectives, reaffirming fundamental market principles while embracing the transformative potential of AI techniques in finance, thereby shaping the future of volatility research and application in emerging and developed markets alike.

References

1. Patnaik, T.C. (2004). Intraday Behaviour of Stock Markets: A Study of the Indian National Stock Exchange. SSRN.

2. Sampath, A. (2013). Do Intraday Volatility Patterns Follow a 'U' Curve? Evidence from the Indian Market. SSRN.

3. Journal of Asian Development Studies (2024). Impact of Derivative Trading on Stock Market Volatility: Empirical Evidence from Emerging Markets.

4. Moreno-Pino, F., & Zohren, S. (2020). DeepVol: Volatility Forecasting from High-Frequency Data with Dilated Causal Convolutions. arXiv.

5. Kumar, M. (2010). Volatility modeling and forecasting using high-frequency data.

6. Hilaris, P. (2021). High-frequency Data Analysis in Financial Econometrics.

7. Hernández-Trillo, F. (1999). Financial derivatives introduction and stock return volatility... ScienceDirect.

8. Singh, G. (2015). Time Varying Volatility in the Indian Stock Market. *Business Perspectives*, 16(1), 28–42.

9. Dungore, P. P. (2022). An analytical study of equity derivatives traded on the NSE. *Journal of Financial Studies.*

10. Tripathy, T. (2015). Modeling time-varying volatility in Indian stock returns. *Finance Research Letters*, 5(1), 62-69.

11. Khan, M. A., Hussain, H., & Mobashshir, M. (2022). Intraday Price Discovery between Spot and Futures Markets of NIFTY 50. *Indian Financial Research Journal*.