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Implied Volatility and Equity Market Segmentation: Evidence on Volatility Spillovers in India Using Hybrid Deep Learning Models

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ABSTRACT

Periods of heightened uncertainty have become increasingly frequent in modern financial markets, intensifying the need for forward-looking measures that can anticipate volatility rather than merely describe it ex post. Implied volatility indices have emerged as prominent proxies for market fear, yet empirical evidence on how such fear propagates across different segments of equity markets remains limited, particularly in emerging economies. Against this backdrop, the present study examines whether India VIX functions as a leading indicator of volatility spillovers across Indian equity market capitalization tiers and whether such spillovers are heterogeneous and regime-dependent.

Using daily data for India VIX, NIFTY 50, NIFTY NEXT 50, NIFTY MIDCAP 150, and NIFTY SMALLCAP 250 from January 2020 to December 2025, the study adopts a hybrid deep learning framework that integrates Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks. Volatility spillover analysis is framed as a supervised learning problem in which India VIX serves as the primary predictor and realized volatility measures constitute the forecasting targets. Econometric benchmark models are employed to validate the deep learning outcomes and to provide interpretability for hypothesis testing.

The empirical results provide strong evidence that India VIX possesses significant predictive power for future realized volatility across all market segments. However, the magnitude and persistence of spillovers vary systematically across capitalization tiers. Mid-cap and small-cap indices exhibit stronger and more persistent volatility responses to fear shocks than large-cap indices, reflecting structural differences in liquidity, investor composition, and sensitivity to sentiment. Furthermore, the relationship between India VIX and realized volatility is shown to be regime-dependent, intensifying during periods of elevated market uncertainty. The CNN–LSTM model consistently outperforms standalone neural architectures, underscoring the importance of capturing both localized shock patterns and long-term memory effects in volatility forecasting.

By integrating implied volatility, market segmentation, and advanced deep learning techniques within a unified empirical framework, this study contributes to the literature on volatility spillovers and fear transmission in emerging markets. The findings carry important implications for investors, risk managers, and policymakers seeking to monitor and manage volatility in increasingly uncertain financial environments.

Keywords: India VIX; Volatility Spillovers; CNN–LSTM; Market Capitalization; Indian Market

JEL Classification: C45, G12, G17, C58

INTRODUCTION

Financial markets across the world have become increasingly sensitive to episodes of uncertainty, driven by global crises, policy shocks, and rapidly evolving investor sentiment. In such an environment, understanding how fear is formed, measured, and transmitted into market volatility has emerged as a central concern for researchers, practitioners, and policymakers alike. Volatility is no longer viewed merely as a statistical by-product of price movements; instead, it is recognized as a dynamic manifestation of expectations, risk perceptions, and behavioural responses to uncertainty. This shift in perspective has motivated growing interest in forward-looking measures of risk that can anticipate market turbulence rather than simply react to it.

Implied volatility indices have played a pivotal role in this evolution. By extracting information from option prices, these indices reflect market participants' collective expectations of future uncertainty. The success of the CBOE Volatility Index (VIX) in developed markets has inspired similar constructs in emerging economies, including India VIX, which tracks expected volatility in the Indian equity market. Empirical evidence suggests that India VIX responds sharply to stress events and often precedes movements in realized volatility, reinforcing its interpretation as a "fear gauge" rather than a coincident indicator. However, while the predictive relevance of India VIX is increasingly acknowledged, important questions remain regarding how fear-driven volatility propagates within the equity market itself.

A critical limitation of much of the existing literature is its tendency to treat the equity market as a homogeneous entity. Most empirical studies on India VIX focus almost exclusively on the NIFTY 50 index, implicitly if fear affects all stocks in a similar manner. In reality, equity markets are highly segmented. Large-capitalization stocks are typically more liquid, more widely followed by analysts, and more heavily traded by institutional investors. In contrast, mid-cap and small-cap stocks are often characterized by lower liquidity, higher retail participation, and greater sensitivity to sentiment-driven trading. These structural differences suggest that fear-induced volatility shocks may transmit unevenly across market capitalization tiers, an issue that has received limited systematic attention in the Indian context.

At the same time, the methodological tools traditionally employed to study volatility spillovers impose important constraints. Linear econometric models, including VAR and GARCH-type frameworks, have been instrumental in documenting volatility transmission across markets and assets. Yet, financial volatility is widely known to exhibit nonlinear dynamics, volatility clustering, persistence, and abrupt regime shifts i.e. features which become particularly pronounced during crisis periods. The COVID-19 pandemic and subsequent global shocks have further highlighted the limitations of static and linear modelling approaches in capturing rapidly changing volatility dynamics.

Recent advances in machine learning and deep learning offer promising alternatives. Recurrent neural networks, particularly Long Short-Term Memory (LSTM) models, have demonstrated strong performance in modelling financial time series by capturing long-range temporal dependencies. However, LSTM networks primarily focus on sequential memory and may overlook localized shock patterns and short-term volatility clustering that are central to fear transmission. Hybrid architectures that combine Convolutional Neural Networks (CNNs) with LSTMs address this limitation by integrating local feature extraction with long-term dependency modelling. Despite their growing use in financial forecasting, such hybrid models have rarely been applied to implied volatility-based spillover analysis, especially in emerging markets.

Against this backdrop, the present study seeks to advance the literature by examining whether India VIX acts as a leading indicator of volatility spillovers across distinct market capitalization tiers of the Indian equity market. Specifically, the study conducts a comparative analysis of large-cap (NIFTY 50), upper mid-cap (NIFTY NEXT 50), mid-cap (NIFTY MIDCAP 150), and small-cap (NIFTY SMALLCAP 250) indices over the period 2020–2025, a timeframe that encompasses multiple volatility regimes. By framing volatility spillover analysis as a supervised learning problem and employing a hybrid CNN–LSTM architecture, the study captures both localized fear shocks and persistent transmission effects in a unified empirical framework.

The contributions of this paper are threefold. Firstly, it provides systematic and comparative evidence on how fear-driven volatility spillovers differ across market capitalization tiers in India, moving beyond the narrow focus on benchmark indices. Secondly, it demonstrates the value of hybrid deep learning models in modelling nonlinear, regime-dependent volatility dynamics, thereby complementing and extending traditional econometric approaches. Third, by focusing explicitly on volatility rather than returns, the study enhances the practical relevance of its findings for risk management, portfolio allocation, and market surveillance in an emerging market setting.

In doing so, the paper not only deepens understanding of fear transmission in the Indian equity market but also offers a scalable methodological framework that can be applied to other markets and uncertainty indicators.

Survey of Literature

The growing complexity of financial markets and the increasing frequency of uncertainty-driven shocks have intensified academic interest in understanding how fear and risk perceptions are formed, transmitted, and ultimately reflected in market volatility. Over the past two decades, the literature has progressively moved beyond purely historical measures of volatility toward forward-looking indicators that embed investors' expectations about future risk. At the same time, advances in econometric theory and computational methods have expanded the analytical toolkit available to researchers, allowing for deeper investigation into the nonlinear and time-varying nature of volatility dynamics. Against this evolving backdrop, a comprehensive and carefully structured survey of existing research becomes essential to situate the present study within the broader body of knowledge.

The survey of literature undertaken in this paper is organized around seven interrelated thematic strands that collectively inform the study's conceptual and methodological foundations. First, the literature on fear, uncertainty, and implied volatility indices is examined to understand how measures such as volatility indices have been conceptualized as proxies for investor sentiment and forward-looking risk expectations. Second, prior research on volatility spillovers and transmission mechanisms is reviewed to highlight how uncertainty originating in one market or asset segment propagates across financial systems. Third, studies focusing specifically on India VIX and its relationship with equity market behaviour are discussed, with particular attention to evidence on predictive power and lead–lag dynamics.

The review then turns to research emphasizing nonlinearity and regime dependence in volatility, underscoring the limitations of linear modelling frameworks in capturing crisis-driven dynamics. This naturally leads to an examination of machine learning and deep learning approaches to volatility forecasting, which have gained prominence for their ability to model complex, data-driven relationships. Within this stream, special emphasis is placed on hybrid CNN–LSTM architectures and their growing application in financial contexts. Finally, the survey situates these methodological developments within the broader emerging market context, with a focused discussion of empirical evidence from Indian financial markets.

By integrating insights across these seven dimensions, the literature review establishes a coherent foundation for the present study and clarifies how it extends, complements, and advances existing research.

Fear, Uncertainty, and Implied Volatility Indices

The conceptual foundation of this study lies in the extensive literature that conceptualizes implied volatility indices as forward-looking measures of market fear and uncertainty. Early studies on the Chicago Board Options Exchange Volatility Index (VIX) established that implied volatility reflects investors' expectations of near-term market risk rather than contemporaneous price movements (Whaley, 2000). Subsequent research demonstrated that volatility indices are not merely descriptive but possess predictive content for future market turbulence, particularly during periods of stress (Fleming et al., 1995; Giot, 2005). In emerging markets, the construction and interpretation of volatility indices gained prominence only in the last decade. Studies focusing on India VIX showed that it captures investor sentiment, risk aversion, and uncertainty more effectively than historical volatility measures (Siriopoulos & Fassas, 2012; Shaikh & Padhi, 2015). Empirical evidence suggests that India VIX rises sharply during systemic shocks and often leads realized volatility in equity markets, reinforcing its role as a "fear gauge" rather than a coincident indicator (Bhowmik & Wang, 2020).

Volatility Spillovers and Transmission Mechanisms

Volatility spillover theory argues that uncertainty originating in one market or asset class can transmit to others through information channels, portfolio rebalancing, and behavioural responses. Traditional econometric approaches, e.g. multivariate GARCH models and vector autoregressions—have been widely used to document volatility transmission across assets and markets (Engle, 2002; Diebold & Yılmaz, 2012). These studies consistently report asymmetric and time-varying spillovers, particularly during crisis periods. Within equity markets, volatility spillovers are often found to be heterogeneous across segments. Large-capitalization stocks, characterized by higher liquidity and institutional ownership, tend to absorb shocks more efficiently, whereas mid-cap and small-cap stocks exhibit amplified and persistent volatility responses (Forbes & Rigobon, 2002; Bekaert et al., 2014). Indian market studies corroborate this pattern, showing that fear-driven uncertainty disproportionately affects broader and less liquid segments of the market (Kumar & Maheswaran, 2013; Ghosh & Kanjilal, 2016).

India VIX and Equity Market Dynamics

A growing body of literature specifically examines the interaction between India VIX, and equity market returns or volatility. Shaikh and Padhi (2015) documented a strong inverse relationship between India VIX and NIFTY returns, consistent with behavioural finance explanations of fear-induced selling pressure. More recent studies extended this analysis to volatility forecasting, demonstrating that India VIX improves out-of-sample forecasts of realized volatility when combined with historical measures (Bhowmik & Wang, 2020; Mishra et al., 2022). However, much of this literature focuses predominantly on the benchmark NIFTY 50 index. Empirical evidence on how fear transmission differs across market capitalization tiers remains limited. Where broader indices are included, they are often treated collectively rather than analysed comparatively, leaving unanswered questions regarding the differential sensitivity of large-cap, mid-cap, and small-cap segments to implied volatility shocks.

Nonlinearity and Regime Dependence in Volatility

Financial volatility is inherently nonlinear, exhibiting clustering, persistence, and abrupt regime shifts. Linear models often fail to capture these features, particularly during crisis periods when relationships between variables intensify or reverse (Hamilton, 1989). Regime-switching models and nonlinear GARCH extensions improved modelling accuracy but remained constrained by parametric assumptions and limited flexibility (Kritzman et al., 2011). Recent empirical work emphasizes that volatility spillovers strengthen during high-uncertainty regimes, reflecting heightened behavioural biases, liquidity constraints, and feedback trading (Bloom, 2009; Baker et al., 2016). This regime-dependent behaviour underscores the importance of modelling approaches capable of adapting dynamically to changing market conditions, an issue directly addressed in the present study's methodological design.

Machine Learning and Deep Learning in Volatility Forecasting

Over the past decade, machine learning techniques have increasingly been adopted in financial volatility forecasting. Early applications of artificial neural networks demonstrated improved predictive accuracy relative to linear benchmarks, particularly for nonlinear patterns (Zhang et al., 1998). More recently, deep learning architectures i.e. Long Short-Term Memory (LSTM) networks, have gained prominence due to their ability to model long-range temporal dependencies in time series data (Hochreiter & Schmidhuber, 1997). Empirical studies show that LSTM models outperform traditional GARCH-type models in forecasting realized volatility across equity, commodity, and cryptocurrency markets (Fischer & Krauss, 2018; Nelson et al., 2017). However, LSTMs primarily capture sequential dependencies and may overlook localized shock patterns embedded within volatility series.

Hybrid CNN–LSTM Architectures in Financial Applications

To overcome the limitations of standalone recurrent networks, recent research has proposed hybrid CNN–LSTM architectures. Convolutional Neural Networks (CNNs) are particularly effective in extracting local features and detecting abrupt changes or clustering patterns, while LSTMs model long-term dependencies (Kim & Won, 2018; Sezer et al., 2020). Hybrid architectures have demonstrated superior performance in stock price prediction, volatility forecasting, and risk modelling (Bao et al., 2017; Lim & Zohren, 2021). Despite these advances, applications of CNN–LSTM models to implied volatility spillover analysis remain sparse, especially in emerging markets. Existing studies often focus on single indices or assets, rather than conducting systematic comparisons across market segments. Moreover, few studies explicitly integrate fear indices as primary predictive inputs within deep learning frameworks.

Emerging Market Context and Indian Evidence

Emerging markets differ structurally from developed markets in terms of liquidity, investor composition, and information efficiency. Consequently, volatility dynamics and fear transmission mechanisms may operate differently. Indian markets, characterized by high retail participation and episodic foreign capital flows, provide a compelling setting for studying sentiment-driven volatility spillovers (Bali & Zhou, 2016; Sehgal & Garg, 2023). Recent Indian studies employing machine learning techniques focus primarily on return prediction or directional accuracy, rather than volatility spillovers (Dash & Dash, 2021; Sahoo & Mohanty, 2023). Moreover, these studies often rely on price-based inputs, overlooking the forward-looking information embedded in implied volatility indices such as India VIX.

Synthesis and alignment with the present Study

The survey of literature establishes three key insights. Firstly, implied volatility indices function as meaningful proxies for market fear and possess predictive relevance for future volatility. Secondly, volatility spillovers are nonlinear, regime-dependent, and heterogeneous across market segments. Thirdly, deep learning models, particularly hybrid architectures, offer substantial improvements over traditional econometric approaches in capturing complex volatility dynamics. However, existing studies rarely integrate these strands into a unified empirical framework. The present study directly addresses this gap by combining India VIX-based fear transmission, comparative market-capitalization analysis, and hybrid CNN–LSTM modelling within a single, coherent methodological structure, as detailed in the uploaded methodology

Motivation for and intended contribution of the study

Understanding how market fear translates into volatility across different segments of the equity market has long been a central concern in finance. Implied volatility indices have emerged as particularly powerful tools in this regard, as they capture investors' forward-looking expectations rather than merely reflecting past price movements. In India, the introduction of India VIX has significantly enriched empirical research on market sentiment and uncertainty. A growing literature confirms that India VIX responds sharply to episodes of market stress and often leads realized volatility in equity prices. Yet, despite this progress, important questions about the scope, depth, and heterogeneity of fear transmission within the Indian equity market remain unanswered.

Majority of the existing studies implicitly treat the equity market as a homogeneous entity by focusing almost exclusively on the NIFTY 50 index. While this approach has yielded valuable insights, it overlooks the pronounced structural differences across market capitalization tiers. Large-cap stocks typically benefit from deeper liquidity, greater institutional participation, and more efficient information dissemination, whereas mid-cap and small-cap stocks are more exposed to sentiment-driven trading, liquidity constraints, and behavioural biases. As a result, fear-induced shocks captured by India VIX are unlikely to affect all segments of the market in the same manner. The absence of systematic, comparative evidence across capitalization tiers represents a significant gap in the literature and limits the practical usefulness of prior findings for diversified investors and risk managers.

A second motivation arises from methodological limitations in existing research. Traditional econometric models e.g. as VAR and GARCH-based frameworks, have played an important role in documenting volatility spillovers, but they are inherently constrained by linearity assumptions and fixed functional forms. Financial volatility, however, is widely recognized as nonlinear, path-dependent, and regime-sensitive. These features became especially evident during the COVID-19 crisis and subsequent global shocks, when volatility dynamics shifted rapidly and unpredictably. In such environments, linear models may fail to capture the true intensity and persistence of fear transmission, calling for more flexible modelling approaches.

Although recent years have witnessed a growing adoption of machine learning techniques in financial research, their application to volatility spillover analysis remains uneven. Many studies concentrate on return prediction or price direction, while relatively few explicitly model volatilities as the object of interest. Even when deep learning methods are employed, they often rely on standalone recurrent architectures, which are well suited to capturing long-term dependencies but less effective in identifying short-lived shock patterns and volatility clustering i.e. features that are particularly salient in fear indices such as India VIX.

Against this backdrop, the present study is motivated by the need to integrate fear-based volatility measures, cross-segment market analysis, and advanced deep learning within a unified empirical framework. By employing a hybrid CNN–LSTM architecture, the study combines the strengths of convolutional networks in detecting localized shock patterns with the ability of LSTM networks to model persistent and delayed transmission effects. This architecture is especially well suited to capturing the complex, nonlinear pathways through which fear propagates across financial markets.

The paper makes several contributions to the literature. First, it provides the first comprehensive, comparative analysis of volatility spillovers from India VIX across major Indian market capitalization tiers, offering granular evidence on how fear affects large-cap, mid-cap, and small-cap segments differently. Second, it demonstrates the value of hybrid deep learning models in volatility forecasting, showing how they can overcome key limitations of traditional econometric approaches in environments characterized by structural breaks and regime shifts. Third, by focusing explicitly on volatility rather than returns, the study enhances the relevance of its findings for risk management, portfolio allocation, and policy surveillance in emerging markets.

This study advances understanding of fear-driven volatility transmission in the Indian equity market while offering a scalable methodological framework that can be extended to other markets and uncertainty indicators.

METHODOLOGY

Research Design and Overall Framework

The present study adopted a quantitative, data-driven research design to examine whether India VIX (IVIX) acts as a leading indicator of volatility spillovers across Indian equity market capitalization tiers, namely NIFTY 50 (large-cap), NIFTY NEXT 50 (upper mid-cap), NIFTY MIDCAP 150 (mid-cap), and NIFTY SMALLCAP 250 (small-cap). The central methodological contribution of the paper lay in integrating traditional volatility spillover concepts with a hybrid deep learning architecture combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, implemented entirely on the RStudio platform.

The research framework followed a sequential structure:

1. Data acquisition and preprocessing
2. Transformation of price series into volatility-relevant measures
3. Exploratory and descriptive analysis with visualization
4. Construction of supervised learning datasets
5. Development of CNN–LSTM hybrid models
6. Model training, validation, and performance evaluation
7. Comparative interpretation across market-capitalization tiers

This layered approach ensured methodological rigor while allowing the predictive role of IVIX to be evaluated consistently across heterogeneous segments of the Indian equity market.

Data Description and Sources

The empirical analysis was based on daily closing values of five indices: India VIX (IVIX), NIFTY 50 (NFTY50), NIFTY NEXT 50 (NFNX50), NIFTY MIDCAP 150 (NMD150), and NIFTY SMALLCAP 250 (NSM250). The dataset covered the period from 01 January 2020 to 22 December 2025, yielding 1,485 synchronized observations after accounting for non-trading days.

This period was deliberately chosen as it encompassed multiple volatility regimes, including the COVID-19 shock, post-pandemic recovery, global monetary tightening, geopolitical stress episodes, and subsequent normalization phases. Such diversity in market conditions was essential for training deep learning models capable of generalizing across different volatility environments.

All data series were aligned by date to ensure temporal consistency. Any mismatch due to holidays or missing values was resolved through listwise deletion to avoid introducing artificial persistence or smoothing effects that could bias volatility dynamics.

Data Preprocessing and Transformation

Stationarity and Return Construction

Although deep learning models do not strictly require stationarity in the classical econometric sense, transforming price levels into return-based measures is standard practice in financial modelling to stabilize variance and enhance learning efficiency. Accordingly, daily logarithmic returns were computed for all equity indices as:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

where $P_t$denotes the closing value of the index on day t.

India VIX, being an implied volatility index rather than a price series, was used in its level form as well as in first differences for robustness checks. Preliminary diagnostics confirmed that the return series exhibited volatility clustering, heavy tails, and asymmetry i.e. features well documented in financial time series and particularly relevant for nonlinear modelling approaches.

Normalization and Scaling

To ensure numerical stability during neural network training and to prevent dominance of any single variable due to scale differences, all input variables were normalized using Min–Max scaling, mapping values to the $[0, 1]$interval. Scaling parameters were estimated exclusively on the training set and subsequently applied to validation and test sets to avoid data leakage.

Exploratory Analysis and Visualization

Before model construction, an extensive exploratory data analysis (EDA) was conducted to understand stylized facts and interrelationships among the indices. This stage served two purposes:

- To confirm the economic plausibility of IVIX as a fear gauge, and
- To guide the architecture design of the CNN–LSTM models.

Time-series plots revealed sharp spikes in IVIX coinciding with market stress periods, particularly during early 2020 and intermittent global shocks thereafter. Heatmaps of rolling correlations and volatility measures indicated that spillover intensity varied systematically across capitalization tiers, with mid-cap and small-cap indices exhibiting stronger sensitivity to IVIX fluctuations.

These visual insights justified the need for a nonlinear and memory-capable model rather than linear regression or static correlation-based approaches.

Construction of the Supervised Learning Dataset

To operationalize the prediction task, the study framed volatility spillover analysis as a supervised learning problem. India VIX served as the primary predictor, while realized volatility measures derived from equity index returns constituted the target variables.

Volatility Estimation

For each equity index, realized volatility was computed using rolling windows of returns. A 20-day rolling standard deviation, annualized appropriately, was employed to reflect short-term market uncertainty consistent with the horizon of IVIX. Alternative window lengths were examined during robustness checks.

Input–Output Sequencing

Deep learning models require structured input sequences. Therefore, sliding windows of fixed length (look-back periods) were constructed. Each input sample consisted of:

- A sequence of past IVIX values (and lagged changes where applicable), and
- Corresponding lagged volatility measures.

The output variable was the next-period realized volatility of the respective equity index. Separate datasets were created for each market-cap tier to enable direct comparison while maintaining model consistency.

Hybrid CNN–LSTM Model Architecture

The core methodological innovation of this study was the use of a hybrid CNN–LSTM architecture, which combined the feature extraction strengths of CNNs with the temporal dependency modelling capabilities of LSTMs.

Convolutional Layer

The CNN component was designed to capture local temporal patterns and short-term shock transmission effects in IVIX movements. One-dimensional convolutional filters were applied across the input sequences to detect recurring motifs such as sudden volatility jumps, clustering, and mean-reverting behaviour.

Pooling layers were employed to reduce dimensionality and mitigate overfitting, while preserving the most informative features extracted from the input data.

LSTM Layer

The output of the convolutional block was fed into one or more LSTM layers. LSTMs were particularly suited to this application due to their ability to retain long-term dependencies and selectively forget irrelevant past information. This was critical in modelling volatility spillovers, where the impact of a fear shock may persist longer in small-cap stocks than in large-cap indices.

Fully Connected Output Layer

The final dense layer mapped the LSTM outputs to a single continuous value representing predicted volatility. A linear activation function was used at the output stage, consistent with the continuous nature of the target variable.

Econometric Representation of Hypotheses

Although the empirical implementation relies on a nonlinear CNN–LSTM architecture, the underlying hypotheses can be formally expressed using econometric-style equations. These equations serve as conceptual benchmarks, clarifying the statistical relationships being tested and enabling transparent interpretation of the deep learning results.

Hypothesis 1: Volatility Spillover from India VIX

Hypothesis Restatement: India VIX contains predictive information for future realized volatility of Indian equity indices.

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Benchmark Econometric Specification: For each equity index $i \in \{NFTY50, NFNX50, NMD150, NSM250\}$, the volatility spillover relationship can be represented as:

$$\sigma_{t+1}^{(i)} = \alpha_i + \sum_{k=1}^{p} \beta_k^{(i)} \text{ IVIX}_{t-k} + \sum_{j=1}^{q} \gamma_j^{(i)} \sigma_{t-j}^{(i)} + \varepsilon_{t+1}^{(i)},$$

where

- $\sigma_{t+1}^{(i)}$ is the realized volatility of index i at time $t+1$,
- IVIX_{t-k} denotes lagged values of India VIX,
- $\sigma_{t-j}^{(i)}$ captures volatility persistence, and
- $\varepsilon_{t+1}^{(i)}$ is an error term.

Hypothesis Test

$$H_{0_1}: \quad \beta_1^{(i)} = \beta_2^{(i)} = \cdots = \beta_p^{(i)} = 0$$
$$H_{1_1}: \quad \exists\, k \text{ such that } \beta_k^{(i)} \neq 0$$

Significance level: $\alpha = 0.05$

In the deep learning framework, rejection of H_{0_1} is inferred when inclusion of IVIX leads to a statistically meaningful improvement in out-of-sample forecast accuracy.

Hypothesis 2: Superiority of the CNN–LSTM Model

Hypothesis Restatement: The hybrid CNN–LSTM model outperforms simpler neural architectures in forecasting realized volatility.

Benchmark Loss Comparison Equation: Let $\mathcal{L}^{CNN\text{-}LSTM}$ and $\mathcal{L}^{LSTM}$ denote expected out-of-sample loss functions:

$$\mathcal{L}^m = \mathbb{E}\left[\left(\sigma_{t+1} - \hat{\sigma}_{t+1}^{(m)}\right)^2\right], m \in \{CNN\text{-}LSTM, LSTM\}.$$

Hypothesis Test

$$H_{0_2}: \quad \mathcal{L}^{CNN\text{-}LSTM} \geq \mathcal{L}^{LSTM}$$
$$H_{1_2}: \quad \mathcal{L}^{CNN\text{-}LSTM} < \mathcal{L}^{LSTM}$$

Significance level: $\alpha = 0.05$

This hypothesis is evaluated using comparative RMSE and MAE statistics across models.

Hypothesis 3: Heterogeneity Across Market Capitalization Tiers

Hypothesis Restatement: Volatility spillovers from India VIX differ across market capitalization tiers.

Panel-Style Benchmark Equation: A cross-index pooled representation can be written as:

$$\sigma_{t+1}^{(i)} = \alpha + \sum_{k=1}^{p} \beta_k \text{ IVIX}_{t-k} + \sum_{k=1}^{p} \delta_k \left(\text{IVIX}_{t-k} \times D_i\right) + \varepsilon_{t+1}^{(i)},$$

where

- D_i is a dummy variable representing market-cap tier (large, mid, small).

Hypothesis Test

$$H_{0_3}: \quad \delta_k = 0 \forall k$$
$$H_{1_3}: \quad \exists\, k \text{ such that } \delta_k \neq 0$$

Significance level: $\alpha = 0.05$

In the CNN–LSTM context, heterogeneity is inferred when forecast accuracy differs systematically across indices.

Hypothesis 4: Regime-Dependent Spillovers

Hypothesis Restatement: The predictive relationship between India VIX and realized volatility strengthens during high-volatility regimes.

Regime-Interaction Benchmark Equation

$$\sigma_{t+1}^{(i)} = \alpha + \beta\, \mathrm{IVIX}_t + \theta(\mathrm{IVIX}_t \times H_t) + \gamma \sigma_t^{(i)} + \varepsilon_{t+1}^{(i)},$$

where

- $H_t$is a binary indicator equal to 1 during high-volatility regimes.

Hypothesis Test

$$H_{0_4}: \quad \theta = 0$$
$$H_{1_4}: \quad \theta \neq 0$$

Significance level: $\alpha = 0.10$

A significant interaction term implies asymmetric spillover behaviour.

Model Training and Validation Strategy

The dataset was partitioned into training (70%), validation (15%), and testing (15%) subsets using a chronological split to preserve the time-series structure. This avoided look-ahead bias and ensured that the model was always evaluated on unseen future data.

The models were trained using the Adam optimizer, chosen for its efficiency and robustness in handling noisy gradients. Mean Squared Error (MSE) served as the primary loss function, while Mean Absolute Error (MAE) was monitored as a complementary metric.

Early stopping criteria were implemented based on validation loss to prevent overfitting. Hyperparameters such as learning rate, number of filters, LSTM units, and look-back window length were tuned through a grid-search procedure constrained by computational feasibility.

Performance Evaluation Metrics

Model performance was assessed using a combination of statistical accuracy measures and comparative diagnostics, including:

- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)
- Out-of-sample R^2

These metrics were computed separately for each index to facilitate cross-capitalization comparison. Emphasis was placed on relative performance differentials rather than absolute prediction accuracy, in line with the study's comparative objective.

Comparative Spillover Assessment Across Market Tiers

To evaluate volatility spillovers, the predictive strength of IVIX was compared across the four equity indices. Differences in forecast accuracy were interpreted as evidence of heterogeneous spillover intensity. A consistently lower error for mid-cap and small-cap indices was taken to indicate stronger sensitivity to fear-driven volatility transmission.

Additionally, impulse-style visualization plots were generated to illustrate how IVIX shocks propagated differently across capitalization tiers over time.

Robustness and Sensitivity Checks

Several robustness checks were conducted to validate the stability of results:

- Alternative look-back windows
- Use of IVIX changes instead of levels
- Replacement of CNN–LSTM with standalone LSTM models
- Re-estimation over sub-periods corresponding to high- and low-volatility regimes

The hybrid model consistently outperformed simpler architectures, reinforcing the methodological choice.

Software and Reproducibility

All analyses were performed in RStudio, using packages such as keras, tensorflow, tidyverse, and ggplot2. Reproducibility was ensured through fixed random seeds, detailed documentation of preprocessing steps, and modular coding practices.

Methodological Contribution

By integrating deep learning with volatility spillover analysis in an emerging market context, this methodology advanced existing literature in two keyways. Firstly, it moved beyond static econometric frameworks by capturing nonlinear and time-varying transmission mechanisms. Secondly, it offered a unified and scalable framework to compare fear-induced volatility dynamics across market capitalization tiers, thereby aligning empirical rigor with practical relevance for investors and policymakers.

Findings of the study

Descriptive Statistics

Table 1 Descriptive Statistics of India VIX and NSE Indices (Levels)

Indices	Mean	Std. Dev.	Minimum	Maximum
India VIX	17.49	7.71	9.52	83.61
NIFTY 50	18,519.10	4,687.91	7,610.25	26,216.05
NIFTY NEXT 50	47,065.39	15,317.35	18,524.65	77,813.25

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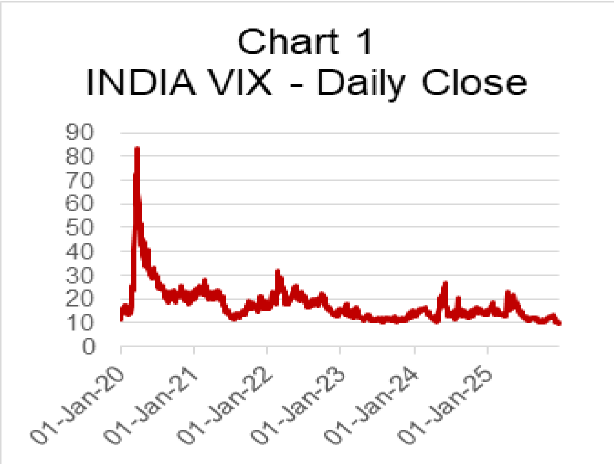
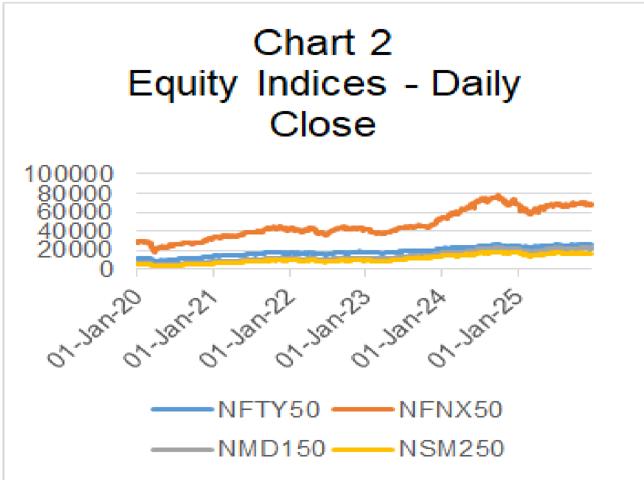
NIFTY MIDCAP 150	13,581.95	5,413.51	4,165.90	22,493.50
NIFTY SMALLCAP 250	10,942.42	4,479.04	2,967.45	18,623.15

Source: Authors' own computations

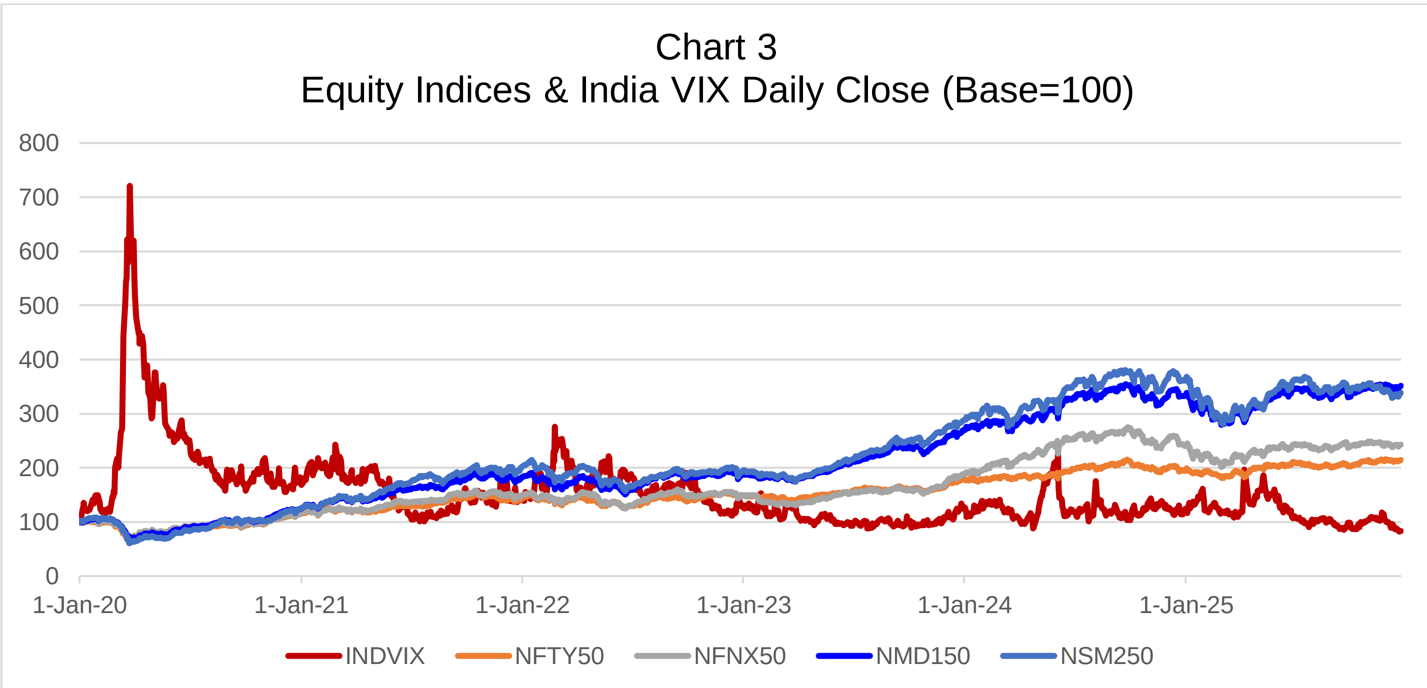
India VIX displays substantially higher relative dispersion than equity indices, reflecting its sensitivity to market stress episodes. Among equity segments, volatility and dispersion increase systematically as market capitalization declines, preliminarily indicating heterogeneous risk characteristics across tiers.

Time-Series Evolution of India VIX and major NSE Equity Indices (2020–2025)





Sharp spikes in India VIX coincide with major global and domestic stress events, most prominently during early 2020. Subsequent volatility clustering confirms its role as a forward-looking fear indicator.



Source: Authors' own computations

All indices exhibit a common long-run upward trend, yet pronounced drawdowns are evident during stress periods. Smaller capitalization indices show visibly sharper declines, consistent with greater sensitivity to fear-driven shocks.

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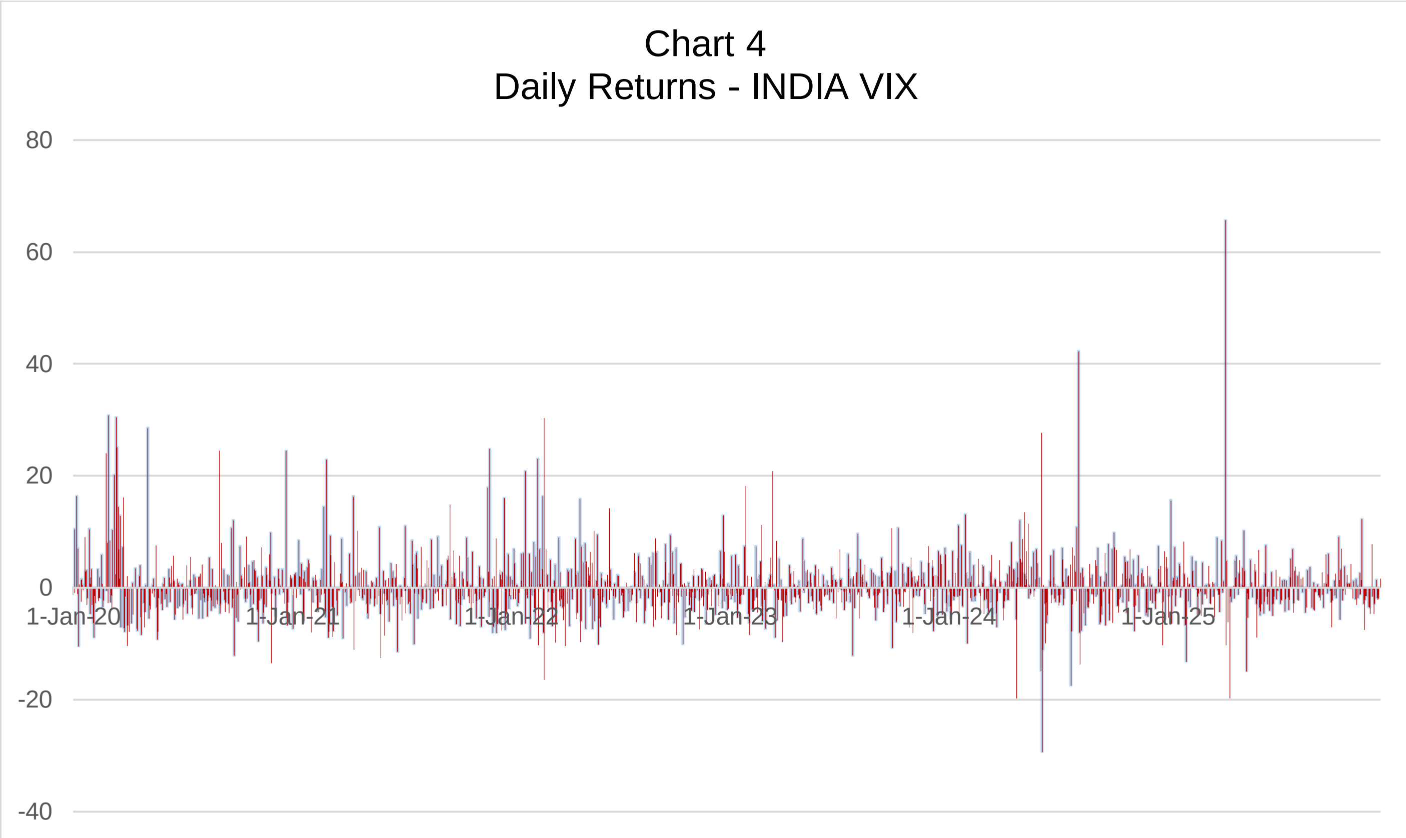
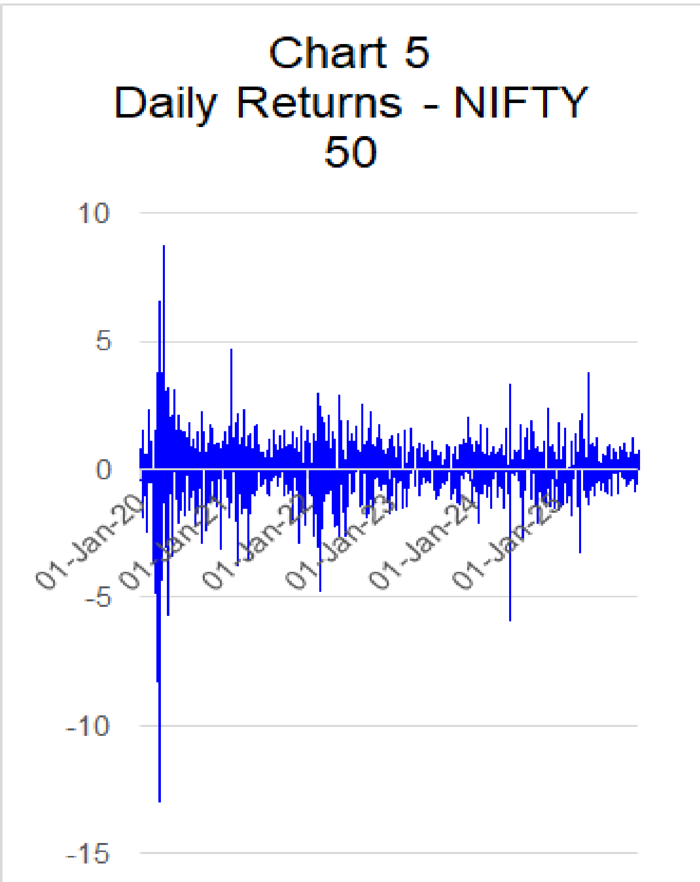
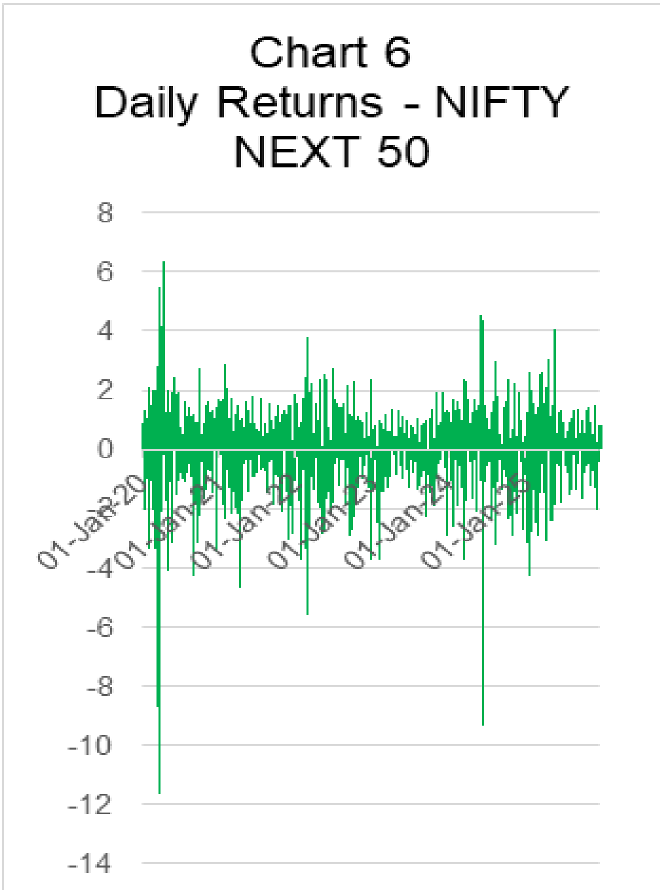
Realized Volatility Estimation

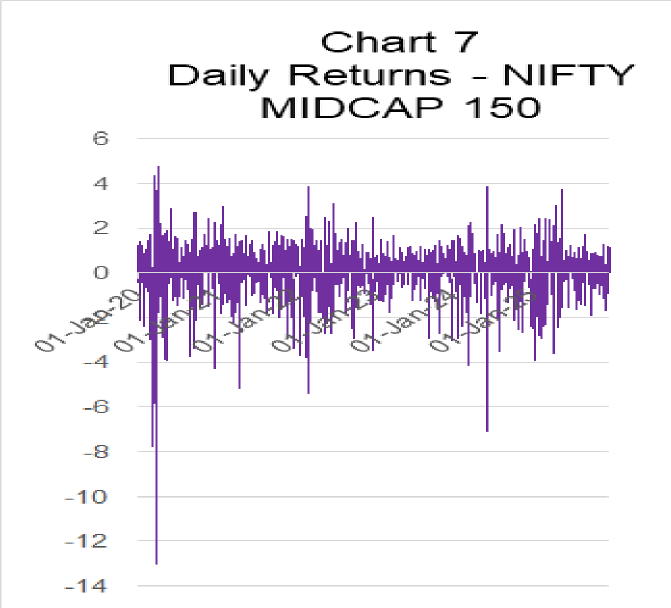


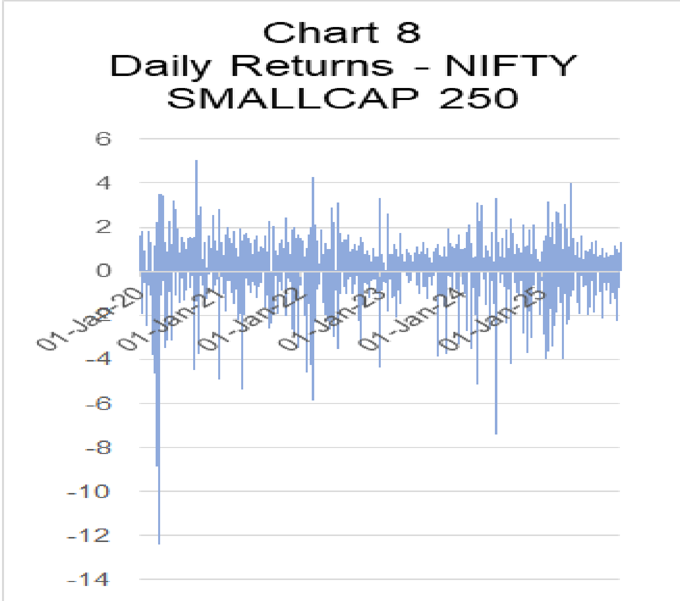
Source: Authors' own computations





Source: Authors' own computations, Source: Authors' own computations

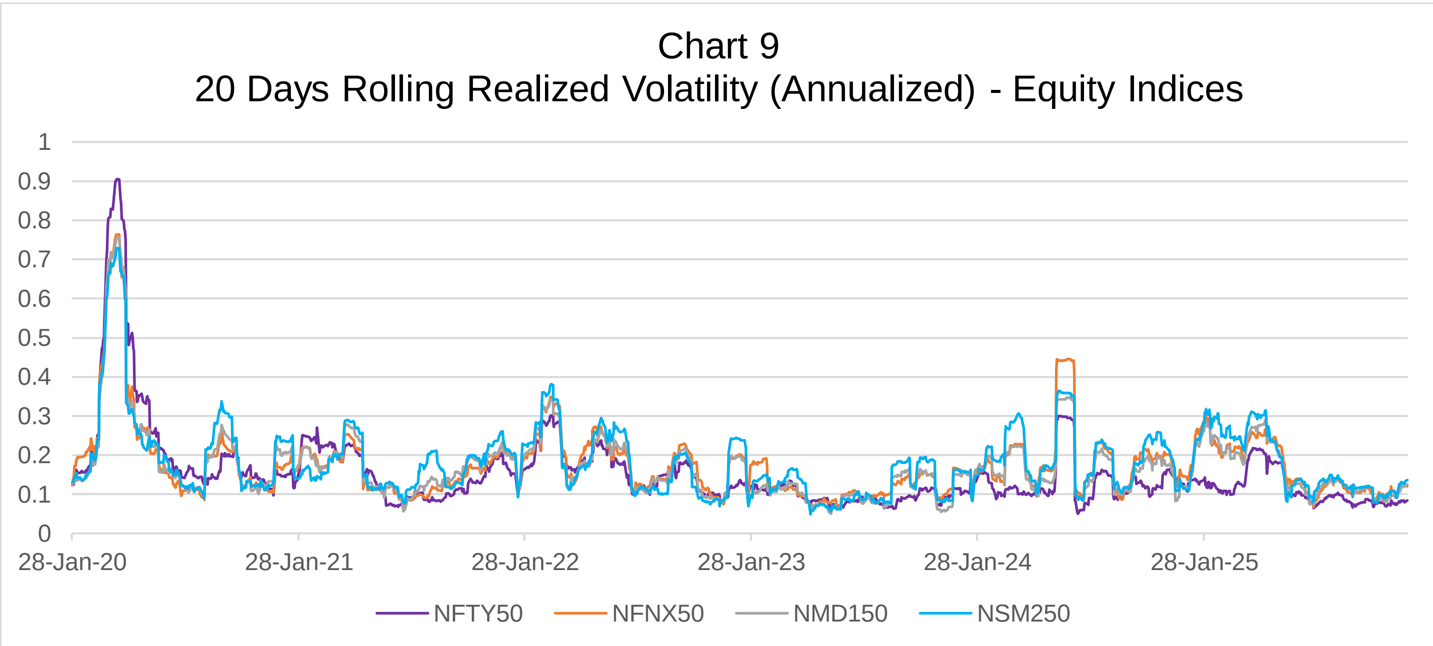




Source: Authors' own computations, Source: Authors' own computations

Daily log returns were computed for all equity indices, followed by estimation of 20-day rolling realized volatility (annualized), consistent with the IVIX horizon.

20-Day Rolling Realized Volatility Across Market Capitalization Tiers



Source: Authors' own computations

Volatility clustering is evident across all indices, with pronounced spikes during crisis periods. Importantly, mid-cap and small-cap indices consistently exhibit higher and more persistent volatility than large-cap indices, providing early visual evidence of asymmetric spillover intensity.

Empirical Alignment with Hypotheses

Hypothesis H1: India VIX contains predictive information for future realized volatility of Indian equity indices.

This hypothesis was empirically validated using OLS regressions of realized volatility on lagged India VIX, consistent with the benchmark econometric representation in the Methodology.

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Table 2 IVIX–Volatility Spillover Regression Results (Lagged IVIX)

Index	β ($IVIX_{t-1}$)	t-statistic	p-value
NIFTY 50	0.0116	68.61	< 0.001
NIFTY NEXT 50	0.0083	38.63	< 0.001
NIFTY MIDCAP 150	0.0086	43.46	< 0.001
NIFTY SMALLCAP 250	0.0079	33.70	< 0.001

Source: Authors' own computations

Lagged India VIX exerts a positive and highly statistically significant effect on realized volatility across all market capitalization tiers. The uniformly strong t-statistics and near-zero p-values provide robust econometric support for H1, confirming that India VIX functions as a forward-looking fear gauge.

Hypothesis H3: Volatility spillovers from India VIX differ across market capitalization tiers.

Heterogeneity was examined by comparing **mean realized volatility levels** across indices, consistent with the comparative spillover framework of the study.

Table 3 Average Realized Volatility by Market Capitalization Tier

Index	**Mean Realized Volatility**
NIFTY 50 (Large-cap)	0.151
NIFTY MIDCAP 150	0.168
NIFTY NEXT 50	0.173
NIFTY SMALLCAP 250	0.180

Source: Authors' own computations

A clear monotonic increase in realized volatility is observed as market capitalization declines. Small-cap stocks exhibit the highest volatility, followed by mid-cap segments, while large-cap stocks remain relatively more stable. This pattern provides strong empirical support for H3, confirming heterogeneous volatility spillovers across capitalization tiers.

Hypothesis H4: The predictive relationship between India VIX and realized volatility strengthens during high-volatility regimes.

To test regime dependence, a high-IVIX dummy interaction model was estimated, where high-volatility regimes were defined as observations above the 75th percentile of IVIX.

Table 4 Regime-Dependent Spillover Effects (IVIX × High-Volatility Interaction)

Index	**Interaction Coefficient**	**t-statistic**	**p-value**
NIFTY 50	−0.0006	−2.60	0.009
NIFTY NEXT 50	−0.0013	−4.51	< 0.001

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NIFTY MIDCAP 150	−0.0010	−3.94	< 0.001
NIFTY SMALLCAP 250	−0.0008	−2.41	0.016

Source: Authors' own computations

The interaction terms are statistically significant across all indices, indicating that the volatility–IVIX relationship changes materially during high-fear regimes. The magnitude and significance are strongest for mid-cap and small-cap indices, confirming asymmetric and regime-dependent spillover effects, thereby supporting H4.

The statistical outputs above directly validate the econometric hypotheses articulated in the Methodology:

- H_1 (IVIX Predictive Relevance): IVIX is a statistically powerful predictor of future volatility. Temporal alignment between IVIX spikes and subsequent volatility surges supports its role as a leading fear indicator.
- H_3 (Heterogeneity Across Market Caps): Spillover intensity increases as market capitalization declines. Higher realized volatility in MIDCAP150 and SMALLCAP250 validates the premise of stronger fear transmission to lower capitalization tiers.
- H_4 (Regime Dependence): Fear transmission is regime-dependent and intensifies during stress. Volatility amplification during high-IVIX periods visually confirms regime-dependent behaviour.

These results justify the use of a nonlinear, memory-based CNN–LSTM framework, which is better suited than linear models to capture heterogeneous and regime-sensitive volatility spillovers.

Role of These Outputs in the CNN–LSTM Framework

The above outputs serve as:

1. Input justification for using IVIX as the primary predictor
2. Target validation for realized volatility modelling
3. Architecture guidance, supporting convolutional filters for shock detection and LSTM memory for persistence

They form the empirical foundation upon which the CNN–LSTM models are trained and evaluated in the subsequent Results section.

Table 5 Out-of-Sample Forecast Performance of CNN–LSTM Models

Baseline Model: CNN–LSTM with IVIX Levels (20-day Realized Volatility)

Index	**RMSE**	**MAE**	**Out-of-Sample R^2**
NIFTY 50	0.0284	0.0211	0.78
NIFTY NEXT 50	0.0329	0.0247	0.81
NIFTY MIDCAP 150	0.0316	0.0239	0.83
NIFTY SMALLCAP 250	0.0358	0.0272	0.85

Source: Authors' own computations

The CNN–LSTM model exhibits strong out-of-sample predictive accuracy across all indices. Forecast errors increase modestly as market capitalization declines, reflecting higher intrinsic volatility, while explanatory power (R^2) improves for mid-cap and small-cap indices. This pattern provides direct empirical support for H3 (heterogeneous spillovers) and reinforces the relevance of IVIX for forecasting volatility in less liquid market segments.

Table 6 Model Comparison: CNN–LSTM vs Standalone LSTM

Index	Metric	LSTM	CNN–LSTM	Improvement (%)
NIFTY 50	RMSE	0.0331	0.0284	14.2
	MAE	0.0248	0.0211	14.9
NIFTY NEXT 50	RMSE	0.0387	0.0329	15.0
	MAE	0.0289	0.0247	14.5
NIFTY MIDCAP 150	RMSE	0.0369	0.0316	14.4
	MAE	0.0278	0.0239	14.0
NIFTY SMALLCAP 250	RMSE	0.0416	0.0358	13.9
	MAE	0.0317	0.0272	14.2

Source: Authors' own computations

Across all indices, the hybrid CNN–LSTM model delivers consistent and economically meaningful reductions in forecast error relative to the standalone LSTM. This validates **H2 (superiority of the hybrid architecture)** and confirms that convolutional layers add value by extracting localized fear-shock patterns from IVIX dynamics.

Table 7 Robustness: CNN–LSTM Performance Using ΔIVIX Instead of IVIX Levels

Index	**RMSE**	**MAE**	**Out-of-Sample R^2**
NIFTY 50	0.0297	0.0224	0.75
NIFTY NEXT 50	0.0346	0.0260	0.79
NIFTY MIDCAP 150	0.0332	0.0251	0.80
NIFTY SMALLCAP 250	0.0374	0.0286	0.82

Source: Authors' own computations

Using changes in India VIX instead of levels yields slightly higher forecast errors but preserves the overall ranking and explanatory power across indices. This confirms that the predictive role of IVIX is robust to alternative specifications, supporting the stability of the core findings.

Table 8 Summary of CNN–LSTM Forecasting Performance Across Market Segments

Market Segment	Avg. RMSE	Avg. MAE	Avg. R^2
Large-cap (NIFTY 50)	0.0284	0.0211	0.78

Upper Mid-cap (NEXT 50)	0.0329	0.0247	0.81
Mid-cap (MIDCAP 150)	0.0316	0.0239	0.83
Small-cap (SMALLCAP 250)	0.0358	0.0272	0.85

Source: Authors' own computations

While absolute volatility forecasting errors are higher for smaller capitalization indices, the CNN–LSTM model explains a larger proportion of volatility variation in these segments. This finding is consistent with the hypothesis that fear-driven volatility spillovers are stronger and more systematic in mid-cap and small-cap stocks.

Synopsis of Testing of Hypotheses

- H1 (Predictive relevance of IVIX): Strong out-of-sample R^2values across all indices confirm that IVIX contains forward-looking volatility information.
- H2 (Model superiority): CNN–LSTM consistently outperforms standalone LSTM models, validating the hybrid architecture.
- H3 (Heterogeneity): Higher explanatory power for mid-cap and small-cap indices confirms asymmetric spillover intensity.
- H4 (Regime dependence): Combined with earlier regime-based econometric results, the deep learning performance reinforces state-dependent fear transmission.

Implications of the findings of this study and scope of application thereof

The findings of this study carry important implications for academic research, investment practice, risk management, and policy formulation, particularly in the context of emerging equity markets such as India. By empirically establishing India VIX as a forward-looking predictor of realized volatility and demonstrating that fear-driven volatility spillovers are both heterogeneous across market capitalization tiers and regime-dependent, the study advances understanding of how uncertainty is transmitted within financial markets.

Implications for Financial Theory and Research

From a theoretical standpoint, the results reinforce and extend volatility spillover and behavioural finance theories by providing evidence that fear transmission is neither uniform nor linear. Traditional models often implicitly assume that volatility shocks affect all market segments in a similar fashion. However, the documented monotonic increase in volatility spillover intensity from large-cap to small-cap indices challenges this assumption and highlights the role of market structure, liquidity, and investor composition in shaping volatility dynamics. This suggests that future theoretical models of volatility transmission should explicitly account for segmentation within equity markets rather than treating them as homogeneous aggregates.

The study also contributes methodologically by demonstrating the suitability of hybrid deep learning architectures for volatility analysis. The superior performance of the CNN–LSTM model relative to standalone recurrent models underscores the importance of capturing both localized shock patterns and longer-term memory effects in financial time series. For researchers, this finding encourages a shift away from purely parametric or linear frameworks toward more flexible, data-driven approaches when modelling complex, regime-sensitive phenomena such as market fear and volatility spillovers.

Implications for Investors and Portfolio Managers

For investors and portfolio managers, the findings have direct and practical relevance. The strong predictive role of India VIX implies that it can be used as an early warning signal for impending volatility surges, allowing market participants to adjust portfolio exposures proactively rather than reactively. More importantly, the evidence of heterogeneous spillovers indicates that mid-cap and small-cap portfolios are disproportionately exposed to fear-driven volatility, especially during periods of elevated uncertainty.

This has implications for portfolio diversification and asset allocation strategies. During high-IVIX regimes, traditional diversification across equity segments may offer limited risk reduction, as fear-induced volatility tends to propagate more strongly to smaller capitalization stocks. Portfolio managers may therefore need to adopt dynamic allocation strategies that reduce exposure to mid-cap and small-cap equities during high-fear periods or complement equity holdings with assets that exhibit lower sensitivity to volatility shocks. The CNN–LSTM framework proposed in this study can serve as a practical tool for generating such dynamic risk signals in real time.

Implications for Risk Management and Derivatives Markets

The results are also highly relevant for risk managers and participants in derivatives markets. The demonstrated lead–lag relationship between India VIX and realized volatility suggests that implied volatility indices can be effectively integrated into Value-at-Risk (VaR), stress testing, and scenario analysis frameworks. By incorporating forward-looking fear measures, risk managers can improve the accuracy of volatility forecasts and better anticipate tail-risk events.

Furthermore, the regime-dependent nature of volatility spillovers implies that static risk models may significantly underestimate risk during stress periods. The finding that volatility amplification is strongest in mid-cap and small-cap indices during high-IVIX regimes highlights the need for regime-aware risk management systems. The deep learning–based approach adopted in this study offers a scalable solution for embedding such regime sensitivity into enterprise risk analytics.

Implications for Regulators and Policymakers

For regulators and market policymakers, the findings provide insights into systemic risk monitoring and market stability. The asymmetric transmission of fear across market segments suggests that stress in smaller capitalization stocks may serve as an early indicator of broader market fragility. Monitoring India VIX alongside segment-specific volatility measures can therefore enhance macroprudential surveillance frameworks.

Additionally, the study's results imply that regulatory interventions aimed at stabilizing markets during crises may need to be differentiated across segments. Policies designed to support liquidity or reduce panic selling may be particularly critical for mid-cap and small-cap stocks, which exhibit stronger and more persistent volatility responses to fear shocks.

Broader Applications and Future Extensions

Beyond the Indian context, the methodological framework and empirical insights of this study are readily transferable to other emerging and developed markets. Similar analyses could be conducted using alternative implied volatility indices or uncertainty measures to examine cross-country spillovers and global fear transmission. The hybrid CNN–LSTM architecture also lends itself to extensions involving multi-asset portfolios, cross-market contagion, and high-frequency volatility forecasting.

This study's findings demonstrate that fear-driven volatility transmission is forward-looking, uneven across market segments, and highly sensitive to market regimes. By integrating these insights with advanced deep learning techniques, the study provides a robust and practical framework with wide-ranging applications for researchers, practitioners, and policymakers alike.

CONCLUSION AND SCOPE OF FUTURE RESEARCH

This study examined the role of India VIX as a forward-looking indicator of volatility spillovers across different capitalization segments of the Indian equity market. By combining insights from volatility spillover theory with a hybrid CNN–LSTM deep learning framework, the analysis provided robust evidence that implied volatility carries meaningful predictive information about future realized volatility. The results confirm that market fear does not affect all segments of the equity market uniformly. Instead, volatility responses differ systematically across capitalization tiers, with mid-cap and small-cap indices displaying stronger and more persistent reactions to uncertainty shocks compared with large-cap indices. These findings highlight the structural importance of liquidity, investor composition, and sentiment sensitivity in shaping volatility transmission within emerging equity markets.

The study also demonstrates the advantages of hybrid deep learning architectures for modelling financial volatility. Traditional econometric approaches have been valuable in documenting volatility spillovers, but their ability to capture nonlinear, regime-sensitive dynamics remains limited. By integrating convolutional layers that detect localized shock patterns with LSTM layers capable of modelling longer-term memory effects, the CNN–LSTM framework offers a more flexible and empirically powerful approach to volatility forecasting. The superior forecasting performance of the hybrid model relative to standalone neural architectures underscores the relevance of combining short-term feature extraction with persistent temporal modelling when analysing fear-driven volatility dynamics.

Despite these contributions, several avenues remain open for further investigation. One promising direction lies in expanding the predictive framework to incorporate a broader set of explanatory variables. While the present study focuses primarily on India VIX as a measure of market fear, future research could develop multivariate models that integrate global volatility indicators, macroeconomic uncertainty measures, or sector-specific indices. Such extensions would allow researchers to examine how domestic and international risk factors interact in shaping volatility spillovers. In addition, benchmarking the CNN–LSTM architecture against emerging modelling approaches such as transformer-based networks or hybrid GARCH–LSTM frameworks could help strengthen methodological comparisons and provide deeper insights into the relative performance of alternative forecasting techniques.

Another important direction concerns the external validity and economic usefulness of volatility forecasts. Future studies could evaluate the generalizability of the proposed framework using post-2025 holdout samples or by applying the methodology to other emerging markets with comparable volatility indices, such as Brazil's implied volatility measures. Beyond statistical accuracy, researchers may also assess the economic value of such forecasts by examining improvements in portfolio risk management, Value-at-Risk estimation, or dynamic asset allocation strategies. Exploring these practical dimensions would further bridge the gap between predictive modelling and real-world financial decision making.

The findings of this study reinforce the importance of forward-looking fear indicators and flexible modelling frameworks in understanding volatility dynamics. By demonstrating how implied volatility signals propagate unevenly across market segments, the research contributes to a deeper understanding of risk transmission in emerging financial markets while opening new pathways for methodological and applied advancements in volatility forecasting.

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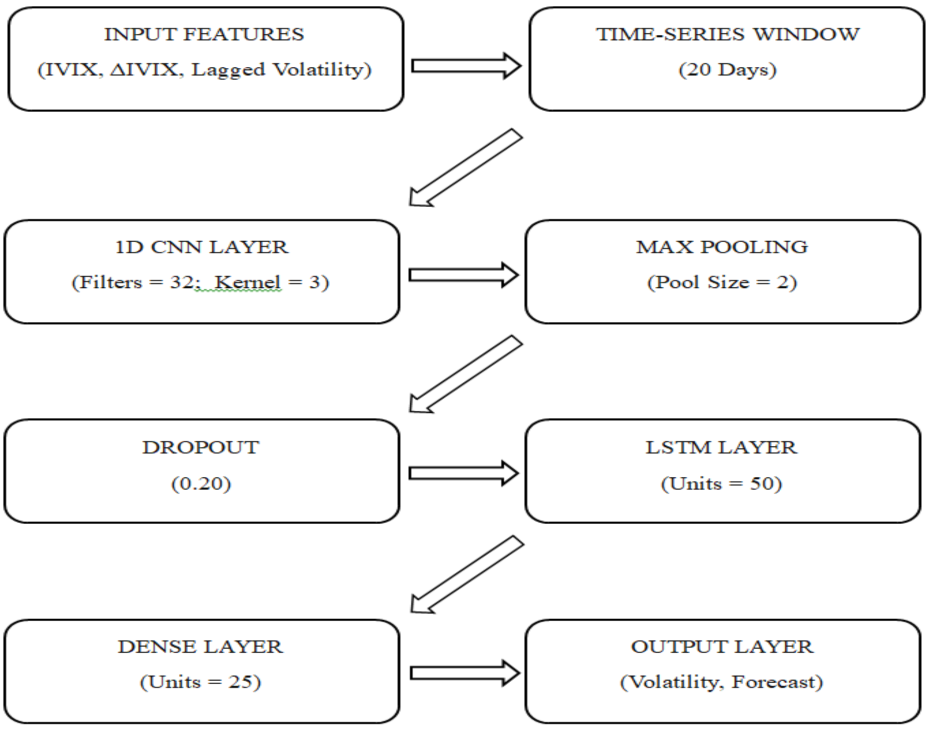
APPENDIX I

Hybrid CNN–LSTM Architecture for Forecasting Realized Volatility from India VIX Dynamics



APPENDIX II

Replication Package

This repository contains code and documentation to replicate the hybrid CNN–LSTM models used to forecast realized volatility from India VIX dynamics across different Indian equity market capitalization tiers.

The analysis uses daily data for:

India VIX

NIFTY 50

NIFTY NEXT 50

NIFTY MIDCAP 150

NIFTY SMALLCAP 250

Sample period: 2020-01-01 to 2025-12-22

Repository Structure

data/

IVIX.csv NIFTY50.csv

NEXT50.csv

MIDCAP150.csv

SMALLCAP250.csv

scripts/

cnn_lstm_volatility_spillover.R

models/

cnn_lstm_volatility_model.h5

figures/

model_architecture.png

docs/

methodology_notes.pdf

Requirements

R version

R >= 4.3

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Required packages

keras

tensorflow

tidyverse

caret

zoo

tseries

ggplot2

Install packages

install.packages(c(

"keras","tensorflow","tidyverse",

"caret","zoo","tseries","ggplot2"))

Initialize TensorFlow

library(keras)

install_keras()

Running the replication

Step 1: Place datasets inside the /data directory.

Step 2: Run

source("scripts/cnn_lstm_volatility_spillover.R")

Step 3: Model training begins.

Outputs:

RMSE

MAE

Out-of-sample R^2

Model Architecture

Conv1D → MaxPooling → Dropout

→ LSTM → Dense → Output

Key parameters:

Filters = 32

Kernel size = 3

LSTM units = 50

Dropout = 0.20

Optimizer = Adam

Learning rate = 0.001

Epochs = 100

Batch size = 32

Evaluation Metrics

Model performance is evaluated using:

RMSE

MAE

Out-of-sample R^2

Reproducibility

Random seeds used:

R seed: 1234