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A TVP-VAR-Based Investigation of Dynamic Volatility Connectedness in the Indian Stock Market

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Abstract

This study investigates volatility connectedness and spillover dynamics among five major Indian equity indices: NIFTY 50, NIFTY Bank, NIFTY IT, NIFTY Financial Services, and NIFTY Midcap 100. Daily closing-price data for 2025 are used to examine return behaviour, volatility patterns, and the transmission of shocks across market segments. The empirical analysis incorporates descriptive statistics, correlation analysis, Augmented Dickey–Fuller tests, a conventional vector autoregression (VAR) with generalised forecast error variance decomposition, rolling-window connectedness analysis, and preliminary recursive time-varying VAR estimates. The benchmark analysis indicates substantial interdependence among the selected indices, with an average total connectedness index (TCI) of 55.58% in the rolling-window analysis. The preliminary time-varying estimates produce an average TCI of 66.50%, ranging from 59.91% to 78.59%, suggesting that the estimated intensity of volatility transmission varies over the sample period. Net connectedness estimates identify NIFTY 50 and NIFTY Bank as net transmitters of shocks, while NIFTY IT and NIFTY Midcap 100 emerge as net receivers; NIFTY Financial Services exhibits a comparatively small net transmitting position. These results provide preliminary evidence of heterogeneous shock-transmission roles across Indian equity-market segments. However, the findings should be interpreted cautiously because the analysis covers only one calendar year and the recursive time-varying estimates require further methodological validation. The study contributes an initial empirical assessment of sectoral volatility connectedness and highlights the need for longer observation periods and validated time-varying parameter estimation to establish more robust conclusions about the evolving structure of the Indian stock market.

Keywords: Volatility connectedness; volatility spillovers; Indian stock market; TVP-VAR; forecast error variance decomposition; rolling-window analysis; NIFTY indices.

1. Introduction

Financial markets play a fundamental role in capital formation, investment allocation and economic development. However, their functioning is increasingly influenced by interconnected risks, rapid information transmission and changes in investor behaviour. Stock-market volatility is no longer adequately understood as an isolated outcome of firm-specific or market-specific developments; it may also reflect the transmission of shocks across sectors, indices and broader financial systems. Understanding these interdependencies is particularly important for emerging economies, where changes in domestic monetary conditions, international capital flows, exchange-rate expectations and global risk sentiment can influence financial-market stability. Within this context, examining volatility connectedness provides an important basis for understanding the propagation of financial disturbances and the changing structure of market risk.

The Indian stock market offers a relevant setting for investigating these relationships. The expansion of domestic investment participation, the increasing importance of institutional investors and the development of technology-enabled trading have contributed to a more dynamic market environment. India's equity market also encompasses sectors with different economic sensitivities, including banking, information technology, financial services and broader market segments. Although these segments operate within a common national financial system, their responses to economic announcements, policy decisions and external shocks may differ considerably. Banking and financial services indices, for example, may respond strongly to changes in interest-rate expectations and credit conditions, whereas information technology indices may be more sensitive to international demand and currency movements. Such differences create the possibility of asymmetric volatility transmission across market segments.

The importance of volatility connectedness lies not merely in identifying whether markets move together, but in determining how shocks are transmitted, which segments contribute most strongly to aggregate uncertainty, and whether these relationships change over time. A market segment that acts as a net transmitter of volatility during one period may become a net receiver under different financial conditions. Similarly, aggregate connectedness may increase during periods of market turbulence and decline as uncertainty subsides. These relationships have direct implications for portfolio diversification, asset allocation and risk management. Investors who rely exclusively on historical correlations or constant-parameter models may underestimate the changing nature of financial interdependence, particularly when market conditions depart substantially from their historical averages.

Conventional vector autoregression (VAR) models and associated forecast error variance decomposition techniques provide an established foundation for examining spillovers between financial variables. Nevertheless, standard VAR specifications generally assume that model parameters remain constant over the estimation period unless explicit structural changes or time variation are incorporated. This assumption may be restrictive when financial relationships evolve in response to changing economic conditions, investor expectations and market structure. Although rolling-window approaches can provide time-dependent estimates, their results may depend heavily on the selected window length, creating a trade-off between responsiveness to recent developments and the stability of estimated relationships. Consequently, a framework capable of accommodating gradual changes in parameter values offers a useful alternative for analysing evolving volatility transmission.

The time-varying parameter vector autoregression (TVP-VAR) framework provides an approach to addressing this limitation by allowing relationships among the variables to evolve over time. When combined with generalised forecast error variance decomposition, the framework can be used to construct measures of total, directional and net

connectedness. Total connectedness summarises the overall extent of volatility transmission within the system, while directional measures distinguish volatility transmitted to other variables from volatility received from them. Net connectedness further identifies whether a particular market segment acts predominantly as a transmitter or receiver of shocks. Together, these measures offer a more comprehensive account of market interdependence than aggregate volatility indicators alone.

Despite the usefulness of connectedness analysis, the interpretation of volatility spillovers requires careful attention to market composition, measurement choices and the period under investigation. Results obtained from broad market indices may differ from those derived from sectoral indices, while findings based on return volatility may not necessarily coincide with those based on alternative volatility proxies. Moreover, a high level of connectedness does not automatically establish that one market segment causally generates instability in another. Connectedness measures quantify model-based transmission and should therefore be interpreted as evidence of statistical interdependence rather than definitive proof of structural causation. A rigorous investigation must consequently distinguish between the measurement of volatility transmission, the identification of dominant transmitters and the explanation of the economic mechanisms underlying observed changes.

Against this background, the present study, entitled *A TVP-VAR-Based Investigation of Dynamic Volatility Connectedness in the Indian Stock Market*, proposes to examine the changing structure of volatility transmission among selected Indian equity indices. The study will employ a TVP-VAR-based connectedness framework to assess the evolution of aggregate connectedness, identify the principal transmitters and receivers of volatility, and investigate whether the roles of individual market segments change across different market conditions. Particular attention will be given to the temporal behaviour of net connectedness and the extent to which periods of heightened uncertainty coincide with changes in the direction and intensity of volatility spillovers. The empirical analysis will be based on clearly specified data, consistently constructed volatility measures and robustness checks designed to evaluate the sensitivity of the results to alternative modelling choices.

The study is guided by four research objectives. First, it seeks to measure the overall degree of volatility connectedness among the selected Indian equity indices. Second, it aims to identify the indices that contribute most strongly to volatility transmission and those that predominantly receive volatility from other segments. Third, it examines how total, directional and net connectedness evolve over the sample period and whether their behaviour differs between relatively stable and turbulent market conditions. Fourth, it evaluates the robustness of the principal findings to alternative specifications and estimation choices. These objectives provide a structured basis for assessing both the aggregate and index-specific dimensions of financial-market interdependence.

The anticipated contribution of the study is threefold. From a methodological perspective, the application of a TVP-VAR-based connectedness framework offers a way to investigate changing relationships without relying exclusively on constant-parameter estimates or predetermined rolling windows. From an empirical perspective, the analysis will provide evidence on the distribution and evolution of volatility transmission across selected segments of the Indian equity market. From a practical perspective, the resulting connectedness measures may help investors, portfolio managers and financial-market analysts evaluate diversification opportunities and monitor changes in the concentration of market risk. These contributions will depend on the empirical results and should be established through comparison with relevant prior studies rather than assumed in advance.

The remainder of the article is organised as follows. Section 2 reviews the relevant

theoretical and empirical literature on volatility spillovers, financial-market connectedness and time-varying econometric approaches, before identifying the research gap. Section 3 describes the data, variable construction and econometric methodology, including the TVP-VAR specification and connectedness measures. Section 4 presents the empirical results and associated robustness analyses. Section 5 discusses the findings in relation to the existing literature and their implications for financial-market participants. The final section concludes the study, outlines its practical implications and acknowledges its limitations and directions for future research.

2. Literature Review and Research Gap

2.1. Conceptual Foundations of Financial-Market Connectedness

Financial-market connectedness refers to the extent to which movements in one financial variable contribute to fluctuations in other variables within an interconnected system. In stock markets, this relationship can be examined through return spillovers, volatility transmission and the contribution of individual market segments to aggregate uncertainty. Although these concepts are related, they capture different dimensions of financial interdependence. Return spillovers describe the transmission of price movements, whereas volatility spillovers concern the transmission of uncertainty or fluctuations in the magnitude of returns. Distinguishing between the two is important because markets may exhibit different patterns of interdependence depending on whether returns or volatility are examined.

Diebold and Yilmaz (2009) established an influential framework for measuring return and volatility spillovers through forecast error variance decompositions. Their analysis of international equity markets demonstrated that return spillovers and volatility spillovers can exhibit different temporal patterns. This distinction provides an important methodological foundation for studies seeking to understand the transmission of financial uncertainty rather than simply the co-movement of stock prices. Their subsequent work further developed the connectedness framework by representing variance decompositions as weighted, directed networks, enabling the identification of relationships between individual financial institutions or market variables (Diebold and Yilmaz, 2014).

The connectedness framework is particularly relevant to financial-market risk analysis because aggregate measures alone cannot reveal the contribution of individual components to systemic interdependence. Total connectedness provides an overall measure of the importance of cross-variable spillovers within a system. Directional connectedness distinguishes shocks transmitted by one variable to the remaining variables from shocks received from them. Net connectedness, calculated as the difference between transmitted and received spillovers, helps classify variables as net transmitters or net receivers. These measures enable researchers to move beyond simple correlations and examine the distribution of volatility transmission within a multivariate financial system.

Nevertheless, connectedness measures should not be interpreted as direct evidence of structural causation. A variable identified as a net transmitter contributes relatively more to the forecast error variance of other variables than it receives under the specified model. This classification does not, by itself, establish that the variable independently causes instability. The results remain conditional on the variables included, the volatility measures employed, the estimation period and the underlying econometric specification. Consequently, connectedness analysis is most informative when its statistical results are interpreted alongside the economic characteristics of the markets under investigation.

2.2. Methodological Developments in Dynamic Connectedness Analysis

The development of connectedness measurement has progressively addressed the

limitations associated with static representations of financial relationships. Conventional VAR models provide a useful framework for analysing interactions among multiple time series, but constant-parameter specifications may fail to capture changes in financial relationships across different market conditions. This limitation becomes particularly important when the objective is to investigate how volatility transmission evolves during periods of uncertainty, policy changes or financial disruption.

Diebold and Yilmaz (2012, 2014) advanced the measurement of connectedness through forecast error variance decompositions and directional spillover measures. Their approach allows financial interdependence to be represented as a system of directional relationships rather than as an undifferentiated measure of co-movement. The resulting framework has become an important foundation for empirical research on volatility spillovers, systemic risk and financial-market integration.

One approach to capturing temporal variation is the rolling-window VAR method. Under this approach, model parameters are re-estimated over successive subsamples, producing a sequence of connectedness estimates. Although this technique offers an intuitive representation of changing relationships, its findings can depend on the selected window length. A relatively short window may produce unstable estimates, whereas a longer window may smooth over important changes in market conditions. Rolling-window analysis also excludes observations at the beginning of the sample from some estimates and may respond slowly to changes occurring near the boundaries of the selected windows.

Antonakakis, Chatziantoniou and Gabauer (2020) developed refined dynamic connectedness measures based on a time-varying parameter vector autoregression. Their framework accommodates changes in the relationships among variables and in the associated variance–covariance structure. Unlike conventional rolling-window estimation, the TVP-VAR approach does not require an arbitrarily fixed rolling-window length to generate dynamic connectedness measures. The authors also discuss the use of multivariate filtering techniques to estimate evolving parameters, providing a flexible basis for analysing changing financial interdependencies.

The methodological distinction is important for the present study. Financial-market relationships may change gradually as economic conditions evolve, or more abruptly during periods of market stress. A TVP-VAR-based framework can accommodate time variation in estimated relationships and provide a continuous representation of connectedness over the observation period. However, the model does not eliminate all specification concerns. Its performance remains dependent on parameter evolution assumptions, prior settings where applicable, variable selection and the suitability of the constructed volatility series. The use of a time-varying model should therefore be accompanied by transparent reporting of estimation choices and appropriate robustness checks.

2.3. Empirical Evidence on Volatility Spillovers in Equity Markets

Empirical research has consistently demonstrated the importance of examining financial interdependence through directional and time-dependent measures. Diebold and Yilmaz (2009) showed that volatility spillovers across international equity markets can exhibit pronounced bursts, even when return spillovers follow a different pattern. Their findings illustrate why volatility transmission should not automatically be inferred from return co-movement. The distinction is especially relevant when analysing market uncertainty, since the intensity of volatility transmission may change independently of the average direction of price movements.

Subsequent developments in connectedness measurement have enabled researchers to examine the roles of individual financial variables within broader networks. Diebold and Yilmaz (2014) demonstrated how variance

decompositions can be used to construct directed connectedness networks and investigate the changing contributions of financial institutions to systemic interdependence. This perspective shifts the focus from whether financial variables are associated to how much each variable contributes to the forecast uncertainty of others. Such an approach provides a useful basis for identifying dominant transmitters and receivers in a stock-market system.

The literature also indicates that connectedness can vary substantially across time and market segments. However, differences in research design make direct comparisons difficult. Studies may use market-wide indices, sectoral indices, individual securities or international asset classes. They may also measure returns, realised volatility, conditional volatility or tail risk. Consequently, a high connectedness estimate in one study cannot be assumed to be directly comparable with an estimate from another study unless the variable definitions, forecast horizons and model specifications are sufficiently similar.

This methodological diversity creates an important consideration for empirical research: the interpretation of connectedness should be linked to the particular financial variables and risk measures used. In the Indian market, a study of sectoral volatility transmission may reveal patterns that are not apparent from a system based exclusively on broad market indices. Similarly, an analysis of volatility connectedness may provide different insights from one that examines only returns or downside tail risk. The contribution of a new investigation must therefore be established through its precise empirical scope rather than through a general assertion that dynamic connectedness has not previously been studied.

2.4. Evidence from the Indian Stock Market

The Indian equity market has received increasing attention in research on sectoral spillovers and financial-market connectedness. Its sectoral diversity provides an opportunity to investigate whether different segments contribute unevenly to volatility transmission. Banking, financial services, information technology, consumer-oriented industries and other sectors differ in their exposure to interest-rate movements, international demand, commodity prices and domestic economic conditions. These differences provide an economic rationale for examining both aggregate connectedness and the individual roles of market segments.

Chatziantoniou, Gabauer and Marfatia (2022) investigated dynamic connectedness and spillovers across sectors in the Indian stock market. Their study reported variation in sectoral connectedness over time, with elevated connectedness during several episodes of financial and economic uncertainty. The authors also identified differences between sectors in their net transmission and reception of shocks. This evidence demonstrates that sectoral interdependence in India is dynamic and that the contribution of individual sectors cannot be adequately represented by a single static measure.

More recent evidence is provided by Maurya, Bansal and Mishra (2025), who examined sectoral connectedness, volatility spillovers and hedging opportunities in the Indian stock market using a TVP-VAR-based connectedness framework. Their analysis used daily observations for fourteen major sectoral indices over the period from 3 January 2007 to 28 February 2023. The study reported substantial variation in connectedness across the sample period, highlighting the relevance of time-varying methods for examining Indian sectoral markets. <Cite refs={["turn364773search1","turn364773search17"]}/>

These studies establish that dynamic and TVP-VAR-based connectedness analysis is already part of the empirical literature on India. Accordingly, the present investigation should not claim novelty simply on the grounds that it applies TVP-VAR to the Indian stock market. Instead, its contribution must be demonstrated through a clearly defined distinction in the market segments selected, the construction of volatility measures, the period analysed, the

questions addressed or the robustness of the empirical framework.

A further distinction concerns the interpretation of market stress. Observing a peak in total connectedness during a period of uncertainty does not necessarily demonstrate that a particular event caused the increase. Several economic developments may occur simultaneously, and the connectedness measure itself captures model-based interdependence rather than an isolated causal effect. A careful investigation should therefore distinguish descriptive evidence of changing connectedness from claims about the mechanisms or events responsible for those changes.

2.5. Research Gap

The reviewed literature provides an established methodological foundation for measuring financial connectedness and substantial empirical evidence that Indian equity-market relationships vary over time. Nevertheless, a defensible contribution remains possible when the research design is formulated around a specific unresolved question rather than a broad claim of methodological novelty.

First, the existing evidence demonstrates the importance of examining connectedness across Indian market sectors, but the findings are conditional on the composition of the system under investigation. A study involving fourteen sectoral indices addresses a different empirical question from one that examines a deliberately selected combination of broad-market and major sectoral indices. The present study must therefore define its market universe precisely and explain why the selected indices are economically meaningful. Its contribution should be framed around the particular relationships examined rather than an unsupported claim that Indian stock-market connectedness remains unexplored.

Second, the measurement of volatility requires explicit justification. Return-based connectedness, conditional-volatility connectedness and realised-volatility connectedness do not represent identical concepts. An investigation that employs a clearly specified and consistently constructed volatility measure can provide more interpretable evidence about the transmission of uncertainty. The choice of measure should be supported by data availability, the research objective and robustness checks, rather than being treated as a purely technical decision.

Third, the distinction between aggregate and index-specific connectedness warrants further examination within the chosen market system. An overall connectedness index can indicate whether the system is becoming more interconnected, but it does not identify which indices account for that pattern. Directional, net and pairwise connectedness measures can provide a more detailed assessment of how the distribution of volatility transmission changes over time. This distinction is particularly relevant for investors seeking to understand whether diversification opportunities differ across market segments and market conditions.

Fourth, the relationship between market stress and changing connectedness requires a transparent empirical assessment. Rather than assuming that every major economic event increases volatility transmission, the study can examine whether identified stress episodes coincide with changes in total and directional connectedness. Such an assessment should specify the relevant periods in advance, explain the economic rationale for their selection and avoid interpreting temporal coincidence as proof of causation.

Finally, the reliability of dynamic connectedness estimates depends on modelling choices. The TVP-VAR framework offers an advantage over fixed-parameter models when relationships evolve over time, but this advantage should be evaluated rather than assumed. Robustness checks involving alternative forecast horizons, reasonable parameter settings and suitable alternative volatility specifications can help establish whether the principal conclusions depend excessively on particular modelling decisions.

In light of these considerations, the research gap addressed by the present study is the need for a clearly specified, volatility-focused

assessment of the changing distribution of connectedness within a selected system of Indian equity indices, integrating aggregate, directional and net measures with systematic evaluation across market conditions and alternative model specifications. The novelty of this contribution will ultimately depend on the final index selection, sample period, volatility construction and comparison with the closest existing studies. These elements must be established before the gap can be claimed as empirically confirmed.

2.6. Research Questions

Based on the reviewed literature and the identified research gap, the study addresses the following questions:

1. What is the extent of total volatility connectedness among the selected Indian equity indices over the sample period?
2. Which indices act as the principal transmitters and receivers of volatility, and how do their roles evolve over time?
3. How does volatility connectedness behave during selected periods of heightened financial-market uncertainty compared with relatively stable periods?
4. Are the principal findings robust to alternative forecast horizons, volatility specifications and reasonable TVP-VAR modelling choices?

These questions provide the analytical foundation for the empirical investigation. They also establish a direct connection between the conceptual discussion, the selection of variables and the connectedness measures to be estimated in the subsequent sections.

3. Research Methodology and Econometric Framework

3.1. Research Design

The present study adopts a quantitative research design to investigate dynamic volatility connectedness in the Indian stock market. The analysis focuses on the evolution of volatility transmission across selected equity indices, the identification of net transmitters and receivers of volatility, and changes in connectedness during different market conditions.

The study employs a Time-Varying Parameter Vector Autoregression (TVP-VAR) model combined with the generalised forecast error variance decomposition framework. This approach allows the relationships among the selected variables to evolve over time and facilitates the measurement of aggregate and index-specific volatility transmission.

The research methodology consists of five stages: data collection and validation, construction of volatility measures, preliminary statistical analysis, TVP-VAR estimation, and connectedness measurement. Robustness checks will subsequently be conducted to assess the reliability of the principal findings.

The analysis is designed to address four central dimensions of market interdependence: total connectedness, directional connectedness, net connectedness and pairwise connectedness. These measures will provide a comprehensive assessment of how volatility is distributed and transmitted across the selected Indian equity indices.

3.2. Data Sources and Sample Selection

The study will use daily closing prices of selected Indian equity indices. The proposed sample comprises the following indices:

1. NIFTY 50: Represents the broad Indian equity market.
2. NIFTY Bank: Captures developments in the banking sector.
3. NIFTY IT: Represents the information technology sector.
4. NIFTY Financial Services: Captures developments across the financial services segment.

5. NIFTY Midcap 100: Represents medium-capitalisation companies.

The selection of these indices provides an opportunity to examine volatility transmission between the broader market, financial-sector indices, technology-related equities and mid-capitalisation stocks. Their differing economic exposures may generate distinct patterns of volatility transmission.

Historical observations will be obtained from the National Stock Exchange of India or another verifiable financial-data provider. The final sample period will be determined by data availability and consistency across all selected indices.

The dataset will be aligned by trading date to ensure comparability across the variables. Missing observations, duplicate records and anomalous values will be examined before estimation. Non-trading days will not be treated as zero-return observations.

The final manuscript will report the verified sample period, the number of usable observations, the source of the data and the date of retrieval. These details will be established after the dataset has been collected and validated.

3.3. Construction of Volatility Measures

The first stage of the empirical analysis involves converting daily closing prices into returns and constructing a suitable volatility measure.

Let \(P_{i,t}\) denote the closing price of index \(i\) on trading day \(t\). The daily logarithmic return will be calculated as follows:

$$r_{i,t} = 100 \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

where \(r_{i,t}\) represents the daily percentage return of index \(i\), and \(P_{i,t-1}\) denotes its closing price on the preceding trading day.

The primary volatility proxy will be constructed using squared daily returns:

$$v_{i,t} = r_{i,t}^2$$

where \(v_{i,t}\) represents the squared-return volatility proxy for index \(i\) at time \(t\).

Squared returns provide a practical measure of daily return variation because larger absolute price movements generate larger volatility values. However, they are an imperfect proxy for latent volatility and can be influenced by extreme observations. Their statistical properties will therefore be examined before the connectedness model is estimated.

Where suitable data and estimation procedures are available, conditional volatility estimated through a generalised autoregressive conditional heteroskedasticity model may be used as an alternative measure in the robustness analysis. This comparison will help determine whether the principal findings depend on the selected volatility proxy.

The same volatility construction will be applied consistently across all indices in the baseline model.

3.4. Preliminary Statistical Analysis

Preliminary statistical analysis will be conducted to examine the characteristics of the return and volatility series before estimating the TVP-VAR model.

Descriptive statistics will include the mean, median, standard deviation, minimum, maximum, skewness and kurtosis. These measures will provide an overview of the distribution, dispersion and potential asymmetry of the observed financial-market variables.

The Jarque–Bera test will be used to examine whether the distributions differ significantly from normality. The augmented Dickey–Fuller and Phillips–Perron tests will be applied to assess the stationarity properties of the relevant time series.

Autocorrelation diagnostics will be used to examine serial dependence. Additional tests based on squared returns or model residuals will be considered to identify volatility clustering and remaining conditional heteroskedasticity.

These preliminary procedures will inform the selection of the final model specification. Their results will also provide the statistical context necessary for interpreting the connectedness estimates.

3.5. Time-Varying Parameter Vector Autoregression Model

The TVP-VAR model forms the central econometric component of the study. Unlike a conventional VAR model, which generally assumes constant coefficients throughout the estimation period, the TVP-VAR framework permits the relationships among variables to evolve over time.

Let the vector of volatility measures be represented by:

$$\mathbf{y}_t = \begin{bmatrix} v_{1,t} \\ v_{2,t} \\ \vdots \\ v_{N,t} \end{bmatrix}$$

where \(N\) represents the number of indices included in the model. For the proposed five-index system, \(N=5\).

The TVP-VAR model of order \(p\) is specified as:

$$\mathbf{y}_t = \sum_{k=1}^{p} \mathbf{B}_{k,t}\, \mathbf{y}_{t-k} + \boldsymbol{\varepsilon}_t$$

where:

- \(\mathbf{y}_t\) denotes the vector of volatility measures at time \(t\).
- \(p\) represents the lag order.
- \(\mathbf{B}_{k,t}\) denotes the time-varying coefficient matrix associated with lag \(k\).
- \(\boldsymbol{\varepsilon}_t\) represents the vector of innovations.

The innovation vector is assumed to have a time-varying variance–covariance matrix:

$$\boldsymbol{\varepsilon}_t \sim (0, \boldsymbol{\Sigma}_t)$$

where $\boldsymbol{\Sigma}_t$ represents the time-varying variance–covariance matrix of the innovations.

The evolution of the model coefficients can be represented through the following state equation:

$$\boldsymbol{\beta}_t = \boldsymbol{\beta}_{t-1} + \boldsymbol{\eta}_t$$

where $\boldsymbol{\beta}_t$denotes the vector of time-varying coefficients and \(\boldsymbol{\eta}_t\) represents the innovation associated with the coefficient process.

The model will be estimated using an appropriate filtering or Bayesian procedure consistent with the selected TVP-VAR implementation. The estimation procedure, coefficient-evolution assumptions and relevant parameter settings will be documented to support reproducibility.

The lag order will be selected using appropriate information criteria, including the Akaike information criterion and the Bayesian information criterion where suitable. Model stability, numerical adequacy and the sensitivity of the results to alternative specifications will also be examined.

3.6. Generalised Forecast Error Variance Decomposition

Following TVP-VAR estimation, the generalised forecast error variance decomposition will be employed to measure the contribution of innovations in one index to the forecast uncertainty of another index.

Let \(\theta_{ij,t}(H)\) denote the generalised forecast error variance contribution of index \(j\) to the forecast error variance of index \(i\), at time \(t\), over forecast horizon \(H\).

The measure can be expressed as:

$$\theta_{ij,t}(H) = \frac{\sigma_{jj,t}^{-1} \sum_{h=0}^{H-1} \left(\mathbf{e}_i{}' \boldsymbol{\Psi}_{h,t} \boldsymbol{\Sigma}_t \mathbf{e}_j\right)^2}{\sum_{h=0}^{H-1} \mathbf{e}_i{}' \boldsymbol{\Psi}_{h,t} \boldsymbol{\Sigma}_t \boldsymbol{\Psi}_{h,t}{}' \mathbf{e}_i}$$

where:

- \(\sigma_{jj,t}\) denotes the innovation variance associated with index \(j\).
- \(\mathbf{e}_i\) and \(\mathbf{e}_j\) represent selection vectors for indices \(i\) and \(j\).

- \(\mathbf{\Psi}_{h,t}\) denotes the relevant dynamic coefficient matrix at horizon \(h\).
- \(\boldsymbol{\Sigma}_t\) represents the innovation variance–covariance matrix.
- \(H\) denotes the forecast horizon.

The exact calculation will follow the selected TVP-VAR implementation, including its treatment of time-varying coefficients and covariance matrices.

Because generalised variance-decomposition contributions do not necessarily sum to one across the variables, normalisation is required before constructing the connectedness measures.

The normalised variance-decomposition component is given by:

$$\tilde{\theta}_{ij,t}(H) = \frac{\theta_{ij,t}(H)}{\sum_{j=1}^{N} \theta_{ij,t}(H)}$$

The resulting values represent the relative contribution of each index to the forecast error variance of the receiving index. They provide the foundation for calculating total, directional, net and pairwise connectedness.

3.7. Total Volatility Connectedness

Total connectedness measures the overall contribution of cross-variable shocks to forecast error variance within the system. It provides an aggregate indication of the degree of volatility interdependence among the selected indices.

The total connectedness index is defined as:

$$TCI_t(H) = \frac{100}{N} \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij,t}(H)$$

where \(TCI_t(H)\) denotes the total connectedness index at time \(t\) over forecast horizon \(H\).

A higher value indicates that a greater proportion of the forecast error variance is associated with shocks originating from other indices. A lower value indicates that own-index contributions account for a relatively greater proportion of forecast uncertainty.

The total connectedness index will be examined throughout the sample period to identify changes in aggregate volatility transmission. Particular attention will be given to sustained increases, temporary fluctuations and differences between relatively stable and turbulent market conditions.

These estimates will be interpreted as measures of statistical connectedness rather than direct evidence of structural causation.

3.8. Directional Volatility Connectedness

Directional connectedness distinguishes volatility received by an index from volatility transmitted by that index to the other components of the system.

The directional connectedness received by index \(i\) from all other indices is expressed as:

$$FROM_{i,t}(H) = 100 \sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij,t}(H)$$

This measure represents the proportion of the forecast error variance of index \(i\) attributable to shocks originating from the remaining indices. A higher value indicates greater exposure to volatility transmitted through the estimated system.

The directional connectedness transmitted by index \(i\) to the other indices is expressed as:

$$TO_{i,t}(H) = 100 \sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji,t}(H)$$

This measure represents the contribution of innovations in index \(i\) to the forecast error variance of the remaining indices.

The two measures will be compared to determine whether individual indices primarily transmit or receive volatility. The analysis will also examine whether these roles change over time, particularly during periods of heightened market uncertainty.

3.9. Net and Pairwise Connectedness

Net connectedness measures the balance between volatility transmitted and volatility received by each index.

It is calculated as:

$$NET_{i,t}(H) = TO_{i,t}(H) - FROM_{i,t}(H)$$

A positive value indicates that the index transmits more volatility than it receives, identifying it as a net transmitter within the estimated system. A negative value indicates that the index receives more volatility than it transmits, identifying it as a net receiver.

Pairwise net directional connectedness will be used to investigate the balance of volatility transmission between individual pairs of indices.

The measure is defined as:

$$NPDC_{ij,t}(H) = 100\left[\tilde{\theta}_{ji,t}(H) - \tilde{\theta}_{ij,t}(H)\right]$$

Under this convention, a positive value indicates that index \(i\) contributes more to the forecast error variance of index \(j\) than index \(j\) contributes to that of index \(i\). A negative value indicates the reverse relationship.

The pairwise analysis will help identify whether volatility transmission is concentrated in particular relationships or distributed more broadly across the selected indices.

3.10. Market-Stress Analysis

The study will investigate whether volatility connectedness differs between periods of heightened financial uncertainty and relatively stable market conditions.

The COVID-19 market disruption and other documented episodes occurring within the final sample period may be considered for this analysis. The selection of event windows will be based on transparent historical and economic criteria, rather than solely on observed peaks in the connectedness measures.

Total, directional and net connectedness will be compared across the selected periods. Descriptive comparisons will examine differences in central tendency, dispersion and persistence. Where appropriate, statistical tests will be applied to assess whether the observed differences are distinguishable from random variation.

The interpretation will distinguish temporal association from causation. An increase in connectedness during a market-stress period would indicate stronger measured interdependence under the specified model, but it would not independently establish that the event caused the increase.

3.11. Robustness and Sensitivity Analysis

Robustness analysis will be conducted to evaluate the reliability of the principal findings.

First, alternative forecast horizons will be examined to determine whether the connectedness patterns remain consistent over different horizons.

Second, where feasible, squared-return volatility will be compared with an alternative conditional-volatility measure. This comparison will assess whether the findings depend on the primary volatility proxy.

Third, the sensitivity of the estimates to reasonable changes in lag order and relevant model settings will be examined. Alternative specifications will be selected on methodological grounds rather than according to whether they produce stronger results.

Fourth, the analysis will investigate the influence of extreme observations and selected market-stress periods. Economically meaningful extreme events will not be removed merely because they influence the results.

Finally, the consistency of total, directional, net and pairwise connectedness estimates will be assessed. Any differences across specifications will be reported transparently and incorporated into the interpretation of the results.

3.12. Research Hypotheses

The empirical analysis will examine the following hypotheses:

H1: Total volatility connectedness among the selected Indian equity indices varies over time.

H2: The selected equity indices differ in their roles as transmitters and receivers of volatility.

H3: Volatility connectedness differs between selected periods of heightened market uncertainty and relatively stable market conditions.

H4: The principal connectedness patterns remain broadly consistent under reasonable alternative forecast horizons and volatility specifications.

H1 will be examined through the temporal behaviour of the total connectedness index. H2 will be assessed through directional and net connectedness measures. H3 will be evaluated by comparing predefined market-stress and comparison periods. H4 will be assessed through the robustness analyses.

The hypotheses will be evaluated using the actual empirical estimates. No hypothesis will be treated as supported before the relevant results and statistical evidence have been obtained.

3.13. Methodological Limitations

The methodology has several limitations that must be considered when interpreting the findings.

First, squared daily returns provide a proxy for volatility rather than a direct observation of latent market uncertainty. Alternative volatility measures may therefore produce different estimates.

Second, the findings will be conditional on the selected indices and cannot automatically be generalised to all Indian equities or international financial markets.

Third, TVP-VAR connectedness estimates depend on the model specification, coefficient-evolution assumptions and estimation procedure. These choices will be reported transparently and assessed through sensitivity analysis.

Fourth, net transmitters and receivers are identified through model-based forecast error variance contributions. These classifications do not independently establish structural causation.

Finally, comparisons across market-stress periods identify changes in connectedness associated with those periods but cannot isolate the causal effect of individual events without an additional identification strategy.

4. Data Analysis and Results

4.1. Data Preparation and Descriptive Overview

The empirical analysis uses daily closing values for five Indian stock market indices: NIFTY 50, NIFTY Bank, NIFTY IT, NIFTY Financial Services and NIFTY Midcap 100. The dataset covers the 2025 calendar year. Each index contains 249 closing observations, producing 248 daily log-return observations after the first observation is used to calculate the initial return. The five series were aligned by trading date to ensure consistency in the subsequent statistical analysis.

Daily log returns were calculated as:

$$r_{i,t} = 100 \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

where $r_{i,t}$represents the closing value of index (i) on day (t). Squared daily log returns were also calculated as a proxy for volatility to examine the transmission of fluctuations across the selected indices.

Table 1. Data coverage and preparation

Index	Closing observations	Return observations	Missing closing values
NIFTY 50	249	248	0
NIFTY Bank	249	248	0
NIFTY IT	249	248	0

NIFTY Financial Services	249	248	0
NIFTY Midcap 100	249	248	0

Source: Calculated from the supplied daily index data.

4.2. Descriptive Statistics and Market Performance

Table 2 presents the closing-value changes, mean daily returns and volatility characteristics of the five indices. NIFTY Financial Services recorded the highest closing-value increase of 16.91%, followed closely by NIFTY Bank at 16.69%. NIFTY 50 increased by 10.05%, while NIFTY Midcap 100 recorded a gain of 5.28%. In contrast, NIFTY IT experienced a decline of 12.66% between its first and last closing observations.

Table 2. Descriptive statistics of the selected indices

Index	**Price change (%)**	**Mean daily return (%)**	**Daily SD (%)**	**Annualised volatility (%)**
NIFTY 50	10.05	0.0386	0.7440	11.81
NIFTY Bank	16.69	0.0622	0.7887	12.52
NIFTY IT	−12.66	−0.0546	1.3371	21.23
NIFTY Financial Services	16.91	0.0630	0.8474	13.45
NIFTY Midcap 100	5.28	0.0207	1.1390	18.08

Note: Annualised volatility is calculated as the standard deviation of daily log returns multiplied by the square root of 252. Price change is calculated between the first and last closing observations in the dataset.

The results reveal considerable differences in performance and risk across the market segments. NIFTY IT exhibited the highest annualised volatility at 21.23%, followed by NIFTY Midcap 100 at 18.08%. NIFTY 50 recorded the lowest volatility at 11.81%, indicating comparatively lower variability in daily returns during the observation period. The negative mean return of NIFTY IT is consistent with its decline between the first and last observations. These differences support the importance of examining sector-specific volatility rather than relying exclusively on a broad-market index.

4.3. Correlation Analysis

The correlation matrix in Table 3 examines the strength of contemporaneous linear relationships among the daily returns. The strongest relationship was observed between NIFTY Bank and NIFTY Financial Services, with a correlation coefficient of 0.9547. NIFTY 50 also exhibited strong positive correlations with NIFTY Financial Services (0.8830), NIFTY Bank (0.8687) and NIFTY Midcap 100 (0.7974).

Table 3. Correlation matrix of daily log returns

Index	**NIFTY 50**	**NIFTY Bank**	**NIFTY IT**	**NIFTY Financial Services**	**NIFTY Midcap 100**
NIFTY 50	1.0000	0.8687	0.6552	0.8830	0.7974
NIFTY Bank	0.8687	1.0000	0.4058	0.9547	0.7432

NIFTY IT	0.6552	0.4058	1.0000	0.4141	0.4805
NIFTY Financial Services	0.8830	0.9547	0.4141	1.0000	0.7015
NIFTY Midcap 100	0.7974	0.7432	0.4805	0.7015	1.0000

Source: Calculated from the supplied daily closing values.

The high correlation between the banking and financial-services indices suggests substantial overlap in their daily return movements. The positive correlations between NIFTY 50 and the other indices further indicate broad-market co-movement. However, correlation measures contemporaneous association and does not establish the direction of volatility transmission. Directional connectedness measures are therefore necessary to examine whether particular indices predominantly transmit or receive shocks.

4.4. Stationarity Analysis

The Augmented Dickey–Fuller (ADF) test was applied to the daily log-return series to assess whether the returns exhibit a unit root. Table 4 presents the test statistics and corresponding probability values.

Table 4. ADF stationarity test results

Index	ADF statistic	p-value	Decision at 5%
NIFTY 50	−15.6285	<0.001	Reject unit-root null
NIFTY Bank	−9.7062	<0.001	Reject unit-root null
NIFTY IT	−16.0227	<0.001	Reject unit-root null
NIFTY Financial Services	−16.4001	<0.001	Reject unit-root null
NIFTY Midcap 100	−14.5900	<0.001	Reject unit-root null

The ADF results reject the unit-root null hypothesis for all five return series at the 5% significance level. This indicates that the daily log returns are stationary under the specified test settings. The results support the use of return-based time-series analysis, although further diagnostic checks remain necessary before finalising the dynamic model specification.

Augmented Dickey–Fuller (ADF) test

The ADF test examines the null hypothesis that a return series contains a unit root. The test was conducted on daily log returns using an intercept, with the lag length selected by the Akaike Information Criterion (AIC).

Index	Observations	ADF statistic	ADF lags (AIC)	p-value	Decision at 5%
NIFTY 50	248	−15.6285	0	< 0.01	Reject Null (Stationary)

4.5. Forecast Error Variance Decomposition and Connectedness

To explore volatility transmission, squared daily log returns were used as a volatility proxy. A generalised forecast error variance decomposition (GFEVD) was calculated from a one-lag VAR model using a 10-step forecast horizon. The resulting connectedness estimates are presented in Table 5. Each row represents the percentage contribution of shocks from the column index to the forecast error variance of the row index, after normalisation.

Table 5. GFEVD connectedness matrix based on squared returns (%)

Receiving index	**NIFTY IT**	**NIFTY Midcap 100**	**NIFTY Financial Services**	**NIFTY Bank**	**NIFTY 50**
NIFTY IT	51.62	10.56	11.09	8.77	17.96
NIFTY Midcap 100	8.52	40.01	15.27	16.61	19.59
NIFTY Financial Services	6.01	11.71	29.98	27.65	24.67
NIFTY Bank	4.93	12.91	28.47	30.67	23.02
NIFTY 50	10.35	14.76	23.96	21.71	29.22

Note: Diagonal values represent own-index contributions; off-diagonal values represent contributions from other indices. Values are rounded.

The results indicate that own-index contributions differ considerably across the five indices. NIFTY IT recorded an own contribution of 51.62%, while the corresponding values were 40.01% for NIFTY Midcap 100, 30.67% for NIFTY Bank, 29.98% for NIFTY Financial Services and 29.22% for NIFTY 50. The lower own-index contributions for the banking, financial-services and broad-market indices indicate that shocks originating in other indices account for a larger share of their forecast uncertainty within this specification.

The largest cross-index contribution in the matrix is the 28.47% contribution from NIFTY Financial Services to NIFTY Bank. The contribution from NIFTY Bank to NIFTY Financial Services is similarly substantial at 27.65%. This pattern is consistent with the strong return correlation observed between these two indices and highlights their close statistical relationship.

4.6. Directional Connectedness and Net Spillovers

Table 6 summarises the directional connectedness measures derived from the GFEVD matrix. The “FROM” measure represents the contribution of other indices to an index's forecast error variance, excluding its own contribution. The “TO” measure represents the contribution that an index transmits to the other indices. Net connectedness is calculated as TO minus FROM.

Table 6. Directional connectedness measures based on squared returns (%)

Index	**FROM**	**TO**	**NET**	**Classification**
NIFTY IT	48.38	29.80	−18.58	Net receiver
NIFTY Midcap 100	59.99	49.94	−10.05	Net receiver
NIFTY Financial Services	70.02	78.79	+8.77	Net transmitter
NIFTY Bank	69.33	74.73	+5.40	Net transmitter
NIFTY 50	70.78	85.24	+14.46	Net transmitter

Note: Positive net connectedness indicates that an index transmits more forecast variance to the remaining indices than it receives; negative values indicate the opposite.

The results identify NIFTY 50 as the strongest net transmitter under this preliminary model specification, with net connectedness of 14.46%. NIFTY Financial Services and NIFTY Bank also act as net transmitters, with positive net values of 8.77% and 5.40%, respectively. In contrast, NIFTY IT exhibits the largest negative net connectedness at

−18.58%, followed by NIFTY Midcap 100 at −10.05%.

These findings suggest that the broad-market, banking and financial-services indices play important roles in the estimated transmission of volatility. The negative net values for NIFTY IT and NIFTY Midcap 100 indicate that they receive more forecast variance from the other indices than they transmit under this specification. These classifications are conditional on the selected variables, volatility proxy, lag structure and forecast horizon.

4.7. Rolling Connectedness Across Market Conditions

To examine how connectedness changes through the year, the GFEVD calculation was repeated using rolling windows of 60 return observations. A one-lag VAR was estimated within each window, and the total connectedness index (TCI) was calculated from the off-diagonal variance contributions. Since the analysis uses rolling windows, the first estimate becomes available only after the initial 60 observations.

Table 7. Rolling connectedness of the squared-return volatility proxy

Period	Mean TCI (%)	Minimum TCI (%)	Maximum TCI (%)
March 2025*	45.96	45.89	46.03
April 2025	52.41	41.28	55.81
May 2025	64.07	53.93	68.83
June 2025	70.03	69.02	71.13
July 2025	74.81	71.78	77.86
August 2025	45.32	42.83	47.17
September 2025	46.56	45.13	48.89
October 2025	49.34	48.62	50.59
November 2025	48.50	44.60	49.65
December 2025	47.18	44.08	49.72

Note: March contains only two rolling-window estimates. Each subsequent monthly statistic summarises the rolling estimates ending during that month.

The rolling results show substantial variation in estimated connectedness over the observation period. The mean TCI increased from 52.41% in April to 74.81% in July, before declining to 45.32% in August. Across all 189 rolling windows, the TCI ranged from 41.28% on 3 April 2025 to 77.86% on 31 July 2025, with an overall mean of 55.58%.

This pattern indicates that estimated volatility connectedness was not constant throughout 2025. The increase into July suggests a period of stronger cross-index variance transmission within the rolling model, while the decline in August indicates weaker estimated connectedness in the subsequent windows. These changes should be interpreted as features of the preliminary rolling-window analysis rather than definitive evidence of specific economic causes.

Table 8. TVP-VAR-Based Dynamic Volatility Connectedness of Indian Stock Market Indices

Market index	Average net connectedness (%)	Role in volatility transmission
NIFTY 50	+13.74	Net transmitter
NIFTY Bank	+3.78	Net transmitter
NIFTY IT	−17.36	Net receiver
NIFTY Financial Services	+0.90	Net transmitter
NIFTY Midcap 100	−1.06	Net receiver

Source: Preliminary time-varying VAR estimates based on the supplied daily index data for 2025.

Table 9. Summary of the TVP-VAR Connectedness Index

Statistical measure	TCI (%)
Average total connectedness	66.50
Minimum total connectedness	59.91
Maximum total connectedness	78.59
Range	18.68

Note: TCI denotes the Total Connectedness Index. The range is calculated as the maximum TCI minus the minimum TCI.

Interpretation

The preliminary TVP-VAR estimates indicate substantial connectedness among the five selected Indian stock market indices, with an average Total Connectedness Index (TCI) of 66.50%. The TCI ranged from 59.91% to 78.59%, indicating that the estimated degree of volatility transmission varied over the observation period. NIFTY 50 recorded the highest positive net connectedness at 13.74%, identifying it as the strongest net transmitter under the estimated specification. NIFTY Bank and NIFTY Financial Services also exhibited positive net connectedness, at 3.78% and 0.90%, respectively. In contrast, NIFTY IT recorded the most negative net connectedness at −17.36%, followed by NIFTY Midcap 100 at −1.06%, indicating that these indices were net receivers of forecast variance. Overall, the estimates suggest that volatility transmission was unevenly distributed across the market segments, highlighting the importance of examining both the magnitude and direction of connectedness.

5. Results and Discussion

The TVP-VAR-based analysis examines the dynamic volatility connectedness among NIFTY 50, NIFTY Bank, NIFTY IT, NIFTY Financial Services and NIFTY Midcap 100 using daily observations for 2025. The preliminary estimates reported in Tables 8 and 9 indicate an average Total Connectedness Index (TCI) of 66.50%, with a minimum of 59.91% and a maximum of 78.59%. This variation suggests that the estimated degree of volatility transmission among the selected indices changes over time rather than remaining constant throughout the observation period. The directional connectedness results identify NIFTY 50 as the strongest net transmitter, with net connectedness of 13.74%, followed by NIFTY Bank at 3.78% and NIFTY Financial Services at 0.90%. In contrast, NIFTY IT records the most negative net connectedness at −17.36%, while NIFTY Midcap 100 records −1.06%, indicating that these two indices are net receivers of forecast variance under the estimated specification. The prominent transmitter role of NIFTY 50

suggests that broad-market shocks may contribute meaningfully to fluctuations in the other market segments, while the negative net connectedness of NIFTY IT indicates greater exposure to shocks originating elsewhere in the system. The results also highlight the relevance of distinguishing between overall connectedness and the directional roles of individual indices, as a high level of market interdependence does not imply that all segments contribute equally to volatility transmission. From a practical perspective, these findings may assist investors and portfolio managers in evaluating the changing distribution of market risk and considering diversification strategies across equity segments. However, the estimates should be interpreted as preliminary because the analysis covers only the 2025 calendar year and uses a recursive time-varying VAR specification. Further diagnostic testing, robustness analysis and validation against an established TVP-VAR connectedness implementation are necessary before the numerical estimates can be treated as definitive empirical findings.

6. Conclusion

6. Conclusion

This study investigates dynamic volatility connectedness among five major Indian stock market indices—NIFTY 50, NIFTY Bank, NIFTY IT, NIFTY Financial Services and NIFTY Midcap 100—using daily observations for 2025 within a preliminary time-varying vector autoregression framework. The findings indicate substantial interdependence among the selected indices, with an average Total Connectedness Index (TCI) of 66.50%. The TCI ranges from 59.91% to 78.59%, suggesting that the estimated intensity of volatility transmission varies over time. The directional connectedness results identify NIFTY 50 as the strongest net transmitter, with net connectedness of 13.74%, followed by NIFTY Bank at 3.78% and NIFTY Financial Services at 0.90%. Conversely, NIFTY IT exhibits the strongest net receiver position, with net connectedness of −17.36%, while NIFTY Midcap 100 records −1.06%. These findings suggest that volatility transmission is unevenly distributed across market segments and that broad-market and banking indices may play important roles in the propagation of shocks within the estimated system. The results highlight the value of examining both the magnitude and direction of connectedness when evaluating financial-market interdependence. For investors and portfolio managers, such information can support risk assessment and the consideration of diversification strategies across market segments. Nevertheless, the findings remain preliminary because the analysis covers one calendar year and employs a recursive time-varying VAR specification. Further validation of the model, robustness testing and analysis over a longer observation period are necessary to establish the stability of these relationships and strengthen their implications for financial risk management. Overall, the study provides an initial quantitative assessment of volatility connectedness in the Indian stock market and establishes a basis for more comprehensive investigation using a fully validated TVP-VAR framework.

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