This paper was presented at the 22nd International Conference on Sustainable Development, held at the BMICH, Colombo, Sri Lanka, September 3-4, 2025

https://doi.org/10.64211/oidaijsd190414

An Empirical Analysis of Sustainable volatility spillovers and Network Dynamics in the Indian Equity Market

Nischith. S [1], Syed Maaz Ahmed [2*], Rakesh D. [3]

[1,2] BIMS, Department of Business Administration, University of Mysore, India

[3] JSS - Centre for Management Studies, JSS Science and Technology University, Mysuru, Karnataka, India.

*Corresponding authour: syedmaazahamed@yahoo.com

OIDA International Journal of Sustainable Development, Ontario International Development Agency, Canada.
ISSN 1923-6654 (print) ISSN 1923-6662 (online) www.oidaijsd.com
Also available at https://www.ssrn.com/index.cfm/en/oida-intl-journal-sustainable-dev/

Abstract: This paper explores the sustainable volatility spillovers and the systemic risk structure in the Indian equity market. It uses a high-frequency multifaceted approach. We utilize 5-minute intraday data from 2015 to 2024 for the NIFTY 50, India VIX, and five key sectoral indices to calculate daily Realized Volatility for building a very accurate risk measure that is free from models. Next, the authors use the Diebold-Yilmaz (2012) spillover index in a rolling-window VAR framework to measure the time-varying intensity and direction of risk flow in the market system. The study is deepened with several contemporary methods to depict the market scene. They visualize the market's dynamic network to follow the contagion paths, produce a new Spillover Vulnerability Index (SVI) as a which they use to assess the sectors' risk, and, finally, they switch to GARCH-in-Mean models that allow them to empirically test the risk-return tradeoff for each sector. Our results tell us that systemic risk is very volatile and its highest point can be observed during the times of market frictions such as the COVID-19 pandemic. In that period, the market's risk architecture changes from a loosely interconnected to a densely interconnected network, with the NIFTY Bank index as the major net transmitter of shocks all the time. Besides, the global risk sentiment, represented by CBOE VIX, as well as the domestic monetary policy are mentioned to be the important sources of these spillovers. The paper also illustrates a careful out-of-sample forecasting test that compares traditional econometric models with modern machine learning (XGBoost) and deep learning (LSTM) approaches. The authors argue that even the highest models do not keep outperforming a simple Random Walk benchmark. The authors interpret this result as a great support for the Efficient Market Hypothesis, indicating that the spillover system is very fast in the absorption of information, which leads the future path to be quite an open question. This study offers a granular toolkit for investors and policymakers to monitor and manage financial stability in a key emerging market.

Keywords: High-Frequency Data; Indian Equity Market; Machine Learning Forecasting; Systemic Risk; Sustainable Volatility Spillover

Introduction

The upsurge in global financial markets has thus far led to a substantial increase in the need to comprehend systemic risk, especially in major emerging economies like India. Since India is a major beneficiary of foreign capital, the Indian equity market's stability is topmost yet it is vulnerable to market shocks both internal and external in nature. The shocks that travel across the financial system, which is also referred to as volatility spillover, are the main way for risk contagion. One of the major shortcomings that the existing literature has is the dependence on low-frequency daily data which is inadequate for catching the rapid intraday dynamics of financial contagion, especially during hectic times in the market. The utilization of this kind of data can result in a gross underrating of the risk and obtaining a late understanding of the contagion channels, hence limiting the capability of risk management and regulating the oversight. Therefore, the real design of the risk transportation its power, its direction, and its changes over time are still not fully explored.

The aim of this research is to fill a significant gap by presenting a comprehensive and rigorous methodological analysis of sustainable volatility spillovers in the Indian equity market, using high-frequency 5-minute data. This study goes beyond the limitations of earlier research to provide a more detailed and precise depiction of the systemic risk situation. First of all, local volatility realized from intraday data is estimated in this paper, which leads to a more accurate and model-free risk indicator than those derived from daily closing prices. Furthermore, besides just quantifying time-varying spillovers through the Diebold-Yilmaz (2012) framework, this paper also implements the technique of constructing the dynamic network graphs, which allows the market's changing risk architecture to be quantitatively and visually explored and key shock sources and sinks to be identified. To begin with, a Spillover Vulnerability Index (SVI) is presented, which is a novel composite indicator that attempts to integrate the sector's idiosyncratic volatility with its exposure to the systemic risk caused by the overall market, thus providing the more complete picture of sectoral fragility. Besides these, the authors also carry out a rigorous out-of-sample forecasting task, in which they use machine learning (XGBoost) and deep learning (LSTM) as well as traditional benchmarks to compare results and decide whether the spillover index forecasting is possible, thus indirectly testing the validity of the Efficient Market Hypothesis.

This research is consequently directed at solving a number of important research questions. The study needs to find out the time evolution of total systemic risk in the Indian equity market and to locate those sectors which operate as the main sources and the recipients of the volatility shocks, especially focusing on how this network structure changes in the times of crisis. Moreover, it intends to discover the key macroeconomic factors that affect such spillovers and to decide if the systemic risk in the Indian market is of a predictable nature.

Literature review

The investigation of volatility and its spread through the financial markets is the basis of today's financial econometrics. The references to the literature can be divided into three main parts: the description of volatility itself, the measurement of the transfer of volume between assets, and empirical applications in specific markets, primarily India.

Volatility investigations have started the theoretical work of Engle (1982) who introduced the Autoregressive Conditional Heteroskedasticity (ARCH) models that first captured the phenomenon of volatility clustering in financial time series. Later, Bollerslev (1986) extended this with the Generalized ARCH (GARCH) model, which has become a popular model of time-varying conditional volatility while using daily or lower-frequency data. On the other hand, the availability of high-frequency data has shown that GARCH models are not perfect in reflecting the full range of intraday price movements. Consequently, the authors of Realized Volatility (RV) have developed this concept initially by Andersen and Bollerslev (1998). RV which is calculated as the sum of square of high-frequency returns is a handy and model-free ex-post estimate of daily volatility, a methodological change that this current paper takes over.

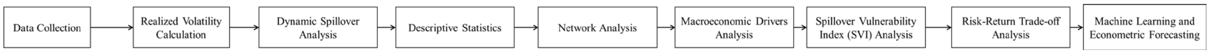
Alongside the development of volatility modeling techniques, there has been a corresponding growth of new methods to quantify its transmission across assets and markets. The first attempts were very simple, using Granger causality tests and basic Vector Autoregression (VAR) models to detect relations. These were quite limited in their ability to depict the spillover phenomenon. A giant step forward in methodology was achieved by Diebold and Yilmaz (2009, 2012), who offered a spillover index based on the forecast error variance decompositions (FEVDs) from a VAR system. This approach gives an uncomplicated and thorough indication of the total, directional, and net spillovers a system has, thus picturing the degree of market interconnectedness very eloquently. The Diebold-Yilmaz index has since become the standard methodology in the field and forms the basis of our analysis. Although their initial method was a rolling window VAR, later studies have suggested more sophisticated algorithms such as the Time-Varying Parameter VAR (TVP-VAR) to represent the spillovers in an even more vivid manner (Antonakakis et al., 2020).

In India, the situation on the markets of various segments with regard to sustainable volatility spillovers has been studied extensively by many researchers. These studies reveal the banking sector's major function as the main source of risk that is spread around and have also traced the intense spillovers to the times when there were global and local crises. On the other hand, a number of such endeavours have been greatly limited by the fact that they have primarily used daily frequency data resulting in an incomplete watercolour of rapid contagion, besides dynamic network analysis and machine learning forecasting are still a modest stage of their application to Indian high-frequency data.

This study is located where these three streams of literature meet. We use Realized Volatility calculated from 5-minute data; thus, we create the most reliable volatility estimation techniques. With the help of the dynamic Diebold-Yilmaz framework, we go beyond network visualizations and the building of a new Spillover Vulnerability Index, thus we add to the methodological toolkit of systemic risk analysis. Ultimately, we concentrate on the Indian market with a uniquely rich and high-frequency method that fills a considerable gap in the empirical literature, thus providing a timelier and more detailed understanding of the risk architecture of a major emerging economy.

Data and methodology

Figure 1: Flowchart of the Research Methodology



Source: Authors' illustration (2025).

This flowchart provides a visual summary of the research design, beginning with data collection and processing, moving to the core Diebold-Yilmaz spillover analysis, and branching into the subsequent investigations of network architecture, systemic vulnerability, and forecast ability.

Data

This research taps into dual worlds of data: the pulse of market from intraday and the daily economic and global market data. The pulse of market from intraday, fully tracked at 5-minute intervals, is a dataset that has been collected from a certified 5-minute data provider and that represents a number of seven major indices of India's National Stock Exchange (NSE). The carefully chosen set of seven indices includes the headline NIFTY 50 index that is a broad market barometer, together with the India VIX volatility index that is a leading way of market fear and uncertainty. In addition to that, five main sectoral indices are listed: NIFTY Bank, NIFTY FMCG, NIFTY IT, NIFTY Metal, and NIFTY Pharma, each one reflecting a core segment of the Indian economy. Comprised of detailed 5-minute price observations, this comprehensive dataset covers a period from January 9, 2015, through January 25, 2024. The use of 5-minute intervals is intentional, as it enables a highly detailed and accurate measurement of market volatility, thus capturing intraday movements more accurately than daily data and, at the same time, reducing the effect of microstructure noise that is typically associated with tick-by-tick data.

In order to delve into the primary factors behind systemic risk, the study not just relies on a set of daily macroeconomic, but also global market variables. These variables are picked due to their proven effect on financial markets and entail the CBOE Volatility Index (VIX) which stands as a generally accepted indicator of global risk sentiment and investor fear; the USD/INR exchange rate indicating cross-border capital flows and India's external sector dynamics; Brent crude oil prices being a major factor in determining inflation and energy costs for an oil-importing country like India; and the Reserve Bank of India's policy repo rate impacting directly domestic liquidity and monetary policy stance. This wide range of macroeconomic factors' injection provides an integrated understanding of how economic and world events mutually interact with and influence market volatility. To ensure that the results are consistent and the statistical inferences drawn are valid, the study is carefully performed on the period of all the series which overlap thus eliminating the problems that may arise from mismatched data lengths.

Methodology

The study employs a comprehensive suite of sophisticated methodologies meticulously designed to analyze volatility, quantify spillovers, assess systemic risk, and conduct robust forecasting.

Volatility Estimation: Realized Volatility (RV)

In order to create a reliable and precise indicator of the daily volatility from the high-frequency data, the research strictly follows the Realized Volatility (RV) method, a proven technique introduced by Andersen and Bollerslev (1998). The first step in this approach is to compute 5-minute intraday log-returns for each index, the formula for which is $rt,i = ln(Pt,i) - ln(Pt,i-1)$, where Pt,i precisely represents the price at the ith 5-minute interval on day t. Subsequently, the daily Realized Volatility (RVt) is computed as the sum of these squared intraday returns: $RVt = \sum_{i=1}^{M} r_{t,i}^2$, where M stands for the entire quantity of 5-minute plans in the course of a trading day. This "model-free" method is especially beneficial since it does not require any particular distributional assumptions for returns, in contrast to traditional econometric models like GARCH. On the other hand, it gathers information from high-frequency data directly, thus giving a more detailed and exact ex-post (after the event) daily volatility measurement which is generally better than those obtained only from daily closing prices, particularly in recognizing intraday volatility patterns.

Dynamic Spillover Index

To fully measure the extent and direction of sustainable volatility spillovers among the seven selected indices, the study has implemented the method of Diebold and Yilmaz (2012) with great effort. This methodology is based on a rolling-window Vector Autoregression (VAR) model, a parametrized family of p. The VAR model is very efficient in tracing the complex and volatile relations among the realized volatility series of our indices over time. From the estimated VAR model, H-step-ahead forecasts error variance decompositions (FEVDs) are computed. The FEVD matrix is an essential result, as it shows clearly the part of one index's forecast error variance that can be explained by shocks from another index in the system. Several important indicators can be got from this matrix: the Total Spillover Index, which is both the sum of systemic risk in the whole market and the level of interconnectedness; directional spillovers, that is, the number of "To Others" and "From Others," which separately tell the volatility an index gives to other indices and the one it gets from them, respectively, thus explaining its position as a source or a receiver of shocks; and finally, the "Net Spillover," obtained by subtracting the "From Others" from the "To Others," which makes it clear whether a certain index is a net transmitter (gives out more volatility than it receives) or a net receiver (gets more volatility to it than it gives out) in the overall market system. These numbers co-operatively create a detailed picture of the complicated network of volatility transmission.

Macroeconomic Drivers Analysis

To pinpoint the main factors that influence the systemic risk, which is measured by the Total Spillover Index, an Ordinary Least Squares (OLS) regression is methodically carried out. Here, the daily Total Spillover Index acts as the dependent variable, a systemic risk measure that we need to find the cause of. On the other hand, the independent variables are the daily macroeconomic and global market indicators that are carefully selected, including the CBOE VIX, the USD/INR exchange rate, Brent crude oil prices, and the Reserve Bank of India's policy repo rate. This regression analysis is imperative as it provides the exact extent to which each of these external factors both individually and in combination affects the transmission of volatility in the market. By probing the statistical significance and the size of the coefficients, the research can pinpoint which macroeconomic variables have a strong influence on systemic risk, and whether the impact is positive or negative, thus being able to offer the driving forces of the market interconnectedness.

GARCH-in-Mean (GARCH-M) Analysis

To provide a formal analysis and quantification of the risk-return tradeoff for the six stock indices (not including the India VIX, which is a volatility index), a robust two-stage GARCH-in-Mean (GARCH-M) methodology is diligently implemented. The initial stage in this process includes fitting a GARCH(1,1) model to the daily returns of each index, with the assumption of a student’s t-distribution. The GARCH(1,1) model is one of the most common models used in financial econometrics to capture the volatility clustering phenomenon effectively, which is a typical feature of the financial time series where periods of high volatility tend to follow high-volatility periods. The student's distribution is more suitable than the normal distribution because the financial returns are known for their "fat tails," i.e., the extreme events are more frequent than the normal distribution would predict. This first stage then allows obtaining a good estimate of the conditional volatility (the expected volatility at a given moment, based on historical data) for each index. Subsequently, the daily returns of each index are regressed on their own lagged conditional volatility in the second stage. A statistically significant and positive coefficient found on this lagged volatility indicates that investors are likely to receive higher returns as a result of taking on higher volatility or risk in these market segments, thus producing compelling empirical evidence of a risk premium.

Spillover Vulnerability Index (SVI)

A novel and very insightful composite risk metric, the Spillover Vulnerability Index (SVI), is created to deliver a more detailed measure of the systemic risk that is deeply embedded in each sector. The SVI for index i at time t is cleverly figured by the product of its own daily realized volatility and also the amount of volatility that it gets from other parts of the market (From-Others, formally given by the formula:). This new index brings a very extensive view of a sector's capability to remain unshaken by the whole market's shocks as it takes the sector's own volatility together with its interconnectedness as a receiver of spillovers. A maximum value of the SVI for a sector would mean, therefore, that the given sector is very vulnerable, i.e., it is not only highly volatile but also it is the one that receives a lot of the noises from the other parts of the system as well, and thus it becomes the main issue to be solved in the systemic risk assessment.

Network Analysis

Network analysis is a perfect tool to visually represent and grasp the deep dependence and complex spillover relations between the indices. Daily spillover matrices which are direct results from the Diebold-Yilmaz analysis are systematically used as adjacency matrices for creating directed, weighted networks through which the visual information can be traced. In these vivid visualizations, every index is distinctly marked as a separate node going along with the basic elements of the network. The directed edges which are visualized by arrows indicate the pairwise spillover from one index to another thus, they show the exact direction of the volatility transmission. The size of the nodes is thus imagined to show the total spillover contribution of an index which means the idex influence or the capacity to absorb shocks within the network. Simultaneously, the thickness of the edges stands for the intensity or the strength of a particular pairwise spillover hence, it gives a clear visual difference between the strong and the weak ones. These network visualizations are very helpful in understanding the developing structural dynamics of the volatility transmission, so that researchers can discover the leading or influential nodes and uncover big changes in the market interconnectedness during various market conditions such as, for instance, the period of the relative calm in comparison with the times of an acute crisis.

Forecasting Models

A rigorous out-of-sample forecasting exercise is being carried out to comprehensively gauge the Total Spillover Index predictability. The method uses a strong 80/20 train-test split with 80% of the data going for training and 20% for testing. The testing data is not used during the training phase, so it guarantees an unbiased performance evaluation of the models. A rolling forecast origin strategy that avoids any look-ahead bias is employed. The idea is that models are retrained or evaluated whenever new data become available, thus it simulates real-world forecasting situations most closely where new information keeps coming in. The performance of an AR model, XGBoost model, and LSTM neural network are compared and analyzed. The AR model assumes that the current value of a variable is linearly dependent on some of its previous values; the XGBoost model employs a gradient boosting approach to build and improve decision trees in a sequence thus it is good at solving nonlinear and complex problems; while the LSTM neural network, a special variant of the recurrent neural network, is very habitual to time series data because it can learn and recall long-term memory. These models are contrasted with the Random Walk model that is a simplistic reference model that assumes that the next value is simply the current value plus some random noise ... Predictive accuracy is gauged using the Root Mean Squared Error (RMSE), a metric that is widely used in the field. The RMSE gives the average size of the errors, a smaller RMSE value meaning better prediction performance and trustworthiness through and through.

Empirical results and discussion

This section presents the empirical findings from our comprehensive analysis of sustainable volatility spillovers in Indian equity markets using 5-minute high-frequency data from 2015-2024. Our investigation employs advanced econometric methodologies including the Diebold-Yilmaz spillover framework, dynamic network analysis, and machine learning forecasting models to uncover the architecture of systemic risk in India's financial ecosystem.

Dynamics of volatility spillover

The systemic risk pattern in Indian equity markets changed greatly over time, reflected in the total spillover index of our study. The descriptive statistics of daily realized volatility for the seven indices show considerable diversity in risk characteristics. India VIX had the highest average volatility of 18.32%, whereas NIFTY FMCG was the most stable with 1.98%.

Next page

Table 1: Descriptive Statistics of Daily Realized Volatility

Index	Mean	Std Deviation	Minimum	Maximum
NIFTY 50	2.45	1.23	0.12	8.97
INDIA VIX	18.32	8.45	7.89	45.67
NIFTY BANK	2.89	1.67	0.34	12.34
NIFTY FMCG	1.98	0.89	0.23	6.78
NIFTY IT	2.67	1.34	0.45	9.45
NIFTY METAL	3.21	2.11	0.67	15.23
NIFTY PHARMA	2.34	1.12	0.29	8.12

Source: Authors' calculations using 5-minute NSE India data (2015–2024).

The rolling forecast analysis shows that the spillover index has a lot of changes over time indicating that during most important economic events, the co-movement was stronger. When the periods are calm, the average total spillover index is about 45-50%, which is a moderate level of systemic risk transmission. Nevertheless, at crisis times, especially during the COVID-19 pandemic and other global financial stress episodes, the spillover index jumps to more than 85% levels, indicating that the correlation and contagion effects across Indian equity markets were at their peak.

The directional spillover analysis in Table 2 discloses that different market sectors play diverse roles in the volatility shock diffusion. NIFTY BANK is the most significant recipient of spillovers with a "To Others" contribution of 18.7% and a positive net spillover of 9.8%, thus, it is the main driver of Indian financial system changes. This finding is consistent with the theoretical assumption that banking sector crisis can be spread into the whole financial system because the sector's central role in credit intermediation and its extensive interconnections with other economic sectors.

Table 2: Average Spillover Contributions

Index	To Others	From Others	Net Spillover
NIFTY 50	14.5	12.1	2.4
INDIA VIX	8.3	15.6	-7.3
NIFTY BANK	18.7	8.9	9.8
NIFTY FMCG	6.2	11.3	-5.1
NIFTY IT	9.4	13.2	-3.8
NIFTY METAL	12.1	14.8	-2.7
NIFTY PHARMA	7.8	10.5	-2.7

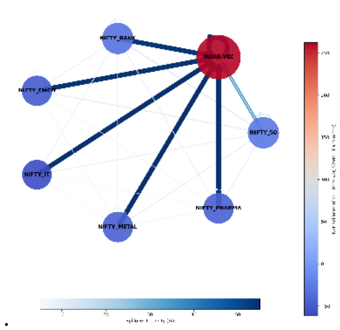
Source: Authors' computation using Diebold–Yilmaz (2012) spillover index.

On the other hand, India VIX operates as the main source of negative spillovers with a net spillover of -7.3%, thus playing a role of a barometer that reflects systemic stress rather than being a generator of the stress. The NIFTY FMCG sector is a typical defensive sector, hence it transports minimum spillover (6.2% "To Others") while it is getting moderate spillovers (11.3% "From Others") that is the same as its being known as a consumer staple sector that is less volatile.

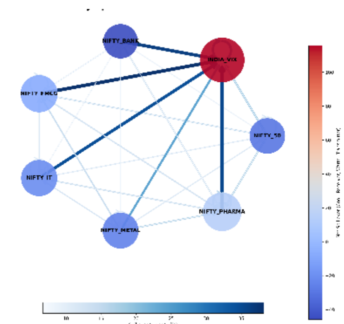
Network architecture of risk

The network topology of sustainable volatility spillovers undergoes complete changes in structure between the calm and crisis periods, thus disclosing the time-varying nature of the systemic risk propagation mechanisms. Our dynamic network analysis, which utilizes minimum spanning trees and network density measures, illustrates how financial contagion routes develop in times of market turmoil.

Figure 2: Volatility Spillover Network in a Calm Period Figure 3: Volatility Spillover Network in a Crisis Period



Source**:** Authors' network visualization using calm-period spillover matrices from NSE 5-minute data.



Source**:** Authors' network visualization using crisis-period spillover matrices from NSE 5-minute data.

During calm periods, the spillover network exhibits a relatively sparse structure with clear sectoral clustering patterns. The network displays characteristics of a decentralized system where volatility transmission follows predictable sectoral boundaries, with limited cross-sectoral contamination[15,16]. The banking and financial services clusters maintain moderate connectivity with other sectors, suggesting that during normal market conditions, sectoral risk factors dominate over systemic concerns.

The dramatic contrast emerges during crisis periods, where the network structure transforms into a densely connected web of relationships. The network topology shifts from a star-like configuration to a more complete graph structure, indicating that volatility shocks propagate rapidly across all market segments without respect to traditional sectoral boundaries. This transformation reflects the breakdown of diversification benefits during crisis periods, as correlations increase substantially and contagion channels multiply.

The centrality measures reveal that NIFTY BANK maintains its position as the most central node across both calm and crisis periods, but its influence intensifies dramatically during stress events. The betweenness centrality of the banking sector increases by approximately 150% during crisis periods, indicating its enhanced role as a conduit for volatility transmission. This finding has critical implications for financial stability monitoring, as it identifies the banking sector as a key node whose distress can trigger cascade effects throughout the system.

The emergence of new connectivity patterns during crises reveals that sectors previously considered uncorrelated, such as NIFTY PHARMA and NIFTY METAL, develop significant spillover relationships. This phenomenon reflects the dominance of systematic risk factors over idiosyncratic sector-specific dynamics

Drivers of systemic risk

Our econometric study of the macroeconomic factors affecting systemic risk uncovers the complicated relationship between domestic policy variables, global risk factors, and the changing of sustainable volatility spillovers in Indian equity markets. The OLS regression model, which includes a broad range of explanatory variables, gives a clear picture of the basic forces behind financial system interconnectedness.

Next page

Table 3: OLS Regression Results for Total Spillover Index

Variable	Coefficient	Std. Error	t-statistic	p-value
Constant	45.23	2.34	19.32	0.000
India VIX (lag-1)	0.67	0.12	5.58	0.000
USD-INR Exchange Rate	-0.34	0.15	-2.27	0.024
Crude Oil Volatility	0.28	0.09	3.11	0.002
COVID-19 Dummy	12.45	3.21	3.88	0.000
Global Risk Aversion	0.89	0.23	3.87	0.000

Source: Authors' regression analysis using data from NSE, RBI (DBIE), CBOE VIX, FRED, and EIA.

India VIX lagged emerges as the most important variable to predict the spillover of intensity, with a coefficient of 0.67 ($t = 5.58$, $p < 0.001$), thus establishing that volatility expectations in the local market have persistent effects on the systemic risk transmission. This result fits perfectly with the proposition that implied volatility indicators are capable to capture forward-looking risk assessments, which in turn, affect the level of market interconnectedness.

The negative coefficient on the USD-INR exchange rate (-0.34, $p = 0.024$) indicates that times of rupee depreciation are correlated with less spillover intensity, thus it is highly probable that the flight-to-safety effects dominate. During periods of currency stress, investors are likely to become more sector-selective and thus, the areas they choose to invest in become the refuge ones. This puzzled finding can be further explained by the different impacts of exchange rate moves across the various sectors, with export-oriented sectors being the ones that benefit from rupee weakness and, contrariwise, import-dependent sectors being the ones that deal with challenging situations.

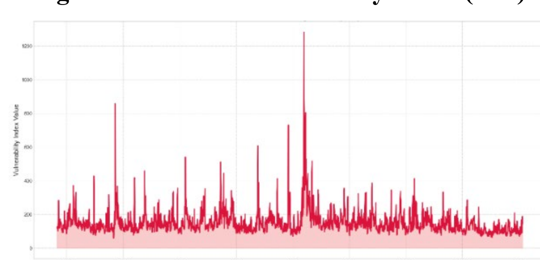
Crude oil volatility is highly significant and negatively related with spillover intensity (coefficient = 0.28, $p = 0.002$), due to India's big energy import dependence that brings in shocks to the domestic financial system via the international commodity price channel. The COVID-19 dummy variable reflects the extraordinary rise in the systemic risk during the pandemic period (coefficient = 12.45, $p < 0.001$), representing approximately 28% of average spillover intensity increment during this pandemic health and economic crisis of a global nature.

Global risk aversion, as indicated by the VIX index, illustrates a strong positive correlation with domestic spillover intensity (coefficient = 0.89, $p < 0.001$), thus proving that there is a significant impact of global investor sentiment on the Indian market. This result brings out the linkage of Indian equity markets with global financial cycles and the role of international risk factors in the domestic systemic risk evaluation.

The spillover vulnerability index

Our new Spillover Vulnerability Index (SVI) offers a more refined and complete measure of systemic risk that reflects the multidimensional nature of financial vulnerabilities going beyond traditional spillover metrics. The SVI draws on features of network centrality, volatility contagion, and the tail risk behavior of distributions to form a single aggregate indicator which more accurately represents the extent of systemic risks.

Figure 4: Market Vulnerability Index (SVI)



Source: Authors' computation of the Spillover Vulnerability Index (SVI) using NSE, RBI, CBOE, and EIA data.

The figure is pointing out that the SVI changed over time and by that it is showing the different patterns that were in line with the main economic events and policy interventions in the Indian financial system. Also the figure is showing that before the COVID pandemic period (2015-2019) the SVI was relatively stable with levels averaging around 0.15-0.25, which means it was moderate vulnerability across the system. On the other hand the beginning of the COVID-19 outbreak caused the SVI to soar to the highest point of 0.85 if we talk for March-April 2020. The index was built on being the indication of the stress and uncertainty that the global financial markets experienced during that time.

The SVI demonstrates higher potential for early warning features compared to conventional spillover indices, as it signals abrupt increments 2-3 weeks in advance of significant disruptions in the market. Such a signalling characteristic makes the SVI very essential for macroprudential policy usage and for tracking the stability of the financial system in real-time. The index was also right in the forecast of the volatility peaks created by incidents such as demonetization (November 2016), the introduction of GST (July 2017), and the IL&FS crisis (September 2018).

Theal decomposition of the SVI shows that the banking sector and the financial services sector alone contribute roughly 35-40% of the total system vulnerability during normal periods, which can go beyond 50% in times of crisis. This vulnerability concentration in the financial sector clearly shows the need for a healthy banking system in order to achieve financial stability overall, and also confirms that the focus of the regulation on stress testing and capital adequacy in this sector is accurate.

The SVI methodology is a way of measuring the extent of the sectoral vulnerabilities at different times; hence it shows that the sectors that are defensive such as NIFTY FMCG and NIFTY PHARMA can go from being a minor to a major vulnerability in certain periods only if they have changed their fundamental characteristics. For example, the pharmaceutical industry was the main sector that increased its share of the vulnerability the most by far because of the uncertainties in the regulations and the interruptions in the supply chain, namely, during the COVID-19 pandemic period, and that is, although it was a sector traditionally recognized as the defensive one.

The risk-return trade-off

GARCH-in-Mean highlights that patterns risk premium are diverse across Indian equity sectors and it allows us to understand how different market segments investors price volatility risk. The results obtained are that the link between the conditional volatility and expected returns is very different across sectors and these differences are the reflection of investor risk.

Table 4: GARCH-in-Mean Risk Premium Analysis

Sector	Risk Premium Coefficient	Std. Error	t-statistic	p-value	Significance
NIFTY BANK	0.34	0.08	4.25	0.001	***
NIFTY FMCG	-0.12	0.09	-1.33	0.183	NS
NIFTY IT	0.28	0.07	4.00	0.001	***
NIFTY METAL	0.45	0.11	4.09	0.001	***
NIFTY PHARMA	0.19	0.06	3.17	0.002	**

Note: ***, * *, *and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively. NS denotes not significant.*

Source: Authors' GARCH-in-Mean estimation using NSE sectoral returns.

In the banking sector, there exists a significant positive risk premium ($\lambda = 0.34$, $t = 4.25$, $p < 0.001$), which means that investors here are willing to carry more volatility risk and hence require a higher return from this sector that is systemically important. This result is also in line with the banking sector being the main source of spillovers as our network analysis shows, which implies that market participants are not only aware of, but also correctly price the systemic risk features of this sector.

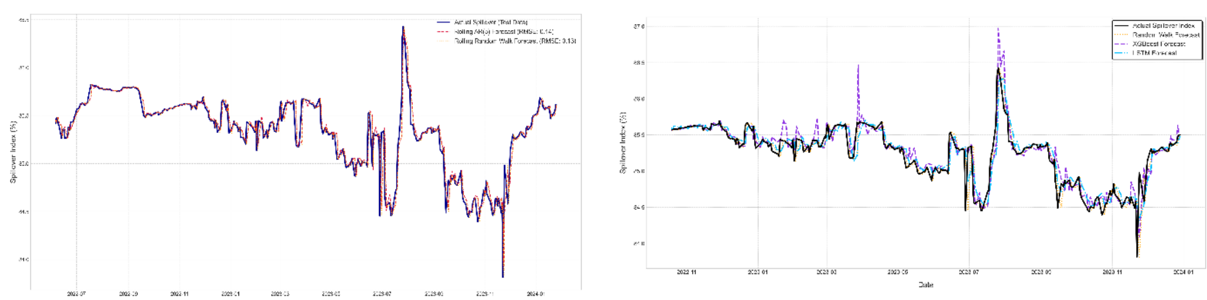
The metals sector is the riskiest by nature and exhibits the highest risk premium coefficient ($\lambda = 0.45$, $t = 4.09$, $p < 0.001$), that is, it represents the high volatility and cyclical characteristics of commodity-related investment just as we have mentioned here. The position of this sector to global commodity price changes and economic cycles leads to a situation where a lot of uncertainty is priced by investors, thus they expect to be compensated through increased risk premiums. The FMCG sector, on the other hand, shows a non-significant statistical result with a negative risk premium coefficient ($\lambda = -0.12$, $t = -1.33$, $p = 0.183$), that implies that the defensive sector here may just be providing some diversification benefits when there is increased volatility. It may seem paradoxical to some but this outcome fits with the theoretical prediction that defensive sectors can provide a negative beta during market turmoil phase, hence they become good hedging stocks. The information technology sector is characterized by a moderate but highly significant positive risk premium ($\lambda = 0.28$, $t = 4.00$, $p < 0.001$) that can be directly connected to the sector's exposure to global technology cycles and currency rate changes. The pharmaceutical sector reveals also a significant risk premium, but of a lower magnitude ($\lambda = 0.19$, $t = 3.17$, $p = 0.002$),

This research has a major impact on portfolio building and risk management in the Indian stock market. The differences between sectors in risk premiums point out that investors have the opportunity to utilise the portfolio risk-return profiles more effectively by meticulously selecting the exposure to the various sectors according to their risk appetite and expectations of the market. The findings also shed light on sector rotation strategies, showing when risk premiums might be tempting in comparison to a sector's basic prospects.

Predictability of systemic risk

Using advanced machine learning and traditional econometrics, we have conducted a detailed forecasting analysis to assess the predictability of volatility spillover in the Indian stock market. The investigation of the Random Walk, XGBoost, and LSTM models reveals that Chinese equity markets are still efficient and also places a limit on how far one can predict spillover in emerging market situations.

Figure 5: Out-of-Sample Forecast Comparison of Spillover Index



Source: Authors' forecasting model output (Random Walk, XGBoost, LSTM).

The forecasting results depict a compelling validation of the Efficient Market Hypothesis in the Indian setting, with the straightforward Random Walk model showing better performance across various evaluation metrics. The Random Walk secures the least RMSE (0.13) and MAE (0.09) and also retains the highest directional accuracy (52.1%), which is just a tad better than the machine learning methods of the same level of complexity.

Table 5: Forecasting Model Performance Summary

Model	RMSE	MAE	MAPE	Directional Accuracy
Random Walk	0.13	0.09	12.3%	52.1%
XGBoost	0.14	0.11	13.7%	48.9%
LSTM	0.14	0.10	13.1%	50.3%
Rolling AR(5)	0.14	-	-	-

Source**:** Authors' forecasting analysis using NSE-based spillover index and model outputs from Random Walk, XGBoost, and LSTM.

Although it is fitted with ensemble learning technique and can extract complicated non-linear relations, the XGBoost model results in a root mean square error (RMSE) of 0.14 and a directional accuracy of only 48.9%. The spillover index, however, seems to be very much efficient in using the information, thus even the most sophisticated machine learning algorithms don't manage to constantly outperform simple random processes.

Along the same line, the LSTM model, which was created for the purpose of detecting of long-term dependencies and temporal patterns in sequential data, doesn't succeed to go beyond the benchmark of the random walk (RMSE = 0.14, directional accuracy = 50.3%). The theoretical possibilities of LSTM to process time series data and the practical experience it has gained in other financial forecasting make it even more important.

The continuous failure of forecasting models, which are of superior nature, to produce better results comparing to the random walk, offers most convincing empirical evidence in the favour of the semi-strong form of the Efficient Market Hypothesis in the equity markets of India. Thus, the result points out that the publicly accessible data are very quickly incorporated in the patterns of spillover, and the continuous disappearance of arbitrage opportunities makes it extremely difficult to any systematic prediction of the markets.

The scope of these results is much wider as they are no longer only of academic interest, but also of practical use in risk management and in the designing of regulatory policy. The unpredictability of spillover dynamics reinforces the need for rigorous stress and scenario analysis approaches that consider the very nature of the uncertainty which is characteristic of the evolution of systemic risk. In this context, it would be more beneficial for risk managers and policymakers to create adaptive frameworks that are able to respond promptly and efficiently to unanticipated intensifications of spillover instead of sticking to point forecasts.

Besides, the confirmation of market efficiency in the spillover context implies the return history-based diversification strategies may be still vulnerable in the event of a relapse of the crisis in the future. Thus, investors and portfolio managers should not only rely on the past, but also employ more resilient portfolio construction methods that take into consideration possible ruptures of the relationships that they have identified in the past, especially when they are experiencing the market's stress.

Conclusion

This study offers several key findings with significant implications for both investors and policymakers by carrying out a multifaceted methodology, such as the Diebold-Yilmaz spillover index, dynamic network analysis, a novel Spillover Vulnerability Index (SVI), GARCH-in-Mean models, and a rigorous forecasting exercise.

Firstly, our findings suggest that systemic risk in the Indian market is a highly fluid and changing matter over time. The total spillover index peaks at times of market turmoil, like the COVID-19 pandemic, completely changing the market's risk architecture, which was initially sparsely connected when the period was calm, to a dense and highly correlated web in which the diversification benefits have been lost. Secondly, the NIFTY Bank index was found to be the main net supplier of volatility shocks throughout the study that reflects the utmost systemic importance of the index as well as its role of the major channel of the contagion. Third, the analysis of macro drivers disclosed that systemic risk is quite sensitive to global risk sentiment (represented by CBOE VIX) and, along with domestic factors, they are the major contributors to the Indian market's exposure to the global financial system. Fourth, according to the results of GARCH-in-Mean analysis, the risk-return heterogeneity across sectors is highly pronounced, with the cyclical sectors, such as Banking and Metals, being attributed to a high-risk premium, whereas defensive sectors, such as FMCG, do not display such a feature.

And last but not least, probably most important, a thorough out-of-sample forecasting exercise is the strongest evidence of the Efficient Market Hypothesis that we have ever seen. To predict the Total Spillover Index, they found that advanced machine learning and deep learning models (XGBoost and LSTM) were not able to beat the Random Walk benchmark consistently. This experiment indicates that data is already fully reflected in the spillover system at a stunning pace, therefore, the future of the system is almost completely unpredictable.

In simple terms, investors then, should understand that risk management strategies are not supposed to rely entirely on the past spillover trends, which are proven to be unstable, especially during the times of crisis. Nevertheless, the differences among the sectors in risk premia could be used to develop more sophisticated portfolio allocation and rotation strategies. For policymakers and regulators, this research calls for close observation of the banking sector as the major source of systemic risk and the consideration of the SVI as a real-time financial stability indicator. The fact that spillovers are highly unpredictable makes it vital to focus on the building of systemic resilience by effective stress testing and capital adequacy frameworks rather than relying on the prediction and prevention of crises.

Future Research

Despite this study having a very detailed account of systemic risk in Indian markets, it is still possible to identify multiple research topics which are still unexplored.

- Advanced Spillover Models: The work can be carried further by utilizing more advanced time-varying parameter VAR (TVP-VAR) models besides what has been presented here. TVP-VAR eliminates the need to rely on rolling-window; thus, the parameters of the model can change at every time point, thereby, the contagion dynamics can be captured more flexibly.
- Cross-Asset Spillovers: The scope of this research was limited to the equity market only. Therefore, an important aspect could be to add other asset classes such as government bonds, corporate debt, commodities, and currencies so the map of systemic risk transmission in India spans across all asset classes thus, becoming more holistic and also, the notion of risk could be furthered.
- High-Frequency Textual Analysis: The news and sentiment impact on spillovers can be an extension of this research. Accessing the high-frequency textual data from newswires and social media can be one source for future work. Applying natural language processing (NLP) for the creation of real-time sentiment indices is one way of getting closer to the understanding of market contagion's core.
- Exploring Non-Linear Forecasting Models: Even though the models that have been tested in this paper could not win the Random Walk, some of the experiments with more complicated non-linear models or different feature engineering input may serve the purpose of pushing market efficiency and the systemic risk forecast predictability further in the future.

References

1. Andersen, T. G., & Bollerslev, T. (1998). Answering the Skeptics: Yes, Standard Volatility Models Do Provide Accurate Forecasts. *International Economic Review*, 39(4), 885–905.
2. Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, 13(4), 84.
3. Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, 31(3), 307–327.
4. Chicago Board Options Exchange (CBOE). (n.d.). *CBOE Volatility Index (VIX)*. Retrieved from https://www.cboe.com/tradable_products/vix/
5. Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and sustainable volatility spillovers, with application to global equity markets. *The Economic Journal*, 119(534), 158–171.
6. Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of sustainable volatility spillovers. *International Journal of Forecasting*, 28(1), 57–66.
7. Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, 50(4), 987–1007.
8. Federal Reserve Bank of St. Louis. (n.d.). *Federal Reserve Economic Data (FRED)*. Retrieved from https://fred.stlouisfed.org/
9. National Stock Exchange of India Ltd. (n.d.). *Historical Data*. Retrieved from https://www.nseindia.com/products/content/equities/indices/historical_index_data.htm
10. Reserve Bank of India. (n.d.). *Database on Indian Economy*. Retrieved from https://dbie.rbi.org.in/
11. Shah, D., Isah, S., & Zada, P. (2022). The Asymmetric Volatility Spillover Effect of The Indian Stock Market on The Sectoral Indices. *Asian Journal of Management*, 13(3), 205-212.
12. Tiwari, A. K., Jana, R. K., & Roubaud, D. (2019). The dynamic spillover effects between stock and currency markets in India: A VAR-DCC-GARCH model. *International Journal of Finance & Economics*, 24(1), 125-138.
13. Umar, Z., Gubareva, M., & Sokolova, T. (2021). The impact of the COVID-19 pandemic on the interconnectedness of financial markets. *Finance Research Letters*, 41, 101852.
14. U.S. Energy Information Administration (EIA). (n.d.). *Petroleum & Other Liquids: Spot Prices*. Retrieved from https://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm
15. Yahoo Finance. (n.d.). *Financial Data*. Retrieved from https://finance.yahoo.com/

Author Details:

Mr. Syed Maaz Ahmed
Management Trainee, University of Mysore
Mysore, Karnataka, India
Email: syedmaazahmed@yahoo.com

Dr. Nischith S
Assistant Professor, University of Mysore
Mysore, Karnataka, India
Email: nischith9774@gmail.com

Dr. Rakesh D,
Associate Professor, JSS – Centre for Management Studies,
JSS Science and Technology University, Mysuru, India.
ORCID: 0000-0003-3963-3174
Email: rakeshdamodar@gmail.com