Unraveling COVID-19-induced volatility spillover: a study of the dynamic interplay between NIFTY 50 spot and options markets

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Abstract

This study unravels the transmission of volatility spillovers between NIFTY 50 spot prices and the options market, addressing a significant gap in existing studies. It captures how market connectedness evolved during the pre-COVID, COVID and post-COVID periods, offering fresh insights into price discovery and risk management during systemic shocks. The analysis applies the Dynamic Conditional Correlation-GARCH (DCC-GARCH) model to examine volatility spillovers and assess dynamic connectedness between NIFTY 50 spot prices and options. Furthermore, the Baruník and Krehlík (2018) and Diebold and Yilmaz (2012) models are employed for variance decomposition, providing insights into time-frequency connectedness and offering a detailed view of spillover effects across different time horizons.

The findings reveal volatility spillovers between the NIFTY index and option markets across various moneyness levels (ATM, ITM, and OTM) during pre-COVID, COVID and post-COVID periods. The results show persistent long-run spillovers but no significant short-term effects. ATM and ITM options emerge as key volatility transmitters, while the NIFTY index acts as a net absorber, particularly during the COVID-19 crisis. A sharp rise in market connectedness is observed during COVID, which remained elevated in the subsequent period. The results hold important implications for option pricing, hedging and regulation. Persistent long-term spillovers emphasize the importance of models that account for time-varying risk across different moneyness levels. The surge in connectedness during the COVID-19 pandemic highlights the need for dynamic hedging strategies and stronger regulatory oversight, particularly in emerging markets. This study is among the first to analyze volatility spillovers between NIFTY 50 and the options market, with a specific focus on the COVID-19 pandemic.

Keywords Volatility spillover, Option market, Spot market, Nifty 50, GARCH, Diebold Yilmaz

Paper type Research article

1. Introduction

Volatility spillover has attracted considerable interest in financial research due to its relevance in asset pricing, risk management and trading strategies. It describes the process by which

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price volatility in one market impacts another, shaping asset behavior and market interactions. Financial markets show increasing interconnectedness as investors and market players participate in cross-market trading for speculation, portfolio diversification and risk management. Numerous studies have explored volatility spillovers in emerging markets like China and South Korea, particularly focusing on the interactions between spot and futures markets (Kang *et al*., 2013; Kim and Lim, 2019). These investigations emphasize the importance of understanding market interconnections, especially during periods of heightened volatility. While research in developed economies has delved into areas such as price discovery and the functioning of derivative instruments, limited attention has been given to the study of volatility transmission and spillover effects (Atilgan *et al*., 2016).

Using wavelet analysis, Aloui *et al*. (2018) investigated the volatility relationships between stock indices and stock index futures in both developed and emerging countries across various geographical regions. Their research found that the degree of correlation between spot and futures markets tends to vary with changes in market volatility. This finding aligns with Ross's (1989) theory that higher volatility enhances information flow and facilitates the transmission of information between markets. Based on their conclusions, Aloui *et al*. (2018) suggested conducting further research on spillover mechanisms across various asset classes. Building upon this global context, it becomes essential to explore how these volatility dynamics play out in the Indian market. Therefore, analyzing how volatility in the Nifty 50 spot market influences the pricing and volatility of call-and-put options is crucial for enhancing the understanding of market dynamics and risk transfer across financial instruments. Although these financial interdependencies exist, traditional finance research has mainly focused on individual markets, usually ignoring the effect of volatility transmission between markets on overall market behavior. Specifically, in India, while Nifty 50 index option contracts exist, there is a notable lack of research into the volatility spillover effects between the Nifty 50 spot market and its corresponding options market.

The Efficient Market Hypothesis suggests that new information is rapidly incorporated into both spot and derivative markets, which theoretically minimizes the chances for arbitrage opportunities (Fama, 1970). However, real-world factors such as transaction costs and information asymmetry challenge this ideal (Stoll and Whaley, 1990). Due to market inefficiencies, a lead-lag relationship often emerges in which price discovery occurs in highly liquid markets with minimal transaction costs and fewer regulatory constraints. Therefore, price discovery, which determines an asset's equilibrium price, is essential for market functioning and investor decision-making (Lehmann, 2002).

Volatility, a key measure of price fluctuations, is widely used by investors to anticipate future market movements and make informed investment decisions. Thus, the relationship between spot and derivatives markets becomes a key area of analysis. Understanding the integration and co-movement between these markets is essential, as derivatives trading can significantly affect the liquidity, volatility and information flow of the underlying cash markets. With rising trading volumes in derivatives, it becomes increasingly important to examine how quickly markets incorporate new information and how this affects overall market stability. As volatility is closely tied to information flow (Ross, 1989), analyzing the volatility linkages between the Nifty 50 spot and options markets can provide valuable insights to investors and regulators, helping improve pricing accuracy, manage risk more effectively and enhance market efficiency.

To address this gap, this study seeks to examine how volatility in the Nifty 50 spot market spillovers into the options markets, particularly call-and-put options. By providing insights into these spillover effects, this research will enhance the broader understanding of interconnected financial markets and support more informed, strategic decision-making by market participants and regulators.

This study attempts to address the following questions:

(1) Is there volatility spillover from Nifty 50 to option prices (both call and put) in the short and long run?

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(2) Does the volatility spillover from Nifty 50 to call options differ from that to put options in the short and long run?

(3) How did volatility spillover dynamics in the Indian options market change before and after the COVID-19 period?

This study offers three significant contributions to the current literature. First, by examining the spillover dynamics between Nifty 50 and call and put options, the research offers a new perspective on index options pricing by identifying the directional and asymmetric nature of volatility spillovers between the Nifty 50 and both types of options across varying moneyness levels. Second, the DCC-GARCH model provides a new approach to studying the volatility spillover between the Nifty index and the options market. Furthermore, the frameworks suggested by Diebold and Yilmaz (2012) and Baruník Krehlík (2018) help understand the flow of information and interconnectedness of these markets. This methodological integration advances the literature by uncovering both short- and long-term spillover effects and demonstrating the evolving interconnectedness and information flow between the spot and options markets in an emerging market context. Third, COVID-19 is considered a major structural break to assess its impact on volatility spillover dynamics (De Davide, 2018; Gupta, 2023). These findings offer valuable insights for risk managers and investors, including market participants, by illustrating how volatility transmission between the Nifty and options can impact portfolio diversification opportunities and risk management strategies.

This study comprises five sections. It starts with an introduction, followed by a literature review in the second section. The third section describes the data and econometric models employed in the study. Section four presents the results and discussion, while the fifth section concludes with policy implications.

2. Literature review

2.1 Price discovery and volatility in derivatives markets

The relationship between spot, futures and options markets has been widely researched, with particular attention given to the lead-lag dynamics between spot and futures markets. However, the research on the options market, particularly focusing on volatility transmission and price discovery, remains relatively limited. Most of the studies have been aimed at understanding how the markets are related, with studies by Pizzi *et al*. (1998) proposing a bidirectional relationship between spot and futures markets. In contrast, studies such as those by Koutyos and Tucker (1996) explored spillover effects using a bivariate EGARCH model, finding that unpredictability tends to flow from the futures market to the spot market, with little evidence of the reverse.

The application of GARCH models to analyze the volatility spillover is well documented, with univariate GARCH models commonly used to understand these dynamics in various markets (Rastogi, 2010). A univariate EGARCH model was employed to study volatility spillover in stock markets in six countries. Rastogi and Srivastava (2011) examined the conditional volatility between Indian and U.S. stock markets. Moving to more complex modeling (Sinha, 2017), utilized multivariate GARCH models, specifically BEKK GARCH and DCC-GARCH, to study spillover between futures and spot markets, mainly focusing on the agricultural commodity Black Pepper, and found positive spillover effects between the two.

In the Indian context, studies have also examined the volatility dynamics across various market segments. For instance, Rastogi and Athaley (2019) examined the integration of volatility across spot, futures, and options markets based on the Generalized Method of Moments (GMM). The study noted the interconnectivity between these markets, albeit with less advanced treatment of options markets than futures and spot markets. Prominent research by Rastogi and Srivastava (2011) discussed the effect of exchange-traded currency derivatives on spot exchange rate volatility using a GARCH (1,1) model, supporting the role of derivatives in market volatility. Sehgal *et al*. (2015) presented an inclusive study of the Indian market,

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validating the price discovery and the volatility spillover effects of the NSE spot, future, and options markets. They found evidence of high bidirectional short-term spillover volatility in the spot and futures markets, with comparable behavior in the long run, using an exponential GARCH (EGARCH) model. In the case of options and spot markets, they found evidence of short-term one-way spillover from options to spot, while in the long run, there was a spillover, albeit only in the second and third moments. The study also emphasizes that options markets are prone to leading to risk hedging, again emphasizing the use of options in price discovery.

Futures and options markets are widely recognized because they have more information than spot markets. This is partly because of the greater understanding of traders in these markets and their involvement in larger transactions. Several studies, including those by Ghosh (1993) and Kang *et al.* (2013), have shown that futures prices typically lead to their corresponding underlying indexes. Whereas Yang *et al.* (2012) and Lucian (2008) suggest that the spot index may lead to its associated futures index. A multitude of studies have investigated the correlation between spot and futures markets, frequently concluding that futures markets prevail in price discovery, assimilating market-wide information more effectively than spot markets (Chou and Chung, 2006; Stoll and Whaley, 1990; Brooks *et al.*, 2011; Pizzi *et al.*, 1998; Ghosh, 1993). On the contrary, Bhattacharya (1987) and Fleming *et al.* (1996) show that option prices can exceed stock market prices, particularly for options with high trading volumes (Stephan and Whaley, 1990).

2.2 COVID-19 and stock market volatility: global evidence

Numerous studies have examined how the COVID-19 epidemic has affected the volatility and performance of the world's financial markets. For instance, Duttilo *et al.* (2020) examined the effect of COVID on the returns and volatility of stocks in 18 Eurozone countries using a Threshold GARCH (1,1)-in-mean model. Their findings show that the first pandemic wave considerably raised conditional volatility in markets like Finland, Italy, Austria, France, Belgium, Germany, Ireland, the Netherlands and Spain. Only the Belgian stock market had a major volatility response during the second wave.

As far as developing markets are concerned, Fakhfekh *et al.* (2021) applied a wider set of GARCH family models, including TGARCH, FIEGARCH, FIGARCH and EGARCH, to identify the volatility of 12 sectors in the Tunisian stock market by using daily data from 4th January 2016 to 30th April 2020. Their study unveiled that volatility persistence increased across all sectors during COVID-19. Sectors such as banking, consumer services and financials showed strong asymmetric effects, reacting more sharply to negative news during the pandemic than in the pre-COVID period. These results are further validated by Vuong *et al.* (2022), who observed that volatility spillovers from China to the United States intensified during the COVID-19 period.

In the Indian context, the National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE) observed substantial declines in early 2020, followed by periods of erratic fluctuations as the crisis evolved. Empirical studies applying advanced GARCH models confirm that market volatility intensified significantly during COVID, with higher persistence and spillover effects from global markets such as China, the United States and Germany (Maharana *et al.*, 2024). These dynamics reflected economic uncertainty and heightened investor sensitivity to pandemic-related news and global financial signals. Although the Indian market was initially unstable, it showed signs of recovery by the end of 2021 and demonstrated strength during systemic shocks (Chaudhary *et al.*, 2020). Although existing studies primarily address stock market volatility in India, they offer limited insight into the derivatives segment, revealing a significant gap in research on volatility transmission from the spot market to the options market within the Indian context.

The present study aims to bridge that gap in understanding volatility spillover between the spot and options markets by employing econometric models such as DCC GARCH, Diebold and Yilmaz and Barunik and Krehlik. Furthermore, it aims to identify which market exerts a

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greater influence on the other, thereby contributing to a more nuanced understanding of their interrelationships.

3. Data and econometric models

3.1 Data description

This study analyzes data from the NIFTY 50 Spot Index and its call and put options over ten years, from 1 January 2014 to 31 December 2023. The weekly price data for the NIFTY spot index and NIFTY index call and put option contracts were acquired from the National Stock Exchange (NSE) website for the designated timeframe. Weekly data are used instead of daily or high-frequency data to reduce expiry-related distortions and market noise, thereby capturing medium-term patterns more accurately. It ensures data dependability over time, simplifies rollover adjustments for options and aligns with previous research (Chiang and Fong, 2001; Floros and Salvador, 2016). The returns for the NIFTY spot index, call options and put options are calculated using the formula $R_t = n\left(\frac{P_t}{P_{t-1}}\right)$ where P_t is the current price and $P_{t\text{-}1}$ is the previous price. The data are divided into three segments: (1) the pre-COVID period, from 1 January 2014 to 31 December 2019; (2) the COVID period, from 1 January 2020 to 31 December 2021, which is emphasized to incorporate the shocks from COVID-19 (Gupta and Katoch, 2024); (3) the post-COVID period, from 1 January 2022 to 31 December 2023 and (4) overall period, from 1 January 2014 to 31 December 2023.

Furthermore, Table 1 presents the total number of observations across the three moneyness categories, where options are classified as out-of-the-money (OTM) when $S_t/K < 0.97$, at-the-money (ATM) when $0.97 \leq S_t/K < 1.03$ and in-the-money (ITM) when $S_t/K \geq 1.03$ (Shvimer and Zhu, 2024). Based on the moneyness ratio S_t/K, one representative strike was selected each week for ITM, ATM and OTM categories. When multiple strikes qualified, the option with moneyness closest to the category threshold was chosen. The number of observations for ATM, ITM and OTM options is 558, 556 and 562, respectively, resulting in 1,676 observations.

We began our analysis of the unpredictable spillover effects between the spot and option markets by applying the Jarque-Bera test. To determine the stationarity of the data, we applied the Augmented Dickey–Fuller (ADF) test proposed by Dickey and Fuller (1981) and the Phillips and Perron (1988) test. An econometric model, such as the DCC-GARCH, is applied to estimate dynamic conditional correlations, capturing short-term volatility interactions and co-movements. Furthermore, the techniques proposed by Diebold and Yilmaz (2012) and Baruník and Krehlík (2018) were applied to assess directional linkages and spillover effects across different time-frequency domains, include the pre-COVID, COVID and post-COVID periods.

3.2 Econometric models

This section defines the quantitative methodologies employed in the study. To analyze the interconnectedness and volatility transmission among the NIFTY index, call and put option markets, a three-tiered modeling framework is employed: the DCC-GARCH model, the Diebold and Yilmaz (2012) connectedness approach, and the Baruník–Krehlík (BK)

Table 1. Pairs and exercise prices according to moneyness category classification

Category	Pair	Number of observations
1	ATM call and ATM put options	558
2	ITM call and OTM put options	556
3	OTM call and ITM put options	562

Source(s): Authors' own creation

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frequency-domain model. The DCC-GARCH model allows for the estimation of dynamic conditional correlations, capturing short-term volatility interactions and co-movements. The Diebold-Yilmaz method provides measures of overall, directional and net spillovers, helping to identify dominant sources and recipients of market shocks. The BK model further breaks down these spillovers across different time horizons, short, medium, and long, offering a clearer view of both transient and enduring market linkages. Together, these models offer a comprehensive perspective on the evolving dynamics of the Indian derivatives market.

3.2.1 The Dynamic Conditional Correlation GARCH (DCC-GARCH). DCC-GARCH model builds upon Bollerslev's (1990) Constant Conditional Correlation (CCC-GARCH) framework, further developed by Engle (2002), to allow for time-varying correlations between variables. This involves a two-step procedure where individual GARCH models are first applied to estimate the volatility of each series, and then the standardized residuals derived from these models are used to compute dynamic correlations over time (Thas Thaker and Ah Mand, 2021).

Let $r_t = (r_{1t}, r_{2t}, \ldots\ldots, r_{Nt})'$ be an $N \times 1$ vector of asset returns at time t, with conditional covariance matrix H_t.

The form of Engle's DCC model is as follows:

$$H_t = D_t R_t D_t \tag{1}$$

Where:

H_t is the $N \times N$ conditional covariance matrix,

$D_t = \mathrm{diag.}(h_{1t}^{1/2}, \ldots, h_{Nt}^{1/2})$ is a diagonal matrix of conditional standard deviations from the univariate GARCH (1,1) model.

Each variance term h_{it} is modeled as:

$$\mathrm{h_{it}} = \omega_\mathrm{i} + \alpha_\mathrm{i}\varepsilon_{i,t-1}^2 + \beta_\mathrm{i}\,\mathrm{h_{i,t-1}}, \mathrm{i} = 1, 2, \ldots\ldots.\mathrm{N} \tag{2}$$

where:

$\omega_i > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$, and $\alpha_i + \beta_i < 1$,

$\varepsilon_{i,t-1}$ is the lagged innovation for asset i,

α_i and β_i measure the short-term shock and persistence effects, respectively.

The standardized residuals are computed as:

$$\mathrm{u_t} = D_t^{-1}\,\varepsilon_t \tag{3}$$

where $\varepsilon_t = r_t$, assuming a zero-mean return series.

The dynamic conditional correlation matrix R_t is based on a rescaled version of the time-varying covariance matrix Q_t, defined as:

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha u_{t-1} u_{t-1}' + \beta Q_{t-1}. \tag{4}$$

Where:

$\overline{Q}$ is the unconditional covariance matrix of standardized residuals u_t,

α and β are scalar parameters controlling the dynamics of correlations,

$\alpha + \beta < 1$ is required for stationarity.

The dynamic conditional correlation matrix R_t is obtained by standardizing Q_t:

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$$R_t = \mathrm{diag}(Q_t)^{-1/2}\, Q_t\, \mathrm{diag}\,(Q_t)^{-1/2} \tag{5}$$

Here, diag(Q_t) is a diagonal matrix containing the square roots of the diagonal elements of Q_t, ensuring that R_t is a proper correlation matrix with unit diagonal elements.

Thus, the DCC-GARCH model captures both the time-varying volatilities of individual return series (through GARCH α_i, β_i) and their dynamic correlations (through DCC parameters dcca1 = α, dccb1 = β).

3.2.2 Time-varying and frequency-based connectedness methodologies. 3.2.2.1 Time-varying connectedness: Diebold and Yilmaz (2012) model. This study applies the Diebold and Yilmaz (2012) spillover framework to estimate dynamic connectedness among variables using Generalized Forecast Error Variance Decomposition (GFEVD).

Let

$Y_t = (r_{NIFTY,t}, r_{CALL,t}, r_{PUT,t})'$ denotes a vector of return series at time t, where each element corresponds to returns of NIFTY, CALL and PUT options.

The VAR(q) model is defined as

$$Y_t = \sum_{i=1}^{q} \Phi_i Y_{t-i} + \varepsilon_t \tag{6}$$

The moving average (MA) representation of the above VAR is

$$Y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{7}$$

Where A_i is a matrix of MA coefficients derived from the VAR process, and ε_t is a vector of shock terms with covariance matrix Σ.

The H-step-ahead generalized forecast error variance decomposition (GFEVD) for shock transmission from variable j to i is given by:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_i\right)^1} \tag{8}$$

Where e_j is a selection vector with 1 in the jth position and 0 elsewhere, and σ_{jj} is the jth diagonal element of Σ.

To ensure comparability, the variance shares are normalized as:

$$\breve{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{9}$$

The total spillover index is computed as:

$$S^g(H) = \frac{\sum_{i,j=1, i\neq j}^{N} \widetilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}^{g}(H)} \times 100 \tag{10}$$

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The directional volatility spillovers that market *I* from others are:

$$S^g_{i\leftarrow}(\mathrm{H}) = \sum_{\mathrm{j=1, j \neq i}}^{N} \widetilde{\theta}^g_{ij}(H) \tag{11}$$

The spillover transmitted by market *i* to others is:

$$S^g_{i\rightarrow}(\mathrm{H}) = \sum_{\mathrm{j=1, j \neq i}}^{N} \widetilde{\theta}^g_{ji}(H) \tag{12}$$

The Net Volatility Spillover from market *i* is given by:

$$NS^g_i(H) = S^g_{i\leftarrow}(H) - S^g_{i\rightarrow}(H) \tag{13}$$

A positive net spillover indicates a net transmitter of shocks, whereas a negative value implies a net receiver.

3.2.2.2 Frequency-based connectedness: Barunik and Krehlik (2018) model. The Baruník and Krehlík (2018) framework is employed to examine connectedness over various time horizons: short, medium and long term. This method separates overall spillovers into distinct frequency components by utilizing the spectral decomposition of the VAR process.

The method is built upon the frequency response function as shown in Equation (14):

$$\psi\left(e^{-i\omega}\right) = \sum_{h=0}^{\infty} e^{-ih\omega} A_h \tag{14}$$

Where:

$\omega \in [-\pi, \pi]$ is the frequency,

The generalized forecast error variance decomposition (GFEVD) at frequency ω is defined as:

$$\theta_{ij}(\omega) = \frac{\sigma_{jj}^{-1}\left|\left(\psi(e^{-iw})\Sigma\right)_{ij}\right|^2}{\left(\psi(e^{-iw})\Sigma\psi'(e^{iw})\right)_{ii}} \tag{15}$$

To assess spillover in a specific frequency band d = (d_1, d_2), the cumulative connectedness measure is computed as:

$$\widetilde{\theta}_{ij}(d) = \int_{d_1}^{d_2} \widetilde{\theta}_{ij}(\omega)d\omega \tag{16}$$

Using this, total, directional and net spillovers over band d are calculated analogously to the Diebold and Yilmaz (2012) framework.

4. Empirical results and interpretation

4.1 Descriptive statistics and unit root test

This section presents the descriptive statistics and unit root test results of the Nifty index and option options (CALL_OPTIONS and PUT_OPTIONS) across three option types: ATM, ITM and OTM. Table 2 describes the distribution properties of ATM, ITM and OTM options. Table 3 presents the results of Unit root tests applied to the variables to confirm their stationarity. The results indicate that Nifty is stationary at first difference, while Call and Put options are stationary at the level.

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Table 2. Descriptive statistics – ATM, ITM and OTM options

1. ATM options (call and put)				2. ITM options (ITM call and OTM put)			3. OTM Options(OTM call and ITM put)		
Variables	Nifty	Call_ options	Put_ options	Nifty	Call_ options	Put_ options	Nifty	Call_ options	Put_ options
Mean	0.0022	(0.0016)	(0.0002)	0.0023	0.0000	(0.0017)	0.0024	(0.0038)	0.0003
Median	0.0031	(0.1298)	(0.1451)	0.0032	(0.0432)	(0.2277)	0.0031	(0.2084)	(0.0335)
Maximum	0.1197	2.6628	6.2956	0.1197	3.4416	8.1897	0.1197	6.8628	2.0187
Minimum	(0.1296)	(2.4947)	(5.4510)	(0.1296)	(3.5483)	(6.8303)	(0.1296)	(7.5689)	(2.3998)
Std. Dev.	0.0216	0.6325	0.7732	0.0217	0.4723	1.3838	0.0220	1.5116	0.3905
Skewness	(0.4098)	0.7925	1.3483	(0.4105)	(0.0007)	0.7800	(0.2551)	0.5493	(0.3181)
Kurtosis	8.4778	4.5824	22.2648	8.3947	16.2573	9.6706	8.6124	7.5557	9.3797
Jarque-Bera	713.2675	116.6252	8797.8960	689.8205	4071.6570	1087.2340	743.6844	514.2607	962.5315
p-value	0	0	0	0	0	0	0	0	0
Observations	558	558	558	556	556	556	562	562	562

Note(s): Figures in brackets represent negative values

Source(s): Authors’ own creation

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Table 3. Results of augmented Dickey–Fuller and Phillips and Perron based on unit root test

1. ATM options (call and put)				2. ITM options (ITM call and OTM put)			3. OTM options (OTM call and ITM put)		
Test	Nifty	Call-options	Put-options	Nifty	Call-options	Put-options	Nifty	Call-options	Put-options
ADF	(7.739)	(4.9637)	(4.8055)	(7.603)	(4.6346)	(5.671)	(7.77)	(11.929)	(3.8918)
PP	(538.2)	(218.65)	(280.42)	(538.5)	(260.55)	(401.25)	(545.7)	(132.33)	(253.71)
Remarks	Nifty: Stationary at First Difference, Call and Put Options: Stationary at Level								

Note(s): Figures in brackets represent negative values

Source(s): Authors' own creation

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Table 2 presents descriptive statistics for ATM options, showing the distribution and properties of the NIFTY index, CALL_OPTIONS and PUT_OPTIONS. The NIFTY index shows low volatility with a standard deviation of 0.0226. CALL_OPTIONS has a negative mean and positive skewness (0.7925), indicating a right-skewed distribution. PUT_OPTIONS show high kurtosis (22.2647), suggesting heavy tails. Both CALL and PUT Options have high Jarque-Bera statistics, indicating non-normality

For ITM options, the NIFTY index has low volatility (SD = 0.0217), while CALL_OPTIONS and PUT_OPTIONS have higher standard deviations. CALL_OPTIONS has near-zero skewness (symmetrical), and PUT_OPTIONS has positive skewness (0.78). CALL_OPTIONS shows high kurtosis (16.2572), and all variables have high Jarque-Bera values, indicating non-normality.

For OTM options, the standard deviations for call (1.5116) and Put options (0.3904) reveal considerable disparity, with call options demonstrating significantly greater price volatility. Furthermore, call options exhibit positive skewness (0.5492), suggesting a tendency for occasional, sharp upward spikes, while put options display negative skewness (−0.3180), indicating infrequent but substantial price declines.

Table 3 presents the results of unit root tests (ADF, PP) on Nifty, Call and Put options data for ATM, ITM and OTM options. The *p*-value for all tests is 0.01, indicating that all variables are stationary at either level or first difference. Specifically, Nifty is stationary at first difference, while Call and Put Options are stationary at the level. This implies that the Call and Put Options are not time-dependent, while Nifty's values depend on their previous values.

4.2 Results of dynamic conditional correlation GARCH

We employ the DCC-GARCH model, developed by Engle in 2002, to examine how spot markets influence options markets. This model is advantageous because it can identify changes in conditional correlations over time, revealing how investors adjust their behavior in response to new information. Furthermore, DCC-GARCH overcomes the limitation of standard GARCH models, which often assume constant correlations when dealing with multiple assets and varying volatility. DCC-GARCH provides a more accurate and comprehensive understanding of market behavior by allowing for time-varying correlations.

In the DCC-GARCH model, ω (omega) signifies constants, whereas the parameters α_1 (alpha 1) and β_1 (beta 1) pertain to the ARCH and GARCH components. The α (alpha) parameter measures the influence of historical shocks on short-term variance, whereas the β (beta) value reflects the persistence of volatility, illustrating the impact of market disturbances on long-term conditional correlations (Yadav *et al.*, 2022, 2023; Gupta, 2023). For volatility to exhibit persistence, both α_1 and β_1 must be mathematically significant and positive at the 5% significance level. Additionally, to assess the temporal evolution of volatility and determine the presence of time decay, α_1 and β_1 values must be lower than 1 for both series presented in Table 4.

4.2.1 Pre-COVID. Before COVID, NIFTY showed higher volatility persistence than call options in ATM and OTM categories, with $\alpha + \beta$ values of 0.9704 and 0.9696, compared to 0.4637 and 0.8390 for call options, respectively. In ITM, call options had higher persistence (0.9989) than NIFTY (0.9698). Across all categories, αDCC was insignificant, while βDCC was significant, indicating long-run spillover. For put options, $\alpha + \beta$ was 0.7029 (ATM), 0.2829 (ITM) and 0.9513 (OTM), with significant βDCC values, suggesting consistent long-term information flow from NIFTY to put options.

4.2.2 During COVID. During COVID, both call and put options across the ATM and OTM categories showed very high volatility persistence (above 0.997), exceeding NIFTY's 0.8481 in the ATM. Although αDCC remained insignificant in all cases, βDCC was consistently significant (0.0000), indicating strong long-run spillover. In ITM options, call options showed zero α and β, indicating poor GARCH behavior, yet βDCC was still significant. Put options in ITM had a persistence of 0.9722, with only βDCC significant, confirming long-term information flow from NIFTY to options.

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Table 4. Results of dynamic conditional correlation GARCH of ATM, ITM and OTM options

1. ATM options (call and put)				2. ITM Options(ITM call and OTM put)			3. OTM Options(OTM call and ITM put)		
	Estimate	t Value	*P*r(>|*t*|)	Estimate	*t* value	*P*r(>|*t*|)	Estimate	*t* value	*P*r(>|*t*|)
1. Pre-COVID									
DCC from NIFTY to call options									
Mean NIFTY	0.0022	2.3032	0.0213	0.0022	2.3024	0.0213	0.0022	2.3006	0.0214
ωNIFTY	0.0000	5.9424	0.0000	0.0000	6.4803	0.0000	0.0000	6.4188	0.0000
αNIFTY	0.0463	8.5425	0.0000	0.0460	8.8546	0.0000	0.0464	8.7023	0.0000
βNIFTY	0.9241	89.4767	0.0000	0.9238	91.3450	0.0000	0.9232	89.5075	0.0000
Mean return of Call options	0.0193	0.4540	0.6498	0.0046	0.3279	0.7430	0.0089	0.0760	0.9394
ωCall options	0.2662	5.9708	0.0000	0.0440	3.5779	0.0003	0.4798	0.2908	0.7712
αCall options	0.4637	1.1260	0.2602	0.8442	4.5655	0.0000	0.2000	1.0075	0.3137
βCall options	0.0000	0.0000	1.0000	0.1548	1.6509	0.0988	0.6391	0.8130	0.4162
αDCC	0.0000	0.0040	0.9968	0.0000	0.0035	0.9972	0.0000	0.0033	0.9973
βDCC	0.9060	5.8962	0.00000*	0.9283	3.3475	0.0008	0.9186	12.3684	0.00000*
DCC from NIFTY to put options									
Mean NIFTY	0.0022	2.3032	0.0213	0.0022	2.3024	0.0213	0.0022	2.2999	0.0215
ωNIFTY	0.0000	5.9424	0.0000	0.0000	6.4803	0.0000	0.0000	6.4189	0.0000
αNIFTY	0.0463	8.5425	0.0000	0.0460	8.8546	0.0000	0.0464	8.7044	0.0000
βNIFTY	0.9241	89.4767	0.0000	0.9238	91.3451	0.0000	0.9232	89.5599	0.0000
Mean return of put options	0.0302	0.7889	0.4302	−0.0164	−0.2342	0.8148	−0.0079	−0.4135	0.6792
ωPut options	0.3313	3.2854	0.0010	1.6661	4.5707	0.0000	0.0067	1.3140	0.1889
αPut options	0.7030	2.7079	0.0068	0.2830	2.7644	0.0057	0.1072	2.4879	0.0129
βPut options	0.0000	0.0000	1.0000	0.0000	0.0000	1.0000	0.8441	13.3831	0.0000
αDCC	0.0000	0.0017	0.9987	0.0000	0.0007	0.9994	0.0182	1.2833	0.1994
βDCC	0.9226	5.0265	0.00000*	0.9174	1.8159	0.0694	0.9517	23.1608	0.00000*

(*continued*)

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Table 4. Continued

1. ATM options (call and put)				2. ITM Options(ITM call and OTM put)			3. OTM Options(OTM call and ITM put)		
	Estimate	t Value	*P*r(>|*t*|)	Estimate	*t* value	*P*r(>|*t*|)	Estimate	*t* value	*P*r(>|*t*|)
2. During COVID									
DCC from NIFTY to call options									
Mean NIFTY	0.0059	2.6937	0.0071	0.0056	2.6641	0.0077	0.0055	2.6455	0.0082
ωNIFTY	0.0001	1.7360	0.0826	0.0001	1.8277	0.0676	0.0001	1.8744	0.0609
αNIFTY	0.2756	1.8765	0.0606	0.2913	1.9080	0.0564	0.2937	1.9241	0.0543
βNIFTY	0.5726	4.0658	0.0000	0.5524	3.8733	0.0001	0.5500	3.9186	0.0001
Mean return of call options	−0.0083	−0.1333	0.8940	0.0861	1.7053	0.0881	−0.0221	−0.1833	0.8546
ωCall options	0.0000	0.0000	1.0000	0.0870	1.7449	0.0810	0.0000	0.0005	0.9996
αCall options	0.0000	0.0000	1.0000	0.9990	1.1008	0.2710	0.0000	0.0000	1.0000
βCall options	0.9982	2686.9284	0.0000	0.0000	0.0000	1.0000	0.9980	3654.3884	0.0000
αDCC	0.0000	0.0151	0.9879	0.0000	0.0008	0.9994	0.0000	0.0793	0.9368
βDCC	0.9012	13.6174	0.00000*	0.9317	4.6289	0.00000*	0.8978	13.0795	0.00000*
DCC from NIFTY to put options									
Mean NIFTY	0.0059	2.6937	0.0071	0.0056	2.6641	0.0077	0.0055	2.6455	0.0082
ωNIFTY	0.0001	1.7360	0.0826	0.0001	1.8277	0.0676	0.0001	1.8744	0.0609
αNIFTY	0.2756	1.8765	0.0606	0.2913	1.9080	0.0564	0.2937	1.9241	0.0543
βNIFTY	0.5726	4.0658	0.0000	0.5524	3.8733	0.0001	0.5500	3.9186	0.0001
Mean return of put options	−0.0102	−0.1698	0.8652	−0.0179	−0.1753	0.8608	−0.0041	−0.0921	0.9266
ωPut options	0.0001	0.0315	0.9748	0.0296	0.6016	0.5475	0.0001	0.0095	0.9924
αPut options	0.0000	0.0000	1.0000	0.0000	0.0000	1.0000	0.0000	0.0000	1.0000
βPut options	0.9990	1663.1532	0.0000	0.9723	18.4921	0.0000	0.9990	490.6263	0.0000
αDCC	0.0000	0.0592	0.9528	0.0000	0.0340	0.9729	0.0000	0.0142	0.9887
βDCC	0.9076	12.9518	0.00000*	0.9176	14.9644	0.00000*	0.9109	9.3668	0.00000*

(*continued*)

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Table 4. Continued

1. ATM options (call and put)	Estimate	t Value	$Pr(>\|t\|)$	2. ITM Options(ITM call and OTM put) Estimate	t value	$Pr(>\|t\|)$	3. OTM Options(OTM call and ITM put) Estimate	t value	$Pr(>\|t\|)$
3. Post- COVID									
DCC from NIFTY to call options									
Mean NIFTY	0.0021	1.3700	0.1707	0.0021	1.3243	0.1854	0.0020	1.3772	0.1685
ωNIFTY	0.0000	2.8221	0.0048	0.0000	3.3618	0.0008	0.0000	2.6163	0.0089
αNIFTY	0.0765	4.9296	0.0000	0.0743	5.6037	0.0000	0.0786	4.5861	0.0000
βNIFTY	0.8798	50.7239	0.0000	0.8816	55.5068	0.0000	0.8776	48.0547	0.0000
Mean return of call options	−0.0145	−0.0427	0.9659	−0.0067	−0.2741	0.7840	−0.0285	−0.2733	0.7847
ωCall options	0.0004	0.0027	0.9979	0.0001	0.0236	0.9812	0.0045	0.1205	0.9041
αCall options	0.0000	0.0000	1.0000	0.0000	0.0000	1.0000	0.0000	0.0000	1.0000
βCall options	0.9990	194.0674	0.0000	0.9990	680.3550	0.0000	0.9990	244.0876	0.0000
αDCC	0.0000	0.0147	0.9882	0.0000	0.0025	0.9980	0.0825	0.5949	0.5519
βDCC	0.8988	9.0803	0.00000*	0.9110	10.3593	0.00000*	0.6993	4.9662	0.00000*
DCC from NIFTY to put options									
Mean NIFTY	0.0021	1.3735	0.1696	0.0021	1.3288	0.1839	0.0020	1.3686	0.1711
ωNIFTY	0.0000	2.8108	0.0049	0.0000	3.3460	0.0008	0.0000	2.6021	0.0093
αNIFTY	0.0765	4.9164	0.0000	0.0743	5.5730	0.0000	0.0786	4.5756	0.0000
βNIFTY	0.8798	51.3943	0.0000	0.8816	56.6916	0.0000	0.8776	47.3339	0.0000
Mean return of put options	−0.0107	−0.0891	0.9290	−0.0188	−0.2070	0.8360	−0.0033	−0.1335	0.8938
ωPut options	0.0001	0.0027	0.9978	0.0021	0.0976	0.9222	0.0002	0.0548	0.9563
αPut options	0.0000	0.0000	1.0000	0.0000	0.0000	1.0000	0.0000	0.0000	1.0000
βPut options	0.9990	1283.9266	0.0000	0.9990	428.6591	0.0000	0.9990	156.7718	0.0000
αDCC	0.0925	1.5600	0.1188	0.0965	1.2369	0.2161	0.0118	0.1886	0.8504
βDCC	0.7785	10.2901	0.00000*	0.7592	9.0918	0.00000*	0.9358	4.3094	0.00000*

(*continued*)

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Table 4. Continued

	1. ATM options (call and put)			2. ITM Options(ITM call and OTM put)			3. OTM Options(OTM call and ITM put)		
	Estimate	t Value	*P*r(>|*t*|)	Estimate	*t* value	*P*r(>|*t*|)	Estimate	*t* value	*P*r(>|*t*|)
4. OVERALL									
DCC from NIFTY to call options									
Mean NIFTY	0.0028	3.5901	0.0003	0.0028	3.5717	0.0004	0.0027	3.5785	0.0004
ωNIFTY	0.0000	2.2341	0.0255	0.0000	2.1895	0.0286	0.0001	2.1385	0.0325
αNIFTY	0.1462	2.9487	0.0032	0.1468	2.9292	0.0034	0.1503	2.9189	0.0035
βNIFTY	0.7478	10.4150	0.0000	0.7426	9.7927	0.0000	0.7421	9.5853	0.0000
Mean return of call options	0.0279	0.7262	0.4677	0.0026	0.1703	0.8648	0.0523	1.0044	0.3152
ωCall options	0.2533	4.8725	0.0000	0.0622	3.3155	0.0009	0.3403	1.1631	0.2448
αCall options	0.4507	1.1571	0.2472	0.9231	2.9860	0.0028	0.1843	2.2560	0.0241
βCall options	0.0000	0.0000	1.0000	0.0759	0.7779	0.4367	0.6723	3.6242	0.0003
αDCC	0.0000	0.0009	0.9993	0.0089	1.2892	0.1973	0.0000	0.0001	1.0000
βDCC	0.9123	11.7808	0.00000*	0.9738	80.4309	0.00000*	0.9017	13.3650	0.00000*
DCC from NIFTY to put options									
Mean NIFTY	0.0028	3.5901	0.0003	0.0028	3.5704	0.0004	0.0027	3.5730	0.0004
ωNIFTY	0.0000	2.2341	0.0255	0.0000	2.1940	0.0282	0.0001	2.1388	0.0325
αNIFTY	0.1462	2.9487	0.0032	0.1468	2.9238	0.0035	0.1503	2.8996	0.0037
βNIFTY	0.7478	10.4149	0.0000	0.7426	9.7949	0.0000	0.7421	9.5771	0.0000
Mean return of put options	0.0165	0.5088	0.6109	0.0520	0.9974	0.3186	−0.0020	−0.1482	0.8822
ωPut options	0.0045	0.3135	0.7539	0.7073	2.5190	0.0118	0.0050	2.0524	0.0401
αPut options	0.0443	1.4217	0.1551	0.3191	2.2058	0.0274	0.0749	3.3966	0.0007
βPut options	0.9498	19.7333	0.0000	0.3123	1.5594	0.1189	0.8798	25.4484	0.0000
αDCC	0.0000	0.0002	0.9998	0.0081	0.3664	0.7140	0.0107	1.4528	0.1463
βDCC	0.9221	7.3895	0.00000*	0.7964	8.3237	0.00000*	0.9693	48.7991	0.00000*

Note(s): *signifies significant at 5% level of significance
- ω, α and β are the parameters of the univariate GARCH (1,1) models
- ω represents the constant term, α captures the short-term impact of shocks (ARCH effect), and β represents the persistence of volatility (GARCH effect)
- αDCC and βDCC are the dynamic conditional correlation parameters governing the evolution of the time-varying correlation matrix
- Mean refers to the unconditional mean of the return series
- Call Options, Put Options and NIFTY represent the returns of call options, Put options and NIFTY index, respectively

Source(s): Authors' own creation

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4.2.3 Post-COVID. During the post-COVID period, all call options across ATM, ITM and OTM categories exhibit very high volatility persistence ($\alpha + \beta = 0.9989$–0.9990), consistently higher than NIFTY (0.956), while αDCC remains insignificant and βDCC highly significant (0.0000), indicating strong long-run spillovers. Put options also show high persistence in ATM (0.9990) and OTM (0.8797) with significant βDCC, though ITM put options reflect low persistence (0.3123), still maintaining long-term spillover as βDCC remains significant.

Across all periods before, during, and after COVID, as well as in the overall analysis, the results consistently show no short-term volatility spillover from NIFTY to Call and Put options, as reflected by the insignificant dcca1 coefficients across ATM, ITM and OTM options. However, the βDCC coefficients remain significant in all cases, indicating a strong and persistent long-run volatility spillover from the NIFTY index to both call and put options, irrespective of the option moneyness. Additionally, Call and Put options generally exhibit higher volatility persistence than the NIFTY, particularly during and after the COVID period, suggesting that the options market became more sensitive to shocks over time (Chaudhary *et al*., 2020; Khan *et al*., 2024; Emenike, 2025). These findings confirm that, although short-run dynamics are absent, a dominant and stable long-term information transmission exists from the spot market to the options market across all phases, possibly due to market inefficiency or participant behavior.

4.3 Results of Diebold and Yilmaz (2012) model

The Diebold–Yilmaz (DY) connectivity model quantifies spillover effects between financial markets or assets. It uses forecast error variance decompositions from a vector autoregression (VAR) model to determine how much shocks in another asset explain the forecast error variance of one asset. The DCC-GARCH model delineates spillover effects in both the long and short terms, albeit with differing magnitudes. In response, Diebold and Yilmaz (2012) created a model. The diagonal entries in the table signify intra-market connections, whilst the off-diagonal entries denote inter-market connections.

Table 5 presents the findings of the connectedness analysis using the Diebold and Yilmaz (2012) method to examine spillover effects between the NIFTY index and Options (call and put) across different moneyness categories ATM, ITM and OTM. In this table, "From" indicates the spillover received from other markets, while "To" denotes the spillover transmitted to different markets.

The Diebold and Yilmaz (2012) connectedness analysis reveals significant shifts in volatility transmission dynamics across ATM, ITM and OTM options before, during and after the COVID-19 pandemic.

Before the pandemic, the overall market connectedness was moderate, with ATM options showing a total spillover of 27.72%. Call options had a nearly neutral net spillover of 0.05, while puts were net receivers at 0.70. NIFTY absorbed more shocks than it transmitted (−0.74). In the ITM segment, connectedness was low (7.94%); calls acted as strong absorbers (−2.28) and puts as transmitters (2.78). OTM options also showed low spillover (6.94%), with calls transmitting (1.05) and put absorbing (−0.92). NIFTY consistently played a passive role here, too (−0.14). This reflects a period of market stability where option activity remained relatively segmented, and NIFTY reacted more to external volatility than generating it.

During the COVID period, markets were dominated by extreme uncertainty, fear of economic collapse, and rapid shifts in investor sentiment. These conditions increased trading activity in options markets, especially ATM and OTM contracts, which are highly sensitive to volatility changes. The spike in total connectedness for ATM options to 32.29% and OTM options to 26.09% reflects the sharp rise in systemic volatility transmission. ATM call options became strong transmitters (1.33), while puts became net receivers (−1.03); NIFTY remained an absorber (−0.30). In the ITM segment, connectedness rose to 11.13%, with calls switching to net transmitters (1.42) and puts to receivers (−0.75). OTM calls were key shock sources (1.99) and put absorbed volatility (−1.64), while NIFTY continued to receive shocks (−0.35).

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Table 5. Results of connectedness using Diebold and Yilmaz (2012) represent the to, from, net and overall spillover connectedness – based on moneyness (ATM, ITM and OTM options)

Series	Call. options	Put. options	NIFTY	From	net(sp)	overall (sp)	Series	Call. options	Put. options	NIFTY	From	net(sp)	overall (sp)
ATM (Call and Put)-Pre—COVID							*ATM (Call and Put)-DURING COVID*						
Call. options	59.97	37.28	2.75	13.34	0.0481	27.7173	Call. options	57.21	38.86	3.93	14.26	1.3268	32.2947
Put. options	35.95	62.96	1.09	12.35	0.6959		Put. options	43.09	53.81	3.1	15.4	−1.0317	
NIFTY	4.22	1.85	93.92	2.03	−0.7440		NIFTY	3.67	4.24	92.09	2.64	−0.2951	
TO	13.39	13.04	1.28	27.72			TO	15.59	14.36	2.34	32.29		
ITM (Call ITM and Put OTM) Pre-COVID							*ITM (Call ITM and Put OTM) DURING COVID*						
Call. options	86.02	13.79	0.19	4.66	−2.28058	7.9358	Call. options	88.06	5.45	6.49	3.98	1.4162	11.1329
Put. options	6.6	92.63	0.76	2.46	2.7832		Put. options	7.5	89.76	2.74	3.41	−0.7498	
NIFTY	0.54	1.92	97.54	0.82	−0.5026		NIFTY	8.69	2.54	88.78	3.74	−0.6663	
TO	2.38	5.24	0.32	7.94			TO	5.4	2.66	3.08	11.13		
OTM (Call OTM and Put ITM) Pre-COVID							*OTM (Call OTM and Put ITM) DURING COVID*						
Call. options	92.19	4.41	3.39	2.6	1.0517	6.9439	Call. options	68.31	29.15	2.54	10.56	1.9924	26.0903
Put. options	7.64	91.57	0.79	2.81	−0.9156		Put. options	33.57	61.72	4.71	12.76	−1.6393	
NIFTY	3.32	1.27	95.41	1.53	−0.1361		NIFTY	4.1	4.2	91.69	2.77	−0.3530	
TO	3.65	1.9	1.39	6.94			TO	12.56	11.12	2.42	26.09		

Series	Call. options	Put. options	NIFTY	From	net(sp)	overall (sp)	Series	Call. options	Put. options	NIFTY	From	net(sp)	Overall (sp)
ATM (Call and Put)-POST COVID							*ATM (Call and Put)-OVERALL*						
Call. options	59.93	39.29	0.78	13.36	0.2313	27.47106	Call. options	61.09	37.63	1.28	12.97	−0.0933	26.6221
Put. options	39.09	60.32	0.59	13.23	0.2024		Put. options	36.56	62.67	0.78	12.44	0.6118	
NIFTY	1.68	0.99	97.33	0.89	−0.4337		NIFTY	2.08	1.54	96.38	1.21	−0.5184	
TO	13.59	13.43	0.46	27.47			TO	12.88	13.06	0.69	26.62		
ITM (Call ITM and Put OTM) POST COVID							*ITM (Call ITM and Put OTM)-OVERALL*						
Call. options	65.68	34.2	0.13	11.44	−2.25643	21.4995	Call. options	87.8	11.52	0.67	4.07	−1.6577	6.8925

(*continued*)

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Table 5. Continued

Series	Call. options	Put. options	NIFTY	From	net(sp)	overall (sp)	Series	Call. options	Put. options	NIFTY	From	net(sp)	Overall (sp)
Put. options	26.24	73.18	0.57	8.94	3.1439		Put. Options	6.12	93.5	0.39	2.17	1.9640	
NIFTY	1.31	2.05	96.64	1.12	−0.8875		NIFTY	1.11	0.87	98.02	0.66	−0.3063	
TO	9.18	12.08	0.23	21.5			TO	2.41	4.13	0.35	6.89		
OTM (Call OTM and Put ITM) POST COVID							*OTM (Call OTM and Put ITM)-OVERALL*						
Call. options	92.7	6.93	0.37	2.43	−0.1907	5.2872	Call. options	91.83	6.31	1.85	2.72	1.1524	7.2859
Put. options	5.18	93.4	1.42	2.2	0.2480		Put. Options	9.96	89.06	0.99	3.65	−1.1819	
NIFTY	1.55	0.41	98.04	0.65	−0.0573		NIFTY	1.67	1.08	97.25	0.92	0.0295	
TO	2.24	2.45	0.6	5.29			TO	3.87	2.47	0.95	7.29		

Source(s): Authors' own creation

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Post-COVID, ATM connectedness normalized to 27.47%. Calls and puts showed small net transmissions (0.23 and 0.20), with NIFTY still absorbing (−0.43). ITM options saw a sharp rise in connectedness to 21.50%, driven by calls absorbing (−2.26) and puts transmitting (3.14) shocks. OTM options dropped back to 5.29% connectedness, with near-neutral net spillovers for calls (−0.19) and puts (0.25). NIFTY again showed a minor absorbing role (−0.06).

This shift suggests that while broader market conditions calmed, investors increasingly used ITM options for strategic positioning and protection, intensifying their influence.

In the overall case, ATM options were most interconnected (26.62%), with puts acting as net transmitters (0.61) and calls as slight absorbers (−0.09). In ITM options, puts dominated transmission (1.96) while calls absorbed (−1.66); connectedness was lowest at 6.89%. OTM options showed moderate connectedness (7.29%), with calls as transmitters (1.15) and puts as absorbers (−1.18). NIFTY maintained its role as a consistent net shock absorber, except for a marginal positive value (0.03) in the OTM.

The overall pattern highlights the dominance of the options market, particularly ATM options, in shaping volatility dynamics, while the NIFTY index consistently remained more reactive than proactive in transmitting systemic shocks.

In conclusion, the Diebold–Yilmaz analysis reveals that the Indian options market played a central role in transmitting systemic volatility across all phases, with ATM and ITM options emerging as key contributors. The NIFTY index consistently acted as a net shock absorber, particularly during high-stress periods like COVID-19, reflecting its reactive nature to derivative-driven volatility (Chaudhary *et al.*, 2020; Khan *et al.*, 2024). The shift in connectedness patterns post-COVID, especially the rising influence of ITM options, underscores the evolving role of options in risk management and market sentiment transmission.

The DY spillover results in Figures 1–3 highlight the evolving volatility dynamics across ATM, ITM and OTM options during Covid-19. The NIFTY index consistently acted as a net

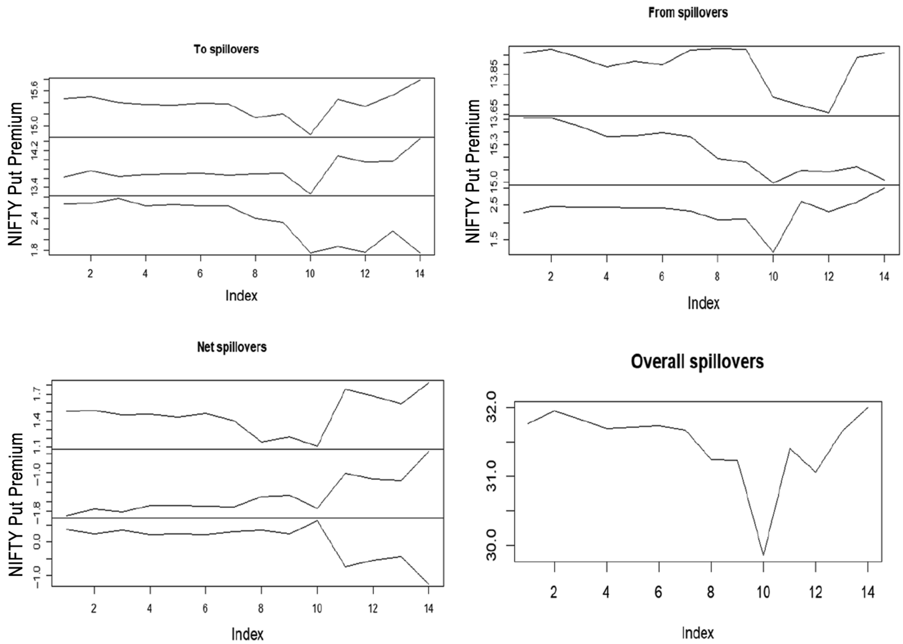

Figure 1. Results of connectedness using Diebold and Yilmaz (2012) represent the to, from, net and overall spillover based on moneyness – ATM options (during COVID). Source: Authors' own creation

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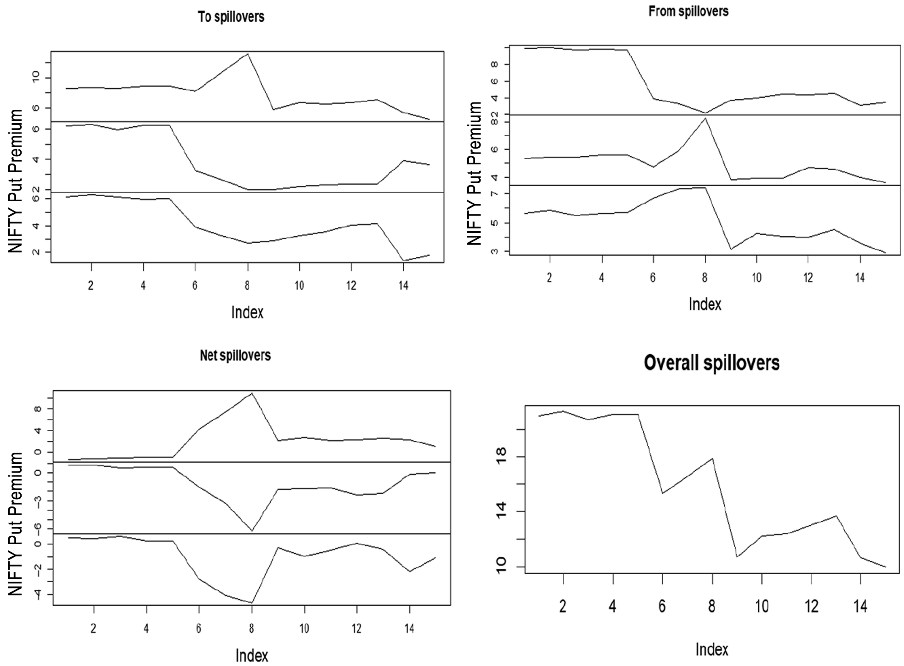

Figure 2. Results of connectedness using Diebold and Yilmaz (2012) represent the to, from, net and overall spillover based on moneyness – ITM options (DURING COVID). Source: Authors' own creation

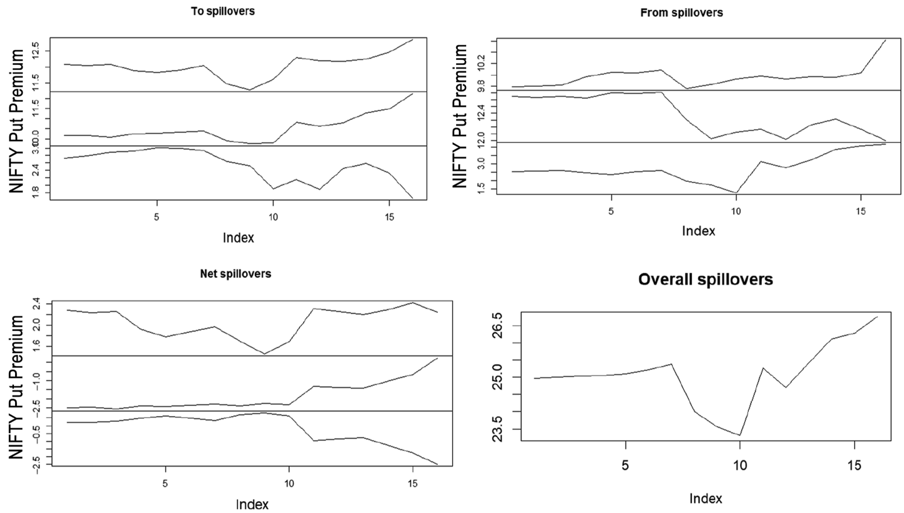

Figure 3. Results of connectedness using Diebold and Yilmaz (2012) represents the to, from, net and overall spillover based on moneyness – OTM options (DURING COVID). Source: Authors' own creation

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shock absorber, particularly during high-stress periods like COVID-19, reflecting its reactive nature to derivative-driven volatility. Call options are generally mild absorbers, while put options act as transmitters during the crisis, indicating heightened risk aversion. ITM options exhibit relatively lower spillovers, suggesting greater resilience, whereas ATM and OTM options display stronger interconnectedness. Although spillovers declined post-COVID, NIFTY continued to absorb volatility, maintaining its position as a central but reactive component in the volatility transmission network.

5. Results of Baruník and Krehlík (2018)

Our analysis employs the methodology established by Baruník and Krehlík (2018) to improve the comprehension of market connectedness over different time horizons. We categorize overall market interconnections in Table 6 into three specific time frames: short-term (1–4 days), medium-term (4–10 days) and long-term (10 days to infinity) (Yadav *et al.*, 2022). The findings of this breakdown are displayed in the tables. In these tables, the term "WTH" denotes within-market connectedness. "ABS" denotes absolute connectedness. "FROM" indicates spillover effects originating from other markets. "TO" signifies spillover effects that are conveyed to different markets. This method enables the capture of dynamic spillover effects and their development across various time scales.

The analysis of spillovers using the Baruník and Křehlík (2018) model in Table 6 reveals notable variation across time scales and moneyness levels. Before COVID-19, the market exhibited strong own shocks, particularly in the short term (1–4 days). For instance, ATM call options retained 56.6% of their own volatility and put options 59.23%, with limited transmission to others (To_WTH = 13.65% and 13.8%, respectively). Long-term spillovers (from 10 days to ∞) were relatively low, e.g. ATM call options spilled only 11.24% to others, and put options 6.98%. Similarly, in ITM call and OTM put options, short-term own effects were dominant (call = 81.91%, put = 87.86%), with minimal outward spillovers (To_WTH = 2.44% and 5.62%). OTM call and ITM put options showed similar behavior with high own retention (call = 87.36%, put = 86.17%) and long-term To_WTH values of 3.64% and 3.0%, respectively. During COVID-19, volatility spillovers surged across all option types. ATM options remained the most dominant, with TO_WTH rising to 33.9% (1–4 days), 23.38% (4–10 days) and 22.46% (10+ days), reflecting intense market interconnectedness. They also received substantial shocks, with FROM_WTH at 14.9%, 10.96% and 10.43%. OTM options followed closely in volatility transmission, peaking at 26.97% in the short term, while ITM options had lower TO_WTH and FROM_WTH across all horizons. The market was highly reactive, with elevated spillovers in both directions and across all timeframes.

During the post-COVID period, volatility spillovers declined but did not return to pre-COVID levels. ATM options continued to lead with TO_WTH at 29.81% (1–4 days), 14.64% (4–10 days) and 12.5% (10+ days). FROM_WTH also remained elevated at 14.56%, 6.65% and 5.73%, showing ATM options were still central to market volatility. ITM options gained more influence than before, with TO_WTH reaching up to 23.45% in the short term. The market stabilized, but ATM and ITM contracts were elevated in spillover transmission.

Over the overall period, ATM options consistently dominated both volatility transmission and reception. Their TO_WTH was the highest across all horizons: 28.23% (1–4 days), 16.37% (4–10 days) and 15.4% (10+ days). ITM options played a moderate role, while OTM options contributed the least across all horizons. This reflects the central role of ATM options in the volatility network as primary channels through which systemic shocks move in the NIFTY options market.

The analysis indicates that before COVID-19, volatility was largely self-contained with minimal spillovers. During the pandemic, market connectedness spiked, with ATM options emerging as the primary transmitters and receivers of shocks. In the post-COVID period, spillovers declined but remained higher than pre-COVID levels. Across all phases, ATM options consistently served as the key drivers of volatility in the NIFTY options market as they

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Table 6. Spillovers between Nifty 50 and options across moneyness on the basis of time scales

ATM (Call, Put, NIFTY)						ITM (ITM Call, OTM Put)						OTM (OTM Call, ITM Put)					
	Call. options	Put. options	NIFTY	FROM_ ABS	FROM_ WTH		Call. options	Put. options	NIFTY	FROM_ ABS	FROM_ WTH		Call. options	Put. options	NIFTY	FROM_ ABS	FROM_ WTH
The spillover corresponds from 1 day to 4 days																	
1. Pre-COVID																	
Call. options	56.6	35.34	2.71	12.68	14.35	*Call. options*	81.91	13.69	0.16	4.62	5.18	*Call. options*	87.36	3.88	3.34	2.4	2.72
Put. options	33.5	59.23	1.05	11.52	13.03	*Put. options*	6.04	87.86	0.75	2.26	2.54	*Put. options*	7.5	86.17	0.67	2.72	3.08
NIFTY	2.71	1.26	72.74	1.32	1.5	*NIFTY*	0.48	1.35	75.28	0.61	0.69	*NIFTY*	2.2	0.75	73.11	0.98	1.11
TO_ABS	12.07	12.2	1.26	25.52		*TO_ABS*	2.17	5.01	0.3	7.49		*TO_ABS*	3.23	1.54	1.34	6.11	
To_WTH	13.65	13.8	1.42		28.88	*To_WTH*	2.44	5.62	0.34		8.4		3.66	1.75	1.51		6.92
The spillover corresponds from 4 days to 10 days																	
Call. options	2.3	1.33	0.04	0.45	5.88	*Call. options*	2.78	0.08	0.02	0.03	0.44	*Call. options*	3.3	0.37	0.05	0.14	1.81
Put. options	1.67	2.53	0.03	0.57	7.31	*Put. options*	0.38	3.25	0.01	0.13	1.83	*Put. options*	0.1	3.65	0.08	0.06	0.75
NIFTY	1	0.39	13.92	0.46	5.97	*NIFTY*	0.04	0.38	14.57	0.14	1.93	*NIFTY*	0.73	0.34	14.54	0.36	4.63
TO_ABS	0.89	0.57	0.02	1.48		*TO_ABS*	0.14	0.15	0.01	0.3		*TO_ABS*	0.28	0.23	0.04	0.56	
To_WTH	11.48	7.4	0.28		19.16	*To_WTH*	1.96	2.12	0.13		4.21	*To_WTH*	3.59	3.04	0.56		7.19
The spillover corresponds from 10 days to infinity																	
Call. options	1.06	0.61	0	0.21	5.28	*Call. options*	1.34	0.03	0.01	0.01	0.34	*Call. options*	1.53	0.17	0	0.06	1.48
Put. options	0.79	1.2	0.01	0.27	6.86	*Put. options*	0.18	1.53	0	0.06	1.68	*Put. options*	0.05	1.75	0.04	0.03	0.73
NIFTY	0.52	0.2	7.26	0.24	6.19	*NIFTY*	0.02	0.19	7.7	0.07	1.92	*NIFTY*	0.39	0.18	7.75	0.19	4.81
TO_ABS	0.44	0.27	0	0.71		*TO_ABS*	0.07	0.07	0	0.14		*TO_ABS*	0.14	0.12	0.01	0.28	
To_WTH	11.24	6.98	0.11		18.33	*To_WTH*	1.83	2.03	0.08		3.94	*To_WTH*	3.64	3	0.38		7.02
DURING COVID (the spillover corresponds from 1 day to 4 days)																	
Call. options	52.92	34.88	2.93	12.6	14.9	*Call. Options*	82.84	5.42	5.92	3.78	4.4	*Call. options*	63.15	25.47	1.69	9.05	10.72
Put. options	39.86	48.65	1.97	13.94	16.48	*Put. options*	6.68	83.95	1.57	2.75	3.2	*Put. options*	31.65	56.43	2.57	11.41	13.5

(*continued*)

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Table 6. Continued

ATM (Call, Put, NIFTY)	Call. options	Put. options	NIFTY	FROM_ ABS	FROM_ WTH
NIFTY	3.19	3.39	65.99	2.2	2.6
TO_ABS	14.35	12.76	1.63	28.74	
To_WTH	16.96	15.08	1.93		33.9
The spillover corresponds from 4 days to 10 days					
Call. options	2.88	2.66	0.64	1.1	10.96
Put. options	2.18	3.47	0.73	0.97	9.68
NIFTY	0.3	0.53	16.65	0.27	2.74
TO_ABS	0.83	1.06	0.45	2.34	
To_WTH	8.25	10.6	4.54		23.38
The spillover corresponds from 10 days to infinity					
Call. options	1.42	1.32	0.37	0.56	10.43
Put. options	1.06	1.69	0.39	0.48	8.94
NIFTY	0.18	0.32	9.45	0.17	3.09
TO_ABS	0.41	0.55	0.25	1.21	
To_WTH	7.65	10.11	4.69		22.46
2. AFTER COVID (the spillover corresponds from 1 day to 4 days)					
Call. options	55.44	36.53	0.75	12.43	14.56
Put. options	36.08	55.52	0.43	12.17	14.27
NIFTY	1.53	0.97	68.72	0.83	0.98
TO_ABS	12.54	12.5	0.4	25.43	
To_WTH	14.69	14.65	0.46		29.81
The spillover corresponds from 4 days to 10 days					
Call. options	3.06	1.88	0.01	0.63	6.65

ITM (ITM Call, OTM Put)	Call. options	Put. options	NIFTY	FROM_ ABS	FROM_ WTH
NIFTY	7.4	2.08	62.07	3.16	3.67
TO_ABS	4.69	2.5	2.5	9.69	
To_WTH	5.46	2.91	2.91		11.27
Call. options	3.55	0.02	0.37	0.13	1.47
Put. options	0.55	3.85	0.72	0.42	4.75
NIFTY	0.82	0.27	16.56	0.36	4.07
TO_ABS	0.46	0.1	0.36	0.92	
To_WTH	5.14	1.09	4.06		10.29
Call. options	1.67	0.01	0.2	0.07	1.3
Put. options	0.27	1.96	0.45	0.24	4.68
NIFTY	0.47	0.19	10.15	0.22	4.31
TO_ABS	0.25	0.07	0.21	0.53	
To_WTH	4.84	1.28	4.18		10.3
Call. Options	59.2	32.4	0.11	10.84	12.82
Put. options	23.54	68.76	0.49	8.01	9.48
NIFTY	1.08	1.82	66.11	0.97	1.14
TO_ABS	8.21	11.41	0.2	19.81	
To_WTH	9.71	13.5	0.24		23.45
Call. options	4.35	1.23	0.01	0.41	4.17

OTM (OTM Call, ITM Put)	Call. options	Put. options	NIFTY	FROM_ ABS	FROM_ WTH
NIFTY	3.66	3.31	65.52	2.32	2.75
TO_ABS	11.77	9.59	1.42	22.78	
	13.93	11.35	1.68		26.97
Call. options	3.48	2.48	0.53	1	9.97
Put. options	1.3	3.56	1.36	0.89	8.85
NIFTY	0.28	0.56	16.57	0.28	2.77
TO_ABS	0.53	1.01	0.63	2.17	
To_WTH	5.24	10.07	6.27		21.58
Call. options	1.68	1.21	0.32	0.51	9.31
Put. options	0.62	1.73	0.77	0.46	8.48
NIFTY	0.17	0.33	9.6	0.17	3.05
TO_ABS	0.26	0.52	0.36	1.14	
To_WTH	4.78	9.41	6.65		20.83
Call. options	85.7	6.59	0.35	2.32	2.72
Put. options	4.94	85.55	1.15	2.03	2.39
NIFTY	1.42	0.21	69.41	0.54	0.64
TO_ABS	2.12	2.27	0.5	4.89	
	2.49	2.67	0.59		5.75
Call. options	4.74	0.24	0.01	0.08	0.87

(*continued*)

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Table 6. Continued

ATM (Call, Put, NIFTY)						ITM (ITM Call, OTM Put)						OTM (OTM Call, ITM Put)					
	Call. options	Put. options	NIFTY	FROM_ ABS	FROM_ WTH		Call. options	Put. options	NIFTY	FROM_ ABS	FROM_ WTH		Call. options	Put. options	NIFTY	FROM_ ABS	FROM_ WTH
Put. options	2.06	3.27	0.1	0.72	7.57	*Put. options*	1.84	3.04	0.05	0.63	6.36	*Put. options*	0.18	5.26	0.16	0.11	1.19
NIFTY	0.1	0.02	18.03	0.04	0.42	*NIFTY*	0.15	0.16	18.93	0.1	1.06	*NIFTY*	0.09	0.12	17.93	0.07	0.73
TO_ABS	0.72	0.63	0.04	1.39		*TO_ABS*	0.66	0.46	0.02	1.15		*TO_ABS*	0.09	0.12	0.06	0.27	
To_WTH	7.6	6.66	0.38		14.64	*To_WTH*	6.69	4.67	0.23		11.59	*To_WTH*	0.94	1.25	0.6		2.79
The spillover corresponds from 10 days to infinity																	
Call. options	1.43	0.88	0.01	0.3	5.73	*Call. options*	2.12	0.57	0	0.19	3.41	*Call. options*	2.26	0.1	0	0.03	0.65
Put. options	0.94	1.54	0.06	0.33	6.47	*Put. options*	0.87	1.38	0.03	0.3	5.37	*Put. options*	0.06	2.58	0.11	0.06	1.06
NIFTY	0.04	0.01	10.59	0.02	0.3	*NIFTY*	0.07	0.07	11.6	0.05	0.87	*NIFTY*	0.04	0.08	10.69	0.04	0.74
TO_ABS	0.33	0.29	0.02	0.65		*TO_ABS*	0.31	0.21	0.01	0.54		*TO_ABS*	0.03	0.06	0.04	0.13	
To_WTH	6.34	5.7	0.46		12.5	*To_WTH*	5.61	3.84	0.2		9.65	*To_WTH*	0.62	1.13	0.7		2.45
3. OVERALL (the spillover corresponds from 1 day to 4 days)																	
Call. options	57.17	35.32	1.17	12.16	14.01	*Call. options*	82.87	11.34	0.63	3.99	4.56	*Call. options*	86.48	5.48	1.79	2.42	2.79
Put. options	33.97	58.69	0.64	11.54	13.28	*Put. options*	5.32	88.23	0.31	1.88	2.15	*Put. options*	9.62	83.34	0.57	3.4	3.91
NIFTY	1.38	1.06	71.13	0.81	0.93	*NIFTY*	0.88	0.48	72.16	0.45	0.52	*NIFTY*	1.11	0.79	71.79	0.63	0.73
TO_ABS	11.78	12.13	0.60	24.51		*TO_ABS*	2.07	3.94	0.31	6.32		*TO_ABS*	3.58	2.09	0.79	6.46	
To_WTH	13.57	13.96	0.70		28.23	*To_WTH*	*2.37*	*4.51*	*0.36*		*7.23*	*To_WTH*	*4.11*	*2.4*	*0.9*		*7.42*
The spillover corresponds from 4 days to 10 days																	
Call. options	2.65	1.56	0.07	0.54	6.33	*Call.options*	3.33	0.13	0.03	0.05	0.66	*Call. options*	3.63	0.56	0.04	0.2	2.36
Put. options	1.75	2.69	0.09	0.61	7.11	*Put.options*	0.53	3.56	0.05	0.19	2.37	*Put. options*	0.22	3.85	0.26	0.16	1.91
NIFTY	0.45	0.31	16.24	0.25	2.93	*NIFTY*	0.15	0.25	16.57	0.13	1.62	*NIFTY*	0.35	0.19	16.34	0.18	2.13
TO_ABS	0.73	0.62	0.05	1.41		*TO_ABS*	0.23	0.13	0.03	0.38		*TO_ABS*	0.19	0.25	0.1	0.54	
To_WTH	8.49	7.26	0.62		16.37	*To_WTH*	2.77	1.54	0.33		4.64	*To_WTH*	2.26	2.93	1.19		6.39

(*continued*)

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Table 6. Continued

ATM (Call, Put, NIFTY)	Call. options	Put. options	NIFTY	FROM_ABS	FROM_WTH	ITM (ITM Call, OTM Put)	Call. options	Put. options	NIFTY	FROM_ABS	FROM_WTH	OTM (OTM Call, ITM Put)	Call. options	Put. options	NIFTY	FROM_ABS	FROM_WTH
The spillover corresponds from 10 days to infinity																	
Call. options	1.27	0.74	0.04	0.26	5.75	*Call. options*	1.6	0.05	0.01	0.02	0.52	*Call. options*	1.73	0.27	0.02	0.1	2.16
Put. options	0.84	1.29	0.05	0.3	6.52	*Put. options*	0.26	1.7	0.03	0.1	2.18	*Put. options*	0.11	1.86	0.15	0.09	1.94
NIFTY	0.25	0.17	9.01	0.14	3.13	*NIFTY*	0.08	0.15	9.29	0.08	1.71	*NIFTY*	0.2	0.11	9.12	0.1	2.26
TO_ABS	0.37	0.31	0.03	0.7		*TO_ABS*	0.11	0.07	0.01	0.19		*TO_ABS*	0.1	0.13	0.06	0.29	
To_WTH	8.01	6.72	0.68		15.4	*To_WTH*	2.58	1.51	0.32		4.41	*To_WTH*	2.27	2.8	1.29		6.36

Source(s): Authors' own creation

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are highly liquid and most responsive to the underlying index (Gemmill, 1986; Gwilym and Buckle, 2001; Rastogi and Athaley, 2019).

The findings reveal consistent evidence of volatility spillovers between the NIFTY index and options (call and put), though the nature and direction of these effects differ across methodologies. All results confirm that ATM options are central channels of volatility transmission in all periods. The DCC-GARCH model indicates an absence of short-run spillovers but confirms a strong and persistent long-run influence from the NIFTY index to both call and put options, regardless of moneyness. The Diebold-Yilmaz model identifies the options market, particularly ATM and ITM options, as key transmitters of systemic volatility, while the NIFTY index behaves as a net absorber of shocks, especially during crisis periods like COVID-19. The Baruník and Krehlík approach supports these observations, showing that volatility mainly remained self-contained before the pandemic. However, during COVID, spillovers intensified, with ATM options emerging as the primary source and recipient of shocks, and this influence continued, though at a reduced level, in the post-COVID phase. A typical pattern in all three results is the ATM options' leading role and the options market's increasing sensitivity over time. The main difference lies in how each method captures the spillover: one focuses on persistence over time, another on net directional flow and the third on shifts across different periods. These complementary results confirm a strong long-term linkage from the spot to the options market and reflect the evolving dynamics of market sentiment and risk transmission during and after the COVID crisis.

6. Conclusion and policy implications

This research highlights the intricate and dynamic relationship between the NIFTY index and the option markets, with significant insights into how volatility spillover varies across different moneyness levels (ATM, ITM and OTM) during pre-COVID, COVID and post-COVID periods. These patterns are examined using DCC-GARCH, Diebold and Yilmaz (2012), and Baruník and Krehlík (2018) frameworks. The DCC-GARCH model reveals a consistent absence of short-term volatility spillovers from NIFTY to options, as indicated by insignificant short-run coefficients. However, significant long-run spillovers persist across all periods, highlighting a strong and stable volatility transmission from the spot market to the options market, regardless of option moneyness. Further analysis of the interplay between call and put options using the Diebold–Yilmaz model underscores that the Indian options market played a central role in transmitting systemic volatility across all phases, with ATM and ITM options emerging as key contributors. The NIFTY index consistently acted as a net shock absorber, particularly during high-stress periods like COVID, reflecting its reactive nature to derivative-driven volatility (Chaudhary *et al.*, 2020; Khan *et al.*, 2024). The shift in connectedness patterns post-COVID, especially the rising influence of ITM options, underscores the evolving role of options in risk management and market sentiment transmission. Further insight is provided by the Baruník and Krehlík decomposition, which reveals that volatility was largely self-contained with minimal spillovers before the COVID-19 pandemic. Market connectivity increased during the pandemic, with ATMs serving as the primary transmitters and receivers of shocks (Fakhfekh *et al.*, 2021). In the post-COVID period, spillovers declined but remained higher than pre-COVID levels. Across all phases, ATM options consistently served as the key drivers of volatility in the NIFTY options market. The synchronized evidence from all three models demonstrates that volatility spillovers became more interconnected and structured during and after the pandemic, indicating a transformation in the Indian derivatives market's role in risk transmission and pricing dynamics.

The findings have significant implications for option pricing, hedging strategies and regulatory oversight, particularly in emerging markets like India. The absence of short-term spillovers from NIFTY to options, alongside persistent long-term volatility transmission, suggests that pricing models should account for structural and time-varying linkages rather than rely on short-term dynamics alone. The dominant role of ATM and ITM options as

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volatility transmitters highlights the importance of hedging strategies that consider long-horizon risks. From a regulatory perspective, the increased connectedness during crisis periods like COVID underscores the need for systems that monitor long-term volatility spillovers. Adaptive margining policies and enhanced transparency in derivative markets can help mitigate systemic risks and improve market resilience.

This study paves the way for several potential extensions. Future research could focus on sector-specific indices (e.g. Nifty Bank and Nifty IT) to explore whether volatility spillover dynamics differ across industries. Additionally, incorporating alternative derivative instruments such as futures, VIX-based products or currency options could broaden the understanding of interconnectedness in financial markets. Exploring the liquidity, maturity and implied volatility dimensions of options would further enhance pricing efficiency and the analysis of investor behavior. Employing high-frequency data and non-linear or AI-based models may also help capture short-term asymmetries and provide predictive insights that traditional models might overlook.

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