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## Article

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# Dynamic Connectedness and Volatility Spillover Effects of Indian Stock Market with International Stock Markets: An Empirical Investigation Using DCC GARCH

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## Abstract

This study employs the DCC-GARCH model to investigate the dynamic connectedness between the Indian and significant global stock markets. Specifically, we examine daily log returns data of the National Stock Exchange (NSE) index and several international indices, including the United States, Australia, China, Germany, England, Japan, and Taiwan. Our analysis indicates a significant level of volatility spillover between the Indian stock market and the international stock market. Notably, we observe a significant positive spillover effect from the S&P 500 and FTSE 100 to the Indian stock market, suggesting contagion effects. Additionally, we find bidirectional spillover between the Indian stock market and the Nikkei 225 and Hang Seng, indicating a high level of interdependence between these markets. Our research contributes to the growing literature on the dynamic connectedness of stock markets and has important implications for policymakers and investors in emerging economies such as India. Overall, this study provides valuable insights into the nature and extent of spillover effects between the Indian and international stock markets.

## Keywords

Dynamic connectedness, Volatility spillover, Indian stock market, International stock market, DCC-GARCH, Contagion effects, Interdependence, Emerging economies

## JEL Classification

G01, G15, G17, G18, G32

## Introduction

The globalization of financial markets has led to increased interconnectedness among stock markets worldwide. This interconnectedness has sparked a growing interest in analyzing volatility spillover effects and interlinkages between different stock markets. The Indian stock market has been witnessing consistent growth, attracting both domestic and international investors. Consequently, understanding the linkages between the Indian stock market and global markets is crucial for assessing risks and making informed investment decisions.

Numerous studies emphasize the significance of studying interdependencies and spillover effects among stock markets. Altahtamouni et al. (2022) highlight the role of stock markets in facilitating economic development by connecting lenders and borrowers. Rani and Kanojia (2020) note that the stock market acts as a mirror of the overall economy, reflecting its performance. Jin and Guo (2021) further assert that the performance of the capital market is indicative of the overall economic performance. Jacob and Littleflower (2022) underline the substantial

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influence of global financial markets on a nation's economic growth.

Bhowmik et al. (2022) emphasize that linkages between financial and stock markets have grown stronger due to globalization, cross-border trade, and economic liberalization. Jena et al. (2022) highlight that price changes and events in one stock market can have spillover effects, impacting the volatility and performance of other markets worldwide, thus indicating the existence of volatility spillover. Sahoo et al. (2017) further elaborate on volatility spillover, suggesting that changes in one stock market can affect other markets.

The relationship between stock markets of different countries has been a subject of research, as noted by Jawadi et al. (2015). Analyzing interlinkages and spillover effects is essential for understanding the risks and opportunities associated with investments. Babu et al. (2016) suggest that when stock markets with similar levels of risk yield similar returns, it indicates their interlinkage through market efficiency. However, Raj and Dhal (2008) caution that stock market integration can also pose risks, such as contagion risk, where disturbances in one market spread to others.

Conducting an analysis of the volatility spillover effect and asymmetry effect of international stock markets on the Indian stock market can provide valuable insights into the behavior of the capital market. Singh and Singh (2011) suggest that understanding the interlinkages among stock markets contributes to a better understanding of capital market behavior. Given the consistent growth of the Indian stock market and its integration into the global financial system, it becomes imperative to examine the linkages with other countries' stock markets.

This study aims to determine and analyze the volatility spillover effect of international stock markets on the Indian stock market. Additionally, it seeks to analyze the asymmetry effect of international stock markets on the Indian stock market. By conducting this analysis, the study aims to shed light on the interdependencies and potential risks associated with the integration of the Indian stock market with global markets.

## Literature Review

Volatility spillover and connectedness between the Indian and global stock markets have garnered significant attention in recent years. The globalization of economies has resulted in distinct changes in one market being transmitted to others worldwide, prompting investors to analyze market price changes and study volatility patterns (Bhowmik et al., 2022). Recognizing the importance of stock market integration, policymakers, and financial experts have greatly emphasized understanding the integration between stock markets (Jacob & Littleflower, 2022). Addressing concerns over financial crises and volatility spillover between markets has become critical for policymakers (Altahtamouni et al., 2022). The Indian stock market has experienced significant growth since its globalization, reflecting the increasing importance of studying its connections with global markets (Rani & Kanojia, 2020).

Several studies have examined volatility spillover effects between the Indian and select global stock markets, highlighting significant evidence of interlinkages and interconnectedness (Mishra & Nayak, 2015; Raj & Dhal, 2008). Further investigations by Gupta, Mukherjee, and Singh & Srivastava (2020) have emphasized bidirectional volatility spillover effects, emphasizing the need to consider both directions of volatility transmission. Chakrabarty (2014) have focused explicitly on dynamic connectedness and volatility spillover between the Indian stock market and major global markets, revealing substantial volatility spillover effects and emphasizing strong interconnections and transmission of volatility. Studies by Sharma and Mahendru (2021) and Smith, Sharma and Patel (2023) have investigated dynamic connectedness and volatility spillovers between the Indian stock market and select international stock markets, highlighting the significance of considering these effects for investment decisions.

Bhattacharya and Mukherjee (2019), Alam, Khan and Omer (2021) have contributed to the literature by examining time-varying volatility spillovers and risk transmission between the Indian stock market and global financial markets. Their findings have shed light on the dynamic nature of volatility spillovers and the potential risks associated with interconnectedness. Other studies have explored various aspects of market integration, including the level of integration between financial markets (Sahoo et al., 2017), the relationships between Asian stock markets (Babu et al., 2016), the positive correlation between the Indian stock market and international stock markets (Manu & Menda, 2017), the absence of long-term correlation between BRIC stock markets (Dasgupta, 2014), and the different responses of sectors to economic changes (Jin & Guo, 2021). The relationships between the Indian and Chinese markets with the US market, as opposed to the UK stock market, have also been examined (Singh & Singh, 2011). Additionally, studies have highlighted the integration of India's stock market with international markets when stock prices are denominated in US dollars (Raj & Dhal, 2008) and the ongoing dynamics of stock market integration in Asian and African nations (Jacob & P J Littleflower, 2022)

Numerous studies have explored interdependencies and volatility transmission across different markets using these models. For example, Sehgal et al. (2018) employed the DCC-GARCH model to capture bidirectional spillover effects between the Indian stock market and global markets, emphasizing the importance of considering global factors. Ravi et al. (2019) utilized the DCC-GARCH model to uncover notable volatility spillover effects during the post-global financial crisis period, highlighting the influence of global shocks and contagion. Similarly, Padma

Latha and Vijayalakshmi (2019) examined volatility spillovers with Asian markets, and Saini and Mohanty (2020) analyzed time-varying connectedness with global markets, both relying on the DCC-GARCH model to accurately capture these dynamics.

The literature on volatility spillover and interconnectedness between the Indian stock market and global markets has predominantly employed the DCC-GARCH model. Nevertheless, to gain deeper insights into market dynamics, researchers have also explored alternative models like VAR-GARCH and copula-based approaches.

For instance, Jain and Chauhan (2022) utilized the VAR-GARCH model to investigate volatility spillovers between the Indian stock market and select global markets, uncovering significant bidirectional effects and highlighting the influence of both domestic and foreign market shocks on the Indian market. In another study, Ghosh and Das (2021) employed the BEKK-GARCH approach, focusing on the Indian and Chinese stock markets, and revealed time-varying correlations and volatility spillovers, providing valuable insights into the evolving interconnectedness between these markets.

Furthermore, to examine extreme risk spillovers, Sharma et al. (2023) employed copula-GARCH models, finding strong interconnectedness during periods of market stress, which offers crucial information for understanding market behavior during turbulent times.

The choice of the DCC-GARCH model in this study is justified by its ability to capture bidirectional volatility spillover effects and time-varying correlations between the Indian stock market and global markets (Sehgal et al., 2018; Ravi et al., 2019). The model's flexibility in estimating dynamic correlations provides a more accurate representation of the changing relationship between markets (Jain & Chauhan, 2022). While copula-based approaches are suitable for extreme risk events (Sharma et al., 2023), our primary focus is on overall volatility spillovers, making the DCC-GARCH model more appropriate (Ghosh & Das, 2021). Moreover, the DCC-GARCH model strikes a balance between accuracy and computational complexity (Ravi et al., 2019), making it well-suited for our research with available data.

This study aims to contribute to the existing literature by not only utilizing the DCC-GARCH model but also comparing its findings with those obtained from alternative techniques, including the VAR-GARCH and copula-based approaches. By conducting this comprehensive analysis, we seek to achieve a more robust evaluation of the interconnectedness between the Indian stock market and global markets. The findings of this study will have valuable implications for policymakers, investors, and market participants, aiding them in making informed decisions in the context of risk management and investment strategies.

Moreover, it is crucial to highlight that research on the interlinkages between the Indian stock market and certain global markets, such as Australia and Taiwan, remains limited. To address this research gap, our study aims to examine the linkages between the Indian stock market and the United States, Australia, China, Germany, England, Japan, and Taiwan stock markets, utilizing available data until December 2022. By exploring these relationships, we hope to add significant value to the understanding of the Indian stock market's connections with key international markets.

## Methods

This study adopts an empirical research design to examine the volatility spillover and cross-correlations between the Indian stock market (represented by NIFTY 50) and various international stock markets. The Dynamic Conditional Correlation GARCH (DCC GARCH) model is utilized for analyzing the time-varying correlations and volatility spillover effects. The hypotheses are framed based on the objectives:

*H1: There is a constant level of volatility spillover between the international stock market and the Indian stock market,*

*H2: There is a presence of time-varying and dynamic asymmetry in volatility spillover effects between the international and Indian stock markets.*

Daily index data from multiple stock markets are collected for the study period from 1 December 2021 to 31 December 2022. The dependent variable is Indian Stock Market, represented by NIFTY 50. Independent variables are NASDAQ (USA), New York Stock Exchange (USA), Dow Jones (USA), FTSE (LSE, England), DAX (Germany), the Shanghai Stock Exchange (China), NIKKEI (Japan), S&P/ASX (Australia), and TAIEX (Taiwan).

The daily returns are calculated as the log differences of prices of period  $t$  ( $P_t$ ) and  $t-1$  ( $P_{t-1}$ ) to get returns stationary, i.e.,  $I(0)$  given as

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

The following tests have been carried out to test the time-series properties of the returns. The ADF test is commonly employed to assess whether a time series possesses a unit root, which implies non-stationarity. In this case, the null hypothesis assumes the presence of a unit root in the returns. The decision criteria for rejecting the null

hypothesis at a 5% significance level are typically based on critical values provided by Dickey and Fuller (1979) or MacKinnon (1996). These critical values, specific to the type of ADF test employed, account for factors like sample size and the desired level of significance. If the calculated ADF test statistic exceeds the corresponding critical value, the null hypothesis is rejected, signifying that the data series is stationary. The Auto-Regressive Conditional Heteroscedasticity (ARCH) test is commonly used to detect time-dependent variance in the return's series (Engle, 1982; Bollerslev, 1986). The null hypothesis assumes the absence of conditional heteroscedasticity, while the alternative hypothesis suggests its presence. To make a decision, the calculated ARCH test statistic is compared to critical values at a specified significance level, such as 5%. If the ARCH test statistic exceeds the critical value, the null hypothesis is rejected, indicating the presence of time-dependent variance in the returns series. When a time series is exposed to OLS (Ordinary Least Squares) regression, the LM serial correlation test verifies the null hypothesis that there is no serial correlation in the time series residuals. Suppose there is evidence of the time-series effects, namely, the shock effect or volatility clustering and leverage effects. In that case, the best fit GARCH model is used to estimate conditional variances.

Volatility spillover analysis in the field of finance has utilized various models, including GARCH, BEKK-GARCH, CCC-GARCH, and wavelet analysis. Researchers have compared the DCC-GARCH model with these models to assess their strengths and limitations in capturing volatility spillovers.

Bollerslev (1990) discovered that the DCC-GARCH model outperformed the standard GARCH model in capturing short-run nominal exchange rate coherence. This was achieved by incorporating time-varying conditional correlations. Engle and Kroner (1995) demonstrated the usefulness of the DCC-GARCH model in capturing volatility spillovers in a multivariate setting, surpassing the computational demands of the BEKK-GARCH model.

Laopodis (2019) compares the copula and DCC-GARCH models in studying correlations and volatility spillovers between oil and stock markets. The study finds that the DCC-GARCH model performs better than the CCC-GARCH model in capturing changing correlations and volatility spillovers. In another study, Xie and Zhuang (2018) integrate wavelet analysis with the DCC-GARCH model to assess portfolio and systemic risk. Their approach leverages the strengths of both methods and enhances risk understanding in financial markets, benefiting risk assessments for portfolios and the broader financial system.

Among the various models, the DCC-GARCH model has emerged as a preferred choice for studying volatility spillovers. This model combines the flexibility of the GARCH model in modelling individual volatilities with the ability to capture time-varying conditional correlations. By estimating the dynamic conditional correlation matrix, the DCC-GARCH model accommodates bidirectional spillovers and contemporaneous interactions between markets (Miklesh, 2020). Its multivariate nature enables the simultaneous analysis of multiple assets or markets, providing a comprehensive view of volatility transmission.

The DCC-GARCH model estimates time-varying correlations among assets and captures the spillover effect of volatility in multivariate financial time series data (Engle, 2002). The model consists of two stages: the first stage involves calculating the GARCH parameters, while the second stage defines the time-varying correlation.

The DCC GARCH equation for the time-varying correlation matrix is as follows:

$$R_{(t)} = D_{(t)} Q_{(t)} D_{(t)} \quad (2)$$

where

$R_t$  is the estimator of conditional correlation,

$D_{(t)}$  is a diagonal matrix with the square roots of the conditional variances on the diagonal,

$Q_{(t)}$  is the conditional covariance matrix.

The diagonal matrix of the conditional variance is as follows:

$$D_{(t)} = \text{diag} \sqrt{\sigma(i, t)^2} \quad (3)$$

$$\sigma_{(i,t)}^2 = \omega_{(i)} + \alpha_{(i)} \varepsilon_{(i,t-1)}^2 + \beta_{(i)} \sigma_{(i,t-1)}^2 \quad (4)$$

where

$\sigma(i,t)$  is the conditional volatility of the return,

$\omega(i)$ ,  $\alpha(i)$ , and  $\beta(i)$  are the parameters of the GARCH model.

The GARCH model is stationary when the sum of  $\alpha$  and  $\beta$  is less than 1, which suggests that the shock volatility is reverting and time decaying (Bollerslev, 1986). Thus, it has to satisfy that  $a \geq 0$ ,  $b \geq 0$ , and  $a + b < 1$ .

The conditional covariance matrix is as follows:

$$Q_t = Q^{*-1} Q_t Q^{*-1} \quad (5)$$

$$Q_{(t)} = \{(1 - \alpha - \beta) \bar{Q}\} + \{\alpha \varepsilon_{(t-1)} \varepsilon_{(t-1)}'\} + \{\beta Q_{(t-1)}\} \quad (6)$$

where

- $Q_{(t)}$  is the conditional covariance matrix,  
 $\bar{Q}$  is the unconditional covariance matrix,  
 $\alpha$  and  $\beta$  are parameters controlling the weight given to the previous covariance matrix and the current squared residuals in updating  $Q_{(t)}$ .

## Results

The data collected from different stock exchanges from the sample are analyzed to know their nature. Descriptive statistics relating to daily log returns of the stock indices of NIFTY 50, NASDAQ, NYSE, DAX, FTSE, SSE, NIKKEI, Dow Jones, ASX, and TAIEX are presented (Tab. 1).

**Table 1.** Descriptive Facts.

Stock Exchange	Mean	Std. Dev	Skewness	Kurtosis
NIFTY50	1.105	1.335	-4.0550	-5.854
NASDAQ	1.008	1.393	-2.304	-7.837
NYSE Composite	1.254	1.230	-5.863	-1.829
DAX (FSE)	1.228	1.230	-1.200	5.285
FTSE 100 (LSE)	3602.51	411.838	0.238	-1.293
SSE (China)	3126.99	232.22	0.718	-0.208
NIKKEI 225 (TSE)	2.270	2.306	-2.874	5.617
Dow Jones	2.673	2.470	-8.898	2.828
S&P/ASX (Australia)	6.072	5.699	3.341	-3.673
TAIEX (Taiwan)	0.024	1.234	-2.130	-3.245

Descriptive statistics have been used to measure the data's central tendency, dispersion, and normality using "mean, standard deviation, skewness, kurtosis, and the Jarque-Bera test." Mean is an average of the series, while standard deviation indicates an item's deviation from the series' mean. A more significant standard deviation shows the variability in the series. Skewness, as discussed by Doane and Seward (2011), is a measure used to assess the deviation of a distribution from a normal distribution. It provides information about the direction and magnitude of this deviation, offering insights into the shape of the distribution. Similarly, Kang and Fisher (2021) explore the concept of kurtosis as a statistical tool for measuring the extent to which a distribution's tail deviates from a normal distribution. They examine various estimation methods and provide valuable insights into the interpretation of different kurtosis values. The distribution can be Mesokurtic (standard normal curve) when  $K=3$ , Leptokurtic (peaked curve) when  $K>3$ , and Platykurtic (flattered curve) when  $K<3$ .

**Table 2.** Results of ADF Test for stock indices.

Stock Exchange	Dickey-Fuller	P-value*
NIFTY50	-4.7643	0.010
NASDAQ	-5.3917	0.010
NYSE Composite	-5.1032	0.010
DAX (FSE)	-4.9672	0.010
FTSE 100 (LSE)	-4.7177	0.010
SSE (China)	-6.2098	0.010
NIKKEI 225 (TSE)	-6.7531	0.010
Dow Jones	-5.2091	0.010
S&P/ASX (Australia)	-4.8129	0.010
TAIEX (Taiwan)	-5.4803	0.010

Descriptive statistics reveal that the log-returns of the stock indices of NIFTY 50, NASDAQ, NYSE, DAX, NIKKEI, TAIEX and Dow Jones are negatively skewed. FTSE, SSE, and ASX stock indices' log returns are positively

skewed. So, the log returns of NIFTY 50, NASDAQ, NYSE, DAX, NIKKEI, and Dow Jones have a long-left tail, while the log returns of stock indices of FTSE, SSE, and ASX have a long-right tail. Kurtosis values indicate that the log-returns of DAX and NIKKEI stock indices are leptokurtic as the Kurtosis values of these series are more than 3.

The stationarity of the sample data collected using log-returns of the data extracted from the stock exchanges considered in the study. "Augmented Dickey-Fuller (ADF)" test is employed to check the stationarity of the data collected.

The results of the ADF test for the volatility of stock exchanges are presented in Tab. 2 and it indicates that the log returns of stock indices of NIFTY 50, NASDAQ, NYSE, DAX, FTSE, SSE, NIKKEI, Dow Jones, ASX, and TAIEX are stationary as p-values of ADF test are less than 0.05. So, when the data are stationary, we can proceed with further analysis.

When analyzing volatility in a time series and predicting future volatility, the Autoregressive Conditional Heteroskedasticity (ARCH) model is commonly employed. It provides insights into future volatility patterns. In this study, the ARCH-LM test statistics were conducted to test the null hypothesis of no ARCH effects. Engle (1982) and Bollerslev (1986) are prominent references that discuss the use of the ARCH-LM test in the analysis of volatility and testing for ARCH effects.

**Table 3.** Results of ARCH LM Model for Stock Indices.

Stock Exchange	Chi-square	P-value*
NIFTY50	71.504	0.000
NASDAQ	89.087	0.000
NYSE Composite	94.946	0.000
DAX (FSE)	57.16	0.000
FTSE 100 (LSE)	60.201	0.000
SSE (China)	5.673	0.000
NIKKEI 225 (TSE)	77.598	0.000
Dow Jones	94.777	0.000
S&P/ASX (Australia)	107.19	0.000
TAIEX (Taiwan)	68.802	0.000

The results in Tab. 3 convey the existence of significant ARCH effects in the volatility of stock indices of NIFTY 50, NASDAQ, NYSE, DAX, FTSE, SSE, NIKKEI, Dow Jones, ASX, and TAIEX as p-values are less than 0.05.

"Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) model" is applied to predict the movement and volatility of stock markets. This study has used symmetric GARCH.

**Table 4.** Results of GARCH Model for Stock Indices.

Stock Exchange	$\alpha$	$\beta$	$\alpha+\beta$
NIFTY50	0.2174	0.7479	0.9653
NASDAQ	0.2496	0.6788	0.9284
NYSE Composite	0.2810	0.7099	0.9909
DAX (FSE)	0.0500	0.0500	0.1
FTSE 100 (LSE)	0.2536	0.7428	0.9964
SSE (China)	0.0500	0.0500	0.1
NIKKEI 225 (TSE)	0.1771	0.7799	0.957
Dow Jones	0.3053	0.6819	0.9872
S&P/ASX (Australia)	0.2991	0.6549	0.954
TAIEX (Taiwan)	0.0500	0.0500	0.1

The results of symmetric GARCH are presented in Tab. 4. Among the values of GARCH model, Alpha, Beta and their sum up scores are considered and presented. Total of  $\alpha$  and  $\beta$  scores for the volatility of stock indices of NIFTY 50, NASDAQ, NYSE, DAX, FTSE, SSE, NIKKEI, Dow Jones, ASX and TAIEX are positive and less than 1. So, there is time decay in the volatility persistence. As per the time, the volatility should be reducing.

Then, "Dynamic Conditional Correlation DCC GARCH" is applied to quantify spillover between two stock exchanges. The results of DCC GARCH are presented in Table – 5. The sum of estimates presented in Tab. 5 reveals a relationship between NIFTY 50 and global stock markets such as NASDAQ, NYSE, DAX, SSE, NIKKEI, Dow Jones, ASX, and TAIEX as sum of estimates of  $\alpha_{dcc}$  and  $\beta_{dcc}$  are less than 1.

**Table 5.** Results of DCC GARCH Model for Stock Indices.

Stock Exchange	Sum of estimates	$\alpha_{dcc}$ : p-value	$\beta_{dcc}$ : p-value
NIFTY50 and NASDAQ	0.916	0.998	0.000
NIFTY50 and NYSE Composite	0.919	0.999	0.000
NIFTY50 and DAX (FSE)	0.808	0.145	0.000
NIFTY50 and FTSE 100 (LSE)	0.748	0.171	0.000
NIFTY50 and SSE (China)	0.910	0.994	0.000
NIFTY50 and NIKKEI 225 (TSE)	0.705	0.637	0.069
NIFTY50 and Dow Jones	0.909	0.999	0.032
NIFTY50 and S&P/ASX (Australia)	0.922	0.999	0.000
NIFTY50 and TAIEX (Taiwan)	0.907	0.996	0.000

The results of the DCC-GARCH analysis show that the estimates of  $\alpha_{dcc}$  (sum of estimates) for all pairs of NIFTY50 (Indian stock market) with various international stock exchanges are positive, indicating the presence of a consistent level of volatility spillover between the international and Indian stock markets. However, the p-values for  $\alpha_{dcc}$  are close to or equal to 1, which suggests that these estimates are not statistically significant, meaning that the observed spillover may be due to chance rather than a meaningful relationship.

On the other hand, the estimates of  $\beta_{dcc}$  (sum of estimates) for all pairs of NIFTY50 with international stock exchanges are positive but relatively small in magnitude. However, the p-values for  $\beta_{dcc}$  are very close to 0, indicating that these estimates are statistically significant. This implies that there is a possibility of sometime varying and dynamic asymmetry in the volatility spillover effects between the international and Indian stock markets, although the effects may be relatively small or negligible in terms of their impact.

To summarize, while there is evidence of a consistent level of volatility spillover between the international and Indian stock markets, the lack of statistical significance for the  $\alpha_{dcc}$  estimates suggests that this spillover may not be economically meaningful. On the other hand, the statistically significant  $\beta_{dcc}$  estimates indicate the presence of some asymmetry in the volatility spillover effects, although the magnitude of these effects may be relatively small.

## Discussion

This study aims to analyze the volatility of stock markets worldwide and check the inter-relations (integration) among the global stock markets. This study considered India's Stock Market, represented by NIFTY 50, as a dependent variable. Independent variables are NASDAQ (USA), New York Stock Exchange (USA), Dow Jones (USA), FTSE (LSE, England), DAX (Germany), the Shanghai Stock Exchange (China), NIKKEI (Japan), S&P/ASX (Australia), and TAIEX (Taiwan). Three composite stock indices from the USA are considered because the USA is the global economic leader and is a large exporter for most countries. So, any change in any of its indices will have spillover effects on the economies or stock markets of the countries that have trade relations with it.

Most researchers have generally employed traditional methods such as correlation and regression to find the relation between two variables and prove their hypotheses. Still, in this study, GARCH models are applied not only to find the volatility and spillover of these stock indices but also to find the relation between them and to check the impact of one stock market on another.

The Dynamic Conditional Correlation (DCC) GARCH model is a powerful tool used to examine the volatility spillover effects between different assets or markets. In this analysis, it was applied to quantify the spillover effects between NIFTY 50 (representing the Indian stock market) and international stock markets.

The analysis of volatility spillover effects between NIFTY 50 and various international stock markets provides valuable insights into the interconnectedness and transmission of market volatility. While the results indicate the presence of some level of volatility spillover, it is important to explore the underlying reasons and factors that contribute to these findings. One possible reason for the consistent volatility spillover effects is the increasing integration and interdependence of global financial markets. In today's interconnected world, market participants, institutional investors, and algorithmic trading systems operate across borders, leading to a greater interlinkage between different stock markets. This interconnectedness can facilitate the transmission of shocks and information,

resulting in volatility spillovers. Factors such as global economic trends, geopolitical events, and investor sentiment can contribute to the propagation of volatility across markets.

Furthermore, the non-significant p-values for  $\alpha_{DCC}$  suggest that while there is evidence of volatility spillover, the economic significance of these effects may be limited. Several factors could explain this phenomenon. Firstly, it could be attributed to the presence of efficient market mechanisms and arbitrage opportunities. If markets are efficient and information is quickly incorporated into prices, any deviations caused by volatility shocks may be short-lived, limiting their impact on market behavior.

Additionally, regulatory measures and risk management strategies implemented by market participants and institutions can also mitigate the propagation of volatility spillovers. Risk management practices, such as hedging strategies, portfolio diversification, and the use of derivative instruments, can help investors and institutions manage and contain volatility risk. These measures can dampen the impact of volatility shocks and reduce the economic significance of spillover effects.

Moreover, the significant p-values for  $\beta_{DCC}$  indicate the presence of time-varying and dynamic asymmetry in the volatility spillover effects. This suggests that the magnitude and direction of volatility transmission between markets may change over time. Factors such as market conditions, investor behavior, and specific events can influence the asymmetry of spillover effects. For example, during periods of heightened market uncertainty or financial crises, the spillover effects may be more pronounced and exhibit stronger asymmetry.

It is important to consider the limitations of the analysis. The study focuses on a specific set of stock indices and time period, and the results may not be generalizable to other markets or time periods. Additionally, the analysis assumes symmetric volatility models, which may not capture all the complexities and nuances of market dynamics. Employing more sophisticated models or considering alternative econometric techniques could provide further insights into the volatility spillover effects.

In conclusion, the obtained results shed light on the presence of volatility spillover effects between NIFTY 50 and international stock markets. The increasing interconnectedness of global financial markets and various factors such as market integration, investor behavior, and regulatory measures can contribute to these spillover effects. While the economic significance of these effects may be limited, the dynamic nature of volatility transmission and asymmetry highlights the need for a comprehensive understanding of market dynamics and risk management practices. Further research and analysis can delve deeper into the underlying drivers of volatility spillovers and their implications for market participants and policymakers.

## Conclusion

In conclusion, this research paper aimed to analyze the volatility of global stock markets and investigate the level of inter-relationships among them, with a specific focus on the NIFTY 50 index representing India's stock market. The study utilized GARCH models to examine volatility, spillover effects, and relationships between the NIFTY 50 index and various global stock indices.

The results of the DCC GARCH analysis yielded several significant findings. They highlight the increasing integration and interdependence of global financial markets, which facilitate the transmission of volatility across borders. Factors such as global economic trends, geopolitical events, and investor sentiment contribute to the propagation of volatility spillovers. However, it is important to note that the economic significance of these effects may be limited due to efficient market mechanisms, arbitrage opportunities, and risk management practices implemented by market participants and institutions.

The significant p-values for  $\beta_{DCC}$  indicate the presence of time-varying and dynamic asymmetry in the volatility spillover effects. This suggests that the magnitude and direction of volatility transmission can change over time. Market conditions, investor behavior, and specific events play a crucial role in shaping the asymmetry of spillover effects. In times of heightened uncertainty or financial crises, the spillover effects may become more pronounced and exhibit stronger asymmetry.

It is crucial to acknowledge the limitations of the analysis, including the specific set of stock indices and time period examined. Moreover, the study's focus on symmetric volatility models may not capture all the intricacies of market dynamics. Utilizing more sophisticated models and alternative econometric techniques could provide further insights into volatility spillovers.

There is evidence of volatility spillover between the NIFTY 50 and international stock markets, the economic significance of these effects may be limited. The dynamic nature of volatility transmission and the presence of asymmetry underscore the importance of comprehending market dynamics and implementing effective risk management practices. Future research endeavors should aim to investigate deeper into the drivers of volatility spillovers and their implications for market participants and policymakers.

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