Faculty of Management & Finance
University of Colombo

Colombo Business Journal
International Journal of Theory & Practice
Vol. 15, No. 02, December, 2024

Interconnectedness and Spillover Effects amongst Stock Markets of the US, China, Germany, Japan and India using DCC-GARCH Model and Diebold Yilmaz Method

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Abstract

In a rapidly globalising world, economic boundaries are dissolving as stakeholders seek broader opportunities. Corporations are now multinational, and investors are increasingly turning to global stock markets to maximise gains. Volatility serves as a crucial benchmark, guiding investment decisions in this interconnected landscape. The current study looks at the time-varying spillover effects of the returns of the indices from January 6, 2020, until March 15, 2024, of the five economies of the world, namely, the S&P (United States), SSE (China), Nikkei (Japan), DAX (Germany), and Nifty (India). The conditional correlations and volatility spillovers are measured using the DCC-GARCH model and the Diebold and Yilmaz method. The study concludes that the transmission of information between the indices occurs in the long run except between Germany and China. Further, Germany and the US are net transmitters of volatility spillover, while China, Japan, and India are net receivers. The total spillover among the indices of these five economies is 39.37%.

Keywords: DCC-GARCH Model, Diebold and Yilmaz Method, Dynamic Connectedness, Transmission of Information, Volatility Spillover

Received:	Accepted revised version:	Published:
08 June 2024	24 November 2024	31 December 2024

Suggested citation: Agarwal, A., Dhankhar, N. & Mehla, S. (2024). Interconnectedness and spillover effects amongst stock markets of the US, China, Germany, Japan and India using DCC-GARCH Model and Diebold Yilmaz Method. *Colombo Business Journal, 15*(2), 162-189.

DOI: https://doi.org/10.4038/cbj.v15i2.197

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Introduction

Global stock markets are increasingly interconnected. Interconnectedness is a broad concept that describes how different markets, economies, or assets are linked or correlated. It reflects the degree to which these entities influence each other, either through direct relationships (like trade, and financial ties) or common external factors (like global economic conditions) (Karğin et al., 2018; Diebold & Yilmaz, 2012). Spillover is a specific manifestation of interconnectedness. It refers to the transmission of shocks, volatility, or economic disturbance from one market or economy to another. Spillovers occur because of the underlying interconnectedness between markets. Without interconnectedness, there would not be any spillover effect.

Agarwal and Dhankhar (2024) have analysed the impact of news on returns of sixteen indices of the Indian stock market using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. They found that there exists an inverse relationship between volatility decay and future returns. Similarly, an understanding of internationally interconnected markets becomes necessary, and a recognition of these linkages between returns and volatilities is critical to help investors, governments and financial institutions to make informed decisions, especially when diversifying portfolios internationally (Zhou et al., 2012). As international capital flows allow investors to access global markets with ease, understanding these spillover effects becomes crucial (Jebran & Iqbal, 2016). Global stock markets are more susceptible to external news and events, making it essential for investors to be aware of the effect of volatility on returns spread across different markets to make optimum trading decisions. The existence or absence of volatility spillovers serves as a vital guide for optimum portfolio diversification.

Application of the Dynamic Conditional Correlation - Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model is used to analyse the time-varying correlations between multiple financial time series. The model extends the GARCH framework to allow for dynamic conditional correlations between different assets or indices. The GARCH model captures the volatility of a single time series by accounting for time-varying volatility (heteroskedasticity). It specifies that the current volatility is dependent on past squared errors (ARCH term) and past volatility (GARCH term).

The DCC component extends the GARCH model to a multivariate context, allowing the time-varying conditional correlation between multiple series to be captured. It calculates how correlations between assets evolve, capturing periods when assets may become more or less correlated due to changing market conditions. Therefore, the DCC-GARCH model provides an understanding of the relative connectedness and volatility between different financial series (multivariate). The application of the model to analyse different stock markets facilitates investors in their long-term and short-term investment decisions.

While the interconnectedness is captured through the DCC-GARCH model, an equally significant aspect is to understand the intensity of the spillover amongst the different markets, which can be explained by using the Diebold and Yilmaz method. The Diebold and Yilmaz method highlights the transmission of volatility between markets in quantitative terms. In other words, Diebold and Yilmaz method can be used to assess the resilience or the vulnerability of different markets.

Volatility spillover effects between stock markets can be understood through several stylised facts (concepts or non-formal theories) explaining interconnectedness. Herding describes how investors often move collectively in response to market signals, which can intensify market volatility. A prominent example of this was the 2008 Global Financial Crisis, during which Lehman Brothers' collapse triggered widespread panic, leading to a global market sell-off and escalating volatility (Nofsinger, 2012). De Grauwe and Ji (2013) have analysed the Eurozone Debt Crisis to understand how the financial troubles of Greece caused investors to reassess the stability of other Eurozone nations. This concept, known as the wake-up call hypothesis (Goldstein, 1998) suggests that a significant event in one market can alert investors to potential risks in others, leading to increased volatility. Trade linkages play a role in transmitting volatility, as economic ties between countries can spread market shocks. The US-China trade war from 2018-2019 exemplifies this, with tariffs leading to stock market fluctuations on both sides and globally (Bown, 2019). Further, financial linkages illustrate how interconnected financial institutions can amplify volatility. Together, these theories provide a comprehensive framework for understanding how shocks in one market can trigger volatility across global financial markets. While these stylised facts (namely, herding, wake-up call hypothesis, trade linkages and financial linkages) play a crucial role in volatility spillovers in interconnected markets, there is yet another important stylised fact that spreads like a contagion from one financial market to another. Contagion happens when financial instability in one particular country spreads to other countries, as seen in the 1997 Asian Financial Crisis (Radelet et al., 1998), where the collapse of the Thai Bhat triggered panic among the investors, leading to significant declines in stock markets across Asia, despite some countries being fundamentally stable.

In recent times, the effects of volatility spillovers of the black swan event of COVID-19 spread to financial markets across the globe with the result that very few economies were spared of the consequences of the pandemic. Coronavirus was not only contagious medically but economically as well (Baldwin & Tomiura, 2020). Global manufacturing was severely affected resulting in 'supply chain contagion' (Agarwal & Hussain, 2023), triggering a decline in the stock markets around the world.

The COVID-19 pandemic brought about an unprecedented global shutdown, leaving no country untouched by its impact. A significant research gap exists in understanding how COVID-19 affected stock markets worldwide. The pandemic introduced unparalleled levels of volatility and interconnectedness in financial markets, yet these dynamics remain insufficiently explored. The individual and collective economic repercussions of COVID-19 were profound, causing widespread disruptions across global financial systems. In particular, the economic volatility and shifting correlations between the economies of the United States (US), China, Germany, Japan and India warrant a more comprehensive investigation.

The current study uses the technique of DCC-GARCH model to analyse the dynamic interconnectedness and the volatility of the stock markets of five countries of the world, namely, the US, China, Germany, Japan and India. Further, to assess the degree of interconnectedness amongst the financial markets of these five countries the Diebold Yilmaz method has been applied. The Diebold Yilmaz method identifies the markets which are 'net receivers' or 'net transmitters' of volatility or shocks.

The introduction is followed by a literature review, which highlights the importance of the DCC-GARCH model as well as the Diebold and Yilmaz method. The research methodology gives a clear process of the steps followed in the empirical analysis and the use of relevant models. The empirical analysis shows the findings, which are discussed in the subsequent section. The conclusion underlines the outcomes of the empirical analysis and its relevance for the investors. Finally, the study concludes with the limitations and suggestions for further research.

Literature Review

Theoretical Underpinnings

The spillover effect among stock markets of different countries is defined as the transmission of shocks, price movements, or volatility from one market to another (Katusiime, 2018; Xiong & Han, 2015). This phenomenon arises from the interconnectedness of global financial markets through trade, common currencies, and cross-border investments (Jithendranathan, 2013). Bilateral linkages via trade and finance – such as direct trade flows, bilateral bank lending, and trade competition- are critical determinants of how shocks originating in large economies propagate to markets worldwide (Forbes & Chinn, 2004). Moser (2003) further identified key mechanisms of spillover, including international trade, counterparty defaults, and portfolio rebalancing. Financial linkages, as emphasised by Claessens and Forbes (2004), also play a significant role in driving contagion. The increasing integration of global markets has also heightened cross-country correlations in economic output, consumption, and investment (Kose et al., 2003). Consequently, a shock in one market can rapidly transmit to others, triggering contagion or spillover effects (Jithendranathan, 2013).

The spillover effect is underpinned by several theoretical frameworks rooted in finance, economics, and behavioural sciences. Contagion Effect Theory (CET) explains how financial shocks spread across markets, emphasising the mechanisms of transmission. Researchers such as Forbes and Rigobon (2002) explored the channels of contagion, highlighting the role of Information Transmission Theory (ITT), which posits that information is not confined to a single market but disseminates across interconnected systems. The Wake-Up Call Hypothesis, proposed by Goldstein (1998), offers an additional perspective, suggesting that a crisis in one country prompts investors to scrutinise the economic fundamentals of others. This increased awareness leads to strategic adjustments, as evidenced by Karas et al. (2013) in the banking sector. Behavioural explanations also contribute to the theoretical understanding of spillovers. Herding Behaviour Theory (Banerjee, 1992) highlights investors 'tendency to mimic others' actions, particularly during periods of uncertainty, leading to irrational market movements and amplifying spillovers. Together, these frameworks illuminate the complexities of financial contagion, emphasising the importance of understanding interconnected market systems. As for policymakers, economists, and investors, such insights are critical for assessing global risks, improving portfolio strategies, and enhancing financial stability.

Empirical Evidence

There are numerous studies that have examined the connectedness of financial series and the intensity of this connectedness. The real financial networks and their connectedness can occur within an economy or across different economies. The studies emphasise the critical importance of understanding spillover effects, especially given the interconnected nature of global markets, as noted by Frank and Hesse (2009). Choudhry and Jaysekera (2014) reported an increase in spillover effects from established markets such as the US and Germany to struggling European economies during the 2008 financial crisis. In their study, Xiong and Han (2015) examine the effects of volatility spillover between the forex (foreign exchange) and the stock markets, particularly post-reform of the RMB (Renminbi) exchange rate mechanism. Using the GC-MSV (Granger Causality-Multivariate Stochastic Volatility) model, they find that dynamic price spillovers between these markets are negatively correlated. The study reveals asymmetric spillover effects based on different stages of the RMB's value-whether it is appreciating steadily or experiencing a constant shock that reduces its appreciation. Over time, these spillover effects have diminished. The authors conclude that the RMB exchange rate plays a crucial role in maintaining the internal and external balance of China's economy, while the stock market reacts quickly to even minor changes in the real economy. Li and Giles (2015) also found unidirectional spillover between developed markets (like the US and Japan) and emerging Asian markets (such as China, India and Indonesia) using the DCC-GARCH model. Further, Jebran and Iqbal (2016) examined volatility spillover among Asian stock markets, identifying bi-directional spillover between Hong Kong and Sri Lanka, as well as China and Japan. In contrast, most other markets displayed unidirectional volatility transmission. Karğin et al. (2018) examined Turkey's stock market, discovering that global risk levels minimally affected the BIST 100 index when risk was low, while the S&P index had the greatest impact regardless of global risk. Additionally, Siddiqui and Khan (2018) analysed volatility patterns in four developed and emerging markets to inform portfolio construction, revealing both self-contained and cross-market volatility spillover, except between India, China, and Japan. Umer et al. (2018) found that developed markets influenced EAGLE (Emerging and Growth Leading Economies) markets like China, India, and Brazil, with time-varying positive spillover effects. Gamba-Santamaria et al. (2019) highlighted spillover effects across major global stock markets, including Australia, Canada, and Germany. Uluceviz and Yilmaz (2020) have analysed the real-financial connectedness in the Swiss economy using the KOF Economic Barometer[1] and Real Activity Index (RAI). Their findings reveal that the real economy acts as a net source of connectedness based on KOF analysis, while RAI indicates that the real economy is primarily a net receiver of shocks from the financial market, particularly the stock

[1]KOF Economic Barometer refers to Konjunkturforschungsstelle, which is German for the Swiss Economic Institute. The KOF institute is part of the Swiss Federal Institute of Technology (ETH Zürich) and is well-known for its research and forecasting related to economic indicators, including the KOF Economic Barometer

market. This highlights the different roles the real economy plays depending on the indicator used.

Su (2020) analysed volatility spillovers across G7 stock markets - specifically, those of the US, Japan, Germany, the UK, France, Canada, and Italy - using a time-frequency spillover approach. The study revealed that the volatility spillovers are sensitive to crisis and behave similarly to a memory-less process. The key takeaway from this study is the time-frequency spillover, which signifies that spillovers change over time and at different frequencies (short-term vs. long-term), describing how market volatility relationships evolve and react over time. Su also highlights that volatility spillovers are crisis sensitive, meaning they increase during financial crises or periods of economic uncertainty, and finally, the memory-less process, which clearly indicates that the past volatility does not strongly influence future volatility spillovers.

Karkowska and Urjasz (2021) analyse the connectedness of sovereign bond markets in Central and Eastern European (CEE) countries with global and European markets from 2008 to 2020, including the COVID-19 pandemic. Using directional methods and dynamic conditional interconnectedness models, they found that CEE bond markets are more interconnected with each other than with global markets. Zhong and Liu (2021) studied China and Southeast Asian markets, suggesting that diversifying across these regions reduces risk. Mishra et al. (2022) examined how returns and volatility moved between India's stock market and key Asian and global equity markets, particularly before and after the 2008 financial crisis. Using a GARCH-BEKK model, they observed that Indian market volatility had a stronger effect on Asian markets as compared to global markets. Vuong et al. (2022) found that volatility in China significantly affected the US stock market. Meanwhile, Reza et al. (2022) confirmed a volatility spillover between China's water indices and four other Asian markets, revealing a persistent positive effect among these markets.

Several researchers have explored the phenomenon of spillover effects across different domains. For instance, Malhotra et al. (2024), Wu and Jiang (2023), Tan et al. (2022), Maitra and Dawar (2019), and Raza et al. (2016) have delved into spillover effects in various sectors, while studies like those by Jebran et al. (2017), Jin and An (2016), Balli et al. (2015), Gupta and Guidi (2012) have focussed on the co-movement of stock prices between different international financial markets. Shaik and Rehman (2023) explored how economies in regions like the US, Latin America, Europe, and others interacted through ESG stock indices from 2010 to 2021, using the DCC-GARCH model. They found that markets in Africa, the Middle East, and Latin America transmitted shocks that allowed investors and portfolio managers to optimize their portfolios. Other studies focussed on broader contexts. For example, Khan (2023) identified both short- and long-term spillover effects from India to BRICS nations, indicating that BRICS markets are not ideal for Indian portfolio diversification. Wang et al. (2023) examined volatility spillover dynamics between FinTech and China's traditional financial industry (TFI), focussing on total, directional, and net spillover indices. The study found a time-varying, inverse U-shaped spillover pattern from 2017-2021, with FinTech generally acting as a net receiver of volatility. However, during the COVID-19 pandemic, FinTech became a net exporter of volatility to the TFI. Mohanty et al. (2023) studied how foreign exchange rates influenced Indian stock market indices, noting a positive link between exchange rate fluctuations and stock market volatility. Joseph et al. (2024) assessed the relationship between cryptocurrencies and major African financial markets, identifying a one-way spillover effect from cryptocurrencies to African markets but not vice-versa.

Research Methods

According to Report, as of October 2023, the top five economies based on GDP values include the United States of America (US) with a GDP of USD 26.93 trillion, People's Republic of China with a GDP of USD 17.73 trillion, Japan with a GDP of USD 4.23 trillion, Federal Republic of Germany having a GDP of USD 4.10 trillion, and India with a GDP of USD 3.73 trillion (*IMF*, 2023).

The study identifies the stock exchanges from these countries, namely the Standard & Poor 500 (S&P) of the New York Stock Exchange (US), the Shanghai Stock Exchange (SSE) (China), Nikkei of the Tokyo Stock Exchange (Japan), Deutscher Aktien Index (DAX) of the Frankfurt Stock Exchange (Germany), and Nifty of National Stock Exchange (India) for its empirical analysis.

The current study uses the daily closing prices of the stock indices for each of these countries for the period January 6, 2020 to March 15, 2024. The data has been filtered to take only those dates for which data was available for all the five indices. This preserves the uniformity in the process of data collection.

The study uses secondary data downloaded from www.investing.com. The empirical analysis has been done using R-Studio software.

The return of the series has been computed by differencing the natural logarithm of the index series. The return series of indices from stock markets studied in the study are represented as rsp for S&P index (of the New York Stock Exchange, US), rsse for SSE index (of the Shanghai Stock Exchange, China), rnikkei for Nikkei index (of Tokyo Stock Exchange, Japan), rdax for DAX index (of the Frankfurt Stock Exchange, Germany), and rnifty for Nifty index (of National Stock Exchange, India).

The Augmented Dickey Fuller (ADF) test has been applied for checking stationarity.

DCC-GARCH Model

DCC-GARCH (Engle & Shepard, 2001) model has been applied to examine the dynamic interconnectedness and volatility among the five economies of the study. DCC-GARCH can capture time-varying correlations and volatility dynamics across multiple time series.

The general form of DCC-GARCH (1,1) is shown in Equation 1.

$$y_t = \mu_t + \varepsilon_t \qquad \varepsilon_t | F_{t-1} \sim N(0, H_t)$$

$$\varepsilon_t = H_t^{1/2} u_t \qquad u_t \sim N(0,1)$$

and

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

where,

$y_t, \mu_t, \varepsilon_t\ and\ u_t$ are the N×1 dimension vectors
R_t, D_t, H_t are N×N dimension matrix
y_t= time series under consideration,
μ_t = conditional mean,
ε_t = error term,
F_{t-1}= all information available up to time period t-1,
u_t= standardised error term
R_t= dynamic conditional correlation,
D_t= time-varying conditional variance
H_t= time-varying conditional variance-covariance matrix

The time-varying conditional variance is shown in Equation 2:

$$D_t = diag(h_{11}^{\frac{1}{2}}, \dots \dots, h_{NN1}^{\frac{1}{2}}) \tag{2}$$

D_t is measured by using the univariate GARCH model given by Bollerslev (1986) for every sample by assuming one shock and one persistency parameter which is shown in Equation 3.

$$h_{ii,t} = \omega + \alpha\varepsilon_{i,t-1}^2 + \beta h_{ii,t-1}$$

and,

$$R_t = diag.(q_{11t}^2, \dots, q_{NNt}^2)Q_t diag.(q_{11t}^{\frac{1}{2}}, \dots., q_{NNt}^{\frac{1}{2}}) \tag{3}$$

Q_t is the $N \times N$ positive definite symmetric matrix, which is shown as,

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha u_{t-1}\acute{u}_{t-1} + \beta Q_{t-1}$$

where,

$$u_t = \frac{\varepsilon_{it}}{\sqrt{h_{iit}}}$$

Diebold and Yilmaz Method

Under Diebold and Yilmaz method, H-step forward forecast error variance ($\theta_{pq}^g(H)$) decomposition is computed which helps to calculate the own variance shares and cross variance shares. Own variance is the fraction of $\theta_{pq}^g(H)$ in forecasting x_p due to shock x_p and cross variance shares is the fraction of $\theta_{pq}^g(H)$ in forecasting x_p that are due to shock x_q. This is shown in Equation 4.

$$\theta_{pq}^g(H) = \frac{\sigma_{qq}^{-1}\sum_{h=0}^{H-1}(e_q' A_h \Sigma\, e_p')^2}{\sum_{h=0}^{H-1}(e_q' A_h \Sigma\, A_h')} \tag{4}$$

where p, q = 1, 2, …., n and $p \neq q$, $\sum$= variance matrix for ε i. e., error vector, σ_{qq}= standard deviation of error term, $e_{p=}$ selection vector, with 1 for p^{th} element and 0 otherwise.

Total Spillover

The total spillover effect has been calculated as shown in Equation 5.

$$S^g(H) = \frac{\sum_{\substack{p,q=1 \\ p\neq q}}^{N} \tilde{\theta}_{pq}^{g}(H)}{\sum_{p,q=1}^{N} \tilde{\theta}_{pq}^{g}(H)} \times 100 \tag{5}$$

$$= \frac{\sum_{\substack{p,q=1 \\ p\neq q}}^{N} \tilde{\theta}_{pq}^{g}(H)}{N} \times 100$$

where,

$$\tilde{\theta}_{pq}^{g}(H) = \frac{\theta_{pq}^{g}(H)}{\sum_{q=1}^{N} \theta_{pq}^{g}(H)} \text{ and } \sum_{q=1}^{N} \tilde{\theta}_{pq}^{g}(H) = 1; \sum_{p,q=1}^{N} \tilde{\theta}_{pq}^{g}(H) = N$$

It represents the normalisation of the variance decomposition matrix by the row sum for calculating total spillover, which measures the contribution of spillover of volatility shocks across the financial market.

Directional Spillover

Directional spillover is the measure of volatility spillover received by the market *p* from all other markets *q* and is represented by Equation 6.

$$S_{p.}^{g}(H) = \frac{\sum_{\substack{q=1 \\ p\neq q}}^{N} \tilde{\theta}_{pq}^{g}(H)}{\sum_{p,q=1}^{N} \tilde{\theta}_{pq}^{g}(H)} \times 100 \tag{6}$$

$$= \frac{\sum_{\substack{q=1 \\ p\neq q}}^{N} \tilde{\theta}_{pq}^{g}(H)}{N} \times 100$$

Similarly, the directional volatility spillover transmitted from the market *q* to all other market *p* is calculated by Equation 7.

$$S_{.p}^{g}(H) = \frac{\sum_{\substack{q=1 \\ p\neq q}}^{N} \tilde{\theta}_{qp}^{g}(H)}{\sum_{p,q=1}^{N} \tilde{\theta}_{qp}^{g}(H)} \times 100 \tag{7}$$

$$= \frac{\sum_{\substack{q=1 \\ p\neq q}}^{N} \tilde{\theta}_{qp}^{g}(H)}{N} \times 100$$

The set of directional spillovers can be viewed as breaking down total spillovers into components that originate from or are directed towards a specific source.

Net Spillover

The net spillover effect from the market p to all other markets q can be calculated by simply differencing the gross volatility shocks transmitted to and received from the other markets.

$$S_p^g(H) = S_{.p}^g(H) - S_{p.}^g(H) \tag{8}$$

It provides the summary of the contribution of each market to the volatility of the market in question.

Results of Empirical Analysis

Table 1 gives the descriptive statistics of the return series of all the indices. It shows that the standard deviation is lowest at 0.0133 for rsse (China) and it is highest at 0.0151 for rsp (US). This indicates that the returns from US indices are most volatile among all the indices studied. The mean value of all the indices is positive except that of rsse (China). The highest average return has been witnessed in the indices of rnifty (India) followed by rnikei (Japan).

Table1: Descriptive Statistics

	rnifty	**rsp**	**rnikkei**	**rdax**	**rsse**
Minimum	-0.0867	-0.1277	-0.0627	-0.1305	-0.0887
Maximum	0.0840	0.0897	0.0773	0.1041	0.0542
Mean	0.0007	0.0005	0.0006	0.0004	-0.0001
Median	0.0013	0.0009	0.0008	0.0009	0.0002
Standard deviation	0.0134	0.0151	0.0138	0.0149	0.0133
Skewness	-0.8617	-0.9844	0.0841	-0.5690	-0.6419
Kurtosis	9.2689	13.2187	3.0329	12.7944	3.8560
Jarque Bera	3282.10	6592.80	341.76	6090.50	610.94
(*p*-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. of Observations	881	881	881	881	881

Table 1 also shows that the skewness of all the indices is negative except that of rnikkei. A negatively skewed distribution means that most of the data points are concentrated on the higher end of the scale, while a few lower values extend the distribution to the left. The opposite is true for a positively skewed distribution, in which most of the values are clustered around the lower end of the scale, with fewer higher values extending the distribution to the right. As a result, the mean can be supplemented by the median for a more accurate analysis. In this case, the median return is highest for rnifty, followed by rsp and rdax. The lowest median value is found in rsse, which is consistent with the mean analysis.

Moreover, the return indices are leptokurtic or fat-tailed, implying the presence of extreme values in the series. Further, the distribution of all the series is not normal as the p-value(s) of the Jarque-Bera test are less than 5% significance level.

The 'Augmented Dicky-Fuller (ADF)' test has been applied to check for stationarity of the return series. According to Table 2, the *p*-value is < 0.05 for all indices. This indicates that the null hypothesis stands rejected for the presence of a unit root, confirming that the series is stationary.

Table 2: Augmented Dicky Fuller Test (ADF)

	rnifty	**rsp**	**rnikkei**	**rdax**	**rsse**
t-statistic	-9.2563	-9.2682	-9.7018	-8.9593	-9.8266
p-value	0.01	0.01	0.01	0.01	0.01

Table 3 depicts the pair-wise association between the indices to understand the correlation amongst the return indices. Karl Pearson Coefficient of Correlation is applied, wherein the null hypothesis is that there is no correlation amongst the series. Since, the *p*-value is < 0.05, the null hypothesis can be rejected. The correlation coefficients are calculated at 5% significance levels. The correlation coefficients between rnifty with rsp, rnifty with rnikkei, rnifty with rdax and rnifty with rsse are 0.46, 0.42, 0.52 and 0.18 respectively. Similarly, the correlation coefficients for rsp, rnikkei, rdax and rsse are computed pair-wise.

Figure 1 shows the volatility clustering of each of the individual return series graphically. Volatility clustering is identified when large changes follow 'the large changes, and small changes follow the small changes' (Mandelbrot, 1963). Such volatility clustering is witnessed in all the return series.

Figure 1: Volatility Clustering of Return Series

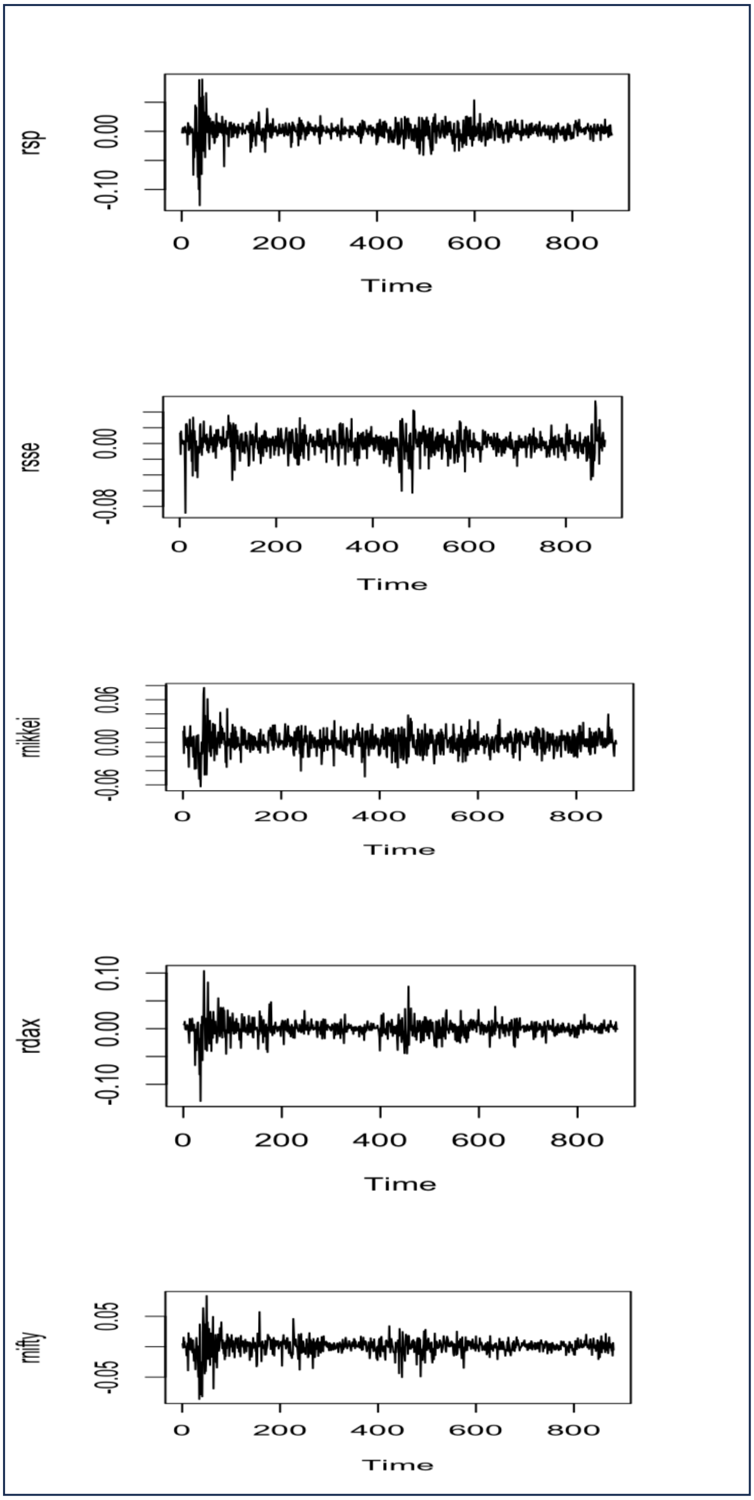


Table 3: Correlation between Return Series using Karl Pearson's Correlation Coefficient

		rnifty	rsp	rnikkei	rdax	rsse
rnifty	Coef.	1.00	0.46	0.42	0.52	0.18
	p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0058)
rsp	Coef.	0.46	1.00	0.26	0.64	0.19
	p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
rnikkei	Coef.	0.42	0.26	1.00	0.41	0.21
	p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0008)
rdax	Coef.	0.52	0.64	0.41	1.00	0.20
	p-value	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
rsse	Coef.	0.18	0.19	0.21	0.21	1.00
	p-value	(0.0058)	(0.0000)	(0.0008)	(0.0002)	(0.0000)

Interconnectedness among Markets

The evidence of volatility clustering leads to the application of the DCC-GARCH model. The DCC-GARCH model consists of two main components. First, the GARCH model captures the time-varying volatility within each individual time series, meaning it tracks how the variability (or risk) of a series changes over time. Second, the DCC model measures the conditional correlation between the residuals of different time series. In other words, while the GARCH model focuses on the volatility of individual series, the DCC model determines how the relationships between different series evolve over time (see Equation 1).

Table 4 describes the first component, namely the GARCH model. All the coefficients meet the stability conditions of $\alpha, \beta, \omega \geq 0$. The coefficients α and β are significant as their *p*-value(s) ≤ 0.05 for all indices. Additionally**,** the time-decaying effect of volatility is measured by $(\alpha + \beta) < 1$, thereby fulfilling the conditions of the GARCH model. $(\alpha + \beta)$ indicates the volatility persistence, and VDR indicates the Volatility Decay Rate of the return series. Volatility persistence within the GARCH framework refers to the degree to which current volatility is influenced by past volatility, while VDR indicates the rate at which market shock fades, indicating the stability of an asset's returns after a period of high volatility.

For rnifty, $\alpha + \beta$ is 0.9919, indicating a very high persistence of volatility. As a result, VDR is 0.0081, which is the lowest amongst all the return series. This implies that the volatility in rnifty tends to decay slowly after a shock. The lowest persistence of volatility (0.9340) and highest VDR of (0.066) is observed in rsse, indicating that its volatility decays faster making it potentially less risky in the short-term.

Table 4: GARCH Model for Return Series

		μ	ω	α	B	$\alpha + \beta$	VDR = [1-(α+β)]
rnifty	Estimate	0.0010	0.0000	0.0917	0.9002	0.9919	0.0081
	Pr(>|*t*|)	0.0017***	0.3976	0.0059***	0.0000***		
rsp	Estimate	0.0008	0.0000	0.0846	0.8894	0.9740	0.0260
	Pr(>|*t*|)	0.2252	0.8316	0.0196**	0.0000***		
rdax	Estimate	0.0008	0.0000	0.1636	0.8136	0.9772	0.0228
	Pr(>|*t*|)	0.0463**	0.4657	0.0025***	0.0000***		
rnikkei	Estimate	0.0008	0.0000	0.0742	0.8774	0.9516	0.0484
	Pr(>|*t*|)	0.0589	0.0000***	0.0000***	0.0000***		
rsse	Estimate	-0.000167	0.000012	0.125122	0.808834	0.9340	0.0660
	Pr(>|*t*|)	0.6661	0.0000***	0.0000***	0.0000***		

Note: ** and *** denote $p < .05$ and $p < .01$ respectively

The second component, namely the DCC-GARCH model, is shown in Table 5. It depicts the short-run and long-run information spill-over amongst return series by dcc α and dcc β in such a way that dcc α represents the short-run spillover and dcc β represents the long-run spillover.

There is the absence of short-run information connectedness between these return series, as dcc α is positive but not significant. The only exception is the relationship between rdax and rsse, which shows dcc α of 0.0765 at a 5% level, indicating the persistence of standardised residuals from the previous period.

In contrast, dcc β is significant in pair-wise long-term spillover effects between rnifty and rsp (0.8792), rnifty and rdax (0.9488), rnifty and rnikkei (0.9663), rnifty and rsse (0.9872), which are positive and significant. In the same way, pair-wise long-run volatility spillover is also witnessed between rnikkei and rdax, rnikkei and rsse, rsp and rnikkei, rsp and rdax, as well as rsp and rsse.

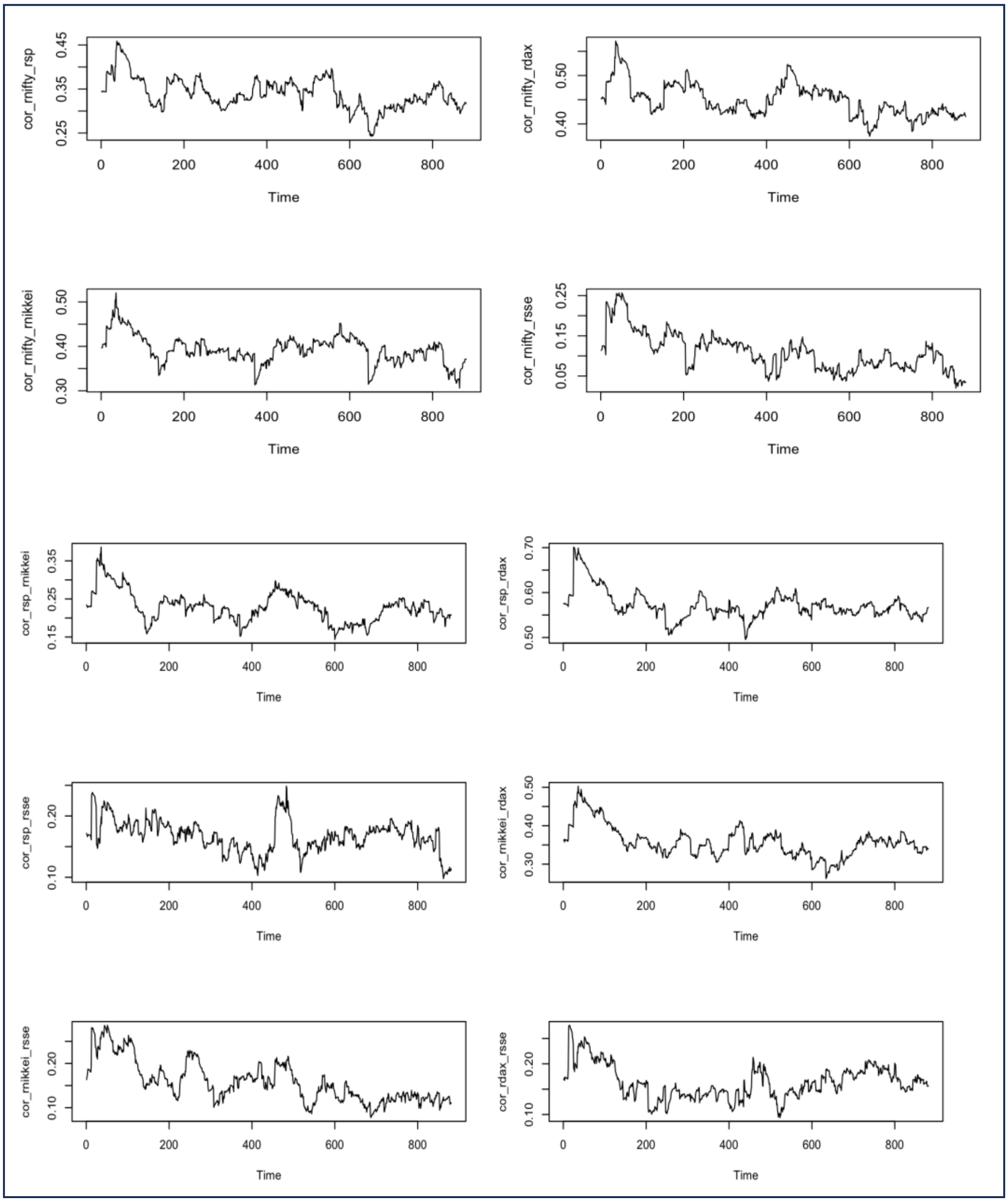
There is the absence of pairwise long-run volatility spillover between rdax and rsse. The total spillover between rdax and rsse (0.0765) highlights that only the short run interconnectedness is significant, with no long-term spillover being noticed.

Table 5: Spillover Effects among Markets of DCC-GARCH Model

		[Joint] dcc α	**[Joint] dcc β**	**dcc α + dcc β < 1**
rnifty-rsp	coef.	0.0269	0.8792	0.9062
	p-value	-0.279	**(0.0000)**	
rnifty – rdax	coef.	0.0102	0.9488	0.959
	p-value	-0.2362	**(0.0000)**	
rnifty- rnikkei	coef.	0.0072	0.9663	0.9734
	p-value	-0.4287	**(0.0000)**	
rnifty – rsse	coef.	0.0088	0.9872	0.996
	p-value	-0.0899	**(0.0000)**	
rsp – rdax	coef.	0.0086	0.952	0.9605
	p-value	0.1861	**(0.0000)**	
rsp– rnikkei	coef.	0.0072	0.9663	0.9734
	p-value	0.4287	**(0.0000)**	
rsp– rsse	coef.	0.021	0.6609	0.6819
	p-value	0.5042	**(0.0000)**	
rnikkei - rdax	coef.	0.0265	0.9198	0.9463
	p-value	0.3058	**(0.0000)**	
rnikkei– rsse	coef.	0.0246	0.9526	0.9771
	p-value	0.3111	**(0.0000)**	
rdax – rsse	coef.	0.0765	0.0000	0.0765
	p-value	**(0.0196)**	1.0000	

Figure 2 reveals the dynamic conditional correlation between bivariate series, where time is presented on *x*-axis and value of correlation on the *y*-axis. The Figure displays the volatility spillover amongst the return series.

Figure 2: Plot of Dynamic Condition Correlation between Return Series



Magnitude of Spillover Effect

Table 6 shows the Diebold and Yilmaz method (Equation 5), used to quantify the magnitude of spillover effects between the return series. The diagonal element (in bold) represents the internal spillover while off-diagonal elements indicate the cross-market spillover effects. The overall spillover between the return series is 39.37%.

Table 6: Spillover Effects among Markets using Diebold and Yilmaz Method

	rnifty	**rsp**	**rnikkei**	**rdax**	**rsse**	**From**
rnifty	**57.16**	15.33	8.17	17.79	1.55	8.57
rsp	13.72	**53.72**	6.80	22.91	2.85	9.26
rnikkei	6.93	17.16	**52.61**	21.13	2.17	9.48
rdax	14.22	22.45	9.14	**52.30**	1.89	9.54
rsse	1.92	4.04	2.42	4.23	**87.39**	2.52
To	7.36	11.80	5.31	13.21	1.69	**39.37**

Note: (Volatility spillover received by the market *p* from all other markets *q*) is represented by Equation 6:

$$S_{p.}^{g}(H) = \frac{\sum_{\substack{q=1 \\ p\neq q}}^{N} \tilde{\theta}_{pq}^{g}(H)}{\sum_{p,q=1}^{N} \tilde{\theta}_{pq}^{g}(H)} \times 100$$

Volatility spillover transmitted from the market *q* to all other market *p* is represented by Equation 7:

$$S_{.p}^{g}(H) = \frac{\sum_{\substack{q=1 \\ p\neq q}}^{N} \tilde{\theta}_{qp}^{g}(H)}{\sum_{p,q=1}^{N} \tilde{\theta}_{qp}^{g}(H)} \times 100$$

The internal market spillover is highest in rsse at 87.39%, followed by rnifty at 57.16%. The return series, rsp, rnikkei and rdax have an internal spillover of 53.72%, 52.61% and 52.30%, respectively.

Specifically, the rnifty receives 8.57% spillover from other return series and transmits 7.36% to others. The rdax has the most significant influence on rnifty, contributing 17.79 %, closely followed by rsp contributing 15.33%. The rsse has the least spillover effect on rnifty, contributing just 1.55%.

The rsp is most influenced by rdax with a significant spillover effect of 22.91%, followed by rnifty, contributing 13.72%. The spillover effect of rnikkei on rsp is 6.80%. The least significant spillover effect on rsp is that from rsse, totalling 2.85%, which is the highest contribution of rsse on any other return series.

The rnikkei receives 21.13% of spillover effect from rdax. This is followed by rsp, contributing 17.16% and rnifty 6.93%. The series rsse has the least influence of 2.17%.

Similarly, rdax receives 22.45% of spillover effect from rsp, 14.22% from rnifty, 9.14% from rnikkei and rsse contributes just 1.89%.

The spillover effect from other markets on rsse are relatively minor, with rdax contributing 4.23%, rsp 4.04%, rnikkei 2.42% and rnifty only 1.92%. The lowest spillover, both "from" and "to", is witnessed in rsse.

In the context of spillover effects between return series, the "From" value represents the percentage of the spillover effect that an index receives from other indices (Equation 6). On the other hand, the "To" value represents the percentage of the spillover effect that an index transmits to other indices (Equation 7). To ascertain whether an index is a net transmitter or net receiver, the spillover effect is calculated by subtracting the "From" value from the "To" value (Equation 8).

Table 7 provides a summary of the net spillover effect.

If the net spillover result is negative, the index is a Net Receiver. In other words, it absorbs more spillover than it transmits. If the net spillover result is positive, the index is a Net Transmitter, or it sends out more spillover than it receives.

Table 7: Net Spillover Effect (%) for Each Market

	To	**From**	**Net Spillover = To - From**	**Results**
rnifty	7.36	8.57	**-1.21**	Net receiver
rsp	11.80	9.26	**2.54**	*Net transmitter*
rnikkei	5.31	9.48	**-4.17**	Net receiver
rdax	13.21	9.54	**3.67**	*Net transmitter*
rsse	1.69	2.52	**-0.83**	Net receiver
Overall	**39.37**	**39.37**		

According to calculations in Table 7 (Equation 8), rnikkei, rnifty and rsse are net receivers of the spillover effect, whereas rdax is the largest net transmitter, followed by rsp. The rsse contributes the least to the spillover effect.

Discussion

The empirical GARCH analysis reveals that the Indian stock market is the most volatile among the five stock markets. While VDR for India is the lowest, China's VDR is the highest. A lower VDR means volatility persists longer, signalling higher risk. Investors may prefer assets with higher VDR for short-term strategies as these assets stabilise faster, potentially reducing exposure to prolonged volatility. VDR can influence decisions on when to buy or sell an asset.

The analysis of the DCC Model shows that the financial markets of China, Germany, India, Japan, and the US are dynamically interconnected with each other. These markets are influencing each other and at the same time, are being influenced by shocks or events of the other financial markets.

The DCC Model shows that long-term pair-wise spillover effects are present between all countries except between Germany and China. In this case, there is no significant long-term pair-wise spillover between Germany and China. However, short-term pair-wise spillover between Germany and China is significant, even though short-term pair-wise spillover is not significant for other countries. This short-term spillover between Germany and China underlines the substantial trade and investments between these two countries.

The magnitude of the spillover effect studied reveals that the internal spillover for indices of developed economies—namely, Germany, Japan, and the US, is lower than that of China and India. China is unique as it is largely self-driven with a high internal variability. China stands out as the least influenced by other markets, and at the same time, it has minimal spillover effects on the other markets, thus indicating its relative insulation. China has more internal spillover as compared to external spillover.

Further, the spillover effect shows that Japan, India, and China are net receivers, whereas the United States and Germany are net transmitters.

The findings of this study are in line with the research of Khan (2023), who found both the long-term and short-term spillover from the Indian market to BRICS countries, and with Jebran and Iqbal (2016), who found the existence of a spillover effect in different Asian market, i.e. Pakistan, India, Sri Lanka, China, Japan, and Hong Kong. A strong volatility spillover effect from the US to Japan and the Asian emerging market was documented by Li and Giles (2015) for long-term and short-term periods. A study by Vuong et al. (2022) also found the positive volatility spillover from China and US stock markets during the Covid-19 period which provided insight into the risk contagion between these markets. This presence of the interconnectedness between financial markets guides the investor in formulating their investment strategy in order to diversify their risk and maximise return. Zarezade et al. (2024) mentioned that emerging economies are the potential destination for Chinese investors to diversify their portfolios to reduce risk.

The study also measured the magnitude of the spillover effect amongst the five economies and found that the internal spillover for indices of developed economies—namely, Germany, Japan and the US, is lower than that of China and India.

Gamba-Santamaria et al. (2019) examined the magnitude of the spillover effect among the different global financial markets, namely, US, Brazil, Chile, Colombia and Mexico, indicating that Brazil is a net volatility transmitter while Chile, Mexico, and Colombia are net receivers.

Conclusion

The COVID-19 pandemic had a significant impact on the interconnectedness of these markets, as the global spread of the virus led to extensive economic disruptions and lockdowns. The consequences of the pandemic resulted in a significant decline in stock prices and increased volatility in global financial markets.

The financial markets of the major five economies of the world, as per GDP, exhibit a complex web of interconnectedness, wherein developments in one market can swiftly reverberate across others. These markets wield substantial influence on each other, both in terms of shaping market sentiment and reacting to external stimuli over extended periods.

The study concludes that the effect of an unprecedented pandemic impacted the financial markets around the world. The interconnectedness of the markets resulted in greater volatility in most of the markets except in China, which continued to remain an isolated market.

China's Shanghai Stock Exchange (SSE) stands out due to its tightly regulated nature by the state, leading to a pronounced prevalence of internal spillover effects. Despite its more insulated nature, immediate transmission of news is observed in the short-term, particularly between Germany and China, underscoring the substantial bilateral trade and investment ties between the two nations. The observations of minimal spillover, both outbound and inbound, in the return series of the Chinese SSE highlight its unique position within the global financial ecosystem, characterised by a combination of regulatory controls, domestic market dynamics, and evolving economic factors.

Investors focusing on long-term investments need to be aware of the interconnectedness because they may experience spillovers from other markets over time. However, this does not imply that they should avoid long-term investments. Instead, they should consider diversifying their portfolios or hedging against potential risks.

This study provides a guideline to the market participants for making informed decisions regarding diversified portfolios and enhancing their risk-adjusted returns. Investors need to develop more robust risk management practices and investment strategies so that they can construct an optimal portfolio and acquire abnormal returns from the selected markets.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and publication of this article.

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