International Journal of Accounting and Economics Studies, 12 (5) (2025) 1050-1061

International Journal of Accounting and Economics Studies

Website: www.sciencepubco.com/index.php/IJAES
https://doi.org/10.14419/wvbbkc30
Research paper

Connectedness and The Impact of Major Spillovers on Global Stock Markets: An Empirical Analysis

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Received: August 12, 2025, Accepted: September 21, 2025, Published: September 27, 2025

Abstract

The diversity of the global stock market composition depicts distinct degrees of cross-market contagion. Market contagion plays a prominent role in the transmission mechanism. Significant increases in Spillovers were observed after the October 1989 stock market fall. The economists developed an interest in analysing the spillovers after the middle of the 1990s with the extension of financial crises amidst the advanced and emerging economies. Highly advanced and developed nations were also influenced, whose procedures and strategies were applauded by market specialists and financial institutions. DCC-GARCH and BEKK-GARCH were used to evaluate the spillover effect between the global stock markets. This study examines the major spillover impacts on the global stock markets. In this study, the [Joint]dccα1 showed that in the short-run spillover between variables, all the variables had significant p-values, which indicate the short-run spillover except SSE, ASX-200, and TSX, where p-values are insignificant. The [Joint] dccβ1 shows the long-run spillover between variables; all the variables show the long-run spillover as their p-values are significant. They also show a strong positive correlation between variables, as the coefficients are near 1. BEKK-GARCH authorised the results, showing strong positive conditional correlation between the global stock exchanges.

Keywords: *BEKK-GARCH Model; DCC-GARCH Model; Return Spillovers; Stock Markets; Volatility Spillovers.*

1. Introduction

"Stock Market" delegates to the fusion of markets and exchanges where uniform operations of selling, buying, and issuance of securities of publicly listed organizations prevail (Meher and Mishra, 2025).These monetary trade practices are channelled via publicly traded Stock Exchanges or Over-The-Counter (OTC) marketplaces that are governed by a set of policies and guidelines (Khan et al., 2024). It involves financial markets and institutions, investors, services, and regulators. The stock market is also called the Equity Market (Strielkowski, 2024). The term "Stock Exchange" refers to an exchange where selling and buying shares of stock, bonds, and other securities takes place through traders and stock brokers (Karkera, 2024). Although the terms stock market and stock exchange are often used interchangeably, the former is a more general term and the latter a more specific one (Kosowski and Neftci, 2015).Globalisation is an ancient concept. Traders in ancient times used to travel longer distances to different nations to purchase precious and rare goods or products at a cheaper value and then sell them at higher prices in their homelands (Raczynski, 2023). According to the WHO, Globalization can be referred to as "the increased interconnectedness and interdependence of peoples and countries (Oliveira et al., 2024). It is generally understood to include two interrelated elements: the opening of international borders to increasingly fast flows of goods, services, finance, people, and ideas; and the changes in institutions and policies at national and international levels that facilitate or promote such flows (Mendez Ramos, 2025). In the 19th century, the Industrial Revolution brought development in transportation and communication between nations of the world (Simkovits, 2025). The evolution of economic systems has multiplied industrialization and financial opportunities in several countries. Technological developments in international cooperation have connected the world more than ever (Chen et al., 2025). Globalization, in the context of economics, refers to the increased free trade among nations that has led to greater economic dependence among them. Globalization enhances the manufacturing of products/goods, diversification, economic expansion, and paradigm of living (Lestari and Aslama, 2024). It helps in creating jobs in the developing economies, which in turn helps them to flourish. Now the governments of different nations are engaged in removing trade tariffs and promoting international commerce (Bojnourdi et al., 2024). Internationalization provides opportunities for investors to invest their money in different stock markets around the world (Sarwar, 2022). Numerous studies have been done on the relationship between the world's stock markets by applying different econometric tools (Narayan and Phan, 2019). With globalization, investors feel relaxed to invest their savings in different stock markets of both developed and developing nations because of the ease in restrictions and development of new policies via the governments that safeguard their investments (Han et al., 2024).Securities involve both stocks and bonds and are traded in several stock markets throughout the world (Bilani and Harb, 2014). The stock market manages the buying and selling operations of stocks. The International Stock Market refers to all the international markets that trade stocks from their domestic companies (Solano-Pereira et al. 2025). The instability in the value of stocks is tracked by the indexes. Every stock exchange has its own index to monitor the fluctuations (Bebarta et al. 2012). Some of the indexes are Nifty-Fifty(S&P) and SENSEX(S&P) operated in India, Dow Jones in New York, Nikkei 225 in Japan, NASDAQ in London, and so on. Most financial assets offer investment opportunities (Gao and Zhao, 2023). The international stock market allows corporations to raise a large sum of capital than a single market and also allows investors to possess stocks in a greater number of countries (Al-Nasseri et al. 2021). So, the investors combine domestic as well as international assets. In case of foreign investments, risks are higher because of the currency fluctuations (Checkley et al. 2017). BRICS countries played a vital role in the global economy not only as large producers and consumers of goods and services, but as investment hubs for international investors (Ni et al. 2015). Foreign investors prefer to invest in BRICS countries because of higher investment returns than other developed economies (Y. Wang et al. 2023). Spillover refers the impact of uncertain events in one economy on the other global economies (Liu and Zhang, 2025). The spillover effect can be both positive as well as negative, but generally it is considered as negative impact examples are earth quakes, financial crunches, stock market crashes or other macro level events (Yang and Zhou, 2015). The spill overs in monetary world are of different types like domino effect, the contagion effect, and financial crises. Since the globalization of economies, spillover effects have increased in the trade and capital market world (Liu et al., 2025).A drawback of globalisation is that a downturn in one nation's economy can spread to that nation's trading partners. The economic crunch in September 2008-2009 in the United States is one of the best examples of the spillover effect (Li et al. 2025). Abundant literature is readily available to study the influence of spill overs on the global stock markets (Zhang, 2025). The studies are mostly focused on the developed economies and less on the developing or emerging economies of the world (Bhuyan et al., 2016). Distinct models and techniques were developed to study the spill-over influence on the capital stock markets. After the 1987 stock market's miserable turn, the global stock markets were inflated. The US 2008-2009 economic downfall left the worst effect on the world stock markets, which in turn left an impact on the investing decisions and strategies of investors (Ben Omrane et al., 2017). Investors became more cautious and started questioning their investment plans/strategies (Zhou et al., 2022).From these results, the world stock markets are interlinked with each other. This research focuses on examining the effects of significant spillovers on the international stock markets.

2. Review of Literature

After the financial crunch in the US economy, the implications can be seen widely across the world. About every economy gets halted by this contagion (Marsh and Sharma, 2024). The markets suffered a heavy blow. As a result of the emergency subprime losses that occurred in 2007, the financial crises that occurred in 2008 and 2009 had an impact on a variety of speculative loans and the prices of assets that were over-inflated (W. Wang et al., 2025). Due to heavy losses on loans, the Lehman Brothers bank became bankrupt on September 29, 2008, and at this moment, the US market index fell by 6.9% (Shahbaz et al., 2022). After the financial crisis, it was seen that the sectional and global stock markets had differential wallops on the Indian markets, both in the long and short run (Liu et al., 2025). By evaluating the volatility spillover between the stock indices of 16 EMEs and MMEs, it was found that the financial crisis of 2008-2009 left a significant impact on the stock market returns (Sehgal and Garg, 2016). The co-integration relationship of the Indian stock market with the US and UK was higher than that with Singapore and Hong Kong (Doman and Doman, 2013). The investors' risk appetite altered after the global financial spill over, which has led to deductions for portfolio losses and rebalances (Mensi et al., 2021).
In the 19th century, in October 1987, when the Dow Jones Industrial Average (DJIA) fell by 508.32 points, it shook the global stock markets and triggered financial spillovers. Stock markets like Hang Sang fell by 45.5%, ASX by 41.8%, FTSE by 26.45%(Eun and Shim, 1989). Approximately 600 million shares were traded on the Dow Jones on the day. But after 2007, Dow Jones reached a time high index. This proves that the global stock markets are linked to each other (Natarajan et al., 2014). During the Asian financial crisis, there was no increase in integration between Asian countries, but during and after the spillover effect, a significant increase was found in the co-integration relationships between the Asian countries (Erel et al., 2013). During these crises, the degree of interdependence has greatly increased, indicating the presence of spillover effects in the region (Yang et al., 2020). The Asian financial crisis of 1997-1998 also left an adverse effect on the ASIAN market, but had the least effect on Japan and the US stock markets because these two are the key players in the international stock markets (Liew et al., 2022). The studies investigate the effects of the 1997–1998 Asian financial crisis on the United States and the Greater China Economic Area (Martínez-Ruiz and Pons, 2014). There is a unilateral relationship between the US and Hong Kong and China, but no causal relationship between the US and Taiwan. Later, after the crisis, bi-lateral causality existed between the US and the Greater China Economic Area stock markets (H. Wang et al., 2025).
There is an increase in the possibility of spillovers on both a national and worldwide scale because of the operation of the market and the integration of financial systems. The asset pricing approach and portfolio investment strategy became more challenging as a result of this (Mi et al., 2025). The risk exposure has changed from international to national matters of the economy (Charles et al., 2017). Due to the US financial crisis 2008-2009, not only researchers but also policy makers and investors have changed their interest in financial markets (Bas et al., 2024). The research indicates that there are high levels of dependence persistence for all market pairs during both bullish and bearish markets (Su, 2017). Highlighting the importance of volatility, claims that data is disclosed in the fluctuation of stock prices rather than the price itself (Greenwood-Nimmo et al., 2025). Volatility and the frequency of data flow were discovered to be positively correlated (Ağca and Mozumdar, 2008). The impact of an innovation from one market on the conditional variance of another market is referred to as "volatility spillovers." (Gagnon and Andrew Karolyi, 2010). The construction of a high-dimensional financial network is accomplished through the utilization of the D-vine copula quantile regression and copula entropy approaches. These techniques are utilized to identify nonlinear dependencies and choose essential predictors (Nankali et al., 2025).
Volatility spillover plays a prominent role in portfolio management for developing investment strategies. Increased integration and financial markets generate a significant phenomenon for policymakers because a shock in a financial market generates fluctuations in emerging financial markets (Kirikkaleli 2020).

3. Methodology

The multivariate generalized autoregressive conditional heteroscedasticity (GARCH) model proposed by Engle (2002), which is used to estimate dynamic conditional correlations (DCC) (Correlations between variables like asset returns that are not constant, but instead change over time, depending on recent market movements or shocks), has three advantages over other estimation methods. First, the

DCC–GARCH model estimates correlation coefficients of the standardized residuals and thus accounts for heteroscedasticity (the variance of the error terms in a regression is not constant across observations) directly. Second, the model allows for including additional explanatory variables in the mean equation to ensure that the model is well specified. Third, the multivariate GARCH model can be used to examine multiple asset returns without adding too many parameters. However, it does not account for the asymmetries in conditional variances, covariances, and Correlations. (Toyoshima and Hamori, 2013) Recently, an asymmetric version of the DCC (asymmetric dynamic conditional correlation) [ADCC] (where positive and negative shocks affect correlations differently) model was developed to deal with the asymmetries in conditional variances, covariances, and correlations of two assets and correlations. The present study tests the existence of co-movement of the US financial subprime crisis between the National Stock Exchange (NSE) and selected International Stock Exchanges (ASX-200, DAX, EURONEXT-100, HSI, KRX, LSX, NASDAQ, NIKKEI-225, NYSE, SSE, SWX, TSX, and TWSE) by a multivariate DCC-GARCH model proposed by Engle (2002) and Engle and Sheppard (2001). Following Bollerslev et al. (1992), Engle (2002), and Engle and Sheppard (2001), the DCC-GARCH model posits that the conditional covariance matrix of asset returns can be separated into the conditional variance of each asset return and the conditional correlation matrix among asset returns. Mathematically, the conditional covariance matrix H_t At time t, it is given by:

$$h_t = D_t R_t D_{t,} \quad (1)$$

h_t is the estimator of conditional correlation.

$$D_t = diag\left\{h^{\frac{1}{2}}{}_{i,t}\right\} \quad (2)$$

D_t is the diagonal matrix of the dynamic correlation matrix.

$$R_t = diag\left(q^{\frac{1}{2}}{}_{i,j,t}\right) Q_t diag\left(q^{\frac{1}{2}}{}_{i,j,t}\right) \quad (3)$$

$R_t$is the dynamic correlation matrix, and Q_t is a positive definite matrix.

$$Q_t = c + \alpha\varepsilon_{t-1}\varepsilon'{}_{t-1} + \beta Q_{t-1} \quad (4)$$

Where α and β are the ARCH and GARCH terms, respectively.
Dynamic condition correlation coefficient (ρijt) is represented as:

$$\rho_{ijt} = \frac{q_{ijt}}{(q_{iit}q_{jjt})^{\frac{1}{2}}} \quad (5)$$

The mathematical presentation of the mean equation is as follows

$$R_t = \mu + €_t \quad (6)$$

Co The variance matrix equation is as follows:

$$H_t = D_t R_t D_t \quad (7)$$

Where, D_t is a diagonal matrix
R is a correlation matrix.
The GARCH-BEKK model, established by Engle and Kroner in 1995, is commonly employed to represent conditional variances, especially in research that examines the transmission of volatility (the way uncertainty or risk in one market, asset, or time period spills over into another) among markets.Bala and Takimoto, 2017);(Arouri et al., 2015); (Olson and Zoubi, 2017). To evaluate the conditional covariance structure across commodity futures, for example, Chang (2009) used a tri-variate complete BEKK-GARCH model, which captures economic bonds. This model effectively incorporates the impact of previous variability on the relationship between different markets, which is essential for knowing cross-market dynamics (Climent and Soriano, 2011). It is crucial to incorporate the covariance factor in the equation for conditional variance to accurately represent these interactions.
The BEKK-GARCH Model is specified as:

$$H_{(t)} = C'C + A'u(t-1)u'(t-1)A + B'H(t-1)B \quad (8)$$

C is the lower triangular matrix, while A and B are general nxn matrices. Thus, every term is an affirmative semi-definite by construction. This part of financial modelling explains how particular matrices, namely positive semi-definite and lower triangular, are utilized to conduct risk analysis in a scenario involving two assets. The model generates the conditional variance by considering previous shocks and previous conditional variances of each asset (which are represented by the matrices). This allows the model to anticipate future volatility based on historical data effectively.

4. Data and Summary Statistics

The study looks at daily closing stock prices of the stock exchanges for a period from 2 April 2001 to 31 March 2022. The data were collected from the Bloomberg database. The validity of the data was checked from the respective stock exchange websites. The US financial subprime crisis acts as a structural break. The study has considered April 2007 to March 2009 as the crisis period. The stock indices used for the study are the most important benchmark indices for each country. All the national stock price indices are in local currency, dividend-unadjusted, and based on daily closing prices in each national market. Following the conventional approach, stock returns are calculated as the first difference of the natural log of each stock price index, and the returns are expressed as percentages. In this study, Interpolation was used to address missing data, which mostly resulted from market holidays. The moving average approach was employed because it offers a straightforward but trustworthy means of estimating the missing values and smoothing out volatility. This method prevented significant distortions while guaranteeing the dataset's continuity. The use of moving averages has no discernible impact on the results' robustness because the percentage of missing data was so small. The descriptive statistics of stock index returns in NSE and the selected International Stock Exchanges are presented in Table 1. Table 1 shows that in the crisis period, NSE is relatively risky compared to other stock exchanges. The standard deviation, which is a simple measure of risk, is the highest for NSE and lowest for the US during the entire sample period. The negative skewness coefficient for the USA is seen during the crisis period, implying that the frequency distribution of the return series no longer tails to the right. Another noteworthy statistic of the stock return series shown in Table 1 is a high value of Jarque-Bera. This suggests that, for these markets, big shocks of either sign are more likely to be present and that the stock return series may not be normally distributed.

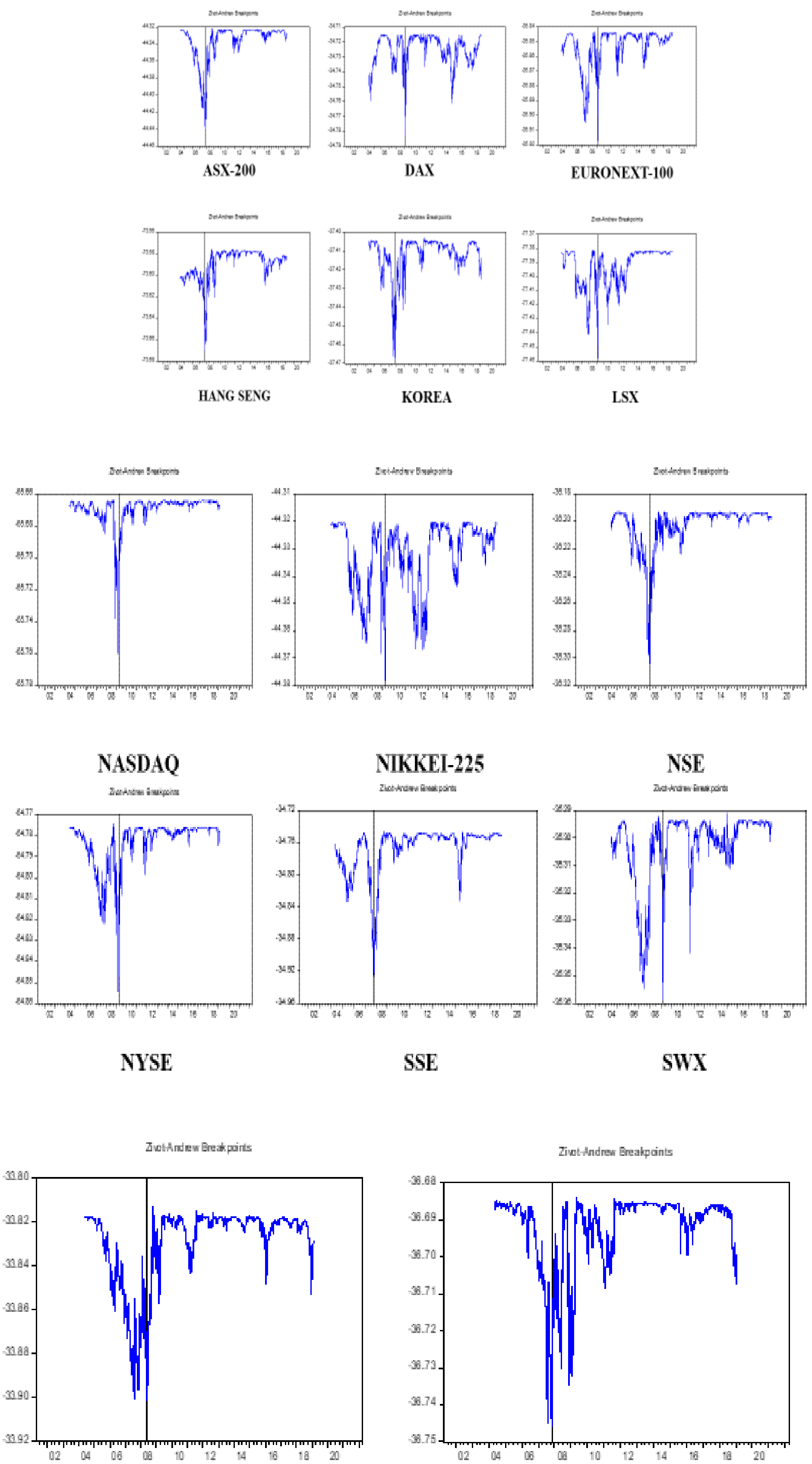
Table 1: Descriptive Statistics of Stock Exchanges

	ASX-200	DAX	EURONEXT-100	Hang Seng	KOREA	LSX	NASDAQ	NIKKEI-225	NSE	NYSE	SSE	SWX	TSX	TWSE
Mean	0.0002	0.0002	0.0001	0.0001	0.0003	0.0006	0.0004	0.0001	0.0005	0.0002	0.0001	0.0001	0.0002	0.0002
Median	0.0006	0.0008	0.0006	0.0006	0.0007	0.0000	0.0008	0.0006	0.0007	0.0005	0.0006	0.0006	0.0007	0.0007
Maximum	0.0541	0.1080	0.1032	0.1018	0.0721	0.2667	0.1116	0.0949	0.1633	0.1153	0.0940	0.1133	0.0696	0.0652
Minimum	-0.0761	-0.0887	-0.0895	-0.0929	-0.1280	-0.1853	-0.0959	-0.1211	-0.1305	-0.1023	-0.0926	-0.1140	-0.1083	-0.0691
Std. Dev.	0.0092	0.0138	0.0126	0.0131	0.0125	0.0210	0.0132	0.0139	0.0128	0.0110	0.0149	0.0115	0.0092	0.0117
Skewness	-0.5530	-0.1544	-0.1473	-0.1161	-0.6174	0.6614	-0.0782	-0.5713	-0.3385	-0.5153	-0.3282	-0.2857	-0.8374	-0.2864
Kurtosis	8.5466	8.5917	9.1750	8.5488	9.0693	20.5553	8.7682	9.4084	15.3826	13.0769	8.2720	14.0812	13.1558	6.7973
Jarque-Bera	7301.3510	7158.5480	8723.2360	7039.9510	8755.8330	70743.7800	7600.0570	9671.6870	35101.7100	23419.6100	6442.3360	28101.8600	24182.1700	3366.0830
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

The Zivot-Andrews test is a statistical test employed in econometrics to ascertain the stationarity of a time series. The Zivot-Andrews test is specifically designed to consider potential structural discontinuities in the time series data, a factor that the ADF (Augmented Dickey Fuller) The test does not consider. This test identifies the break in the time series that has the most substantial influence, out of all the breaks present.

Table 2: The Unit Root and the Structural Break were calculated by employing the ZA Test, which shows the following results

S.NO.	Stock Exchange	T-Statistic	Probability
1.	ASX-200	-44.43973	0.004663
2.	DAX	-34.78298	0.023430
3.	EURONEXT-100	-35.91694	0.022932
4.	HSI	-73.66986	0.027469
5.	KSX	-37.46769	0.022136
6.	LSX	-77.45799	0.017518
7.	NASDAQ	-55.75967	0.002731
8.	NIKKEI-225	-44.37836	0.033837
9.	NSE	-36.30504	0.003775
10.	NYSE	-54.85421	0.012807
11.	SSE	-34.92632	0.000543
12.	SWX	-35.35892	0.027153
13.	TSX	-33.90135	0.031907
14.	TWSE	-36.74576	0.044020



TSX TWSE

Fig. 1: Structural Break Points Across Major Stock Markets

In Table 2, the ZA test clearly showed that the series is stationary at level 1 and there is one significant structural break from 2007 to 2009, the US financial crisis. In Figure 1, the graphs clearly visualize that there is one significant structural break (the US financial crisis) in all the selected stock exchanges during the period ranging from 2007 to 2009.

The GARCH model, which Robert Engle established in the 1980s, is one that is intended to model the time-varying volatility that is present in the financial markets. Volatility clustering is the assumption that the variance of a financial time series is not constant but rather varies over time and is reliant on previous squared observations. This is the assumption that is made. It was specifically built to manage numerous time series at the same time. When modelling the behaviour of many assets, where the returns and volatilities of one item may be related to those of other assets, this is an important consideration.

Assumptions:

a) It is important to evaluate the values of alpha1 and beta1 separately. If the values are affirmative and substantial, this indicates that volatility is still present.
b) Examine the total of the alpha1 and beta1 values for both series: If the value is less than one, this indicates that the volatility persistence has decreased over time. Determine which of the series is rapidly deteriorating.
c) If dcca1 and dccb1 are both positive and substantial, the extent of spillover is both short-term and long-term. [correlations that are close to one percent are strong, close to five percent are moderate, and below five percent are low]
d) If the total of dcca1 and dccb1 is less than 1, it indicates that the DCC values are time varying.

These assumptions combined provide a comprehensive investigation of volatility persistence, spillover effects, and time-varying correlations, which are essential for fulfilling the study's aims.

The data presented in Table 3 displays the estimates and corresponding p-values for different parameters associated with financial time series data. These parameters are related to various returns, NSE/SWX, NSE/SSE, NSE/EURONEXT-100, NSE/ASX-200, NSE/DAX, NSE/HSI, NSE/KSX, NSE/LSX, NSE/NASDAQ, NSE/NIKKEI-225, NSE/NYSE, NSE/TWSE, and NSE/TSX. The estimates consist of parameters represented as [A]α1, [A]β1, [B]α1, [B]β1, [Joint]dccα1, and [Joint]dccβ1, along with their respective p-values. The variables α1 and β1 reflect the measures of conditional volatility and conditional correlation, respectively. [joint]dccα1 denotes the conditional volatility between variables. The term [Joint]dccβ1 denotes the measure of the conditional correlation between variables. The sum of [Joint]dccα1 and [Joint]dccβ1 should be less than one. If the value is less than one, then the conditional correlation between variables are dynamic, i.e., it is time varying. These estimations refer to statistical and economic measurements concerning the conditional volatility, correlation, and joint dynamics of these stock indices.

The DCC GARCH model is designed to incorporate two parameters, primarily (α) and (β), to consider the vigorous nature of correlations in the volatility of the asset market. Each of these characteristics is time-dependent and reflects the changing linkages that exist between asset values over the course of time. A precise quantification of the short-term persistence of volatility shocks is provided by the coefficient (α), which indicates the extent to which the unexpected price movements that occurred yesterday influenced the volatility that occurred today. The coefficient β, which is a component of the DCC GARCH model, serves to quantify the residual impact of previous volatility shocks on the conditional correlations that exist between asset prices. This parameter indicates the length of time that the effects of previous events continue to have an influence on the correlation dynamics that are now being observed. It depicts the persistence of shocks in the correlation dynamics. A constraint that ensures the stability of the model is that the sum of (α) and (β) is less than one. This constraint prevents correlations from becoming permanently set at previous values, which enables dynamic modifications to be made over time. There appears to be a significant correlation in volatility among the various assets, as seen in Table 3. The spillover effect, which was detected across all variables and pairings of variables over the course of the long run, is proof of this observation. The fact that the individual values of alpha and beta are both positive and substantial lends credibility to the persistence volatility. Moreover, the sum of alpha and beta for all of the series is less than 1, which indicates that the volatility persistence has decreased over the course of time. For all pairs in the DCC model, the Joint β coefficient is greater than 0.9, which suggests that the shock impact has a very strong and persistent effect on the conditional correlations between the variables. It may be deduced from this that shocks to one variable have a considerable and long-lasting impact on the correlations with another one. In addition, the study emphasizes the fact that volatility continues to exist throughout time. Also, it has been suggested that the implementation of structural breaks can assist in the reduction of this persistent behavior. During the financial crisis that occurred in the United States, a consistent pattern of dynamic correlations emerged across all variables. This pattern was visible in the DCC graphs (Figure 2) as well. All the factors appear to be interconnected in a way that there exists both a strong and long-lasting effect after considering this.

Table 3: DCC-GARCH Results of NSE and selected International Stock Exchanges

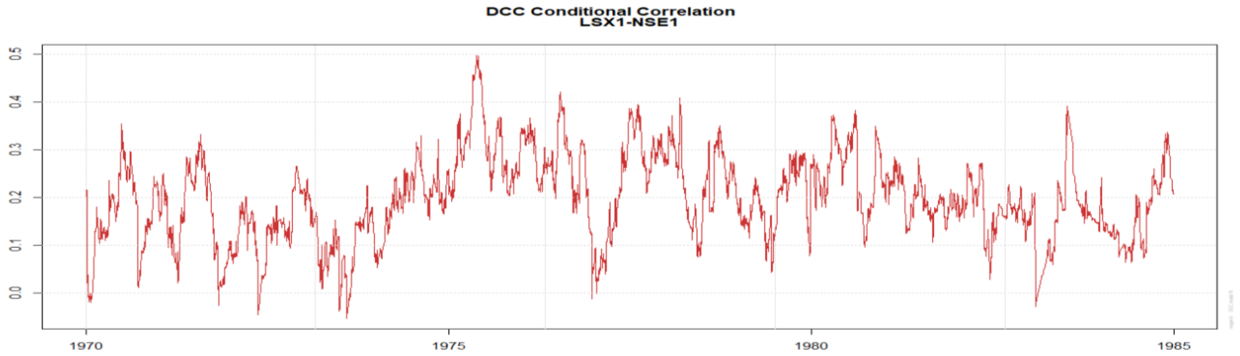
		NSE/SWX		NSE/SSE		NSE/EURONEXT-100		NSE/ASX200		NSE/DAX	
S. No.		Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
1.	[A]α1	0.124787	0.000318	0.124787	0.000334	0.124787	0.000315	0.124787	0.000328	0.124787	0.000314
2.	[A]β1	0.869228	0.000000	0.869228	0.000000	0.869228	0.000000	0.869228	0.000000	0.869228	0.000000
3.	[B]α1	0.141943	0.000000	0.081307	0.199269	0.118396	0.000000	0.098920	0.552425	0.100146	0.000000
4.	[B]β1	0.811987	0.000000	0.916112	0.000000	0.866356	0.000000	0.887312	0.000002	0.883137	0.000000
5.	[Joint]dccα1	0.021497	0.004863	0.003509	0.057283	0.016342	0.004781	0.017860	0.058909	0.017029	0.011623
6.	[Joint]dccβ1	0.951230	0.000000	0.994933	0.000000	0.966652	0.000000	0.954808	0.000000	0.966810	0.000000

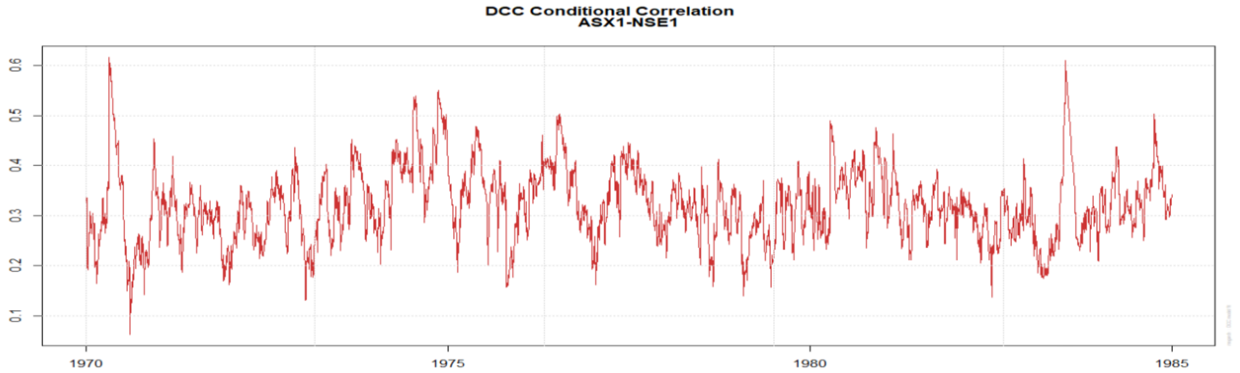
Table 3: DCC-GARCH Results of NSE and selected International Stock Exchanges

		NSE/LSX		NSE/NASDAQ		NSE/NIKKEI225		NSE/NYSE		NSE/TWSE	
S. No.		Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
1.	[A]α1	0.124787	0.000329	0.124787	0.000330	0.124787	0.000332	0.124787	0.000327	0.124787	0.000321
2.	[A]β1	0.869228	0.000000	0.869228	0.000000	0.869228	0.000000	0.869228	0.000000	0.869228	0.000000
3.	[B]α1	0.216661	0.007028	0.125546	0.000000	0.111870	0.000000	0.129129	0.000333	0.080494	0.235334
4.	[B]β1	0.782339	0.054118	0.852310	0.000000	0.868081	0.000000	0.849067	0.000000	0.912065	0.000000
5.	[Joint]dccα1	0.015394	0.006646	0.002597	0.001818	0.013109	0.008628	0.002405	0.014656	0.016131	0.004302
6.	[Joint]dccβ1	0.969471	0.000000	0.996973	0.000000	0.950400	0.000000	0.997350	0.000000	0.944526	0.000000

Table 3: DCC-GARCH Results of NSE and selected International Stock Exchanges

		NSE/TSX		NSE/HSI		NSE/KSX	
S. No.		Estimate	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Pr(>|t|)
1.	[A]α1	0.124787	0.124787	0.000331	0.124787	0.000327	0.000332
2.	[A]β1	0.869228	0.869228	0.000000	0.869228	0.000000	0.000000
3.	[B]α1	0.113775	0.062372	0.930369	0.075788	0.004550	0.011391
4.	[B]β1	0.873326	0.927625	0.243533	0.918839	0.000000	0.000000
5.	[Joint]dccα1	0.004663	0.015536	0.043956	0.020433	0.000026	0.339877


DCC Conditional Correlation
LSX1-NSE1
0.0
0.1
0.2
0.3
0.4
0.5
1970
1975
1980
1985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ASX1-NSE1
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0.2
0.3
0.4
0.5
0.6
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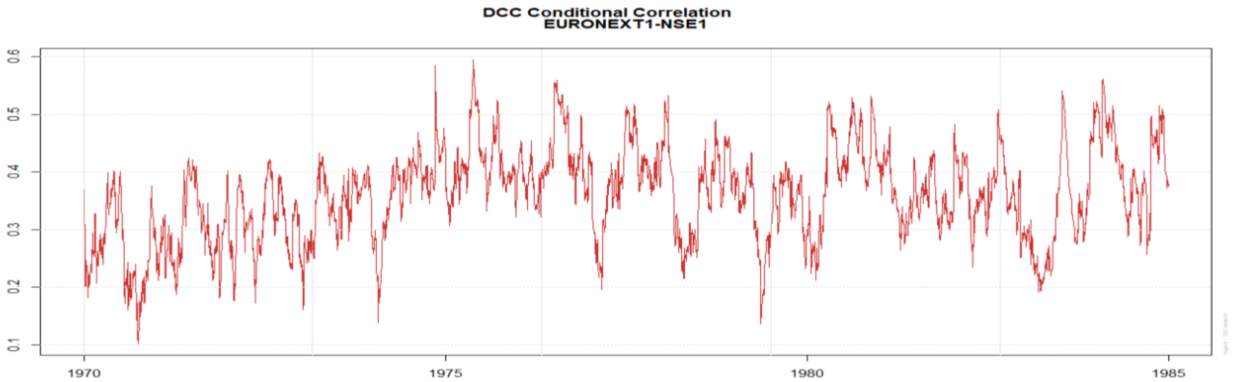
1975
1980
1985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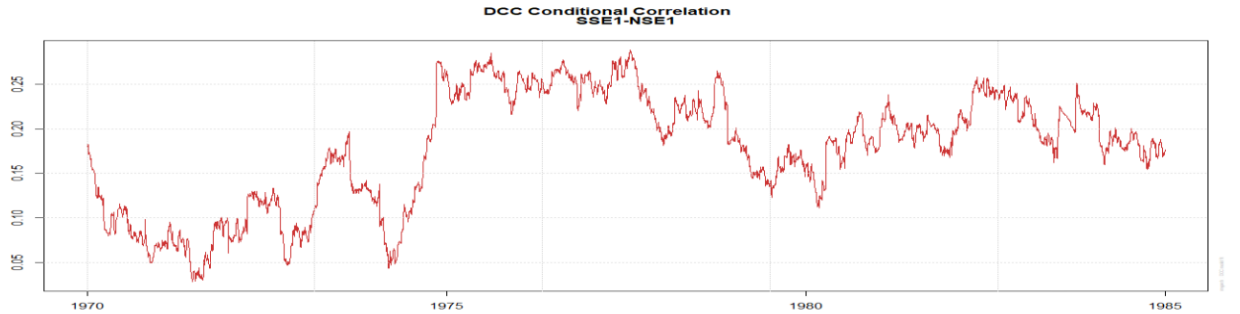
0.3
0.4
0.5
0.6
1970
1975
1980
1985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SSE1-NSE1
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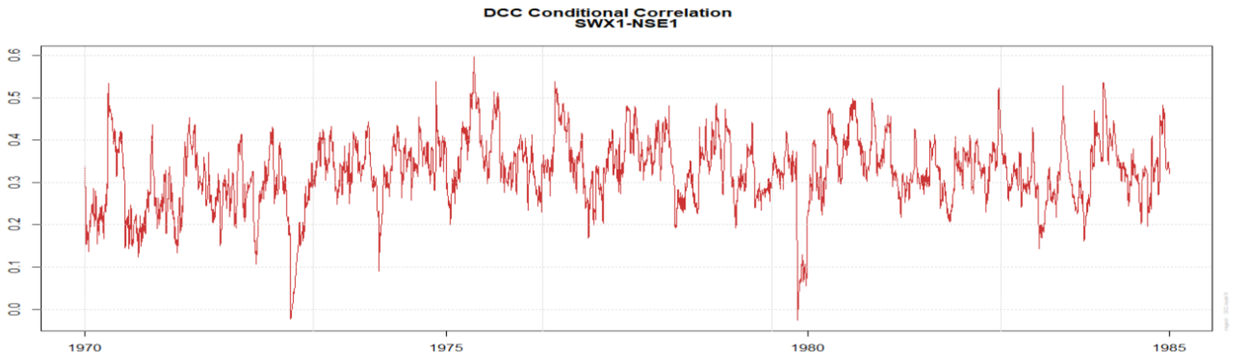
0.10
0.15
0.20
0.25
1970
1975
1980
1985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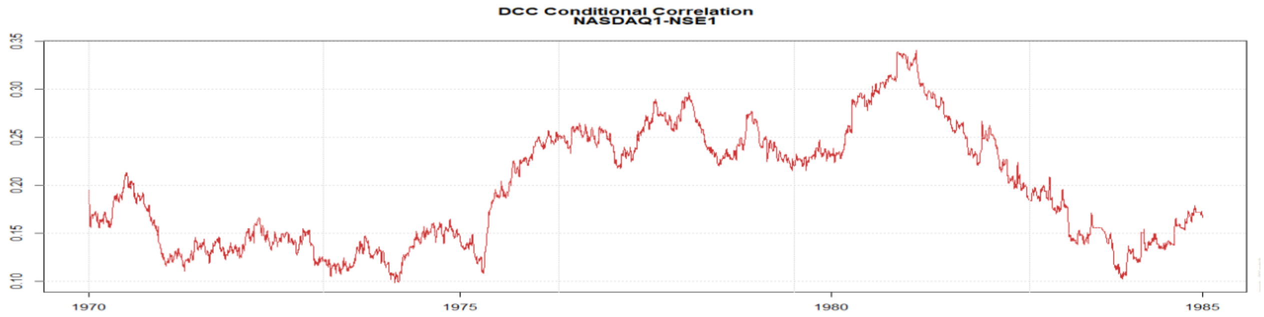
0.3
0.4
0.5
0.6
1970
1975
1980
1985


DCC Conditional Correlation
NASDAQ1-NSE1
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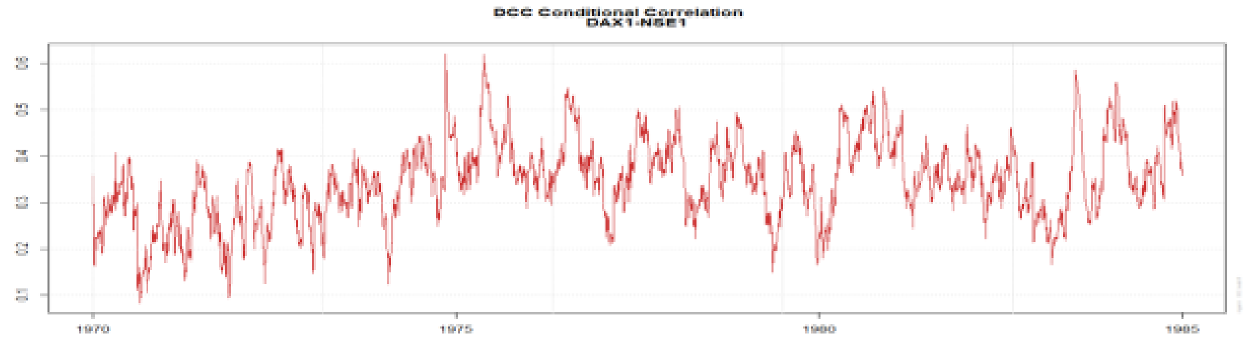
0.10
1970
1975
1980
1985


DCC Conditional Correlation
DAX1-NSE1
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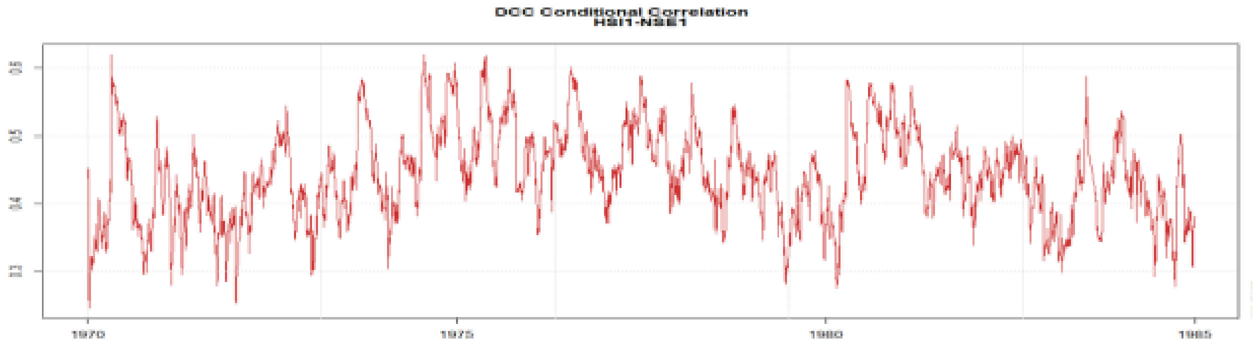
1975
1980
1985


DCC Conditional Correlation
HSI1-NSE1
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1970
1975
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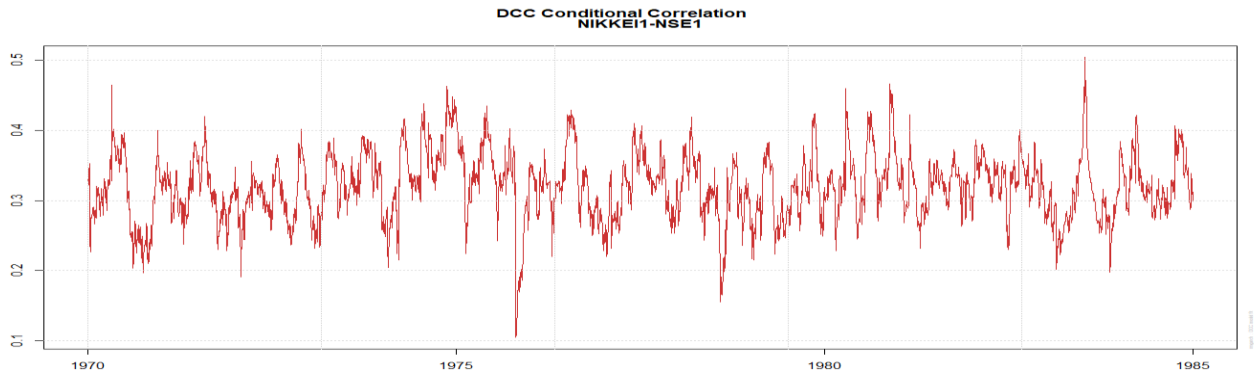
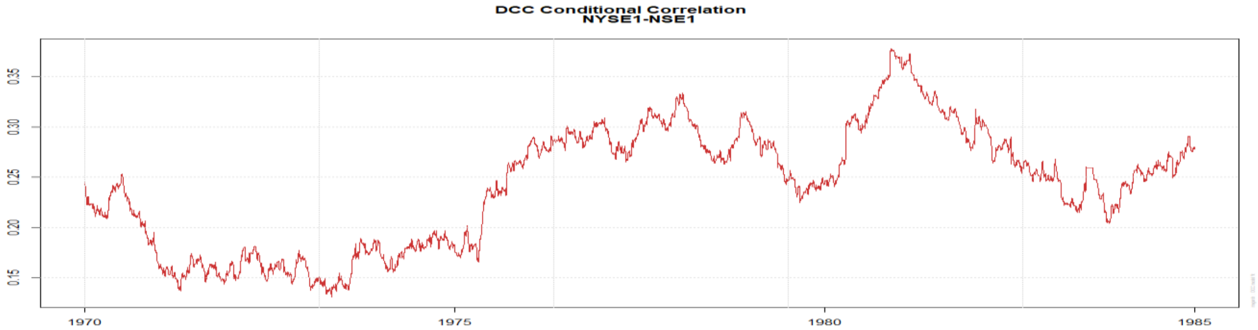
1985


DCC Conditional Correlation
NIKKEI1-NSE1
0.5
0.4
0.3
0.2
0.1
1970
1975
1980
1985


DCC Conditional Correlation
NYSE1-NSE1
0.35
0.30
0.25
0.20
0.15
1970
1975
1980
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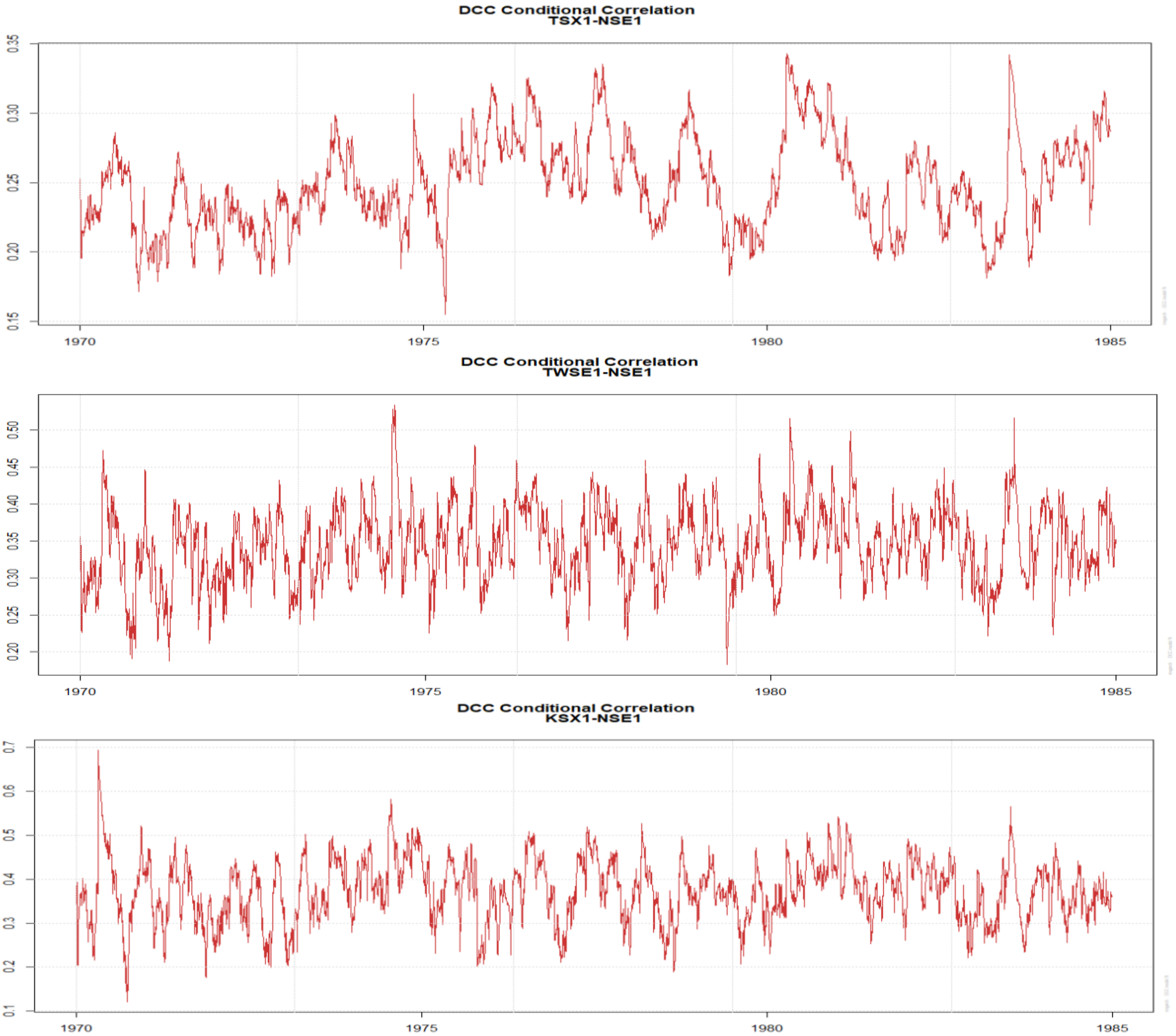

Fig. 2: Conditional Correlation Patterns of NSE with Global Stock Exchanges

Figure 2 visualizes the time-varying conditional correlations among the variables within the DCC model. The figures indicate that correlations surged significantly during the U.S. financial crisis, underscoring significant interdependence in periods of distress. The connections were consistently elevated even post-crisis, indicating enduring impacts of disturbances. The uniformity of this pattern among all pairs suggests that volatility transmission is systemic rather than isolated. The figures substantiate the existence of strong, persistent conditional correlations among the variables across time.

BEKK-GARCH Model

To authorize the above results calculated by employing DCC-GARCH, BEKK-GARCH is used:

Table 4: BEKK-GARCH Results of NSE and selected International Stock Exchanges

VARIABLE	SWX	SSE	EURONEXT100	ASX-200	DAX	HSI	KRX
MEAN	0.0004	0.0001*	0.0005	0.0004	0.0006	0.0004	0.0004
MEAN (NSE)	0.0007	0.0007	0.0007	0.0007	0.0008	0.0007	0.0007
C(1,1)	0.0014	0.0016	0.0014	0.0012	0.0014	0.0015	0.0015
C(2,1)	0.0008	0.0004	0.0005	0.0005	0.0005	0.0006	0.0006
C(2,2)	0.0020	0.0011	0.0014	0.0009	0.0016	0.0009	0.0005
A(1,1)	0.3078	0.3187	0.3164	0.2816	0.3126	0.3327	0.3345
A(1,2)	0.0125*	0.0168*	0.0239	0.0139	0.0252*	0.0509	0.0578
A(2,1)	-0.0096*	0.0117*	0.0080*	0.0650	-0.0306	0.0115*	0.0250*
A(2,2)	0.3455	0.2471	0.2954	0.2712	0.2799	0.2074	0.1976
B(1,1)	0.9479	0.9409	0.9450	0.9557	0.9449	0.9365	0.9350
B(1,2)	-0.0015*	-0.0091*	-0.0045*	-0.0039*	-0.0069*	-0.0162	-0.0208
B(2,1)	-0.0002*	-0.0011*	-0.0044*	-0.0213	0.0088*	-0.0006*	-0.0032*
B(2,2)	0.9154	0.9680	0.9473	0.9560	0.9516	0.9759	0.9799

Source: Author's Calculations

Table 4: BEKK-GARCH Results of NSE and selected International Stock Exchanges

VARIABLE	LSX	NASDAQ	NIKKEI225	NYSE	TWSE	TSX
MEAN	0.0009	0.0006	0.0004	0.0004	0.0005	0.0004
MEAN (NSE)	0.0006	0.0007	0.0008	0.0007	0.0008	0.0008
C(1,1)	0.0012	0.0013	0.0014	0.0014	0.0015	0.0015
C(2,1)	0.0002*	-0.0001*	0.0009	0.0001*	0.0007	0.0002
C(2,2)	0.0035	0.0018	0.0016	0.0014	-0.0007	0.0008
A(1,1)	0.2576	0.2957	0.3117	0.3024	0.3253	0.3190
A(1,2)	0.0150*	0.0170*	0.0675	0.0220	0.0574	0.0353
A(2,1)	0.0105*	-0.0432	-0.0037*	0.0001*	0.0401	0.0195*
A(2,2)	0.5131	0.3094	0.2715	0.3155	0.2231	0.2636
B(1,1)	0.9603	0.9490	0.9480	0.9489	0.9382	0.9434
B(1,2)	-0.0077*	-0.0022*	-0.0159	-0.0041*	-0.0206	-0.0093
B(2,1)	0.0020*	0.0165	-0.0047*	0.0010*	-0.0080	-0.0075
B(2,2)	0.8811	0.9395	0.9514	0.9382	0.9724	0.9601

In Table 4, the results B (2,2) also show that there is long-run spillover or volatility dynamics between the variables; all the variables show the long-run spillover as their p-values are significant. They also show that there is a strong affirmative correlation amongst variables as their GARCH coefficients (0.915, 0.9680, 0.9473, 0.9560, 0.9516, 0.9759, 0.9799, 0.8811, 0.9395, 0.9514, 0.9382, 0.9724, 0.9601) are close to 1. These BEKK-GARCH results in Table 4 support the results shown by DCC-GARCH in Table 3.
In conclusion, the results showed that:

- The [Joint]dccα1 shows the short-run spillover between variables; all the variables had significant p-values, which indicate the short-run spillover except SSE, ASX-200, and TSX, where p-values are insignificant.
- The [Joint]dccβ1 shows the long-run spillover between variables; all the variables show the long-run spillover as their p-values are significant. They also show a strong positive correlation between variables, as the coefficients are close to 1. The results also show that the DCC is mean-reverting.

The DCC-GARCH model revealed a strong positive correlation between variables. This means that the variables tend to move in the same direction: When one variable increases, the other variable also tends to increase. When one variable decreases, the other variable also tends to decrease.

5. Conclusion

The study laid down several distinct conclusions, many of which show popular beliefs. The global stock exchanges are interconnected with each other. Numerous studies have been done to study the interconnectedness of the stock exchanges around the world. These studies have been done by analysing a number of variables like price volatility, spillovers, and causality between stock exchanges. This paper is concentrated on studying the spillover effect on selected international stock exchanges. Different techniques and models have been developed to evaluate the impact of the spillovers of one stock exchange on the other stock exchanges, like Regression Analysis, GARCH, TGARCH, and EGARCH. The result showed that the spillover effect can either be symmetric or asymmetric between the stock exchanges. The leading stock exchanges of the world leave an impact on other global stock exchanges during and after the major contagions. The results revealed that there is positive, insignificant conditional volatility between the NSE and selected International Stock Exchanges in the short run. DCC-GARCH estimates indicate the conditional correlation between the NSE and the selected international stock exchanges is very dynamic and varies over time. The DCC-GARCH findings indicate that the conditional correlations between the assets are strong and significantly long-term, with joint β values exceeding 0.9. This persistence indicates that shocks exert a prolonged influence on correlations, which is essential for formulating efficient hedging strategies. A significant and fluctuating correlation indicates that the hedging ratio requires regular adjustments to maintain efficiency. During the U.S. financial crisis, correlations surged, signifying diminished diversification advantages and elevated hedging ratios. This indicates that investors must assume larger opposing holdings to mitigate dangers. The continued volatility over time underscores the significance of dynamic hedging techniques. The findings indicate that static hedging may be inadequate, necessitating dynamic adjustments of hedge ratios for optimal risk management. This is the importance of the estimates. Based on the findings of the study, the conclusion showed that there is a substantial linkage between the conditional heteroscedasticity estimates of the NSE indices and selected International Stock Indexes. The BEKK-GARCH supported the results drafted by DCC-GARCH. This revealed the fact that economies are dependent on one another, and the stock markets of different countries all over the world are influenced by one another.
Understanding time-varying correlations and volatility dynamics across a variety of financial assets is the focus of this research, which aims to expand upon that understanding. Moreover, it offers practical implications for portfolio diversification and hedging by providing insights into the ways in which shocks and crises influence interconnection. In the process of formulating solutions to reduce systemic risks, the findings can serve as a guide for politicians, investors, and risk managers. Through the incorporation of structural breaks or regime-switching effects, the model may be expanded upon in further research. In addition, the research paves the way for the investigation of the effectiveness of hedging across a variety of asset classes and overseas markets.
The future scope of this study involves expanding the dataset to encompass recent market advancements, integrating other emerging and developed markets to facilitate a thorough analysis, and undertaking studies focused on specific sectors. Additionally, it entails analyzing the influence of technological progress, macroeconomic variables, political occurrences, and ESG considerations on market connections. Utilizing sophisticated econometric models and analyzing real-time data can yield more precise and timely insights. Conducting comparative research between the eras before and after the pandemic will provide insights into the lasting impacts of global crises on the integration of stock markets. These outlets will bolster investment strategies and provide valuable insights for making informed policy decisions to ensure the stability of financial markets.

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