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Volatility Spillover Effect from Foreign Stock Exchanges to National Stock Exchanges

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Abstract: The present study examines the volatility spillover from foreign stock exchanges viz. NYSE Composite, NASDAQ 100, Nikkei 225 and FTSE 100 to national stock exchange viz. CNX Nifty. The time series daily closing data of seven years has been collected for the period starting from 1st April 2008 to 31st March 2015 for the study. For analysis econometric tools such as, descriptive analysis, ADF test for unit root, D-W Statistic, L-Jung Box Q Statistic, Breusch-Pagan Test, AR (1) Model, GARCH (1,1) and EGARCH (1,1) Model has been used. The objective of the paper is to determine if volatility spillover in one market influence the volatility of returns in the other market. GARCH (1, 1) and EGARCH (1,1) models used for modelling of spillover between returns of foreign stock exchanges and National stock exchange. This study concludes that volatility spillover between foreign stock exchanges and national stock exchange must be measured or predicted by EGARCH (1,1) model because it is more significant than GARCH (1,1) model.

Keywords: Volatility Spillover, Stock Market, GARCH, EGARCH

INTRODUCTION

A stock market or equity market is the aggregation of buyers and sellers of stocks; these may include securities listed on a stock exchange as well as those only traded privately. There are now stock markets in virtually every developed and most developing economies, with the world's largest markets being in the United States, United Kingdom, Japan, India, China, Canada, Germany (Frankfurt Stock Exchange), France, South Korea and the Netherlands. The objective of this study is to inspect the volatility spillovers between Indian stock market i.e. NSE and foreign exchange markets. Gloablization of stock markets, liberalized capital flows, huge foreign investment in Indian equity markets have led stock and foreign exchange markets to be increasingly interdependent. An understanding of the inter-market volatility is important for the pricing of securities within and across the markets for trading and hedging strategies as well as for formulation of regulatory policies in an emerging market like India that is rapidly getting integrated into the global economy.

World's Top 4 Stock Markets

Four largest stock exchanges in the world by market capitalization in 2015, according to world federation of exchanges:

New York Stock Exchange (NYSE)

NYSE is the largest stock exchange in the world by both market capitalization and trade value with a market capitalization of 17,949.88 USD Billions. NYSE is the premier listing venue for the world's leading large- and medium-sized companies. Featuring more than 8000 listed issues it includes 90% of the Dow Jones Industrial Average and 82%of the S&P 500 stock market indexes volume. The NYSE Composite Index is designed to measure the performance of all common stocks listed on the NYSE, including ADR (American Depository Receipt), REIT (Real Estate Investment Trust) and tracking stocks. The index is weighted using free-float market capitalization and calculated on both price and total return basis.

NASDAQ OMX

This is the second largest stock exchange in the world by market capitalization and trade value with a market capitalization of about 6,804.97 USD Billions. The exchange is owned by NASDAQ OMX Group which also owns and operates 24 markets, 3 clearinghouses and 5central securities depositories supporting equities, options, fixed income, derivatives, commodities, futures and structured products. It is a home to approximately 3,400 listed companies and its main index is the NASDAQ Composite, which has been published since its inception. Stock market is also followed by S&P 500 index. The NASDAQ-100 Index includes 100 of the largest domestic and international non-financial securities listed on The NASDAQ Stock Market based on market capitalization. The Index reflects companies across major industry groups including computer hardware and software, telecommunications, retail/wholesale trade and biotechnology. It does not contain securities of financial companies including investment companies.

Tokyo Stock Exchange (TSE)

The third largest stock exchange market in the world by aggregate market capitalization of its listed companies with a market capitalization of about 4,543.17 USD Billions. It had 2,292 companies which are separated into the First Section for large companies, the Second Section for mid-sized companies, and the Mothers section for high growth start-up companies. The main indices tracking Tokyo Stock Exchange are the Nikkei 225 index of companies selected by the Nihon Keizai Shimbun, the TOPIX index based on the share prices of First Section companies, and the J30 index of large industrial companies. The Nikkei-225 Stock Average is a price-weighted average of 225 top-rated Japanese companies listed in the First Section of the Tokyo Stock Exchange. The Nikkei Stock Average was first published on May 16, 1949, where the average price was ¥176.21 with a divisor of 225. It has been calculated daily by the Nihon Keizai Shimbun (Nikkei) newspaper since 1950. It is a price-weighted index (the unit is yen), and the components are reviewed once a year. Currently, the Nikkei is the most widely quoted average of Japanese equities, similar to the Dow Jones Industrial Average. In fact, it was known as the "Nikkei Dow Jones Stock Average" from 1975 to 1985.

London Stock Exchange (LSE)

It is the oldest and fourth-largest stock exchange in the world with a market capitalization of about 4,428.98 USD Billions. The Exchange was founded in 1801 and its current premises are situated in Paternoster Square close to St Paul's Cathedral. It is the most international of all the world's stock exchanges, with around 3,000 companies from over 70 countries admitted to trading on its markets. The FTSE 100 Index, also called FTSE 100, FTSE, or, informally, the "footsie" is a share index of the 100 companies listed on the London Stock Exchange with the highest market capitalization. It is one of the most widely used stock indices and is seen as a gauge of business prosperity for business regulated by UK company law. The index is maintained by the FTSE Group, a subsidiary of the London Stock Exchange Group. FTSE stands for Financial Times Stock Exchange.

National Stock Exchange

National Stock Exchange (NSE) was established in 1992 as a demutualised electronic exchange with a Market Capitalization more than $1.4 trillion. It is world's top twenty stock exchanges by market capitalization. NSE's flagship index, the CNX Nifty, is used extensively by investors in India and around the world to take exposure to the Indian equities market. The CNX Nifty is a well diversified 50 stock index accounting for 23 sectors of the economy. It is used for a variety of purposes such as benchmarking fund portfolios, index based derivatives and index funds. CNX Nifty is owned and managed by India Index Services and Products Ltd. (IISL). IISL is India's first specialised company focused upon the index as a core product. The CNX Nifty Index represents about 66.85% of the free float market capitalization of the stocks listed on NSE as on June 30, 2014. The total traded value for the last six months ending June 2014 of all index constituents is approximately 50.39% of the traded value of all stocks on the NSE. Impact cost of the CNX Nifty for a portfolio size of Rs. 50 lakhs is 0.07% for the month June 2014. CNX Nifty is professionally maintained and is ideal for derivatives trading.

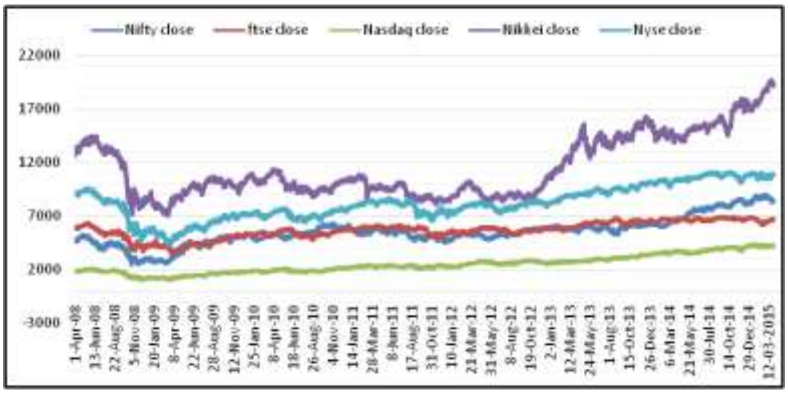


Fig-1: Daily Closing Rates of Sample Stock Index
Source: Websites of NSE, TSE, LSE, NYSE, NASDAQ.

VOLATILITY

Volatility is a statistical measure of the dispersion of returns for a given security or market index. Volatility can either be measured by using the standard deviation or variance between returns from that same security or market index [1]. Commonly, the higher the volatility, the riskier the security. Volatility measures the risk of a security. It is used in option pricing formula to gauge the fluctuations in the returns of the underlying assets. Volatility indicates the pricing behavior of the security and helps estimate the fluctuations that may happen in a short period of time.

If the prices of a security fluctuate rapidly in a short time span, it is termed to have high volatility. If the prices of a security fluctuate slowly in a longer time span, it is termed to have low volatility [2].

Types of Volatility

There are basically two types of volatility i.e. Historical Volatility and Implied Volatility. For the present study historical volatility has been found which has been shown in below figure no. 2. The brief descriptions about different types of volatility are below:

Historical (Realized) Volatility

The realized volatility of a financial instrument over a given time period. Generally, this measure is calculated by determining the average deviation from the average price of a financial instrument in the given time period. Standard deviation is the most common but not the only way to calculate historical volatility. This measure is frequently compared with implied volatility to determine if options prices are over- or undervalued. Historical volatility is also used in all types of risk valuations. Stocks with a high historical volatility usually require a higher risk tolerance [3].

- **High – Low Volatility**

$$\boldsymbol{s = k\sqrt{1/n \sum \log(\frac{H_t}{L_t})^2}} \qquad \textbf{........(1)}$$

Where, s = S.D., k = 1, n = no. of days, H_t = Day's High and L_t = Day's Low

- **High – Low – Open – Close Volatility**

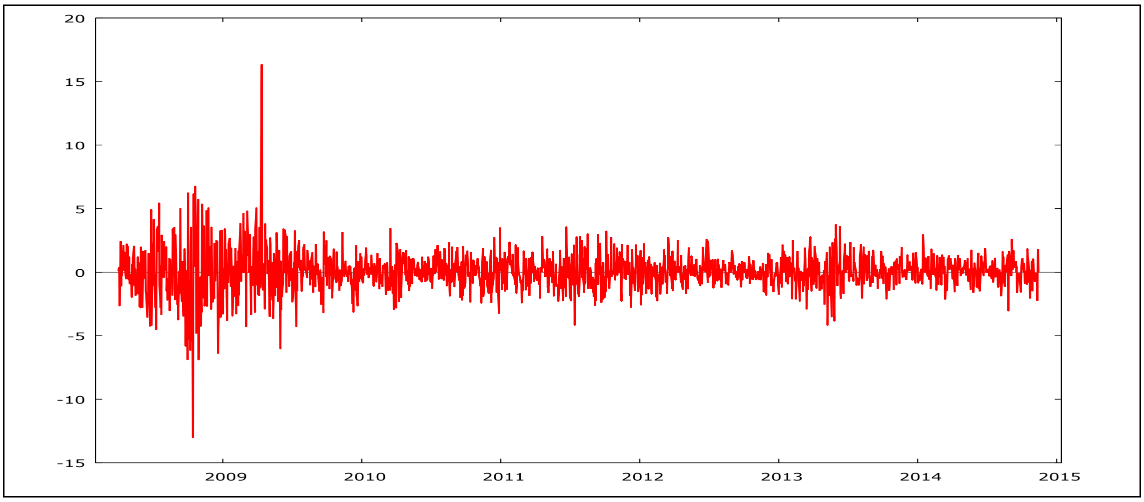
$$\boldsymbol{s = \sqrt{1/n \sum \left(\frac{1}{2}\right)[\log(H_t/L_t)]^2 - [2\log(2) - 1][\log(C_t/O_t)]^2}} \qquad \textbf{......(2)}$$

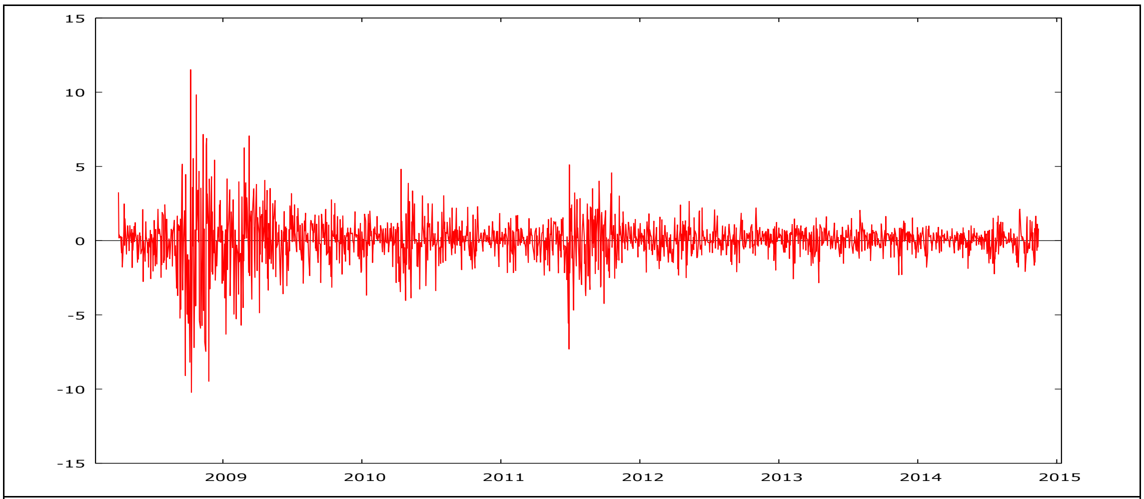
Where, s = S.D., n = no. of Days, H_t = Day's high, L_t = Day's Low, C_t = Day's Close, O_t = Day's Open

Implied Volatility

Implied volatility is the theoretical value which represents the future volatility of the underlying financial asset for an option as determined by today's price of the option.

- Black – Scholes & Local Volatility
- Stochastic Volatility

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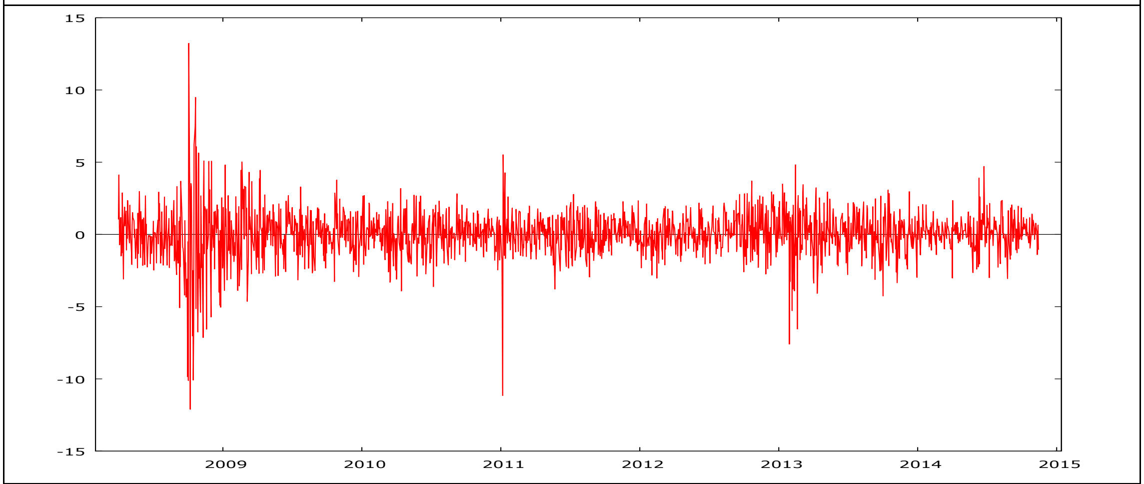
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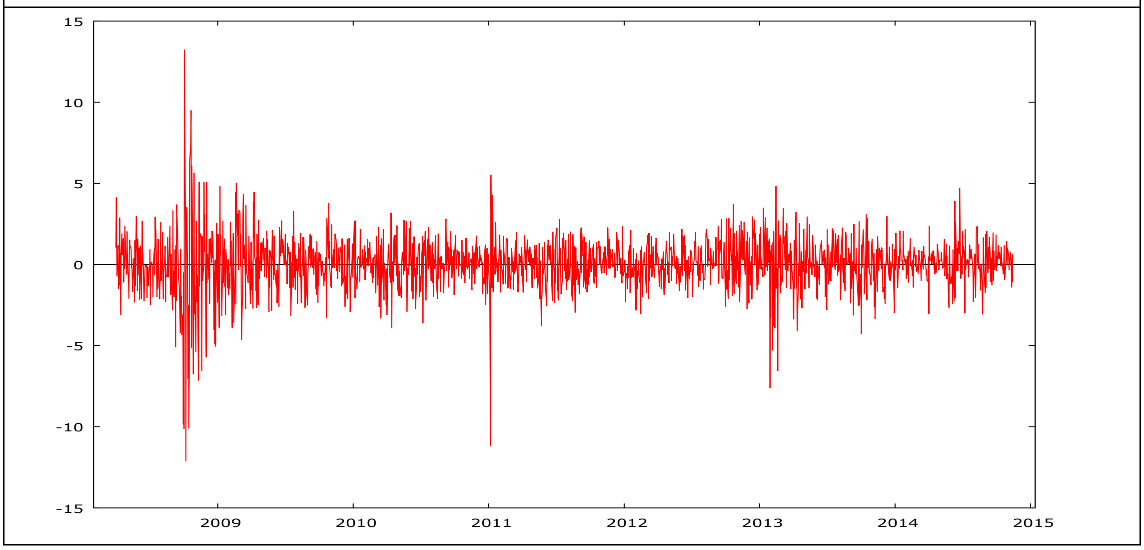
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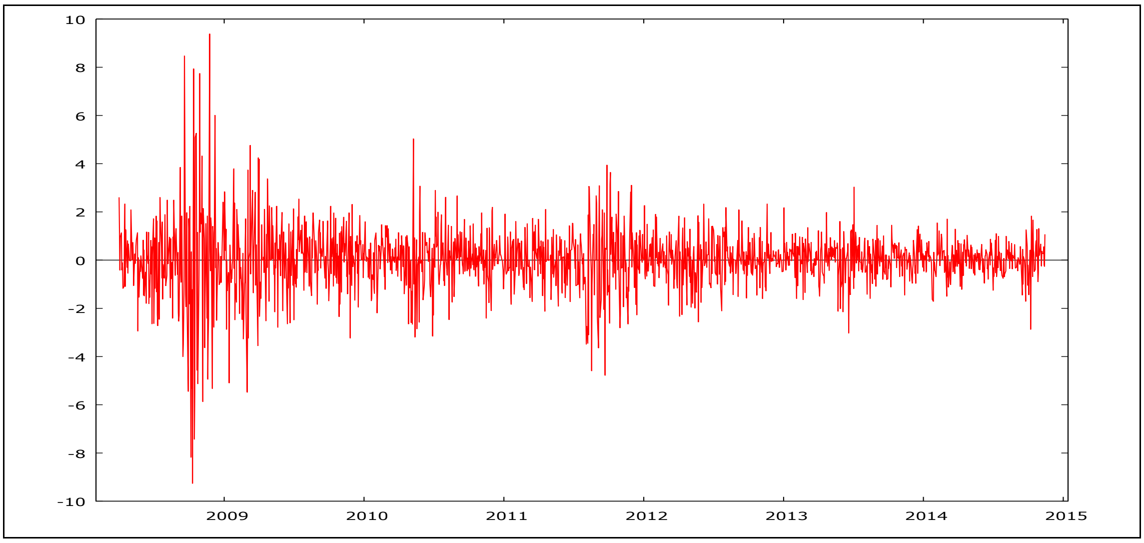

Fig-2: Daily Returns/Volatility of Sample Indices of Stock Exchanges

Spillover Effect

It is a secondary effect that follows from a primary effect, and may be far removed in time or place from the event that caused the primary effect. For the present study the researcher found the volatility spillover effect from foreign stock exchanges to National stock exchanges.

REVIEW OF LITERATURE

Many studies related to volatility spillover has been done by research in the past years. The studies related to volatility and volatility spillovers are given as under to find the gap for the study.

Mohandas and Renukadevi [4] had studied to model the volatility of the BSE Sectoral indices. The return of the BSE sectoral indices exhibits the characteristics of normality, stationarity and heteroskedasticity. Also the ACF and PACF indicate that ARMA (1, 1) is the suitable one for modeling the average return. The residuals of the ARMA (1, 1) of the sectoral index returns except for IT and TECH are heteroskedastic. Hence, a non-linear model is to found to model the volatility of the return series. An attempt is made to model the volatility of the return series and found that GARCH (1, 1) model is the best one. Gahan *et al.* [5] studied the volatility pattern of BSE Sensitive Index (Sensex) and NSE Nifty (Nifty) during the post derivative period. MA (q, p), GARCH (q, p), EGARCH (q, p) and IGARCH (q, p) have been employed for the calculation of volatility in Sensex and Nifty during pre-derivative period, past-derivative period and whole period of study. Joshi [6] uses three different models: GARCH(1,1), EGARCH(1,1) and GJR-GARCH(1,1) to forecast daily volatility of Sensex of Bombay Stock Exchange of India from January 1, 2010 to July 4, 2014. The finding indicates that the stock market exhibits the persistence of volatility, mean reverting behavior and volatility clustering. Bordoloi and Shankar [7] have found evidence of increase in volatility due to certain negative factors in all the equity markets by using ARCH, GARCH, TARCH and EGARCH. Panait and Slavescu [8] used GARCH-in-mean model to investigate volatility and persistence at different frequencies for Bucharest stock exchange during 1997-2012.

Mishra *et al.* [9] found that both the markets move in tandem with each other and there is a long run relationship between these two markets. Nateson *et al.* [10] found volatility transmission from the BSE Sensex to BSE Auto, BSE Bankex, BSE Consumer Durables, BSE Capital Goods, BSE FMCG, BSE Healthcare, BSE IT, BSE Metal, BSE Oil & Gas, BSE Realty and BSE PSU. Beirne *et al.* [11] tested volatility spillovers from mature to emerging stock markets, changes in the transmission mechanism during turbulences in mature markets, and examines the implications for conditional correlations between mature and emerging market returns.

Due to the Globalization, any positive or negative change always affects form one country to another country/s. In all stock market, we can find more or less volatility. But this volatility transmits or spillover from one market to another market or not. The present study helps to find the volatility spillover effect of foreign stock exchange towards NSE and no study has been found in the present area.

OJECTIVES OF THE STUDY

- To study volatility spillover effect from New York Stock Exchange (NYSE) to National Stock Exchange.
- To study volatility spillover effect from NASDAQ OMX to National Stock Exchange.

- To study volatility spillover effect from Tokyo Stock Exchange to National Stock Exchange.
- To study volatility spillover effect from London Stock Exchange to National Stock Exchange.

RESEARCH METHODOLOGY

The Study

The present study is Descriptive Cross-Sectional Research. Since, Descriptive Cross- Sectional Research means to describe the business or market characteristics by collecting information from a sample of a population at only one point of time. Volatility Spillover, as a characteristic, the researcher wants to check for National Stock Exchange by selecting major stock index of selected stock exchanges.

Sample Size

The attempt has been made on the sample World's Top Four Foreign Exchanges viz. NYSE Composite, NASDAQ 100, Nikkei 225 and FTSE 100 to National stock exchange viz. CNX Nifty.

Data Collection

Secondary data of daily closing of various indices has been collected from the websites various stock exchanges such as, National Stock Exchange, NYSE, NASDAQ, TSE, LSE and others.

Period of the Study

The time series daily data of total seven years has been collected for the period starting from 1st April 2008 to 31st March 2015. The rationale behind the selection of a seven years period for the study is to cover the time series of data.

Research Tools

The collected data has been analysed in Eviews 7 with the help of various econometric tools such as, descriptive analysis, ADF test for unit root, D-W test, L-Jung Box Q Statistic, Breusch-Pagan Test, AR (1) Model, GARCH (1,1) and EGARCH (1,1) Model.

RESULTS AND DISCUSSIONS

For the present study research has applied econometrics and statistical tools viz. descriptive analysis, Jarque-Bera Statistics, KPSS Test, ADF Test, D-W Statistic, Breusch-Pagan Test, GARCH and EGARCH etc. The results are as follows:

Table-1: Descriptive Analysis

Stock Indices	NYSE Composite	NASDAQ 100	Nikkei 225	FTSE 100	CNX Nifty
Mean	0.0125	0.0507	0.0247	0.0098	0.0338
Median	0.0819	0.1019	0.0647	0.0074	0.0564
Minimum	-10.2321	-11.1149	-12.111	-9.2646	-13.0142
Maximum	11.5258	11.8493	13.2346	9.3842	16.3343
Std. Deviation	1.5261	1.4969	1.6898	1.3059	1.5232
Skewness	-0.39	-0.17	-0.56	-0.11	0.28
Ex. Kurtosis	9.09	8.5	8.51	8.69	12.41
Jarque-Bera	5951.95	5176.93	5269.55	5410.01	11038.92
No. of Days	1729	1729	1729	1729	1729

The above table no. 1 shows the descriptive analysis of all the stock exchanges. It has been found that NASDAQ 100 has the highest mean of 0.0507 among five indices and FTSE 100 has the lowest mean of 0.0098. The FTSE 100 Index is least volatile as it has the smallest Standard deviation of 1.3.59 among five indices and Nikkei 225 is the most volatile as it has the highest Standard deviation of 1.6898 among five indices. According to Skewness statistics, CNX Nifty has positive Skewness, indicating that large positive returns are more than large negative returns. And NYSE Composite, NASDAQ 100, FTSE 100, Nikkei 225 has negative Skewness, indicating that large negative returns are more than large positive returns. The Kurtosis statistics show that all of the return series are leptokurtic.

Jarque-Bera Statistics

The Jarque–Bera test is a goodness-of-fit test of whether sample data have the skewness and kurtosis matching a normal distribution. The test is named after Carlos Jarque and Anil K. Bera. [12]. The test statistic *JB* is defined as

$$\boldsymbol{Jarque - Bera} = \frac{\boldsymbol{N}}{\boldsymbol{6}}\left(\boldsymbol{s}^2 + \frac{(\boldsymbol{K}-\boldsymbol{3})^2}{\boldsymbol{4}}\right) \qquad \textbf{.(3)}$$

Where,S= Skewness and K = Kurtosis. For Jarque-Bera's normality test, we need chi-square's critical value at degree of freedom 2 at 1%, 5% and 10%.

Table-2: Jarque-Bera Test for Normality

TEST	DF	Right tail α value	Critical value
Chi – Square Test	2	0.01	9.21034
		0.05	5.99146
		0.1	4.60517

The above table no 2 shows the result of Jarque-Bera test. Since JB > Chi square critical (1%, 5%, 10%), it means return of all indices are not normally distributed.

KPSS Test

KPSS is known as Kwiatkowski–Phillips–Schmidt–Shin. It is used for testing null hypothesis that a time series is stationary against the alternative that time series is not stationary. A stationary time series is a stochastic process whose joint probability distribution does not change when shifted in time. Consequently, parameters such as the mean and variance, if they are present, also do not change over time and do not follow any trends [12].

$$\boldsymbol{y_t = \alpha + \beta_t + d\sum_{i=1}^{t} u_i + \varepsilon_t} \qquad \dots(4)$$

Where, u_i and ε_t are both covariance stationary and short memory with zero mean and $d \in (0,1)$

Table-3: Results of KPSS Test

Index	KPSS (Observed)	KPSS (Critical)	P-Value	Alpha
NYSE Composite	0.086	0.147	0.234	0.05
NASDAQ 100	0.072		0.329	
Nikkei 225	0.037		0.770	
FTSE 100	0.061		0.428	
CNX Nifty	0.062		0.420	

From the above table no. 3 of KPSS test, researcher found KPSS(C) > KPSS(O) and P- Value > Alpha, so we can not reject null hypothesis. It means time series is stationary.

Augmented Dickey-Fuller (ADF) Test

ADF is a test for a unit root in a time series. It is useful for a larger and more complicated set of time series models. The ADF statistic, used in the test, is a negative number. The more negative it is, the stronger the rejections of the hypothesis that there is a unit root at some level of confidence [13].

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t, \quad \textbf{..(5)}$$

Where $\alpha$is a constant, $\beta$the coefficient on a time trend and $p$the lag order of the autoregressive process.

Table-4: Results of ADF Unit Root Test

Index	ADF (Observed)	ADF (Critical)	P-value	Alpha
NYSE Composite	-12.05	-0.9	0.0001	0.05
NASDAQ 100	-11.629			
Nikkei 225	-11.763			
FTSE 100	-12.061			
CNX Nifty	-11.36			

From the above table no. 4 of ADF test, we found ADF(O) < ADF(C) and P-Value < Alpha, so null hypothesis is rejected. It means there is no unit root in time series.

Durbin-Watson Test

The Durbin–Watson statistic is a test statistic used to detect the presence of autocorrelation in the residuals from a regression analysis. Durbin and Watson applied this statistic to the residuals from least squares regressions, and developed bounds tests for the null hypothesis that the errors are serially uncorrelated against the alternative that they follow a correlation [12].

$$\boldsymbol{d = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2}} \qquad \textbf{.........(6)}$$

Where, T = no. of observations and e_t = error terms.

Table 5: Results of Durbin-Watson Test

Index	Durbin Watson (D)	Lower Limit (DL)	Upper Limit (DU)	Decision
NYSE Composite	2.0096	1.9255	1.9275	Rejected
NASDAQ 100	2.0093			Rejected
Nikkei 225	1.9993			Rejected
FTSE 100	2.0005			Rejected
CNX Nifty	1.9945			Rejected

The above table no. 5 provides the result of Durbin Watson test. Since, D > DL for all index, so we rejected null hypothesis for all index. It means there is a correlation in return of all index.

L-Jung Box Q Statistic

It tests the overall randomness based on a number of lags. It tests for the null hypothesis that data are random against the alternative that data are not random. A random sequence of events, symbols or steps has no order and does not follow an intelligible pattern or combination [12].

$$Q_{LB} = (n(n+2)\sum_{j=1}^{h}\frac{\rho^2(j)}{n-j} \qquad \text{......(7)}$$

Where n is the sample size, $r(j)$ is the autocorrelation at lag j, and h is the number of lags being tested.

Table-6: Results of L-J Box Q Test

Index	Lag Order	Q Stats	p-value	Decision
NYSE Composite	1	11.94	0.001	Rejected
	2	19.57	0	
	3	21.8	0	
	4	21.99	0	
	5	27.89	0	
	6	29.06	0	
NASDAQ 100	1	15.52	0	Rejected
	2	22.06	0	
	3	26.23	0	
	4	26.44	0	
	5	28.3	0	
	6	28.46	0	
Nikkei 225	1	4.33	0.037	Rejected Accepted*
	2	4.35	0.114*	
	3	4.89	0.18*	
	4	6.83	0.145*	
	5	7.25	0.203*	
	6	7.25	0.298*	
FTSE 100	1	0.65	0.419*	Rejected Accepted*
	2	11.27	0.004	
	3	18.83	0	
	4	35.09	0	
	5	42.60	0	
	6	44.82	0	
CNX Nifty	1	7.41	0.006	Rejected Accepted*
	2	9.11	0.01	
	3	9.46	0.024	
	4	9.94	0.042	
	5	10.6	0.06*	
	6	13.52	0.035	

From the above table no. 6 of L-Jung Box Q test, we have to reject null hypothesis for all the five indices for different lags. The results show that data are not random.

Breusch-Pagan Test

The Breusch–Pagan test is used to test for heteroskedasticity.It tests whether the estimated variance of the residuals from a regression are dependent on the values of the independent variables. In that case, we have heteroskedasticity in our model. It tests for the null hypothesis that residuals are homoscedastic against the alternative that residuals are heteroscedistic. When the standard deviations of a variable, monitored over a specific amount of time, are non-constant then it is called as heteroskedasticity. For this test, we need lag range Multiplier yields the test statistic for Breusch Pagan test which is calculated as given below [13].

$$LM = \left(\frac{\partial l}{\partial \theta}\right)' \left(-E\left[\frac{\partial^2 l}{\partial \theta \partial \theta'}\right]\right)^{-1} \left(\frac{\partial l}{\partial \theta}\right). \quad \textbf{... (8)}$$

Table-7: Results of Breusch-Pagan Test

Index	LM (Observed)	LM (Critical)	DF	P-Value	Alpha
NYSE Composite	148.863	3.841	1	0.0001	0.05
NASDAQ 100	95.928				
Nikkei 225	20.985				
FTSE 100	149.701				
CNX Nifty	88.989				

From the above table no. 7 of Breusch-Pagan test, given values LM(Observed) > LM(Critical) for all index and P-value < Alpha value, so null hypothesis is rejected. It means residuals of returns are heteroscedastic.

AR (1) Model

An autoregressive process operates under the premise that past values have an effect on current values. A process considered AR (1) is the first order process, meaning that the current value is based on the immediately preceding value. It describes certain time-varying processes in nature, economics, etc. The autoregressive model specifies that the output variable depends linearly on its own previous values [12].

$$\boldsymbol{AR(1) = c + \tau y_{t-1} + \varepsilon_t} \quad \textbf{........(9)}$$

Where, c is constant, ε_t is white noise error term, y_{t-1} is previous period return.

GARCH/EGARCH (1,1) Models

GARCH is known as Generalized Autoregressive Conditional Heteroscedasticity. EGARCH is known as Exponential Generalized Autoregressive Conditional Heteroscedastic. The GARCH/EGARCH process is often preferred by financial modelling professionals because it provides a more real-world context than other forms when trying to predict the prices and rates of financial instruments.

GARCH models are used mainly for computing the volatility on liquid and tradable assets such as stocks in financial options; this model is sometimes used for other traded assets such as price of oil and price of electricity. GARCH is a term that incorporates a family of models that can take on a variety of forms, known as GARCH (P,Q), where P and Q are positive integers that define the resulting GARCH model and its forecasts. In most cases for financial instruments, a GARCH (1,1) is sufficient and is most generally used. The GARCH (P,Q) model allows for different positive P and Q integer lag parameters for the mean (news) and variance equations [13].

The general process for a GARCH/EGARCH model involves three steps. The first is to estimate a best-fitting autoregressive model; secondly, compute autocorrelations of the error term and lastly, test for significance. GARCH/EGARCH models are used by financial professionals in several area as including trading, investing, hedging and dealing. Two other widely-used approaches to estimating and predicting financial volatility are the classic historical volatility method and the exponentially weighted moving average volatility method [13].

GARCH model allows the conditional variance to be dependent upon previous own lags apart from the past innovation. One of the primary restrictions of GARCH model is that they enforce a symmetric response of volatility to positive and negative shocks. This arises due to the conditional variance being a function of the magnitudes of the lagged residuals and not their signs. The EGARCH model uses natural log of the conditional variance to address this drawback of GARCH model.

To model the volatility spillover effect, we evaluate GARCH (1,1) and EGARCH(1,1) models. The following equations provide the simplest example of a GARCH (1,1) model:

$$\boldsymbol{\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2} \quad \textbf{..........(10)}$$

The following equation provide the simplest form of EGARCH(1,1) model:

$$\boldsymbol{log\sigma_t^2 = \omega + \sum_{k=1}^{q} \beta_k g(Z_{t-k}) + \sum_{k=1}^{p} \alpha_k log\sigma_{t-k}^2} \quad \textbf{.........(11)}$$

Where, $g(Z_t) = \theta Z_t + \lambda(|Z_t| - E(|Z_t|))\sigma_t^2$ is the conditional variance. $\omega, \beta, \alpha, \theta \; and \; \lambda$ are coefficients.

Table-8: Results of AR (1) Model

INDEX	Lag	C	ε	T-Ratio	p-value	R- Squared
NYSE Composite	0	0.0281	0.0238	1.181	0.2378	0.0051
	1	0.0627	0.0238	2.635	0.0085***	0.0083
NASDAQ 100	0	0.0086	0.0243	0.3541	0.7233	0.0043
	1	0.0539	0.0243	2.226	0.0262**	0.0071
Nikkei 225	0	0.0207	0.0215	0.9623	0.3360	0.0048
	1	0.0152	0.0251	0.7045	0.4812	0.0046
	2	-0.0109	0.0215	-0.5056	0.6132	0.0044
	3	-0.0267	0.0215	-1.24	0.2153	0.0052
	4	0.0197	0.0215	0.9158	0.3599	0.0050
	5	0.0251	0.0215	1.167	0.2435	0.0054
	6	0.0622	0.0215	2.895	0.0038***	0.0095
FTSE 100	0	-0.0086	0.0279	-0.3075	0.7585	0.0043
	1	-0.0040	0.0279	-0.1436	0.8858	0.0043
	2	0.0315	0.0279	1.126	0.2604	0.0050
	3	0.0009	0.0279	0.0317	0.9747	0.0043
	4	-0.0755	0.0279	-2.707	0.0069***	0.0088
CNX Nifty	1	0.0355	6.0357	0.0059	0.9953	0.0044
	2	-0.0347	0.0241	-1.443	0.1492	0.0055
	3	-0.0107	0.0241	-0.4450	0.6564	0.0044
	4	-0.0139	0.0241	-0.5807	0.5615	0.0047
	5	-0.0155	0.0241	-0.6416	0.5212	0.0049
	6	-0.0423	0.0241	-1.76	0.0787*	0.0065

The given result, *** and ** and * indicates significance at 1%, 5%, 10% respectively

From the above result in table no. 8 of AR (1) model, C represents as coefficient. The value of c is positive as well as negative in given results. Therefore the meaning of positive value is that effect of negative shocks is higher than positive shocks to NSE from all selected stock exchanges and the meaning of negative value is that the effect of positive shocks is higher than negative shocks.

R-Squared value represents relationship between selected benchmarks and CNX Nifty. R-squared value is highest at sixth lag of Nikkei 225 (0.0095) indicates spillover effect is highest at sixth lag of Nikkei 225 from TSE to NSE. Same interpretation for FTSE 100 at fourth lag (0.0088), NYSE Composite at first lag (0.0083), NASDAQ 100 at first lag (0.0071) and CNX Nifty itself at sixth lag (0.0065).

Table-9: Results of GARCH (1,1) Model

INDEX	Lag	C	α_0		α_1		β_1	
			z	P *	z	P ***	z	P ***
NYSE Composite	0	-0.0066	1.68	0.0929	5.07	<0.00001	67.3	<0.00001
	1	0.0133	1.69	0.0909	5.02	<0.00001	66.55	<0.00001
NASDAQ 100	0	-0.0080	1.68	0.0925	5.07	<0.00001	67.26	<0.00001
	1	0.0120	1.69	0.0912	5.03	<0.00001	66.57	<0.00001
Nikkei 225	0	-0.0047	1.68	0.0924	5.04	<0.00001	66.95	<0.00001
	1	0.0274	1.68	0.0926	5.08	<0.00001	66.93	<0.00001
	2	-0.0081	1.68	0.0928	5.02	<0.00001	66.60	<0.00001
	3	-0.0227	1.69	0.0909	4.99	<0.00001	65.38	<0.00001
	4	0.0499	1.75	0.0802	5.03	<0.00001	66.01	<0.00001
	5	-0.0113	1.69	0.0903	5.06	<0.00001	66.83	<0.00001
	6	0.0168	1.69	0.0895	4.98	<0.00001	65.87	<0.00001
FTSE 100	0	-0.0139	1.68	0.0928	5.07	<0.00001	67.23	<0.00001
	1	0.0164	1.68	0.0926	5.01	<0.00001	66.73	<0.00001
	2	0.0395	1.71	0.0877	4.99	<0.00001	65.20	<0.00001
	3	-0.0143	1.69	0.0918	4.97	<0.00001	65.78	<0.00001
	4	-0.0085	1.68	0.0922	5.02	<0.00001	66.16	<0.00001
CNX Nifty	1	0.0675	1.74	0.0815	4.92	<0.00001	66.2	<0.00001
	2	0.0048	1.70	0.0889	4.99	<0.00001	66.43	<0.00001
	3	-0.0295	1.74	0.0818	4.88	<0.00001	65.17	<0.00001
	4	-0.0030	1.68	0.0920	5.03	<0.00001	66.49	<0.00001
	5	-0.0033	1.68	0.0925	5.05	<0.00001	66.49	<0.00001
	6	-0.0166	1.72	0.0863	4.99	<0.00001	66.28	<0.00001

The given result, *** and ** and * indicates significance at 1%, 5%, 10% respectively

Table-10: Results of EGARCH (1,1) Model

INDEX	Lag	C	α		γ		β	
			z	P ***	z	P ***	z	P ***
NYSE Composite	0	0.0267	5.03	4.84e-07	-4.37	1.25e-05	185.8	0
	1	0.0157	4.92	8.71e-07	-3.79	0.0001	173.8	0
NASDAQ 100	0	0.0284	5.07	3.72e-07	-4.38	1.19e-05	184.1	0
	1	0.0146	4.93	8.15e-07	-3.75	0.0002	172.5	0
Nikkei 225	0	0.0157	4.53	6.05e-06	-4.38	1.17e-05	177.7	0
	1	0.0187	4.56	5.10e-06	-4.49	7.04e-06	181.9	0
	2	0.0225	4.6	4.23e-06	-4.59	4.36e-06	182.5	0
	3	0.0127	4.65	3.25e-06	-4.05	5.03e-05	170	0
	4	-0.0011	4.43	9.50e-06	-3.62	0.0003	162.5	0
	5	0.0004	4.33	1.49e-05	-3.33	0.0009	173.9	0
	6	0.0128	4.84	1.31e-06	-3.56	0.0004	163.5	0
FTSE 100	0	0.0068	4.36	1.32e-05	-3.42	0.0006	179.9	0
	1	-0.0060	4.21	2.55e-05	-3.29	0.001	169	0
	2	0.0006	4.28	1.90e-05	-3.43	0.0006	175.4	0
	3	0.0066	4.5	6.79e-06	-3.36	0.0008	178.1	0
	4	0.0054	4.47	7.90e-06	-3.41	0.0007	178.9	0
CNX Nifty	1	0.0069	4.3	1.70e-05	-1.98	0.0481	189.2	0
	2	0.0012	4.43	9.62e-06	-2.65	0.0081	172.4	0
	3	0.0271	5.04	4.70e-07	-3.84	0.0001	171.5	0
	4	0.0293	5.24	1.59e-07	-4.69	2.62e-06	177.9	0
	5	0.0195	4.92	8.67e-07	-4.71	2.44e-06	168	0
	6	0.0285	5.29	1.25e-07	-5.45	4.92e-08	189.1	0

The given result, *** and ** and * indicates significance at 1%, 5%, 10% respectively

Generally, GARCH/EGARCH model is used for measuring volatility or forecasting volatility. It gives the best result when p- value is 0 or very near to 0 of all parameters of model. In GARCH model, α_1 and β_1 have p- value which is very near to 0 (<0.00001) but α_0 is not near to 0. In EGARCH model, p- value of β is 0 and α and γ have very near to 0. So, from above result of GARCH (1,1) and EGARCH (1,1) shown in table no. 9 and table no .10 respectively, we can say that volatility must be measured or predicted by EGARCH (1,1) model because p- value of all parameters of EGARCH (1,1) model is very near to 0 in comparison of GARCH (1,1) model.

CONCLUSION

This paper explores the issue of volatility spillovers between index foreign stock market such as NYSE Composite of New York Stock Exchange, NASDAQ 100 of American Stock Exchange, Nikkei 225 of Tokyo Stock Exchange and FTSE 100 of London Stock Exchange with CNX Nifty of National Stock Exchange of India. The objective of the paper is to determine if volatility spillover in one market influence the volatility of returns in the other market. GARCH (1,1) and EGARCH (1,1) models used for modelling of spillover between returns of foreign stock exchanges and National stock exchange. This study concludes that volatility spillover between foreign stock exchanges and national stock exchange must be measured or predicted by EGARCH (1,1) model because it is more significant than GARCH (1,1) model.

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