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VOLATILITY ANALYSIS AND VOLATILITY SPILLOVER ACROSS EQUITY MARKETS BETWEEN INDIA AND SELECTED GLOBAL INDICES

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Abstract *The purpose of this paper is to study the volatility comparison and volatility spillover effects in India and major global indices. The analysis used a vector autoregression model with various GARCH models in order to measure conditional volatility (GARCH), asymmetric effect in the conditional volatility (T-GARCH), volatility persistence in conditional volatility (E-GARCH), impact of conditional volatility on conditional returns (M-GARCH), and volatility spillover (GARCH (1, 1) with exogenous variable) for the period 2005 to 2018. The major results regarding volatility spillover posit that the Indian stock market had a strong impact on selected global indices. Volatility spillover was found to be in existence from the Indian stock market to the global indices, and vice-versa. These findings have substantial inferences and repercussions for portfolio managers, analysts, and investors for investment assessments and decisions regarding asset allocations. Higher volatility will lead to higher level of fretfulness among market participants and investors, which will push them to be more risk-averse. The results of the study also have pertinent effects for policy makers with respect to the Indian stock market and the global countries. This paper would support the existing literature by studying how the Indian index has an impact on global indices like the USA, Brazil, Japan, Russia, China, Hong Kong, South Korea, France, Germany, the United Kingdom, and Eurozone. The author considers that these results would magnify the volatility comparisons and volatility spillovers between the Indian index and global indices.*

Keywords: *Volatility Spillover, GARCH, Co-Integration, E-GARCH, Asymmetric Volatility*

JEL Classification: *C32, C58, G15, F65*

INTRODUCTION

Global capital market integration over the last 30 years has been noticed through major strategic deviations under which international investment limits were reduced, exchange control was almost eliminated, free movement of capital, humans, and technology was promoted, and the fundamental structures of most of the worldwide markets were transformed. Such progress in markets can change the relationship among different markets across the globe. Market integration has been promoted through liberalisation, which has critical implications on investment decisions and policies.

The stock market is connected with a sharp increase of uncertainty, both in developed and emerging markets. Stock market behaviour analysis offers information about the future evolution of the stock market.

Volatility spillover attained great importance in recent times due to the increasing role of financial markets in the economy across the world. The dynamics of the progress of economy is inevitable. Nowadays, there is great attention towards the analysis of links among global stock markets. Through financial integration, the native country can be linked to the international capital markets.

The studies of Arshanapalli et al. (1995); Masih and Masih (1997); and Kizys and Pierdzioch (2011), among others, have reported interlinks among developed markets of the USA, Japan, and Europe. Interlinks between the US, Japan, and Asian markets were evidenced by Arshanapalli et al. (1995); Anoruo et al. (2003); and Asgharian et al. (2013), among others. Further, these studies attributed the decline in the stock indices after the United States stock market crash of October 1987, the Asian Financial Crisis of 1997, and the Global Financial Crisis of 2008, to co-integration and interlinks of stock markets. These studies were primarily focused on connectedness among the developed stock markets. Hamao et al. (1990) found volatility spillover from the USA to the UK to Japan. Along the same line, Koutmos and Booth (1995) found that the negative innovations in the USA, the UK, and Japan markets increase the volatility in other markets, to trade more, compared to positive innovations.

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LITERATURE REVIEW

Yilmaz (2010) measured the returns and volatility spillovers in East Asia. He found significant difference in the returns and volatility spillover in the East Asian markets during the crisis and non-crisis time periods. He also concluded that the volatility spillovers were more than the return spillovers.

Nath and Mishra (2010) studied co-integration and volatility spillover between India and its Asian neighboring countries. Their results found the co-existence of intraday volatility spillovers. These spillovers were found to be bi-directional and significant. They also concluded that there had been a substantial flow of information from other Asian countries to India.

Nishimura and Men (2010) examined volatility spillover effects in equity markets between China and the G5 countries using the E-GARCH model. Wang and Wang (2010) studied returns and volatility spillover effects between Greater China and the US and Japan for a sample of over two decades, using daily prices. They found statistically significant impacts of volatility spillovers from Chine to the USA and Japan markets.

Goudarzi and Ramanarayanan (2010) studied the Indian market volatility using the GARCH (1, 1) models, and there were significant implications of the findings for the policy decisions.

Gupta et al. (2013) studied various arrays of volatility and its behaviour in the Indian stock indices. They used the GARCH models in the study and concluded that information spillover existed in the Indian stock indices and the dummy variable coefficient was found to be significant in the improved model.

Uyaebo et al. (2015) studied the daily all share index of the USA, Germany, China, and three countries of the African region, namely South Africa, Nigeria, and Kenya, using the daily prices for the period 2000 to 2013. They used various GARCH models to construct the best suited volatility models for each of the markets, to relate the volatility in the returns of these sample markets. These models were equated with relation to the reaction of conditional volatility to market shocks.

Mohammadi and Tan (2015) studied the dynamic forces of volatility and daily returns for the USA, China, and Hong Kong markets for a period of 13 years, by using multivariate GARCH models and found that there was a unidirectional volatility and returns spillover from the USA market to other markets. They also concluded that there were significant correlations between China and other markets.

Li and Giles (2015) studied the relationships of stock indices across Japan, the USA, and six Asian countries for a period of around two decades. They also found unidirectional volatility spillovers from the USA market to Japan and other Asian markets.

Jebran et al. (2017) studied the volatility spillover among five emerging markets of Asia before and after the 2007 crisis time period. They used multivariate E-GARCH model for the study and found the existence of bi-directional volatility spillover between India and Sri Lanka, both before and after the crisis period. For the post-crisis period, unidirectional volatility spillover was found from the China market to all other markets in the sample. Their study also measured asymmetric volatility spillover among the sample markets.

Xuan, Vinh and Ellis (2018) investigated the co-integration between the Vietnamese market and other developed markets, to study the returns relationship and volatility spillover for the time period before and after the sub-prime crisis of 2008. They used VAR-GARCH-BEKK models and the results were found to be statistically significant. MacDonald et al. (2018) studied volatility comparisons and spillover effects within the Eurozone markets.

Kumar and Khanna (2018) studied volatility behaviour and its spillover of four Asian stock indices using bivariate GARCH-BEKK model, and found that past volatility had more impact on current volatility, compared to the shocks in the markets.

DATA SOURCES

To examine the volatility and volatility spillover, the sample indices were identified; Indian index (SENSEX) and 11 major indices from different regions, namely France (CAC40), Germany (DAX), Eurozone (EURO STOXX50), the United Kingdom (FTSE100), Brazil (BOVESPA), America (DJIA), Japan (NIKKEI), China (SCI), Hong Kong (HIS), South Korea (KOSPI), and Russia (RTSI).

The daily closing prices of the selected indices were collected from the official websites of the stock exchanges. In case the data was not available for a particular index, the data was collected from Bloomberg. The study used the data for the period 2005 to 2018.

METHODOLOGY AND HYPOTHESES

GARCH (1, 1) Model

Stock index prices exhibit large volatility, leading to time-varying variances, violating the assumption of a constant variance (homoscedasticity). GARCH models can be used to verify the volatility clustering in such time-series data. For examining the volatility clustering of the markets, ARCH LM test was applied on the residuals of the ARMA

(1, 1) estimation model for markets in the sample. For investigating the fauna of conditional volatility in the sample indices, the GARCH (1, 1) model was adopted (Kumar & Dhankar, 2009).

For comparing various components of conditional volatility, such as asymmetric effects of positive and negative shocks on conditional volatility, comparing the size effects and sign effects of the shocks, and impact of conditional volatility on conditional returns in the sample markets, T-GARCH, E-GARCH, and M-GARCH models were used, respectively.

This study will support the literature by analysing the impact of the Indian market on other countries, and vice-versa. The findings of the study would strengthen the methodological acceptance of volatility spillover between the Indian market and the global stock indices, and vice-versa.

In GARCH models, systematic variance change over time is allowed to detect its departure from random walk. GARCH (***p, q***) model, with ***p*** lagged squared error term and ***q*** lagged conditional variance term, also known as the GARCH (1, 1) model, has proved useful in modelling returns of financial assets. GARCH (1, 1) test is based on the following equation:

$$r_t = \beta_0 + \beta_1 r_{t-1} + \beta_2 \sigma_{t-1}^2 + \varepsilon_t \tag{1}$$

$$\sigma_t^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \alpha_1 \sigma_{t-1}^2 \tag{2}$$

The GARCH (1, 1) model checks for changes in the random walk and allows the error term to deviate from the assumption of being normally distributed, independent, and homoscedastic. In the above model, σ_t is the conditional variance of error term ε_t of the GARCH (1, 1) model. Parameters γ_0, γ_1, and α_1 represent changing volatility. The model measures three important things; first, the change in slope and intercept of the model, represented by β_0 and β_1, second, time-varying variance of error term, and third, level of risk by measuring conditional variance of log returns.

The Threshold GARCH Model (T-GARCH)

The T-GARCH model was adopted in the study to investigate the asymmetric effect of negative and positive shocks on conditional volatility in the sample indices. There can be asymmetric volatility in the markets because of shocks in the system or various responses of the stakeholders.

The T-GARCH is an improved version of GARCH, as it has the ability to enforce asymmetric response to different shudders. The previous studies confirmed that the asymmetric response of the index to the unforeseen negative shudder to the time series will be the grounds for higher volatility, in comparison to a positive shudder of the same extent. In this study, the TARCH model along with dummy, representing the presence of negative shocks in the lagged error terms, are used to analyse the volatility in the selected stock markets.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma \mu_{t-1}^2 I_{t-1} \tag{3}$$

The Exponential GARCH Model (E-GARCH)

The E-GARCH model can be generalised to describe more lags in the conditional variance. The non-negativity constraints on the parameters are not there in the E-GARCH model. The ARCH term will be categorised into two independent variables, which indicate the sign effect of shocks on index volatility and the size (magnitude) effect of shocks on the volatility.

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left| \frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right| \tag{4}$$

The GARCH in Mean Model (M-GARCH)

The objective of adopting the M-GARCH model was to investigate the response of the price discovery process with respect to any change in conditional volatility. The conditional volatility is found to be significant and positive, if the conditional volatility is found to be associated with returns.

$$Index\ Return_t = \alpha + \beta_1 y_{t-1} + \beta_2 \varepsilon_{t-1} + \beta_3 \sigma_t^2 \tag{5}$$

The GARCH (1, 1) Model with Exogenous Variable

For studying the volatility spillover effects of SENSEX on the global markets, the GARCH (1, 1) model was adopted, including the SENSEX volatility as the exogenous variable in the GARCH equation (Yilmaz, 2009). For studying the volatility spillover effects of the global markets on SENSEX, the GARCH (1, 1) model was adopted, including the global market volatility as the exogenous variable in the GARCH equation. The squared residuals of the ARMA (1, 1) model were estimated and were considered as the volatility substitutes for the sample markets. Such squared residuals were used as exogenous variables in the model.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma \mu_{t-1}^2 I_{t-1} \tag{6}$$

Table 1: Summary Statistics of Sample Indices

	SENSEX	CAC40	DAX	STOXX50	FTSE100	BOVESPA	DJIA	HIS	KOSPI	NIKKEI	SCI	RTSI
Mean	0.06	0.02	0.04	0.01	0.02	0.04	0.13	0.03	0.04	0.03	0.04	0.04
Median	0.09	0.04	0.1	0.02	0.01	0.02	0.09	0.03	0.06	0.06	0.06	0.08
Max.	17.34	11.18	11.4	11	9.84	14.66	56.8	14.35	11.95	14.15	9.45	22.39
Min.	−10.96	−9.04	−7.16	−7.88	−8.85	−11.39	−30.31	−12.7	−10.57	−11.41	−8.84	−19.1
Std. Dev.	1.52	1.45	1.4	1.45	1.19	1.79	4.71	1.56	1.31	1.57	1.75	2.25
Skewness	0.32	0.2	0.17	0.17	0.03	8.67	34.04	12.82	11.36	10.65	6.77	13.9
Kurtosis	12.53	9.48	9.46	9.19	11.33	0.22	2.16	0.3	−0.36	−0.25	−0.37	0.09
JB Statistic	10688.63	5121.59	5077.95	4462.43	8548.11	3820.28	116304.8	11528.07	8290.24	6876.55	1744.42	14179.01
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	170.96	46.04	115.76	39.37	46.72	108.51	355.6	72.68	104.01	74.97	127.04	111.13
Sum. Sq. Dev.	6511.39	6098.94	5713.4	5852.77	4181.57	9044.04	63093.	6952.6	4837.4	6907.84	8680.2	14460.
ADF Test	-49.23^{**}	-56.55^{**}	-54.08^{**}	-26.21^{**}	-26.07^{**}	-53.83^{**}	-16.04^{**}	-55.05^{**}	-52.11^{**}	-55.35^{**}	-52.12^{**}	-48.95^{**}
ARCH Test	76.163^{**}	105.623^{**}	77.307^{**}	127.049^{**}	57.397^{**}	87.198^{**}	127.589^{**}	542.806^{**}	156.104^{**}	433.639^{**}	105.704^{**}	141.355^{**}

Source: Results in E-Views, **Significant at 1% level.

Hypotheses Development

H_0^1: There are no ARCH or GARCH errors.

H_0^2: There is no asymmetric effect of negative and positive shocks on conditional volatility.

H_0^3: There is no effect of volatility persistence on imminent conditional volatility.

H_0^4: There is no significant impact of conditional volatility of the indices returns on the conditional returns.

H_0^5 (a): There is no volatility spillover from SENSEX to Global Indices.

H_0^5 (b): There is no volatility spillover from Global Indices to SENSEX.

ANALYSIS AND RESULTS

Descriptive Analysis, Stationarity Analysis, and Volatility Clustering

The descriptive statistics, depicted in Table 1, show that mean returns of all the indices in the sample were positive, though it was found that the mean daily return of SENSEX was highest (0.06) among all the indices, followed by DAX index, whereas the average daily return of STOXX50 index was the lowest (0.01). The fact that the emerging markets are more volatile is evident from statistics on standard deviation of daily returns in these markets. In general, the developed market returns are less volatile, with standard deviation lesser than the emerging markets.

Skewness values exhibit an asymmetrical distribution with a long tail to the right. All the Kurtosis values of the stock markets investigated in this study display a value more than three, showing a leptokurtic curve, which demonstrates that the distribution of stock returns in these countries contain extreme values. The values of Kurtosis accompanied with those of Jarque-Berra statistic, clearly indicate that the returns of these markets are not normally distributed. The ADF test was performed for each of the indices in the sample included.

As can be seen from Table 1, the p-value is less than 5% for all the variables at the first difference level. It was found that all the stock indices prices are non-stationary at the original level and they are stationary at the first difference.

Volatility clustering was found to exist in each of the indices in the sample at different levels. As the p-value of F statistics and observed R-squared was less than 1%, it indicated the existence of volatility clustering in the stock markets. The main explanation for different levels of volatility clustering may be because of the development of these indices and mysterious behavioural aspects of stockholders.

Conditional Volatility

For investigating the fauna of conditional volatility in the sample indices, the GARCH (1, 1) model was adopted. The results of the GARCH (1, 1) analysis are shown in Table 2. The results shown that the p-value of the coefficient of ARCH and GARCH were found to be less than 1%. These results show that there is a significant impact of residuals and GARCH term at the first lag. The findings also show that the sum total of both independent terms was less than one, but the projected decaying rate of volatility in the sample indices is different. Hence, the NH-1, There are no ARCH or GARCH errors, was rejected.

Table 2: GARCH (1, 1) Analysis for Conditional Volatility

Index	Intercept	GARCH (−1)	RESID (−1)^2	Decaying Rate
SENSEX	1.89E−06 (0.0000)**	0.912 (0.0000)**	0.086 (0.0000)**	2.1%
CAC40	4.02E−06 (0.0000)**	0.933 (0.0000)**	0.126 (0.0000)**	1.9%
DAX	3.02E−06 (0.0000)**	0.906 (0.0000)**	0.113 (0.0000)**	1.7%
STOXX50	3.66E−06 (0.0000)**	0.910 (0.0000)**	0.132 (0.0000)**	2.9%
FTSE100	5.14E−06 (0.0000)**	0.932 (0.0000)**	0.087 (0.0000)**	2.1%
BOVESPA	7.66E−06 (0.0000)**	0.891 (0.0000)**	0.102 (0.0000)**	3.0%
DJIA	2.52E−06 (0.0000)**	0.875 (0.0000)**	0.147 (0.0000)**	2.1%
HIS	2.75E−06 (0.0000)**	0.901 (0.0000)**	0.093 (0.0000)**	1.4%
KOSPI	1.05E−06 (0.0000)**	0.921 (0.0000)**	0.086 (0.0000)**	0.9%
NIKKEI	9.09E−06 (0.0000)**	0.811 (0.0000)**	0.168 (0.0000)**	3.6%
SCI	7.38E−06 (0.0000)**	0.779 (0.0000)**	0.145 (0.0000)**	9.6%
RTSI	7.89E−06 (0.0000)**	0.906 (0.0000)**	0.086 (0.0000)**	1.4%

Source: Results in E-Views, **Significant at 1% level.

The decaying rate of volatility was found to be highest in SCI (9.6%), followed by NIKKEI (3.6%), and STOXX50 (2.9%), and the least was found in the case of RTSI (1.4%). These results were supported by previous studies like Karmakar (2005), Kumar and Dhankar (2009), and Gupta et al. (2013).

Asymmetric Volatility

The analysis of asymmetric volatility indicated in Table 3 shows that the p-value of slope coefficient of ARCH term, GARCH term, and the dummy variable were found to be significant. Therefore, NH-2, There is no asymmetric effect of negative and positive shocks on conditional volatility, was rejected. These results indicated that volatility in the sample markets have a significant persistence level, it is affected by the unpredicted shocks, and the stakeholders had asymmetric responses to negative shocks as well as positive shocks.

Table 3: T-GARCH Analysis for Asymmetric Effect in Conditional Volatility

Index	Intercept	RESID (−1)^2	GARCH (−1)	RESID(−1) ^2*RESID (−1)<0
SENSEX	2.05E−06 (0.0000)**	0.048 (0.0000)**	0.912 (0.0000)**	0.111 (0.0000)**
CAC40	4.57E−06 (0.0000)**	−0.005 (0.0000)**	0.891 (0.0000)**	0.212 (0.0000)**
DAX	3.51E−06 (0.0000)**	0.003 (0.0000)**	0.903 (0.0000)**	0.171 (0.0000)**
STOXX50	3.49E−06 (0.0000)**	−0.003 (0.0000)**	0.881 (0.0000)**	0.213 (0.0000)**
FTSE100	5.24E−06 (0.0000)**	−0.009 (0.0000)**	0.921 (0.0000)**	0.136 (0.0000)**
BOVESPA	6.99E−06 (0.0000)**	0.033 (0.0000)**	0.899 (0.0000)**	0.119 (0.0000)**
DJIA	2.31E−06 (0.0000)**	−0.009 (0.0000)**	0.222 (0.0000)**	0.876 (0.0000)**
HIS	3.57E−06 (0.0000)**	0.051 (0.0000)**	0.896 (0.0000)**	0.087 (0.0000)**
KOSPI	1.45E−06 (0.0000)**	0.033 (0.0000)**	0.915 (0.0000)**	0.111 (0.0000)**
NIKKEI	8.66E−06 (0.0000)**	0.063 (0.0000)**	0.835 (0.0000)**	0.163 (0.0000)**
SCI	7.15E−06 (0.0000)**	0.162 (0.0000)**	0.781 (0.0000)**	−0.047 (0.0000)**
RTSI	5.78E−06 (0.0000)**	0.011 (0.0000)**	0.934 (0.0000)**	0.096 (0.0000)**

Source: Results in E-Views, **Significant at 1% level.

E-GARCH (1, 1) Model

The E-GARCH model indicated the effect of volatility persistence on imminent conditional volatility in the returns of the indices (Table 4). Hence, NH-3, There is no effect of volatility persistence on imminent conditional volatility, was rejected. The results indicated that the conditional volatility of the sample indices had an inverse relation with the sign of shock. The same relation was indicated by the coefficient of slope.

Table 4: E-GARCH Analysis for Persistence in Conditional Volatility

Index	Intercept	GARCH Term	Sign Effect of ARCH Term	Size Effect of ARCH Term
SENSEX	−0.291 (0.0000)**	0.190 (0.0000)**	−0.082 (0.0000)**	0.986 (0.0000)**
CAC40	−0.351 (0.0000)**	0.135 (0.0000)**	−0.153 (0.0000)**	0.975 (0.0000)**
DAX	−0.349 (0.0000)**	0.156 (0.0000)**	−0.126 (0.0000)**	0.974 (0.0000)**
STOXX50	−0.311 (0.0000)**	0.132 (0.0000)**	−0.167 (0.0000)**	0.981 (0.0000)**
FTSE100	−0.240 (0.0000)**	0.101 (0.0000)**	−0.130 (0.0000)**	0.140 (0.0000)**
BOVESPA	−0.333 (0.0000)**	0.167 (0.0000)**	−0.091 (0.0000)**	0.981 (0.0000)**
DJIA	0.395 (0.0000)**	0.165 (0.0000)**	−0.162 (0.0000)**	0.973 (0.0000)**
HIS	−0.311 (0.0000)**	0.179 (0.0000)**	−0.063 (0.0000)**	0.985 (0.0000)**
KOSPI	−0.243 (0.0000)**	0.162 (0.0000)**	−0.072 (0.0000)**	0.991 (0.0000)**
NIKKEI	−0.612 (0.0000)**	0.243 (0.0000)**	−0.111 (0.0000)**	0.955 (0.0000)**
SCI	−0.915 (0.0000)**	0.263 (0.0000)**	0.028 (0.0000)**	0.905 (0.0000)**
RTSI	−0.192 (0.0000)**	0.097 (0.0000)**	−0.086 (0.0000)**	0.989 (0.0000)**

Source: Results in E-Views, **Significant at 1% level.

M-GARCH (1, 1) Model

The results of the M-GARCH model, indicated in Table 5, depicted that the slope coefficient of the M-GARCH model equation was insignificant. Therefore, it can be inferred that there was no significant impact of conditional volatility of the indices returns on the conditional returns of these indices. Therefore, NH-4 was not rejected. The results have shown that in high volatile periods, selected indices did not provide high returns as expected, as per risk-return tradeoff theory. No relationship was found between conditional volatility and conditional returns of these indices.

Table 5: M-GARCH Analysis for Impact of Conditional Volatility on Conditional Returns

Index	Intercept	GARCH Term
SENSEX	0.002 (0.0018)**	0.875 (0.659)
CAC40	0.000 (0.5011)	1.712 (0.391)
DAX	0.000 (0.1812)	2.012 (0.3891)
STOXX50	0.000 (0.3217)	2.612 (0.1715)
FTSE100	−0.002 (0.3801)	3.012 (0.1786)
BOVESPA	−0.003 (0.8421)	3.543 (0.0000)
DJIA	0.000 (0.0003)	2.453 (0.196)
HIS	0.003 (0.177)	0.712 (0.706)
KOSPI	0.002 (0.401)	0.777 (0.726)
NIKKEI	0.000 (0.302)	3.753 (0.083)
SCI	0.001 (0.612)	−0.933 (0.581)
RTSI	0.603 (0.705)	−0.003 (0.091)

Source: Results in E-Views.

Volatility Spillover

The p-value of SENSEX volatility as an exogenous variable was found to be significant for all global indices used in the study. It can be inferred from Table 6 that there has been volatility spillover at a significant level from SENSEX to the Global Indices.

Table 6: Volatility Spillover from SENSEX to Global Indices

Index	Intercept	RESID (−1)^2	GARCH (−1)	Volatility Spillover
CAC40	4.62E−06 (0.0000)**	0.131 (0.0000)**	0.833 (0.0000)**	0.033 (0.0000)**
DAX	3.27E−06 (0.0000)**	0.112 (0.0000)**	0.861 (0.0000)**	0.032 (0.0000)**
STOXX50	3.17E−06 (0.0000)**	0.136 (0.0000)**	0.829 (0.0000)**	0.036 (0.0000)**
FTSE100	4.78E−06 (0.0000)**	0.091 (0.0000)**	0.903 (0.0000)**	0.014 (0.0000)**
BOVESPA	1.44E−06 (0.0000)**	0.118 (0.0000)**	0.892 (0.0000)**	0.072 (0.0000)**
DJIA	2.18E−06 (0.0000)**	0.145 (0.0000)**	0.829 (0.0000)**	0.036 (0.0000)**
HIS	2.86E−06 (0.0000)**	0.087 (0.0000)**	0.891 (0.0000)**	0.027 (0.0000)**
KOSPI	1.82E−06 (0.0000)**	0.104 (0.0000)**	0.838 (0.0000)**	0.049 (0.0000)**
NIKKEI	8.93E−06 (0.0000)**	0.168 (0.0000)**	0.813 (0.0000)**	0.021 (0.0000)**
SCI	5.37E−06 (0.0000)**	0.131 (0.0000)**	0.771 (0.0000)**	0.091 (0.0000)**
RTSI	7.23E−06 (0.0000)**	0.082 (0.0000)**	0.914 (0.0000)**	0.018 (0.0000)**

Source: Results in E-Views, **Significant at 1% level.

Table 7: Volatility Spillover from Global Indices to SENSEX

Index	Intercept	RESID (−1)^2	GARCH (−1)	Volatility Spillover
CAC40	1.13E−06 (0.0000)**	0.091 (0.0000)**	0.912 (0.0000)**	0.014 (0.0000)**
DAX	1.27E−06 (0.0000)**	0.086 (0.0000)**	0.901 (0.0000)**	0.015 (0.0000)**
STOXX50	1.31E−06 (0.0000)**	0.090 (0.0000)**	0.899 (0.0000)**	0.012 (0.0000)**
FTSE100	1.29E−06 (0.0000)**	0.077 (0.0000)**	0.925 (0.0000)**	0.003 (0.0000)**
BOVESPA	8.77E−06 (0.0000)**	0.090 (0.0000)**	0.897 (0.0000)**	0.011 (0.0000)**
DJIA	1.89E−06 (0.0000)**	0.087 (0.0000)**	0.874 (0.0000)**	0.055 (0.0000)**
HIS	2.17E−06 (0.0000)**	0.097 (0.0000)**	0.903 (0.0000)**	0.072 (0.0000)**
KOSPI	1.88E−06 (0.0000)**	0.088 (0.0000)**	0.868 (0.0000)**	0.059 (0.0000)**
NIKKEI	1.38E−06 (0.0000)**	0.096 (0.0000)**	0.901 (0.0000)**	0.009 (0.0000)**
SCI	1.14E−06 (0.0000)**	0.099 (0.0000)**	0.853 (0.0000)**	0.005 (0.0000)**
RTSI	1.53E−06 (0.0000)**	0.095 (0.0000)**	0.895 (0.0000)**	0.006 (0.0000)**

Source: Results in E-Views, **Significant at 1% level.

The p-value of global index volatility as an exogenous variable was found to be significant for SENSEX. It can be inferred from these results in Table 7 that there has been volatility spillover at a significant level from global indices to SENSEX.

CONCLUSION

This paper investigated volatility and volatility spillover between India and 11 global indices using various GARCH models. The results have shown the existence of volatility clustering in all the indices used in the study, which was indicated by the residuals of the ARMA (1, 1) estimation model. GARCH (1, 1) model was applied on the sample indices, and the slope coefficient of ARCH term and GARCH term were found to be statistically significant, which established the existence of conditional volatility.

Table 8: Summary of Hypotheses Developed

Hypothesis Statement	Overall Results for Null Hypothesis
H_0^1: There are no ARCH or GARCH errors.	Rejected**
H_0^2: There is no asymmetric effect of negative and positive shocks on conditional volatility.	Rejected**
H_0^3: There is no effect of volatility persistence on imminent conditional volatility.	Rejected**
H_0^4: There is no significant impact of conditional volatility of the indices returns on the conditional returns.	Not Rejected
H_0^5 (a): There is no volatility spillover from SENSEX to Global Indices.	Rejected**
H_0^5 (b): There is no volatility spillover from Global Indices to SENSEX.	Rejected**

Note: **Significant at 1% level.

For comparison of various constituents of conditional volatility in the sample, various GARCH family models were applied on the residuals of the ARMA (1, 1) model. The results of T-GARCH model showed the existence of significant asymmetric effect on conditional volatility. The results show that the impact of negative shocks was much higher than positive shocks. The results of E-GARCH model show the existence of volatility persistence in conditional volatility. The slope coefficient of size effect was found to be positive, and the coefficient of sign effect was found to be negative for all indices. This indicated the inverse relationship of conditional volatility with sign of the index. The results of the M-GARCH model indicated that there was no significant impact of conditional volatility on conditional returns of the indices in the sample.

The results regarding volatility spillover posit that the Indian stock market had a strong impact on selected global indices. Volatility spillover was found to be in existence from the Indian stock market to the global indices, and vice-versa. The coefficients were found to be positive, which indicated the positive impact of volatility of one market on the other.

RESEARCH IMPLICATIONS

A knowledge of the basics and the driving forces of volatility and cross-correlation among various markets is crucial for stakeholders, policy makers, and investors. Previous studies found a very high positive link between returns related to shocks and the co-integration among the stock markets. This paper emphasises the development of a new feature of time-varying shock spillover concentrations, as the co-integration has a vital impact on the cost of equity capital, as well as being considered a significant factor in various macroeconomic models.

These findings have substantial inferences and repercussions for portfolio managers, analysts, and investors for investment assessments and decisions regarding asset allocations. The findings show that more consideration should be given to co-integration among markets and their volatility movements. Higher volatility will lead to higher level of fretfulness among market participants and investors, which will push them to be more risk-averse. Singhal and Ghosh (2016) suggested that investors tend to diversify their investment portfolio and hedging to maximise returns and minimise risks.

The results of the study also have pertinent effects for policy makers with respect to the Indian stock market and the foreign countries. Market traders, hedgers, and portfolio managers will be capable of understanding the interrelation of volatility association among the stock indices. According to Xuan, Vinh and Ellis (2018), "globalisation and financial integration is the outgoing trend to promote further international connectedness".

LIMITATION OF THE STUDY

This study is based on the daily closing price data; seasonal anomalies were ignored. This study was not able to generalise the findings, as it had used SENSEX and only a few selected countries.

SCOPE FOR FURTHER RESEARCH

This study can be conducted by taking into consideration other indices, such as BRIC countries. This study can be carried out by using individual stocks or other significant indices (e.g. Nifty-50) as the sample.

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