SPILLOVER EFFECT FROM GLOBAL STOCK MARKETS TO INDIAN STOCK MARKET

ABSTRACT

Purpose – The study aims to examine the transmission of spillover effects from global stock markets to the Indian stock market. The chosen global markets are CAC-40, DJIA, FTSE 100, SMI, KOSPI, DAX, HANG SENG, and NIKKEI with respect to S&P BSE SENSEX.

Design/Methodology/Approach – The study uses secondary data. The study period is from 1^{st} January 2000 to 4^{th} June 2021. The required data for the study has been collected from the Thomson Reuters database. Later the collected data has been tested for stationarity by running the ADF test. Since we found an arch effect in the collected time series data, we ran the GARCH model to investigate the spillover effect from developed stock markets to the Indian stock market by running all the three suggested models such as Normal Gaussian Distribution, Student t Distribution, and GED with fixed parameter. To capture the leverage effect, the researchers have run the EGARCH model to capture spillover asymmetry in the Indian stock market.

Findings – The ARCH, GARCH, and EGARCH revealed that there was a significant information spillover effect from CAC-40, FTSE 100, SMI, KOSPI, HANG SENG, and NIKKEI on S&P BSE SENSEX. DJIA and DAX were not capable of spreading the spillover effect on BSE SENSEX. The EGARCH revealed that negative shocks in the foreign market created a significant spillover effect in the Indian stock market.

Originality and Value – This study's empirical analysis would help market participants in understanding the forecasted volatility of Sensex returns and can take this sign as an advantage to converting their holdings into returns. The market participants can also make a decision as to whether they can invest in the Indian stock market and diversify their portfolios.

Keywords: Spillover effect, ARCH, GARCH, EGARCH, ADF Test

JEL Classification: G15

I. INTRODUCTION

The spillover effect originates from a single source and its impact has a ripple effect on nonparticipating economies. It can either have a positive or negative effect on economies. Some countries don't get affected due to spillovers, as they are considered safe-haven economies where investors invest when a downturn occurs. A positive spillover effect occurs when an action in the environment leads to an increase in one or more pro-environmental behaviour. For example, the COVID-19 pandemic caused some positive spillover effects. In early 2020, when all countries across the world enforced lockdown measures, it was reported that the pollution level fell significantly due to a reduction in human activities. In India, New Delhi's India Gate could be seen without the smog blocking the view. Butler, A. W., Fauver, L., & Spyridopoulos, I. (2019), conducted a study to point out the positive spillover effects from an IPO on the economy in the form of increased local employment, business and real estate outcomes. Gerschewski, S. (2013) to identify the positive or negative spillover effects from FDI on local firms conducted a study to find there was an inter-industry positive spillover effect. A negative spillover effect is the opposite of a positive spillover. Its occurrence in the environment elevates unwanted social, political, and economic behaviours. For example, the COVID-19 pandemic, a single event arising from Wuhan, China, spread to the whole world to become the disaster of the 21^{st} century. Gerschewski, S. (2013), the researcher also found the existence of a negative spillover between the same firms in the market as the MNEs absorbed the smaller firms due to overcrowding of the MNEs. Therefore, it created an economic crisis in one country which had a network effect in other countries. An economic crisis is defined as a sharp decline in the economic state of a country, which in turn leads to a decline in the living standards of the population and a decrease in the real gross national product. For example, the great depression of 1929-39 was the worst financial and economic disaster of the 20^{th} century. It was assumed to be triggered by the wall street crash of 1929, banking panics, and a decline in the economy, the gold standard, and international trading and lending. It lasted for almost 10 years and resulted in massive loss of income, unemployment, and output loss in industrialised nations.

Information spillover among stock markets helps investors to understand the co-movements among the stock markets and also helps identify which country's stock market is suitable for investing. Chen, J. H., & Huang, C. Y. (2010) conducted a study on stock indices and EFTs using the GARCH-ARMA and EGARCH-ARMA models to investigate the spillover and leverage effect of returns and volatilities among nine indices. They found a leverage effect (positive and negative), which played a vital role in decision-making to be taken by an investor as the ETFs had an impact on the indices. The ETFs had a lower return than the indices in emerging economies and a higher return in developed economies. The spillover effect arises due to the interconnection between public news and the returns and volatility of indices. Kim, S. J. (2003) points out in his paper the spillover effects from US and Japan on the advanced Asia-Pacific stock market due to economic news announcements. The findings indicated that the advanced Asia-Pacific stock markets closely followed the US and Japan and had a direct relation with disaggregated information flow and indirect relation with aggregated information flow. To examine the integration and impact between the various global indices Zhou, X., Zhang, W., & Zhang, J. (2012) found that there was significant information spillover from the Chinese stock market to the Japanese and Indian stock markets. The integration among Chinese, US, and UK stock markets was also present but not as distinct as the interconnection between the Asian markets. There was a direct relationship between the Chinese market and the Japanese and Indian stock markets whether it a was positive or negative information spillover.

Stock market volatility can be a function of the company, industry, or worldwide publicly available information. The relationship between the Indian stock market with other countries' stock indices helps a large number of forecasters. A timely forecast provides valuable information to the financial market participants. Bhatia, P., & Gupta, P. (2020) investigated the impact of two global shocks that is US subprime mortgage crisis and COVID-19 on the volatility of Indian banking sectoral indices. The findings indicated that there was a leverage effect during the US subprime mortgage crisis in all the sectors of Indian banks. During COVID-19 only PSUBI faced a leverage effect. Forecasting helps portfolio managers to decide whether to include other countries' stocks along with Indian company stocks. Yadav, M. P., & Pandey, A. (2019) investigate whether an investor can diversify his holdings in MINT nations with comparison to the Indian stock market and find favourable results as there was no volatility spillover from India to MINT nations. Overall, the results of this study are consistent with previous studies on the spillover effect from global stock markets to the Indian stock market (Yu, Y., & Yi, R., (2019); Engle, R. F., & Ng, V. K. (1993); GC, S. B. (2016); Sruthi, R., & Shijin, S. (2017); Rastogi, S. (2010); Panda, P., & Deo, M. (2014); Mitra, P. K. (2017); GC, S. B. (2016)). The remainder of the paper is as follows: Section two deals with the various studies undertaken on the investigation of volatility spillover and its impact on various stock markets across the globe. However, section three outlines the research methodology employed for the purpose of the current study, section four discusses the analysis of the data collected from various secondary sources, and in section five a brief discussion has been made.

II. LITERATURE REVIEW

The Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are important tools for analyzing time series data mainly in forecasting volatility and leverage effect (Black, 1976). Its application is in portfolio management and optimization, asset pricing models, and risk management (Ahmed & Suliman (2011), Naimy, (2013), Kingsley & Peter, (2019). Engle and Ng (1993) advocate that volatility is to be treated as the causal variable in forecasting expected return. Variations in asset prices/returns are auto-correlated and follow a cluster pattern in the period of volatility. GARCH model is suitable to analyze volatility when there are more observations (Robert Engle, (1982; Bollerslev T (1986); Scott L.O (1991) and Hussain et al. (2019). The constant volatility argument will not hold well in the dynamic setting of time series data (Cambell et al., (1997). However, Rydberg, (2000) argues that these models are not effective in the assumption of a symmetric response between returns and volatility. Studies use the student t-test to capture Skewness and kurtosis present in non-normal distribution over ARCH and GARCH models (Baillie and Bollerslev (1987) and Fernandez and Steel (1998).

The returns and volatility linkages exist between the emerging and developed stock markets. Using VR tests, ARMA, GARCH model, and BDS test it is seen that Asian emerging stock markets exhibit weak form efficiency, and hence short-term volatility indicators are more relevant than long term (Bhowmik & Wang (2018). Athukoralalage (2011), proves that the positive spillover effect is unidirectional from developed to emerging markets by using M-GARCH and Diagonal BEKK model ARCH and GARCH techniques. Kapusuzoglu & Ceylan (2018) use the GARCH model and evidence the existence of a significant relationship between trading volume and the number of information events resulting in volatility in index prices. Maqsood et al, (2017) and Wagala et al., (2012) use symmetric and asymmetric GARCH models to estimate volatility in the returns of stocks. There is no significant GARCH effect seen in the mean model. Asymmetric models reveal that positive shock impacts the magnitude and volatility in returns to a greater extent than negative shocks. The ability to capture asymmetric impact/variation is seen high in TGARCH (1, 1) model in capturing both volatility and leverage in stock price distribution (Banumathy & Azhagaiah (2015). Epaphra (2017) applies the ARCH-GARCH and EGARCH models in measuring the effect of volatility clustering and leverage effect in exchange rates. The results of the study are similar to Meese and Rogoff (1983), Brooks (2008), and Amudha &Muthukamu (2018), and Abdalla (2012). The test reveals (1) a downward pattern (depreciation) in the currency which is also followed by higher volatility (leverage effect) and (2) a negative correlation between price movements and volatility. The EGARCH model provides a better fit than the GARCH model, validating the presence of the leverage effect. This result is evidenced in studies (Pandey, 2005; Srinivasan 2015; Floros, 2008 and Guidi, 2009) relating to Egypt, India, the UK, and Israel stock markets.

Walid et al. (2011) prove that there exists a strong asymmetric relationship between stock markets and foreign exchange markets using the Markov-Switching-EGARCH model. Asset prices are more volatile to negative shocks as proved in (Black, (1976), Engle and Ng (1993), Varughese & Mathew (2017), and Saurabh Singh & L. K. Tripathi (2016). Volatility from the previous period explains the condition of present/current volatility in exchange rates. Cryptocurrencies exhibit high and erratic price movements. The study identifies no ARCH effect in residuals. The study also considers back-testing the GARCH model as every model has a different distribution of residuals using a fixed-rolling window scheme with iterations. Asymmetric GARCH models are suitable for forecasting volatility in Cryptocurrencies (Ngunyi et al. 2019). A similar result is obtained by Wang (2021). The study concludes that leverage effect and presence are absent of the asymmetric effect of prices to shocks and hence this can be added to a portfolio of investments. When financial markets fall under similar shocks, Bitcoin shows dropping and a positive coupling effect, compared with gold, and suggests Bitcoin does not act as a hedge in equity investments. However, results may vary depending on the maturity of such markets. (Klein et al. (2018). Efthymia and Konstantinos (2018) indicate short-term return spillovers from energy and technology stocks to Bitcoin and asymmetric spillovers between Bitcoin and stock prices. The AR-CGARCH model is optimal in explaining volatility and returns in Bitcoin (Paraskevi (2018). Sathyanarayana & Gargesa (2017) conducted research to investigate the impact of policy announcements on stock market volatility. The authors employed the GARCH (1,1) model to explore the impact, the study confirmed the existence of ARCH and GARCH effects in the Indian stock market.

Ugrulu (2014) states there exists a significant persistent impact of news on volatility shocks and GARCH, GJR-GARCH, and EGARCH effects are seen in the Czech Republic, Hungary, Poland, and Turkey stock markets whereas Bulgarian markets do not witness its effect. Emerging markets are not cointegrated with benchmark markets or developed markets and exhibit regional characteristics, as revealed by the VEC model and M-GARCH model (Scheicher, 2000). Analyzing the Czech Republic, Hungary, Poland, and Slovakia using both univariate and multivariate GARCH models (GARCH, NGARCH, EGARCH, GJR-GARCH, AGARCH, NAGARCH, and VGARCH), Haroutonian and Price, 2010 finds no asymmetric effects in the markets.

Ching Mun Lim & Siok Kun Sek (2013) exchange rate and crude oil price have a significant impact on the Malaysia stock market volatility (Pre-Crisis) whereas, no impact is seen in the post-crisis period. Yuanwell Hu et al. (2020) conclude that the ARMA model has a better prediction effect on the volatility and stock returns of bank stocks, but the ARMA model has a much better fit for the prediction of stock yields than the GARCH model.

The coefficient has a likely indication both in EGARCH (negative, significant) and TGARCH (positive, significant) models. EGARCH (1, 1) model fits better to capture the asymmetric volatility (Bedanta Bora and Anindita Adhikary (2019). Another study by Sathyanarayana et al., (2018) tried to explore the impact of a spillover effect from commodity (crude prices) on the stock market and found a significant impact of commodity spillover on the stock market.

Previous studies have focused on information spillover effects from developed to developing countries, and some studies with Asian or US markets to Indian markets. There are very studies with the application of the E-GARCH model to test asymmetry in stock prices mainly in developing or emerging market economies. This paper tries to address the following research questions:

1. Is there any volatility spillover and return spillover from the global market to the Indian markets?
2. Are various global markets integrated, if yes to what extent?

3. Is there any information asymmetry in the Indian stock market to global stock markets?

III. RESEARCH DESIGN

OBJECTIVES OF THE STUDY

1. To determine whether is there any significant information spillover effect from the developed stock market (such as SMI, KOSPI, Nikkei, Hang Seng, DAX, FTSE100, DJIA, and CAC40) on the developing stock market (India).
2. To identify whether is there any information asymmetrical spillover effect from global stock markets on chosen benchmark index (S&P BSE Sensex)
3. To capture the existence of any Leverage effect and to forecast the volatility based on historical data.

HYPOTHESIS OF THE STUDY

H0 = the overseas stock markets do not influence the volatility in the Indian stock market

H1 = the overseas stock markets do influence the volatility in the Indian stock market

MEAN EQUATION

ISR = C1 + C2*DJIA + e

VARIANCE EQUATION

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1) + C(6)*FTSE100 + C(7)*CAC40 + C(8)*Nikkei + C(7)*Hang Seng + C(8)*DAX + C(9)*DJIA + C(10)*KSOPI + C(11)*SMI

H0 = the overseas stock market does not cause movement in the Indian stock markets.

H1 = the overseas stock markets are the cause for movements in the Indian stock markets.

DATA COLLECTION

Secondary data in the report play a very important role in the study. The secondary data is collected from the Thomson Reuters database. The data includes closing prices and returns of nine indices for 21 years that is from 1st March 2000 to 30th September 2021 daily. The following is the list of indices collected for the study. S&P BSE Sensex, SMI, KOSPI, Nikkei, Hang Seng, DAX, FTSE100, DJIA and CAC-40.

PLAN OF ANALYSIS

The data collected from various stock exchanges for ten years is matched as per the dates of the BSE data, as the days when different market observes a close is different. Those days on which data from other markets are not available as per BSE are not considered for the study. For performing the stationarity test the method used is the Augmented Dickey-Fuller (ADF) test which gives us a fair idea as to how to proceed further for the test of econometrics applied for the study. In the second phase, descriptive statistics have been run to understand the pattern. In the last phase ARCH(1,1), GARCH(1,1), and EGARCH(1,1) model has been run to understand the cause of transmission of volatility in the Indian stock market. Later a brief summary of findings has been arrived at, a scheme of suggestions has been offered and meaningful conclusions have been drawn.

IV. DATA ANALYSIS AND RESULTS

Analysis: The mean value for Sensex for the study period was 0.000405 with a standard deviation of 0.014278. The reported Sample Kurtosis of 12.84960 and skewness of -0.387128. The maximum value recorded for the study period was 0.159900 and the minimum recorded for the study period was -0.141017. However, the Jarque-Bera statistics for the period were 22829.50 with a p-value of 0.0000. This indicates the data is not normally distributed.

TABLE No. 1

TABLE SHOWING ADF TEST RESULTS (UNIT ROOT TEST)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-72.27382	0.0000
Test critical values:	1% level	-3.959672	
	5% level	-3.410605	
	10% level	-3.127079	

Source: Desk Research

Analysis: In order to check the stationary of the time series data of Sensex Index (Returns) was tested for the stationary by using the ADF test. It is evident from Table No 1 that ADF test statistics 72.27382 with a critical value at 1% of 3.959672, at 5% of 3.410605, and 10% with 3.127079 which is higher than the three critical values indicating acceptance of a null hypothesis. Therefore, there is no unit root in the time series data or the data is stationary.

GRAPH No. 1

GRAPH SHOWING RETURNS OF SENSEX

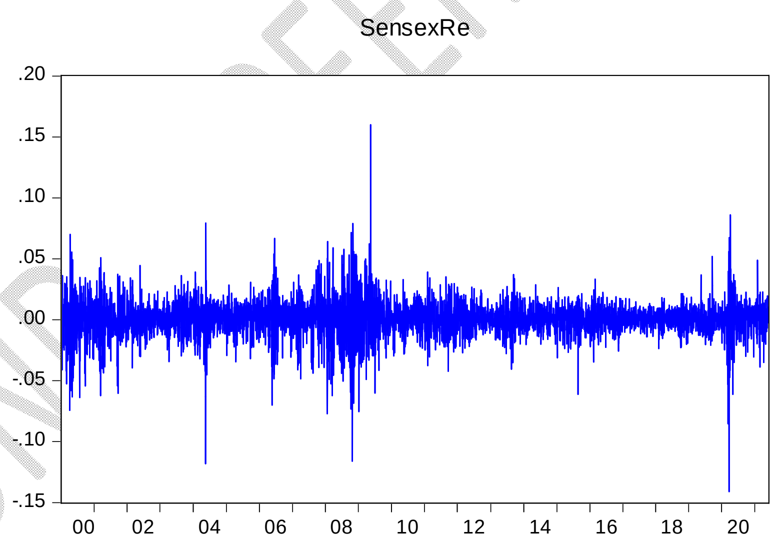


TABLE No. 2

TABLE SHOWING HETEROSKEDASTICITY TEST: ARCH

F-statistic	228.2634	Prob. F (1,5610)	0.0000
Obs*R-squared	219.4170	Prob. Chi-Square (1)	0.0000

Source: Desk Research

Analysis: To determine the ARCH effect in the time series data set (Sensex Returns), an ARCH test has been run. It is evident from the above Table No 2 that the F- statistic 228.2634 with a p-value of 0.0000 (<0.05), there is an ARCH effect in the data set. Since the researcher found an ARCH effect in all the data set chosen for the study (evidenced through Heteroskedasticity), the researcher ran the ARCH (1,1), GARCH (1,1), and EGARCH (1,1) test. To run the test, the researcher has employed the following three suggested models

1. Normal Gaussian distribution
2. Student t distribution
3. GED with Fixed parameter

Later the strength of the individual model has been tested by taking a level of significance of ARCH and GARCH, Adj R^2 Value, AIC, Hannan-Quinn, and SIC criteria, and Durbin-Watson test for autocorrelation.

To forecast the volatility in the Indian stock market, the researcher has conducted the following model selection criteria:

TABLE No. 3

TABLE SHOWING MODEL SELECTION

	X1	X2	X3	X4	X5	X6	X7	X8
Normal Gaussian Distribution	√	√	√	√	x	√	x	√
Student t Distribution	√	√	√	√	x	√	x	√
GED with Fixed-Parameter	√	√	√	√	x	√	x	√

	Adj R^2	DW	AIC	SIC	H-QC	ARCH	CQS	Norm
Normal Gaussian Distribution	0.264	2.040	-6.346	-6.332	-6.341	NO	NO	x
Student t Distribution	0.262	2.078	-6.394	-6.377	-6.388	NO	NO	x
GED with Fixed-Parameter	0.262	2.077	-6.392	-6.375	-6.386	NO	NO	x

X1: SMI; X2: KOSPI; X3: Nikkei; X4: Hang Seng; X5: DAX; X6: FTSE100; X7: DJIA and X8: CAC-40
DW: Durbin-Watson statistics
AIC: Akaike info criterion
SIC: Schwarz criterion
H-QC: Hannan-Quinn criterion
ARCH: for ARCH effect
C Q S: Correlogram Squared Statistics
Norm: Normal distribution

Source: Desk Research

Analysis: The researcher has applied the above Table No 3 to select the appropriate model for forecasting volatility in Sensex: Under Normal Gaussian Distribution we found six chosen stock markets were significant, Adjusted R-Squared for the model was 0.264, where Durbin-Watson statistics was 2.040, AIC was -6.346, SIC was -6.332 and H-QC was -6.341. However, in residual diagnostics, we did not find any ARCH effect, no autocorrelation, and data were not normally distributed. Under Student t Distribution, we found six chosen stock markets were significant, Adjusted R-Squared for the model was 0.262, where Durbin-Watson statistics was 2.078, AIC was -6.394, SIC was -6.377 and H-QC was -6.388. However, in residual diagnostics, we did not find any ARCH effect, no autocorrelation, and data were not normally distributed. Under GED with Fixed-Parameter, we found six chosen stock markets were significant, Adjusted R-Squared for the model was 0.262, where Durbin-Watson statistics was 2.077, AIC was -6.392, SIC was -6.375 and H-QC was -6.386. However, in residual diagnostics, we did not find any ARCH effect, no autocorrelation, and data were not normally distributed. Therefore, the final model selection was student t distribution.

STUDENT t DISTRIBUTION WITH FIXED PARAMETER

TABLE No 4

TABLE SHOWING STUDENT t DISTRIBUTION WITH FIXED PARAMETER

GARCH = C(12) + C(13)*RESID(-1)^2 + C(14)*GARCH(-1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000602	0.000111	5.416696	0.0000
SMIRE	0.048038	0.017931	2.679020	0.0074
KOSPIRE	0.117493	0.012288	9.561971	0.0000
NIKKIERE	0.036378	0.010660	3.412615	0.0006
HANGSENGRE	0.245733	0.012488	19.67752	0.0000
DAXRE	0.022408	0.018859	1.188231	0.2347
FTSERE	0.070654	0.023213	3.043756	0.0023
DJIARE	-0.004477	0.013523	-0.331042	0.7406
CAC40RE	0.066356	0.023907	2.775623	0.0055
SENSEXRE (-1)	0.019185	0.011789	1.627339	0.1037
SENSEXRE (-2)	-0.004564	0.011474	-0.397784	0.6908
Variance Equation				
C	1.48E-06	2.60E-07	5.685603	0.0000
RESID (-1) ^2	0.086754	0.006798	12.76159	0.0000
GARCH (-1)	0.899762	0.007188	125.1825	0.0000

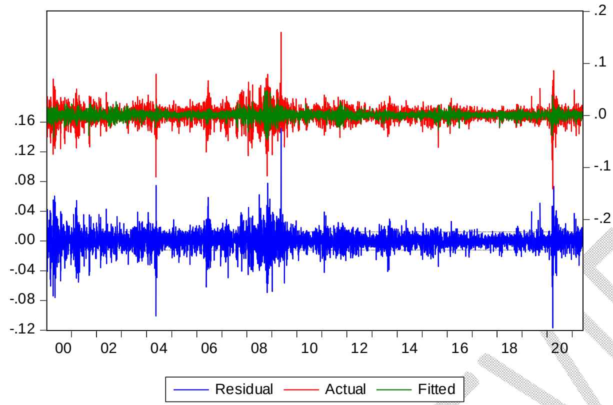
Source: Desk Research

Analysis: It is evident from the above Table No 4 that there is a significant information spillover effect of transmission of volatility from SMI to Sensex with a positive coefficient of 0.048038, with z-Statistic 2.679020 with a p-value of 0.0074 (<0.01) which was statistically significant. Similarly, KOSPI was also capable of spreading spillover effect on Sensex with a positive coefficient of 0.117493, with z-Statistic 9.56197 with a p-value of 0.0000 (<0.01) which was statistically significant. Nikkei was also capable of spreading spillover effect on Sensex with a positive coefficient of 0.036378, with z-Statistic 3.412615 with a p-value of 0.0006 (<0.01) which was statistically significant. Hang Seng was also capable of spreading spillover effect on Sensex with a positive coefficient of 0.245733, with z-Statistic 19.67752

GARCH were also statistically significant. Adjusted R squared for the study period was 0.261820 and Durbin-Watson statistics was 2.077691 meaning that there was no autocorrelation in the time series data.

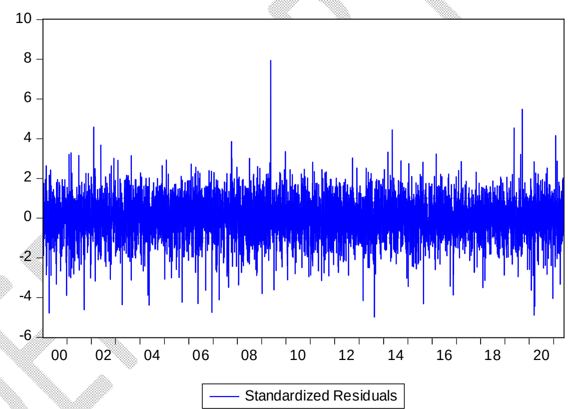
GRAPH No 2

GRAPH SHOWING RESIDUAL, ACTUAL, AND FITTED DATA



GRAPH No 3

GRAPH SHOWING STANDARDISED RESIDUALS



RESIDUAL DIAGNOSTICS

Autocorrelation test: This test represents the degree of similarity in a given set of time series data and the lagged version of the same time series data over consecutive intervals. It measures the relationship of a variable's current value with its past value. An autocorrelation of +1 indicates a perfect positive correlation and -1 indicates a perfect negative correlation. The Durbin-Watson is always used to test for autocorrelation. The Durbin-Watson number ranges from 0 to 2.5.

TABLE No 5

TABLE SHOWING AUTOCORRELATION

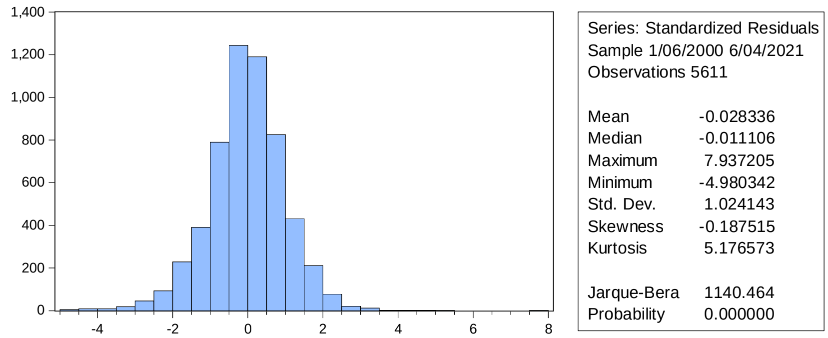
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.009	0.009	0.4321	0.511
		2	0.010	0.010	0.9869	0.611
		3	0.026	0.026	4.4914	0.213
		4	0.013	0.012	5.3135	0.257
		5	-0.001	-0.002	5.3168	0.378
		6	0.007	0.006	5.5425	0.476
		7	-0.001	-0.002	5.5461	0.594
		8	-0.022	-0.022	8.1566	0.418
		9	0.010	0.010	8.6832	0.467
		10	0.022	0.022	11.271	0.337
		11	-0.025	-0.024	14.472	0.208
		12	-0.030	-0.030	19.156	0.085
		13	0.014	0.014	20.259	0.089
		14	0.008	0.009	20.592	0.113
		15	-0.014	-0.013	21.628	0.118
		16	0.000	-0.001	21.628	0.156
		17	0.015	0.015	22.748	0.158
		18	0.003	0.004	22.781	0.199
		19	-0.020	-0.022	24.861	0.165
		20	-0.003	-0.005	24.921	0.204
		21	0.000	0.003	24.922	0.251
		22	0.001	0.003	24.925	0.301
		23	-0.007	-0.009	25.155	0.342
		24	0.002	0.002	25.178	0.396
		25	-0.018	-0.015	26.839	0.364
		26	-0.025	-0.025	30.185	0.260
		27	-0.016	-0.018	31.611	0.247
		28	-0.010	-0.007	32.120	0.270
		29	-0.013	-0.008	32.987	0.278
		30	-0.008	-0.008	33.363	0.307
		31	-0.002	-0.003	33.391	0.352
		32	-0.018	-0.015	35.012	0.327
		33	-0.003	-0.002	35.076	0.370
		34	0.005	0.004	35.229	0.410
		35	0.016	0.017	36.524	0.398
		36	-0.017	-0.016	38.141	0.372

*Probabilities may not be valid for this equation specification.

A normality test: The normality test commands perform hypothesis tests to examine whether or not the observations follow a normal distribution. The test is done to check whether the data series is well modelled in a normal distribution. The test determines how likely is a random variable in the data series normally distributed.

GRAPH No 4

GRAPH SHOWING STANDARDISED RESIDUALS



Analysis: It is evident from the above Graph No 4 that the residuals were not normally distributed as the Jarque Bera statistics was 1140.464 with a p-value of 0.0000 (<0.01).

TABLE No 6

TABLE SHOWING HETEROSKEDASTICITY TEST: ARCH

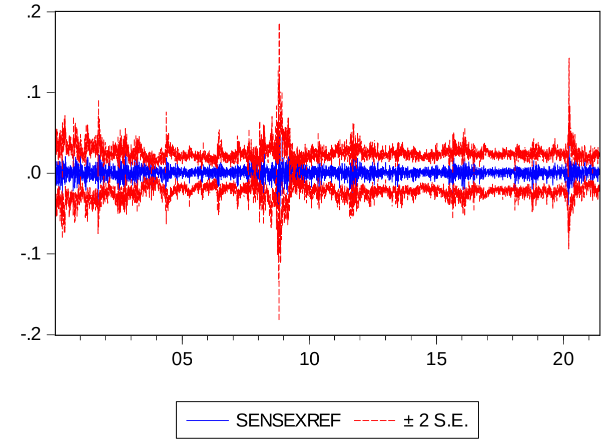
F-statistic	0.34831	Prob. F(1,5608)	0.5013
Obs*R-squared	0.33293	Prob. Chi-Square(1)	0.5113

Source: Desk Research

Analysis: In order to determine the ARCH effect in the time series data set, an ARCH test has been run. It is evident from the above Table No 6 that the F- statistic 0.34831 with a p-value of 0.5113 (> 0.05), there is no ARCH effect in the data set.

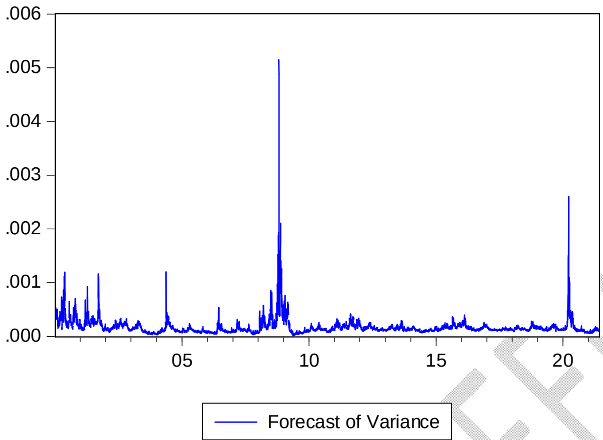
GRAPH No 5

GRAPH SHOWING DYNAMIC FORECASTING



Forecast: SENSEXREF
Actual: SENSEXRE
Forecast sample: 1/03/2000 6/04/2021
Adjusted sample: 1/07/2000 6/04/2021
Included observations: 5610

Root Mean Squared Error	0.012244
Mean Absolute Error	0.008265
Mean Abs. Percent Error	NA
Theil Inequality Coefficient	0.591954
Bias Proportion	0.000125
Variance Proportion	0.415204
Covariance Proportion	0.584671
Theil U2 Coefficient	NA
Symmetric MAPE	130.9476



Inference: It is evident from the above GARCH forecasting graph (dynamic forecasting) that Sensex would continue to be highly volatile for the next few months.

LEVERAGE EFFECT

To forecast the volatility in the Indian stock market, the researcher has conducted the following model selection criteria:

TABLE No 7

TABLE SHOWING MODEL SELECTION

	X1	X2	X3	X4	X5	X6	X7	X8
Normal Gaussian Distribution	√	√	√	√	x	√	x	√
Student t Distribution	√	√	√	√	x	√	x	√
GED with Fixed-Parameter	√	√	√	√	x	√	x	√

	Adj R^2	DW	AIC	SIC	H-QC	ARCH	CQS	Norm
Normal Gaussian Distribution	0.263	2.029	-6.356	-6.339	-6.350	NO	NO	x
Student t Distribution	0.260	2.027	-6.403	-6.387	-6.398	NO	NO	x
GED with Fixed-Parameter	0.261	2.027	-6.400	-6.383	-6.394	NO	NO	x

X1: SMI; X2: KOSPI; X3: Nikkei; X4: Hang Seng; X5: DAX; X6: FTSE100; X7: DJIA and X8: CAC-40
DW: Durbin-Watson statistics
AIC: Akaike info criterion
SIC: Schwarz criterion
H-QC: Hannan-Quinn criterion
ARCH: for ARCH effect
CQS: Correlogram Squared Statistics
Norm: Normal distribution

Source: Desk Research

Analysis: The researcher has applied the above Table No 7 to select the appropriate model for forecasting volatility in Sensex: Under Normal Gaussian Distribution we found six chosen stock markets were significant, Adjusted R-Squared for the model was 0.263, where Durbin-Watson statistics was 2.029, AIC was -6.356, SIC was -6.339 and H-QC was -6.350. However, in residual diagnostics, we did not find any ARCH effect, no autocorrelation, and data were not normally distributed. Under Student t Distribution, we found six chosen stock markets were significant, Adjusted R-Squared for the model was 0.260, where Durbin-Watson statistics was 2.027, AIC was -6.403, SIC was -6.387 and H-QC was -6.398. However, in residual diagnostics, we did not find any ARCH effect, no autocorrelation, and data were not normally distributed. Under GED with Fixed-Parameter, we found six chosen stock markets were significant, Adjusted R-Squared for the model was 0.261, where Durbin-Watson statistics was 2.027, AIC was -6.400, SIC was -6.383 and H-QC was -6.394. However, in residual diagnostics, we did not find any ARCH effect, no autocorrelation, and data were not normally distributed. Therefore, the final model selection was student t distribution.

STUDENT t DISTRIBUTION WITH FIXED PARAMETER

TABLE No 8

TABLE SHOWING STUDENT t DISTRIBUTION WITH FIXED PARAMETER

LOG(GARCH) = C(10) + C(11)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(12)*RESID(-1)/@SQRT(GARCH(-1)) + C(13)*LOG(GARCH(-1)) + C(14)*SENSEXRE(-1) + C(15)*SENSEXRE(-2) + C(16)*SENSEXRE(-3)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000504	0.000111	4.535146	0.0000
SMIRE	0.049753	0.018072	2.753073	0.0059
KOSPIRE	0.116506	0.012580	9.261321	0.0000
NIKKIERE	0.037498	0.010710	3.501306	0.0005
HANGSENGRE	0.243616	0.012522	19.45538	0.0000
DAXRE	0.018089	0.019898	0.909096	0.3633
FTSERE	0.076477	0.023235	3.291509	0.0010
DJIARE	-0.003852	0.014327	-0.268840	0.7881
CAC40RE	0.064582	0.024812	2.602905	0.0092
Variance Equation				
C(10)	-0.258639	0.025417	-10.17589	0.0000
C(11)	0.155384	0.011851	13.11187	0.0000
C(12)	0.008782	0.013304	0.660110	0.5092
C(13)	0.984743	0.002302	427.7094	0.0000

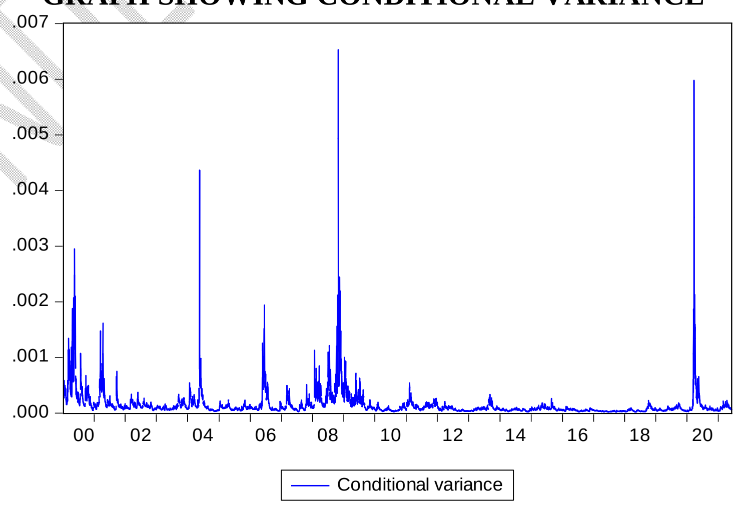
C(14)	-12.02600	1.581842	-7.602525	0.0000
C(15)	2.034219	1.895644	1.073102	0.2832
C(16)	4.083818	1.462091	2.793135	0.0052

Source: Desk Research

Analysis: It is evident from the above Table No 8 that there is a significant information spillover effect of transmission of volatility from SMI to Sensex with a positive coefficient of 0.049753, with z-Statistic 2.753073 with a p-value of 0.0059 (<0.01) which was statistically significant. Similarly, KOSPI was also capable of spreading spillover effect on Sensex with a positive coefficient of 0.116506, with z-Statistic 9.261321 with a p-value of 0.0000 (<0.01) which was statistically significant. Nikkei was also capable of spreading spillover effect on Sensex with a positive coefficient of 0.037498, with z-Statistic 3.501306 with a p-value of 0.0005 (<0.01) which was statistically significant. Hang Seng was also capable of spreading spillover effect on Sensex with a positive coefficient of 0.243616, with z-Statistic 19.45538 with a p-value of 0.0000 (<0.01) which was statistically significant. FTSE 100 was also capable of spreading spillover effect on Sensex with a positive coefficient of 0.076477, with z-Statistic 3.291509 with a p-value of 0.0010 (<0.01) which was statistically significant. CAC-40 was also capable of spreading spillover effect on Sensex with a positive coefficient of 0.064582, with z-Statistic 2.602905 with a p-value of 0.0092 (<0.01) which was statistically significant. However, DAX (German Index) was not able to create a spillover effect on the Indian benchmark Sensex with a positive coefficient of 0.018089, with z-Statistic 0.909096 with a p-value of 0.3633 (>0.05) which was not statistically significant. Similarly, DJIA was not able to create a spillover effect on the Indian benchmark Sensex with a negative coefficient of -0.003852, with z-Statistic -0.268840 with a p-value of 0.7881 (>0.05) which was not statistically significant. EGARCH along with the log of GARCH were also statistically significant and we found an information asymmetry between the positive and negative news. We also found that the negative news significantly contributed to the spillover effects from the global markets to the Indian stock market. Adjusted R squared for the study period was 0.262796 and Durbin-Watson statistics was 2.038629 meaning that there was no autocorrelation in the time series data.

GRAPH No 6

GRAPH SHOWING CONDITIONAL VARIANCE

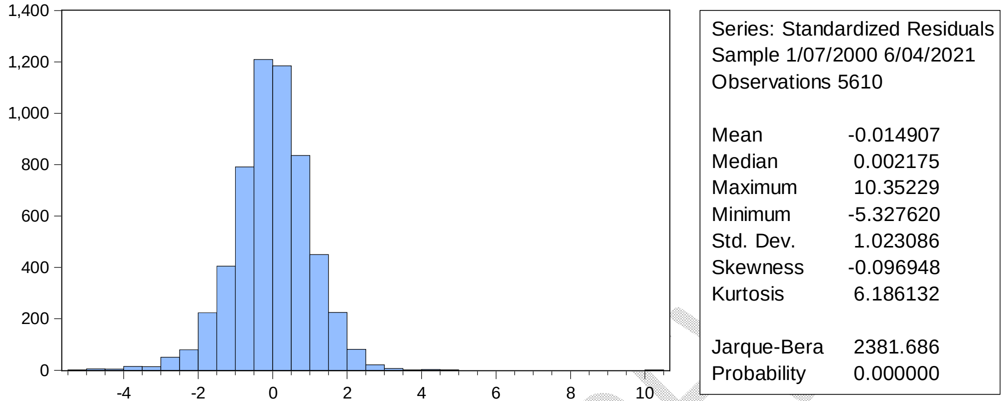


RESIDUAL DIAGNOSTICS

Normality test: The normality test commands perform hypothesis tests to examine whether or not the observations follow a normal distribution. The test is done to check whether the data series is well modelled in a normal distribution. The test determines how likely is a random variable in the data series normally distributed.

GRAPH No 7

GRAPH SHOWING STANDARDISED RESIDUALS



Analysis: It is evident from the above Graph No 7 that the residuals were not normally distributed as the Jarque Bera statistics was 2381.686 with a p-value of 0.0000 (<0.01).

Autocorrelation test: This test represents the degree of similarity in a given set of time series data and the lagged version of the same time series data over consecutive intervals. It measures the relationship of a variable's current value with its past value. An autocorrelation of +1 indicates a perfect positive correlation and -1 indicates a perfect negative correlation. The Durbin-Watson is always used to test for autocorrelation. The Durbin-Watson number ranges from 0 to 2.5.

TABLE No 9

TABLE SHOWING AUTOCORRELATION

Q-statistic probabilities adjusted for 5 dynamic regressors

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.001	-0.001	0.0005	0.982
		2	0.024	0.024	0.1411	0.932
		3	0.016	0.016	0.2027	0.977
		4	0.003	0.002	0.2045	0.995
		5	-0.056	-0.056	0.9720	0.965
		6	-0.010	-0.010	0.9950	0.986
		7	0.071	0.074	2.2610	0.944
		8	0.020	0.023	2.3645	0.968
		9	0.018	0.015	2.4512	0.982
		10	0.032	0.025	2.7046	0.988
		11	-0.090	-0.094	4.7800	0.941
		12	-0.157	-0.154	11.080	0.522
		13	-0.055	-0.052	11.862	0.539
		14	-0.058	-0.052	12.725	0.548
		15	0.019	0.029	12.822	0.616
		16	0.026	0.024	13.001	0.673
		17	0.034	0.015	13.302	0.716
		18	0.005	0.007	13.310	0.773
		19	-0.008	0.007	13.326	0.821
		20	-0.047	-0.034	13.909	0.835
		21	0.011	0.033	13.939	0.872
		22	-0.003	0.006	13.941	0.904
		23	-0.069	-0.099	15.216	0.887
		24	0.099	0.064	17.896	0.808
		25	0.058	0.032	18.819	0.806
		26	-0.077	-0.100	20.457	0.769
		27	-0.028	-0.025	20.673	0.801
		28	-0.006	-0.004	20.683	0.838
		29	-0.028	-0.008	20.906	0.863
		30	-0.013	0.018	20.951	0.889
		31	-0.028	-0.050	21.178	0.907
		32	0.018	-0.003	21.274	0.925
		33	0.030	0.052	21.521	0.938
		34	0.000	-0.021	21.521	0.952
		35	0.010	0.003	21.552	0.964
		36	0.006	0.044	21.563	0.973

TABLE No 10

TABLE SHOWING HETEROSKEDASTICITY TEST: ARCH

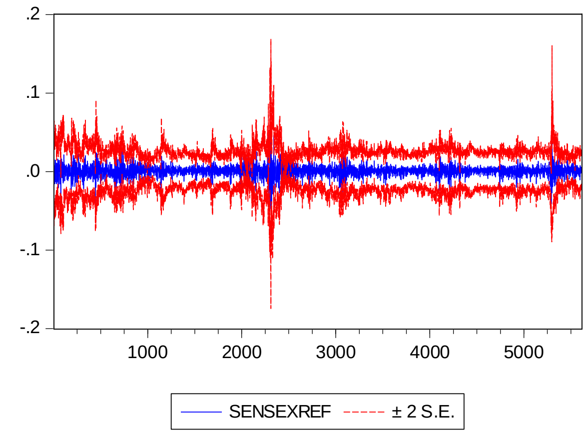
F-statistic	3.544877	Prob. F(1,5607)	0.0598
Obs*R-squared	3.543901	Prob. Chi-Square(1)	0.0598

Source: Desk Research

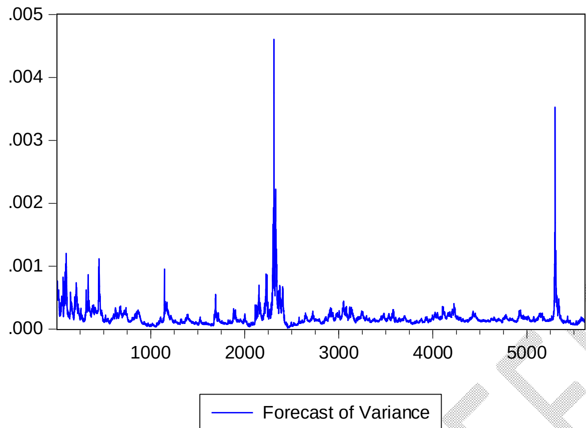
Analysis: In order to determine the ARCH effect in the time series data set, an ARCH test has been run. It is evident from the above Table No 10 that the F statistics 3.544877 with a p-value of 0.0598 (>0.05), there is no ARCH effect in the data set.

GRAPH No 8

GRAPH SHOWING DYNAMIC FORECASTING



Forecast: SENSEXREF	
Actual: SENSEXRE	
Forecast sample: 1 6000	
Adjusted sample: 4 5614	
Included observations: 5611	
Root Mean Squared Error	0.012233
Mean Absolute Error	0.008268
Mean Abs. Percent Error	NA
Theil Inequality Coefficient	0.586852
Bias Proportion	0.000024
Variance Proportion	0.398401
Covariance Proportion	0.601576
Theil U2 Coefficient	NA
Symmetric MAPE	130.6150



Inference: It is evident from the above EGARCH forecasting graph (dynamic forecasting) that Sensex would continue to be highly volatile for the next few months.

5. DISCUSSION AND CONCLUSION

The spillover effect is defined as an impact that is an unconnected event of one nation that could have on the economy of another nation. They can either be considered positive or negative shocks. The term spillover is usually considered when there is a negative event in one nation and how another country's economy is impacted due to the same. The negative event could be an earthquake or a pandemic or any macroeconomic event. The spillover effect is a kind of network effect that increased since globalisation in trade and stock markets deepened the financial connections between economies. The effect in return causes an economic crisis or shocks in the market like booms or crashes. The current study entitled "Spillover effect from the major global stock markets such as DJIA, FTSE 100, CAC-40, DAX, HangSeng, Nikkei, SMI and KOSPI bench Index" have been undertaken to understand the information spillover effect of the major global stock markets on Indian bench market index Sensex so that the investors can make efficient decision making by understanding the interrelation between different markets. To realize the stated objectives, the researcher has collected the data from the Thomson Reuters database for a period from 31.03.2000 to 30.09.2021. The collected data has been tested for stationarity by running the ADF stats. Later, in the second phase, the collected data has been analysed by investigating the existence of the ARCH effect. Therefore, GARCH (1,1) test has been run to understand the relationship. In the current study, we found a significant correlation coefficient among the chosen indices where the highest correlation coefficient was found between DAX and CAC-40 with a Pearson correlation coefficient of 0.90, and the least correlation coefficient was found between Nikkei and DJIA with 0.147. In the current study we found a significant information spillover effect transmitting from SMI to BSE Sensex, followed by KOSPI to Sensex, Nikkei to Sensex, Hangseng to Sensex, FTSE 100 to Sensex, and CAC-40 to Sensex. Therefore, we can conclude that there was a significant information spillover effect from SMI, KOSPI, Nikkei, Hangseng, FTSE 100, and CAC-40 to the Indian Stock Market. However, in the current study, we did not find any evidence of information spillover from DJIA and DAX on Sensex. When we assess the impact of volatility by taking both indigenous variables and exogenous variables by running GARCH(1, 1) it revealed the following facts. The independent variables FTSE 100, CAC 40, Hang Seng Nikkei, SMI, and KOSPI stock spillover effect was significant in the volatility of the Sensex, apart from the internal shocks ARCH 1 and GARCH 1 were also statistically significant. The current study has also revealed that there was an information asymmetry or leverage effect in the information spillover as the E-GARCH coefficient was statistically significant, meaning that the stock market was likely to capture negative information spillover more than the positive information spillover. The above conclusion has been arrived at after running all the tests under Normal Gaussian distribution, student t distribution, and GED with fixed parameters. The later residual was investigated for diagnostic checkings such as autocorrelation, normality, and ARCH effect. Therefore, most of the chosen stock markets barring DJIA and DAX were responsible for transmitting volatility in the Indian stock market. Therefore, it is recommended to the participants take these factors into consideration as the volatility of these stock markets as clues to take the right decisions. Out of the various stock markets chosen for the study Sensex recorded a moderate degree of volatility. However, when the returns of the chosen stock markets were compared Sensex recorded the highest degree of volatility among the exchanges chosen, although it shared a low degree of correlation among these nations. Therefore, market participants like traders, FIIs, Brokers, and investors can take this sign as an advantage to converting their holdings into returns.

The independent variable SMI is significant in the volatility of the dependent variable (Sensex returns). Apart from that, ARCH 1 and GARCH1 are also significant at a 5% level. Therefore, whatever is the impact on SMI it is likely to affect the Indian stock market hence, it is suggested to the market participants to observe SMI and the internal factors closely for momentum as the stock market is capable of transmitting volatility in the Indian stock market. The independent variable KOSPI is significant in the volatility of the dependent variable (Sensex returns). Apart from that, ARCH 1 and GARCH1 are also significant at a 5% level. Therefore, whatever is the impact on KOSPI it is likely to affect the Indian stock market hence, it is suggested to the market participants to observe KOSPI and the internal factors closely for momentum as the stock market is capable of transmitting volatility in the Indian stock market. The independent variable Nikkei is significant in the volatility of the dependent variable (Sensex returns). Apart from that, ARCH 1 and GARCH1 are also significant at a 5% level. Therefore, whatever is the impact on Nikkei it is likely to affect the Indian stock market hence, it is suggested to the market participants to observe Nikkei and the internal factors closely for momentum as the stock market is capable of transmitting volatility in the Indian stock market. The independent variable Hang Seng is significant in the volatility of the dependent variable (Sensex returns). Apart from that, ARCH 1 and GARCH1 are also significant at a 5% level. Therefore, whatever is the impact on Hang Seng it is likely to affect the Indian stock market hence, it is suggested to the market participants to observe Hang Seng and the internal factors closely for momentum as the stock market is capable of transmitting volatility in the Indian stock market. The independent variable FTSE 100 is significant in the volatility of the dependent variable (Sensex returns). Apart from that, ARCH 1 and GARCH1 are also significant at a 5% level. Therefore, whatever is the impact on FTSE 100 is likely to affect the Indian stock market hence, it is suggested to the market participants to observe FTSE 100 and the internal factors closely for momentum as the stock market is capable of transmitting volatility in the Indian stock market. The independent variable CAC-40 is significant in the volatility of the dependent variable (Sensex returns). Apart from that, ARCH 1 and GARCH1 are also significant at a 5% level. Therefore, whatever the impact on CAC-40 is likely to affect the Indian stock market hence, it is suggested to the market participants to observe CAC-40 and the internal factors closely for momentum as the stock market is capable of transmitting volatility in the Indian stock market.

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