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Assessing Volatility of Returns in Select Stock Markets: Evidence from India, Singapore and USA

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ABSTRACT

Volatility can be regarded as one of the crucial aspects to judge movements of stock price while making financial decisions. This article tried to articulate the movements of stock return during the time comprising before, after COVID-19 pandemic period empirically. To accurately incarcerate the volatility of asset returns, the study presented the commonly used GARCH (1,1) volatility model for assessing the volatility of daily returns of STI (Singapore), Dows and Jones (USA), BSE Sensex (India) stock prices from 1st Jan 2018- 31st Dec 2022, where from 1st Jan 2018 to 16th Jan 2020 is denoted as pre covid-19 phase and From 17th Jan 2020- 31st Dec 2022 is considered as during COVID- 19 phase. The findings suggest that all the markets under study had strong GARCH effect and the volatility clustering is relatively relentless and also the effect of older news upon volatility is quite persistent. In upcoming period, researchers can assess the performance of time series models with multiple variables using day by day return data of more such global markets.

Keywords: Volatility, stock return, Covid-19, Singapore, USA, India

JEL classification: G10, G12, C22

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1. Introduction

The share markets play significant role to economic development of countries because they promote opportunities for investment and transfer funds from savers to investors (Bello et al. 2022). But, excessive volatility would result in diminution of booms followed by collapses, eroding millions of investors' funds and bankrupting traders (Jebabli et al. 2022). It is always moving and volatility arising out of stock price movement is also time varying. Gains and losses are something the market indices always experience and occasionally, the market goes through abrupt price fluctuations, a phenomenon known as "volatility." It can be pronounced that volatility is considered to be one of the crucial factors while making financial decisions. Since return may be derived from volatility and price can be calculated depending upon the return, it is necessary to estimate volatility as accurately as possible. Modelling and predicting the volatility of monetary time series has recently gained significant concentration from intellectuals and practitioners, and has become a prolific subject of research in the meadow of finance. This is mainly because of the reason that a lot of economic purposes, like risk management, portfolio optimisation, and asset pricing depend on the concept of volatility. Volatility's unique characteristic is that it cannot be directly observed. Tsay,R.S (2010) defines volatility as "the conditional variance of the underlying asset returns". Consequently, for enhancing portfolio allocation, risk management, or the valuation of financial derivatives, economic forecasters are particularly interested to obtain correct approximation of the conditional variance.

Straightforward statistical approaches had been earlier attempted to estimate future instability in stock market through averaging and smoothing methods. Still, these uncomplicated models had limited predictive capability, as economic time series are likely to deal with definite special characteristics like volatility clustering. Little (Big) changes(ups and downs) in asset prices tend to be followed by little (big) changes in price of the equivalent amount, commonly known to be volatility clustering[Mandelbrot (1963) and Fama (1965)]. Previous studies conducted and continued for couple decades on this issue divulge no agreement on the subject of which model or technique can endow with the most perfect predictions of asset returns. But one thing is certain that changes in volatility of stock returns are predictable in the long run.

To accurately capture the volatility of asset returns, we can use a time series model. The chosen time series model must be compatible with the heteroscedasticity condition. The volatility fluctuations over the time horizon are described by heteroscedasticity. Nonlinear time series can arise either from conditional variance or from conditional mean or both. Markov switching models or threshold autoregressive models (TAR) are used to model nonlinear time series of conditional mean. However, Engle (1982)'s autoregressive conditional heteroscedasticity (ARCH) models can be applied if conditional variance causes the nonlinearity. Engel's model describes the current error's variance term as a function of the error terms from earlier times. Engle's model was improved by Bollerslev (1986) to the Generalised Autoregressive Conditional Heteroskedasticity model (GARCH), which takes into account variations in the time-dependent volatility, such as volatility that is either dropping or growing within the identical series. Right from that period, there have been a number of GARCH model derivations where the root name is followed by letters from the alphabet. According to Levendis (2018), the volatility clustering suggested by the ARCH as well as GARCH models indicate broader tails than usual.

Several studies [Hansda, S. K et.al (2002), Singh, P., et.al. (2008),Li, Y. and Giles, E.(2013), Rejeb, A. B. Et.al.(2015)], found dynamic interlinkages between the sprouting Indian equity market and developed equity market of the US and also Singapore stock exchanges. The SGX Nifty is a derivative of the Nifty 50 index, which is traded on the Singapore Exchange allowing international investors to access Indian markets without unswervingly trading on Indian exchanges. Since SGX Nifty or Singapore Nifty replicates the predictable performance of the Nifty, its movement can persuade investors’ reaction in India. On the other hand, US stock market, predominantly the S&P 500, has a well-built historical association with the Nifty 50. So,a mounting US dollar can direct to foreign institutional investors (FIIs) pulling out investments from Indian equities, as they search for safer, dollar-denominated assets, turning promising markets like India less eye-catching. This rationale instigates us to undertake volatility assessment on these three prominent stock markets of the world during pandemic induced crisis period.

2. Review of Existing Literature

There is a voluminous existing texts on the modeling of volatility in stock market and forecasting stock price movements in developed as well as developing economies across the world. Despite numerous econometric models under different market conditions have been applied by financial analysts to explore volatility characteristics, there is no denying the fact that no single model can predict and explain volatility under different market situations.

D. Hamadu et al (2010) investigated the instability of every day returns of insurance stocks in Nigeria for several insurance industries. The empirical research findings obtained in the study demonstrate that the EGARCH model performs better than the prevailing many similar models in model-estimation evaluation, making it more appropriate for estimating stock price returns and perceiving insurance industry's stock risk in Nigerian stock market.

P. Srinivasan (2011) strives to build model and predict the volatility (conditional variance) of the S&P 500 Index returns of United States stock market, which uses daily basis data ranging from January 1, 1996 to January 29, 2010. The researcher, regardless of the presence of the leverage effect, finds that GARCH models outperform asymmetric GARCH models in projecting conditional variance of S&P 500 index return.

Abdalla et al (2012) found that there is an affirmative risk premium in market of African exchanges, one from Sudan and another from Egypt, supporting the notion that volatility and predicted stock returns are optimistically correlated. Additionally, the asymmetric GARCH models discover a substantial amount of evidence for asymmetry in stock returns in the studied markets, validating the existence of the leverage impact in the returns sequences.

Islam, M.A (2013) evaluated the volatility of financial asset return in three Asian markets—Malaysia, Indonesia, and Singapore using GARCH models. The study disclosed that risk and return are positively correlated across the board. The market in Indonesia has been determined to be more volatile than the other two. Furthermore, result revealed that the estimated coefficient of risk premium for the market in Indonesia which was discovered to be more unstable and unpredictable than the existing two markets, risk premium coefficient appeared to be statistically significant, and demonstrating that taking on greater risk enhances returns.

Ugurlu,E et al (2014) investigated instability of stock markets returns for four European emerging countries and Turkey using daily data from emerging markets using similar type of GARCH models. The result showed that GJR-GARCH ,GARCH and EGARCH effects are evident for returns of 4 markets while for one market like SOFIX ,there exists no considerable GARCH effect. For all markets, the result found that volatility shocks are fairly continual and the effect of older news upon volatility is considerable.

Joshi,P and Vidyanagar, G (2014) studied the day by day volatility of the BSE Sensex of India using similar type but distinct models: EGARCH (1, 1), GARCH (1, 1) and GJR-GARCH (1, 1) and to gauge forecasting accuracy, RMSE, MAE, MAPE, and TIC metrics were employed. The findings indicated the existence of the leverage effect, indicating that both good and negative news have different effects and further revealed that GARCH (1, 1) is the most precise forecasting model.

Banumathy, K et. al (2015) ,explain the volatility pattern of the Indian Stock Market using GARCH models, both symmetric and asymmetric type, and exhibited that the most effective models to incarcerate symmetric and asymmetric volatility respectively are determined to be GARCH (1, 1) and TGARCH (1,1) estimation. Additionally, EGARCH (1,1) and TGARCH (1,1) models' asymmetric effects demonstrate that negative shocks significantly affect conditional variance volatility.

Quite a few articles investigates dynamic interactions of stock market between China stock market and the US market ,Indian stock market and the US market, using integrated vector error correction (FIVECM) model to measure cross-market co-integration.

Lobo et.al(2016) appraise first and second-moment spillover effects simultaneously by including multivariate GARCH component to FIVECM. The result displayed that the US stock market controls the other two markets , while the Chinese and Indian stock markets interact.

Maqsood, A. et.al (2017), using GARCH models for the assessment of volatility of the day by day returns of the stock market in Kenya from March 2013 to February 2016, observed that the volatility process is extremely persistent, thus, showing substantiation of the subsistence of risk premium for the NSE index return series which holds the affirmative correlation hypothesis between expected stock returns and volatility.

S.A Awalludin et al (2018), using GARCH(1,1) for estimating the volatility of day by day returns of stock prices of Indonesia from 2007 to 2015, showed that GARCH(1,1) designate substantiation of clustering of volatility in the returns of few stock prices in Indonesia stock market and the return of some Indonesia stock prices has GARCH effect.

Marobhe, M. et al (2019) , using (GARCH) models including GARCH (1, 1), E-GARCH (1, 1), and P-GARCH (1, 1)to estimate the volatility of stock returns for both symmetrical and asymmetrical modelling ,demonstrated that all three (3) models were noteworthy in envisaging the volatility of stock returns at the DSE. Both GARCH (1, 1) and P-GARCH (1,1) results showed that positive news has a greater impact on volatility than bad news does. The leverage impact linked to stock returns was demonstrated by the E-GARCH model (1, 1), which can be harmful to the capital structures of trading organisations. Based on both the Theil Inequality Coefficient (TIC) and the Root Mean Squares Error (RMSE), P-GARCH (1, 1) , result was found to be more accurate in forecasting stock returns.

Abounoori, E et.al (2020) assesses conditional variance by applying 4 GARCH based techniques like EGARCH, GARCH, GIR-GARCH, and RGARCH and used two realized volatility estimators with the help of intraday data of gold and found that the RGARCH method for GOLD outperforms the other methods in both ways.

Arman and Zakaria (2020) examined the Indonesia Stock Exchange (IDX), noting significant monthly variations by sector. Mining and agriculture saw sharp gains in April and July, while consumer goods and miscellaneous industries experienced drops in May.

Iqbal, N et.al (2021) investigated the effect of COVID-19 upon the volatility of returns in Australian stock market. The study explores the news (shocks) effect by exploring the shocks of asymmetric nature as well as effect of leverage upon volatility using GARCH technique and enlarge their exploration applying the EGARCH model to incarcerate irregularity and purportedly leverage for a period covering 27 January 2020 to 29 December 2020. The experimental results recommended the EGARCH model fits better in capturing asymmetry and leverage than the GARCH model in assessing the volatility of the Australian stock returns.

Mishra, A.K.,et.al. (2022), using multivariate GARCH-BEKK model , observe the return and volatility spillover between India and four most important Asian markets viz, Japan, China, Hong Kong and Singapore) and two international equity markets, viz the United Kingdom and the United States).The result showed an inclination of the Indian stock market index similar to Hong Kong and the US market indices.

Jumintang and Utami (2022) investigated the IHSG index and detected a month-of-the-year effect in April. Global indices like the DJIA, SSEC, and N225 showed similar effects in October, September, and July, respectively, indicating that such anomalies continue to impact stock returns and may lead to market inefficiencies.

Elangovan et al. (2022) studied month-of-the-year effects in the Indian stock market using BSE Ltd and NSE broad market cap indices (S&P BSE 500 and NIFTY 500). Their findings revealed a "March effect".

Mamilla, R et.al (2023) investigates the impact of instability upon the returns of several NSE indices amidst the COVID-19 catastrophe using GARCH model for explaining the effect of volatility upon stock returns as well as investors' risk. The result revealed that the COVID-19 period did better than pre-COVID-19 and entire periods. Since the Nifty Realty Index is the most volatile, Nifty related industries' investors earned superior returns in the midst of COVID-19 than precovid period.

Acharya et. al. (2024) used GARCH models to analyse daily time series data of Sensex and Nifty from 1996 to 2021. They found evidence of a "September effect" in the return series of both stock markets in India.

Naz Farah et.al (2024) investigated the calendar anomalies in the context of the local market by analyzing the Pakistan Stock Exchange (PSX) considering closing prices of KSE-100, KSE-30 and KSE for the period 2009-21. The results suggest monthly seasonality, with significant April, July, and September effect in PSX indices returns.

The literature review suggests that there exists probably no consensus on estimating the impact of COVID-19 on the volatility of return in India as well as other two integrated stock market like USA and Singapore owing to coronavirus outbreak. None of the recent earlier research explored day of the week effect in stock return along with volatility framework considering 'pre-COVID' and 'during COVID' time frameworks in Indian context so elaborately. Consequently, it made us responsible to investigate the effects of several significant events that vibrate the whole world in 2020. The paper fills the emptiness in the literature existed and contributes to the literature by documenting stock market volatility for selected developed and emerging markets using GARCH models before and after the COVID phase. This article is significant since a lot of people interested to invest in stock market and expects to gain from it focuses on stock market trading and try to understand how stock returns, risk, and volatility influence their decision making practicability.

2.1. Research Objectives

In view of this above prelude, regardless of the ruthless impact of COVID-19 upon the stock market of the whole economy of the world, there is inadequate study on it, particularly in an emerging economy like India. Therefore, considering daily data on closing stock prices of stock markets of India, Singapore and USA from January1, 2018 to August 30, 2022, we are trying to assess stock market volatility for selected developed and emerging markets using GARCH models before and after the COVID phase. With the fulfilment of this objective, it is possible to identify whether there are discrepancies in the volatility of stock returns and whether a high or low return is linked with the successive high or low return for a given day.

2.2. Research Questions

1. Is there any significant difference in volatility across pre, during and entire covid period in single markets as well as different periods across different countries' stock market?
2. Do all the stock markets under study have strong GARCH effect?

2.3. Hypotheses

Since the present study aims to observe empirically stock market volatility for selected developed and emerging markets using GARCH models before and after the COVID phase, the following hypotheses are formulated:

- H_{0A}(Null Hypothesis): There is no significant difference in volatility across pre, during and entire covid period in single markets as well as different periods across different countries' stock market.
- H_{1A}(Alternate hypothesis): There is significant difference in volatility across pre, during and entire covid period in single markets as well as different periods across different countries' stock market.
- H_{0B}(Null Hypothesis): All the stock markets under study has no strong GARCH effect.
- H_{1B}(Alternate hypothesis): All the stock markets under study has strong GARCH effect.

3. Research Methodology

This part outlines the econometric procedures that were applied in this study to analyse the volatility of stock returns. These methods include assessing volatility using GARCH (1, 1) and extracting returns from stock price data.

We used daily closing prices of STI, Dow Jones and BSE Sensex from 1st Jan 2018- 31st Dec 2022, where from 1st Jan 2018 to 15th Jan 2020 is denoted as pre covid-19 phase and from 16th Jan 2020- 31st Dec 2022 is considered as post covid- 19 phase. The entire data has been collected from respective stock markets website as well as from yahoofinance.com.

By comparing the log of the price from one day to the previous, we were able to get return series from stock price data. It can be interpreted as the constantly compounded return at day t (between end of day t-1 and end of day t).

$R_t = (\ln P_t - \ln P_{t-1}) * 100$

Where, R_t= log return for time t

P_t= Price for time t

P_{t-1}= Price for previous time of t

The day by day closing prices were taken from the authorized websites of BSE and NSE for the period from January1, 2018 to August 30, 2022. The pre-COVID period (Period 1) is assumed to be a time period starting from January 1, 2018 until the lockdown announcement in India on March 25, 2020. The 'during COVID (Period 2) period is from March 25, 2020, to August 30, 2022, consisting of the entire period from the date of announcement of the first lockdown in India on March 25, 2020, to August 30, 2020. Within the sample period,BSE closing price data consists of a total of 1155 observations in terms of working days in the stock market except notified holidays, Saturdays and Sundays, out of which 549 observations are related to the pre-COVID period and 606 observations are related to the during COVID ' period. On the other hand, NSE closing price data consists of a total of 1151 observations in terms of working days, out of which 547 observations are related to the pre-COVID period and 604 observations are related to the during COVID period. Instead of using the term post-COVID' period, we use the term 'during COVID' because WHO has not yet declared the end of the COVID-19-induced pandemic.

In the estimations, we take the natural logarithm of each price data point to reduce the observed skewness in the stock price data distribution. The stock return data used in this research consists of the logarithmic first difference of closing stock prices, which is defined symbolically as follows:

To calculate the return, the following formula has been used:

$$R_t = lnP_t - lnP_{t-1} \quad (1)$$

Here, R_t= daily stock return
P_t= closing price of the stock at time t
and P_{t-1} = previous day's closing price at time t-1
whileln symbolizes the natural log

Using the GARCH framework, we examine the day of the week effect on returns and volatility. As explanatory variables, we incorporate appropriate lagged values of returns. This will make certain that no specification inadequacies exist either in the conditional mean or in the conditional variance of return.

The GARCH model was introduced by Bollerslev (1986), which was a generalised version of a seminal paper originated by Engle (1982), who pioneered the ARCH model. The GARCH model is considered to be a unique model that could effectively include the original volatility of financial variables (Bera and Higgins, 1995). We could have made use of the standard OLS technique, which was executed in the existing literature, for estimating the return as well as the volatility of the stock market. But this model has two drawbacks. First, errors in the model may be auto correlated, and the second drawback is that the variance of the error terms may not be constant over time. Especially to solve the second drawback, the variance of the error terms is allowed to be time-dependent so as to include conditional heteroskedasticity. So, error terms have a zero mean and a variance that is changing with time.

There are different types of conditional heteroskedasticity models suggested in the literature. The main two are the ARCH and GARCH models. The ARCH model developed by Engle (1982) permits the variances of the forecasted return terms to change with the squared lag values of the previous error terms. Therefore, he suggests a model that allows the forecast variance of the return equation to vary symmetrically over time. Here, the assumption is that conditional variance depends upon the past squared residual from the return equation, which is known as the Autoregressive Conditional Heteroskedasticity Model (ARCH):

$$h_t = V_c + \sum_{j=1}^{q} V_j \varepsilon_{t-j}^2 \quad (2)$$

Conditional variance may affect stock market return. The above-mentioned equation assumes the existence of constant variance. It may cause ineffective estimates if there is a time-varying variance. As a result, we incorporate the varying variance into our estimation. Here, we assume that the error term of the return equation has a normal distribution with a zero mean and a time-varying conditional variance.

$$\varepsilon_t \left| \psi_{t-1} \sim N(0, h_t) \right. \quad (3)$$

ψ_{t-1} is the set of information at time t-1. ε_t is response to the error which is conditional to previous information ψ_{t-1}. The generalized version of the ARCH model seen above is developed by Bollerslev (1986) adding also the h_t terms.

$$h_t = V_c + \sum_{j=1}^{q} V_{Aj} \varepsilon_{t-j}^2 + \sum_{j=1}^{p} V_{Bj} h_{t-j} \quad (4)$$

h_t s are conditional variances specified as GARCH(p,q).This model is known as GARCH (p,q). Here, this specification requires that $\sum_{j=1}^{q} V_{Aj} + \sum_{j=1}^{p} V_{Bj} < 1$ in order to satisfy the non-explosiveness of the conditional variance and each of $V_A > 0$; $V_B > 0$; $V_C > 0$. These must be positive to satisfy the non-negativity of the conditional variance. Furthermore, it is likely to include exogenous variables in the GARCH model, and its specifications are usually used in the literature.

Before applying the GARCH model, the time series analysis has been checked for unit root presence. The non-stationary time series in financial returns may lead to complications in informal testing efficiency with successful forecasting models (Timmermann& Granger, 2004).To check whether a time series was stationary or non-stationary at level and first difference, the Dickey Fuller (1979) and Philips and Perron (PP) tests have been used. To test heteroscedasticity errors, the PP test is preferred. The ADF test is based on the estimate of the following regression:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum \lambda_i \overset{k}{\underset{t=1}{\Delta}} Y_{t-1} + \varepsilon_t$$

Where Y_t represents the variable in question, t is the trend, β is the coefficient on the time trend; γ and λ are parameters; k is the lag length and ε_t is a random variable assumed to be a white noise.

This augmented specification is then used to test for the following hypothesis:

- H_o: Y_t has a unit root/or non-stationary (H_o: $\gamma = 0$);
- H_1: Y_t has no unit root/ or stationary (H_1: $\gamma < 0$).

Rejection of the null hypothesis denotes stationary in the series.

The ADF test adds the lagged difference term of the regression to take care of possible serial correlation in the error term.

4. Analysis of Results

The descriptive statistics of return series are displayed in Table 1. The table's most significant values are skewness, kurtosis, and Jarque Bera statistics. Leptokurtosis, volatility clustering or volatility pooling, and leverage effects—most of which are present in financial data—cannot be fully explained by linear structural (and time series) models. For the returns on financial assets, leptokurtosis, volatility clustering or pooling, and leverage effects are tendencies.

Positive skewness denotes a large right tail in the distribution, while negative skewness denotes a long left tail. The normal distribution's kurtosis is 3. When the kurtosis is greater than 3, the distribution is peaked (leptokurtic) with relation to the normal, and when it is less than 3, the distribution is flat (platykurtic) with relation to the normal . The Jarque Bera test, which uses a normal distribution as the null hypothesis and is distributed as having 2 degrees of freedom, is used to test for normality.

The USA and Indian markets had positive mean values in both the pre-covid and post-covid phases. The mean value of the Singapore market was negative in both the pre-covid and post-covid phases. All series with negative skewness and high kurtosis are lepokurtic at the 1% level of significance, indicating that the series are lengthy and negatively skewed. However, positive skewness with high kurtosis during the Covid era of Singapore and the pre-Covid phase of India suggests that the series are long favorably skewed and are lepokurtic at the 1% level of significance. At the 1% level of significance, the Jarque-Bera test shows that the data from all three countries are not normal because the values are more than 0.05, rejecting the null hypothesis.

Table 1. Descriptive Statistics

	Singapore			USA			India		
	Pre covid	*During Covid*	*Entire Period*	*Pre covid*	*During covid*	*Entire period*	*Pre covid*	*During covid*	*Entire period*
Mean	-0.00712	-0.00134	-0.00402	0.032551	0.016571	0.023095	0.041422	0.050597	0.046861
Median	0.000000	0.036532	0.012226	0.093842	0.048497	0.072822	0.059384	0.101167	0.081814
Maximum	2.314857	8.716615	8.716615	4.864331	10.76433	10.76433	5.185886	8.594739	8.594739
Minimum	-3.04292	-7.63729	-7.63729	-4.71428	-13.8418	-13.8418	-2.36694	-14.1017	-14.10174
Std. Dev	0.731795	1.110551	0.953687	0.966952	1.603805	1.379339	0.829210	1.468430	1.248191
Skewness	-0.28373	0.03772	-0.02384	-0.64737	-0.89099	-0.92624	0.482154	-1.60240	-1.48547
Kurtosis	4.098109	18.09279	18.49696	6.739256	18.76456	20.94914	6.421788	20.22865	23.46608
Jarque-Bera	33.42177	5780.375	11347.47	335.3500	7813.090	17080.61	264.3557	9404.851	22061.51
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	-3.740041	-0.817241	-4.557282	16.73125	12.34528	29.07653	20.79392	37.18916	58.01362
Sum Sq.Dev.	280.6146	749.8612	1030.485	479.6535	1913.711	2393.442	344.4825	1582.715	1927.223
Observation	525	609	1134	514	745	1259	502	735	1238

Source: Authors' own computation from complied data

In addition to inquiries on the data's stationary nature, the level series are defined. Table 2 demonstrates that the modulus function of ADF is greater than the critical t-value at 1% level of significance for all variables at their level only. On the basis of these calculated results, the null hypothesis that the series have unit roots at their level I(0) is rejected. It indicates that the series are stationary at their level only [they are integrated of the order zero i.e I(0)]. For all three countries' stock market indexes, augmented Dickey-Fuller (ADF) statistics decisively reject the unit root null hypothesis at the 1% level of significance. Results of the ADF test are compiled in Table 2.

Table 2. Unit root test

	Without Trend		With Trend	
Variables	ADF Tests	Prob.	ADF Tests	Prob.
Singapore	-12.67052	0.0000	-12.67731	0.0000
USA	-10.91320	0.0000	-10.90907	0.0000
India	-12.14638	0.0000	-12.14692	0.0000
Test Critical Value			1% Level	-3.959143
			5% level	-3.410345
			10% level	-3.126925

Ho: series has unit root; H_1: series is trend stationary;

Source: Authors' own computation from complied data

The Table 3 demonstrates that for all the markets i.e. Singapore, USA and India, negative mean rank is less than positive mean rank. This suggests that post-COVID period returns are higher than pre-COVID period returns. Therefore, it appears that the COVID phenomenon has enhanced the stock market's performance parameter in terms of stock returns.

Table 3. Wilcoxon signed rank Test-Panel-A

Singapore				
		N	Mean Rank	Sum of Ranks
post covid - pre covid	Negative Ranks	251[a]	272.83	68480.00
	Positive Ranks	274[b]	254.00	69595.00
	Ties	0[c]		
	Total	525		
a. post covid < pre covid				
b. post covid > pre covid				
c. post covid = pre covid				

Source: Authors' own computation from complied data

Panel-B

USA				
		N	Mean Rank	Sum of Ranks
post covid - Pre covid	Negative Ranks	251[a]	260.76	65452.00
	Positive Ranks	263[b]	254.38	66903.00
	Ties	0[c]		
	Total	514		
a. post covid < Pre covid				
b. post covid > Pre covid				
c. post covid = Pre covid				

Source: Authors' own computation from complied data

Panel-C

India				
		N	Mean Rank	Sum of Ranks
post covid - pre covid	Negative Ranks	240[a]	244.86	58767.00
	Positive Ranks	262[b]	257.58	67486.00
	Ties	0[c]		
	Total	502		
a. post covid < pre covid				
b. post covid > pre covid				
c. post covid = pre covid				

Source: Authors' own computation from complied data

Table 4 shows that the model has ARCH effect on their residuals as their p- value of Obs *R-squared is less than 0.05. Therefore now we can model residual terms by GARCH models.

Table4. Heteroskedasticity Test (ARCH LM Test)

	Obs*R-squared	p
Singapore	84.75059	0.0000
USA	153.1629	0.0000
India	40.09301	0.0000

Source: Authors' own computation from complied data

More precisely, we have presented the volatility through pictorial presentation in Figure (1) for three countries namely Singapore, India and USA.

Singapore

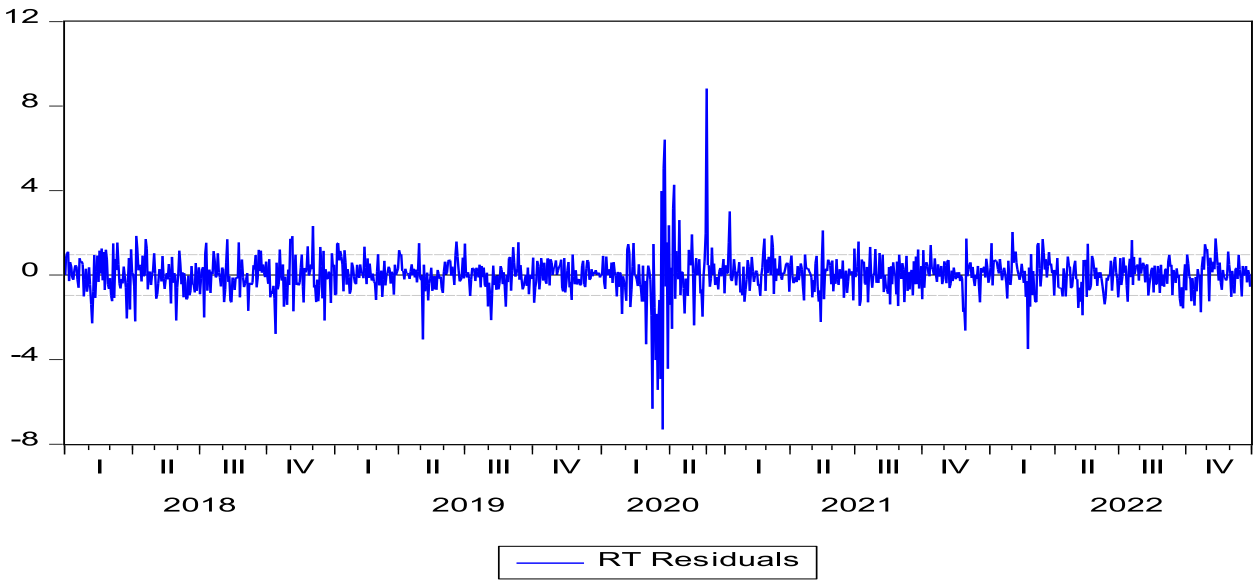
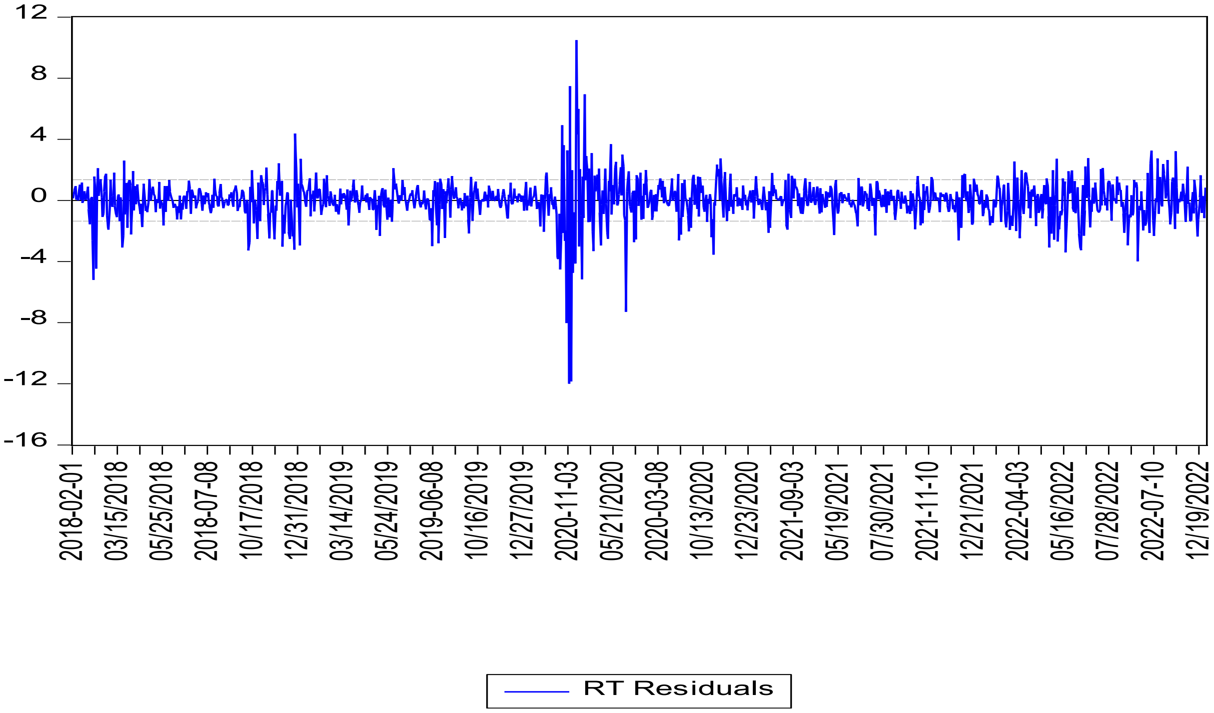


Figure 1. Graphical Representation

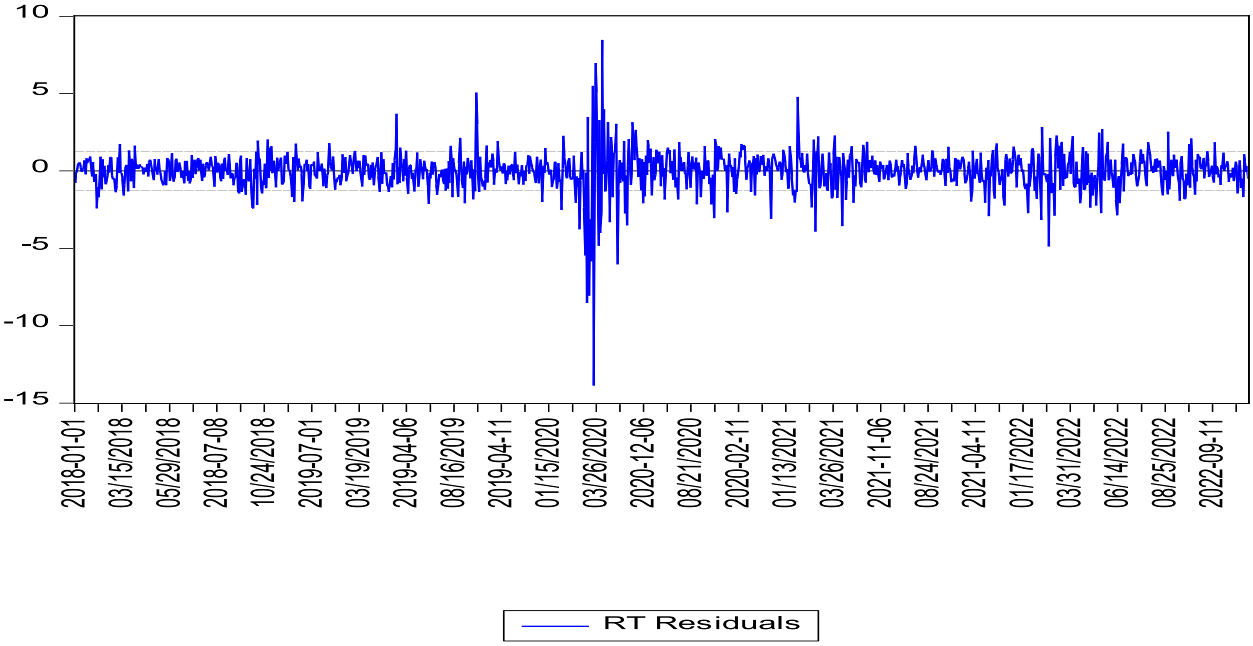
Source: Authors' own computation from complied data

USA



Source: Authors' own computation from complied data

India



Source: Authors' own computation from complied data

Table:5. Autocorrelation test

GARCH(1,1)						
Lag	*Singapore*		*India*		*USA*	
	Q- Stas(k)	Prob	Q- Stas(k)	Prob	Q- Stas(k)	Prob
25	34.865	0.054	17.009	0.809	19.439	0.675
30	39.456	0.074	21.676	0.796	25.310	0.611
35	44.741	0.083	31.126	0.561	29.205	0.657

Source: Own estimate

H_0: There is no Auto correlation; H_1: There is Auto correlation

In each case, 35 lags are taken into account, and only the Q-Stat (k) values accompanied by lags 25, 30, and 35 have been reported. From the Ljung-Box statistic values in the above Table, we see that no significant autocorrelation has been noticed for standardised residuals in the entire period after GARCH (1, 1) have been applied. On the contrary, after applying OLS,if we apply the correllogram Q-stat test, it shows the presence of autocorrelation(result not shown here). This indicates that OLS is not a suitable measure for judging the stability of the day of the week effect; precisely, with the presence of autocorrelation, if we apply GARCH (1, 1) ,it removes autocorrelation to a large extent. Thus, the method of including higher lags may lead to an improved and revised Ljung-Box *Q* statistic for all study periods.

Table 6. Stock market volatility in pre-covid, during-covid and entire sample period [GARCH (1, 1) technique]

		IND			SINGAPORE			USA		
		Entire	PRE	POST	Entire	PRE	POST	Entire	PRE	POST
Return Equation	C	0.1068 (0.0000)**	0.0822 (0.0235)*	0.1354 (0.002)*	0.0250 (0.2235)	0.0107 (0.7087)	0.0308 (0.2832)	0.08742 (0.0001)**	0.090 (0.000)**	0.070 (0.0373)*
	γ	0.0818 (0.8612)	0.1802 (0.8232)	-0.8524 (0.000)**	-0.2903 (0.7716)	-0.0253 (0.9943)	-0.7764 (0.0064)	-0.5227 (0.3730)	0.8550 (0.000)**	-0.5297 (0.2779)
	δ	-0.0221 (0.9625)	-0.1316 (0.8710)	0.8910 (0.000)*	0.2889 (0.7896)	0.0137 (0.9969)	0.7432 (0.0151)	0.4941 (0.4089)	-0.9106 (0.000)**	0.4860 (0.3342)
Variance Equation	C	0.0345 (0.0027)*	0.0443 (0.0878)	0.0381 (0.0301)	0.0832 (0.0011)*	0.0028 (0.6765)	0.1275 (0.0031)	0.0424 (0.0012)*	0.0392 (0.0264)*	0.059 (0.0098)*
	ARCH (α)	0.0985 (0.0000)**	0.0847 (0.0281)	0.1017 (0.0001)**	0.1373 (0.0001)**	0.0321 (0.0432)	0.2027 (0.0009)	0.1893 (0.0000)**	0.1586 (0.0007)**	0.1999 (0.000)**
	GARCH (β)	0.8724 (0.0000)**	0.8505 (0.000)**	0.8766 (0.000)**	0.7467 (0.0000)**	0.9620 (0.000)**	0.6573 (0.000)**	0.7964 (0.0000)**	0.8136 (0.000)**	0.7816 (0.000)**

Source: Authors' own computation from complied data

*signifies 5% level of significance ** signifies 1% level of Significance

Table 6 displays that co- efficient is significantly positive for both India and US stock market in pre COVID phase, during COVID phase as well as for the entire period, however co-efficient is positive but insignificant for Singapore market for all the studied period. The result indicates that the average return of the stock is 0.1068, 0.025and 0.08742 for India, Singapore and US market respectively for entire period, 0.0822, 0.0107, and 0.090for India, Singapore and US market respectively for pre COVID period and 0.1354, 0.0308 and 0.070 for India, Singapore and US market respectively during the COVID period. These research outcomes evidently founded the ground for the existence of time varying conditional volatility of returns for all markets under consideration and during all periods studied here. The end result also designates the persistent nature of volatility shock for all the market in all the period as the sum of $\alpha\ and\ \beta$is near to one. It indicates that the consequence of today's shock will persists in the forecast of variance for coming periods in the future time. We can also see that the value of α is positive and significant which indicates that the effect of older news upon volatility is quite persistent.

Moreover, if the sums of α and β are less than 1 for all time periods, these estimates are said to satisfy the non-explosiveness of the implied variances. In our study, the sum of the coefficients of the GARCH (1, 1) equation without a constant term, in the case of all three markets namely India, Singapore and USA, is less than one and all of them are positive and statistically significant. Therefore, we do not have negative or explosive implied variances as suggested by Bollerslev (1986) for the specification test. Conversely, since the sum of these two coefficients is close to one, it indicates that the volatility is persistent in all the stock markets under our study and is decaying.

However, the coefficient of ARCH (α) is positive and considerably significant in 3 markets of our consideration, which implies the existence of the ARCH effect. The significantly positive asymmetric effect also indicates the existence of an asymmetric effect, and this also indicates that positive news of shocks tends to enhance volatility, and periods of high volatility are followed by more high volatility, and periods of low volatility are followed by more low volatility. Overall, it also signifies that past news does have an impact on current volatility. Further, the coefficient of GARCH (β) was observed to be significantly positive in all three markets, which implies that volatility clustering persisted in the stock markets under study. Since α > β, it indicates the reason for volatility is persistence. Persistent volatility ensures that today's return is having an outsized effect on the unconditional variance of many periods in the future. Simply put, it can be interpreted that if the market mood is off, it will remain off for some days without any reason; even if positive news comes immediately or tomorrow, the market will remain volatile.

5. Conclusions

In the research study, we attempted to analyse stock market volatility for selected developed and emerging markets using GARCH models before and after the COVID phase within the GARCH(1,1) framework. The Wilcoxon signed rank test indicates that returns in the post-COVID period are higher than in the pre-COVID period, although always not positive. We have observed strong substantiation of this result from descriptive analysis. We found that there is a difference in volatility across pre, during and entire covid period in single markets as well as different periods across different countries' stock market under consideration. The result shows that all the markets had strong GARCH effect and the volatility clustering is quite persistent and also the impact of old news on volatility is quite persistent.

Analysing stock market performance can be one of the best indicators to analyse the growth of economies. In the study, we have taken developed, emerging and emerged market and employed GARCH model to specify volatility in returns of their stock markets. This study might possibly assist to understand the trend of mean stock return and its volatility in the Indian stock market as well as other major markets under study. Diversifying portfolios for stakeholders and investors amidst such abnormal situations might be a severe assignment for portfolio managers. This research study divulges that, depending on the endurance of an economic phenomenon, volatility's persistence may possibly change. Consequently, strategists should concentrate more on the fundamental character of a shock for diversifying investors' portfolios as well as diminishing the risk exposure of potential investors.

Policy Implications and Future Research

The results of the study have vital implications for economic policy makers as well as investors. In one hand, these results are significant for policy makers of economic affairs for protecting the financial sector from global fiscal shocks. From the perspective of economic policy makers, the information about volatility pattern between financial markets is expected to be of superior interest for those policy makers to maintain financial solidity because integration of financial markets entails financial sectors' integration, consequently the policy makers necessitate to devise such policies that intend to uphold the financial sector from the global economic shocks. They would be competent to envisage any potential catastrophes, provided they have a number of past chronological information about financial market integrations. Moreover, they might be capable of executing fruitful policies by having information about behavioral patterns of financial markets.

On the other hand, the investors can make use of this information for making competent portfolio which will lessen their risk and boost their returns. The results of this study are also essential for investors, intending to compose well-organized portfolios and formulating capital budgeting decisions in the preferred markets. The institutional and individual investors can gain from portfolio diversification as well as prevent themselves from the financial emergencies of markets by investing in non-correlated markets which results in diminishing their risk menace and improve their returns. In future, researchers can make an enquiry on the performance of multivariate time series models applying daily data return of more such international markets. Furthermore, comparable studies can be conducted to observe the spillover effect over a variety of unexpected events and its impact on portfolio diversification over a wide range of emergent and developed markets.

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