Thailand and The World Economy
P-ISSN: 2630-0931
E-ISSN: 2651-0529
Homepage : *https://www.tci-thaijo.org/index.php/TER*
Vol. 40, No.2, May - August 2022 **Page [145-167]**

The Impact of COVID-19 on Stock Market Returns & Volatility: A Study of Thailand and Indian Bourses

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Received 14 September 2021, Received in revised form 20 October 2021,
Accepted 17 January 2022, Available online 2 May 2022

Abstract

The outbreak of COVID-19 has triggered a fall in the pandemic has completely changed the worldandtransformedour lives, the patterns of economies, and the behaviour of businesses. The market has the tendency to perceive long-term shocks which economy can give to the market, but contrary to generalization, short-term shocks are more vulnerable. The objective of the study was to provide an overview of the impact of the 'Outbreak of COVID-19 Pandemic Shockwaves on the returns and volatility of Thailand and Indian Stock Market. It also analysed whether both countries were reacting similarly to the pandemic. The data was divided into three categories, i.e. Before COVID-19 pandemic, During COVID-19 pandemic and the Whole Period collectively. The 'Pre-Pandemic Time Period' was taken from 1st July 2019 to 31st January 2020, 'During Pandemic Time Period' from 1st February 2020 to 31st August 2020 and the 'Whole Time Period' from 1st July 2019 to 31st August 2020. Three Stock Exchange Indices of both markets were monitored in the study. The standard GARCH models like GARCH, EGARCH, TGARCH, and PARCH models were used to assess the volatility of both markets. The study revealed that the negative shocks had greateraimpact on these markets than the positive shocks during the pandemic period. However, most of the parameter estimates were found to be statistically significant in all models, which meant there was the presence of leverage effect in returns of both stock markets.

Keywords:COVID-19 Pandemic, Stock Market Volatility, Thailand Stock Market, Indian Stock Market etc.
JEL Classifications:G12, G13, G14.

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┼ This paper was presented in 6th International Conference on 'Drivers of Global Economic Recovery' organized by Maharaja Agrasen Institute of Management Studies (MAIMS), Delhi (India) in partnership with the Faculty of Economics, Thammasat University, Thailand, and Waljat College of Applied Sciences, Oman on April 23, 2021.

1. Introduction

The outbreak of COVID-19 has triggered fall in shareprices. The pandemic has completely changed the world andtransformed our lives, the patterns of economies, and the behaviour of businesses.And so is the stock market which has shown the ups and downs of various share prices. The vital tendencies have enhanced, pushing few corporates forward at record speed,whilefor some, headwinds have twisted into hurricanes. Starting from the fact that investors are aware that both the stock market and the economy are not same,it is clear that both are very much influenced by each other and very highly correlated. This is known to everyone that if something happens in the economy, it can have a strong impact onthe market and thatmarket activities and events can also have influence on the economy. The market has the tendency to perceive long-term shocks, which the economy can give to the market, but in contrastto general, short-term shocks are more vulnerable. Short-term events have more immediate and surprising impacts, which sometimes go unnoticedand hence, can be more damaging and disastrous. In March 2020, initially when COVID-19 started spreading globally, which resulted inlockdowns in many nations, there was asharp drop in the stock market and almost every sector was severely negatively affected. Since that time, the economicconditions have remained challenging despite several breath-takingefforts on the part of regulatory authorities, and others with an eye on the pandemic's steep spread. COVID-19 crushed a few industries to an unexpected level. A few of them are the oil and gas industry, the tour and travel industry, the hospitality sector,and last but not the least,real estate. The commercial real estate sector has to face headwinds during this pandemic. This sector is facing challenges from various technology options which opened up during COVID-19. Due to lockdowns, the demand for fuel fell sharply, which forced the producers and OPEC to restrict production. The road ahead for these sectors,i.e., commercial real estate, oil and gas sector, will be challenging, and a lot of fast innovations may be requiredto get their pace back to make a balance in the near future. Covid- 19 explored new arenas as well. Some of the sectors that were already growing were given a boost.The pandemic made it really essential to have one thing, and this is none other than automation because the use of technology was at its peak. The investments were also accelerated in the virtual infrastructure as big corporations and large business houses were keen ondelivering their services digitally. One more thing that caught the attention during the pandemic was how fear and hope prevailed to the extreme levels. It was with fear that the market faced a broad selloff.Even themajor market indices,like Nasdaq, DJIA, S&P 500 were down by double digits. Qualitystocks aroundthe world were selling at a significant discount. For example, Apple Inc. was down more than 20% in February 2020. There were a few like Walmart Inc., which powered through the sell-off because of their well-known reputation, but business was affected as investors were running for the exits. The wind of fear does not settle easily and takes its own good time,which is an unlikely hope that has a short existence, but slowly the market showed the sign of revival and many stocks performed unexpectedly on the higher side,i.e. Netflix Inc, Zoom Video Communications Inc, etc. Many stocks, particularly technology stocks, rose to triple digitsin the last year. The pandemic has had various effects onthe market. It has beaten some sectors and helpedothers. It has perceived the upsurge of individual investors as a market force. It has also prompted investors to believe that the market itself is a replication of optimism and distress rather than what is truly happening in the economy.

2. Literature review

Kaur (2004) investigated the nature and characteristics of stock market volatility in the Indian stock market during 1993-2003 in terms of its time varying nature, the presence of certain characteristics such as volatility clustering, day-of-the-week effect, calendar month effect, and whether there existed any spillover effect between the domestic and the US stock markets. The volatility in the Indian stock market exhibited characteristics similar to those found earlier in many of the major developed and emerging stock markets, viz. autocorrelation and negative asymmetry in daily returns. Karmakar (2007) investigated the behavior of the Indian equity market by means of diverse GARCH Models. The standard GARCH approach was used to examine whether stock market volatility changes over time or not, and if so, whether it is foreseeable. Then, E-GARCH Models were applied to inspect whether there wasasymmetric/irregular volatility. There was an indication of time varying volatility which displays clustering, very high persistence and predictability. It was seen that volatility playedan asymmetric role of previous novelty, increasing proportionally during market decay. Bordoloi& Shankar (2008) revealed other models from the ARCH (Autoregressive Conditional Heteroskedasticity) or its generalization, Generalized-ARCH (GARCH) family, to assess volatility in the Indian equity market. The stock yields were found to own the asymmetrical property. The Threshold-GARCH (T-GARCH) Models clarifiedthe instabilities of both the BSE and the S&P CNX 500 in an improved way, while the Exponential GARCH (E-GARCH) models clarified about NIFTY. A signal of an upsurge in volatility due to certain adverse aspects was seen in the equity markets. Kumar and Dhankar (2009) investigated the cross-correlation in South Asian Markets, their provincial integration and linkage with global stock markets. ARCH and GARCH Models meaningfully clarified the conditional volatility in stock markets under the study. Joshi (2010) examined the souk volatility in the emerging equity markets of India and China. The results noticed the presence of non-linearity and conditional Heteroskedasticity was recognized with the ARCH-LM test. The findings discovered that the GARCH (1,1) model efficaciously observes non-linearity and volatility clustering. It was concluded that the persistence of volatility is less in the Indian equity market as compared to the Chinese equity market.

Srinivasan and Ibrahim (2010) endeavoured to modelandpredictthe volatility of the Sensex returns in theIndian equity market. The forecasting models used rangefrom the simple GARCH Model to comparatively complex GARCH Models (including Exponential GARCH and Threshold GARCH models). The results revealed that despite the existence of leverage effect, the Symmetrical GARCH Model performs better in predicting volatility of the Sensex yield than the Asymmetrical GARCH Models. Abdalla (2012) discovered stock market volatility in the Saudi stock market. The study used GARCH (Generalized Autoregressive Conditional Heteroskedasticity) with both asymmetric and symmetric models. The GARCH Model found strong signals of the persistence of volatility. Leon (2008) considered the association between expected equity market yields and volatility in the stock market of the West-African Economic & Monetary Union, which is popularly known as the BRVM. The study discovered that stock returnshavea uni-directional but not significant association with volatility.

Fakhfekh et al. (2021) used the GARCH model to understand the volatility dynamics of the Tunisian sectorial stock market during the COVID-19 period. They found that following the COVID-19, volatility was more persistent. The results showed that building constructionmaterials, construction sector and the food and beverage sectors had an insignificant asymmetric effect in return volatilities, whereas the consumer service sector, financials and distribution, basic materials and bankingsector return volatilities had comparatively high positive and significant asymmetric effects. Le and Tran (2021) investigated the presence of financial contagion from the U.S. stock market to the Vietnamese and the Philippine stock markets during the globalfinancial crisis and the COVID-19 crisis. It was seen that there was no evidence of contagion to the Philippine stock market from the U.S stock market that couldbe present during the global financial crisis, whereas the Vietnamese stock market was influenced by this effect. In addition, both these developing stock markets,i.e., the Vietnamese stock market and Philippine stock market, were influenced by the contagion effect in COVID-19. However, during the coronavirus pandemic, the contagion effect crisis in Vietnam was lessthan that during the global financial crisis,and for the Philippines, it was exactly the reverse. Abuhommous and Alqaralleh (2021) investigated the existence of conditional volatility in the Saudi Arabia stock market. They used the nonlinear GARCH models along with the best fitting distribution, accounting for the skewness and excess kurtosis in return modelling. The results revealed evidence of a reversed asymmetric effect before theCOVID-19 pandemic. Though, a robust indication of the news effect was noticed as the health crisis began.

Olayungbo (2021) examined the volatility effects of the oil price on the stock price returns in Nigeria using GARCH and non-linear GARCH models. He found the existence of heteroscedasticity by using the ARCH test and volatility clustering through the returns. The study is beneficialto investors as it provides an information on financial dataand the GARCH models, which can be used to model international oil price instability and as a result, reduce financial risk in stock market. Liu et al. (2021) investigated the impact of the COVID-19 pandemic on the stock market crash in China. They estimated the conditional skewness of the return distribution from a GARCH with skewness (GARCH-S) model, and the proxy for the equity market was the Shanghai Stock Exchange. It was seen that conditional skewness reacted negatively to daily growth in the total confirmed positive cases, signifying that the pandemic surgedstock market crash risk. Furthermore, the fear sentiment worsens such a risk, particularly with regard to the effect of COVID-19. Thus, when the fear sentiment was very high, the stock market crash risk was affected by the COVID-19 strongly and significantly. Haque and Shaik (2021) found that the extraordinary worldwide turn of events, mainly due to the blowout of the highly infectious corona pandemic, has led to an extensive decrease in crude oil prices. They aimed to use two methods,i.e. ARIMA (Autoregressive Integrated Moving Average) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) to predict the WTI crude oil prices. GARCH ARIMA model was recommended for forecasting as it has a lower root mean squared error (RMSE) and mean absolute error (MAE).

Chuan et al. (2021) investigated the volatility of two Asian stock markets, Bursa Malaysia and the Singapore Exchange. They estimated standard GARCH Models like GARCH, GARCH-M, TGARCH, EGARCH and PARCH. The results showed that both stock market returns are tenacious, and the tenacity of both stock market returns declined during the pandemic. Besides, the normal distribution workedwell for Malaysian and Singaporean stock markets before the COVID-19 and switched to a student's t (skewed normal) during the COVID-19. It was found that the standard GARCH, GARCH-M and EGARCH performed well for both stock market returns, and the EGARCH indicated the existence of the leverage effect when stock market returns were negatively correlated to its volatility. Khanthaporn and Wichitaksorn (2021) found that the GG estimation method outperformed the benchmark quasi-maximum likelihood estimation method. Further, they examined the seven stock markets where the results from the in-sample period before the COVID-19 pandemic justified the use of the proposed GARCH models. Ganguly (2021) studied the volatility and leverage effect of the selected countries' stock market index during the COVID-19 outburst. The standard deviation value substantiated the growing volatility in the select stock market index during COVID-19. The GARCH results validated the stronger presence of volatility in all the selected stock markets, except Russia, during the pandemic. The EGARCH result confirmed that there was no leverage effect in the selected stock market during the COVID-19. Nugroho and Robiyanto (2021) examined variables that affected the Jakarta Composite Index (JCI) volatility during the COVID-19. The independent variables that are used are gold return volatility and USD/IDR return volatility. It was proved that during the COVID-19 pandemic, gold return volatility absolutely affected the JCI volatility. On the other hand, USD/IDR volatility negatively affected JCI volatility. This study can be used as a consideration for investors in selecting their investment during the outbreak of a pandemic or financial crisis by investigating gold and the USD/IDR volatility effect on JCI volatility.

Özdurak and Karataş (2021) attempted to test the 'time-varying' and 'time-scale dependent' volatilities of key technology stocks, FAANG and Microsoft, to analyze the likelihood of an additional knowhow fizz in the markets. Their findingsindicated that major technology companies perform and move as if they were all single stocksduringthe COVID-19 period, which about a subsequent dotcom crisis as 26% of S&P 500 market cap is driven by FAANG and Microsoft stocks. Rai and Garg (2021) examined the influence of outbreak of COVID-19 pandemic on active correlations and volatility spillovers between stock returns and exchange rates in BRIICS economies. They demonstrated substantial negative dynamic correlations and volatility spillovers amid exchange and stock returns in many of the BRIICS economies. Moreover, the relationship was reinforced during the initial days of lockdowns. Their findings indicated that there have been significant risk transmissions between the two markets, during the COVID-19 pandemic, which led to a weakening in domestic stock returns and successive capital outflows, thus increasing the exchange rates. Xu, L. (2021) investigated the dynamic responses of stock returns to the unpredicted changes in the COVID-19 cases and the uncertainty accompanying with the pandemic. He found that there was a negative effect of the rise in the COVID-19 cases on the stock market in general. Furthermore, the stock returns were asymmetric in the rise and decline in the cases in Canada. The asymmetry was instigated by the negative impact of uncertainty about the pandemic. He also found that uncertainty unfavorably affects the US stock market. Thoughthe magnitude was small,Szczygielski (2021) investigated the timing and measured the impact of COVID-19 related uncertainty on volatility and stock returns for regional market aggregates using ARCH/GARCH Models. It was found that Asian markets were more robust than others. In terms of returns and volatility, Latin American markets were most impacted. There was also evidence of a growing effect of COVID-19 related uncertainty, which has scatteredas the crisis progresses.

Yousfi et al. (2021) investigated the active conditional correlation and the asymmetric effects of shockwaves on the association between the US and Chinese stock markets before and during the COVID-19 crisis. They found that the dynamic correlation approach is in favor of the presence of volatility spillovers between the US and Chinese stock markets, particularly during the fast spread stage of COVID-19 in the US. Secondly, it was seen that the shockwaves hittingthe US and Chinese markets have asymmetric impacts on the correlation between both markets. Lastly, they found a persistent connection between the US returns, uncertainty, and the pandemic during the outbreak. They proved that the pandemic has exposed harmful implications for financial markets and the US economy. Chang et al. (2021) investigated the outcome of the governments' responses to COVID-19 on the returns of the stock market. They indicated that the overall government response, stringency, containment and health have an enormous positive effect on stock market returns. Explicitly, government policy responses,likeshutting down offices, cancellingpublic events, limiting public assemblies and global travel, giving income support, and applying fiscal measures can increasestock market returns. Umar et al. (2021) analysed the influence of COVID-19 on the stock market returns of China and other four countries affected by the pandemic. The results of the GARCH analysis showed that liquidity in stock markets was hit hard by the news of the pandemic. They did not find the presence of any short-term connection between new cases of COVID-19 or deaths and illiquidity. Moreover, there was no long-term relationship between the pandemic and stock market illiquidity, which suggests no indication of the impact of COVID-19 on stock market liquidity. Duttilo et al. (2021) aimed to inspect the influence of the two waves of COVID-19 pandemic on the volatility and returns of the stock market. They revealed that euro area stock markets reacted contrarily to COVID-19. Precisely, the first wave of COVID-19 contaminations had a prominent effect on stock market volatility of euro area nations, whereas the second wave had a significant effect only on the stock market volatility of Belgium. Baek and Lee (2021) studied volatility transmission effects betweenthe US stock market and the COVID-19. They found that the US stock market volatility depends on bothits own previous shocks and former COVID-19 shocks. Additionally, they also found that the US stock market volatility was positively affected significantly by the death rate, i.e., bad news while the recoveryrate, i.e., good news had a negative effect on the US stock market volatility. The results showed that there was an asymmetric volatility effect of the COVID-19 pandemic on the US stock market: the bad news affected the US stock market considerably more than the good news. The fixed effect panel regression results supported the volatility spillover effects.

Kakinuma (2021) investigaed the return and volatility spillover effects in Southeast Asian Stock Markets, gold, and bitcoin before and during the COVID-19 pandemic. Chancharat & Meeprom (2021) examined the volatility transmission effects between stock returns and the growth rate of total confirmed COVID-19 cases. They revealed that the pandemic negatively related tostock returns in the hospitality and tourism industries. Stock market returns are significantly negatively associated with daily growth in total confirmed COVID-19 cases. Marome & Shaw (2021) emphasized the health resources in the country and focusedon the response through community-level public health systems and legislative measures. They suggested that one opportunity for enhancing resilience in Thailand is to strive for more multilevel governance that engages with various stakeholders and to support grassroots and community-level networks. The COVID-19 pandemic recovery is a chance to recover better while leaving no one behind. For an inclusive long-term recovery plan for the various impacted countries, theyneedto take a holistic approach to address existing gaps and work towards a sustainable society.

3. Methodology

STE (Stock Exchange of Thailand) is the largest and only stock exchange inThailand. The Bombay Stock Exchange (BSE) and National Stock Exchange (NSE) are two main stock exchanges of India. The Bombay Stock Exchange (BSE) is the oldest stock exchange inIndia. TheNational Stock Exchange (NSE) is an entirely automated stock exchange.

The objective of the study is:

-to see how the outbreak of COVID-19 Pandemic shockwaves has impacted on the returns and volatility of Thailand and Indian stock market.

-to see whether both countries are reacting similarto the pandemic or not.

The current study is based on the one and only stock index of the Stock Exchange of Thailand, i.e., SET 50, and two indices of Bombay Stock Exchange and National Stock Exchange,i.e., S&P BSE Sensex, and S&P Nifty. The daily data of closing prices of all three indices were taken for the study. The data has been divided into three categories, the first one is before theCOVID-19 pandemic, the second is during the COVID-19 pandemic and the third isfor the whole period collectively. The Pre-Pandemic period has been taken from 1st July 2019 to 31st January 2020. During Pandemic period has been taken from 1st February 2020 to 31st August 2020,and the whole period has been taken from 1st July 2019 to 31st August 2020. The data has been collected from the yahoofinance.com. Unit root tests like Augmented-Dickey-Fuller test, Phillips Perron (PP) Test and Kwiatkowski Phillips Schmidt Shin (KPSS) Test are applied to check the stationarity of data used in the study. The standard GARCH models like GARCH, EGARCH, TGARCH, and PARCH have been used to assess the volatility of the Indian stock market. For the purpose of data analysis, the Eviews 12 software is used. To estimate the returns, the logarithmic variance of two periods is calculated by using the following:

$$R_t(\text{In } P_t - \text{ In } P_{t-1}) * 100 \tag{1}$$

However, where R_t is the returns of period t, P_t and P_{t-1} are the daily closing price values of the indices at time t and t-1.

3.1 Unit Root Test

For testing stationarity, an AR (1) model is considered:

$$\gamma_t = p_1\gamma_{t-1} + \varepsilon_t \tag{2}$$

The AR (1) model specified in the above equation is termed as *random walk model*. According to this model, if $|p_1|<1$, in that case, the series is I(0), i.e., stationary in level, but if $p_1 = 1$, then the unit root problem is prevalent, i.e., series is non-stationary. Some economic experts think that differencing is warranted if estimated $p > 0.9$; while some others believe that it is warranted when estimated $p > 0.8$. In addition to this, there are a few other ways of testing thestationarity of any series.

3.1.1 Augmented Dickey Fuller Test

Augmented Dickey Fuller Test (Dickey & Fuller; 1981) includes assessing the regression equation and carrying out the hypothesis test. The modest approach to testing of a unit root is with an AR(1) model. AR(1) model is:

$$\gamma_t = c + p\gamma_{t-1} + \varepsilon_t \tag{3}$$

However, *c* and ρ are parameters and arepresumed to be white noise. If $-1<p<1$, y is a stationary series, whereas if $\rho=1$, y is a non-stationary series. If the absolute value of ρ is greater than one, it means there is volatility in the series. Therefore, the hypothesis of a stationary series requires knowing if the absolute value of ρ is firmly less than one. The test is conducted by assessing an equation with y_{t-1}beingsubtracted fromboth sides of the equation:

$$\Delta y_t = c + \gamma y_{t-1} + \varepsilon_t \qquad (4)$$

The ADF test is valid if the series is an AR(1) process. If it is found that the series is correlated at higher order lags, in that case, the assumption of white noise turbulenceis violated. The ADF regulates for higher order correlation by accumulating lagged difference in terms of the dependent variable to the right-hand side of the regression:

$$\Delta y_t = c + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \ldots. + \delta_p \Delta y_{t-p} + \varepsilon_t \qquad (5)$$

This augmented description is then verified for in this regression.

$$H_0: \gamma = 0$$
$$H_1: \gamma < 0$$

3.1.2 Phillips Perron (PP) Test

The Phillips Perron (PP) Test is a unit root test. It is practiced in time series study to check the null hypothesisthat a series is integrated of order 1. It is basedon the Dickey–Fuller test of the null hypothesis $\delta = 0$in

$$\Delta yt = \delta y_{t-1} + \mu t \qquad (6)$$

Here, Δ is the first difference operator. The Augmented Dickey Fuller Testandthe Phillips Perron Test discoursethe problem that the process generating data for y_t can have an advanced order of autocorrelation than is recognized in the test equation which makesy_{t-1} endogenous, hence, overturning the Augmented Dickey Fuller Test. The Augmented Dickey Fuller Test hearsays this matter by presenting lags of Δy_t as regressors in the test equation.The Phillips Perron Test presents a non-parametric rectification to the t-test statistics. The test is dynamic with regard to imprecise autocorrelation and the heteroscedasticity present in the disturbance process of the test equation.

3.1.3 Kwiatkowski Phillips Schmidt Shin (KPSS) Test

Kwiatkowski Phillips Schmidt Shin (KPSS) test is used to test the null hypothesis that a time series is stationary around a deterministic trend. These models were proposed by Alok Bhargava in 1982. The series is stated as the sum of a deterministic trend, a stationary error, and arandom walk. Kwiatkowski Phillips Schmidt Shin (KPSS) tests are proposed to accompanyunit root testslike the Dickey–Fuller test. By testing both hypotheses, i.e., the unit root hypothesis and the stationarity hypothesis, one can differentiate series thatappear to be stationary series thatseemto have a unit root and apparently, series for which the data is not adequately useful to be certain whether the series is stationary or integrated.

3.2 Heteroscedasticity

Before applying the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) methodology, one must first inspect the residuals for an indication of heteroscedasticity. To test the existence of the heteroscedasticity in the residuals of

SENSEX and Nifty indices return series, the Lagrange Multiplier (LM) test for ARCH effects given by Engle (1982) is used. The test procedure is completed by first obtaining the residuals *e* from the ordinary least squares regression of the conditional mean equation, which might be an autoregressive (AR) process, moving average (MA) process or a combination of AR and MA processes(ARMA) process. For example, in ARMA (1,1) process the conditional mean equation will be as follows:

$$r_t = \emptyset r_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} \qquad (7)$$

After finding the residuals *t e*, the subsequent step is regressing the squared residuals on a constant and q lag as in the following equation:

$$e_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \alpha_2 e_{t-2}^2 + \ldots + \alpha_q e_{t-q}^2 + v_t (8)$$

The null hypothesis that there is no ARCH effect up to order q can be formulated as:

$$H_0 : \alpha_1 = \alpha_2 .. = \alpha_q = 0 \quad (9)$$

against the alternative:

$$H_1 : \alpha_i > 0 \quad (10)$$

for at least one i = 1, 2, …, q

3.2.1 The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

In this model, the conditional variance is signified as a linear function of its own lags. The model specification is the GARCH (1,1) model:

$$Mean\ Equation \quad r_t = \mu + \varepsilon_t \qquad (11)$$

$$Variance\ Equation \quad \sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (12)$$

$where\ \omega > 0\ and\ \alpha_1 \geq 0\ and\ \beta_1 \geq 0, and$
$r_t = return\ of\ the\ asset\ at\ time\ t$
$\mu = average\ return$
$\varepsilon_t = residual\ returns, defined\ as$:
$\varepsilon_t = \sigma_t z_t$

Where$z_t$is standardized residual returns (i.e., random variable with zero mean and variance 1), and α^2_t is conditional variance. For GARCH (1,1), the constraints $\alpha_{\geq 0}$ and $\beta_{1 \geq 0}$ are needed to ensure α^2_t is strictly positive. In this model, the mean equation is written as a function of constant with an error term. Since α^2_t is the one –period ahead forecast variance based on past information, it is called the conditional variance. The conditional variance equation is specified as a function of three terms:

- A constant term:ω
- News about volatility from the previous period, measured as the lag of the squared residual from the mean equation:ε_{t-1}^2 *(the ARCH term)*
- Last period forecast variance:σ_{t-1}^2 *(the GARCH term)*

The general specification of GARCH is, GARCH (p, q) is as follows:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_i \sigma_{t-1}^2 \qquad (13)$$

where, *p* is the number of lagged α^2 terms and *q* is the number of lagged ε^2 term

3.2.2 The Exponential GARCH (E-GARCH) Model

This model captures the asymmetric responses of the time-varying variance to shocks, and, at the same time, ensures that the variance is always positive. It was developed by Nelson (1991) with the following specifications:

$$Ln(\sigma_t^2) = \omega + \beta_1 Ln(\sigma_{t-1}^2) + \alpha_1 \left\{ \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (14)$$

where γ is the asymmetric response parameter or leverage parameter. The sign of γ is expected to be positive in most empirical cases, so that a negative shock increases future volatility or uncertainty, while a positive shock eases the effect on future uncertainty. In macroeconomic investigation, monetary marketplaces and corporate finance, a negative shock generally impliesbad news, leading to a more uncertain future. The EGARCH (1,1) model is given above (see Equation 15) . Higher order E-GARCH models can be specified in a similar way.EGARCH (p, q) is as follows:

$$Ln(\sigma_t^2) = \omega + \sum_{j=1}^{p} \beta_j \, Ln\left(\sigma_{t-j}^2\right) + \sum_{i=1}^{q} \alpha_i \left\{ \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma_t \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \quad (15)$$

3.2.3 The Threshold GARCH (T-GARCH) Model

Another volatility model commonly used to handle leverage effects is the threshold GARCH (or T-GARCH) model. In the T-GARCH (1,1) version of the model, the specification of the conditional variance is:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (16)$$

Where d_{t-1} $is\ a\ dummy\ variable, that\ is:$

$$d_{t-1} = \left\{ \begin{array}{l} 1\ if\ \varepsilon_{t-1} \leq 0 \quad bad\ news \\ 0\ if\ \varepsilon_{t-1} \geq 0, \quad good\ news \end{array} \right\}$$

The coefficient γ is known as the asymmetry or leverage term. When $\gamma = 0$, the model collapses to the standard GARCH forms. Otherwise, when the shock is positive (i.e., good news), the effect on volatility is α_1, but when the news is negative (i.e., bad news), the effect on volatility is $\alpha_{1+}\gamma$. Hence, if γ is significant and positive, negative shocks have a larger effect on σ^2_t than positive shocks. In the general specification of this model, T-GARCH (p,q), the conditional variance equation is specified as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} (\alpha_1 + \gamma_i d_{t-1}) \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 (17)$$

α_i, γ_i and β_j $are\ non-negative\ parameters\ satisfying\ conditions\ similar\ to\ those\ of\ GARCH\ models.$

3.2.4 The PARCH Model

The PARCH (1,1) model is shown below. Parameter is the power term; whenequation resembles the classic GARCH model with a leverage effect, and when the model conditions volatility on the standard deviation. A statisticalevidenceshows that negative shocks persuade larger volatility than positive shocks.

$$r_t = c + \mu_t \quad (18)$$

$$\sigma_t^{\delta} = \alpha + \theta_1 \sigma_{t-1}^{\delta} + b_1(|\mu_{t-1}| - \gamma_1 \mu_{t-1})^{\delta} \quad (19)$$

4. RESULTS AND DISCUSSION

4.1 Descriptive Statistics

The details of descriptive statistics of SET, SENSEX and NIFTY returns for Pre-pandemic, Post-pandemic and the whole period are presented in Table 1. This comprises mean, median, maximum, minimum, standard deviation, skewness test, kurtosis and Jarque-Bera test.

Table 1 showsthat the average daily return of SET was 0.09% during the pandemic, while the SENSEX returns during the pandemic was -0.07%, as compared to the 0.02% before the pandemic. In the case of NIFTY, the average daily returns during the pandemic were -0.03% as compared to the 0.1% before the pandemic. The standard deviation during the pandemic was the highest or all three series, i.e., SET, SENSEX AND NIFTY. Kurtosis was increasing, and negative skewness was decreasing during the pandemic which means there can be a possibility of small gains. The Jarque-Bera indicated a lack of normal distribution in returns, signifying a lack of symmetric nature of SET, SENSEX and NIFTY returns. Figure 1 depicts the comparison of returns of STE, SENSEX and NIFTY.

Table 1: Descriptive Statistics of SET, SENSEX and NIFTY Returns

Panel A: SET Returns

Variable	**During Pandemic**	**Pre-Pandemic**	**Whole Period**
Mean	0.095	0.096	0.099
Median	-0.149	0.073	0.047
Maximum	11.428	2.935	8.595
Minimum	-7.653	-1.850	-14.102
Std. Dev.	2.274	0.717	1.932
Skewness	1.563	0.319	-1.567
Kurtosis	10.891	4.367	16.742
Jarque-Bera	420.207*	13.746*	2350.932*
Observations	140	145	284

Panel B: SENSEX Returns

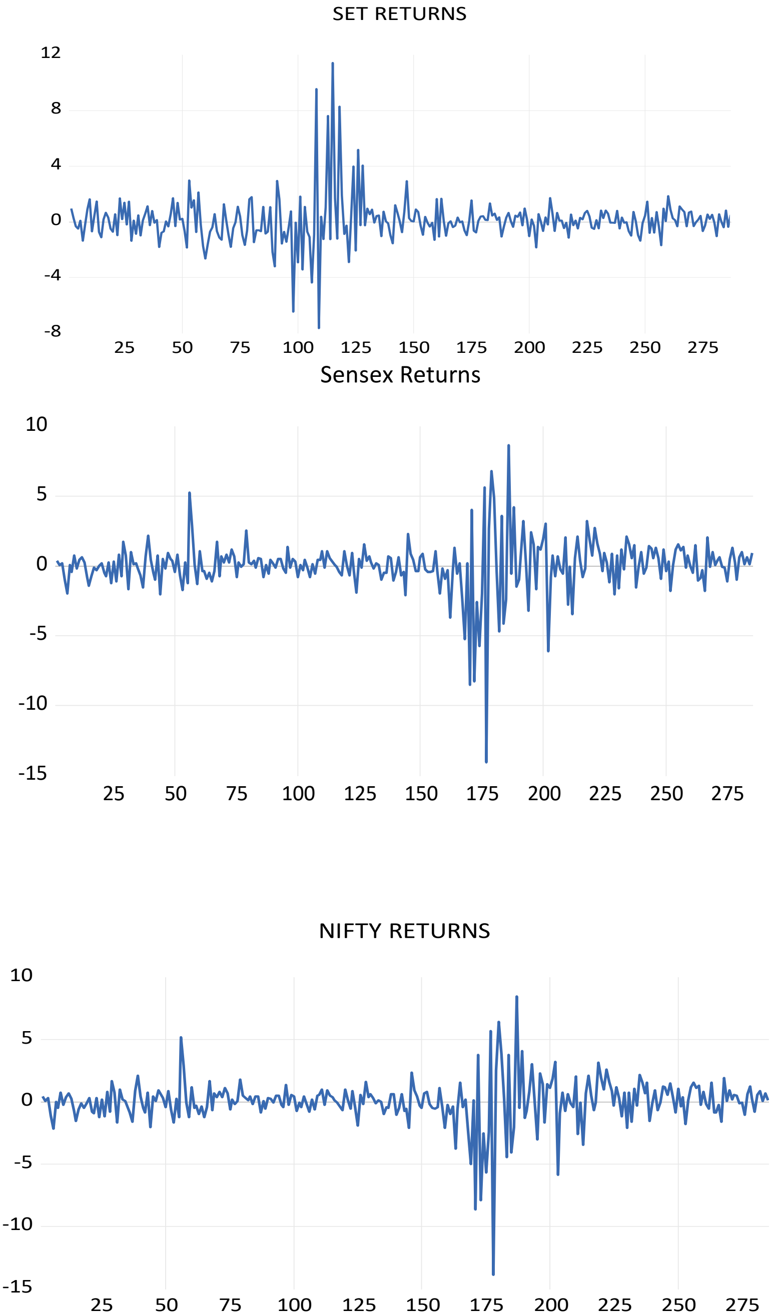
Variable	**During Pandemic**	**Pre-Pandemic**	**Whole Period**
Mean	-0.007	0.022	-0.002
Median	0.175	0.057	0.093
Maximum	8.595	5.186	8.595
Minimum	-14.102	-2.084	-14.102
Std. Dev.	2.576	0.923	1.932
Skewness	-1.392	1.240	-1.567
Kurtosis	10.559	9.383	16.742
Jarque-Bera	381.260*	275.457*	2350.932*
Observations	141	141	284

Panel C: NIFTY Returns

Variable	During Pandemic	Pre-Pandemic	Whole Period
Mean	-0.004	0.010	-0.009
Median	0.160	0.055	0.083
Maximum	8.400	5.182	8.400
Minimum	-13.904	-2.161	-13.904
Std. Dev.	2.520	0.929	1.894
Skewness	-1.455	1.191	-1.618
Kurtosis	10.770	9.206	16.903
Jarque-Bera	404.469*	259.617*	2411.258*
Observations	141	141	284

Source: Self-made by Authors

Figure1 :Comparison of SET, SENSEX and NIFTY Returns



Source: Self-Made by Authors

4.2 Unit Root Test

The results of unit root test are shown in Table 2. Panel A presentsthe results of ADF test, Panel B presents the results of PP test, and Panel C presents the results of KPSS test. Augmented Dickey-Fuller, Phillip-Perron and KPSS test were calculated, including intercept and time trend at level and first difference for the SET, SENSEX and NIFTY during the pandemic, before the pandemic and for the whole period.

Table 2: ADF, PP, KPSS Unit Root Test Estimation

Panel A: ADF Test				
	Level		*First Difference*	
Variable	**Trend**	**Trend & Intercept**	**Trend**	**Trend & Intercept**
SET (During)	**-1.000**	**-0.964**	-13.178*	-13.239*
SET (Pre)	**-1.262**	-2.935	-12.488*	-12.444*
SET (Whole)	**-0.641**	-1.841	-18.799*	-18.788*
SENSEX (During)	**-1.285**	-1.587	-13.570*	-13.921
SENSEX (Pre)	**-1.065**	-2.893	-11.396*	-11.417*
SENSEX (Whole)	**-1.438**	-1.225	-18.808*	-18.823*
NIFTY (During)	**-1.216**	-1.596	-13.539*	-13.921*
NIFTY (Pre)	**-1.214**	-2.875	-11.314*	-11.347*
NIFTY (Whole)	**-1.432**	-1.181	-18.699*	-18.724*
Panel B: PP Test				
	Level		***First Difference***	
Variable	**Trend**	**Trend & Intercept**	**Trend**	**Trend & Intercept**
SET (During)	**-1.205**	**-1.139**	-13.132*	-13.173*
SET (Pre)	**-1.239**	-2.951	-12.520*	-12.474*
SET (Whole)	**-0.800**	-2.076	-18.786*	-18.771*
SENSEX (During)	**-1.288**	-1.464	-13.446*	-13.743*
SENSEX (Pre)	**-0.898**	-2.753	-11.574*	-11.707*
SENSEX (Whole)	**-1.639**	-1.475	-18.776*	-18.778*
NIFTY (During)	**-1.314**	-1.468	-13.436*	-13.73*
NIFTY (Pre)	**-1.120**	-2.759	-11.406*	-11.568*
NIFTY (Whole)	**-1.651**	-1.468	-18.727*	-18.732*
Panel C: KPSS Test				
	Level		***First Difference***	
Variable	**Trend**	**Trend & Intercept**	**Trend**	**Trend & Intercept**
SET (During)	137.510*	69.078*	0.567	-0.522
SET (Pre)	360.222*	387.924*	1.631	0.790
SET (Whole)	139.675*	101.244*	1.212	0.167
SENSEX (During)	107.874*	53.137*	-0.042	-1.499
SENSEX (Pre)	277.29*	214.796*	0.292	-0.573
SENSEX (Whole)	170.923*	98.402*	-0.021	-0.697
NIFTY (During)	106.538*	52.401*	-0.022	-1.547
NIFTY (Pre)	289.968*	205.684*	0.136	-0.711
NIFTY (Whole)	167.469*	983.51*	-0.101	-0.792
Critical values at 1%	-3.477	-4.024	-3.477	-4.025
Critical values at 5%	-2.882	-3.442	-2.882	-3.442
Critical values at 10%	-2.578	-3.146	-2.578	-3.146

indicates significant at 1% ** indicates significance at 5% level. * indicates significance at 10% level.*

Source: Self-made by Authors

In the case of ADF and KPSS tests, the trend coefficients of the SET, SENSEX and NIFTY rejected the null hypothesis of a unit root problem. It was found that the return series were stationary. The absolute computed values were higher than the MacKinnon critical values at 1%, 5% and 10% level. Thus, the results showed that the first difference series of SET, SENSEX and NIFTY were stationary. For the KPSS test, the null hypothesis of no unit root problem was accepted for the return series of SET, SENSEX and NIFTY.

4.3 Heteroscedasticity Test

The results of ARCH LM test are shown in Table 3. ARCH LM test is calculated on the return series of SET, SENSEX and NIFTY for the whole period from 1st July 2019 to 31st August 2020. The Lag criteria selected for the test was 2.

Table 3: ARCH LM Statistics

ARCH LM Statistic			
	SET	**SENSEX**	**NIFTY**
F-Statistic	4.17	20.77	19.898
	(0.0000)	(0.0000)	(0.0000)

Source: Self-made by Authors

Table 3 results showed that the null hypothesis of homogenous variance has been rejected for all returns series of SET, SENSEX and NIFTY which means there is thepresence of heteroscedasticity in both series. Thus, GARCH models can be applied.

4.4 Volatility Models

Table 4 reported the results of GARCH (1,1), TGARCH (1,1), EGARCH (1,1) and PARCH (1,1) models for the return series of the SET for the pre-pandemic period from 1st July 2019 to 31st January 2020, during the pandemic period from 1st February 2020 to 31st August 2020, and the whole period from 1st July 2019 to 31st August 2020.

Table 4 showed that in STE (Stock Exchange of Thailand) during the pandemic, thevariance equation of GARCH (1, 1) Model, three coefficients ω (constant) was 9.28E-06, ARCH (α) was 0.2347, and GARCH term (β) was 0.7791. ω (constant) was not significant and the other two coefficients were statistically significant, signifying that current volatility is affected by the news of volatility from the previous periods. The sum of $\alpha+\beta$ (persistence coefficients) is 0.9965 which is close to one which was essential to have a mean reverting variance process, specified that volatility shockwaves were ascetically persistent and took longer time to scatter during the pandemic time period. Persistent coefficient shows volatility persistence has increased during the pandemic period. α shows that shocks to the returns and even the magnitude are greater during the pandemic period as compared to during the pre-pandemic. During the pandemic, in the TGARCH(1,1) model, the value of α (-0.09995) was smaller than that of γ(0.1867), suggesting that negative shocks have a larger effect on conditional volatility related to positive shocks of similar extent during the pandemic period. However, as far as, the EGARCH (1,1) model and PARCH (1,1) model are concerned, during the pandemic, the dependency of volatility on its previous behavior was confirmed, as bothα and β coefficients appear to be statistically significant.

Table 4: Results of GARCH Models of SET 50 Returns

Panel A: During Pandemic				
Variable	**GARCH**	**TGARCH**	**EGARCH**	**PARCH**
		Mean Equation		
C	0.0002	-0.0006	-0.001	-0.0008
		Variance Equation		
ω	9.28E-06	1.46E-06	-0.309	1.32E-10
α	0.235*	-0.099*	0.231*	0.024
β	0.779*	1.041*	0.982*	0.725*
γ	-	0.187*	-0.239*	0.967
δ	-	-	-	4.528201
R-squared	-0.001	-0.005	0.005	-0.006
Adj. R squared	-0.001	-0.005	-0.002	-0.006
Log Likelihood	373.057	385.186	379.31	380.567
AIC	-5.27	-5.431	-5.333	-5.350
SIC	-5.188	-5.326	-5.207	-5.225
Durbin Watson	2.282	2.273	2.284	2.270

Panel B: Pre-Pandemic				
Variable	**GARCH**	**TGARCH**	**EGARCH**	**PARCH**
		Mean Equation		
C	0.001**	-0.010*	0.048	0.001
		Variance Equation		
ω	2.20E-05**	1.48E-06**	-9.965*	2.57E-07
α	-0.068*	-0.052*	-0.081	-0.006
β	0.641*	0.952*	-0.108906	0.873*
γ	-	0.128*	0.024624	-0.968
δ	-	-	-	2.679
R-squared	-0.000	0.098	0.031	-0.000
Adj. R square	-0.000	0.091	0.24	-0.000
Log Likelihood	511.132	521.601	513.263	514.097
AIC	-6.994	-7.111	-6.997	-7.008
SIC	-6.913	-6.989	-6.874	-6.885
Durbin Watson	2.085	2.098	1.967	2.085

Panel C: Whole Period				
Variable	**GARCH**	**TGARCH**	**EGARCH**	**PARCH**
		Mean Equation		
C	0.000	-0.0001	-0.001	2.81E-05
		Variance Equation		
ω	2.43E-06	7.88E-07	-0.278*	0.007
α	0.178*	-0.042*	0.162*	0.101*
β	0.824*	0.905*	0.983*	0.643*
γ	-	0.364*	-0.214*	0.999*
δ	-	-	-	0.643*
R-squared	-0.000	-0.004	0.012	-0.003
Adj. R squared	-0.000	-0.004	0.008	-0.003
Log Likelihood	881.80	894.337	894.654	894.721
AIC	-6.139	-6.219	-6.214	-6.214
SIC	-6.087	-6.155	-6.138	-6.138
Durbin Watson	2.272	2.262	2.227	2.265

*indicates significant at 1% . ** indicates significance at 5% level. *** indicates significance at 10% level.

Source: Self-made by Authors

Table 5: Results of GARCH Models of SENSEX Returns

Panel A: During Pandemic

Variable	GARCH	TGARCH	EGARCH	PARCH
		Mean Equation		
C	0.002**	0.001	-0.000	0.002*
		Variance Equation		
ω	8.54E-06	6.97E-06**	-0.144**	0.004
α	0.178**	-0.259*	-0.301***	0.088**
β	0.818*	0.988*	0.967*	0.927*
γ	-	0.399*	-0.590*	0.991*
δ	-	-	-	0.386
R-squared	-0.009	-0.001	-0.019	-0.008
Adj. R square	-0.009	-0.001	-0.026	-0.008
Log Likelihood	371.966	377.589	375.396	375.702
AIC	-5.205	-5.271	-5.225	-5.230
SIC	-5.101	-5.145	-5.079	-5.083
Durbin Watson	2.287	2.304	2.218	2.289

Panel B: Pre-Pandemic

Variable	GARCH	TGARCH	EGARCH	PARCH
		Mean Equation		
C	1.16E-05	-0.000	-0.461	-0.000
		Variance Equation		
ω	3.10E-05	7.43E-05***	-9.467*	0.011
α	0.089	0.047	0.015	0.042
β	0.524	0.401**	0.002	0.946*
γ	-	0.856*	0.002	1.000*
δ	-	-	-	0.232
R-squared	0.000	-0.003	0.076	-0.002
Adj. R square	0.000	-0.003	0.070	-0.002
Log Likelihood	474.792	474.090	478.584	478.850
AIC	-6.674	-6.380	-6.689	-6.693
SIC	-6.559	-6.255	-6.543	-6.547
Durbin Watson	1.944	1.940	2.104	1.942

Panel C: Whole Period

Variable	GARCH	TGARCH	EGARCH	PARCH
		Mean Equation		
C	0.000	0.000	-0.000	0.000
		Variance Equation		
ω	6.35E-06***	3.46E-06**	-0.369*	0.001
α	0.129*	-0.020	0.195*	0.101*
β	0.849*	0.895*	0.976*	0.919*
γ	-	0.209	-0.178*	0.968*
δ	-	-	-	0.695*
R-squared	-0.001	0.000	-0.005	0.000
Adj. R squared	-0.001	0.000	-0.008	0.000
Log Likelihood	845.057	852.357	850.478	853.662
AIC	-5.916	-5.960	-5.940	-5.962
SIC	-5.852	-5.883	-5.850	-5.872
Durbin Watson	2.272	2.274	2.239	2.275

*indicates significant at 1% . ** indicates significance at 5% level. *** indicates significance at 10% level.

Source: Self-made by Authors

Table 5 reported the results of GARCH (1,1), TGARCH (1,1), EGARCH (1,1) and PARCH (1,1) models for the return series of the SENSEX for the Pre-pandemic period from 1st July 2019 to 31st January 2020, during the pandemic period from 1st February 2020 to 31st August 2020, and the whole period from 1st July 2019 to 31st August 2020. This Table showed that during the pandemic period, in the variance equation, the three coefficients ω (constant) was 8.54E-06, ARCH (α) was 0.1783 and GARCH term (β) was 0.8182. ω (constant) was not significant, and the other two coefficients were statistically significant, signifying that current volatility is affected by the news of volatility from the previous periods.The sum of α+ β (persistence coefficients) is 0.9965 which isnear to one,meaningvolatility shockwaves were highly persistent and took longer time to disperse during the pandemic period. αshows that shocks to the returns and even the magnitude are greater during the Pre-pandemic period as compared to during the pandemic. In the TGARCH(1,1) model, the value of α (-0.2593) was smaller than that of γ (0.3988), suggesting that negative shocks have a larger effect on conditional volatility comparedto positive shocks of similar extent during the pandemic time period.

The EGARCH (1,1) model and PARCH (1,1) modeldependenciesof volatility on theirprevious behaviorwereconfirmed, as bothα and β coefficients appear to be statistically significant. As a result, the earlier findings that negative shocks have greater impact on this market than the positive shocks during the pandemic period were supported. However, as far asthe EGARCH (1,1) model and PARCH (1,1) model are concerned, during the pandemic, the dependency of volatility on its previous behavior was confirmed, as both α and β coefficients appear to be statistically significant.

Table 6: Results of GARCH Models of S& P NIFTY Returns

Panel A: During Pandemic				
Variable	**GARCH**	**TGARCH**	**EGARCH**	**PARCH**
		Mean Equation		
	0.002**	0.000	-0.002	0.002*
		Variance Equation		
ω	6.59E-06	6.30E-06**	-0.267*	0.004
α	0.183**	-0.267*	-0.277**	0.068
β	0.819*	1.002*	0.953*	0.939*
γ	-	0.389*	-0.606*	0.979*
δ	-	-	-	0.168
R-squared	-0.009	-0.001	-0.046	-0.007
Adj. R square	-0.009	-0.001	-0.054	-0.007
Log Likelihood	374.535	380.246	378.126	379.291
AIC	-5.242	-5.308	-5.264	-5.281
SIC	-5.137	-5.183	-5.118	-5.134
Durbin Watson	2.292	2.311	2.124	2.297
Panel B: Pre-Pandemic				
Variable	**GARCH**	**TGARCH**	**EGARCH**	**PARCH**
		Mean Equation		
C	-3.06E-05	-0.000	-0.159	-0.000
		Variance Equation		
ω	2.66E-05	1.99E-05	-9.45*	0.002
α	0.095	0.05	0.041	0.075
β	0.573	0.498**	0.007	0.920*
γ	-	0.515**	0.005	0.999*
δ	-	-	-	0.232
R-squared	0.000	-0.001	0.077	-0.001
Adj. R square	0.000	-0.001	0.070	-0.001
Log Likelihood	473.036	474.517	476.453	476.795
AIC	-6.639	-6.646	-6.659	-6.664
SIC	-6.534	-6.520	-6.513	-6.517
Durbin Watson	1.929	1.928	2.096	1.927
Panel C: Whole Period				
Variable	**GARCH**	**TGARCH**	**EGARCH**	**PARCH**
		Mean Equation		
C	0.000	-9.21E-05	-0.000	0.000
		Variance Equation		
ω	5.78E-06	0.000	-0.349*	0.000
α	0.145*	0.150	0.197*	0.096*
β	0.835*	0.600	0.978*	0.922*
γ	-	0.050	-0.176*	0.1*
δ	-	-	-	0.634*
R-squared	-0.002	0.000	-0.004	0.000
Adj. R squared	-0.002	0.000	-0.008	0.000
Log Likelihood	848.127	692.105	854.200	856.979
AIC	-5.938	-4.832	-5.966	-5.986
SIC	-5.873	-4.755	-5.876	-5.896
Durbin Watson	-0.002	2.276	-0.004	2.275

*indicates significant at 1% . ** indicates significance at 5% level. *** indicates significance at 10% level.

Source: Self-made by Authors

Table 6 reported the results of GARCH (1,1), TGARCH (1,1), EGARCH (1,1) and PARCH (1,1) models for the return series of the S & P CNX NIFTY for the Pre-pandemic period from 1st July 2019 to 31st January 2020, during the pandemic period from 1st February 2020 to 31st August 2020, and the whole period from 1st July 2019 to 31st August 2020. This Table showed that during the pandemic period, in the variance equation, the three coefficients ω (constant) was 6.59E-06, ARCH (α) was 0.1826 and GARCH term (β) was .8186. ω (constant) was not significant and the other two coefficients were statistically significant, signifying that the current volatility is affected by the news of volatility from the previous periods.The sum of α+ β (persistence coefficients) is 1.0012which means volatility shockwaves were highly persistent and took longer time to disperse during the pandemic period. α shows that shocks to the returns and even the magnitude are greater during the pre-pandemic period as compared to during the pandemic. In the TGARCH(1,1) model, the value of α (-0.2674) was smaller than that of γ (0.3899), suggesting that negative shocks have a larger effect on conditional volatility compared to positive shocks of the similar extent during the pandemic period. The EGARCH (1,1) model and PARCH (1,1) model dependenciesof volatility on theirprevious behaviorwereconfirmed, as both α and β coefficients appear to be statistically significant. As a result, the earlier findings that negative shocks have a greater impact on this market than positive shocks during the pandemic period were supported. However, as far as, the EGARCH (1,1) model and PARCH (1,1) model are concerned, during the pandemic, the dependency of volatility on its previous behavior was confirmed, as bothα and β coefficients appear to be statistically significant. So, this also reinforced those negative shocks have a greater impact on Thailand and Indian market than the positive shocks during the pandemic period. However, in the Pre-pandemic period, α is not statistically significant for all the models, and β is not significant for GARCH and TGARCH models which meansthat the current volatility is not affected by the news of volatility from the previous periods. As far as, EGARCH and PARCH models are concerned, all parameters are statistically significant, which means negative shocks have a greater impact on this market than the positive shocks during the pre-pandemic and the whole pandemicperiod which confirms the presence of leverage effect in Thailand and Indian stock market.

5. CONCLUSION

The market has the tendency to perceive long-term shocks that theeconomy can give to the market, but contrary to general, short-term shocks are more vulnerable. Short-term events have more immediate and surprising impacts, which sometimes get unnoticed,and hencecan be more damaging and disastrous. The data has been divided into three categories; thefirst one is before COVID-19 pandemic, the second is during COVID-19 pandemic, and the thirdisthe whole period collectively. The Pre-Pandemic period has been taken from 1st July 2019 to 31st January 2020. During the Pandemic period has been taken from 1st February 2020 to 31st August 2020. And the whole period has been taken from 1st July 2019 to 31st August 2020. Thailand and Indian stock exchanges have been used to monitor the impact of the pandemic. SET (Stock Exchange of Thailand), BSE (Bombay Stock Exchange), and NSE (National Stock Exchange) were taken as a proxy to represent the Thailand and Indian Stock Market.

It was specified that volatility shockwaves were ascetically persistent and took a longer time to scatter during the pandemic period. The negative shocks have a larger effect on conditional volatility compared to positive shocks of asimilar extent during the pandemic period. The dependency of volatility on its previous behavior was confirmed. So, this also supported the earlier results that negative shocks have a greater impact on Thailand and Indian stock markets than the positive shocks during the pandemic period as compared to the pre-pandemic period. COVID-19 has adversely affected both Thailand Stock Market and Indian stock market. This is mainly because of fewereconomic activities during the pandemic and some policy implications like lockdown, no or less travelling, social distancing etc. All these have affected a number of businesses, and hence the stock market was highly volatile during the pandemic.

References

Abdala, S.Z.S. (2012). Modelingstock returns volatility: Empirical evidence from Saudi stock exchange. *International Research Journal of Finance and Economics*, *85*, 166-179.

Abuhommous, A. A. A., &Alqaralleh, H. (2021). Testing the conditional volatility of Saudi Arabia stock market: Symmetric and Asymmetric Autoregressive Conditional Heteroskedasticity (GARCH) approach. *Academy of Accounting and Financial Studies Journal*, *25*(2). Page number?

Baek, S., & Lee, K. Y. (2021). The risk transmission of COVID-19 in the US stock market. *Applied Economics*, *53*(17), 1976-1990.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307-327.

Bordoloi, S., & Shankar, S. 2008. Estimating volatility in the Indian stock markets: Some *E*xplorations. *Money and Finance Conference, IGIDR*.1-23.

Chancharat, S., &Meeprom, S. (2021). The effect of the COVID-19outbreak on hospitality and tourism stock returns in Thailand. *Anatolia*, 1-12.

Chang, C. P., Feng, G. F., & Zheng, M. (2021). Government fighting pandemic, stock market return, and COVID-19virus outbreak. *Emerging Markets Finance and Trade*, *57*(8) 2389-2406.

Chuan, J. N., Mahdi, S., & Kenneth, R. (2021). The impact of COVID-19pandemic on stock market return volatility: Evidence from Malaysia and Singapore. *Asian Economic and Financial Review*, *11*(3), 191-204.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, *49*(4), 1057-1072.

Duttilo, P., Gattone, S. A., & Di Battista, T. (2021). Volatility modeling: an overview of equity markets in the euro area during COVID-19 Pandemic. *Mathematics*, *9*(11), 1212.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom Inflation. *Econometrica: Journal of the Econometric Society*, *50*(4), 987-1007.

Fakhfekh, M., Jeribi, A., & Ben Salem, M. (2021). Volatility dynamics of the Tunisian stock market before and during the COVID-19 outbreak: Evidence from the GARCH family models. *International Journal of Finance & Economics*, 10.1002/ijfe.2499.

Ganguly, S (2021). Estimation of volatility and leverage effect during the outbreak of COVID-19 Pandemic: A study based on selected international stock markets.*Indo-Asian Journal of Finance and Accounting*,1(2), 177-187.

Haque, M. I., & Shaik, A. R. (2021). Predicting crude oil prices during a pandemic: A comparison of Arima and Garchmodels. *Montenegrin Journal of Economics*, *17*(1), 197-207.

Joshi, P. (2010). Modelingvolatility in emerging stock markets of India and China. *Journal of Quantitative Economics*, *8*(1), 86-94.

Kakinuma, Y. (2021). Nexus between Southeast Asian stock markets, bitcoin and gold: Spillovereffect before and during the COVID-19 pandemic. *Journal of Asia Business Studies*.

Karmakar, M. (2007). Stock market asymmetric volatility and risk-return relationship in the Indian stock market. *South Asia Economic Journal*, *8*(1), 99-116.

Kaur, H. (2004). Time varying volatility in the Indian stock market. *Vikalpa-The Journal of Decision Makers*, *29*(1), 25-42.

Khanthaporn, R., &Wichitaksorn, N. (2021). Modelingstock returns using asymmetric garch-Icapm with mixture and heavy-tailed distributions: An application to COVID-19pandemic forecasts. Retreivedhttps://ssrn.com/abstract=3814533

Kumar, R., &Dhankar, R. S. 2009. Asymmetric volatility and cross correlations in stock returns under risk and uncertainty. *Vikalpa-The Journal of Decision Makers*, *34*(2),25-36.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics*, *54*(1-3), 159-178

LE, T. P. T. D., & TRAN, H. L. M. (2021). The contagion effect from US stock market to the Vietnamese and the Philippine stock markets: The evidence of DCC-GARCH model. *The Journal of Asian Finance, Economics, and Business*, *8*(2), 759-770.

Liu, Z., Huynh, T. L. D., & Dai, P. F. (2021). The impact of COVID-19 on the stock market crash risk in China. *Research in International Business and Finance*, *57*, 101419.

Marome, W., & Shaw, R. (2021). COVID-19 response in Thailand and its implications on future preparedness. *International journal of environmental research and public health*, *18*(3), 1089.

Mehta, K., & Sharma, R. (2011). Measurement of time varying volatility of Indian stock market through GARCH model. *Asia-Pacific Business Review*, *7*(1),34-46.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the Econometric Society*, *59* (2), 347-70.

Nugroho, A. D., &Robiyanto, R. (2021). Determinant of Indonesian stock market's volatility during the COVID-19pandemic. *JurnalKeuangan dan Perbankan, 25*(1), 1-20.

Olayungbo, D. O. (2021). Volatility effects of the global oil price on stock price in Nigeria: Evidence from linear and non-linear GARCH. In *Linear and Non-Linear Financial Econometrics-Theory and Practice*.

Özdurak, C., &Karataş, C. (2021). COVID-19 and the technology bubble 2.0: Evidence from DCC-MGARCH and Wavelet approaches. *Journal of Applied Finance and Banking*, *11*(2), 109-127.

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*(2), 335-346.

Rai, K., & Garg, B. (2021). Dynamic correlations and volatility spillovers between stock price and exchange rate in BRIICS economies: Evidence from the COVID-19 outbreak period. *Applied Economics Letters*,1-8.

Srinivasan, P., & Ibrahim, P. 2010. Forecasting stock market volatility of BSE-30 index using GARCH models. *Asia-Pacific Business Review*, *6*(3), 47-60.

Szczygielski, J. J., Bwanya, P. R., Charteris, A., &Brzeszczyński, J. (2021). The only certainty is uncertainty: An analysis of the impact of COVID-19 uncertainty on regional stock markets. *Finance research letters*, 43, 101945.

Umar, M., Rubbaniy, G., & Rizvi, S. K. A. (2021). COVID-19 and stock market liquidity: An international evidence.

Xu, L. (2021). Stock return and the COVID-19 pandemic: Evidence from Canada and the US. *Finance Research Letters, 38,* 10172.