Journal of **N**onlinear **A**nalysis and **O**ptimization
Vol. 15, Issue. 1, No.2 : 2024
ISSN : **1906-9685**

ANALYSIS OF VOLATILITY OF STOCK MARKET WITH SPECIAL REFERENCE TO COVID 19

Yashwant Patel Research Scholar, School Of Management, Eklavya University, Damoh, M.P,India Email: yashwantpatel349@gmail.com
Dr. Ankur Randhelia, Associate Professor, School Of Management, Eklavya University, Damoh, M.P,India Email: ankurrandhelia@gmail.com

The global economy has been severely impacted during the Covid-19 period. The U.S.stock market has also experienced greater volatility. Based on data from January 2020 to June 2021, this paper studies the volatility of daily returns on the stock market in theUnited States. The Standard and Poor's 500 (SPX) index and eight companies traded on major exchanges such as the New York Stock Exchange and the Nasdaq are used tocalculate volatility. Combining the statistical analysis methods GARCH, GARCH-M, and TARCH, the time series of each security is modeled. It is demonstrated that the conditional heteroskedasticity of stock returns depends not only on the observed historical volatility (ARCH term) but also on the conditional heteroskedasticity of prior periods (GARCH term). As expected for financial markets, the COVID-19 outbreak increased the volatility of U.S. stock market returns. After the COVID-19 outbreak, the volatility of the U.S. stock market rose dramatically. It reached an extremely high levelfor the first quarter of 2020 and continued to move downwards in the following quarters.The significant heteroskedasticity in the return volatility indicates that external variables significantly affect the stock. Furthermore, this study combines the Capital Asset Pricing Model (CAPM) and the research of Engle et al. (1987), which provides away to quantify the liquidity premium. However, with the results of the GARCH-M model, this study does not find a significant liquidity premium over time. Additionally,The TARCH model reveals a significant asymmetry in stock market returns during thisepidemic, suggesting that negative news has a more substantial impact on U.S. financial markets. For investors and financial institutions, this research helps identify potential volatility in the face of similar risk events. It is helpful for investors to comprehensively consider various factors when investing in special periods or consider other investmentportfolios to reduce investment risks in specific periods based on research results.
Key Words: COVID 19, Garch, stock market

INTRODUCTION

The stock market is prone to volatility and is influenced by a variety of events, including political decisions at the national level, natural calamities, and corporate restructuring. According to Estrada et al. (2021) and Shahzad et al. (2021), the outbreak had a significant influence on the general direction of the stock market movement. Rizvi and Itani (n.d.) contend that the emergence of COVID-19 is to blame for the current severe recession that the global economy is experiencing, which is the worst on record. Consequently, the drop in economic and financial market indicators can be linked to the majority of commercial entities, organizations, and enterprises battling to stay afloat during COVID-19 (Bartik et al., 2020). This conclusion can be drawn from the fact that COVID-19 occurred.

As of March 2020, over one hundred countries had instituted either a partial or full lockdown, and the majority of key cultural and auxiliary events had been canceled. The number of people traveling by air and between cities dropped by 70–90% compared to March 2019 figures for significant cities around the world (Ashraf, 2020a). The response that has been taken on a national basis to the sickness is likewise unprecedented. On the one hand, the government is taking emergency measures

to manage the disease, such as closing schools to keep a social distance, investing in testing, isolating suspected cases, and treating proven cases (Ashraf, 2020b). On the other hand, the disease is spreading rapidly. On the other side, Dougherty and Biase (2021) noted that governments from the treasury to the central bank are rolling out support and stimulus measures to minimize the economic damage. Dougherty and Biase's explanation was based on the fact that governments are trying to prevent further economic damage. A study by Ezeaku and Nnanna (2021) on the influence of the COVID-19 outbreak on the performance of the Nigerian stock market revealed losses in stock returns. It further demonstrates that stock returns have been highly variable during COVID-19, and the data were not reliable. The study was conducted in Nigeria.
an exponential general autoregressive conditional heteroskedasticity (EGARCH) model was applied for the analysis. Liu et al. (2020a) also assessed the short-term impact of the coronavirus outbreak on 21 major stock market indices worldwide in their research. They focused on countries like Japan, South Korea, Singapore, the United States, the United Kingdom, and Germany. Using event research techniques, Sayed and Eledum (2021) and Liu et al. (2020b) revealed that stock markets in the significant viruses affected countries had fallen rapidly, with Asian countries facing more abnormal returns than other countries. Because investors are concerned about the future and are pessimistic about their returns, anomalous returns on stock market indexes have been caused by the negative effects of COVID-19's headwinds. In their 2017 study, Del and Paltrinieri investigate how the Ebola virus affected the investment decisions of African mutual fund investors. The mutual fund flows and performance data of 78 mutual funds in Africa from 2006 to 2015 showed that the pandemic had a negative impact on the flow of funds. This was determined by conducting the analysis. As a direct consequence of this, retail financial specialists withdrew their investments in these funds (Bartik et al., 2020). Zaremba et al. (2020) employed Regression models to investigate 67 countries from 1 January 2020–through 3 April 2020 and came to the conclusion that government interventions increase the volatility of worldwide stock markets. Duttilo et al. (2021) examined data from European stock markets from the period of 4 January 2016–31 December 2020 using the Threshold GARCH measurement method to determine how the first wave of pandemics affected the volatility of stock markets in euro area nations with middle-large financial centers. However, the second wave of pandemics only impacted the volatility of stock markets in Belgium. Substantial financial contagion in most developed and emerging markets showing sizeable business relations with China throughout the COVID-19 period was found by Gherghina, Arm, and Joldes (2021) in their analysis of China and its key trading partners' index futures contracts using the Bivariate asymmetric dynamic conditional (ADCC) GARCH model from 1 August 2015 to 31 July 2020. This was determined through the use of the ADCC GARCH model. Liu and Sheng (2021) examined the South Korean stock market using VAR, OLS, and GARCH econometric models in order to conduct their research on the phase Covid-19 vs Volatility index that spanned from 2 January 2019 to 31 August 2020. According to the data, an increase in the number of new illness cases was responsible for a rise in the volatility of the stock market. During the course of the epidemic, the Indian stock market had a great deal of volatility; Bora and Basistha (2021), employing the GJR GARCH model, drew their conclusions from the Nifty and the Sensex.

Stock indices for the phase that runs from 3 September 2019 until 10 July 2020. Gherghina and oldes (2021) found that volatility diffusion was significantly negative from the COVID-19 to gold, palladium, and brent in the oil markets, but that it was positively spread to the WTI oil market. These findings are the conclusions of an analysis of precious metals, industrial metals, and energy markets conducted with the BEKK-MGARCH model. Shi (2021) used spillover analysis in the time and frequency domain model to study 16 of the most important equity markets in the world from 24 January 2019 to 30 December 2020. He came to the conclusion that after the outbreak of the COVID-19 pandemic, the integration of global stock markets significantly increased, as did the market risk contagion between them. Contessi and Pace (2021) examine data spanning the time period from 24 January 2019 to 30 December 2020 for 18 key stock market indexes. They apply the Generalized Supremum ADF (GSADF) test to measure the volatility spread from the Chinese equities market to all other markets. Through the use of GARCH models, the DCC process, and wavelet coherence on the S&P 500 index and the CSI 300 index, Mensi and Kang (2021) came to the conclusion that there was a higher volatility spillover across the U.S. and Chinese stock markets during the pandemic period compared to the time before the pandemic. There is evidence from empirical studies to imply that an increase in volatility persistence can be expected for all series following COVID-19.

The outbreak of COVID-19 has caused widespread disruption around the globe. stock markets' supply chains as a whole. Disruptions in the supply chain arise in the context of responsible administration of stock markets as a result of the economic downturn brought on by COVID-19. Many Countries all across the world are competing against one another to be economically successful and a secure financial position. This is due to the global stock market. The structure is being advanced with the participation of the markets. Economic expansion and, at the national level, financial integration degree of. Co-movement of stock prices was investigated by a number of academics. The role of financial integration as measured by markets (Zhang) Ashraf et al. 2020; et al. 2020). There are negative effects as a result. On topics pertaining to finance, such as the stock market generated by a variety of crises, with the cumulative effect of these crises being detrimental co-moves through the restriction of market activities (Ali) et al. 2020). By way of co-movement while also serving as a tool to current research is being used to examine and evaluate the economic addition.

Data Collection

We selected the closing prices of the S&P 500 and the top 8 companies with the highest market capitalization from January 2020 to June 2021 to track the performance of the U.S. stock market. There are a total of 377 observations for each variable. The quoted data are all from the New York Stock Exchange (NYSE, n.d.). The selected securities are detailed in Table 1.

Table 1 *Variables' descriptions*

Variables	Description
Variable regarding the American financial market	
SPX	The Standard and Poor's 500 is a stock market index that tracks theperformance of 500 significant firms listed on the U.S. stock exchanges.
AAPL	Apple Inc. designs, produces, and sells smartphones, tablets, wearables, accessories, and variousrelated services. Industry: Technology Hardware, Storage & Peripherals
AMZN	Amazon.com, Inc. delivers a variety of goods and services toconsumers. Merchandise and material acquired for resale anditems sold by third-party merchants are available via its storefronts. Industry: Internet & Direct Marketing Retail
BAC	Bank of America Corporation (BAC) is a financial holding company and a bank holding company (BHC). Consumer Banking, Global Wealth & Investment Management (GWIM),Global Banking, and Global Markets are the company's segments. Industry: Banks

GOOGL	Alphabet Inc. is a holding corporation that owns Google. Google Services, Google Cloud, and Other Bets are the company's segments. Industry: Interactive Media & Services
PG	The Procter & Gamble Company provides people across the globe with branded consumer packaged products. Beauty, Grooming, Health Care, Fabric & Home Care,and Baby, Feminine & Family Care are the company's five segments. Industry: Household Products
TSLA	Tesla, Inc. develops, produces, sells, and leases completely electric automobiles and energy generating and storage systems and provides associated services. Industry: Automobiles
UNH	UnitedHealth Group Incorporatedis a diversified health care company that operates Optum andUnitedHealthcare platforms. Industry: Health Care Providers & Services
XOM	Exxon Mobil Corporation is a company that deals with energy. The company's main businesses include crude oil and natural gas exploration and production and the manufacturing, trading, transportation, and sale of crude oil, natural gas, petroleum products, petrochemicals, and a variety of specialty goods. Industry: Oil, Gas & Consumable Fuels

Note. All the information is retrieved from the NYSE (n.d.).

Calculation Formula

In order to account for the non-stationarity of the raw series of stock prices, we calculate the logarithmic returns of each day's price data. The following is the formula for calculating the logarithmic daily return, which was taken from Bodie et al. (2014), Ang (2021), and Gherghina et al. (2021):

$$R_{i,l} = \ln\left(\frac{P_{i,l}}{P_{i,l-1}}\right) \qquad (6)$$

where Rii,l represents the logarithmic yield of return of asset ii in period l, Pii,l represents the price of asset ii in period l, and Pii,l1 represents the price of asset ii in the time before this one (l minus 1 period). In this investigation, we decided to use the natural logarithm as our primary measuring tool because, if the data follows a normal distribution, the natural logarithm will provide the most accurate results.

Experimentation

Preliminary Statistics

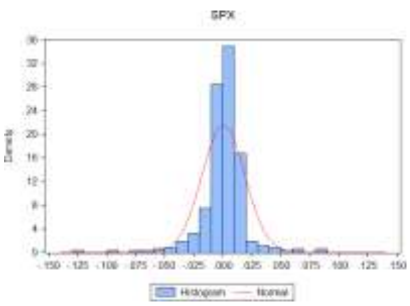
Table 2 displays the descriptive statistics for the daily logarithmic return, which may be found under the heading "Variables." In addition, the histogram of the distribution of returns on the chosen stocks is presented in Figure 1, as shown above. In this graph, we have the ability to make an intuitive comparison between the density of the processed data and the theoretical normal distribution.

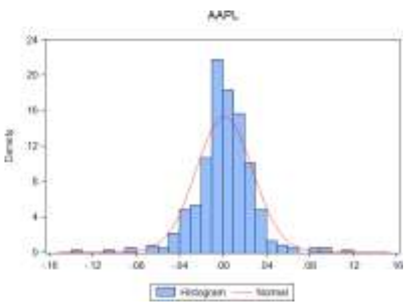
Table 2 *Descriptive statistics for daily logarithmic return[10]*

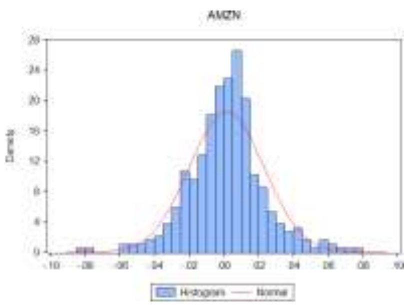
Variables	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
SPX	0.000737	0.018573	-0.97833	14.88255	2272.035	0
AAPL	0.001598	0.026086	-0.24726	7.568457	330.8069	0
AMZN	0.001582	0.021564	0.021962	4.720054	46.3814	0
BAC	0.000387	0.031667	-0.05617	10.16512	804.5086	0
GOOGL	0.00154	0.022138	-0.395	7.688089	354.1026	0
PG	0.000237	0.017683	0.139952	13.15697	1617.464	0
TSLA	0.005497	0.051242	-0.31755	6.225287	169.2914	0
UNH	0.000835	0.025849	-0.69315	14.95054	2267.549	0
XOM	-0.00031	0.02984	-0.07373	6.025914	143.7871	0

In order to provide a concise summary of the properties of the data, descriptive statistics and density histograms can both be utilized. According to Hartwig and Dearling (1979), the skewness value is a measurement of how symmetric the data distribution is. A normal distribution has a value of 0 for the skewness value. According to the findings of the statistical analysis, the skewness values are negative in almost all of the selected shares, with the exception of AMZN and PG. This indicates that the data is skewed to the left, or that the left tail is longer than the right tail, as seen by the histogram.

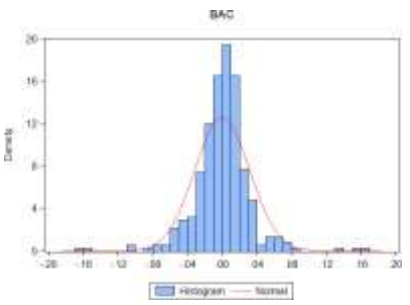
SPX AAPL AMZN

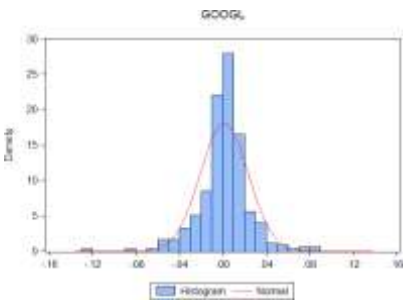


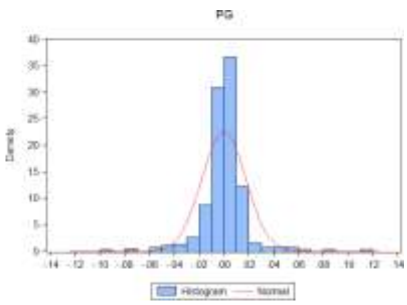




BAC GOOGL PG







TSLA UNH XOM

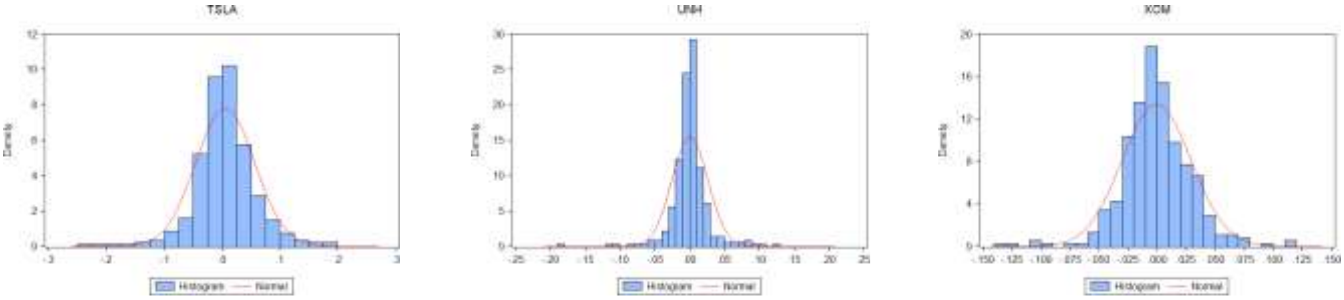


Figure 1 *Histogram for daily logarithmic returns[10]*

When investigating outliers or extreme results, statisticians frequently turn to the kurtosis indicator. It is possible to use it to identify whether or not the data follow a normal distribution with heavy tails or light tails. As can be seen in Table 2, the values of kurtosis are significantly larger than those of the standard normal distribution.3 Hartwig and Dearling's 1979 publication. Heavy tails are able to provide an explanation for the data set of log returns.

In addition, the Jarque–Bera test is another option for determining whether or not the data set in question conforms enough to the standard normal distribution in terms of its skewness and kurtosis (Min, 2019). The fact that the p-values of the Jarque-Bera test are both equal to zero, which corresponds to the result of the descriptive statistic shown in Table 2, indicates that it is appropriate to reject the null hypothesis that the data are normally distributed. As a consequence of this, there is no indication that the logarithmic return on the variables follows a normal distribution.

Figure 2 depicts the quantile-quantile plots, sometimes known as Q-Q plots for short. The Q-Q plot is a useful diagnostic tool that can be utilized to establish whether or not the data set in question originates from a theoretical distribution, such as a normal or exponential distribution. As a result, we are able to make a direct comparison of the two distributions using the quantile-quantile graph. These points ought to come together to form a reasonably straight line if the two numbers come from the same distribution or if the data set follows a normal distribution. On the other hand, the findings of the present study imply that the distribution is not typical. The dots in the centre of the graph move downward along a line in a gradual manner before beginning an abrupt ascent. However, the curve finally deviates at the ends, which shows that there are more extreme values in the data than would be predicted by a normal distribution.

Both the histogram (which can be found in Figure 1) and the Q-Q plot (which can be found in Figure 2) show that the data sets, when compared to the normal distribution, have a fat tail. The data sets display leptokurtosis and fat-tail characteristics, as determined by an investigation of descriptive statistics. If this is the case, we can draw the conclusion that there is a chance of volatility clumping.

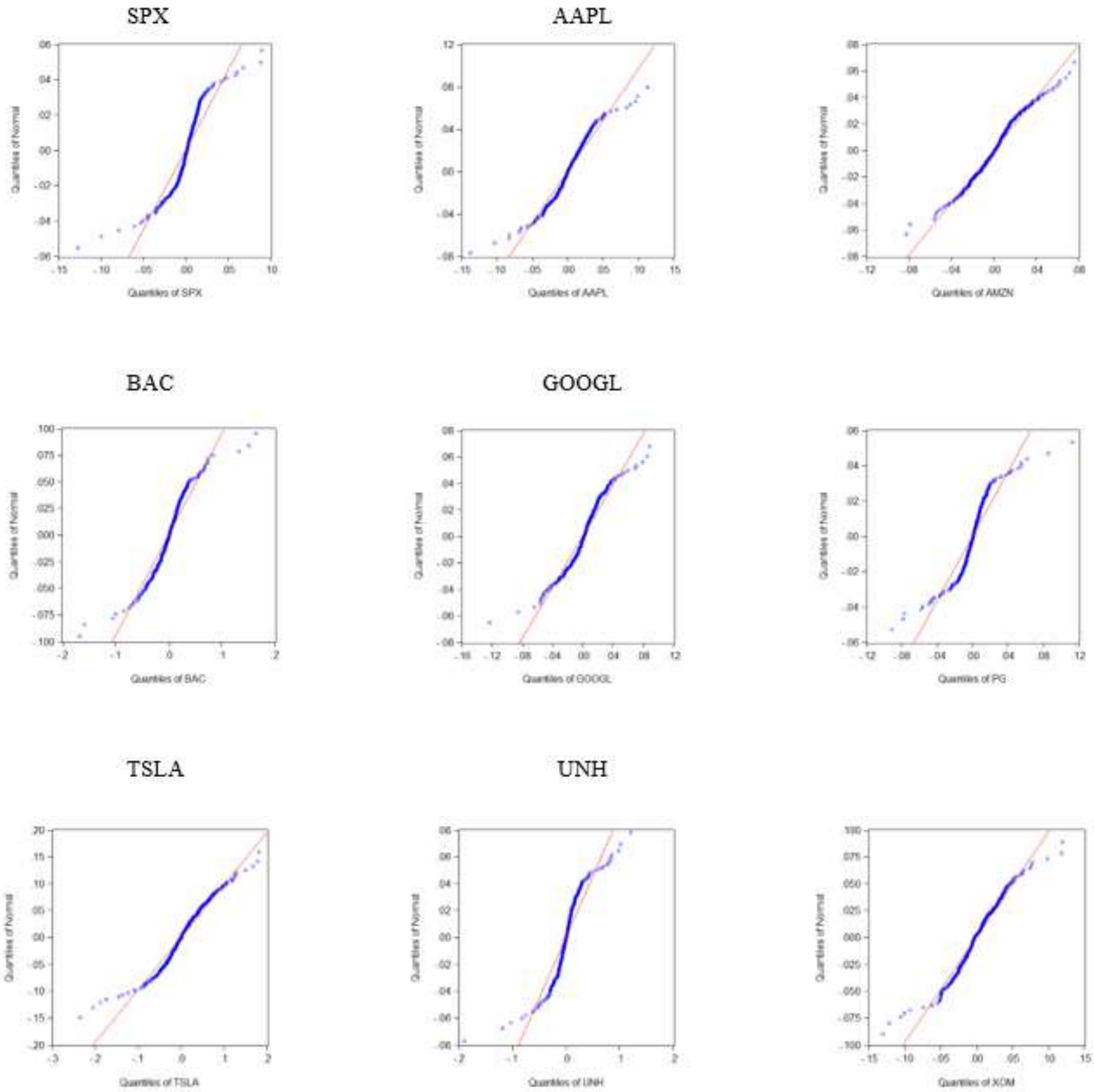


Figure 2. *Q-Q plots for daily logarithmic returns*

A specific stationary process, such as the so-called white noise process, should be used for our data collection if we want to avoid difficulties associated with spurious regression (Gujarati & Porter, 2009). This is one of the conditions that must be met. The Augmented Dickey-Fuller (ADF) test is a traditional approach to time series analysis, and we used it to determine whether or not the returns were stationary. In this experiment, the alternative hypothesis is that the time series is stationary, while the null hypothesis is that the data set does not have at least one unit root and is not stationary. The null hypothesis will be tested against the alternative hypothesis. The outcomes of the ADF test are summarized in the table that can be found below.

Table 3 *ADF test results for daily logarithmic returns[10]*

Variables	ADF Test Statistic	1% Level	5% Level	10% Level	Probability
SPX	-5.2061	-3.4480	-2.8692	-2.5709	0.0000
AAPL	-24.5687	-3.4476	-2.8690	-2.5708	0.0000
AMZN	-21.7946	-3.4476	-2.8690	-2.5708	0.0000
BAC	-6.4607	-3.4479	-2.8692	-2.5709	0.0000
GOOGL	-25.3532	-3.4476	-2.8690	-2.5708	0.0000
PG	-6.2173	-3.4480	-2.8692	-2.5709	0.0000

TSLA	-19.6222	-3.4476	-2.8690	-2.5708	0.0000
UNH	-9.0124	-3.4479	-2.8692	-2.5709	0.0000
XOM	-20.8860	-3.4476	-2.8690	-2.5708	0.0000

Intercept is included in test equation. Lag length criterion: Automatic selection based on Schwarz Info Criterion.

Based on our prior information, we are able to draw the conclusion that the logarithmic yields of returns on the variables do not increase throughout the course of time. According to the results presented in Table 3, the daily logarithmic return time series does not have a unit root. This conclusion is supported by the fact that all of the p-values (0.0000) obtained from the test fall below the significance threshold of 0.05. This indicates that the non-stationary alternative to the null hypothesis ought to be rejected. According to the findings of the empirical ADF stationarity test, the variables that were investigated are therefore considered to be stationary, and their integration order is I (0).

Linear plots of the daily log returns for each variable are shown independently in Figure 3, which depicts these plots. There is a possibility that some evidence of conditional heteroscedasticity might be found in the fact that a time of high chocks is typically followed by a period of high volatility and vice versa. As a consequence of this, the data set may suggest the existence of "volatility clustering" effects (Gujarati & Porter, 2009). In the following phases, we will conduct an experiment to test this theory.

Discussion

Hypothesis 1

The primary objective of this paper is to investigate the change in volatility of the U.S.stock market during COVID-19. The results of descriptive statistics and linear regression showed the presence of autocorrelation and heteroskedasticity. The basic GARCH model solves the two problems mentioned above and again confirms the pooling effect of volatility. This finding is comparable to Agarwalla et al. (2021) and Malik et al. (2021), whose research reveals the significant volatility spillover of BRIC countries (Brazil, Russia, India, and China). However, Youssef et al. (2021) state no significant autocorrelation and ARCH error in stock market returns for Spain and Italy.

Based on the conditional volatility of the GARCH regression model, it can be observedthat the increase in volatility of the U.S. stock market coincides with the outbreak of COVID-19. As Yu et al. (2022) indicated, the anxiety index is highly correlated to stockmarket volatility in the United States. The outbreak of COVID-19 caused a sharp increase in the anxiety index, resulting in an increase in stock market volatility. Therefore, hypothesis 1 of the COVID-19 outbreak increasing the volatility of the U.S.financial markets is accepted.

Hypothesis 2

The second hypothesis of this study, that there is a direct linear relationship between stock returns and the changing volatility was not confirmed. The conditional volatility, or risk premium term, is represented by the conditional standard deviation added into the mean equation. According to the GARCH-M (1,1) model's regression results, the stock market's risk premium is not significantly distinct from zero.

Hypothesis 3

The third hypothesis presented in this paper is supported. The TARCH (1,1) model's regression results indicate that the impact of negative news is significantly greater than that of positive news. The significant asymmetric estimate, γ, reinforces the impact of negative news on stock market volatility (except for AMZN and TSLA). The outbreak increases volatility while contributing to the stock performance of the companies selected in this paper. However, as noted by Curto and Serrasqueiro (2022), firms in the energy sector were negatively affected.

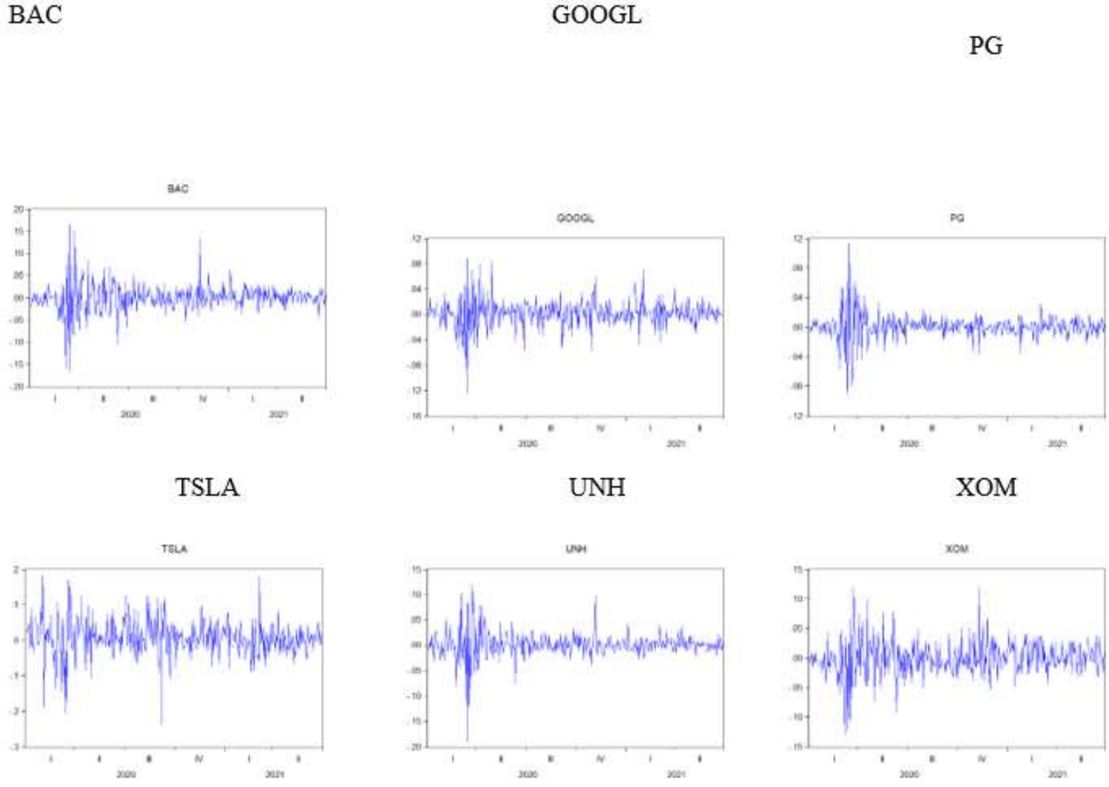


Figure 3 *Daily value of the logarithmic returns[10]*

CONCLUSION

The study of volatility is a constant topic in financial markets, especially in a time of great uncertainty. Previous studies on the U.S. stock market volatility almost focused on the early stages of the COVID-19 outbreak. The limited sample size of the previousresearch may lead to biased estimates, which motivates us to analyze the volatility by gathering additional data. In addition, this paper investigates the direct linear relationship between stock market returns and the changing volatility over this period.Finally, the consistency of the impact of positive news and negative news on the stock market is also the subject of this study.

As a result of the presence of potentially conflicting information at both the micro and the macro levels, the stock markets have historically been characterized by a high degree of volatility. Researchers from all around the world have looked into this phenomena in the context of various shocks that have been special to companies, industries, countries, and the world as a whole. The outcomes are unpredictable since they are dependent not only on the context and pace of the information content but also on a market's capacity to take it in.

The stock returns may have a direct association with volatility as well as the consequences that it has on other markets, which is then followed by a sustained shock. The purpose of the current research was limited to determining the effect that two global shocks, namely the subprime mortgage crisis in the United States and COVID-19, have had on the level of volatility seen in the Indian banking sectoral indices. In addition, the volatility caused by these two occurrences has also been compared in order to determine which of them had a greater impact on the market. It has also been looked into whether or not it would be possible to diversify one's holdings in public and private banks sectoral indexes in the event of such a worldwide crisis.

According to the symmetric model, the findings suggested that the volatility persistence was highest for NBI and lowest for PSBI throughout the subprime crisis. This was the case even though the symmetric model predicted otherwise. It has been at its lowest for PSUBI, which is due to asymmetric impacts.

During the subprime mortgage crisis, the leverage effect was found to have a considerable impact on all three indices; however, during COVID-19, this effect was only found to have a significant impact on the PSUBI. Based on these findings, one could draw the conclusion that the negative impact of the subprime mortgage crisis lasted longer than any other positive news during that time period for any and all indices. The same had not been valid for COVID-19; NBI and PSBI might be a good source for investors to use in the long run to hedge their portfolios. In addition, PSUBI is the only index out of the three that has shown volatility that has sustained with a symmetric impact, and volatility has been the highest for PSBI when analyzed using an asymmetric effect. Consequently, one could get the conclusion that the leverage effect was evident for NBI, PSUBI, and PSBI throughout the crisis that was caused by subprime mortgages. On the other hand, during the prelockdown phase of COVID-19, it has only been detected for PSUBI. When the post-lockdown time was also taken into account, the previously observed pattern did not change. In comparison to COVID-19, the subprime mortgage crisis has been able to produce an effect that has persisted for a longer period of time. During both of the worldwide shocks that were investigated in this study, the sectoral indices for the banking industry exhibited a high degree of volatility. The aggregate findings have demonstrated that the subprime mortgage crisis has brought about leverage effects that are greater than those seen in COVID-19. After the COVID-19 outbreak, investors can adopt the technique of holding onto their equities as a strategy, particularly the NBI and PSBI stocks. In addition, it has been found that there is a considerable disparity between the coefficient values brought about by these two worldwide shocks to the markets. In the beginning, the subprime mortgage crisis had an effect that was comparable on NBI, PSUBI, and PSBI. The fact that the differences between the coefficients during this time period were very insignificant demonstrates that the crisis had a lasting effect on all of the indices. PSUBI was the index that had been most affected by the COVID-19 pre-lockdown phase, as indicated by the significant difference in coefficient values between it and the other indices. When the pre-lockdown phase and the post-lockdown phase were compared, there was a smaller gap between the indices than there was before the lockdown. The expectation has been that the lockdown will occur since the volatility has spread to the same extent across all indices. Therefore, it is possible to draw the conclusion that the post-lockdown period has resulted in an increase in the volatility of these indices. It may be a difficult task for managers to diversify an investor's portfolio when markets are behaving in such an unexpected manner.

It is necessary to take preventative measures and maintain vigilant watch over the trends rather than the fluctuations in return rates. When it comes to investing in banking stocks and other connected sectors, banking indices may be one of the most important indicators to look at. It is possible to get a glimpse into connected industries such as manufacturing, telecom, and retail from this sector, which happens to be the industry that serves as the nerve center for all other businesses. Nevertheless, the focus of this investigation has been on banking indices and the erratic behavior they exhibited in response to two worldwide shocks. According to the findings of the study, the research shows that the volatility persistence may shift based on how long an event lasts. As a result, strategists may concentrate on the underlying characteristics of a shock in order to diversify the holdings of investors and reduce the amount of risk exposure they are subject to.

REFERENCES

[1]. Agarwalla, S. K., Varma, J. R., & Virmani, V. (2021). The impact of COVID-19 on tail risk: Evidence from Nifty index options. Economics Letters, 204, 109878. https://doi.org/10.1016/j.econlet.2021.109878

[2]. Aharon, Jacobi, A., Cohen, E., Tzur, J., & Qadan, M. (2021). COVID-19, governmentmeasures, and hospitality industry performance. PloS One, 16(8), e0255819–e0255819. https://doi.org/10.1371/journal.pone.0255819

[3]. Albulescu. (2021). COVID-19 and the United States financial markets' volatility. Finance Research Letters, 38, 101699–101699. https://doi.org/10.1016/j.frl.2020.101699

[4]. Ang, C. S. (2021). Analyzing Financial Data and Implementing Financial Models Using R. Springer International Publishing. https://doi.org/10.1007/978-3- 030-64155-9
[5]. Ashraf. (2020a). Stock markets' reaction to COVID-19: Cases or fatalities? Research in International Business and Finance, 54, 101249–101249. https://doi.org/10.1016/j.ribaf.2020.101249
[6]. Ashraf. (2020b). Economic impact of government interventions during the COVID-19 pandemic: International evidence from financial markets. Journal of Behavioral and Experimental Finance, 27, 100371–100371. https://doi.org/10.1016/j.jbef.2020.100371
[7]. Aven. (2016). Risk assessment and risk management: Review of recent advances on their foundation. European Journal of Operational Research, 253(1), 1–13. https://doi.org/10.1016/j.ejor.2015.12.023
[8]. Baek, Mohanty, S. K., & Glambosky, M. (2020). COVID-19 and stock market volatility: An industry level analysis. Finance Research Letters, 37, 101748–101748. https://doi.org/10.1016/j.frl.2020.101748
[9]. Bartik, Bertrand, M., Cullen, Z., Glaeser, E. L., Luca, M., & Stanton, C. (2020). The impact of COVID-19 on small business outcomes and expectations. Proceedings of the National Academy of Sciences - PNAS, 117(30), 17656–17666. https://doi.org/10.1073/pnas.2006991117
[10]. Kunyu Liu, Xue Zhang, " Stock Market Volatility in the Context of Covid-19" Thesis submitted to JON KOPING University", May 2022.
[11]. Bartik, Bertrand, M., Cullen, Z., Glaeser, E. L., Luca, M., & Stanton, C. (2020). The impact of COVID-19 on small business outcomes and expectations. Proceedings of the National Academy of Sciences - PNAS, 117(30), 17656–17666. https://doi.org/10.1073/pnas.2006991117
[12]. Bodie, Z., Kane, A., & Marcus, A. J. (2014). Investments (Tenth edition). McGraw-Hill Education.
[13]. Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity.Journal of Econometrics, 31(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1
[14]. Bora, & Basistha, D. (2021). The outbreak of COVID-19 pandemic and its impact on stock market volatility: Evidence from a worst-affected economy. Journal of Public Affairs, 21(4), e2623–n/a. https://doi.org/10.1002/pa.2623
[15]. Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). Time Series Analysis: Forecasting and Control. John Wiley & Sons.
[16]. Centers for Disease Control and Prevention. (2022a). COVID-19 Timeline. Retrieved May 15, 2022, fromhttps://www.cdc.gov/museum/timeline/covid19.html#Late-2020