"Impact of Covid-19 pandemic on stock market returns volatility of Gulf Cooperation Council countries"

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IMPACT OF COVID-19 PANDEMIC ON STOCK MARKET RETURNS VOLATILITY OF GULF COOPERATION COUNCIL COUNTRIES

Abstract

This study examined the asymmetric impact of the COVID-19 pandemic on the Gulf Cooperation Council (GCC) stock market return volatility. The data included daily closing prices of the GCC stock market from the day of the acknowledgment of the first case of COVID-19 in each country to March 6, 2021. In addition, the study employed generalized autoregressive conditional heteroscedasticity (GARCH) family models. According to the Akaike information criterion, GARCH and exponential GARCH (EGARCH) were the most accurate models. The findings of the GARCH model indicate that the COVID-19 pandemic affected the GCC stock markets. The EGARCH model also confirmed the impact of the COVID-19 pandemic on the GCC stock markets, confirming that the COVID-19 negatively affected GCC stock market returns. The value of the persistence of this volatility continued over a long period. This study has potential implications for investors and policymakers in diversifying investment portfolios and adopting strategies to maintain investor confidence during such crises. Moreover, mechanisms must be developed for reducing risks in financial markets in times of crisis, and central banks should take financial measures to mitigate risks to capital markets.

Keywords	TGARCH, EGARCH, GCC, stock market return, COVID-19
JEL Classification	G10, C22, C58

INTRODUCTION

The COVID-19 pandemic began in December 2019, and by the end of February 2020, countries started to impose border closures, lockdown and quarantine practices, and compulsory social distancing. Its impact on the global economy included fear of job loss and investors' uncertainty in times of economic volatility. According to Subramaniam and Chakraborty (2021), economic growth rates slowed, risks increased, and oil and gold rapidly prices declined. Global trade was disrupted to the extent that some enterprises were working at a quarter level of potential capacity. In addition, numerous economic agents delayed investment decisions while awaiting the development of the crisis. On both the demand and supply sides of the economy, such investor behavior generated an immediate shock (Shafiullah et al., 2021).

Stock markets have a pivotal role in countries' economic growth, as they form a channel through which funds flow from fiscal surplus units to deficit units. Stock markets contribute through mobilizing financial savings (Elhassan & Braima, 2020), providing liquidity to investors (an indicator that demonstrates the state of an economy), and encouraging the increase of joint-stock companies and investment funds. The occurrence of any stock market risk leads to a decline in

its contribution to economic growth. The COVID-19 pandemic affected all economic sectors, including the financial sector, which led to a deterioration of stock market returns.

Based on the Gulf Cooperation Council (GCC) strategic plan, the aim was to develop the financial sector to become a diversified and prosperous economic force. GCC investments and savings had a considerable influence on the development of the financial market. It was considered the largest liquid financial market in the Middle East. Undoubtedly, the GCC stock market witnessed a decline due to the COVID-19 pandemic. The UAE Ministry of Health recorded the first case on January 29, 2020; Bahrain recorded the first case on February 21, 2020; Kuwait and Oman recorded their first cases on February 24, 2020; and Saudi Arabia recorded the first case on March 2, 2020. These countries implemented programs to educate citizens about the COVID-19. Precautionary measures, including curfews, border closures, online education, and the prevention of crowds, were then pursued.

Most previous studies have found that the Covid-19 pandemic affected stock markets. In addition to this impact, the Gulf countries also faced a sharp drop in oil prices, which led to an economic recession. It is important to investigate the impact of the pandemic on the returns of the GCC stock markets. Understanding the impact will aid professionals and policymakers in developing appropriate strategic preparedness measures and actions. Additionally, the study will contribute as a supplement to studies examining the impact of the COVID-19 pandemic on stock markets, adding new knowledge related to GCC countries. It also contributes to emerging economic literature examining the impact of COVID-19 on GCC stock market return applying generalized autoregressive conditional heteroscedasticity (GARCH) models.

1. LITERATURE REVIEW

Previous studies have examined the impact of the COVID-19 pandemic on stock markets from various perspectives. Some focused on the comparative study of developed and emerging economies. Others have studied the impact of the pandemic on different economic sectors. The results of this study regarding the impact of COVID-19 on the stock market differ widely; some of them found a significant negative impact on stock markets, whereas others found only a slight effect. These studies are detailed below.

Siriopoulos et al. (2021) conducted a study of the first four months of 2020 using a VAR panel, generalized impulse response functions (GIRFs), and variance decomposition methods. They found that 34% of the volatility were related to the overall volatility of the Chinese stock market; however, 7% of the volatility were associated with international uncertainty. In European stock markets, the impact of the COVID-19 was found to be very small (less than 1%), indicating that the European stock markets reacted to the two risks of transmission shocks from the Chinese stock market and international uncertainty. Albulescu (2021) investigat-

ed the United States by employing OLS regression, concluding that the announcement of new infections was globalized and rising financial fluctuations in the United States and the death rate had a significant and positive effect on the financial fluctuations. Comparing the worldwide impact of COVID-19 data against the United States, it was revealed that the United States experienced greater financial impact. Gherbi and Alsedrah (2021) used an autoregressive distributed lag estimate model, collecting monthly data in Saudi Arabia from January 2018 to October 2020. It was concluded that COVID-19 had a positive significant effect on the financial crisis in the short term. The Granger casualty index revealed that the capital market index caused the financial crisis; however, in the long term, the market size index had a considerable effect on market value. The trade value indicator had a negative effect on the financial crisis. Harjoto and Rossi (2021) investigated daily stock data using Carhart and GARCH approaches to compare market responses between the COVID-19 pandemic and the 2008 global financial crisis in emerging and developed countries. They found that the effect was significantly negative and the effect of the COVID-19 pandemic on emerging stock markets was very evident in comparison to

developed nations' stock markets. In the emerging markets, a substantial negative impact was evident for companies with small market capitalization and growth stocks. The effect of COVID-19 on energy and financial markets was extremely strong in both emerging and developed stock markets. Izzeldin et al. (2021) employed the daily data in the G7 countries from April 24, 2018, to April 24, 2020, by applying a new smooth transition heterogeneous autoregressive method to estimate the model. They concluded that the COVID-19 pandemic affected the G7 countries, but the impact varied from one country to another and from sector to sector within each nation. The pandemic had the greatest impact on the healthcare and consumer services sectors, and telecommunications and technology sectors were the least affected by the pandemic. The UK and the US were the countries most affected by the COVID-19, especially in the business sector. Choi and Jung (2021) employed the daily data of the Korean stock returns from January 28, 2020, to January 13, 2021, using the GARCH (1, 1) to estimate the model. They found that the asymmetric effect was increased and confirmed cases on the stock returns. The second pandemic wave led to further decreases in certain sectors, especially the food and beverage sector. Yong et al. (2021) applied the GARCH family model to examine daily data from Bursa Malaysia and the Singapore Exchange from July 1, 2019, to August 31, 2020, finding the stock returns to be relatively stable, while the stock returns fell in both stock markets at the advent of the COVID-19 outbreak. Yousfi et al. (2021) employed the multivariate GARCH model from January 5, 2011 to September 21, 2020 to examine the US and Chinese stock markets, discovering indirect fluctuations between the stock markets in the US and China. The markets were exposed to shocks that had asymmetric effects in the reciprocal relationship between them. Finally, the pandemic had a clear negative impact on the US economy. Fernandez-Perez et al. (2021) investigated the daily data in 62 countries in 2019, employing a regression model and revealing that the culture had a significant effect on the size and fluctuation of abnormal returns. Alam et al. (2020) examined the daily data from February 24 to April 17, 2020, using the market model event methodology. The results indicated a positive relationship between market interaction and average abnormal returns during the pandemic lock-

down period. Investors' reaction to the closure was positive, whereas the reaction was found to be negative prior to the closure. Finally, the closure had an overall positive effect on the stock market performance. Kusumahadi and Permana (2021) employed OLS regression and threshold GARCH (TGARCH) models to daily data from 15 countries from January 2019 to June 2020 to examine the effect of COVID-19 on stock return volatility. The study found that changes in exchange rates had a negative impact in all countries except the UK. The continuation of the COVID-19 pandemic positively affected the stock return volatility. Alsedrah and Gherbi (2021) examined the impact of market type for investors on the total value of market trade in Saudi Arabia throughout the COVID-19 pandemic using weekly data for the period of January 7, 2020 to September 24, 2020. They applied autoregressive distributed lag (ARDL) and time-series analyses methods, demonstrating that both nets traded values and ownership of holding values had a negative impact on trading operation development in the short term. Moreover, trading operations showed a negative development effect during the 3-month lockdown period, specifically in Saudi Arabia. In the long term, the net traded value had a significant positive effect on market operation development. Mazur et al. (2021) argued that COVID-19 had a high positive impact on some stock sectors (natural gas stocks, food, healthcare, and programs), whereas a significant decline in the values of the remaining sectors was evident. Furthermore, the losing stocks showed severe asymmetric volatility, which was negatively correlated with stock returns. Baker et al. (2020) concluded that the impact of the pandemic on the US stock markets was stronger than the impact of any previous infectious disease outbreak. Bahrini and Filfilan (2020) employed a panel data regression approach using daily GCC stock market data from April 1, 2020 to June 26, 2020, finding that stock market returns largely responded to the number of confirmed deaths, whereas the response to cases of infection was not found to be significant.

Previous studies used different approaches to examine the impact of the COVID-19 on the stock markets, and some studies applied linear regression approaches, such as ARDL, NARDL, and GARCH. Studies investigated both individual countries and groups of countries. However, only

two studies have examined the impact of the pandemic on the GCC stock markets from different perspectives and approaches but neglected to consider the evaluation of the asymmetric effects of this pandemic. This study endeavored to bridge the gap between these studies by applying the GARCH family methods.

2. METHODS

This study explored the impact of the COVID-19 pandemic on stock market returns in GCC countries by examining the daily closing price of all GCC stock markets. The data were collected from the Saudi Stock Market (Tadawul) website Mubasher (2021). Table 1 presents the GCC stock exchange market indexes following the announcement of the first COVID-19 infection. The logarithmic percentage of the GCC stock market returns were calculated in reference to Cui et al. (2021), Kusumahadi and Permana (2021), and Sahoo (2021), as follows:

$$R_t = 100 \cdot \left(\frac{\ln p_t}{\ln p_{t-1}} \right), \qquad (1)$$

where R_t is the return at time t, p_t represents the closing price of the index for the current period t, p_{t-1} is the closing price of the index for the period $t-1$, and ln is the natural logarithm.

Table 1. The stock exchange market indexes and the announcement of the first COVID-19 infection

Countries	Stock exchanges	Date of the announcement of the first COVID-19 infection
Kuwait	Premier Market Index (PR) (BKP)	February 24, 2020
Saudi Arabia	Tadawul (traded) All Share Index (TASI)	March 3, 2020
Qatar	QE Index (GNRI)	February 27, 2020
UAE	Dubai Financial Market Index (DFMGI)	January 1, 2020
UAE	Abu Dhabi General Index (ADI)	January 29, 2020
Bahrain	Bahrain All Share Index (BSEX)	February 21, 2020
Oman	MSX 30 Index (MSX30)	February 24, 2020

Previous studies have asserted that the ARCH and GARCH models are the most appropriate for estimating stock market returns (Choi & Jung, 2021; Cui et al., 2021; Kusumahadi & Permana, 2021; Yong et al., 2021). These models were applied in the present paper. The stability of the time series followed by the statistical characteristics of time data were examined. In addition, the model was estimated by OLS, and heteroscedasticity tests were conducted to ascertain the suitability of the ARCH and GARCH models (Mohsin et al., 2020).

The ARCH model was considered the most suitable model for studying the stock markets' revenue volatility. Engle (1982), who studied the volatility-clustering phenomenon in financial time series, introduced the ARCH model in 1982. It was applied in the case of non-constant mean and variance.

The ARCH model is presented as follows:

$$h_t = b_0 + \sum_{i=1}^{q} b_i u_{t-1}^2, \qquad (2)$$

where b_0 is a constant and b_i represents the ARCH effects.

The GARCH model is an extension of the ARCH model that was developed by Engle and Bollerslev (1986) and was applied to overcome the heterogeneity arising from high data volatility. Other variations of the GARCH model have also been developed, including the TGARCH model (Zakoian, 1994), which distinguishes between positive and negative effects or good and bad news effects on volatility or leverage effects (Cui et al., 2021; Kusumahadi & Permana, 2021).

The GARCH model is presented as follows:

$$h_t = b_0 + \sum_{i=1}^{q} \theta_i h_{t-1} + \sum_{i=1}^{q} b_1 u_{i=1}^2, \qquad (3)$$

where b_0 is a constant, b_1 is the coefficient of the lagged residuals $u_{i=1}^2$, and θ_i is the coefficient of the lagged conditional variance h_{t-1}.

The TGARCH model is

$$h_t = b_0 + \sum_{i=1}^{q} \theta_i h_{t-1} + \sum_{i=1}^{q} \left(b_1 + \gamma D_{t-1} \right) u_{i=1}^2, \qquad (4)$$

where b_0 is a constant, θ_i is the coefficient of the lagged conditional variance h_{t-1}, b_1 is a measure of a positive shock (good news), γ is a measure of asymmetric impact or leverage term, and negative shock (bad news) impact is measured by $b_1 + \gamma$.

Nelson (1991) developed the exponential GARCH (EGARCH) model to handle financial time series and allow for asymmetric effects of the market return. The model is delineated as follows:

$$\log(h_t) = b_0 + \sum_{i=1}^{q} b_1 \left| \frac{u_{t-1}}{\sqrt{h_{t-1}}} \right| +$$
$$+ \sum_{i=1}^{q} \gamma \frac{u_{t-1}}{\sqrt{h_t}} + \sum_{k=1}^{p} \theta \log(h_{t-k}),$$
(5)

where b_0 is a constant, b_1 is the ARCH effects, γ is a measure of asymmetric (negative and positive) effect or leverage term, θ is a measure of the GARCH effect, $\gamma < 0$ indicates that the volatility of a negative shock is higher than that of a positive shock.

The GARCH, TGARCH, and EGARCH models were adopted in this study to investigate the impact of COVID-19 on GCC stock markets.

3. RESULTS AND DISCUSSION

After confirming the stationarity of the time series and its descriptive statistics, estimation was conducted using the OLS method and the Lagrange multiplier test to assess the ARCH effect. The result of the Lagrange multiplier test verified the existence of heteroscedasticity in the OLS, so the OLS results were considered unstable. To assess the instability of the OLS results, GARCH, TGARCH, and EGARCH estimations were applied to the model.

3.1. Descriptive statistics

Table 2 presents statistical analyses of stationary stock returns. It reveals a positive mean daily return for all indicators other than the MSX30 index, which had a negative daily return. Standard deviation was applied to measure the risks of the underlying assets. A higher standard deviation indicated greater financial market volatility. The substantial gap in the minimum and maximum returns in the indicators revealed how stock prices changed during the COVID-19 pandemic. It was noticed that the Jarque-Bera test for all indicators was very high and its p value was very small, indicating that the time series were abnormally distributed. The kurtosis values for all indicators were higher than 3 (the kurtosis of the normal distribution was 3). Negative skewness showed that all variables differed from zero and deviated to the left, indicating that returns were decreasing more than increasing.

Figure 1 presents the high volatility in GCC stock market returns, with the highest volatility observed in the first quarter of 2020.

Table 2. Descriptive statistics of stock market return indexes

Source: Author's analysis.

Statistics	BKP	MSX30	GNRI	DFMGI	ADI	BSEX
Mean	0.042042	0.013638	0.007477	0.018762	0.050428	0.024528
Median	0.113585	0.006461	0.007714	0.048719	0.060606	0.051697
Maximum	6.144610	2.156696	3.376424	7.064173	8.076176	2.420110
Minimum	11.63402	5.734971	10.20770	8.657797	8.406263	6.000646
Std. Dev.	1.311280	0.583052	0.964353	1.336580	1.307783	0.628633
Skewness	3.146814	1.817696	2.130863	0.970806	0.455246	2.287100
Kurtosis	30.64278	20.02152	25.67294	13.94534	17.07004	22.50165
Jarque-Bera	19657.96	7535.840	13372.14	3120.153	5019.574	9947.347
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
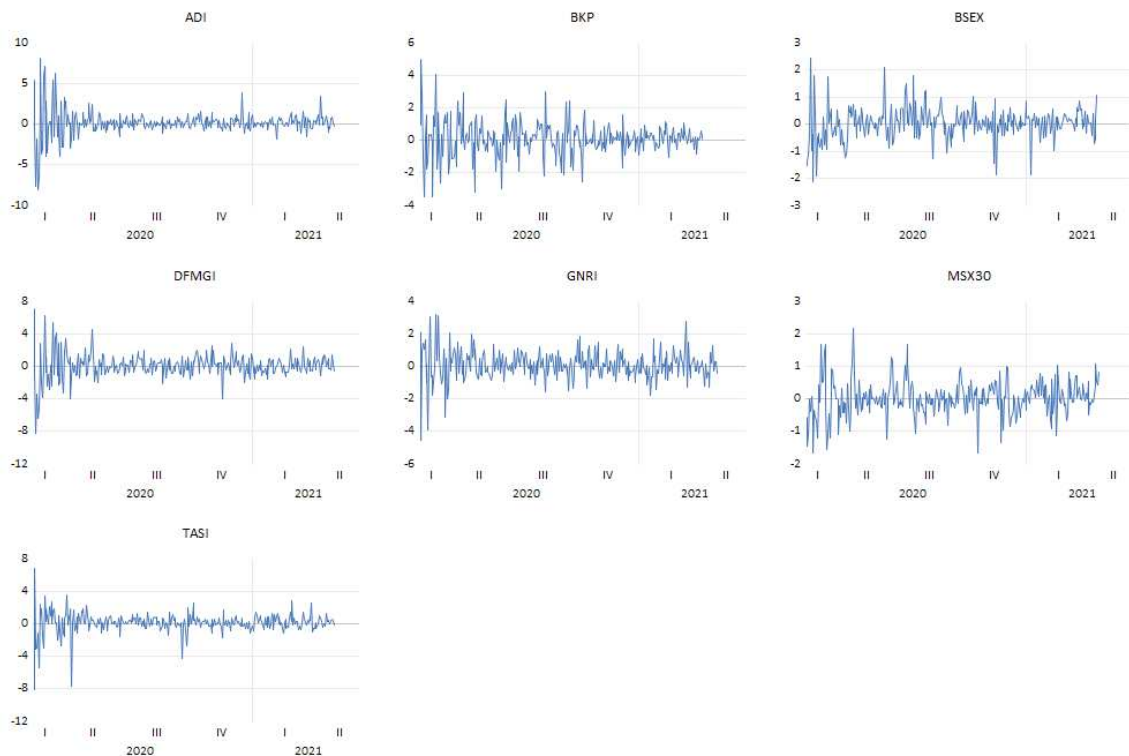
Figure 1. Volatility in GCC stock market return index

3.2. Unit root test

Application of the augmented Dickey-Fuller (ADF) unit root test demonstrates that all of the time series were stationary and at the level as shown in Table 3, indicating rejection of the null hypothesis of the time series with a unit root.

Zivot and Andrews (1992) unit root test was applied to examine the unit root with structural breaks in the series. Table 4 presents the stationarity of the series with different breakpoints, indicating a rejection of the null hypothesis that the time series had a unit root with a structural breakpoint in intercept, trend, or both.

Table 3. ADF unit root test

Source: Author's analysis.

At Level		BKP	ADI	BSEX	DFMGI	GNRI	TASI	MSX30
With Constant	*t*-Statistic	20.8369***	12.1391***	10.6033***	12.0030***	23.4472***	8.5139***	18.1794***
With Constant and Trend	*t*-Statistic	20.8192***	12.2197***	10.5953***	12.0144***	23.4482***	8.5876***	18.2551***
Without Constant and Trend	*t*-Statistic	20.8372***	12.1193***	10.5881***	12.0094***	23.4658***	8.4928***	18.1893***

Note: *** and ** mean significant at 1% and 5%, respectively; probability is based on MacKinnon (1996) one-sided p-values.

Table 4. Zivot and Andrews (1992) unit root test

Source: Author's analysis.

Variables	Break in	*T*-statistic (Prob)	Breakpoint
ADI	intercept	11.38473 (0.0037004)	5/19/2020
TASI	intercept	−7.020879 (0.031586)	1/4/2021
BKP	both	13.96187 (0.007237)	8/28/2020
BSEX	both	8.147990 (0.010852)	9/4/2020
Dfmgi	both	−9.542795 (0.000595)	5/18/2020
GNRI	both	−17.70382 (0.001984)	5/12/2020
Msx30	intercept	−11.98584 (0.005323)	7/23/2020

Table 5. Heteroskedasticity test: ARCH

Heteroskedasticity test	F-statistic	Obs* R-squared
TASI	49.7744 (0.0000)	0.0000)2944.·٤)
DFMGI	7.963890 (0.0051)	7.812612 (0.0052)
ADI	51.41280 (0.0000)	44.30491 (0.0000)
BSEX	7.601619 (0.0000)	7.460902 (0.0000)
GNRI	11.93165 (0.0006)	11.73800 (0.0006)
MSX30	28.19516 (0.0000)	27.00811 (0.0000)
BKP	7.493407 (0.0066)	7.354100 (0.0067)

Table 6. GARCH results

Model			TASI	BSEX	ADI	DFMGI	GNRI	MSX30	BKP
GARCH	Mean	Intercept	0.182387***	0.053736**	0.117473***	0.108833**	0.061701	0.024523	0.073354**
	Variance	Intercept	0.024937***	0.015359***	0.041255***	0.034368**	0.024872**	0.018918**	0.064722***
		ARCH(b_1)	0.035382***	0.050650**	0.153875***	0.051203**	0.056771***	0.104880**	0.301364***
		GARCH(ϑ)	0.907247***	0.864475***	0.788317***	0.910996***	0.894399***	0.819197***	0.648904***
		Error distribution	Student's t	Student's t with fixed df	Student's t with fixed df	Generalized error distribution	Student's t	Student's t	Student's t with fixed df
		Akaike info criterion	2.636761	1.579933	2.695611	3.178595	2.459991	1.446992	2.810065

3.3. ARCH effect test

The ARCH effect test was applied to evaluate the heterogeneous properties of variables. Table 5 presents the rejection of the null hypothesis with no ARCH effect since the variance residuals remained constant. An ARCH effect indicated that the stock return volatility in all stock market return indexes was affected by the shock of the previous period. Doing this enabled the GARCH family models to work (Kusumahadi & Permana, 2021; Mohsin et al., 2020).

3.4. GARCH results

Table 6 presents the GARCH results. The coefficients of the constant variance parameter were positive and statistically significant at the 5% level in all stock market returns, reflecting time-varying volatility. The coefficients of the ARCH (b_1) parameter were positive and statistically significant at the 5% level in all stock markets, suggesting that the volatility of the stock returns on the current day was affected by the shock of the previous day. Moreover, the coefficients of the GARCH (θ) parameter were positive and statistically significant at the 1% level in all stock markets, in-

dicating that the previous period of volatility led to the current period's volatility. This result confirmed the results of Gherbi and Alsedrah (2021), Yong et al. (2021), and Bahrini and Filfilan (2020). Finally, the coefficients fulfilled all the conditions for stability (s).

3.5. News impact curve

Figure 2 presents the news impact curve, revealing that the curve effect of the impact of news on the Gulf stock markets was asymmetric.

3.6. Sign bias test

The sign bias test established by Engle and Ng (1993) was employed to verify the validity of using the asymmetric GARCH model. The null hypothesis had no leverage effects in standardized residuals or lack of asymmetric effect of positive and negative shocks on volatility. The results of the probability of joint-bias of Table 7 reject the null hypothesis, confirming an asymmetric effect on volatility, as negative and positive shocks affect future volatility differently. Rejecting the null hypothesis enables the use of asymmetric GARCH models (TGARCH and EGARCH).
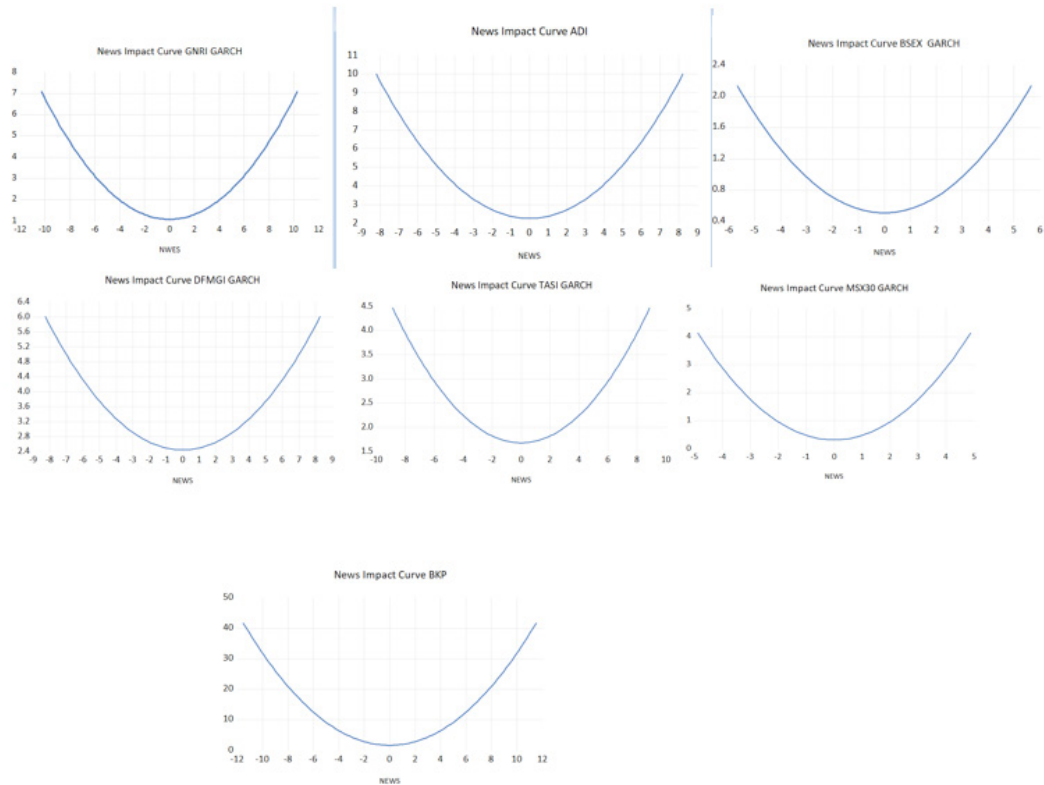
Figure 2. News impact curves of volatility models

Table 7. Sign bias test result

Test	ADI		DFMGI		TASI		MSX30		BSEX		GNRI		BKP	
	T-Statistic	Prob.	T-Statistic	Prob.	T-Statistic	Prob.	T-Statistic	Prob.	T-Statistic	Prob.	T-Statistic	Prob.	T-Statistic	Prob.
Sign-Bias	−2.512687	0.0125	−2.452849	0.0147	−2.733841	0.0066	−1.853727	0.0647	−2.650549	0.0084	−2.649435	0.0085	−2.286299	0.0229
Negative-Bias	−1.975925	0.0490	−2.338322	0.0200	−1.837176	0.0671	−2.328757	0.0205	−2.127495	0.0342	−1.959867	0.0509	−2.047043	0.0415
Positive-Bias	−1.207122	0.2283	−1.082695	0.2798	−1.065320	0.2876	−0.196359	0.8445	−1.163626	0.2455	−1.138950	0.2556	−1.149650	0.2512
Joint-Bias	7.298571	0.0650	7.955077	0.0488	7.892725	0.0502	6.788280	0.0811	8.239666	0.0431	7.737377	0.0537	6.664308	0.0556

3.7. GARCH, TARCH, and EGARCH results

Based on the results of the ARCH effect, the GARCH, TGARCH, and EGARCH models were applied. The best models were selected with the Student's t and generalized error distribution based on the lowest value of Akaike info criterion. From the analysis, it is evident that COVID-19 affected the stock markets in the GCC starting with the announcement of the first case in each country.

3.8. TGARCH result

Table 8 presents the result of TGARCH. The coefficients of the constant variance parameter were

positive and statistically significant at the 5% level in all-stock markets' returns and reflected the time-varying volatility. The coefficients of the ARCH (b_1) parameter were positive and statistically significant at the 10% level in all stock markets, indicating that stocks' volatility on the current day resulted from stocks' volatility on the previous day. Moreover, the coefficients of the GARCH (θ) parameter were positive and statistically significant at the 1% level in all stock markets, indicating that stocks' volatility on the current day resulted from stocks' volatility on the previous day. The coefficients of the asymmetric (γ) parameter were positive and statistically significant at the 5% level in all-stock markets' returns, and reflected the asymmetric news (good/bad), presenting

evidence of the leverage effect; however, the coefficients of BSEX and MSX30 were negative. The coefficients fulfilled all the conditions for stability $(b_1 + \gamma > b_1)$. The overarching results indicate that, since the COVID-19 is measured in bad news, it affected stock market returns.

3.9. EGARCH results

Table 8 presents the result of EGARCH. The coefficients of the constant variance parameter were positive and statistically significant at the 5% level in all-stock markets' returns and reflected the time-varying volatility. The coefficients of the ARCH (b_1) parameter were positive and statistically significant at the 10% level in all stock markets, indicating that the previous day's shock had an impact on the current day's stock returns volatility. Moreover, the coefficients of the GARCH (θ) parameter were positive and statistically significant at the 1% level in all stock markets, indicating that the previous period's volatility

explains the current period's volatility. The coefficients of the asymmetric (γ) parameter were negative and statistically significant at the 5% level in all-stock markets' returns, reflecting a larger effect of bad news on stock markets than of good news. The asymmetric of shocks indicated the existence of the leverage effect, demonstrating that stock market volatility did not respond to the equal magnitude of equally positive and negative shocks. Since the COVID-19 was measured as bad news, it affected the GCC stock markets' returns. The significance of the persistence of negative shocks, known as volatility asymmetry, implies that investors were more sensitive to bad than good news, suggesting the existence of an asymmetric volatility spillover mechanism. This result supported the previous findings of Yong et al. (2021), Choi and Jung (2021), and Yousfi et al. (2021). Finally, it was noticed that the results of the asymmetric estimators in the EGARCH model were better than the results of the TGARCH model.

Table 8. TGARCH and EGARCH results

Source: Author's analysis.

		Models	TASI	BSEX	ADI	DFMGI	GNRI	MSX30	BKP
GARCH	Mean	Intercept	0.182387***	0.053736**	0.117473***	0.108833**	0.061701	0.024523	0.073354 **
	Variance	Intercept	0.024937***	0.015359***	0.041255***	0.034368**	0.024872**	0.018918**	0.064722***
		ARCH(b_1)	0.035382***	0.050650**	0.153875***	0.051203**	0.056771***	0.104880**	0.301364***
		GARCH(ϑ)	0.907247***	0.864475***	0.788317***	0.910996***	0.894399***	0.819197***	0.648904***
		Error distribution	Student's t	Student's t with fixed df	Student's t with fixed df	Generalized error distribution	Student's t	Student's t	Student's t with fixed df
		Akaike info criterion	2.636761	1.579933	2.695611	3.178595	2.459991	1.446992	2.810065
TGARCH	Mean	Intercept	0.145931***	0.068355***	0.105486**	0.031445	0.041710	0.010934	0.046654
	Variance	Intercept	0.054514**	0.008330***	0.032869***	0.067164***	0.023899***	0.023222***	0.069712***
		ARCH(b_1)	0.070998**	0.070995**	0.046835*	0.074207*	0.027295*	0.228622***	0.162341**
		Asymmetric(γ)	0.114987**	−0.088234***	0.120676***	0.097957***	0.081786***	−0.147164**	0.257427***
		GARCH(ϑ)	0.811511***	0.935312***	0.845822***	0.841278***	0.941276***	0.744168***	0.651182***
		Error distribution	Generalized error distribution (GED)	Student's t	Student's t with fixed df	Student's t	Student's t	Student's t with fixed df	Student's t with fixed df
		Akaike info criterion	2.725495	1.535549	2.688589	3.202508	2.411188	1.502179	2.802433
EGARCH	Mean	Intercept	0.153389***	0.038339*	0.095135**	0.016952	0.010421	0.018601	0.062755
	Variance	Intercept	−0.157032***	−0.304708***	−0.215886***	−0.186306***	−0.073431***	−0.369575***	−0.306309***
		ARCH(b_1)	0.197300***	0.254404***	0.272846***	0.255281***	0.072013**	0.249283***	0.367217***
		Asymmetric(γ)	−0.110609***	−0.070726**	−0.072994**	−0.062767**	−0.129305***	−0.082039**	−0.109023**
		GARCH(ϑ)	0.966923***	0.898511***	0.973032***	0.963626	0.968135***	0.880245***	0.937062***
		Error distribution	Generalized error distribution	Generalized error distribution	Student's t	Student's t	Student's t with fixed df	Student's t	Student's t with fixed df
		Akaike info criterion	2.708630	1.707903	2.715136	3.147530	2.324040	1.383677	2.810641

Table 9. News impact and volatility persistence

Asymmetric model	News impact	TASI	BSEX	ADI	DFMGI	GNRI	MSX30	BKP
EGARCH	Good News Impact $1+\gamma$	0.889391	0.929274	0.927006	0.937233	0.870695	0.917961	0.890977
	Bad News Impact $1-\gamma$	1.110609	1.070726	1.072994	1.062767	1.129305	1.082039	1.109023
	Volatility Persistence $b_1+\vartheta$	0.966923	0.898511	0.973032	0.963626	0.968135	0.880245	1.304279

Table 10. Heteroskedasticity test

Models	Statistics	TASI	BSEX	ADI	DFMGI	GNRI	MSX30	BKP
GARCH	F-statistic	0.078929	0.083381	0.007092	0.179035	2.487768	0.044141	0.003239
	Prob	0.7789	0.7730	0.9329	0.6725	0.1157	0.8337	0.9546
	Obs*R-squared	0.079407	0.083903	0.007135	0.180063	2.484028	0.044421	0.003261
	Prob. Chi-Square(1)	0.7781	0.7721	0.9327	0.6713	0.1150	0.8331	0.9545
TGARCH	F-statistic	0.070304	0.242804	1.195551	0.086341	2.207726	0.039177	0.003394
	Prob	0.7911	0.6225	0.2750	0.7691	0.1383	0.8432	0.9536
	Obs*R-squared	0.070721	0.244198	1.198500	0.086842	2.206276	0.039435	0.003416
	Prob. Chi-Square(1)	0.7903	0.6212	0.2736	0.7682	0.1375	0.8426	0.9534
EGARCH	F-statistic	0.003536	0.272043	1.016476	0.059971	2.254700	0.267794	0.369033
	Prob	0.9526	0.6023	0.3141	0.8067	0.1337	0.6052	0.5439
	Obs*R-squared	0.003558	0.273538	1.019543	0.060318	2.253747	0.269349	0.370827
	Prob. Chi-Square(1)	0.9524	0.6010	0.3126	0.8060	0.1333	0.6038	0.5426

3.10. News impact and volatility persistence

Table 9 demonstrates that bad news had stronger impacts than good news in all-stock markets' returns. GNRI was affected by bad news more than the rest of the markets in the EGARCH model. According to the TGARCH model, the TASI was the most affected by bad news. Table 10 demonstrates that the value of the volatility persistence for the EGARCH was close to 1 for all the GCC stock markets' returns, indicating volatility persistence and that the shock required a longer time to end. Since the COVID-19 was measured by bad news, it was shown to affect the GCC stock markets. Because of the impact of bad news of COVID-19, GNRI, TASI, BKP, MSX30, ADI, BSEX, and DFMGI stock markets' returns were collectively affected. According to the volatility persistence in the EGARCH model, GCC stock markets' returns of MSX30, BSEX, DFMGI, TASI, GNRI, ADI, and BKP will recover from the COVID-19 shock.

3.11. Diagnostic test

In the heteroskedasticity test shown in Table 10, the diagnosis demonstrated no problems, since all GCC stock market returns had a p-value greater than 0.05.

CONCLUSION

The study investigated the asymmetric impact of the COVID-19 pandemic on the GCC stock markets' returns. An asymmetric GARCH method was applied to examine the effect of the COVID-19. Moreover, the daily closing prices of the main market index were used from the day of the announcement of the first confirmed case in all countries up to March 6, 2021. A regression equation was applied and indicated a GARCH effect, and the GARCH model was then estimated. A sign bias test found an asymmetric effect on volatility as well as demonstrated that both negative and positive shocks had different effects on future volatility. This result enabled the use of asymmetric GARCH models, including TGARCH and EGARCH. The analysis demonstrated that the GARCH and EGARCH models were the best models

using Student's t and the generalized error distribution based on the lowest value of the Akaike information criterion. Based on the results of the GARCH model, it was clearly evident that all GCC stock markets' returns were affected by the COVID-19. The results of the EGARCH model displayed that the asymmetric coefficient (γ) was negative and statistically significant at the 5% level for all GCC stock markets' returns. This implied that the COVID-19 pandemic affected the GCC stock markets' returns. It also showed the presence of the leverage effect, and the value of the volatility persistence the EGARCH was close to 1 for all the GCC stock markets' returns, indicating that the shock required a longer time to end. According to the results, the impact of the pandemic was monitored by the GCC stock markets' returns including GNRI, TASI, BKP, MSX30, ADI, BSEX, and DFMGI. In view of the continuation of volatility in the EGARCH model, the GCC stock markets' returns that will recover from the shock of COVID-19 include MSX30, BSEX, DFMGI, TASI, GNRI, ADI, and BKP. This study might have implications for investors and policymakers in diversifying investment portfolios and adopting strategies to maintain investor confidence during crises, in addition to the development of mechanisms to reduce risks in the financial markets in times of crisis. Central banks should also take financial measures to mitigate risks to capital markets.

This study focused on the returns in GCC stock markets and could be expanded to include the returns of these markets and constituent sectors for more comprehensive results. Further studies to examine the impact of the COVID-19 pandemic on these economies are also recommended. Finally, it would be interesting to investigate the effect of the availability of the COVID-19 vaccine on GCC stock market returns.

AUTHOR CONTRIBUTIONS

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