Modeling and Forecasting Volatility of Qatar Stock Exchange in light of the blockade and Covid-19 crises Using GARCH Models

نمذجة تقلبات عوائد بورصة قطر والتنبؤ بها في ظل أزمتي الحصار وكوفيد-19 باستخدام نماذج GARCH

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Received: 20/06/2022 Accepted: 09/07/2022 Published: 11/11/2022

Abstract:

This study aims to model the Volatility of the (Qatar Stock Exchange) QSE returns and to forecast them out of the sample using GARCH models using the database of daily closing prices for the QSE index during the period (04/01/2016-07/07/2022). The study concludes that the GARCH model (1,1) is the best model for estimating and forecasting the volatility in the returns of the QSE index out of sample. It is also found that the returns will take stable levels in the short term . despite the critical economic situation and health instability as far as the region and the whole World. From here, we conclude that the blockade crisis prepared Qatar for the COVID-19 crisis, and the COVID-19 crisis prepared Qatar for future crises. Through excellence in various political, economic, financial and social fields.

Key words: modeling, forecasting, GARCH Model, Qatar Stock Exchange, blockade crisis, covid -19 crisis.

ملخص:

تهدف هذه الدراسة إلى نمذجة تقلبات عوائد بورصة قطر(QSE)والتنبؤ بها خارج العينة باستخدام نماذج GARCH باستخدام قاعدة بيانات أسعار الإغلاق اليومية لمؤشر QSE خلال الفترة(2022/07/07-2016/04/01)، خلصت الدراسة إلى أن نموذج(1،1) GARCH هو أفضل نموذج لنمذجة تقلبات عوائد مؤشر QSE والتنبؤ بها خارج العينة. كما بينت كذلك أن العوائد ستأخذ مستويات مستقرة في المدى القصير.

وعلى الرغم من الوضع الاقتصادي الحرج وعدم الاستقرار الصحي بالنسبة للمنطقة والعالم بأسره نستنتج أن أزمة الحصار هيأت قطر لأزمة كوفيد -19 ، وأزمة كوفيد -19 هيأت قطر لأزمات مستقبلية من خلال التميز في مختلف المجالات السياسية والاقتصادية والمالية والاجتماعية

الكلمات المفتاحية : نمذجة، تنبؤ، نموذج GARCH ، بورصة قطر، أزمة الحصار،أزمة كوفيد-19.

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1. INTRODUCTION

Forecasting is one of the most important decision-making tools and the most important element in the planning process for the future. In order to make the right decision, it is necessary to study all available alternatives and analyze past and present variables to determine what is the best decision and what effects will result from this decision.

The urgent need for predicting comes from our lack of knowledge of the future, and thus the high degree of risk in decisions related to the future, especially in the financial markets. To reduce this risk, we rely on the analysis of the phenomenon in the past to determine the features of the future.

Understanding volatility, forecasting it accurately to making sound investment decisions, predicting volatility is critical in many areas of finance (Gabriel AS,2012,p1006)(Al Rahahleh N, Kao R,2018) .

Volatility is a measure of the uncertainty of price changes in financial market indices and has been used as a measure of risk. It also plays a major role for both market practitioners and policy makers, especially in emerging countries. In this regard, many economists have tried to research in the field of volatility modeling and trying to forecast to protect markets from crises (Alshammari T, Ismail M, et al,2020).

In some scenarios, high stock volatility reduces market profits, causes large and dangerous losses, affects the level of confidence of participants in the stock exchange (Mesfer M,2021) especially in periods of crisis. It helps the state to realize the extent to which the crisis will reach and affect it by controlling the crisis stages and trying to address them.

The beginning of December, 2019, the world witnessed the effects of the consequences of the Corona pandemic (Covid 19) in an unprecedented humanitarian, health and economic crisis, as this epidemic swept the world in a short period of time, affecting the largest economies in the world, and governments sought to confront this pandemic by taking many measures. However, this reflected negatively on the stability of the financial markets, and its volatility took a larger turn than expected. In light of these situations came the need to forecast the direction of the financial market indicators and to take the necessary measures at an early date.

There are many models that are used in modeling the returns of financial market indicators and forecasting their future levels. Among these models is the Box-Jenkins Method. For the Box-Jenkins model, its efficiency has been proven in many predictive studies(Al-Ghanam H,2003).

As this model was based on the assumption of stability variance of errors, which often do not take into account the characteristics of financial time series, it required reconsideration of other models that take into account the instability of variance of errors, among these models, the implementation of the Autoregressive Conditionally heterscedasticity (ARCH)(Engel RF,1982) (Bollerslev T,1986). which has proven its efficiency in predicting the returns of financial market indicators, and this has been confirmed by some studies, such as(Curto J, et al ,2002)(Juliana Y ,2002).

Stock market volatility has been extensively researched in developed countries, but it is different for emerging countries where only a few studies have been conducted over the recent years.

Therefore, this paper aims to add knowledge to stock market volatility in emerging countries through modeling and forecasting QSE Volatility during the beginning of the political crisis (the siege crisis of 2017) to a (health crisis) crisis of the Covid-19 pandemic (2020).

2. Literature Review

The concept of volatility is not new. Several studies were made in modeling and forecasting the stock market volatility both in developed and in developing countries(Garikai WB,2019). The following is a review of the most important previous studies, by way of example but not limited to:

Franses and Dijk(1996), used the GARCH model and two of its non-linear modifications to predict the weekly volatility of the stock market, the quadratic GARCH model (QGARCH) (Engel and Ng, 1993) and the (GjR) model proposed by (Glosten Jagannathan and Runkle, 1992). The QGARCH model gives better predictions when the study sample does not contain extreme observations such as the 1987 stock market crash, while the GJR model is not recommended to be used in predicting.

Curto and al (2002) modeled the volatility of the Portuguese stock market as an emerging market (PS 120 index) and compared it with the German and US stock exchanges (DAX, DJIA indices) as developing markets, based on GARCH EGARCH models during the period 12/31/1992 to 12/31/2001. The study concluded that the EGARCH model is the best among the models applied to predict volatility of returns in the financial markets under study.

Goudarzi and Ramanarayanan (2010) modeled the volatility of Indian stock market (BSE 500 Stock Index) as the proxy for ten years using ARCH and GARCH models. The study has reported that GARCH (1, 1) was the most appropriate model for explaining volatility clustering. Banumathy and Azhagaiah (2015), investigated the volatility model of Indian stock market using daily data of S&P CNX Nifty Index from 2003 to 2012 by using symmetric and asymmetric models of GARCH. The study findings showed that the asymmetric effect (leverage) captured by the parameter of EGARCH (1,1) and TGARCH (1,1) models show that negative shocks have significant effect on conditional variance (volatility).

In a study, Ahmed and Suliman (2011) modeled the volatility (conditional variance) of the Khartoum Stock Exchange using the daily closing prices of the market index during the period January 2, 2006-December 31, 2010. Experimental investigation was done through symmetric and asymmetric GARCH models. The accuracy of these models in predicting volatility was also tested. Assuming different distributions of error are the t-distribution and the generalized distribution of error. The study results revealed that a high volatility process is present in KSE Index returns series. The results also provided evidence on the existence of risk premium and indicated the presence of the leverage effect in the KSE index returns series.

Floros (2008) modeled stock market volatility, Based on daily data from Egypt (CMA General index) and Israel (TASE-100 index) using GARCH model, as well as EGARCH, TGARCH, the component GARCH asymmetric component GARCH and the PGARCH model The study results indicated that increased risk has not been found to necessarily lead to a higher return.

Y. Kalyanaraman (2014) estimated the conditional volatility of the Saudi stock market by applying the AR(1)-GARCH(1,1) model to the daily stock returns data for portfolio management, asset allocation, and risk management for the period of 1 August 2004 to 31 October 2013. Kalyanaraman concluded that the linear symmetric GARCH (1,1) model is adequate for estimating the volatility of the Saudi stock market. The finding shows that the returns of this market for the study period are characterized by volatility clustering and follow a non-normal distribution (Al Rahahleh N, Kao R,2018) .

Al Freedi et al. (2012) examined several stylized facts (i.e., heavy-tailedness, leverage effect, and persistence) in terms of the volatility of stock price returns for the Saudi Arabian stock market for the period of 1 January 1994 to 31 March 2009. Their results showed that asymmetric models with heavy-tailed density improve overall estimations of the conditional variance equation. Additionally, they concluded that the first order autoregressive time series [AR(1)]-GJR GARCH model with Student t-distribution outperformed the other models for the period immediately before and the period of the local crisis in 2006, whereas the AR (1)-GARCH model with GED performed better than the other models for the period following the crisis (Al Rahahleh N, Kao R,2018) .

Tamilselvan & Vali (2016) forecasted stock market volatility using four (4) indices from Muscat security market in the period 2001-2015. The study made use of GARCH, EGARCH and TGARCH models and results revealed a positive relationship between risk and return. The findings further showed that GARCH models generated significant evidence of asymmetrical relationship between return shocks and volatility adjustments in all four (4) indices (Marobhe M,2020).

Ahmed Shamiri and Zaidi Isa(2009) investigated the relative efficiency of several different types of GARCH models in terms of their volatility forecasting performance. They compared the performance of symmetric GARCH, asymmetric EGARCH and non-linear asymmetric NAGARCH models with six error distributions (normal, skew normal, student-t, skew student-t, generalized error distribution and normal inverse Gaussian). Their results suggested that allowing for a heavy-tailed error distribution leads to significant improvements in variance forecasts compared to using normal distribution(Mhmoud A S, Dawalbait F M,2015).

Al-Najjar (2016) investigated the volatility characteristics of the Aman Stock Exchange Index (ASE) over the period from 1 January 2005 to 31 December 2014, He used symmetric and asymmetric ARCH /GARCH models that capture the volatility clustering and leverage effect, The study findings showed that the symmetric ARCH /GARCH models can capture characteristics of ASE, and provide more evidence for both volatility clustering, whereas EGARCH output reveals no support for the existence of leverage effect in the stock returns at Amman Stock Exchange.

Adesina (2013) estimated volatility (conditional variance) in the monthly data of the Nigerian Stock Exchange (NSE) over the period from January 1985 to December 2011 of the NSE all share-index. He used symmetric and asymmetric GARCH models. The study results showed that volatility was very high for the NSE return series found no asymmetric shock phenomenon (leverage effect) for the return series.

Wellington Garikai Bonga(2019) examined the volatility of Zimbabwean stock market using monthly return series from January 2010 to January 2019. using Symmetric and asymmetric GARCH models and the best model was selected using the model selection criterion viz., Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC).

Shady I. Y. Al-Telbany, Tariq Abdul Aziz Al-Doub (2020) used symmetric and asymmetric GARCH models to study the impact of positive and negative shocks on stock return volatility in Boursa Kuwait and Dubai Financial Market, using daily data over the period from January 2, 2019 to August 20, 2020 comparing the symmetric and asymmetric GARCH models based on various criteria. The study concludes that the best model to represent the volatility in stock returns in Boursa Kuwait, Dubai Financial Market is GARCH (1,1) model, TGARCH (1,1) model, Respectively The study found that EGARCH (1, 1) was the best model found to be significant. The study concludes that positive and negative shocks have different effects on the stock market returns series. Bad and good news will increase volatility of stock market returns in different magnitude.

This study differs from previous studies in that it dealt with one of the emerging markets that it knows an almost total absence in the research arena despite the availability of data, in addition to the fact that the study period is considered very sensitive (blockade ,Covid-19) and needs to model the volatility of financial market returns and forecast its future levels to help investors make their investment decisions .

3. Methodology

Calculation of Returns

To obtain a stationary series we use the returns

$$Rt = Ln (Pt / Pt-1) *100 \tag{1}$$

Where : Pt is the closing price of the index at date t

Unit root with structural break

A number of different unit root tests have emerged from the research surrounding structural breaks and unit roots. These tests vary depending on the number of breaks in the data, whether a trend is present or not, and the null hypothesis that is being tested.

ADF tests are biased towards the non-rejection of the null hypothesis in the presence of a structural break,(Perron P,1989) unit root tests allows for a break under both the null and alternative hypothesis. These tests have less power than the standard DF type test when there is no break. However, (Perron P,2005) points out that they have a correct size asymptotically and is consistent whether there is a break or not. Moreover, they are invariant to the break parameters and thus their performance does not depend on the magnitude of the break(John G, Nelson P,2007).

Symmetric Volatility Measurement

Over the years numerous models have been devised by researchers seeking to model volatility in stock returns, these have been grouped into symmetrical and nonsymmetrical models. (Engel RF,1982) is considered to be the pioneer of volatility modeling designed Autoregressive Conditional Heteroskedastic (ARCH) model to forecast time series data volatility. After a few years (Bollerslev T,1986) developed a model known as Generalized-ARCH (GARCH) model. The other models include GARCH in Mean Model (GARCH-M) by (Engle RF, Lilien DM, Robins R,1987), Exponential GARCH (EGARCH) model by (Nelson DB,1991) and Threshold-GARCH (TGARCH) by (Zakoian JM,1994).

GARCH Model

The classical econometric models assumed constant variance of errors, but this assumption is considered unrealistic, especially when it comes to financial time series. As most of the financial variables, including the return of financial assets, are characterized by the dynamism and instability of variance errors over time and the phenomenon of asymmetry. But since 1982 Engle (1982), came up with a new class of models called (ARCH), i.e. autoregressive conditional heterscedasticity models following the ARCH model. This model has been generalized by Bollerslev (1986), who proposed GARCH model ARCH models based on the variance of the error term at time t depends on the realized values of the squared error terms in previous time periods. The model is specified as:

In his study of inflation changes in Britain in 1982 (Engel RF,1982) suggested ARCH models, according to these models, the variance of the time series is not fixed, that is, it is related to the sum of the available information.

The simple form of this model is presented as follows

$$r_t = \mu + \varepsilon_t \tag{2}$$

$$h_t = \sigma_t^2 = V\left({}^{\varepsilon_t}/_{\varepsilon_{t-1}}\right) = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \tag{3}$$

Where

$Y_t \to N(\varepsilon_t , h_t)\varepsilon_t \to N(O, h_t)$

$\alpha_0 > 0$ ، $\alpha_1 \geq 0$ We call This model ARCH

Equation (2) is called the mean equation

Equation (3) is a conditional variance equation (i.e. the variance of the error is conditioned by information available in time t), and it has been found that it is better to express this variance as a function of the errors of the previous period. This equation can be generalized to include errors for several previous periods, i.e. it becomes:

$$\mathrm{h_t} = \sigma_t^2 = \mathrm{h}(\varepsilon_{t-1}, \varepsilon_{t-2}, \dots \dots . \varepsilon_p, \alpha) \tag{4}$$

The p-order of the model is called ARCH and the model is denoted by ARCH(p) and α is the ray of the unknown landmark .

It is noticed in the practical works that the expansion of p-values may result in negative values of α, and this contradicts one of the hypotheses of the model. In order to face this problem, Bollerslev (1986) proposed what is known as a Generalized Autoregressive Conditionally heterscedasticity) model (GARCH).

The GARCH (1, 1) model is represented by the following two equations:

$$r_t = \mu + \varepsilon_t$$

$$h_t = \sigma_t^2 = V\left({}^{\varepsilon_t}/_{\varepsilon_{t-1}}\right) = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + B_t h_{t-1} \tag{5}$$

Where :

$B_1 \geq 0\ \alpha_0 > 0$، $\alpha_1 \geq 0$

These last two conditions are sufficient for the conditional inequality to be positive, but they are unnecessary[17]. We note that the conditional variance equation (5) is explained in terms of the mean (α_0)in terms of the squares of the delayed residuals of the mean equation $(\varepsilon_{t-1})$and it is known by the term (ARCH-term) ARCH and it represents Volatility information in the previous periods. And in terms of the variance prediction for the previous period (σ_{t-1}^2) and it is known as the GARCH.

Writing (1.1) GARCH means that there is a first-degree GARCH and a first-degree ARCH, and the equation of the model GARCH (p, q) can be written in the following form:

$$h_t = \sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{p} B_j h_{t-j}^2 \tag{6}$$

4. RESULTS AND DISCUSSION

Data

The data for the study considers daily closing prices of Qatar stock exchange(QSE) index for the period from 4, January 2016 to 7, July 2022, (excluding public holidays). These closing prices have been taken from investing website (www.investing.com) to analyzed the results using Eviews.10 softward.

The study period was divided into two parts:

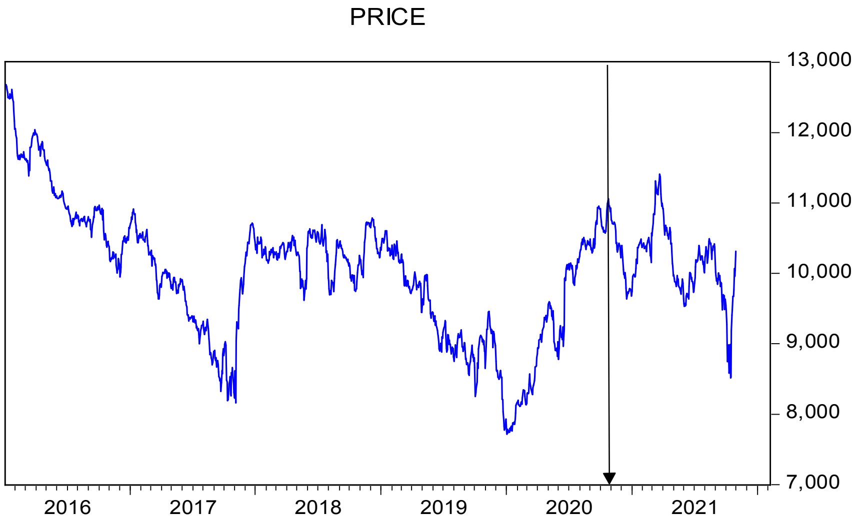
04/01/2016 to 07/02/2022 estimation period (in sample)

08/02/2022 to 07/07/2022 forecast period (out of sample)

Daily Stock Index Prices Trend

Figure 1 shows the evolution of the (QSE) index prices during the period 2016-2022 By reading the figure 1, it becomes clear that the QSE index is characterized by volatility during a period of time.

Figure 1 . Daily Stock Index Prices Trend



Source: *Based on statistical processing by the Eviews.10 software.*

As the performance of the QSE has declined since the beginning of the imposition of Saudi Arabia, the UAE, Bahrain and Egypt on a political and economic blockade on Doha on January 5, 2017, until it reached its lowest level on October 31, 2017, in five years, and this is due to the process of selling shares by institutional investors Saudi Arabia, the UAE and Bahrain to push it down following the imposition of the blockade.

Subsequently, in late November 2017, the CEO of the Stock Exchange announced that the market had overcome the shock of the siege and began to recover as a result of internal decisions mainly related to raising the ceiling of foreign ownership of shares in listed companies to 49%, and the Stock Exchange's management offering a number of products and options to investors of all kinds, as the factors were Foreign affairs have a clear impact on trading in the stock market, most notably the rise in oil prices in international markets.

Until it reached its highest level on December 22, recording 10698 points, while a large number of listed companies recorded growth and increased profits. Qatar Stock Exchange has maintained its position in 2017 as the region's largest emerging market and the region's second largest exchange in terms of market capitalization. QSE investment attractiveness has been the focus of attention for foreign investors including US, European and Asian investment portfolios as well as local investors, citizens and residents (Qatar Stock Exchange,2017). In addition to being ranked among the top 10 financial markets in the world in many indicators included in the QSE Global Competitiveness. If this blockade showed the resilience of Qatar's economy, it also highlights the incapacity of the boycotting countries to put it down.

The year 2018 witnessed the full recovery of the Qatar Stock Exchange from the effects of the blockade, thanks to a number of internal measures and international external factors, and among the most important measures announced was what happened in March, when Qatar Petroleum and

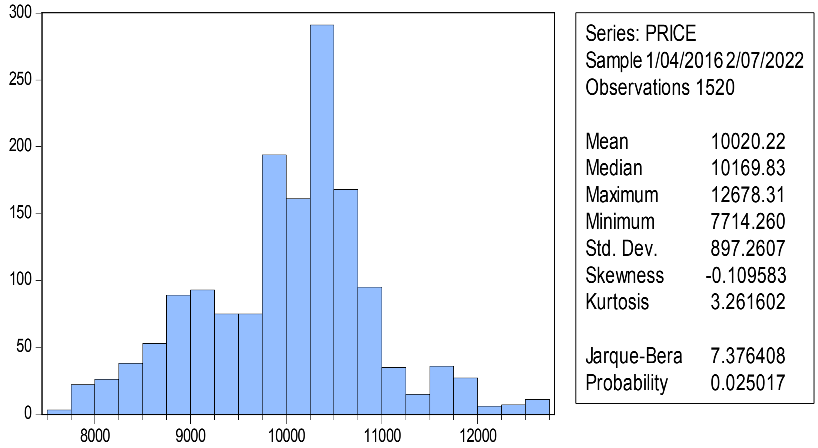
Industry Qatar, two of the major listed companies in the market, announced an increase in the limit of ownership in their shares to non-citizens. Qataris increased from 25% to 49%, which added impetus to trading in the market.

As for the period between 2019-2020, we note a structural change and an increase in volatility the reason is due to the emergence of the covid-19 epidemic, where the first positive case was recorded in Qatar on February 29, 2020, and Qatar recorded an increase of more than 200 cases in one day, as the number of cases reached The recorded cases were 2512 and increased by 719 cases to reach 3231 cases on April 13 which was alarming (Ministry of Public Health,2020).

This increase in the outcome of those infected with COVID-19 affected the Qatar Stock Exchange and this is what is observed through the structural change, as the market index began to collapse almost since November 10, 2020 (according to Figure 01), recording (10,882 points) until December 30, 2020) 9680 points), to gradually recover the market, and this is due to the policies taken by the Qatari government, as well as the precautionary measures applied. But the repercussions of the third wave struck again and led to a decline in the market's performance to record levels, reaching (8517 points) in mid-October 2021. With the end of 2021, the market began to recover, due to several reasons, the most important of which is that Qatar has passed the stage of the peak of the third wave, the emphasis on the application of precautionary rules, and Qatar's hosting of the Arab Cup 2021.

Descriptive statistics

Figure 2. Descriptive statistics Results



Source: *Based on statistical processing by the Eviews.10 software.*

We note that the value of the skewness coefficient is negative, which indicates that the distribution has a long tail on the left. As for the value of the kurtosis coefficient, it is greater than 3, which means that prices do not follow the normal distribution, and this is confirmed by the statistical value of Jacques Berra at a significant level of 1%.

Testing the Presence of Unit Roots

A problem common with the conventional unit root tests ,such as the ADF, DF-GLS and PP tests, is that they do not allow for the possibility of a structural break. Assuming the time of the break as an exogenous phenomenon (Waheed M, Alam M, Ghauri SP,2006) Therefore, we made other tests, such as the unit root test with a structural break.

Unit root test with a structural break

Table 1.ADF Unit root test with a structural break (Index Prices Results)

Prob	t-Statistics	Critical value			ADF with structural break
		%10	%5	%1	
0.4194	-3.439509	-4.193627	-4.443649	-4.949133	Break Date 6/15/2020

Source: Based on statistical processing by the Eviews.10 software.

s the result of ADF unit root test with a structural break on the Qatar stock Exchange index prices series indicates the presence of a unit root in the series by comparing the critical values at 1%, 5%, 10%, and the ADF statistic, as well as the probability value greater than 0.05, in addition to the presence of a structural break at the point 06/15/2020

Table 2.ADF Unit root test with a structural break (Returns Results)

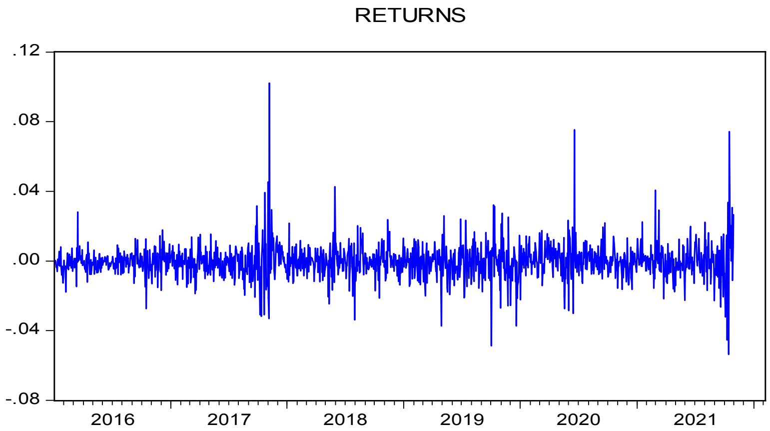
Prob	t-Statistics	Critical value			ADF with structural break
		%10	%5	%1	
0.01	-36.91545	-4.193627	-4.443649	-4.949133	Break Date 6/18/2020

Source: *Based on statistical processing by the Eviews.10 software.*

Table (2) shows the result of ADF unit root test with a structural break on the return series. as well as the acKinnon critical values for rejection of the hypothesis of the existence of a unit root at all levels of significance by comparing the ADF test statistics are larger in absolute values than the critical values, we reject the hypothesis of non-stationary as well as the probability value is less than 0.05, which means that the return series is stationary.

Figure (3) shows that the series of returns on the QSE index is static on average, but not static in variance, and that there are clear fluctuations in returns, as these returns have positive and negative values of different sizes.

Figure 3. Return Series of QSE Index



Source: *Based on statistical processing by the Eviews.10 software.*

Determining the Mean Equations

As a prior step for estimating ARCH family model equation, a mean equation needs to be formulated (Saurabh S, Tripathi LK,2016)

To determine the p,q rank of the ARMA model, we resort to the ACF and PACF functions (A1), after filtering many models (1,1),)(3,1),(1,3),(3,3) and based on the SCHWARZ and AKAIKE criteria, Table (3) it was found that the best model Among the candidate models is ARMA(1,3) model.

Table 3. Results of ARMA Model Comparison of Returns

Model	AIC	SCH
ARMA(1,1)	-6.421363	-6.407338
ARMA(1,3)	-6.425864	-6.411839
ARMA(3,1)	-6.426373	-6.412348
ARMA(3,3)	-6.422301	-6.408276

Source: *Based on statistical processing by the Eviews.10 software.*

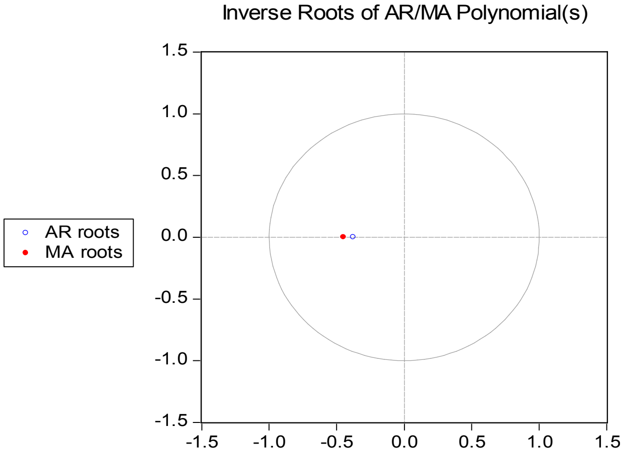
But based on the Parsimony rule, the best model is ARMA (1,1).

Inversible root

In mixed models it must be ensured that the roots of the polynomial associated with the autoregressive portion are greater than The one in absolute value then the pattern is stable, and in order for the model to be reversible, the roots of the polynomial associated with the part of the moving averages must be greater than one in absolute value.

In general, for a model to be stable and reversible, it must be inverted that all roots located within the unitary circle.

Figure 4. Inverse Roots of ARMA(1,1) model



Source: *Based on statistical processing by the Eviews.10 software.*

Figure (4) shows that as long as the unit roots of the ARMA (1,1) model are inside the unit circle, the model is stable and invertible.

ARCH Effects Test

Box and Jenkins' methodology postulates a basic hypothesis which is that the residuals are fixed and do not change with time, so the ARCH effect test for the residuals was conducted.

Table 4. ARCH Effects Test

Heteroskedasticity Test: ARCH

F-statistic	14.96292	Prob. F(1,1516)	0.0001
Obs*R-squared	14.83622	Prob. Chi-Square(1)	0.0001

Source: *Based on statistical processing by the Eviews.10 software.*

Table (4) Shows that Since the corresponding probability value NR2 is less than 0.05, we reject the null hypothesis H0, which states that the variance of errors is stable, that is, the variance of errors is not stable. In other words, there is an effect of ARCH in the series of returns.

One of the most important hypotheses of the ARMA models is the stability of variance, but with the change of time this hypothesis has been disturbed and this is what generally happens if it comes to financial series, it becomes inappropriate to use the ARMA model (1,1) to model the returns of the Qatar stock Exchange Index. Hence the results warrant for the estimation of GARCH family models(Garikai WB,2019).

Symmetric Volatility Measurement

This necessitates resorting to other models that take into consideration the problem of the instability of error variance. Among these models, we find special models belonging to what can be called the ARCH(G) family models.

Relying on the autocorrelation and partial autocorrelation functions of residual squares (A2), several symmetrical ARCH(G) models have been nominated in order to model the volatility of the returns of QSE.

Table 5. ARCH(G) Models Comparison Results

Model	AIC	SIC
ARCH(1)	-6.585301	-6.567770
ARCH(2)	-6.671745	-6.650697
GARCH(1,1)	-6.729756	-6.708719

Source: *Based on statistical processing by the Eviews.10 software.*

Table (5) shows that Among these models are ARCH(1) ,ARCH (2) and GARCH (1,1) models. After comparing them according to the criteria of SCHWARZ and Akaike, the GARCH (1,1) model was nominated as the best symmetric model.

Table 6. GARCH (1,1) model Estimate

Variable	Coefficient	Std. Error	z-Statistic	Prob.
α0	5.09E-06	8.23E-07	6.176427	0.0000
α1	0.204500	0.018985	10.77163	0.0000
δ_1	0.755903	0.022060	34.26587	0.0000

Source: *Based on statistical processing by the Eviews.10 software.*

From the table (6), the conditional variance equation for the returns of the Qatar Stock Exchange index can be written as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \delta_j \, \sigma_{t-j}^2 \quad (7)$$

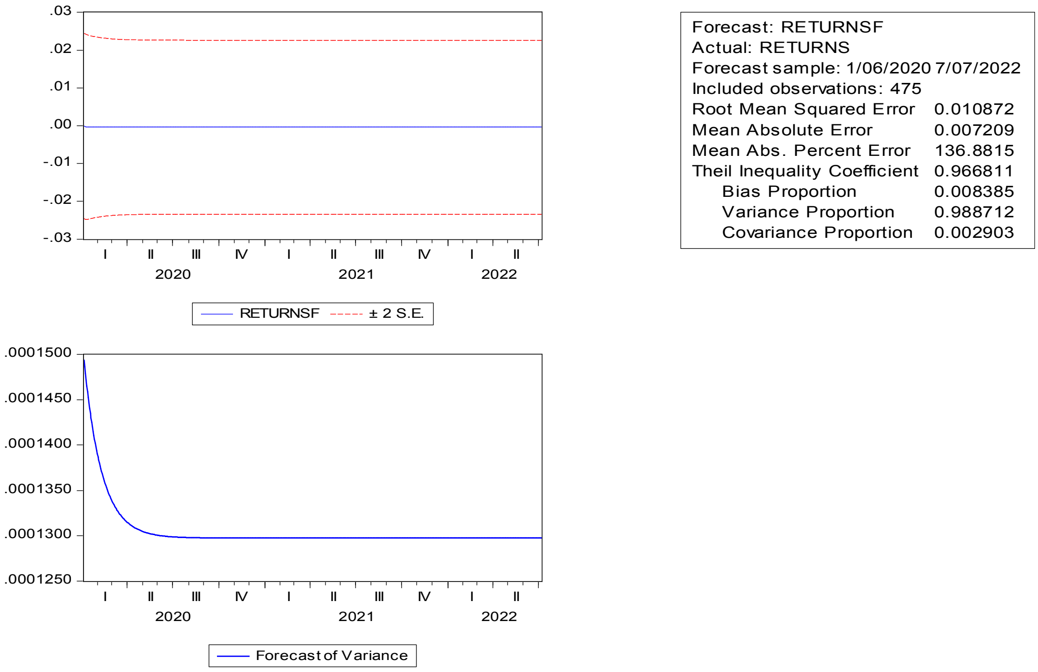
$$\sigma_t^2 = 0.00000509 + 0.20\varepsilon_{t-i}^2 + 0.75\sigma_{t-j}^2 \quad (8)$$

Since $\delta_1 + \alpha_1$ less than one, this indicates the impact of the shock decreases with the passage of time (chou, 1988), in other words the decay of shocks in the Qatar Stock Exchange with the passage of time, meaning that any shock on the current conditional variance will not have a significant impact on the values of future variances, this is what It makes investing in the Qatar Financial Market better compared to other Arab markets that are characterized by continuous fluctuation in the long term.

Forecasting:

After finding the best models, we provided a further application for testing the forecasted volatility values. In fact, understanding modeling and forecasting performance is relevant for investment portfolio management and hedging against risk. This paper contributes to the field by providing the investment community with a model for return volatility and forecasting in the short term (out of sample) in the Qatar Stock Exchange.

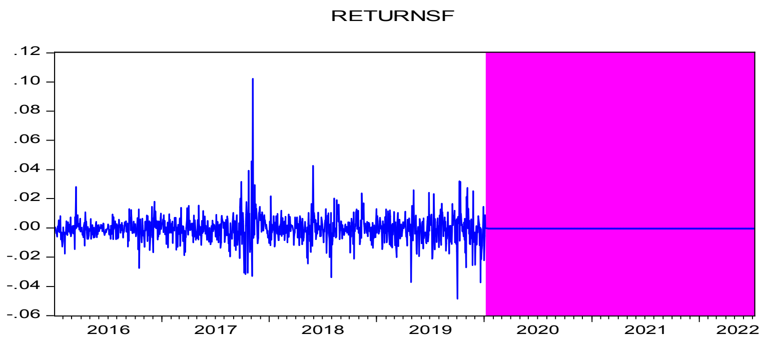
Figure 5. Confidence Range and forecast of Variance



***Source:** Based on statistical processing by the Eviews.10 software.*

Figure (5) shows that the forecasting of the volatility in returns of QSE for the period 08/02/2022-07/07/2022 within the confidence field, as well as the suitability of most criteria such as : RMSE ,MAE, Theil Coefficient.

Figure 6. Forecast returns of QSE



Source: *Based on statistical processing by the Eviews.10 software.*

Figure (6) shows that the Forecasting of the volatility in the returns of the Qatar Stock Exchange index in the short term (2022/07/02-2022/07/07) is stable.

According to the results obtained, the returns of the Qatar Stock Exchange Index follow GARCH (1.1) during the study period, meaning that shocks fade in the short term in the Qatar Stock Exchange , in addition to the similarity of the impact of positive and negative shocks, , and this explains the solidity of the Qatari economy as well as the strength of the Qatari market in addition Qatar's long-term strategy. It was relied on the GARCH(1,1) model to predict the future values of the returns of the QSE Index.

Results were consistent with Ahmed Al-Shamiri and Zaidi Issa (2009), Al-Najjar (2016) without taking into account the study period, and compatible with Shady I. Y. Al-Telbany et al(2020) study, taking into account the study period and is confirmed by the financial and economic indicators in fact during the same period as:

The Qatar Stock Exchange index recorded a level of 14,000 points for the first time since 2014, on 04/06/2022 and settled at these levels during the first quarter of 2022, and this is due to:

- High oil prices in international markets, good financial results for companies and the repercussions of the war on Ukraine.
- The stability of monetary and fiscal policy in the country, as well as positive macroeconomic indicators.
- Hosting Doha Smart City Expo 2022-05-26.
- Political and economic stability of the country.
- Organizing the World Cup.
- Qatar raised the percentage of foreign ownership in the stock exchange.
- Most financial analysts believe that this stability will continue at least until the 2022.

5. Conclusion

As modeling and forecasting the performance of various GARCH models are becoming critical processes for businesses and policy-makers around the world, our results are of benefit to policy-makers.

This study has modeled volatility of stock returns at QSE using symmetrical models so as to ensure that the most efficient forecasting model is identified and put into use in this case the GARCH (1,1) was found to be more accurate So QSE participants are urged to apply this model in their efforts to forecast stock returns volatility and reduce uncertainties associated with these returns.

The study also found that the out-of-sample forecast (2022/02/08-2022/07/07) showed stable levels of QSE returns despite the unstable political and economic conditions. This indicates that the blockade crisis prepared Qatar for the Corona crisis, and the Corona crisis prepared Qatar for future crises. Through excellence in various political, economic, financial and social fields.

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Table of Abbreviation

Abbreviation	meaning of terms
QSE	QATAR STOCK EXCANGE
ARMA	Auto Regressive Moving Average
ARCH	Autoregressive Conditionally heterscedasticity
GARCH	Generalized Autoregressive Conditionally heterscedasticity
ADF	Augmented Dickey-Fuller

Appendex

Correlogram Returns(A1)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.070	0.070	7.3649	0.007
		2	-0.011	-0.015	7.5329	0.023
		3	0.080	0.083	17.397	0.001
		4	0.049	0.037	20.985	0.000
		5	-0.021	-0.025	21.653	0.001
		6	0.029	0.028	22.946	0.001
		7	-0.029	-0.041	24.227	0.001
		8	-0.044	-0.037	27.128	0.001
		9	0.003	0.005	27.143	0.001
		10	0.013	0.014	27.409	0.002
		11	-0.043	-0.035	30.293	0.001
		12	0.014	0.021	30.597	0.002
		13	-0.034	-0.041	32.372	0.002
		14	0.032	0.045	33.981	0.002
		15	0.067	0.060	40.888	0.000
		16	0.020	0.013	41.505	0.000
		17	-0.003	-0.001	41.521	0.001
		18	-0.036	-0.054	43.510	0.001
		19	-0.013	-0.015	43.788	0.001
		20	-0.005	-0.006	43.827	0.002
		21	-0.008	-0.003	43.935	0.002
		22	-0.004	0.007	43.963	0.004
		23	-0.021	-0.013	44.613	0.004
		24	0.027	0.030	45.758	0.005
		25	0.014	0.011	46.064	0.006
		26	-0.033	-0.034	47.738	0.006
		27	-0.027	-0.025	48.906	0.006
		28	0.023	0.024	49.739	0.007
		29	-0.052	-0.059	53.960	0.003
		30	-0.021	-0.012	54.651	0.004
		31	0.030	0.024	56.082	0.004
		32	-0.012	-0.005	56.316	0.005
		33	-0.004	0.016	56.337	0.007
		34	-0.011	-0.022	56.520	0.009
		35	-0.036	-0.029	58.508	0.008
		36	-0.009	-0.005	58.636	0.010

Correlogram Residual Sqaure(A2)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.099	0.099	14.855	0.000
		2	0.137	0.128	43.248	0.000
		3	0.191	0.171	98.616	0.000
		4	0.027	-0.019	99.705	0.000
		5	0.112	0.070	118.80	0.000
		6	0.043	-0.003	121.59	0.000
		7	0.065	0.044	128.00	0.000
		8	0.056	0.014	132.73	0.000
		9	0.059	0.040	138.01	0.000
		10	0.092	0.057	150.98	0.000
		11	0.032	-0.000	152.57	0.000
		12	0.068	0.030	159.65	0.000
		13	0.037	-0.002	161.79	0.000
		14	0.028	0.004	162.99	0.000
		15	0.036	0.001	164.95	0.000
		16	0.008	-0.009	165.05	0.000
		17	0.018	-0.004	165.56	0.000
		18	0.067	0.056	172.49	0.000
		19	0.018	-0.002	172.96	0.000
		20	0.045	0.021	176.11	0.000
		21	0.047	0.017	179.51	0.000
		22	0.010	-0.010	179.67	0.000
		23	0.013	-0.016	179.94	0.000
		24	0.005	-0.010	179.99	0.000
		25	0.004	-0.005	180.01	0.000
		26	-0.001	-0.008	180.01	0.000
		27	0.006	0.001	180.08	0.000
		28	0.037	0.030	182.21	0.000
		29	0.002	-0.005	182.22	0.000
		30	0.004	-0.014	182.25	0.000
		31	0.001	-0.014	182.25	0.000
		32	0.017	0.018	182.68	0.000
		33	-0.006	-0.014	182.74	0.000
		34	-0.001	0.000	182.75	0.000
		35	-0.007	-0.012	182.82	0.000
		36	-0.010	-0.006	182.97	0.000