Gold Price Forecasting using ARIMA-GARCH Model During COVID-19 Pandemic Outbreak

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Abstract. Gold has been considered one of the most reliable assets in finance and a safe-haven investment, especially during turbulent conditions in the economy. Taking this into consideration, a new interest began to take place in the study of gold prices during financial turmoil, especially during the unprecedented COVID-19 pandemic outbreak that started at the end of 2019. The COVID-19 pandemic outbreak had caused a huge dramatic change around the globe in all sectors, especially in financial sectors. The method used in this study is the ARIMA-GARCH model which is an integration of the well-established ARIMA model and GARCH model. This integration model is applied to gold prices and could help to handle the volatility characteristic presented in the data. The analysis of gold prices in this study focuses on modeling of gold prices by splitting the data before and during the pandemic. Thus, this method gives an insight into how the ARIMA-GARCH model performs with the data before and during the pandemic. Based on the study, the ARIMA-GARCH model produces a good result with a low value in MAE, RMSE and MAPE for both periods before and during the pandemic.

INTRODUCTION

The unprecedented declaration of the COVID-19 pandemic outbreak by World Health Organization (WHO) at the end of 2019 transforms all sectors including financial sectors into a massive shock. The pandemic, which the early cluster was detected in Wuhan and eventually later expanded over the world compelled each country to impose a severe lockdown to reduce the virus's spreaders [1]. Thus, these measures impacted the economy significantly since all the sectors need to slow down. As a result, investors must be careful in diversifying their portfolio to gain profit or at least minimise their lost despite the crisis.

One of the initiatives taken by investors during extreme market condition to diversify their portfolios is by investing in gold market. The gold market has long been seen as safe-haven against stock, inflation, and other financial market risks [2]. As a result, a gold price analysis is necessary to assist investors and banks in understanding and forecasting gold price. Analysis on the gold price has been studied in various literatures including Ali et al. [3], Lamouchi and Badkook [4], Yang [5] and Mohd Nasir et al. [6]. Ali et al. [3] focused on the gold price in United States while Mohd Nasir et al. [7] focus on the gold price in Malaysia. While Ali et al. [3] analysed on the gold price from 2014 to 2015 , Yang [5] studied on the gold price during a period between 2013 to 2018 with a similar pricing as in US dollar. All of the studies are essential because they assists investor understand gold as safe-haven asset, particularly during turbulence periods [4].

Due to the time series nature of gold prices, the Box-Jenkins model is one of the most popular model in forecasting gold prices[3]. In another study, Susruth [8] compared the Box-Jenkins model with the Holt and Winters exponential model as well as the Moving Average model. The author discovered that Box Jenkins model performs well and produces higher forecasting accuracy. This also confirms that Box-Jenkins model is considered as the benchmark model among time series models as mentioned in Abdelkader et al. [9], which studies gold prices. Thus, choosing Box-Jenkins model to compare the performance of the Box-Jenkins before and during pandemic for gold price data is considered appropriate.

Nevertheless, the gold prices data consist of volatility clustering that could be handled by Generalised Autoregressive Conditional Heteroscedastic (GARCH) model [4]. Thus, by integrating GARCH model with Autoregressive Integrated Moving Average (ARIMA) model would yield a good performance in forecasting. Yaziz et al. [12] applied

ARIMA-GARCH on gold prices and find a promising result. Incorporating the GARCH model into the ARIMA model could help in handling the non-constant variance errors in time series data [12]. Besides, Yousef and Shahadeh [13] considered GARCH model as an excellent model to identify the volatility in the world gold prices.

This study focuses on the performance of ARIMA–GARCH model in forecasting gold price by splitting the gold prices data into before and during the COVID-19 pandemic. In this study, the gold price data is examined from 3rd January 2015 until 30th July 2021 which is divided into two periods that are before pandemic and during pandemic. The duration before and during pandemic is considered to demonstrate that the forecasting performance would be influenced by the COVID-19 pandemic outbreak. With our limited understanding, it is hope that this study would prevail how well the model would perform within these two durations, before and during the pandemic and either COVID-19 could give effect towards the performance of ARIMA-GARCH model.

LITERATURE REVIEW

The application of Box-Jenkins-GARCH model models in economics and finance have been taken up by various researchers. The related recent studies are summarised in Table 1.

TABLE 1. Selected studies in economics and finance using Box-Jenkins-GARCH models

Researcher	Data	Model	Methods/Procedure
Bouazizi et al. (2020)	-Brent crude oil prices in dollars -The period start from 27th November 2019 to 04 February 2020 in levels	-ARMA, -ARMA-GARCH, -ARMA-EGARCH, -ARMA-GJR, -ARMA-APARCH, -ARMA-IGARCH	-Descriptive statistics -Transform gold price at time t into a return -ARIMA model identification: Akaikae Information Criterion (AIC), Bayesian Information Criterion (BIC) -GARCH model identification: AIC, BIC
Yaziz et al. (2019)	-Daily Malaysia gold price (5-day-per-week) -The data period is from 2nd January 2003 to 12th June 2014 (2845 observations) -The data is quoted in Ringgit -Estimation ratio (in-sample series) to forecast (out-of-sample series) is 90:10	-ARIMA - (standard GARCH, IGARCH and GARCH-M) under three types of innovations that are Gaussian, t and Generalized error distribution	-Transform data: Box-Cox method -Stationary test: ADF, ACF, PACF (first difference) -Model Estimation and Identification: ACF, PACF, AIC, SIC -Diagnostic Test: ARCH Lagrange multiplier (LM) test -Residuals: PACF, Ljung Box test, Jarque-Bera -Model estimation: Maximum likelihood estimation (MLE) -Evaluation: Root Mean Square Error (RMSE), Mean absolute error (MAE), Mean absolute percentage error (MAPE) *One-step ahead
Hasanah et al. (2019)	-Daily gold in bullion$/troy ounce rate -The period of data is from January 2014 to September 2016	-ARIMA-GARCH	-Transform gold price at time t into a return - Stationary Test: Augmented Dickey Fuller Test (ADF) - Model Identification: autocorrelation function (ACF), partial autocorrelation (PACF) - Model Estimation: AIC, Schwarz Information Criterion (SIC) - Diagnostic Check: residuals analysis - Heteroscedasticity Test: Breusch Pagan Godfrey's test (BPG test) - GARCH model estimation: ACF, PACF - Evaluation: Mean absolute percentage error (MAPE)

TABLE 1. Selected studies in economics and finance using Box-Jenkins-GARCH models (continued)

Researcher	Data	Model	Methods/Procedure
Kumari and Tan (2018)	-Gold future prices traded on the COMEX -The period of the data is from January 1990 to June 2014 -In-sample: January 1990 to June 2013 (6373 observations) -Out-of-sample: July 2013 to June 2014(238 observations)	-ARCH -GARCH -ARFIMA -EGARCH -APARCH -TARCH -FIGARCH -FIEGARCH	- Preliminary step: log return - Descriptive statistic - Stationary Test: ADF - Identification, PACF PP, - Parameter: ACF, PACF, AIC, Ljung Box Q-test - ARCH test: ARCH-LM test - Evaluation: MAE, MSE, QLIKE, TIC
Sopipan (2018)	- Daily closed gold prices from London Gold Market Fixing Limited on a day and foreign exchange rate for Baht to US dollars announced by TFEX - The period of data: 2/01/2015 to 31/3/2016(1 313) - In-sample: 291 observations, Out-of-sample: 23 observations	-ARIMA-GARCH	- Descriptive Statistic - Identification: ACF, PACF - Estimation: AIC, SBC - Diagnostic checking: Box-Piece (BP), Ljung-Box (LB) Q-statistic, Engles ARCH test
Senaviratna and Cooray, (2017)	- Daily gold prices in Sri Lanka (gold prices per gram (LKR)) - The period of data is from 02nd January 2007 to 06th January 2017 (2585 observations) -In-sample: 2580 observations, Out-of-sample: 5 observations	- ARMA -VAR-GARCH(EGARCH, -PGARCH, -C-ARCH, -GJR GARCH)	- Descriptive statistic - Stationary Test: ADF - Model parameters: ACF, PACF - Diagnostic test: Jarque-Bera test, Breusch-Godfrey LM test and White's general test - Estimating: VAR, GARCH (SIC, AIC, Hannan-Quinn, Durbin Watson stat - Evaluation:MAPE *Box-Cox transformation for data transformation

METHODOLOGY

Box-Jenkins Model

The five model types that make up the Box-Jenkins model are separated into two groups namely stationary models and non-stationary models. Three models—autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA) are the stationary models. The seasonal autoregressive integrated moving average (SARIMA) and the autoregressive integrated moving average (ARIMA) are the two models that represent the non-stationary model (SARIMA). The gold price data displayed a trend pattern without any evidence of seasonality, hence the ARIMA model was used for this investigation.

An autoregressive integrated moving average of order p and q with order of differencing, d, is written as ARIMA (p,d,q) model. The ARIMA (p,d,q) model using backshift operator is given by Equation (1),

$$\phi_p(B)(1-B)^d y_t = \theta_q(B)a_t. \quad (1)$$

Given that, $|\phi_i| < 1, i = 1,2,..p$, $|\theta_j| < 1, j = 1,2,..q$, $d \neq 0$, $\bigtriangledown = (1-B)$; y_t and a_t are the observed value and random error at time period $t\mu$ is the mean of the model, p and q are the order of AR and MA models respectively, d is the order of differencing, B is the backshift operator and which $\phi_p(B) = 1-\sum_{i=1}^{p} B^i$ for AR model and $\theta_q(B) = 1-\sum_{j=1}^{q} \theta_j B^j$ for MA model.

The random errors, a_t for all the previously mentioned equations in this chapter are assumed as independent identically distributed (iid) sequences taken from a continuous distribution with zero mean and constant variance of σ^2 which is denoted as $a_t \sim iid(0,\sigma^2)$.

GARCH Model

The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) is proposed by Bollerslev [17] to generalized the Autoregressive Conditional Heteroscedasticity (ARCH) model developed by Engle [18]. In GARCH model, the mean model is given in Equation (2) with s_t as a stationary data at time t and a_t as the random error at time period t. The μ_t is the conditional mean of s_t and $a_t = \sigma_t \varepsilon_t$ where ε_t is the innovations of the models and has zero-mean independent and identically distributed sequences with continuous distributions.

$$s_t = \mu_t + a_t \tag{2}$$

The standard GARCH model is expressed in Equation (3) as follows,

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{r} \alpha_i \alpha_{t-1}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-1}^2. \tag{3}$$

where α_i and β_j are the coefficient of the parameters ARCH and GARCH, respectrively. The volatility a_t is the random variable of σ_t. α_i and β_j are nonnegativelconstants $(\alpha_t \geq 0, \beta_t \geq 0)$ and α_0 is a positive constant $(\alpha_0 > 0)$. α_i and β_j should lies between 0 and 1 to satisfy the stationarity [18]. If $r = 0$, the GARCH(r, s) process reduces to the ARCH(s) process, and for $r = s = 0$, a_t is simply white noise.

Box-Jenkins-GARCH Model

Since ARIMA is one of the Box-Jenkins model, the research framework for this study is given by the Box-Jenkins-GARCH modelling as presented in Figure 1. The modelling of Box-Jenkin-GARCH integrates GARCH model into Box-Jenkins model that enables the handling of heteroscedasticity in the gold prices. The standard GARCH model is considered in the Box-Jenkins-GARCH modelling to highlight its parsimonious feature and its broad applications in handling heteroscedasticity in a financial time series [20]. The ratio of estimation used to forecast the time series data and for cross validation follows 90 to 10 ratio [21].

Stage I: Model identification

In the first stage of model identification, the gold price data is transformed by using Box-Cox transformation to ensure the stationarity of data in-variance. Then, the plots of auto-correlation function (ACF) and partial auto-correlation function (PACF) are used to check the stationarity of the in-sample data in-mean and identify the order of time series model. The ACF plots represent the linear relationship between the time series observations separated by lag k and suggesting the order of q for the MA model. The p order for the AR model could be identified in the partial auto-correlation function (PACF). The stationary in-mean is achieved by differencing the gold prices data and tested with the Augmented Dickey-Fuller (ADF) test. The null hypothesis of the ADF test is the time series data is non-stationary in-mean.

Stage II: Parameter estimation

In parameter estimation stage, the Maximum Likelihood Estimation (MLE) is employed to find the parameter values in Box-Jenkins modelling. The method optimizes the probability of obtaining the data that have been studied which minimises the sum of squared errors (SSE) given by $SSE = \sum_{t-1}^{T} \in_t^2$. The two conditions in considering the best significant Box-Jenkins model are: two times the value of standard error less than the value of model coefficient and the p-value$\leq \alpha$. Then, the model with the lowest value of Akaike's Information Criterion (AIC) and Schwarz's Bayesian Information Criterion (BIC/SIC) values is chosen for the next stage.

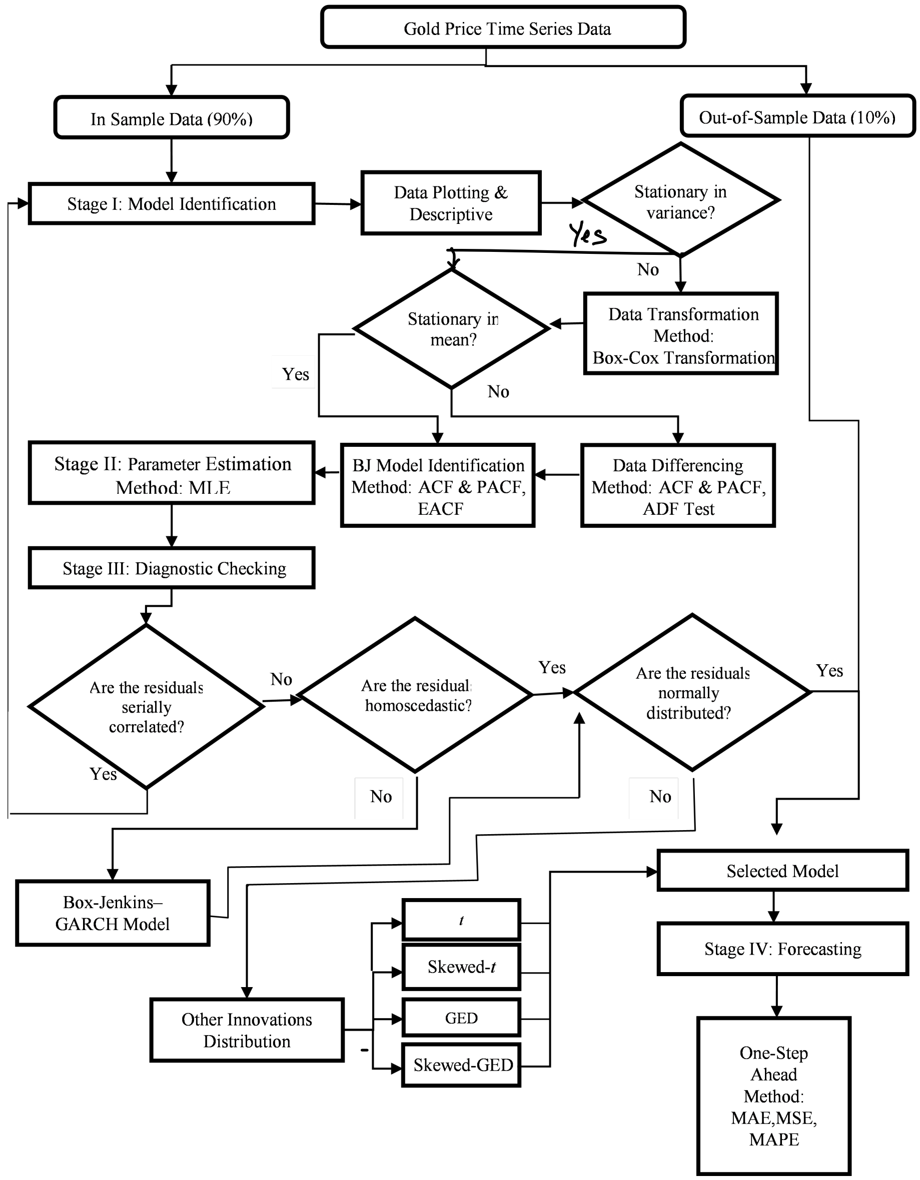


FIGURE 1. Research framework of Box-Jenkins-GARCH

Stage III: Diagnostic Checking

The chosen models from the previous stage are checked in the residual time series data for serial correlation, heteroscedasticity or ARCH effect, and normal characteristics. A well fitted model has small, estimated errors or residuals values, $\hat{a}$, a finite variance and normally distributed. The integration of the ARIMA model with the GARCH model is determined by the presence of the ARCH effect in the residuals. If the ARCH exists in the residuals, the appropriate GARCH model is chosen from the PACF for the squared residuals.

Stage IV: Forecasting

The performance of the model predictions is then assessed using the forecasted result. The validation process employs the following Equation (4), Equation (5), and Equation (6) to calculate the minimum mean mean absolute absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE), respectively,

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |y_i - \hat{y}_t| \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_i - \hat{y}_t)^2}{n}} \tag{5}$$

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n} \left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{6}$$

where y_t and $\hat{y}_t$ are the observed and forecast values at time t and n is the number of time periods t.

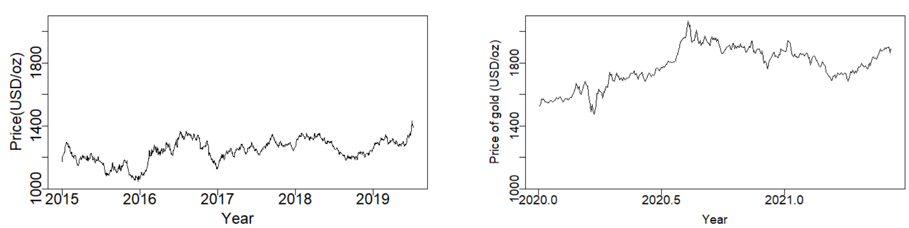
RESULTS AND DISCUSSION

The Dataset

The gold prices used in this study were collected through R Studio using the free Nasdaq Data Link R package, which is based on the London PM fix from the London Bullion Market Association (LBMA). The London Gold Fixing Companies determines and set the prices for Gold Fixing Companies and the international standard of gold price. The gold price is analysed from 3rd January 2015 until 30th July 2021 and are split into the period before pandemic and during pandemic with a total of 1652 observations. The period before pandemic starts from 3rd January 2015 to 30th December 2019 while from 1st January 2020 to 30th July 2022 is the period during pandemic with a total observations of 1254 and 398 observations, respectively. Syahri and Robiyanto [22] considered the start of pandemic is on 1st January 2020. They study on the correlation of gold, exchange rate and CSPI on the impact of Covid-19 pandemic. The data is analysed by using R programming language.

Stage I: Box-Jenkins-GARCH Model identification

The Figure 2(a) and Figure 2(b) illustrate the time series plot for in-sample data of gold prices before and during pandemic, respectively. The in-sample data for the gold prices before the pandemic begins on January 2, 2015, and ends on July 2, 2019, while the in-sample for the gold prices during the pandemic begins on January 2, 2020 and ends on June 4, 2021. In Fig.2, both series demonstrates a random or irregular trend with nonseasonal trends.



(a) Before pandemic from 2nd January 2015 to 2nd July 2019.

(b) During the pandemic from 2nd January 2020 to 4th June 2021

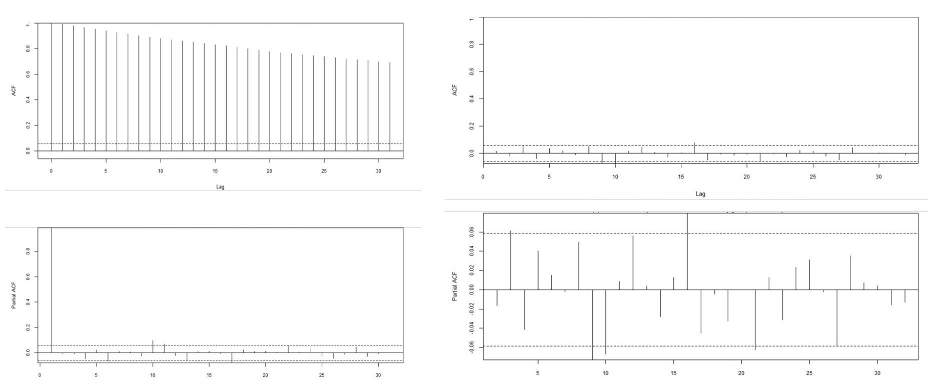
FIGURE 2. Time series plot for the in-sample data of the gold price.

Based on Figure 2(a), the gold prices plummeted at the close of 2016, 2017 and 2018 which stayed low price for a brief time before rebounding. Then as the year progressed, there were numerous ups and downs in the gold prices until the prices started to increase in 2019 with the highest peak at $1431.40. From Figure 2(b), the gold prices depict an upward trend from the early year of 2020 until it reaches the highest peak at the second half of 2020. Then, the gold prices start to show a downward trend after reaching the peaks in the second half of 2020 with an intense fluctuation throughout the period. Because there is no repeated, regular pattern as demonstrated in the time series plot, neither series in Figure 2(a) nor Figure 2(b) are cyclical or seasonal. Based on the lambda value derived from Box-Cox transformation is close to 1 for both in-sample data before the pandemic and during the pandemic. Therefore, a transformation is not considered as the process since both data are considered stationary in variance. Both series, however, are non-stationary in the mean because of irregular trends from the beginning. Furthermore, the ADF-test is utilised to validate the non-stationarity in-mean for both series, with p-values of 0.2118 and 0.7021, before and during the pandemic, respectively. Because the null hypothesis is not rejected at the 5% significance level, the values validate the non-stationary in-mean of the series.

Table 2 shows the comparison of gold prices for in-sample data before and during the pandemic for both stationary and non stationary data for the descriptive statistics component. The highest gold prices were $2067.15 per ounce from January 2, 2015, to July 30, 2021. Moreover, during the pandemic, the minimum, median, and mean of the gold prices were at their highest. Thus, the values of minimum, median and mean, imply that the prices of gold experienced an increment during the COVID-19 pandemic. As seen in Table 2, the variance between the in-sample non-stationary data of gold prices before pandemic and during the pandemic are 5 129.32 and 15 496.67, respectively. Based on the variance, the data of in-sample non-stationary gold prices, spreads more during COVID-19 as compared to before pandemic. Thus, the finding demonstrates that the COVID-19 pandemic had a significant impact on gold prices as gold prices surged throughout the crisis which is consistent with Lamouchi and Badkook [4].

TABLE 2. Descriptive statistics for in-sample non-stationary data and stationary data before and during pandemic.

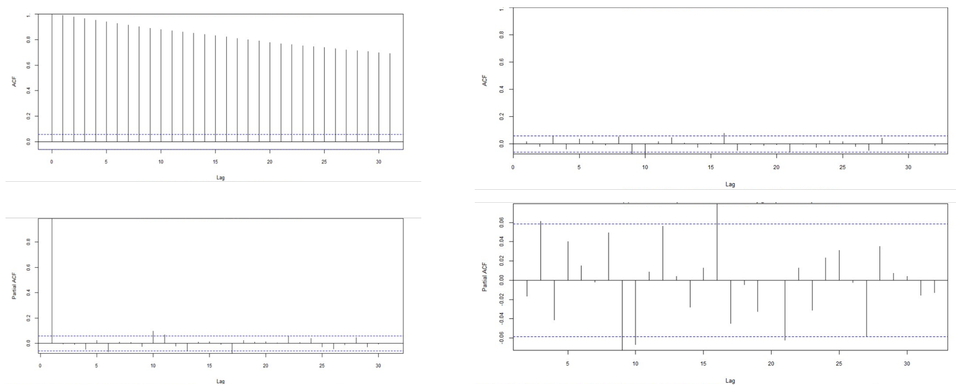
Statistics	Before Pandemic (2/1/2015 – 2/7/ 2019)		During Pandemic (2/1/2020 – 4/6/2021)	
	Non-stationary data	Stationary Data	Non-stationary data	Stationary Data
No of observation	1129	1128	358	357
Minimum	1049.4	-35.3	1474.25	-104.85
Maximum	1431.4	53.35	2067.15	80.35
Mean	1242.33	0.1942	1779.23	1.02
Median	1251.1	-0.15	1787.83	1.65
Variance	5129.32	96.84	15496.67	438.28
Standard Deviation	71.6192	9.841	124.4856	20.935
Skewness	-0.5256	0.3269	-0.3289	-0.5736
Kurtosis	-0.1958	2.5084	-0.687	3.3842



(a) Before the data undergo first order differencing transformation.

(b) After the data undergo first order differencing transformation.

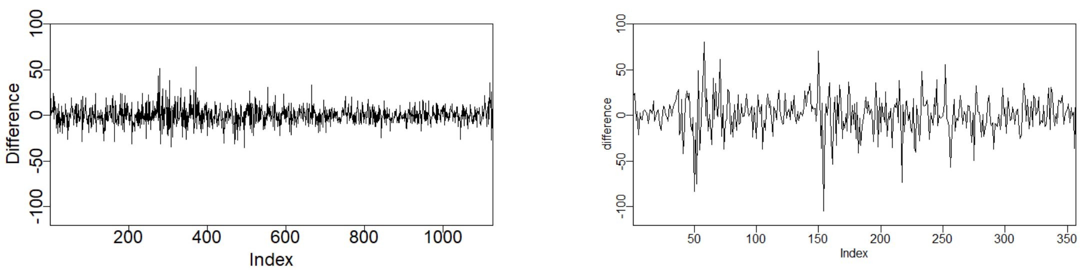
FIGURE 3. ACF and PACF plots for in-sample gold prices data before pandemic 2nd January 2015 to 2nd July 2019.



(a) Before the data undergo first order differencing transformation.

(b) After the data undergo first order differencing transformation

FIGURE 4. ACF and PACF plots for in-sample gold prices data during the pandemic from 2nd January 2020 to 4th June 2021



(a) Before pandemic from 2nd January 2015 to 2nd July 2019.

(b) During the pandemic from 2nd January 2020 to 4th June 2021

FIGURE 5. Time series plot for the first order differenced in-sample data of the gold price.

In Figure 3(a) and Figure 4(a), both ACF and PACF plots before and during pandemic for the gold prices data before the data undergo first order differencing transformation display that the correlograms have no drastic cut off. Thus, the figures confirm both data before and during pandemic need to be transformed with the first order differenced to ensure there is stationarity in-mean in the series. After the first order differencing, the ACF and PACF plots for both before and during pandemic confirm the existence of stationarity for in-sample data before and during pandemic. The ACF and PACF plots before and during pandemic for the first order difference data are depicted in Figure 3(b) and Figure 4(b). Thus, the first order difference data before and during pandemic are used to estimate the parameter of ARIMA model. Figure 5 illustrates the plot of in-sample gold price data before and during the pandemic that confirm to be stationary in-mean, after the first order differencing transformation.

Stage II and Stage III:Parameter estimation and Diagnostic Checking

Table 3 illustrates all the possible models of ARIMA model before and during pandemic, with the value of AIC, BIC, and the parameter significance value. Based on the values of AIC, BIC and significant on parameters, model ARIMA (1,1,1) and model ARIMA (2,1,2) are chosen as the most suited models before and during pandemic, respectively. The models are chosen since both models are considered to be significant at 5% significance level. For all the feasible models before the pandemic, model ARIMA (1,1,1) has the lowest value of AIC and BIC which are 8363.51 and 8383.62, respectively. While, ARIMA (2,1,2) has the lowest value of AIC and BIC of all the potential models for during pandemic, with 3180.65 and 3207.79, respectively.

The descriptive statistics of the series residuals for ARIMA (1,1,1) and ARIMA (2,1,2) are listed in Table 4 to ensure the models' residuals have a generally small, randomly distributed and homoscedasticity characteristics. Both ARIMA (1,1,1) and ARIMA (2,1,2) show that the p-value of Jarque Bera (JB) test is less than $\alpha = 0.05$, therefore the null of hypothesis of the residuals series are normally distributed is rejected.

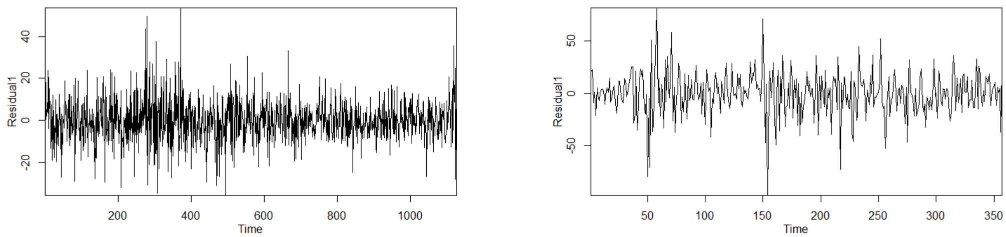
TABLE 3. Possible time series models of ARIMA model before and during pandemic.

No	ARIMA (p,d,q)	Before Pandemic				During Pandemic			
		2*SE < Coefficient	AIC	BIC	Significant on parameters	2*SE < Coefficient	AIC	BIC	Significant on parameters
1	ARIMA (0,1,0)	No	8362.59	8372.65	All not significant	No	3187.7	3195.45	All not significant
2	ARIMA (0,1,1)	No	8364.26	8379.35	All not significant	No	3189.7	3201.33	All not significant
3	ARIMA (0,1,2)	No	8365.83	8385.94	All not significant	No	3189.21	3204.72	1 not significant
4	ARIMA (0,1,3)	No	8363.42	8388.56	2 not significant	No	3190.6	3209.99	2 not significant
5	ARIMA (1,1,0)	No	8364.27	8379.36	All not significant	No	3189.7	3201.33	All not significant
6	ARIMA (1,1,1)	Yes	8363.51	8383.62	All significant	Yes	3191.7	3207.21	All significant
7	ARIMA (1,1,2)	Yes	8364.6	8389.75	1 not significant	Yes	3191.1	3210.49	1 not significant
8	ARIMA (1,1,3)	No	8363.99	8394.16	3 not significant	No	3186.37	3209.64	1 not significant
9	ARIMA (2,1,0)	No	8365.96	8386.07	All not significant	No	3190	3205.51	1 not significant
10	ARIMA (2,1,1)	No	8364.46	8389.6	1 not significant	No	3191.84	3211.22	All not significant
11	ARIMA (2,1,2)	Yes	8367.49	8397.65	All significant	Yes	3183.34	3206.61	All significant
12	ARIMA (2,1,3)	Yes	8361.08	8396.28	1 not significant	Yes	3180.65	3207.79	All significant
13	ARIMA (3,1,0)	No	8363.68	8388.82	2 not significant	No	3191.06	3210.45	2 not significant
14	ARIMA (3,1,1)	No	8363.37	8393.54	2 not significant	No	3185.44	3208.71	1 not significant
15	ARIMA (3,1,2)	No	8360.94	8396.14	1 not significant	Yes	3181.77	3208.91	All significant
16	ARIMA (3,1,3)	No	8362.51	8402.74	All not significant	No	3181.77	3212.79	1 not significant

TABLE 4. The descriptive statistics of the series residuals of ARIMA(1,1,1) model and ARIMA(2,1,2) model.

Statistics	**Before pandemic**	**During pandemic**
No of observation	1128	357
Minimum	-35.5706	-96.9315
Maximum	53.5799	81.2031
Mean	-0.00102	-0.005025
Median	-0.3536	0.906
First Quartile	-5.4811	-10.4089
Third Quartile	4.9664	12.194
Sum	-1.1506	-1.7938
Variance	96.5797	422.9672
Standard Deviation	9.8275	20.5662
Skewness	0.3227	-0.4478
Kurtosis	2.5174	2.8389
JB Test (p-value)	319.7942 (0.0000)	39.2060 (0.0000)

The residual plots for both ARIMA (1,1,1) and ARIMA (2,1,2) models in the Figure 6 below show that the models are randomly distributed, and correlation is almost close to zero. The Ljung-Box (LBQ) test is used to validate the serial correlation of the residual series for both models. The LBQ Test on ARIMA (1,1,1) and ARIMA (2,1,2) models yielded p-value of 0.5054 and 0.1825, respectively which indicate the mean equation ot ARIMA (1,1,1) and ARIMA (2,1,2) to the data series are correctly specified up to lag 10. As a result, the in-sample residual series of the gold prices prior to pandemic and during the pandemic are independent and randomly distributed. Thus, the ARIMA (1,1,1) and ARIMA (2,1,2) are considered adequate to describe the data for the gold prices data prior the pandemic and during the pandemic respectively.

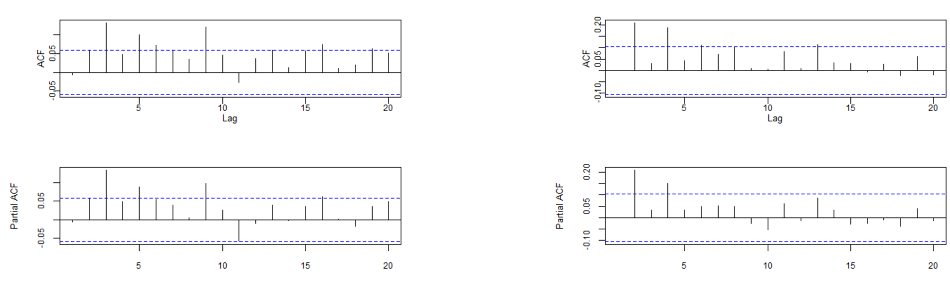


(a) ARIMA(1,1,1) model **(b)** ARIMA(2,1,2) model

FIGURE 6. Residual plot of the squared residuals for ARIMA models.

Based on the p-value of the Ljung-Box test on the squared residual for both ARIMA (1,1,1) and ARIMA (2,1,2) at lag 10 equal 0.000, the null hypothesis of there is no ARCH effect in the residuals series is rejected at 5% significance level. Thus, the integration of GARCH model with ARIMA model is needed to correctly specified the variance equation for both ARIMA (1,1,1) and ARIMA (2,1,2) models which represents for the gold prices data before and during pandemic, respectively. The ACF and PACF plots of squared residuals of both ARIMA (1,1,1) and ARIMA (2,1,2) are used to obtain the order of r and s in GARCH model. Figure 7(a) and Figure 7(b) illustrate the ACF and PACF plots of square residuals for ARIMA(1,1,1) model and ARIMA (2,1,2) model, respectively. Based on the Figure 7(a) the suggested values of r are 0,1,2 and the suggested values of s are 0,1,2. The standard error (SE) limit of two-standard error ACF and two-standard error of PACF in Figure 7(a) are 0.0309 and 0.0298, respectively. Based on the results in the ACF and PACF of the squared residuals of ARIMA model in Figure 7(a), ARIMA (1,1,1)-GARCH (1,1) is chosen as the preferred model for the data before the pandemic. Hence, Table 5 shows that ARIMA (1,1,1)-GARCH(1,1) is the most appropriate model for the gold price data before the pandemic with skewed-GED innovations based on the significance, AIC and BIC.

In Figure 7(b), it is suggested values of r is 1,2 and s is 1,2. Based on Figure 7(b), the series consist of a volatility clustering since there are several spikes in ACF and PACF plots at the beginning of the plots that are beyond two-standard error (SE) limit of two-standard error of ACF = 0.0549 and two-standard error of PACF = 0.0529. The plots also imply that the model of ARIMA(2,1,2) is significant up to lag 20. he ARIMA (2,1,2)-GARCH (1,1) is chosen as the most appropriate model to forecast the data during the pandemic based on the results in the ACF and PACF of the squared residuals of ARIMA model in Figure 7(b). Besides, Table 6 shows that the model is the most appropriate model to represent the gold price data during pandemic.



(a) ARIMA(1,1,1) model **(b)** ARIMA (2,1,2) model

FIGURE 7. ACF and PACF plots of the squared residuals for ARIMA models.

Table 5 lists out the Information Criterion test, and diagnostic checking for ARIMA(1,1,1)–GARCH(1,1) for the model estimated by using the data before pandemic. Model ARIMA(1,1,1)–GARCH(1,1) with skewed-GED innovations is chosen for the next forecasting step for the data gold data prior to pandemic, based on the models' significance, AIC, and BIC.

TABLE 5. Estimation results, information criterion test and diagnostic checking for ARIMA(1,1,1)–GARCH(1,1) model

Parameter	Innovations				
	normal	t	Skewed-t	GED	Skewed-GED
	Parameter Estimation				
μ	0.0455 (0.8010)	-0.0283 (0.8639)	0.0690 (0.6853)	-0.0700 (0.6532)	0.0594 (0.7244)
φ_1	0.3775 (0.2190)	0.3781 (0.0983)	0.4065 (0.0596)	0.3693 (0.0000)	0.3984 (0.0000)
θ_1	-0.3352 (0.2860)	-0.3405 (0.1447)	-0.3738 (0.09108)	-0.3389 (0.0000)	-0.3713 (0.0000)
α_0	0.4437 (0.1030)	0.7111 (0.1067)	0.6844 (0.1115)	0.5827 (0.12613)	0.5540 (0.1287)
α_1	0.0237 (0.0000)	0.0249 (0.00298)	0.0246 (0.00313)	0.0234 (0.0022)	0.0227 (0.0021)
β_2	0.9720 (0.0000)	0.9683 (0.0000)	0.9689 (0.0000)	0.9705 (0.0000)	0.9715 (0.0000)
ς	-	-	1.0646 (0.0000)	-	1.0690 (0.0000)
ν	-	5.5840 (0.0000)	5.6041 (0.0000)	1.2987 (0.0000)	1.2980 (0.0000)
	Information Criterion (IC)test				
AIC	7.3318	7.2814	7.2809	7.2809	7.2796
BIC	7.3586	7.3126	7.3166	7.3121	7.3153
	Diagnostic Checking				
LBQ(10)	18.4032 (0.0485)	18.7350 (0.0438)	18.8380 (0.0424)	18.8140 (0.0427)	18.9240 (0.0412)
LBQ(15)	22.3270 (0.0995)	22.5110 (0.0951)	22.6649 (0.0915)	22.6480 (0.09191)	22.8100 (0.0883)
LBQ2(10)	9.8452 (0.4542)	9.6026 (0.4760)	9.6689 (0.4700)	9.9625 (0.4438)	10.2250 (0.4210)
LBQ2(15)	15.8670 (0.3910)	15.6910 (0.4029)	15.8540 (0.3918)	15.9340 (0.3864)	16.2750 (0.3640)

The Information Criterion test and diagnostic checking for ARIMA (2,1,2)–GARCH (1,1) for the model during pandemic are listed in Table 6. The forecasting stage for the gold price data during pandemic applies ARIMA (2,1,2)–GARCH (1,1) model with normal innovations since it is considered as the appropriate model.

TABLE 6. Estimation results, information criterion test and diagnostic checking for ARIMA(2,1,2)–GARCH(1,1) model

Parameter	**Innovations**				
	normal	**t**	**Skewed-t**	**GED**	**Skewed-GED**
	Parameter Estimation				
μ	1.1340 (0.361)	1.1161 (0.030)	0.7798 (0.1832)	2.3225 (0.0017)	2.0010 (0.0391)
φ_1	0.4905 (0.0004)	1.0000 (NA)	1.0000 (NA)	0.4452 (0.0000)	0.4405 (0.0000)
φ_2	-0.6219 (0.0000)	-0.6070 (0.0004)	-0.5860 (0.0132)	-0.8005 (0.0000)	-0.7778 (0.0000)
θ_1	-0.4730 (0.0000)	-0.9539 (NA)	-0.9546 (NA)	-0.4338 (0.0000)	-0.4290 (0.0000)
θ_2	0.73566 (0.0000)	0.5527 (0.0129)	0.5208 (0.0732)	0.86650 (0.0000)	0.8515 (0.0000)
α_0	28.72842 (0.03193)	22.4626 (0.0813)	23.5669 (0.0685)	25.3003 (0.0800)	25.8106 (0.0711)
α_1	0.1149 (0.00173)	0.1137 (0.0182)	0.1118 (0.0176)	0.1176 (0.0127)	0.1147 (0.0117)
β_1	0.8236 (0.0000)	0.8528 (0.0000)	0.8500 (0.0000)	0.8308 (0.0000)	0.8306 (0.0000)
ς	-	-	0.9209 (0.0000)	-	0.9780 (0.0000)
ν	-	4.1567 (0.0000)	4.2990 (0.0001)	1.1542 (0.0000)	1.1794 (0.0000)
	Information Criterion (IC) Test				
AIC	8.84	8.7619	8.7643	8.767	8.7723
BIC	8.9269	8.8597	8.873	8.8648	8.8809
	Diagnostic Checking				
LBQ(10)	10.7411 (0.3780)	14.3172 (0.1590)	14.4169 (0.1548)	13.6697 (0.1886)	13.3023 (0.2073)
LBQ(15)	14.2770 (0.5046)	19.2361 (0.2032)	19.4204 (0.1953)	16.9767 (0.3203)	16.5566 (0.3461)
LBQ2(10)	18.4913 (0.0472)	21.5045 (0.0178)	21.4246 (0.0183)	19.6421 (0.0328)	19.3036 (0.0366)
LBQ2(15)	21.7350 (0.1149)	23.7644 (0.0692)	23.7140 (0.0701)	22.1458 (0.1040)	21.8887 (0.1108)

Stage IV: Forecasting

ARIMA (1,1,1)–GARCH (1,1) model with skewed-GED innovation in the stationary form to forecast the gold prices before the pandemic is given by Equation (7) where $S_t = y_t - y_{t-1}$ and $a_t = \sigma_t \varepsilon_t$ are the stationary series and random error. The innovations at time t is given by Equation (8).

$$S_t = 0.05938 - 0.6016_{t-1} - 0.3984 S_{t-2} + a_t - 0.3713 a_{t-1}. \tag{7}$$

$$\sigma_t = 0.5540 + 0.02777 a_{t-1}^2 + 0.9714 \sigma_{t-1}^2, \varepsilon_t \sim SGED_{1.2980}^* \tag{8}$$

S_{t-1}, S_{t-2}, y_t, y_{t-1}, and a_{t-1} are the stationary series up to lag 1 (or the previous value), stationary series up to lag 2, the observed values, the predictor up to lag 1 (or the previous value), and the random error up to lag 1 (or the previous value), respectively and σ_t^2 is the conditional variance of S_t. Moreover, ε_t represents the innovations at time t.

The actual stationary gold prices data, forecast stationary gold prices data, actual gold prices data, forecast gold prices data, 95% lower and 95% upper intervals before the pandemic for the last 10 days by using ARIMA (1,1,1) – GARCH (1,1) model is compared in Table 7. For the stationary data, the values of MAE and RMSE are 8.7966 and 12.1381, respectively. The value of MAPE is not obtained since the series consists of zero values. Nevertheless, the out-of-sample's forecast data generates the value of MAE, RMSE and MAPE equal to 8.7966, 12.1381 and 0.5944, respectively. With a small prediction error of MAPE that is below 5%, the model is concluded as the best model for modelling gold price data before pandemic. Figure 8(a) displays a plot of actual data versus forecast data of the gold prices before pandemic by using ARIMA(1,1,1)–GARCH(1,1) model with skewed-GED. The red colour forecast line and blue colour of actual gold price data show a small gap throughout the period.

TABLE 7. Actual stationary gold prices data, forecast stationary gold prices data, actual gold prices data, forecast gold prices data, 95% lower and 95% upper intervals for last 10 days using ARIMA(1,1,1)–GARCH(1,1) model

Date	Actual Stationary Gold Prices	Forecast Stationary Gold Price	Actual Gold Prices Data (USD/oz)	Actual Gold Prices Data (USD/oz)	Lower 95%	Upper 95%
12/12/2019	1	-4.988	1467.8	1461.81	1428.44	1495.18
13/12/2019	-1.2	-2.772	1466.6	1465.03	1431.66	1498.4
16/12/2019	11.3	-0.4002	1477.9	1466.2	1432.83	1499.57
17/12/2019	-2.1	3.1785	1475.8	1481.08	1447.71	1514.45
18/12/2019	-1.75	1.9186	1474.05	1477.72	1444.35	1511.09
19/12/2019	2.65	3.2424	1476.7	1477.29	1443.92	1510.66
20/12/2019	2.3	1.381	1479	1478.08	1444.71	1511.45
23/12/2019	3.1	1.3286	1482.1	1480.33	1446.96	1513.7
27/12/2019	29.4	0.283	1511.5	1482.38	1449.01	1515.75
30/12/2019	3.25	-0.1363	1514.75	1511.36	1478	1544.73

ARIMA (2,1,2)–GARCH (1,1) model with normal distribution in the stationary form, to forecast the gold prices during the pandemic is given by Equation (9). $S_t = y_t - y_{t-1}$ and $a_t = \sigma_t \varepsilon_t$ are applied to calculate the stationary series and random error.

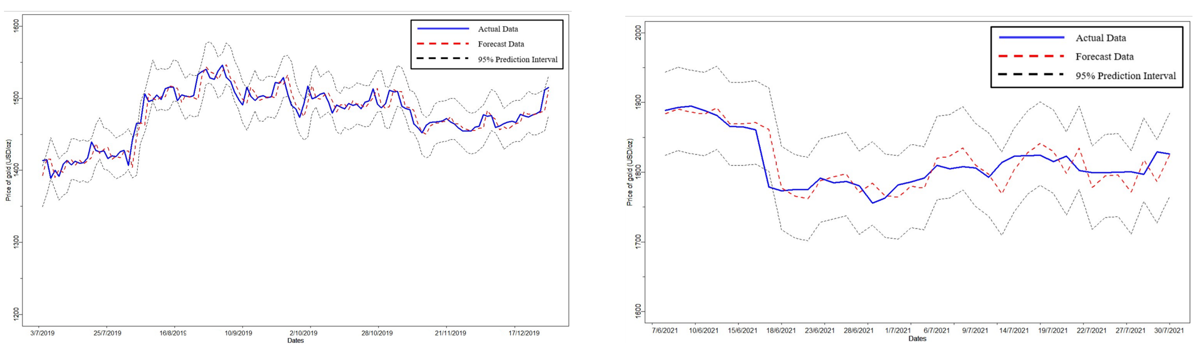
$$S_t = 1.134 + 1.4910 S_{t-1} - 1.1124 S_{t-2} - 0.6219 S_{t-3} + a_t - 0.4730 a_{t-1} + 0.7357 a_{t-2}. \tag{9}$$

S_t, S_{t-1}, S_{t-2}, S_{t-3}, y_t, y_{t-1}, a_t, a_{t-1} and a_{t-2} are the stationary series, stationary series up to lag 1 (or the previous value), stationary series up to lag 2, stationary series up to lag 3, the observed values, the predictor up to lag 1 (or the previous value), the random error at time period t, the random error up to lag 1 (or the previous value) and r the random error up to lag 2, respectively and σ_t^2 is the conditional variance of S_t. Moreover, ε_t represents the error distribution as independent and identically distributed (IID) innovations at time t.

Table 8 compares actual stationary gold prices data, forecast stationary gold prices data, actual gold prices data, forecast gold prices data, 95% lower and 95% upper intervals before pandemic during pandemic for the last 10 days by using ARIMA(2,1,2)–GARCH(1,1) model. The MAE and RMSE values for stationary data are 15.1751 and 21.4967, respectively. Because the series contains zeros values, MAPE cannot be calculated. Nonetheless, the MAE, RMSE, and MAPE values for the out-of-sample forecast data are 15.1751, 21.4967 and 0.8409, respectively. The model is concluded as the best model for modelling gold price data during the pandemic, with a MAPE prediction error of less than 5%. Figure 8(b) shows a plot of actual data versus forecast gold prices prior to the pandemic by using ARIMA(2,1,2)–GARCH(1,1) model with normal innovations.

TABLE 8. Actual stationary gold prices data, forecast stationary gold prices data, actual gold prices data, forecast gold prices data, 95% lower and 95% upper intervals for last 10 days using ARIMA (2,1,2)–GARCH(1,1) model

Date	Actual Stationary Gold Prices	Forecast Stationary Gold Price	Actual Gold Prices Data (USD/oz)	Actual Gold Prices Data (USD/oz)	Lower 95%	Upper 95%
16/7/2021	-9.4	5.1709	1814.9	1829.471	1769.754	1889.187
19/7/2021	8.15	16.8101	1823.05	1798.09	1738.373	1857.807
21/7/2021	-20.9	11.6751	1802.15	1834.725	1775.008	1894.442
22/7/2021	-2.7	-24.3557	1799.45	1777.794	1718.078	1837.511
23/7/2021	0.15	-5.0379	1799.6	1794.412	1734.695	1854.129
26/7/2021	0.6	-3.9654	1800.2	1795.635	1735.918	1855.351
27/7/2021	0.15	-29.0167	1800.35	1771.183	1711.467	1830.9
28/7/2021	-3.75	17.3656	1796.6	1817.716	1757.999	1877.432
29/7/2021	32.7	-9.7273	1829.3	1786.873	1727.156	1846.589
30/7/2021	-3.55	-4.493	1825.75	1824.807	1765.09	1884.524



(a) Before pandemic with ARIMA (1,1,1)–GARCH (1,1) model with skewed-GED innovation.

(b) During pandemic by using ARIMA (2,1,2)–GARCH (1,1) model with normal distributions innovations.

FIGURE 8. Plot of actual data versus forecast data with 95% prediction intervals of the gold prices data

Table 9 shows the MAE, RMSE and MAPE values for the ARIMA (1,1,1) – GARCH (1,1) and ARIMA (2,1,2) – GARCH (1,1) models before and during pandemic, respectively. In overall, the Box-Jenkins–GARCH model performs better before the pandemic as compared to during pandemic. Nevertheless, the performance of the model could be affected by the varied length of data, as the data used for modelling stage before pandemic had a higher number of observations than data used during the pandemic. For future research, this may be overcome by using an equal number of observations for both periods. Nonetheless, both models managed to achieve MAPE values less than 5%.

TABLE 9. The value of MAE, RMSE and MAPE for ARIMA(1,1,1)–GARCH(1,1) and ARIMA(2,1,2)–GARCH (1,1) for the gold price before and during pandemic.

Model	Forecast Evaluation		
	MAE	RMSE	MAPE
ARIMA (1,1,1)–GARCH (1,1) (Before pandemic)	8.7966	12.1381	0.5944
ARIMA (2,1,2)–GARCH (1,1) (During pandemic)	15.175	21.4967	0.8409

The model obtained from the data utilised preceding to and during the COVID-19 pandemic are ARIMA (1,1,1) –

GARCH (1,1) and ARIMA (2,1,2) – GARCH(1,1), respectively. Both models are statistically significant for the data before and during pandemic, respectively with a low value of MAE, RMSE and MAPE. However, in comparison for both ARIMA-GARCH models, ARIMA-GARCH model perform marginally better in the data prior to pandemic.

CONCLUSION

The model obtained from the data utilised preceding to and during the COVID-19 pandemic are ARIMA (1,1,1) – GARCH (1,1) and ARIMA (2,1,2) – GARCH (1,1), respectively. Both models are statistically significant for the data before and during pandemic, respectively with a low value of MAE, RMSE and MAPE. However, in comparison for both ARIMA-GARCH models, ARIMA-GARCH model perform marginally better in the data prior to pandemic. Thus, this research revealed a new insight about how the ARIMA-GARCH model behaves with the data before and during the COVID-19 pandemic. It is advisable that, future studies to make a thorough review, whenever a modelling and forecasting are performed on the gold prices data involving period of financial turmoil.

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