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Gold price volatility and forecasting evaluations with the impact of COVID-19 pandemic

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Abstract

Gold is a precious metal that has always been recognized as a safe-haven investment for many defensive investors. As compared to the stock market, gold is considered less volatile. In early 2020, the Covid-19 pandemic has caused turbulence in the financial market. It is believed that the pandemic has affected the volatility of gold market. This study aims to investigate the volatility of gold market before the Covid-19 pandemic and during the pandemic using several different models including GARCH, EGARCH and GJR-GARCH. The use of EGARCH and GJR-GARCH is meant to capture the leverage effect of the market in order to have a better volatility forecast. With the results from the analysis, other financial applications such as determining value-at-risk and forecasting can be done. The results of this study act as a good reference to investors who are interested in gold investment.

Subject Classification: *91B25, 91B30, 37M10.*

Keywords: *GARCH, Gold market, Value-at-risk.*

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1.0 Introduction

The history of gold can be traced back to 2000 B.C when the ancient Egyptians started forming jewelry. Gold started to act as currency in 560 B.C. The reason of the emergence of this currency was that merchants wanted to create a standardized and easily transferable form of money that would simplify trade (Brock, 2011). Following this, the world was on a gold standard in the 1870s. The gold standard is a monetary system where a country's currency is directly linked to gold. Countries that use gold standard preset a fixed price of gold relative to their currencies and buy or sell gold at that price (Lioudis, 2021). During that time, gold was still used for payments. Fast forward to 100 years later after the world abandoned the gold standard, people did not give up on the precious metal and instead started trading gold in the exchange market. The first gold futures emerged and was traded on COMEX in the year 1974. The 1980s experienced a sharp expansion of over-the-counter (OTC) trading in currencies and gold and the beginning of online trading (The Local, 2021).

Ever since then, gold has always been considered as a safe-haven metal for investment. It is a metal that always has its value and acts as an insurance when all other forms of currencies do not work. Owning gold can hedge against financial uncertainties, inflation and deflation. Adding gold into an investor's portfolio is also a good way to diversify their investments. According to Daltorio (2021), although the U.S. dollar is one of the world's most important reserve currencies, when the value of the dollar falls against other currencies as it did between 1998 and 2008, people tend to flock to the security of gold, which raises gold prices. Daltorio (2021) also mentioned that the price of gold nearly tripled between 1998 and 2008, reaching the $1,000-an-ounce milestone in early 2008 and nearly doubling between 2008 and 2012, hitting around the $1800-$1900 mark.

During times of inflation, most stocks on the stock market tend to plunge whereas the price of gold tends to soar. The reason behind this is that inflation implies a drop of value in fiat currency, causing gold to be priced as those currency units and so the rise in gold price. The economy is weak during times of deflation, this causes people to hold onto valuable items such as the precious metal gold. As a result, gold prices tend to soar while most items out there are losing their values. Gold is sometimes called the "crisis commodity" as it is one of the safest investments during times of crisis. People tend to turn to gold during times of uncertainties and this causes gold to outperform many other investments.

Back in the olden days, gold was traded in the form of gold bullion or gold bar. It was somewhat unsafe to hold onto real gold due to its value, which had raised concerns for many investors. However, it is now easy to trade or invest in gold with derivatives because holding a derivative is much safer than holding real gold. During the Covid-19 outbreak, the price of gold hit its all-time high at around $2,070. It is believed that the Covid-19 pandemic had greatly affected gold volatility. The following analysis were done on the volatility of gold price using ARMA, GARCH and GJR-GARCH models in MATLAB. Results from the analysis were used to further investigate the market condition of gold by forecasting the return of gold and calculating the value-at-risk (VaR) of holding gold.

Volatility is defined to be uncertainty or instability in the English literature. When brought into the context of finance, volatility measures the instability of price movements in the market. Most of the time, the market is considered volatile when there are big swings in the price movements. Volatility is an important factor in the selection of asset. In the first half of the 20th century, researchers who worked on volatility had always assumed volatility to be constant over time which resulted in poor financial models. In the 1980s, Robert F. Engle came up with a model named autoregressive conditional heteroskedastic (ARCH) which had greatly improved the modeling of financial time series. ARCH is a time series model that allows volatility to change over time (Engle,1982), which is a very important aspect in risk management. By allowing the volatility to change, researchers can better forecast future volatility and estimate future stock price movements. Using the ARCH model, risk can be better managed and financial derivatives can be better priced.

Forecasting is one of the important studies in financial market analysis. The accuracy of return and volatility is crucial to provide an accurate risk assessment. A good review of volatility forecasts can be found in the article by Poon and Granger (2003). A combination of forecast methods also provided improvement in the forecast evaluations (Chin and Lee, 2021; Timmermann, 2006). In recent years, some advanced methods have been proposed to improve the accuracy of forecasting. These include artificial intelligence-based methods (Jia and Xiang, 2022), temporal convolutional network-based methods (Zhang et al., 2022), hybrid of particle swarm optimization and group method of data handling (Yuan, 2017), and machine learning approaches (Mailagaha, Lohrmann, Luukka, Porras,2022), among others.

With the development of the ARCH model, Engle won himself the Nobel Memorial Prize in Economics in the year 2003. The name "ARCH" comes from the definition of autoregressive, which means future values depend on past values. The term conditional heteroskedastic refers to the dependency of variance on past variance. An ARCH model normally will weight recent returns more than past returns, which is analogous to the financial market. Several models had been developed following the development of ARCH including the generalized ARCH (GARCH), EGARCH, and Glosten, Jagannathan and Runkle-GARCH (GJR-GARCH). The latter two are extensions of GARCH, which allow the model to capture asymmetry in the financial market. Asymmetry in the market measures leverage effects, where bad news will have a greater impact on volatility than good news. The autoregressive integrated moving average (ARIMA) model is also an important model to better understand and to forecast future values of time series data. This study will analyze the volatility of gold price using the models stated above along with the Box- Jenkins method. The ARIMA model is used to analyze the return series of gold from year 2015 to year 2021 and to forecast future return. On the other hand, the GARCH family models are used to analyze squared return of gold.

It is believed that the gold market has been greatly affected by the Covid-19 pandemic, bringing the commodity to its all-time high in August 2020. This study will analyze the effect of Covid-19 pandemic to the gold market. With the use of ARIMA and GARCH family models, forecasts can be done on the return and volatility of gold. This will help investors examine risk as well as expected return before investing in gold.

The Box-Jenkins method, named after its creators George Box and Gwilym Jenkins is a time series modelling method that consists of three phases (Box et al., 2016). Phase one of the method is the model identification and model selection stage. In this stage, the stationarity of time series data is checked. Differencing is needed if the data shows trends of nonstationarity. The autocorrelation function (ACF) and partial autocorrelation function (PACF) are also used in this stage to check for suggestion of which ARIMA(p, d, q) model (if any) will be fitted.

Moving on to phase two of the process, parameter estimation and diagnostic are done. From phase one, some potential ARIMA(p, d, q) models will be suggested, the Box-Jenkins method then uses a computational algorithm to estimate the coefficients of the potential models. A model will be selected from a set of potential models based on certain criterion. In this study, the Akaike information criterion (AIC) and Bayesian information criterion (BIC) will be used to find the best fitting model. Once the best fitting model has been selected, the process will carry on to the diagnostic stage, where the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residual series will be checked. After performing model diagnostics, we will arrive at the final stage of the Box- Jenkins method, where the selected model will be used for applications such as forecasting future return and volatility, and determining the VaR.

2.0 Methodology

In time series analysis involving autoregressive moving average (ARMA) models, one common assumption is that the series is stationary. There are different types of stationarity. For our case, we will only introduce the weak-sense stationarity. The most standard way of defining weak-sense stationarity is the statistical properties, that is, the mean, variance and autocorrelation structure do not change over time. It is worth mentioning that a stationary series still changes over time, just that their statistical properties such as mean and covariance do not change over a given specific lag duration. When a time series is non-stationary, differencing the series will usually change it to a stationary series (Cowpertwait & Metcalfe, 2009). This is done by taking the difference of the series at time t and time $t-1$, that is $\nabla x_t = x_t - x_{t-1}$.

Financial return series are stationary and have no seasonality. They are often related to the ARMA model. An AR(p) model is the special case ARMA(p, 0), and MA(q) is the special case ARMA(0, q). An ARMA(p, q) model specifies that the output depends linearly on its previous values as well as current and previous error terms. An ARMA(p, q) model is given by

$$x_t = \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \ldots + \alpha_p x_{t-p} + w_t + \beta_1 w_{t-1} + \beta_2 w_{t-2} + \ldots + \beta_q w_{t-q} \quad (1)$$

where $\{w_t\}$ is white noise. One of the advantages of an ARMA model is parameter par- simony, which means an ARMA model will usually be more parameter efficient than a single AR or MA model. Similar to the AR(p) and MA(q) models, an ARMA(p, q) model can also be represented in terms of the lag operator **B**. Rearranging equation (1) and incorporating **B** yields

$$x_t - \alpha_1 x_{t-1} - \alpha_2 x_{t-2} - \ldots - \alpha_p x_{t-p} = w_t + \beta_1 w_{t-1} + \beta_2 w_{t-2} + \ldots + \beta_q w_{t-q}$$

$$x_t - \alpha_1 \mathbf{B} x_t - \alpha_2 \mathbf{B}^2 x_t - \ldots - \alpha_p \mathbf{B}^p x_t = w_t + \beta_1 \mathbf{B} w_t + \beta_2 \mathbf{B}^2 w_t + \ldots + \beta_q \mathbf{B}^q w_t$$

$$(1 - \alpha_1 \mathbf{B} - \alpha_2 \mathbf{B}^2 - \ldots - \alpha_p \mathbf{B}^p) x_t = (1 + \beta_1 \mathbf{B} + \beta_2 \mathbf{B}^2 + \ldots + \beta_q \mathbf{B}^q) w_t \quad (2)$$

Equation (2) can then be expressed as

$$\theta_p(\mathbf{B}) x_t = \phi_q(\mathbf{B}) w_t. \quad (3)$$

The stationarity and invertibility of an ARMA (p, q) model can be determined using the polynomials. The model is stationary if all roots of $\theta_p(\mathbf{B})$ exceed unity in absolute value and the model is invertible if all roots of $\phi_q(\mathbf{B})$ exceed unity in absolute value. An ARMA(p, q) model is an important element in the Box-Jenkins method.

Financial volatility analysis is well-known to have a non-independent property which can be nicely captured by the autoregressive conditional heteroscedasticity (ARCH) models. An ARCH(p) model has a generalized version GARCH(q, p) where q is the order of the GARCH term and p is the order of the ARCH term. The ARCH(p) is the special case GARCH(0, p). The GARCH(q, p) model is a more common model that is widely used in financial applications. The GARCH model uses values of past variance as well as squared returns, given by the equation

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_i \sigma_{t-j}^2 \tag{1}$$

where ε^2 is the squared returns, σ^2 is the past variance, $\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$ for $i > 0$ and $\sum_{i=2}^{p} \alpha_i + \sum_{j=2}^{q} \beta_j < 1.$ The GARCH(1,1) model is a frequently used model in practice.

In fact, a GARCH(1,1) model is sufficient to fit most data sets.

In the financial market, "bad" news or negative shocks tend to cause the market to be more volatile as compared to "good" news or positive shocks (Glosten et al.,1993). This is known as the leverage effect. Standard GARCH(q, p) cannot model this leverage effect due to asym- metry. Several extensions were done on GARCH to cope with asymmetry. These include EGARCH, GJR-GARCH, NGARCH, QGARCH and many other models. The ones that will be discussed and used in this study are EGARCH and GJR-GARCH. In this study, we will illustrate the specifications of the Glosten, Jagannathan and Runkle-GARCH model, or better known as the GJR-GARCH. The GJR-GARCH model also enables the model to capture asymmetry in the financial market. A GJR-GARCH(q, p) model is defined as

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \phi_i I_{t-i} \varepsilon_{t-i}^2$$
$$I_{t-i} = \begin{cases} 1, & \varepsilon_{t-i} < 0 \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

This is an indicator function that would produce a value of 1 if there is a loss and 0 if there are profits when it is applied to financial data (Curto and Serrasqueiro, 2022). In this study, the GJR-GARCH model was slightly modified. An extra term θD_t is added to the model as an exogeneous variable (Curto J.D., Serrasqueiro, in press) to represent the impact of Covid-19 to the volatility of gold price. The resulting model is given by

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \phi_i I_{t-i} \varepsilon_{t-i}^2 + \theta D_t$$

$$I_{t-i} = \begin{cases} 1, & \varepsilon_{t-i} < 0 \\ 0, & \text{otherwise} \end{cases},$$

$$D_t = \begin{cases} 1, & \text{JAN2020 onwards} \\ 0, & \text{otherwise} \end{cases}. \tag{6}$$

3.0 Empirical Study

3.1 *Analysis on daily return*

The data of gold price were downloaded from Yahoo Finance. The data were divided into pre-Covid-19 period and during Covid-19 period to investigate the impact of Covid-19 on the volatility of gold. The pre-Covid-19 period consists of data from January 2015 to December 2019, while the Covid-19 period consists of data from January 2015 to May 2021. Particularly, the Covid-19 period takes the data from pre-Covid-19 period and extends it for another 1.5 year to capture data after the pandemic outbreak. In phase 1 of the Box-Jenkins method, the return series was obtained using the MATLAB function *price2ret*. The return series of gold during the Covid-19 period is shown in Figure 1. It can be seen that the series is a flat-looking series, indicating that it might be stationary hence no differencing was done.

It was also found that the ACF and PACF are consistent with that of a white noise. However, during the verification process by the Ljung-Box Q test, it was observed that the P -value at lags 10 and 15 are less than 0.01, indicating a rejection of the null hypothesis. In other words, the daily return during the Covid-19 pandemic is serially correlated. The results are shown in Figure 2. This suggests the use of an ARMA(p, q) model.

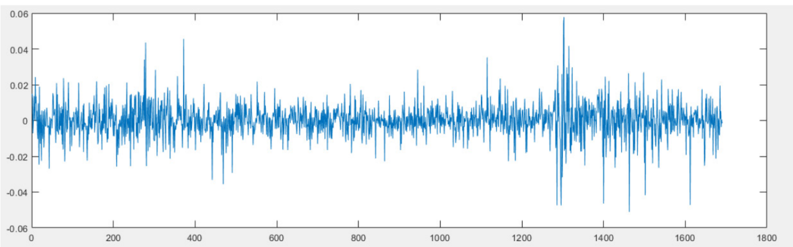


Figure 1

Return series of gold during Covid-19

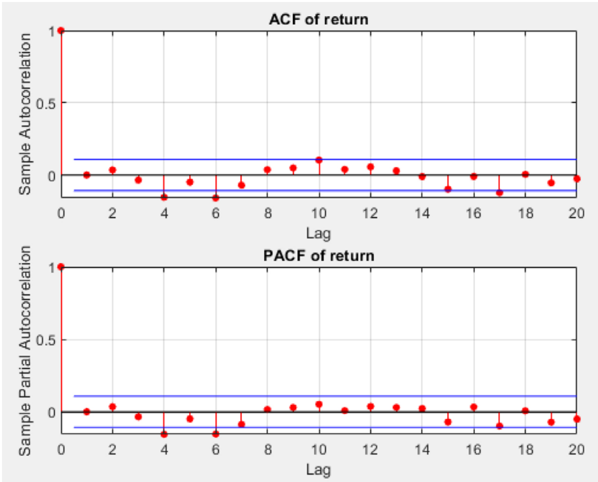


Figure 2

ACF and PACF of return residual during Covid-19

3.2 *Analysis on Volatility*

We now move on to observe the volatility of gold price. From Figure 1, volatility clustering of the series was observed. This is also justified by looking at the ACF and PACF of the squared residual, which showed significant correlation at certain lags as shown in Figure 3.

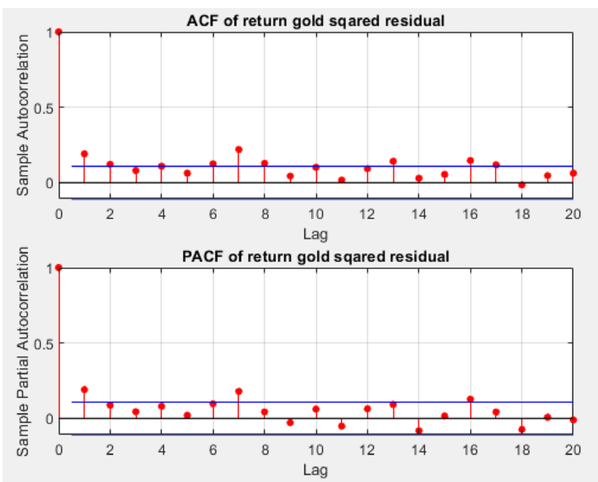


Figure 3

ACF and PACF of squared residual during Covid-19

Table 1

ARCH test during Covid-19

ARCH test	
Lags	***P*-value**
1	8.00E-07
2	2.50E-06
3	8.50E-06
4	2.90E-06
5	8.39E-05
10	2.88E-05
15	1.29E-04

Engle's ARCH test was used to check for the correlation of squared residual. The squared residuals are serially correlated if the null hypothesis of ARCH test is rejected. As can be seen in Table 1, the *P*-values at all the lags are less than 0.01, which resulted in the rejection of null hypothesis. Hence, the squared residuals are serially correlated, a model should be fitted to the series.

3.3 *Estimated Model for Pre-Covid-19*

The next step will be to fit a suitable model to the data. In phase 2 of the Box-Jenkins method, GARCH(1,1), GJR-GARCH(1,1) and EGARCH(1,1) were used for model fitting followed by model diagnostics. The ARMA(p, q) model was not used here because we found no serial correlation of return during the pre-Covid-19 period. From the estimation results, it can be seen that for the EGARCH(1,1) model, most of the *P*-values are less than 0.01, indicating that EGARCH(1,1) model failed the ARCH test. Hence, only the GARCH(1,1) and GJR-GARCH(1,1) model will be taken as a choice of final

Table 2

Comparison of AIC and BIC of different models

AIC and BIC				
	Gaussian distribution		**Student-*t* distribution**	
Model	**AIC**	**BIC**	**AIC**	**BIC**
GARCH(1,1)	–8.4547E+03	–8.4282E+03	–8.5885E+03	–8.5629E+03
GJR-GARCH(1,1)	–8.4607E+03	–8.4453E+03	–8.5976E+03	–8.5771E+03

model selection. The "best" model will be chosen based on the smallest AIC and BIC. The results are shown in Table 2, which suggested the use of GJR-GARCH(1,1) model with the Student-t distribution.

As a summary, the fitted model is as follows:

$$\sigma_t^2 = 0.0000003 + 0.98059\sigma_{t-1}^2 + 0.02450\varepsilon_{t-1}^2 - 0.01894 I_{t-1}\varepsilon_{t-1}^2$$
$$I_{t-1} = \begin{cases} 1, & \varepsilon_{t-1} < 0 \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

3.4 *Estimated Model Included the During of Covid-19*

For this duration of time, the ARMA(p, q)-GARCH(1,1), ARMA(p, q)-GJR-GARCH(1,1) and ARMA(p, q)-EGARCH(1,1) with p = 1, 2 and q = 1, 2 were fitted. The ARMA(2,2)- GJR-GARCH(1,1) model was chosen based on the AIC and BIC. Table 3 shows the AIC and BIC of each model used. The model with smallest AIC and BIC values was chosen.

Table 3

Comparison of AIC and BIC of different models

AIC and BIC				
	Gaussian distribution		**Student-t distribution**	
Model	**AIC**	**BIC**	**AIC**	**BIC**
ARMA(1,1)-GARCH(1,1)	-2.0377E+03	-2.0267E+03	-2.0821E+03	-2.0414E+03
ARMA(1,2)-GARCH(1,1)	-2.0498E+03	-2.0268E+03	-2.0775E+03	-2.0468E+03
ARMA(2,1)-GARCH(1,1)	-2.0495E+03	-2.0264E+03	-2.0774E+03	-2.0467E+03
ARMA(2,2)-GARCH(1,1)	-2.0502E+03	-2.0238E+03	-2.0789E+03	-2.0430E+03
ARMA(1,1)-GJR-GARCH(1,1)	-2.0506E+03	-2.0268E+03	-2.0803E+03	-2.0462E+03
ARMA(1,2)-GJR-GARCH(1,1)	-2.0483E+03	-2.0215E+03	-2.0757E+03	-2.0411E+03
ARMA(2,1)-GJR-GARCH(1,1)	-2.0480E+03	-2.0212E+03	-2.0756E+03	-2.0411E+03
ARMA(2,2)-GJR-GARCH(1,1)	-2.0520E+03	-2.0285E+03	-2.0807E+03	-2.0482E+03
ARMA(1,1)-EGARCH(1,1)	-2.0303E+03	-2.0235E+03	-2.0395E+03	-2.0330E+03
ARMA(1,2)-EGARCH(1,1)	-2.0330E+03	-2.0291E+03	-2.0376E+03	-2.0235E+03
ARMA(2,1)-EGARCH(1,1)	-2.0226E+03	-2.0237E+03	-2.0630E+03	-2.0334E+03
ARMA(2,2)-EGARCH(1,1)	-2.0503E+03	-2.0213E+03	-2.0622E+03	-2.0237E+03

The selected ARMA-GJR-GARCH model for the during COVID-19 period can be expressed as

$$
\begin{gathered}
x_t = 0.3368x_{t-1} - 0.8247x_{t-2} - 0.36122\varepsilon_{t-1} + 0.8501\varepsilon_{t-2} \\
\sigma_t^2 = 0.0000007 + 0.96726\sigma_{t-1}^2 + 0.03713\varepsilon_{t-1}^2 - 0.02071I_{t-1}\varepsilon_{t-1}^2 \\
I_{t-1} = \begin{cases} 1, & \varepsilon_{t-1} < 0 \\ 0, & \text{otherwise} \end{cases}
\end{gathered} \tag{8}
$$

3.5 *Impact of Covid-19 on gold volatility*

Recall that in equation (6), an extra term θD_t was added to the GJR-GARCH model to study the impact of Covid-19 on gold volatility. In MATLAB, there is no function that can calculate θD_t explicitly. However, this can be calculated by taking the difference of equations (7) and (8). The results are summarized in Table 4.

Table 4

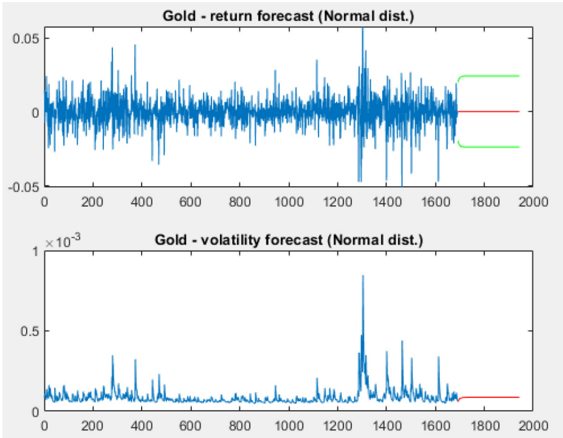
Impact of Covid-19 on GJR-GARCH(1,1) coefficients

Constant, α_0	σ_{t-1}^2	ε_{t-1}^2	$I_{t-1}\varepsilon_{t-1}^2$
0.0000004	–0.01333	0.01263	–0.00176

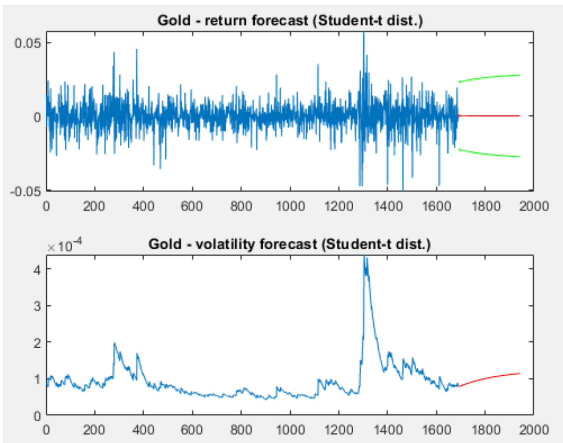
It can be seen that Covid-19 caused a positive shift of 0.0000004 on the constant term and 0.01263 on the ARCH term whereas it caused a negative shift of 0.01333 on the GARCH term and 0.00176 on the leverage effect. It is worth pointing out that in a common GJR-GARCH model, the leverage effect is usually positive, meaning bad news will cause the volatility to be more intense. However, in our analysis, we found that the leverage effect is negative, which means bad news tends to reduce volatility. This might be due to the fact that gold is a safe haven investment and has intrinsic value. When there is bad news to the financial market or during times of economy downturn, most people will hold onto gold instead of trading gold, which will reduce the transaction in gold market and therefore its volatility.

3.6 *Forecasting*

Using the selected model from the previous section, we can now forecast an n-step ahead return and volatility. The model used to forecast a



(a) Forecasting with normal distribution



(b) Forecasting with Student-*t* distribution

Figure 4

Forecasted return and volatility

252-step ahead, equivalent to a year of trading return and volatility is the ARMA(2,2)-GJR-GARCH(1,1) model.

From Figure 4, it is observed that the forecasted daily return and volatility using normal distribution for the next one year of trading is a flat-looking curve, which is not realistic. As for the forecasted value using the Student-*t* distribution, the return has a 99% tendency to fluctuate in between the green lines, which is the 99% confidence interval. As for the volatility, the forecasted result showed that it has a tendency to increase again in the near future.

3.7 *Application in market risk determination*

Risk managers of firms use VaR to measure and control the level or risk exposure. However, there are a few downsides of using VaR to control risk. VaR does not capture operational risk. Any losses that result from ineffective or failed internal processes, system or people are out of the scope of VaR. Generally, there are a few different methods to calculate VaR. They are historical simulation, the variance covariance method, Monte Carlo simulation, and time-varying volatility ARCH method. All of these methods may give different VaR. Commonly, most firms use the 95% or 99% confidence interval to measure VaR. These confidence intervals correspond to the 5% quantile and 1% quantile of a probability distribution. In the following analysis, we will use the GJR-GARCH forecasted results to determine the market risk. This method will compute the VaR using two different distributions, namely the normal distribution and Student-*t* distribution. The formula to calculate VaR using the Student-*t* distribution is given by

$$VaR = \hat{r} - T^{-1}(v, p)\hat{\sigma}_t \tag{9}$$

where $\hat{r}$ is the forecasted return, v is the degree of freedom of a Student-*t* distribution and T^{-1} representing the standardized inverse of *t*-distribution. The VaR obtained is summarized in Table 5.

From a financial point of view, we can say that we are 95% confident that the worst loss will not exceed $17,676 in the next trading day, and we are 99% confident that the worst loss will not exceed $29,203 in the next trading day. The loss amount expressed is based on the VaR calculated using the Student-*t* distribution since the AIC/BIC have suggested that the Student-*t* distribution is a better fit.

Table 5

VaR calculated using ARCH method

VaR		
Confidence Interval	**Normal distribution**	**Student-*t* distribution**
95%	$12,430	$16,265
99%	$17,676	$29,203

4.0 Conclusion

The price of gold has hit its all-time high during the Covid-19 pandemic. With the use of ARIMA and GARCH-type models, the daily return and volatility of gold had been analyzed thoroughly. The analysis was split into two parts, particularly before the Covid-19 pandemic and during the Covid-19 pandemic to study the impact of Covid-19 to the gold market. Using the Box-Jenkins method, it was found that the daily return before the pandemic was not serially correlated, meaning that the daily returns are independent each day, which could not give us any additional information. On the other hand, the analysis done on daily return during the pandemic showed that returns are serially correlated. This means that during the Covid-19 pandemic, daily return of gold depends on past daily returns. Several ARMA(p,q) models were then fitted to the residual of return series to find the "best" model, the ARMA(2,2) model was selected based on AIC and BIC. From the fitted ARMA(2,2) model, it was found that the daily return of gold is related to the return on previous two days by factors of approximately 0.3368 and –0.8247.

In the analysis of volatility, GARCH(1,1), EGARCH(1,1) and GJR-GARCH(1,1) were fitted to the squared residual of the return series. The use of EGARCH and GJR-GARCH was to capture the leverage effect of the gold market. The Box-Jenkins method suggested that the GJR-GARCH model was the "best" model and was used for further applications such as forecasting future return and determining VaR. From the estimated parameter, it can be seen that the volatility is related to volatility on previous day by a factor of approximately 0.97. This means that volatility is highly dependent on volatility of previous day, which is consistent with our observation of volatility clustering.

It was also found that the leverage effect obtained from the fitted model before and during the pandemic are both negative values. In other words, negative shocks or bad news will cause the market to be less volatile, which is counter intuitive. One reason is due to the intrinsic value of gold. During times of economy downturn, most investors will lose their confidence in the share market and will turn to safe-haven investment such as gold because of its intrinsic value. Investors who are holding gold will not do any trading activities on it due to the bad economy and will result in lesser transactions, which then results in the low volatility of gold market. From our estimation result, it was found that the Covid-19 pandemic had caused the leverage effect to experience a negative shift. In other words, the pandemic had in fact affected the volatility of gold market.

To conclude, gold market is less volatile during times of economy downturn as compared to normal market condition and gold has the ability to preserve value. Therefore, gold is a good and safe choice of investment during times of economy uncertainty (Oxford Gold Group, 2021). Investors who are looking for defensive investing strategies can consider going into a long position with gold.

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