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PRECIOUS METALS PRICE FORECAST WITH ARCH FAMILY MODELS IN COVID-19 PANDEMIC PERIOD

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ABSTRACT

The COVID-19 virus, which was detected for the first time in Wuhan, China in December 2019, spread to all countries of the world and, therefore, became a global epidemic. Although more than two years have passed since the outbreak of the COVID-19 pandemic, the economic effects of it continue. One of these is the effect of the pandemic on precious metal prices. Precious metals, which are called safe harbours and used as investment tools, have had a serious volatility in the last century as a result of the economic, political and pandemic factors changing the international balances. From this point of view, in this study, it is aimed to determine the appropriate forecasting model to predict the volatility of gold, silver, platinum and palladium prices, which are called precious metals, during the COVID-19 pandemic period. The econometric analysis covers the period between March 11, 2020, when the global epidemic was declared by the World Health Organization, and September 13, 2021, and includes 326 days of observation. To determine the appropriate forecasting model, ARCH, GARCH, T-GARCH, E-GARCH and PARCH are used as symmetrical and asymmetrical volatility models.

Contribution/Originality: This study investigated which of the ARCH family symmetric and asymmetric models could be the best forecasting model for the volatility of precious metal prices during the COVID-19 pandemic.

1. INTRODUCTION

Since 1973, when the fixed exchange rate regimes came to an end, unprecedented uncertainties began to emerge in the financial markets. The uncertainties that started to be experienced in the financial markets pushed the investors to work on reducing the uncertainty mathematically and statistically. The increasing importance of risk and uncertainty in today's financial world has necessitated the development of econometric time series that enable the modeling of variance and covariance depending on time. The use of conditional variability models has become widespread for analyzing time-dependent variability (volatility) in high-frequency financial data (Telatar & Binay, 2002). Previously, standard deviation was used to determine the volatility in financial markets, then ARCH type statistical methods began to be applied.

Although the history of ARCH -Autoregressive Conditional Heteroskedasticity- models is not very old, academic studies on these models have developed at a remarkable pace. It has been observed that variance, which is a measure of volatility, varies depending on time in financial time series, and models based on fixed variance have begun to fail to meet the needs. In this direction, the autoregressive conditional variable variance model (ARCH) was developed by Engle (1982) to estimate the variance that changes over time. The unconditional variance was assumed to be constant in the model (Engle, 1982; Engle & Ng, 1993).

The GARCH (Generalized Autoregressive Conditional Variance) model is the most widely used financial volatility forecasting model in finance. The model in question is a method that not only measures volatility, but also shows whether shocks on volatility are continuous (Kıran, 2010) The GARCH model developed by Bollerslev (1986) is slightly different from the ARCH model. The reason for this is that the ARCH model was put forward to alleviate some of its problems, such as not being able to fully explain the variance behavior and predicting volatility much larger than it should be due to the slow response to major shocks (Kayalıdere, 2013).

The EGARCH model was developed by Nelson (1991). In this model, the natural logarithm of the conditional variance is conditional on its lagged values and standardized error term. According to Nelson's study, negative shocks of the same size have a greater effect on volatility than positive shocks (Yaman & Koy, 2019).

The PARCH model developed by Ding, Granger, and Engle (1993) takes into account the leverage effect that symmetrical GARCH models ignore. This model was developed as a continuation of ARCH family models, and instead of taking the absolute value or squaring of the time series data, the power of the data is analyzed (Telatar & Binay, 2002). The model which is used to predict asymmetric volatility is the Threshold ARCH (TARCH) model developed by Zakoian (1994). The conditional variance in the model functions as a sign. If the coefficient of the new variable is statistically significant, the ARCH effect has emerged in the conditional variance (KizIlsu, Aksoy, & Kasap, 2001). Other models that take into account the asymmetric effect are Engle and Ng (1993) Model, and GJR Model developed by Glosten, Jagannathan, and Runkle (1993). In asymmetric GARCH models, the conditional variance value depends not only on the lag values of the error terms, but also on the sign of the lag values (Kutlar & Torun, 2013). This study aims to determine the appropriate forecasting model to predict the volatility of gold, silver, platinum and palladium prices, which are called precious metals, during the COVID-19 pandemic period.

2. LITERATURE

The literature on the studies conducted to predict the volatility of financial asset and commodity prices during the COVID-19 pandemic period has been examined in detail. The results of the studies in the literature regarding the aims, the methods they used and the results they obtained are given in Table 1.

Table 1. Literature review

Author(s)	Period	Purpose and Content of the Study	Method(s)	Results
Dury and Bing (2018)	October 2002-May 2016	The aim of the study was to find out which autoregressive conditional variance model applied to gold prices in China has the best prediction accuracy.	ARCH GARCH GARCH-M IGARCH NGARCH EGARCH PARCH NPARCH TARCH	In the analysis for Chinese gold market, Student's t distribution seems to characterize heavier-tailed returns better than the Gaussian distribution. Entities with higher kurtosis are better predicted by a GARCH model with Student's t distribution, while entities with lower kurtosis are better predicted using an EGARCH model.
Kuzu (2018)	2011-2017	In this study, the author has examined which model from the ARCH family can best explain	ARCH GARCH EGARCH TGARCH	It was determined that the GARCH model gives the most successful result among the related models in revealing the return

Author(s)	Period	Purpose and Content of the Study	Method(s)	Results
		the return volatility of the BIST 100 Index.		volatility in the BIST 100 index.
Kumari and Tan (2018)	January 1990-June 2014	This study examined which volatility models could predict the gold futures market.	ARCH GARCH EGARCH APARCH TARCH FIGARCH FIEGARCH	Gold futures market volatility could be forecasted most accurately by the EGARCH and FIEGARCH models which are from linear and nonlinear GARCH family models.
Gyamerah (2019)	January 2014-August 2019	In this study, the author has used three GARCH models to examine which model best explained the volatility of Bitcoin returns.	SGARCH IGARCH TGARCH	It was concluded that the best model to predict the volatility in Bitcoin returns is TGARCH-NIG.
Ambukarasi and Devaki (2020)	January 2017-December 2019	In this study, the authors aimed to predict volatility in the energy commodity derivatives market using ARCH family models.	ARCH GARCH TGARCH EGARCH	This study implies that (i) there is an influence of the volatility of crude oil energy commodity prices on institutional investors by means of GARCH (1,1) model; and (ii) there is an influence of the volatility of natural gas energy commodity prices on institutional investors by means of EGARCH (1,1) model. Overall, the study found that there is an influence of energy commodity market on institutional investors investment pattern by adopting the ARCH family models with Normal Gaussian error distribution.
Krishna (2020)	January 1996-December 2019	The ARCH family model that best explained the India NIFTY 50 Index prediction was being investigated in this study.	ARCH GARCH EGARCH	In the three asymmetric models used in the research, it was determined that the EGARCH model predicted the future better than the other two models.
Irene, Wijaya, and Muhayani (2020)	June 1993-May 2018	In this study, the authors estimated the volatility of gold prices using the APARCH, EGARCH and TGARCH models.	APARCH EGARCH TGARCH	EGARCH (1.1) was found to be the most suitable model to predict world gold prices. As a result of the study, EGARCH (1.1) has the smallest error compared to other models with an Average Absolute Percentage Error (MAPE) value of 4.66%.
Divisekara, Nawarathna, and Nawarathna (2020)	January 2013-January 2018	This study examined which of the GARCH family models would give most accurate predictions for the daily prices of emtia and financial instruments in the global markets.	TGARCH APARCH EGARCH	This study revealed that the GARCH model was best suited to explain financial products such as the Australian Dollar, feeder cattle and coffee. The model that best explained corn and crude oil prices is the APARCH model. EGARCH and TGARCH models were more suitable for treasury bonds and gold. GARCH family models were chosen as better forecasting models than ARIMA models in emtia and financial instruments forecasting.
Abounoori and Zabol (2020)	April 2012-April 2018	This study used the gold five-minutes intra-day data to estimate the	GARCH EGARCH GIR-	The RGARCH model gave the best results for gold.

Author(s)	Period	Purpose and Content of the Study	Method(s)	Results
		conditional variance of GARCH, EGARCH, and GJR-GARCH, and as well as, the RGARCH model using two RV and BV proxies for intra-day realized volatility.	GARCH RGARCH	
Youssef and Surraya (2021)	2001-2019	The authors aimed to evaluate the prediction performance of linear and nonlinear GARCH models in terms of prediction accuracy for Japanese Nikkei225 and Egyptian EGX30 indices, which were selected as examples for developed and developing countries.	ARCH GARCH-IN-MEAN EGARCH GJR-GARCH Multivariate GARCH Nelson's EGARCH	Nelson's GARCH model outperformed other models. Therefore, research recommended using Nelson's GARCH model in studies.

3. DATA AND METHODOLOGY

The data used in the econometric model of the study are the end-of-day values of 326 observations for the period of 11.03.2020-13.09.2021. E-views 9 econometric analysis program is used in the empirical analysis. The variables used in the model are listed in Table 2.

Table 2. Variables.

Variables in the Model	
XAUUSD	Gold / US Dollar Spot Rate
XAGUSD	Silver / US Dollar Spot Rate
XPTUSD	Platinum / US Dollar Spot Rate
XPDUSD	Palladium / US Dollar Spot Rate

Figure 1 shows precious metal price movements during the COVID-19 pandemic period. The left axis of Figure 1 shows the price of gold, platinum and palladium, while the right axis shows the price of silver.

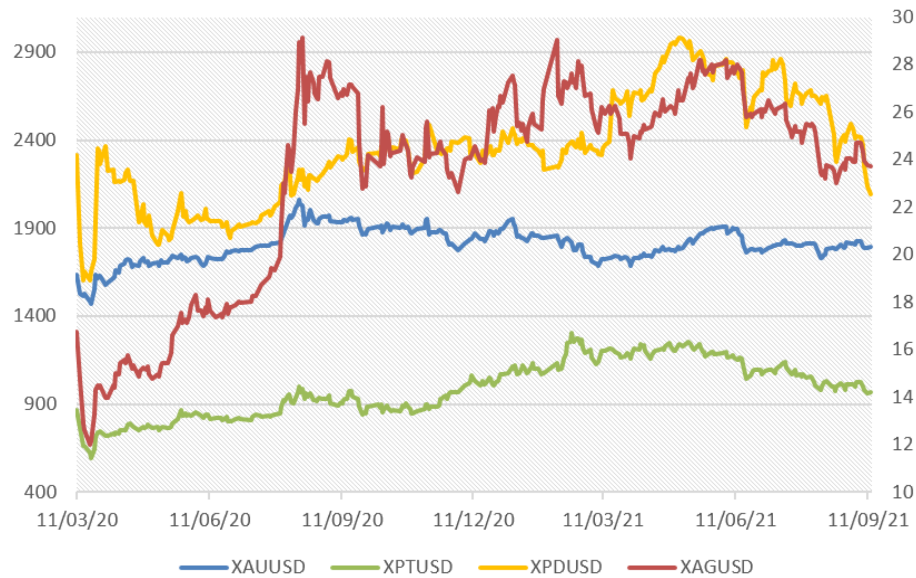

Figure 1. Precious metal price movements between 11/03/2020 and 13/09/2021.

Table 3. Descriptive statistics.

Variables	XAUUSD	XAGUSD	XPDUSD	XPTUSD
Mean	0.012	0.047	-0.013	0.015
Median	0.034	0.021	0.037	0.071
Maximum	2.355	3.927	8.171	4.383
Minimum	-2.889	-5.759	-10.570	-5.923
Std. Dev.	0.540	1.221	1.316	1.060
Skewness	-0.736	-0.764	-1.217	-0.779
Kurtosis	8.522	8.200	21.574	8.355
Jarque-Bera	443.543	398.969	4766.621	422.432
Probability	0.000	0.000	0.000	0.000
Observation	326	326	326	326

The statistical data on the returns of precious metals over daily closing prices are presented in Table 3. Accordingly, the kurtosis values are 8.522, 8.200, 21.574, 8.355, and greater than 3 (excess of flattening). The skewness values are -0.736, -0.764, -1.217, -0.779, and different from zero. These negative values of the skewness indicates that the distribution of the variables is not skewed. In econometric analysis, an excess of flattening corresponds a sharp distribution, while the skewness of the distribution is positive if the tail is longer. In our sample, a large number of observations have a positive value (Merabet, 2021).

When Figure 1 and Table 3 were examined, it was concluded that the series did not move around the mean. Therefore, series can contain unit root. The purpose of unit root testing is that ARCH and GARCH models need stationary time series. In other words, the series to be used in the analysis with ARCH and GARCH models should not include unit root. In this study, the stationarity of the series is examined with the ADF (Augmented Dickey-Fuller) unit root test, which is the most widely used method in analyses (Dickey & Fuller, 1979); (Dickey & Fuller, 1981).The hypotheses that were used to test the existence of a unit root are as follows:

H_1: $\gamma < 0$ ($p < 1$) The series is stationary (1)

H_0: $\gamma = 0$ ($p = 1$) The series is not stationary (2)

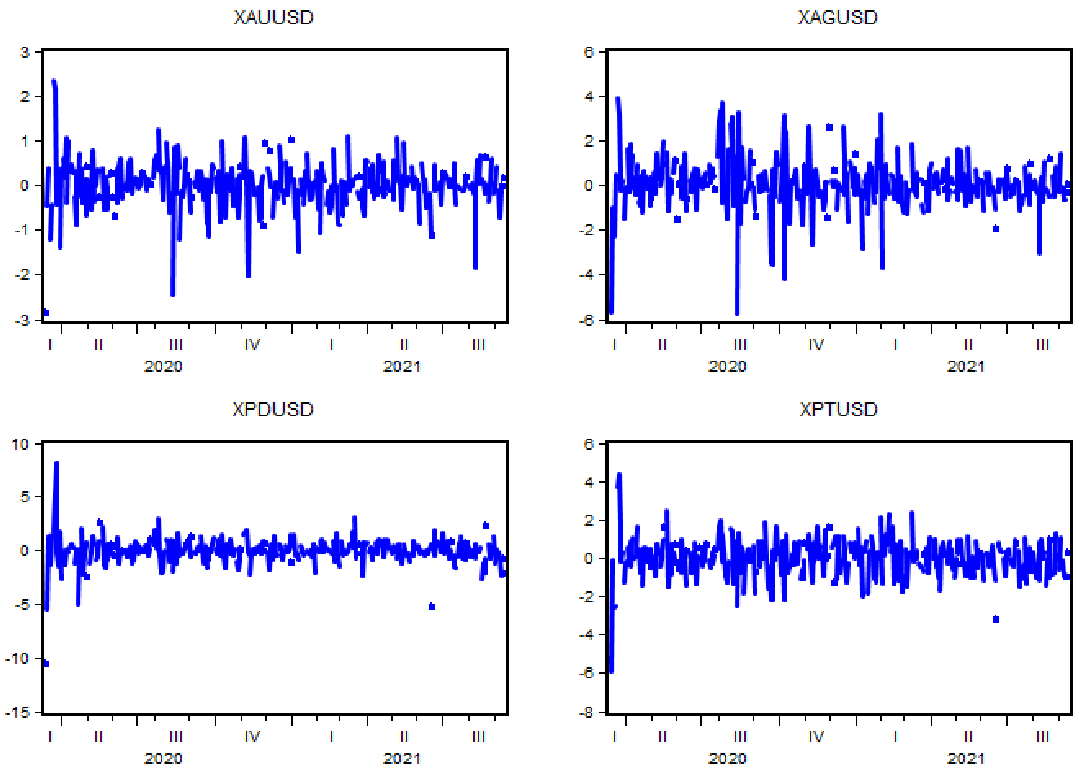

Figure 2. Precious metal price time path graph of logarithmic return series between 11/03/2020 and 13/09/2021.

However, before performing the unit root test, the logarithms of the series must be taken. Figure 2 illustrates the precious metal price time path graph of logarithmic return series between 11/03/2020 and 13/09/2021. As seen in Figure 2, in March, the first period of the pandemic, it is observed that volatility increased significantly. Palladium's return volatility (XPDUSD) has a noticeable difference from other metals.

4. EMPRICAL RESULTS AND DISCUSSION

The ADF test results of the returns of precious metals are given in Table 4. Accordingly, none of the series regarding the precious metal returns contain a unit root and, therefore, all series exhibit stationary properties.

Table 4. Augmented Dickey-Fuller (ADF) test statistics.

Variables	Intercept		Intercept and Trend		None	
	t-Statistics	Probability	t-Statistics	Probability	t-Statistics	Probability
XAUUSD	-17.884	0.000	-18.401	0.000	-18.300	0.000
XAGUSD	-17.884	0.000	-17.954	0.000	-17.886	0.000
XPDUSD	-16.931	0.000	-16.966	0.000	-16.957	0.000
XPTUSD	-16.291	0.000	-16.467	0.000	-16.303	0.000

As can be seen in Table 4, the probability values corresponding to the t-statistics were determined to be less than 5%. Therefore, the H_0 hypothesis was rejected because the probability values were below 5% ($p<0.05$) according to the unit root test statistic (MacKinnon, 1996). These results show that the series is stationary and there is no unit root problem. Thus, it was concluded that ARCH and GARCH models are suitable for analysis.

The ARCH LM test was applied to test whether there is variance and autocorrelation in precious metal prices. These models were tested to several degrees to determine the model that best fits the structure of the series. (Özer & Ece, 2016).

Table 5. ARCH LM test results.

Variables	F-statistic	Obs R-squared	Probability
XAUUSD	4.912	4.869	0.000
XAGUSD	64.165	54.268	0.000
XPDUSD	59.648	50.662	0.000
XPTUSD	115.025	85.345	0.000

According to ARCH LM test results in Table 5, it was concluded that there is variance and autocorrelation in precious metal prices. Therefore, all precious metal returns are suitable for ARCH - GARCH modelling.

Table 6. Statistical results of the models.

XAUUSD

Variables	ARCH (1,1)	GARCH (1,1)	EGARCH (1,1)	TARCH (1,1)	PARCH (1,1)
R^2	0.003	0.002	0.001	-0.0003	-0.003
AIC	1.519	1.461	1.460	1.457	1.473
SIC	1.565	1.519	1.530	1.526	1.554
Hannan-Qui cr.	1.537	1.484	1.488	1.484	1.505
Log likelihood	-242.778	-232.399	-231.292	-230.688	-232.309

XAGUSD

Variables	ARCH (1,1)	GARCH (1,1)	EGARCH (1,1)	TARCH (1,1)	PARCH (1,1)
R^2	-0.001	-0.012	-0.010	-0.011	-0.009
AIC	3.027	2.966	2.970	2.944	2.912
SIC	3.074	3.024	3.090	3.013	2.993
Hannan-Qui cr.	3.046	2.989	2.998	2.971	2.944
Log likelihood	-487.957	-476.956	-476.645	-472.329	-466.133

XPDUSD

Variables	ARCH (1,1)	GARCH (1,1)	EGARCH (1,1)	TARCH (1,1)	PARCH (1,1)
R^2	0.017	0.011	0.006	0.006	0.024
AIC	2.973	2.904	2.952	2.941	2.863
SIC	3.019	2.962	3.022	3.011	2.944
Hannan-Qui cr.	2.991	2.927	2.980	2.969	2.895
Log likelihood	-479.030	-466.840	-473.762	-471.985	-458.193

XPTUSD

Variables	ARCH (1,1)	GARCH (1,1)	EGARCH (1,1)	TARCH (1,1)	PARCH (1,1)
R^2	-0.003	0.004	0.005	0.004	0.004
AIC	2.752	2.707	2.712	2.710	2.715
SIC	2.799	2.765	2.782	2.779	2.796
Hannan-Qui cr.	2.771	2.730	2.740	2.738	2.747
Log likelihood	-443.308	-434.814	-434.711	-434.308	-434.144

Table 6 reveals the econometric analysis results of the study. According to the results, it was determined that the TARCH model is the most suitable model for gold and palladium, while the PARCH model is the most suitable for silver and platinum. Compared to other models, these models have the highest R^2 value and the lowest Akaike, Schwarz, Log Likelihood information criteria.

5. CONCLUSIONS

Volatility is a leading indicator that is always considered when investing. Investors can invest in different financial instruments depending on their attitude towards risk. The ongoing Russia-Ukraine war and the Covid-19 pandemic are causing increased volatility in financial markets. For this reason, it becomes very difficult to predict the volatility in the markets. In this context, the importance of using future volatility forecasts as data and making accurate forecasts in the pricing of precious metals is increasing day by day in today's financial world. This study investigated which of the ARCH family models (ARCH, GARCH, T-GARCH, E-GARCH and PARCH models) will be used in volatility prediction and will help to make more accurate estimations. The data used in the econometric model of the study includes the returns obtained from the values of precious metals for the period of 11.03.2020-13.09.2021. We tried to determine the most suitable model in volatility estimation. According to the results, it was determined that the TARCH model is the most suitable model for gold and palladium, while the PARCH model is the most suitable one for silver and platinum. However, there may be several models that give good results when data with different frequencies and different periods are used. This conclusion was reached in various studies in the literature. As a result, it is thought that the results obtained from the study will provide both investors and decision makers with a useful preliminary information and reference in making appropriate decisions about investment strategies in precious metals.

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