MODELING AND FORECASTING VOLATILITY OF GOLD PRICE USING ARIMA – ANN HYBRID MODEL AND GOLD MARKET BEHAVIOR DURING WORLD CRISES

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ABSTRACT: *Gold is one of the most valuable metals in the world with numerous applications, including jewelry and electronic devices. Countries often utilize gold as an economic health indicator, and financial institutes use gold as a hedge against loans. Additionally, gold is a popular investment asset for diversifying portfolios. Thus, gold price predictions are crucial to making proper future decisions. Understanding the reasons why the price of gold fluctuates is one of the challenging tasks. In earlier research, gold price forecasting had been done using statistical methods. But with the recent developments in machine learning methods, it is now possible to combine conventional statistical models with machine learning to produce a hybrid model that makes better predictions. In the first part of the work, a novel hybrid model was proposed, by using Autoregressive Moving Average (ARIMA), Long-short Term Memory (LSTM), and Prophet. It is also essential to develop models that can predict gold prices during a crisis because, during these times, models will deviate from their typical historical patterns. Hence, another attempt has been made to examine the influence of crude oil, and silver, on gold prices during the 2008 financial crisis and the COVID-19 period, and predict gold prices using regression Analysis, co-integration, Vector Error Correction Model* (VECM)*. It was found that there are short-term causalities between gold and the previous month's crude oil and silver. Therefore, having a joint impact on the current gold price during the crisis periods. Using the models proposed in this paper, better gold price predictions can be made in the future, even during financial crises. Better forecasting leads to better risk management, investment decisions, hedging, economic analysis, and strategic trading giving the opportunity to earn profits.*

Keywords: Autoregressive Moving Average, Long-short term memory, Regression Analysis, Co-integration, Vector Error Correction Model

1. INTRODUCTION

Gold is one of the world's most valuable raw resources. Despite its potential to make valuable products, gold is a popular investment option due to its historical importance as a store of wealth and a hedge against inflation, as well as its usage as a reserve by countries. Numerous factors influence the price of gold, resulting in dramatic price fluctuations. This includes the inflation rate, supply and demand, and political issues. Moreover, because the dollar is the world's market currency, when countries expect the value of the dollar to decrease, the gold price will eventually rise due to increased demand. Literature has identified gold as a safe haven during financial crises due to its significance. Therefore, the price of gold fluctuates and cannot be controlled.

Due to the sudden upwards and downwards trend that has recently emerged in the gold market, it is essential to account for the various price fluctuations of gold. Thus, predicting future gold prices is a very challenging task. Therefore, to get a clear picture of what will happen in the future gold market, it is necessary to decide on a proper model to predict the gold prices in the world.

In previous studies, projecting the price of gold was accomplished by the use of statistical approaches. However, over the past decade, machine learning has gained a lot of popularity for making accurate data forecasts due to advancements in both computing power and the algorithms themselves. Machine learning is a subset of artificial intelligence that gives computers the ability to learn from previous data, recognize patterns, and come up with their own predictions based on what they've seen. This is accomplished without the need for any explicit programming, as it is able to "self-learn" using training data and improve over time. It is possible to combine traditional statistical models with machine learning in order to develop a hybrid model that is capable of producing more reliable predictions. Hence, the first objective of this research work is modeling and forecasting the price of gold using the time-series autoregressive integrated moving average (ARIMA) model in conjunction with the Prophet and long short-term memory (LSTM) models. This study compares the performance of the ARIMA model, the Prophet model, and the LSTM model in predicting the gold price. To predict the future gold price, a novel ARIMA-ANN Hybrid model is introduced.

The second objective of this study was to examine the effect of crude oil and silver prices on gold prices during the 2008 financial crisis and the COVID-19 period. An assessment of whether crude oil prices and silver prices affect gold prices is considered here. Regression analysis, co-integration test, and vector error correction model (VECM) have been used for this purpose.

Due to its low volatility and ability to preserve wealth during inflation and other crises or uncertainties, gold is regarded as one of the safest investment options. Predicting future gold prices is therefore a demanding need, and it is also essential to examine gold price patterns during and after times of crisis.

2. METHODOLOGY

This study relies on two main parts. Forecasting the gold price using the ARIMA-ANN hybrid model and the influence of crude oil and silver prices on the gold price during crisis periods.

Part 1 - Forecasting the Gold price using ARIMA-ANN Hybrid model

This study uses monthly gold price data (in dollars) spanning from 1/1/2007 to 1/7/2022 for the first part. The data was taken from the World Gold Organization website, and the data is divided into two parts: training data (from 1/1/2007 to 1/7/2021) and testing data (from 1/8/2021 to 1/7/2022).

Generally, gold price data is considered to consist of linear and non-linear components. Additionally, it's important to correctly identify the trend or the points where the price of gold increases and decreases.

First, the ARIMA model was applied to the monthly gold price data. The stationarity of the data was checked using the autocorrelation function (ACF) plots. Furthermore, the optimal terms for the model were selected with the help of ACF plots and partial autocorrelation function (PACF) plots. Then, based on the Akaike information criterion (AIC) and Bayesian information criterion (BIC), the optimal ARIMA with the lowest values of AIC and BIC is selected. The Mean absolute percentage error (MAPE) value was used to evaluate the validity of the chosen model.

Since gold prices tend to be seasonal and volatile, ARIMA residuals are passed through the Prophet model to identify seasonality. The model includes a time series that is decomposable into mainly three components: growth (or trend), seasonality, and holidays. But here, the gold prices do not have a significant holiday component. The seasonality was further subdivided to represent monthly, quarterly, semi-annually, and annual seasonalities.

After applying the model and obtaining the residuals from the Prophet model, these data are given as the input to the LSTM model. LSTM is a variety of recurrent neural networks (RNN) that can be used to identify nonlinear components for the model. The output of the LSTM model is obtained, and this output was combined with the ARIMA forecasts. Figure 1 represents the flowchart of the proposed methodology.

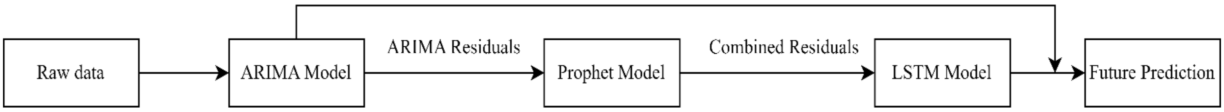

Figure 1. Flowchart of Proposed methodology

Part 2 - Influence of Crude oil and silver price on the Gold Price during Crisis periods

Daily gold prices (in dollars), crude oil prices, and silver prices were taken from the World Gold Organization website, the US Federal Reserve Bank economic database, and the Yahoo Finance website respectively. Two global crises are used here, the 2008-2009 financial crisis and the 2020 crisis caused by the global COVID-19 pandemic. The timeline of in-sample and out-sample data is shown in Table 1.

Table 1. Time period of the data

Crisis	In-sample	Out-sample
Financial Crisis	2/7/2007 - 5/3/2009	4/3/2009 - 10/5/2010
Covid-19	10/31/2019 - 23/3/2020	24/3/2020 - 30/6/2020

The relationship between the prices of crude oil, silver, and gold is first understood through regression analysis. Then, co-integration is employed. In order to ensure that all variables are non-stationary at a particular level and stationery at the next level, which is a condition for the co-integration test, the unit root test must first be conducted. Then determine the order of Value at risk (VAR). The minimal p-value is chosen so that residuals behave as white noise. After determining the number of unit roots, trace or max tests were used to verify the existence of co-integration equations. Finally, the Wald test was applied to determine the existence of short-term causal relationships.

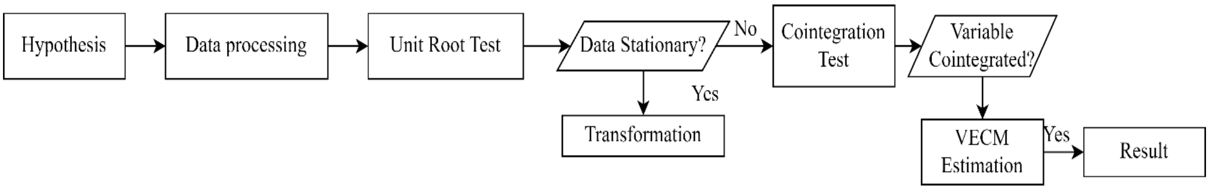

Figure 2. Flowchart of co-integration process

3. RESULTS AND DISCUSSION

Part 1 - Forecasting the Gold price using ARIMA ANN Hybrid model

In the test dataframe time period, the actual gold price shows an upward trend, followed by a moderate decline, and then another upward trend. This implies that the data is not stationary during the data period. The non-stationarity of the data was also confirmed by plotting ACF and PACF graphs. The ACF of the raw data decays very slowly, and the PACF is significant only after the first two lags. In addition, the lack of a particular pattern in the sample ACF graph suggests that there is no seasonality in the gold price data for this time period. Furthermore, the unit root test, and Augmented Dickey-Fuller (ADF) test statistically confirm the dataset is not stationary with ADF value of -2.074 (P-value: 0.255) for the dataset. The critical value for the p-5% significance level is -2.879 which is less than the ADF stat.

ADF test was conducted to confirm the stationarity of the first and second-order difference series. The results at a 5% level of significance show that the data series is stationary at the 1st-order difference (ADF value: -4.247, P-value: 0.001) and 2nd-order difference (ADF value: -7.404, P-value: 0.00). The critical values for the p-5% significance levels are -2.879 and -2.880 respectively.

Using a Python script, auto-regressive (AR) terms, moving-average(MA) terms, and Integration(I) terms for the model were identified. The differencing order was set to 1 initially. It was found that AR(1) Coefficient -0.1346 yields a probability value of 0.033 with a standard error of 0.063 and MA(1) Coefficient -0.9972 yields a probability value of 0.001 with a standard error of 0.103. This indicates that the selected coefficients are accurate enough to build the model with terms AR(1), I(2), and MA(1) with 95% confidence. The prediction results of the ARIMA model are given in Tables 2 and 3.

For the comparison, the raw data was modeled using the Prophet model. The predictions of the model follow the trend of the actual data in most cases, but with an offset. The same was done with the LSTM model as well. The results are summarized in tables 2 and 3.

As for the ARIMA-ANN Hybrid model, the residual from the previous ARIMA model was fed to the prophet model and identified the optimal parameters through a Python library. It was found that trend and yearly seasonality variations show a significant effect on the gold prediction model, but other seasonality components were not significant.

Then the residuals were fed to the LSTM model to further increase accuracy. The LSTM model of 50 LSTM units and 1 hidden layer was chosen, and the model was optimized with 50 epochs using the Adam algorithm. The final predictions of the hybrid model are shown in Figure 3.

Two performance criteria of root mean square error (RMSE) and MAPE were used to evaluate the models. Table 2 compares the in-sample performance, and Table 3 compares the out-of-sample performance of the plain ARIMA, Prophet, LSTM, and proposed novel ARIMA-ANN Hybrid model.

Table 2. Comparison of the in-sample performance of the proposed model with other forecasting models

	ARIMA	Prophet	LSTM	Proposed model
MAPE	0.0483	0.0624	0.0317	0.0174
RMSE	87.3136	99.7307	62.0793	40.7609

The MAPE of the proposed model, 0.0174 is significantly lower than the plain ARIMA, Prophet, and LSTM models. The proposed model also has smaller values for RMSE as compared to the plain models. After fitting the combined model to the data, its adequacy was examined by analyzing its residuals, which displayed a normal distribution. The suggested model is therefore considered to be much more appropriate and effective at forecasting future gold prices.

Table 3. Comparison of the out-sample performance of the proposed model with other forecasting models.

	ARIMA	Prophet	LSTM	Proposed model
MAPE	0.0226	0.0700	0.0307	0.0154
RMSE	50.4239	137.8639	59.9950	34.7609

Compared to ARIMA, Prophet, and the LSTM forecast for the test dataset, the proposed model's out-of-sample forecasts were also more precise. The MAPE of the proposed model, 0.0154 as well as the RMSE value is also significantly lower than the other models.

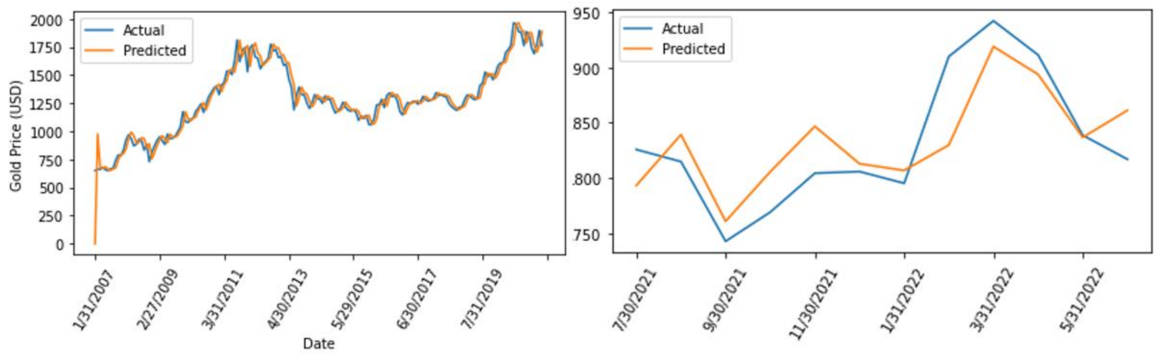

Figure 3. Proposed hybrid model predictions for training data (left) and future out-of-sample predictions (right).

Part 2 - Influence of crude oil and silver price on the gold Price during Crisis periods

This section examines how crude oil, silver, and gold prices changed during the financial crisis of 2008 and Covid 19. This was accomplished through the use of regression analysis and co-integration tests.

a. Descriptive Analysis

The correlation values between the gold price, crude oil price, and silver price have been checked, and the results are reported in Table 4. During the financial crisis, gold and silver prices were highly correlated, and crude oil prices were weakly correlated. Gold has a negative association with crude oil and silver prices for COVID-19.

Table 4. Correlation values among gold price with the crude oil price, and silver price

	Financial Crisis		Covid-19	
	Pearson correlation	P-value	Pearson correlation	P-value
Gold - Crude oil	0.194	0.000	-0.443	0.000
Gold - Silver	0.817	0.000	-0.418	0.000

Table 4 shows a linear relationship between gold prices, crude oil, and silver at 5% significance level. Thus, a regression model was created to determine the association between gold prices and crude oil, silver, and gold prices.

ISBN: 978-955-627-013-6

Regression Model
A regression analysis was conducted to determine the behavior of three variables. The existence of a correlation among the three variables is statistically supported by Table 5.

Table 5. Results of regression analysis for the gold, crude oil, and silver prices

	Financial crisis				Covid-19			
Predictor	Coeffici.	St. Err	t-stat	p-val	Coefficient	St. Err	t-stat	p-val
Constant	590.58	16.42	35.96	0.00	1989.46	15.41	129.14	0.00
Crude oil	-2.16	0.21	-10.41	0.00	-1.65	0.25	-6.50	0.00
Silver	33.74	0.69	49.04	0.00	-4.16	0.76	-5.46	0.00

The coefficients of all predictors for both periods are significant at the 5% significance level, according to Table 5. Following are the identified linear regression equations with estimated parameters,

$$\text{Gold price - crisis} = 591 - 2 \text{ Crude oil} + 34 \text{ Silver}$$
$$\text{Gold price - covid} = 1989 - 2 \text{ Crude oil} - 4 \text{ Silver}$$

Financial crisis 2008 factors predict that the gold price will decrease two times when the crude oil price increases by one and increase 34 times when the silver price increases by one. According to statistics in the Covid period, gold prices decline two times when crude oil prices rise by one and four times when silver prices rise by one.

Table 6. Model Summary for crisis periods

	No Observations	R-sq	R-sq (adj)	Residuals	DW statistic	F-statistic
Financial crisis	1110	0.697	0.696	1107	0.019	1271.00
Covid-19	434	0.208	0.204	431	0.129	56.63

The value of R-sq (69.7% and 20.8% respectively) describes the percentage of variation in the response, which does not indicate the model's accuracy but rather its goodness. Durbin-Watson (DW) statistics in both periods that are less than R-sq and f statistics indicate that the fitted model is affected by serial correlation and there may be a spurious regression (R-sq > DW value). Therefore, it can be concluded that the regression analysis does not adequately explain the relationship between the variables.

By differencing the data, it can eliminate the spurious regression problem, but the long-run information content of the data is lost in the process. However, co-integration enables the preservation of long-term information content. Therefore, the co-integration test was used as the next step.

b. Co-integration Equation
The ADF test was used to verify the pre-condition of the Johansen co-integration test as the p-value of each original data is greater than the 5% significance level, which [I(0)] indicates that the data is not stationary.

As each variable's p-value is less than 5% of the significance level, the ADF test for the first difference series of each variable recommends that all three series are stationary. Consequently, the all-time series is stationary [I(1)]. It indicates that the variables satisfy the precondition. According to that, it was decided to carry out the Johansen co-integration test on VAR based on two different lag lengths.

On the basis of the minimum AIC and BIC values, the existence of a co-integration equation among three factors was examined for the optimal lag. Lag selection has been done to develop co-integration models for three variables. Lag 6 and lag 0 were selected as the optimum lag lengths to develop VEC models for the 2008 crisis period. For the Covid period, lag 9 and lag 0 were selected as optimum lag lengths.

c. The Development of the VEC Model Based on Minimum AIC Value

The hypotheses were evaluated using the Johansen co-integrating test.

H0: No long-run co-integration between gold, crude oil, and silver
H1: A long-run co-integration between gold, crude oil, and silver

Figure 4 presents the co-integration between the three variables for the two periods using trace statistics and max-eigenvalue statistics.

Trace test - Covid-19

r_0	r_1	test statistic	critical value
0	3	37.75	29.80
1	3	16.35	15.49
2	3	6.412	3.841

Trace test - financial crisis

r_0	r_1	test statistic	critical value
0	3	20.04	29.80

Max eigen value test (Covid-19)

r_0	r_1	test statistic	critical value
0	1	21.40	18.89

Max eigen value test (financial crisis)

r_0	r_1	test statistic	critical value
0	1	15.82	18.89

Figure 4. Results of the trace test statistic and maximum eigenvalue test

For the Covid period, there was long-run co-integration between all variables since the critical values were lower than the test statistics. For the crisis period, H0 cannot be rejected, so there is no long-run integration between the variables. Hence, there is enough statistical evidence to fit a vector error correction model (VECM) for three variables during the Covid period.

d. Vector Error Correction Model (VECM)

For the Covid period, the following hypotheses were developed for the VECM.

H0-a : There is no long-run causality running from Crude oil and Silver to Gold
H1-a : There is a long-run causality running from Crude oil and Silver to Gold
H0-b : There is no short-run causality between GOLD and Crude oil
H1-b : There is a short-run causality between GOLD and Crude oil
H0-c : There is no short-run causality between GOLD and Silver
H1-c : There is a short-run causality between GOLD and Silver

The following is a tentative VECM equation for the dependent variable GOLD.

$$\mathrm{D}(GOLD) = C(1) \times (GOLD(-1) + 1818.19 \times \mathrm{CRUDE\ OIL}(-1) + 48.09 \times \mathrm{SILVER}(-1) - 22.08) + C(2) \times D(GOLD(-1)) + C(3) \times D(GOLD(-2)) + C(4) \times D(GOLD(-3)) + C(5) \times D(\mathrm{CRUDE\ OIL}(-1)) + C(6) \times D(\mathrm{CRUDE\ OIL}(-2)) + C(7) \times D(\mathrm{CRUDE\ OIL}(-3)) + C(8) \times D(\mathrm{SILVER}(-1)) + C(9) \times D(\mathrm{SILVER}(-2)) + C(10) \times D(\mathrm{SILVER}(-3)) + C(11)$$

In the VECM equation, $C(1)$ is the coefficient of the co-integrated equation $(GOLD(-1) + 1818.19 \times \mathrm{CRUDE\ OIL}(-1) + 48.09 \times \mathrm{SILVER}(-1) - 22.08)$. The coefficient $C(1)$ is the error correction term or the speed of adjustment of the gold price variable to equilibrium. The significance of the coefficient and the p-values of each term are shown in table 7.

Table 7 contains coefficients with both positive and negative values. This indicates that this VEC model includes both long-term and short-term causal factors. Here, C1 has a negative sign and is statistically significant at a significance level of 5% with a probability value of 0.0001. H0-a is rejected, and long-run causality is accepted for the lag time between the silver price and the gold price. The adjustment ratio needed to reach equilibrium is 12.1%. $C(2)$, $C(3)$, $C(4)$, $C(5)$, $C(6)$, $C(7)$, $C(8)$, $C(9)$, and $C(10)$ are the short run coefficients, and $C(11)$ is constant for the entire system.

Table 7. The probability values of coefficients

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.11	0.29	-4.45	0
C(2)	-0.25	0.2	-2.01	0.08
C(3)	-0.17	0.16	-1.21	0.28
C(4)	-0.19	0.17	-0.78	0.44
C(5)	472.16	201.87	1.5	0.18
C(6)	195.43	278.6	0.9	0.41
C(7)	307.67	202.54	1.71	0.12
C(8)	440.34	184.59	1.99	0.07
C(9)	579.39	190.75	3.13	0.02
C(10)	267.56	200.94	0.82	0.45
C(11)	608.67	376.24	1.63	0.14

The P-value of the C11 coefficient is 0.11, which is greater than the probability value of 0.05, indicating that it is not significant at 5%. Then the Wald test can be used to test for short-term causality from crude oil and silver to gold.

e. Wald Test Results for Short-Run Causalities-Covid-19 period

The Wald test result for $\mathrm{C}(2)$, $\mathrm{C}(3)$, and $\mathrm{C}(4)$ indicates that there is no short-run causality effect from lags one, two, or three from GOLD to present GOLD and the p-value is 0.2084 in the Chi-square test(χ2) and 0.2398 in F stat, which is greater than 5% significance.

The coefficients $\mathrm{C}(5)$, $\mathrm{C}(6)$, and $\mathrm{C}(7)$ are used to evaluate the short-run causality of VECM from CRUDE OIL to GOLD. The null hypothesis H0-b is $C(5) = C(6) = C(7)=0$ checked by the p-value of χ2 which is 0.029, less than the significance level of 5%. As a result, H0-b can be rejected while H1-b can be accepted. These coefficients are assumed to jointly influence Gold so that short-run causality from CRUDE OIL to Gold is accepted.

Wald test results for $C(8)$, $C(9)$, and $C(10)$ of Silver indicate that the null hypothesis H0-c is $C(8) = C(9) = C(10) = 0$ checked by p-value of χ2 which is 0.000 and F-stat is 0.0012, less than the significance level of 5%. Therefore, H0-c, which states "there is no short-term causality between GOLD and SILVER," was rejected and H1-c, which implies that GOLD and SILVER exhibit a joint influence, was accepted.

Therefore, the final VECM for the gold price, crude oil price, and silver price can be written as follows.

$$D(GOLD) = -0.09 \times (GOLD\,(-1) + 1818.19 \times CRUDE\ OIL(-1) + 48.09 \times SILVER(-1) - 22.08)) + 779.90 \times D(CRUDE\ OIL(-1)) + 45.97 \times D(CRUDE\ OIL(-2)) + 18.76 \times D(SILVER(-1)) + 35.54 \times D(SILVER(-2)) + 125.66$$

The adjustment speed towards equilibrium of $GOLD$ is 1.2%, and the AIC value is 18.02, R-sq is 69.2%, and MAPE is 4.42%. The forecasted gold price using equation 7 is in Figure 5.

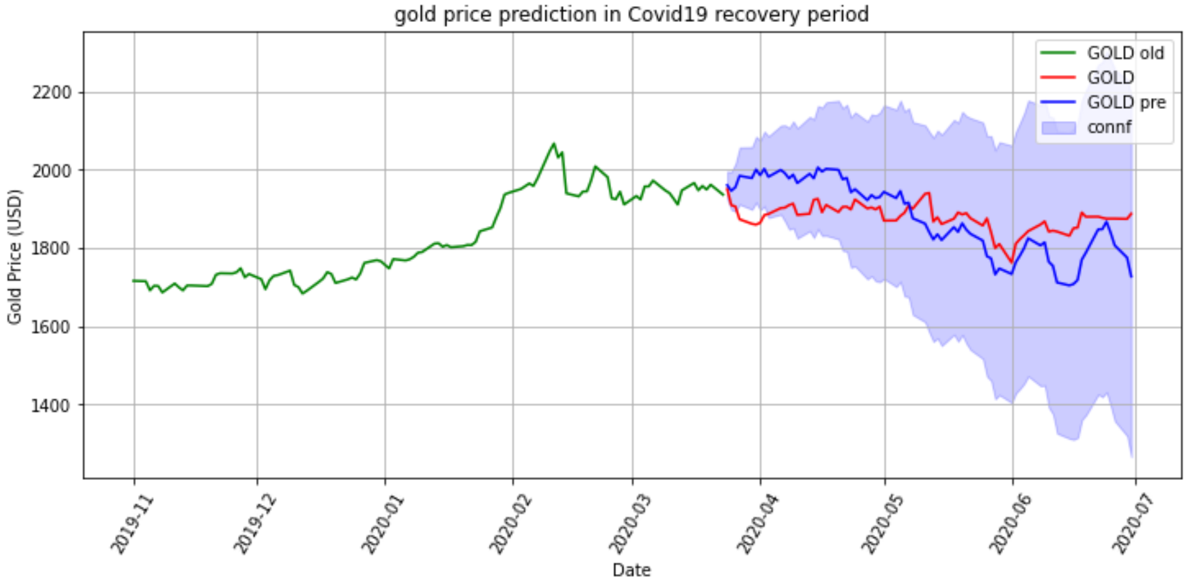

Figure 5. Gold price predictions in the Covid-19 recovery period

4. CONCLUSION

At the end of this study, the following conclusions were drawn based on the statistical results.

For the first phase of the study, time series models such as ARIMA, LSTM, Prophet, and ARIMA-ANN Hybrid models were fitted to forecast monthly gold prices. All models are suitable for gold price forecasting, and among them, the proposed ARIMA-ANN Hybrid model is the most suitable. It is obvious that better forecasting will lead to improved policies in the future. Therefore, policymakers and practitioners may be recommended to adopt the proposed hybrid model for predicting gold price behavior.

The second part of the study was regression analysis and non-stationary analysis for two periods during the 2008 financial crisis and the COVID-19 period. During the financial crisis, gold and crude oil prices had a weakly positive correlation, while silver prices had a strong positive correlation. The correlation between gold and both crude oil and silver prices for the COVID-19 period shows a moderately negative correlation, which can be understood from the ordinary regression analysis. However, regression analysis suggests the presence of spurious regression among the three variables. As a result, in order to determine the relationship between the factors under consideration, a cointegration model has to be used. When creating a VEC model, lag selection based on the minimal AIC and BIC values produces better outcomes. The gold price was considered as the dependent variable in the VEC model created based on minimum AIC and BIC values, implying long-run equilibrium and the presence of short-run causal relationships between the three variables.

For the COVID-19 period, there is a long-run causality running from crude oil and silver to gold. There is a short-run causality between the current gold price and the crude oil price of the previous month and between the current gold price and the silver price of the previous month. Hence, the crude oil and silver prices have a joint impact on the current gold price during the COVID-19 period. So, the developed model can be used to find the effect of various factors and forecast the gold price in a crisis period.

The study can be improved by adding more variables like the stock market index, interest rate, inflation, and consumer price index, along with the gold price. By changing the dependent variables, co-integration models can be made to give a more accurate picture of how the interactions would be affected.

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