Forecasting Spot and Future Gold Coin Price Volatility and Their Predictive Power on Each Other by Using ANN-GARCH Model

Nafiseh Shahmoradi[1], Hasan Ghalibaf Asl[2]

[1] Department of Management, Faculty of Social Science and Economics, Alzahra University, Tehran, Iran.
N.shahmoradi@student.alzahra.ac.ir

[2] Department of Management, Faculty of Social Science and Economics, Alzahra University, Tehran, Iran.
h.ghalibaf@alzahra.ac.ir

Abstract:
A large number of investors have been attracted to the Iran Mercantile Exchange as a result of launching Bahar Azadi Coin future contracts, also known as gold coin future contracts, since 2007. The nature of gold price as a physical-commodity and financial asset, as well as other contributing factors to the gold futures market, extremely complicates the analysis of the relationship between the underlying variables.
One of the methods to forecast the price volatility is the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. However, the high percentage of errors in such prediction has forced researchers to apply a variety of techniques in the hope of more accurate projections. Similarly, in this study, a hybrid model of the GARCH and Artificial Neural Network model (ANN) was used to predict the volatility of gold coin spot and future prices in the Iran Mercantile Exchange.
In this study, variables such as global gold price, spot or future gold coin price (depending on which one is analyzed), US Dollar/IR Rial, world price of OPEC crude oil, and Tehran Stock Exchange Index were considered as factors affecting the price of gold coin. The results of the study indicate that the ANN-GARCH model provides a better prediction model compared to the Autoregressive models. Moreover, the ANN-GARCH model was utilized to compare the predictive power of spot and future gold coin prices, and it revealed that gold coin future price

[1]Corresponding author
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fluctuations predicted spot price of gold coin more accurately.

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1 Introduction

Accurate volatility forecasting is an essential part of risk management, and investors or asset managers try to evaluate securities and investment instruments by analyzing such risk to optimize their portfolio operation. During the last decades, researchers have attempted to find forecasting methods with high accuracy, such as the Autoregressive Conditional Heteroscedasticity model (ARCH) by Engle, 1982 which was generalized by Bollerslev, 1986 and has been known as GARCH models. As a result of studies on forecasting models, the Autoregressive Conditional Heteroscedasticity models were developed to cover the deficiency of previous models. It should be noted, when involving other markets or variables alterations, these models are not so perfect for forecasting. Roh, 2007 mentioned that Financial time series models require strict assumptions about distributions of time series, so it is hard to reflect market variables directly in the models and ANN method can enhance predicting accuracy of these models (p. 1). Therefore, he proposed an integrated approach of GARCH models with an Artificial Neural Network for forecasting stock price index to cover the weakness of financial time series models, and he showed that this model can predict volatility by learning the pattern of other variables without any strict theoretical assumption. Also, Kristjanpoller and Minutolo 2015 applied the Artificial Neural Network to the GARCH method to forecast gold prices volatility which contributed to the improvement of the prediction quality.

Considering the valuable nature of gold for investing, numerous gold-backed securities have been launched as financial instruments all over the world, including Iran. Bahar Azadi Coin is an Iranian bullion gold coin with a purity of 90 percent and weight of around 8.14 g which is minted by the Security Printing and Minting Organization of the Central Bank of the Islamic Republic of Iran (CBI). Furthermore, gold trading in the form of Bahar Azadi coins is booming due to its high liquidity. Moreover, there are some financial instruments such as future contracts in Irans capital market in the form of gold coin-backed securities. In asset backed securities or derivatives markets, investors face ambiguities about the future price of underlying assets and the derivatives pricing. Using statistical and econometric techniques to predict the price of future contracts can reduce ambiguity and uncertainty. So far, various models such as ARIMA and GARCH have been used alone to predict future gold coin volatility in the Iran Mercantile Exchange, but combined models have been used less frequently. Therefore, in this study, the hybrid model of GARCH and Artificial Neural Network is proposed to evaluate its efficiency in improving the quality of forecasting gold coin (Bahar Azadi Coin) spot and future price volatility in Iran.

2 Literature review

In this study, the volatility of gold coin spot and future price is modeled by using an ANN-GARCH method after determining important variables which may affect gold coin price. It is important to choose market variables that can influence the gold and gold coin market. Le and Chang 2012 investigated the impact of oil price fluctuations on gold market returns by utilizing the structural vector autoregressive method to examine the dynamics between the oil price shocks and gold returns. This study showed that oil price shocks have a significant and positive symmetric impact on gold returns. This finding implies that observing oil price fluctuations can help predict movements in the gold prices. Miyazaki and Hamori 2012 investigated the causal relationships between gold and stock market performance by using no uniform weighting cross-correlations. In the sample period, i.e., financial turmoil, they found unidirectional causality in mean from stock to gold, and no causality in variance between them. Therefore, in some situations, investigating the stock market can improve the gold market predictions. Tully and Lucey 2007 investigated macroeconomic influence on gold using an APGARCH model and showed that the most important explanatory variable was the Dollar. Also, Lin et al. 2016 carried out wavelet analysis to examine whether the value of the US dollar drives the price of oil and gold. It appeared that by extending the testing period, pairwise relations became weaker, whereas short-term correlations were much higher. Emphasizing Fed monetary policy as the main driver, financial crises intensify interdependences between oilUS dollar and goldUS dollar and modify the common relationship between them. There are also numerous studies that explore economic conditions on the gold market. Fang et al. 2018 examined whether macroeconomic variables can meliorate forecasting U.S. gold futures volatility by using a mixed data sampling model, i.e., GARCH-MIDAS. It revealed that macroeconomic variables have a considerable impact on the U.S. gold futures volatility in the long term. Therefore, according to these studies on the gold market, macroeconomic variables, oil price, US Dollar, stock market, and Fed rulings are related variables and may affect the gold market.

Along with other variables, the relationship between spot and futures market is one of the important factors. And according to the most common financial theories, the price of a futures contract is always influenced by the spot price of its underlying asset. Nicolau and Palomba 2015 analyzed the dynamic relationship between spot and future prices of gold and some other commodities to investigate the possibility of predicting the spot price by future price and vice-versa. They demonstrated that there is an interaction between spot and future price but it depends on the commodity type and futures contracts maturity. They noted that on the gold market the results showed no possibility of a valid forecasting between spot and futures prices. Also, Kirkulak-Uludag and Lkhamazhapov 2016 investigated the volatility spillover effect between the Russian spot and futures gold markets using the corrected Dynamic Conditional Correlation model (cDCC). The findings indicated a relatively high level of conditional correlation between spot and futures gold returns. In the Indian commodity market, Pradhana et al. 2020 examined the relationship between spot and future prices, including gold and other commodities. By using ARDL bounds-testing technique for examining the long-run relationship and vector error correction model to reveal the nature of Granger causality between them, it was indicated a long-run equilibrium relationship between the spot and futures prices and also unidirectional causality in the short run from the spot to the futures price for gold. According to the above-mentioned studies, there is a correlation between spot and future price of gold. Moreover, interaction and directional causality between spot and future price depend on the period and asset type.

There are numerous studies that focus on volatility forecasting models, but the most widely used are the ARCH models proposed by Engle (1982), and then generalized by Bollerslev 1986. These models are the foundation of many forecasting approaches. Then, Kroner et al. 1995 predicted the volatility of the daily price of some commodities, including gold, by using the combination of the GARCH model and the ISD (Implied Standard Deviation) model. Again, applying time series models to the gold market, Trück and Liang 2012 examined the capability of the GARCH, TARCH, TGARCH, and ARMA models to predict the volatility of gold market, and their results showed that the TARCH models produce the best outcome.

In recent years, most researchers have focused on compound models. Bildirici and Ersin 2009 used the ARCH/GARCH family models with the Artificial Neural Networks to evaluate the volatility of daily returns of the Istanbul Stock Exchange. The ANN integrated models of GARCH approach developed forecasting results. In another case, Saeidi and Mohammadi 2011 studied a wide range of ARCH models to forecast the Tehran Stock exchange index volatility. Furthermore, in order to improve the ability to predict, they compounded models by the Artificial Neural Network which contributed to decrease error. In addition, Monfared and Enke 2014 used a hybrid model GJRGARCH Neural Network for predicting the NASDAQ volatility and argued that compound model prediction was more accurate. Hence, most research on stock market volatility forecasting showed that hybrid models outperformed the sole models. Kristjanpoller et al. 2014 mentioned that an expert system, in particular the ANNGARCH, increases the accuracy of volatility forecasts predicted by GARCH models. The expert system is sensitive to behavior between variables such that the results are improved forecasts.

Utilizing hybrid models of ANN in the gold market, Kristjanpoller and Minutolo 2015 extended the field of expert systems, forecasting, and model by applying an Artificial Neural Network (ANN) to the GARCH method generating an ANNGARCH. The hybrid ANNGARCH model was applied to forecast the gold price volatility, both spot and future. The results revealed an overall improvement in forecasting by using the ANNGARCH as compared to a GARCH method alone. An overall reduction of 25 percent in the mean average percent error was realized using the ANNGARCH. The results were obtained using the Euro/Dollar and Yen/Dollar exchange rates, the DJI and FTSE stock market indexes, and the oil price return as inputs.

In Iran, due to the liquidity of gold coin and its popularity among investors, researchers have focused on gold coin spot and future prices.

Goodarzi and Amiri 2013 studied factors affecting futures price of gold coin and indicated that spot price of gold coin, Dollar/Rial exchange rate, and gold word price are effective factors. Then, by considering those factors and using the Neural Network method to predict the price of gold coin futures contracts, less errors were found in the ANN model compared to the linear multiple regression model. Moreover, Saeidi and Alimohammadi 2014 studied the factors influencing the price changes of future contracts of gold coin in the Iran Mercantile Exchange using the GLS and GARCH approaches. Among the effective factors, the price changes of futures contracts, the world price of gold, the total index of Tehran Stock Exchange, and Dollar/Rial exchange rate have been selected. This study demonstrated that there was a positive relationship between the exchange rate and the price of futures contracts, i.e., with the increase of the exchange rate, the price of futures contracts also increased. However, a significant relationship between the Tehran Stock Exchange index and the price of futures contracts has not been confirmed. To forecast the future and spot price of gold coins, Shams and Naji-Zavareh 2015 predicted the future price of gold coins in the Iran Mercantile Exchange. In this research, a hybrid model based on the fuzzy genetic system (GFS) and the Artificial Neural Network (ANN) was proposed to predict the futures contracts price of gold coins. In this study, first, variables with the greatest impact on the future price of gold coin were identified. Then, the data was divided into k categories using a self-organized neural network. Finally, these categories were entered into the fuzzy genetic system for predicting. Finally, the prediction result of the proposed hybrid model was compared with the prediction result of the Arima linear method. The results showed that the proposed hybrid model has a greater prediction power than the Arima method and has less error in the prediction.

According to the previous studies, the stock exchange index, currency exchange rate, oil price, the world price of gold, and spot/future price are considered as effective elements in future/spot gold coin price volatility. Furthermore, following Kristjanpoller and Minutolo 2015 proposing hybrid model ANN GARCH for predicting gold price due to its advantage on GARCH model, this model will be applied to forecast future and spot price of gold coin in IRAN.

3 Methodology and data

To tackle the shortage of classical methods in time-series with heteroskedastic variance, Engle, 1982 proposed the ARCH model (autoregressive conditional heteroscedasticity) in which the current error variance is a function of the terms of error of previous periods. Then, Bollerslev, 1986 developed the ARCH to GARCH (generalized autoregressive conditional heteroscedasticity). The advantage of the above-mentioned model is strong financial and economic theoretical foundations. On the one hand, the changing market conditions always add error terms, therefore, in order to improve the model, the number of explanatory variables must be increased constantly, but on the other hand, time series models have many restrictive assumptions about the type of time series distribution. Thus, relying on the outputs of these models may lead to inaccurate conclusions. One of the suitable methods for modeling market values is the use of intelligent systems such as an Artificial Neural Network (ANN), which can be adapted to the fluctuations of market variables without being limited to specific and standardized models. However, despite this positive feature, the direct implementation of an Artificial Neural Network for predicting complex financial market variables is associated with some limitations on input variables, and direct use of market variables in the Neural Network without any adjustments may not lead to the best results. In addition, hypothesis testing in the Neural Network models is not as easy and accurate as in normal regression and time series models. Deficiencies in each method result in using a hybrid model such as the ANN-GARCH model.

Before starting the main stages of the research, descriptive statistics of the data will be presented. And due to the heteroscedasticity issue in the residuals of time series models, which is the origin of the parametric volatility forecasting models, the existence of such effects in the series of returns for using GARCH approaches should be ensured by examining and explaining. Subsequently, the appropriate distribution will be selected for estimating GARCH models. In estimating the GARCH model, all observations will be used as training data to estimate the model. For this purpose, the rolling window approach is used. In this approach, it is necessary to consider a constant estimation period that defines a sample in order to estimate the parameters of the variance model. This estimation sample is rolled over the entire data period, and by keeping the estimation period constant, the estimation sample starts from the beginning of the data period based on the study carried out by Keshavarz and Heirani 2015. The rolling window length is 200 days (average data per year), and total days are 1274. The volatility forecasts or outputs are 14 days and 21 days.

In the forecasting process with the GARCH and ANN-GARCH models, instead of using the model for a long time to predict the period ahead, the performance of the model can be examined in comparison with the real data by predicting past periods which are calculated from the estimated model.

The data of the study has been used on a daily basis during the years 2009 to 2016, and since there is a heterogeneity in the data in terms of working days, only common working days in this data have been examined. For predicting the volatility of variables, logarithmic return of data is used. To assess the Tehran Stock Exchange Dividend and Price "total return" Index (TEDPIX) known as TSE index, future and spot price of gold coin and market exchange rate of US Dollar to IR Rial known as USD(free), Rahavard software has been used. Also, the Quandl website has been used to extract the price of OPEC crude oil. Moreover, USD(CBI), the exchange rate of US Dollar to IR Rial which is announced by Central Bank of IRAN, and gold price per Ounce gold(oz) are used as inputs.

In futures transactions of gold coin in the Iran Mercantile Exchange, transactions are conducted in different symbols which are based on the delivery date in different months. What has been used in this research is the weighted average of the prices of tradable symbols in the market, and in order to prevent long-term maturity, only two close maturity symbols have been used. The weight of the near maturity is very close to one and the weight of the symbol with the further maturity is close to zero. Over time, as getting closer to the end of the maturity of the least maturity symbol, its weight declines to zero, and the weight of the symbol with further maturity gets closer to one. This method is repeated up to the end and the last symbols.

To begin with the prediction model, firstly, the time series of daily returns of spot and futures price of gold coins will be entered into the GARCH models as independent variables and the GARCH models will be evaluated. Then, time series extracted from the GARCH models are, in fact, the variables entering the neural network. Considering the ANN-GARCH approach in this study, the impacts of other financial markets for predicting volatility of future and spot returns of gold coin are examined. Moreover, the ANN-GARCH model is utilized to compare the predictive power of spot and future price of gold coin and predict each one by the other.

One of the methods to enter the variables into the neural network is the filter method. In this method, the degree of correlation of inputs should be investigated. In this study, in order to add independent input variables to the layers of the neural network, the correlation matrix of the variables has been tested. Therefore, the variables are first extracted from the GARCH method, and then the input variables of the layers which are ranked are entered in the ANN-GARCH model, respectively. Finally, the forecasting approaches are compared.

It is worth mentioning that the ANN-GARCH (q, p, s) model is a reinforced model of the GARCH method in which a specific function based on the neural network is added, and it is indicated in the following function.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{h=1}^{s} \xi_j \psi(Z_t \lambda_h) + V_t \tag{1}$$

In this function, the ARCH component $\sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$, the GARCH one $\sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$, and also the independent variables $\sum_{h=1}^{s} \xi_j \psi(Z_t \lambda_h)$ will be used as inputs to the neural network system. Realized volatility is the forecasted parameter through a GARCH (1,1) model, an AR(1) model, and the Artificial Neural Network model, and it is computed as the sample variance log returns in a 21 d window to the future (approximately one month of transactions), as shown by the equation.

$$RV_t = \frac{1}{21} \sum_{i=t+1}^{t+21} (r_i - \bar{r_t})^2 \tag{2}$$

The parameters of the ANN are three layers and five neurons per layer as in Kristjanpoller and Minutolos (2015) study. The volatility of the variables which are estimated and extracted from the ARCH and GARCH sections enter into the ANN model as input variables with the series of fluctuations of other variables, respectively. To evaluate the forecasting models, MAD, RMSE, and MAPE are measured as fitness comparing statistics and the emphasis is on MAPE.

4 Results analysis

Since this study is based on the ANN-GARCH approach, it is important to evaluate the impact of other financial markets on predicting future and spot price volatility of gold coins. Figure 1 shows the trend of changes of each variable with other variables and their distribution diagram. As depicted, spot and future price changes of gold coin have simultaneous trend, and the relationship between the spot and future return of gold coin with other variables, except the TSE index, is positive.

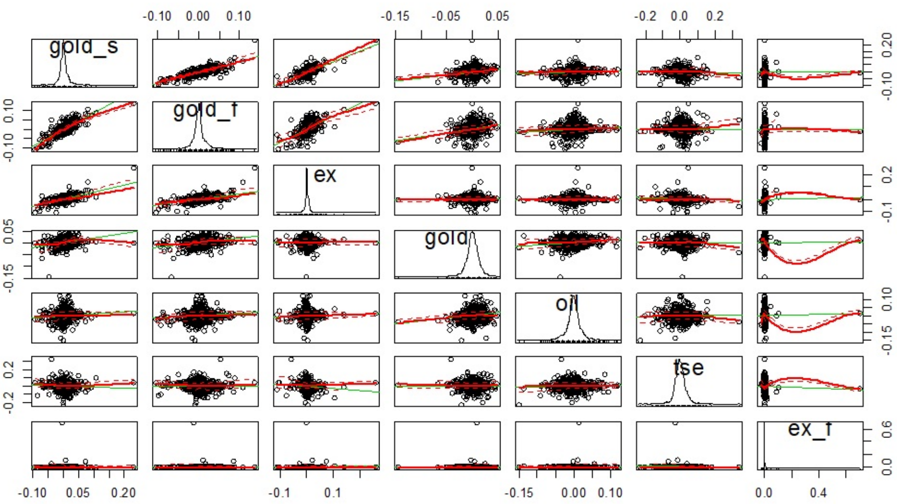

Figure 1: Joint distribution of variables

It should be noted that in order to present the linear dependencies of the variables, descriptive statistics of the logarithmic returns are investigated and demonstrated in Table 1. The normality test is the JarqueBera which shows rejection of the null hypothesis for each series. The abnormality of the future and spot gold coin returns can be seen in the quantile

Mean absolute percentage error
Median absolute deviation
Root-Mean-Square deviation

diagrams of their normal distribution. As can be seen in Figure 2, the distribution of these two variables are fat tailed, so the t-student distribution will be a suitable distribution for estimating the GARCH models.

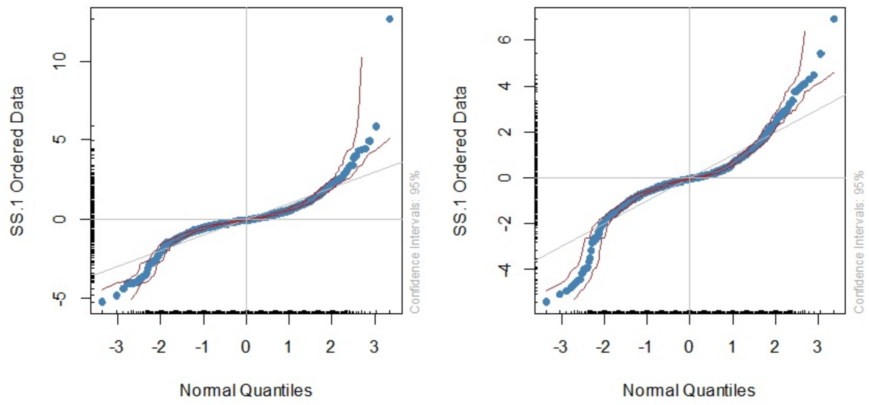

Figure 2: Quantile charts of spot (right) and futures (left) returns of gold coins

Table 1: Descriptive statistics of the logarithmic returns of variables

	Gold(S)	Gold(F)	Gold(oz)	USD(CBI)	USD(free)	TSE	oil
Mean	0.0013	0.00139	0.00020	0.00095	0.00105	-0.0007	-0.0001
Median	0	0.00061	0.00039	0	0	-0.0026	-0.0002
Max	0.2287	0.13565	0.04675	0.70409	0.2567	0.3353	0.1205
Min	-0.0935	-0.10421	-0.14438	-0.0239	-0.1112	-0.2293	-0.1492
Skewness	1.630	0.23265	-1.3489	33.3274	3.4539	0.3977	-0.0741
Kurtosis	27.95	10.7462	17.116	1156.58	70.355	11.9747	9.2401
Jarque-Bera	33615	3196.6	10965	708771	243362	4309.2	2068.2

As the variables correlation matrix in Table 2 indicates, the most correlation is between the spot and future returns of gold coins. According to the correlation matrix, the ranking of spot and future price of gold coin correlation with other variables are the same. USD(free), Gold(oz), oil, TSE Index, and USD(CBI) have the highest correlation with gold coin spot and future price, respectively.

Table 2: Correlation matrix

	Gold(S)	Gold(F)	Gold(oz)	TSE	USD(free)	USD(CBI)	oil
Gold(S)	1						
Gold(f)	0.8099	1					
Gold(oz)	0.2819	0.2761	1				
TSE	-0.0481	-0.0206	-0.0076	1			
USD(free)	0.6710	0.5688	0.0234	-0.1051	1		
USD(CBI)	0.0036	0.0022	0.0106	-0.0357	0.0259	1	
oil	0.0960	0.1175	0.1801	0.0338	0.0393	0.0167	1

To investigate heteroscedasticity (ARCH), the LM test is used, and the DickeyFuller test (ADF) is applied to examine if there is a unit root or non-stationary in some level of confidence. According to the ADF test which is shown in Table 3, the null hypothesis that there is a unit root is rejected, and time series stationary is confirmed in 99 percent of confidence level. Also, the LM-ARCH test affirmed heteroscedasticity in the series.

Table 3: stationary and ARCH effect test

	Gold(S)	Gold(F)	Gold(oz)	TSE	USD(free)	USD(CBI)	oil
ADF	-9.88	-10.66	-11.22	-8.82	-10.39	-10.79	-10.14
Prob.	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LM	66.44	153.4	33.26	21.70	133.2	28.23	73.4
Prob.	0.00	0.00	0.03	0.04	0.00	0.04	0.00

Due to the heteroscedasticity effects, to model the volatility of the future and spot price of gold coin series and due to having cluster turbulence in series, it is necessary to consider a marginal distribution for them to adapt the experimental distribution of returns. Therefore, the ARMA-GARCH model was estimated by t-student distribution due to the fat-tailed distributions. It should be noted that in order to study asymmetric effects on positive and negative shocks of the series, the sign asymmetry test is used. The results of the estimated ARMA(1,0)-GARCH(1,1) and ARMA(1,2)-GARCH(1,1) model with t-student distribution for spot and future price of gold coin, are summarized in Table 4 and 5, respectively.

The results demonstrate that the parameters of the estimated model are significant. Engle test confirmed the null hypothesis that residual heteroscedasticity is not significant. Moreover, the sign asymmetry test rejected the null hypothesis that there are asymmetric effects on positive and negative shocks. Therefore, the standard GARCH model is suitable for investigating both series.

Table 4: The results of the GARCH model with t-student distribution; gold coin spot return

Parameters	Estimate	Std. Error	t value	$Pr(>\|t\|)$
ar1	-0.0937	0.0256	-3.6623	0.0002
omega	0.0000	0.0000	1.1445	0.2524
alpha1	0.1090	0.0286	3.8054	0.0001
beta1	0.8900	0.0335	26.6029	0.0000
shape	3.0859	0.2610	11.8241	0.0000
	Statistic	Shape	Scale	P-Value
ARCH Lag[3]	0.0300	0.5000	2.0000	0.8625
ARCH Lag[5]	0.8458	1.4400	1.6670	0.7792
ARCH Lag[7]	1.3899	2.3150	1.5430	0.8432
	t-value	prob sig		
Sign Bias	0.8923	0.3724		
Negative Sign Bias	0.0370	0.9705		
Positive Sign Bias	0.6439	0.5198		

As it was mentioned, forecasting the volatility of spot and future price of gold coin by the GARCH and ANN-GARCH models will be studied in 14 and 21 days. According to the correlation matrix, the first variable to enter the ANN model is the volatility of future/spot of gold coin-ANN-GARCH1- and the other variables are USD(free), Gold(oz), oil, TSE Index, and USD(CBI). As depicted in Table 6, in the 14-day period, by using the rolling window, the ANN-GARCH6 has the least error, which well reflects that other financial market fluctuations contribute to boosting the power of forecasting volatility of spot price. Therefore, the ANN-GARCH approach is appropriate for increasing the GARCH model capability to predict the volatility of gold coin spot prices. In the 21-day period, by using the rolling window, the ANN-GARCH1, entering future

Table 5: The results of the GARCH model with t-student distribution; gold coin future return

Parameters	Estimate	Std. Error	t value	$Pr(>\|t\|)$
ar1	-0.8547	0.1144	-7.4741	0.0000
ma1	0.8571	0.1169	7.3311	0.0000
ma2	-0.0130	0.0252	-0.5167	0.6054
omega	0.0000	0.0000	1.4224	0.1549
alpha1	0.1225	0.0201	6.0794	0.0000
beta1	0.8765	0.0224	39.2049	0.0000
shape	2.9975	0.1913	15.6710	0.0000
	Statistic	Shape	Scale	P-Value
ARCH Lag[3]	0.0273	0.5000	2.0000	0.8687
ARCH Lag[5]	0.5648	1.4400	1.6670	0.8643
ARCH Lag[7]	1.5286	2.3150	1.5430	0.8156
	t-value	prob sig		
Sign Bias	1.8126	0.1701		
Negative Sign Bias	0.0820	0.9347		
Positive Sign Bias	1.0576	0.2904		

of gold coin, has the least error. Hence, by increasing the predicting period in forecasting spot price of gold coin, the error of the ANN-GARCH model increases.

As shown in Table 7, in 14 and 21-day periods, by using the rolling window for forecasting future price, the ANN-GARCH5 has the least error, which well reflects that other financial market fluctuations, including USD(free), Gold(oz), oil, and TSE Index, respectively, contribute to boosting the power of forecasting the volatility of future price. Therefore, the ANN-GARCH approach is appropriate for increasing the GARCH model ability to predict volatility.

It should be noted, due to the relative increase in the fitness comparing statistics of predictive models, forecasting the volatility of gold coin future price is more difficult compared to predicting the volatility of gold coin spot price, identical to the results obtained by Kristjanpoller and Minutolo 2015.

By calculating the forecasting amelioration of using ANN-GARCH to

Table 6: Comparison of the volatility forecasting models in spot price of gold coin

	14day				21day			
	RMSE	MAE	MPE	MAPE	RMSE	MAE	MPE	MAPE
GARCH	0.0111	0.0093	14.911	48.323	0.0136	0.0090	17.933	45.972
A-G1	0.0104	0.0067	-24.523	40.994	0.0111	0.0067	-9.300	40.865
A-G2	0.0116	0.0070	-25.570	41.760	0.0114	0.0072	-25.008	42.458
A-G3	0.0115	0.0070	-22.936	41.587	0.0106	0.0068	-23.795	41.064
A-G4	0.0126	0.0075	-24.286	44.459	0.0109	0.0070	-24.847	43.629
A-G5	0.0115	0.0072	-24.792	44.794	0.0116	0.0074	-24.568	45.777
A-G6	0.0101	0.0069	-8.510	37.683	0.0109	0.0070	-22.681	43.624

GARCH approaches, as indicated in Table 8, in all of the stages, the error from the GARCH model is more than the ANN-GARCH model, except in one case. The hugest gap belongs to the ANN-GARCH6, considering the prediction of gold coin spot price volatility in a 14-day period that shows the advantage of adding the ANN approach to forecasting model of GARCH.

Moreover, having compared the predictive power of spot and future gold coin prices, the ANN-GARCH model revealed that gold coin future price fluctuations predict gold coin spot price more accurately, as indicated in Table 9.

5 Conclusions

This study compared the forecasting capability of hybrid methods in Bahar Azadi gold coin spot and future prices in Iran through using the Artificial Neural Network with the Generalized Autoregressive Conditional Heteroscedasticity model. Three main contributions of this study were 1) confirming the hybrid model ANNGARCH capability to improve volatility forecasting compared to GARCH models, 2) determining the most important contributing financial variables which affect the volatility of gold coin spot and future prices, and 3) evaluating forecasting power of gold coin spot price and future price in predicting volatility of each other. The results revealed:

Table 7: Comparison of the volatility forecasting models in future price of gold coin

	14day				21day			
	RMSE	MAE	MPE	MAPE	RMSE	MAE	MPE	MAPE
GARCH	0.0201	0.0164	-33.101	48.958	0.0110	0.0077	-28.255	49.296
A-G1	0.0100	0.0072	-24.832	44.920	0.0113	0.0074	-27.293	44.710
A-G2	0.0103	0.0074	-27.024	44.707	0.0111	0.0074	-27.539	45.045
A-G3	0.0105	0.0072	-26.671	43.758	0.0110	0.0074	-27.919	45.202
A-G4	0.0110	0.0070	-21.908	43.386	0.0105	0.0071	-24.682	44.670
A-G5	0.0099	0.0069	-26.951	43.271	0.0102	0.0061	-23.968	40.649
A-G6	0.0117	0.0078	-29.118	49.686	0.0108	0.0076	-26.354	47.412

(i) **Spot price:**The hybrid model ANNGARCH forecast volatility of gold coin spot price more accurately than the GARCH model in a 14-day period, including other financial variables, gold coin(F), USD(free), Gold(oz), oil, TSE Index, and USD(CBI). But by increasing the predicting period to 21 days, the forecasting capability of the ANN-GARCH model deteriorates, and the ANN-GARCH1 which includes only gold coin future price has the least error for forecasting volatility of gold coin spot price. Therefore, ANN-GARCH has more predicting power than the GARCH approach, and it is suggested to use ANN-GARCH1 for forecasting volatility of gold coin spot price by extending the predicting period.

(ii) **Future price:** The hybrid model ANNGARCH capability to forecast volatility of gold coin future price is more than the GARCH model, and it is more suitable for predicting volatility. Also, ANN-GARCH5 which includes gold coin(S), USD(free), Gold(oz), oil, TSE Index has the least error.

(iii) **Forecasting power:** As it is indicated in ANN-GARCH1, after comparing the prediction accuracy of future and spot price of gold coin, future price fluctuations proved to predict spot price of gold coin more accurately.

(iv) **Difficulty in forecasting:**Forecasting volatility of gold coin future price is more difficult than predicting volatility of gold coin spot

Table 8: Comparison of the ANN-GARCH and GARCH models

	Spot		Future	
	14d	21d	14d	21d
	$\Delta MAPE$	$\Delta MAPE$	$\Delta MAPE$	$\Delta MAPE$
GARCH to ANN-GARCH1	7.3293	5.1073	4.0376	4.5854
GARCH to ANN-GARCH2	6.5634	3.5146	4.2508	4.2506
GARCH to ANN-GARCH3	6.7363	4.9089	5.1992	4.0935
GARCH to ANN-GARCH4	3.8641	2.3435	5.5716	4.6259
GARCH to ANN-GARCH5	3.5294	0.1952	5.6864	8.6467
GARCH to ANN-GARCH6	10.6406	2.3489	-0.7283	1.8834

price, just as the results achieved by Kristjanpoller and Minutolo (2015) revealed.

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Table 9: Comparison of forecasting capability of spot and future price

	Spot		Future	
	14d	21d	14d	21d
	$\Delta MAPE$	$\Delta MAPE$	$\Delta MAPE$	$\Delta MAPE$
ANN-GARCH1	40.9943	40.8657	44.9206	44.7106

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