Autoregressive Integrated Moving Average Model for Gold Price Forecasting : Evidence from the Indian Market

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Abstract

The present study was conducted to forecast the gold prices in India by employing ARIMA (1, 1, 2) model on time series data for short term. The stationarity of time series data was tested by using the ADF unit root test. To overcome the problem of autocorrelation, Breusch - Godfrey serial correlation was conducted. The study forecasted gold prices within sample and post sample forecast. Actual values of gold prices and the forecasted values of gold prices moved in the same direction very closely. The post sample forecasted values of gold prices revealed an increasing trend. The predicted six months values of gold prices probably indicated reasonable returns for investors who held gold in their financial portfolios. Hence, the ARIMA (1, 1, 2) model was found to be the best fit to forecast short term gold prices on time series data.

Keywords : **gold prices, time series, autoregressive integrated moving average (ARIMA), investment, stationary, forecasting**

JEL Classification : F470, G170, G130, G150

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Historically, gold has been considered as the symbol of prestige and wealth the world over. All governments maintain significant level of gold reserves equivalent to printed currency. Investors also use gold as an investment to minimize risk of their financial portfolios. Therefore, gold market as well as its demand is growing rapidly due to buoyant gold prices in developing countries like India and China. Although global gold demand fell 10% in Q3 of 2016 to 992.8 tonnes to Q2 of 2016, the demand for exchange - traded products showed positive signs of growth with inflows of 145.6 tonnes. Demand for physical gold like bars, coins, and jewellery curtailed to 16% on an year on year basis (World Gold Council, 2016). India's demand for gold is still weak because the 10% and 15% import duties were imposed on raw gold and on jewellery, respectively. Since April 2013, 145.6 tonnes of gold was added to the existing pool that raised the total AUM (asset under management) to 2,335.6 tonnes (World Gold Council, 2016). The past pattern of gold demand for exchange trade products (ETPs) shows that investment demand is solely driven on the basis of long term position of investors because there is an inverse correlation between gold prices and equity prices and it provides confidence to investors in gold.

Review of Literature

The volatility of gold prices and investor confidence in gold inspired us to review available literature to

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understand the behavior and pattern of gold prices and to identify the best suited forecasting techniques. Nochai and Nochai (2006) forecasted palm oil prices by applying the ARIMA model and found statistical significance of forecasting results by ARIMA Model at different values of *p, q*, and *d* parameters. Jakasa, Androcec, and Sprcic (2011) forecasted electricity prices by using ARIMA model approach and Expert modeler. They identified some seasonal components and properly modeled the same with the ARIMA model. Shankari (2011) found that gold prices itself were the significant factor that influenced the buying behavior of customers while making purchasing decisions regarding gold. Abdullah (2012) applied ARIMA model to forecast the gold bullion coin prices and found ARIMA (2, 1, 2) to be the best fit model for gold coin price forecasting. According to Anand and Dharnidharka (2012), ARIMA model is a traditional approach, yet it has significance in short term forecasting of time series data because it predicts the future value of time series data with accuracy.

Nouri, Oryoie, and Fallahi (2012) used ARIMA-GARCH model to forecast gold return time series where the regressors were selected on the basis of minimum of Akaike's Information Criterion and which had statistical significance for coefficients. Murthy, Anupama, and Deeppa (2012) found that gold price forecasting done through geometric random walk model was better and more reliable than ARIMA models for both in sample and out sample forecast. Khan (2013) applied Box-Jenkins, auto regressive integrated moving average (ARIMA) methodology to forecast gold prices. Davis, Dedu, and Bonye (2014) applied ARMA model for price forecasting and found that the forecasted values of prices fell within the actual values of forecast limits. Adebiyi, Adewumi, and Ayo (2014) used ARIMA model to predict the stock price and found that the ARIMA model played a significant role in stock price forecasting in short term only. Ahmad, Ping, Yaziz, and Miswan (2014) forecasted the selling price of Malaysian gold by using ARIMA-GARCH model and found that the selling prices forecast of 1/oz Malaysian gold was predicted more accurately by employing the combination of ARIMA-GARCH model. Khaemasunun (2014) used multiple regression and auto-regressive integrated moving average (ARIMA) to forecast the Thai gold prices and found the significance of the model in the short run.

Sharma and Baby (2015) found that ARIMA (0,1,1) was the best fit model for the given set of data because it precisely estimated gold prices in the future. Guha and Bandyopadhyay (2016) analyzed historical gold price performance by employing the ARIMA model to predict the future values of gold. They found ARIMA (1, 1, 1) model suitable for predicting the future values of time series analysis. Yaziz, Azizan, Ahmad, and Zakaria (2016) found that the hybrid model of ARIMA (0,1,0) and TGARCH (1,1) provided significant results of gold price forecasting. Ali, Iqbal, Qamar, Akhtar, Mahmood, Hyder, and Jamshed (2016) found that the forecasted values given by ARIMA model were efficient because these values were assessed on different statistical criterion like mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE).

Dhanalakshmi and Reddy (2016) established a deterministic model for gold price forecasting by using Box-Jenkins ARIMA and found the factors which have a major impact on gold price and are used for predicting the gold prices for coming years. Panda and Sethi (2016) found that gold acts as an inflation hedge, gold investment is less risky as compared to stock market investments, and rupee dollar exchange rates have a significant impact on gold returns. Their study rejected gold investments as an alternative to fixed income investment tools during 1971 to 2013.

Statement of the Problem and Objectives of the Study

After reviewing a number of studies, it was found that ARIMA model is very useful in price forecasting of different commodities, particularly gold prices in different countries in the short run only. Therefore, this study is an endeavor to check its suitability in the forecasting of gold prices in Indian rupee denomination.

Research Hypotheses

To achieve the objectives of the study, the following hypothesis set was formed :

- **H0 :** The given set of data is stationary.
- **Ha :** The given set of data is not stationary.

Research Methodology and Theoretical Base

This study is an empirical research based on secondary data for the sample period from April 2003 to December 2016. The monthly average selling price of gold was collected from the World Gold Council website denominated in rupees used to represent domestic gold prices in India. The stationarity of time series data was checked by applying ADF (Augmented Dickey- Fuller) unit root test. To overcome the problem of autocorrelation, Breusch-Godfrey serial correlation test was carried out. At last, Box-Jenkins autocorrelation integrated moving average (ARIMA) technique was applied to forecast the gold prices within the sample and post sample forecast for the next six months.

(1) ARIMA Model : The ARIMA is used to forecast time series data widely. A random variable of time series is stationary if its statistical characteristics over the time have no trend and have constant variance. The ARIMA model is denoted by ARIMA (p, d, q).

where,

p = number of autoregressive terms,
d = order of differences required for stationarity,
q = number of lagged forecast errors in forecasting equation.

General time series equation for forecasting is written as :

$$y_t = \alpha_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \ldots + \beta_p y_{t-p} + \varepsilon_t - \alpha_1 \varepsilon_{t-1} - \alpha_2 \varepsilon_{t-2} - \ldots - \alpha_q \varepsilon_{t-q} \quad (1)$$

where,
y_t = actual value at time t,
α_0 = constant,
ε_t = error term at time t,
β_i ($i = 1, 2 \ldots\ldots p$) and α_j ($j = 1, 2 \ldots\ldots q$) = model parameters.

(2) Augmented Dickey-Fuller (ADF) Unit Root Test : ADF unit-root test is used to determine stationarity of the time series data. The following testing procedure is applied to the model:

$$\Delta y_t = \alpha_0 + \beta_t + \O y_{t-1} + \Sigma^{l}_{j=0} \alpha_j \Delta y_{t-1} + \varepsilon_t \qquad (2)$$

where,
y_t = tested time series,
Δ = first difference of time series,
j = lag order of the autoregressive process.

Results and Discussion

The Figure 1 shows that the original monthly gold price data is plotted to observe trend and stationarity. In Figure 1, the time period is represented on the *X* axis and gold prices are taken along with the *Y* axis. From the Figure 1, it is inferred that the original gold price series is following increasing trend in tandem with time. The graphical presentation reveals the non stationarity of the time series data. Hence, the null hypothesis (H0) is rejected. The studied given set of time series data is not stationary and it is graphically shown in the Figure 1.

As per the model statistics, if the time series data follows either increasing or decreasing trend, then the data series is not stationary or data series is not fit to run the ARIMA model. Therefore, the given time series data requires first-order differentiation to make future forecasts of gold prices.

Figure 1. Historical Line Graph of Original Time Series of Gold Prices *(Y)*

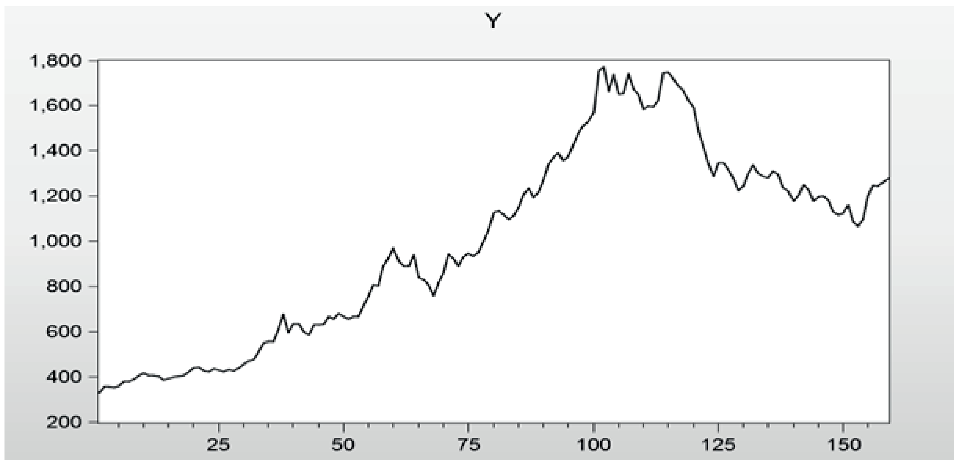


Table 1. Results of ADF Test of Stationarity for Original Gold Price Series *t* - Statistics

			t-Statistics	*p* - value*
	Augmented Dickey-Fuller test statistic		-1.431269	0.5657
Test Critical Values:		1% level	-3.471987	
		5% level	-2.879727	
		10% level	-2.576546	
*Mackinnon (1996) one side p-values.				
Variable	**Coefficient**	**Standard error**	***t* - Statistic**	***p* - value**
Y(-1)	-0.01134	0.007923	-1.431269	0.1544
C	17.26569	8.567213	2.015321	0.0456
R-squared	0.012961		Mean dependent variance	6.001392
Adjusted *R*-squared	0.006634		Standard Deviation dependent variance	42.6901
Standard Error of regression	42.54826		Akaike information criterion	10.35171
Sum squared residuals	282415.3		Schwarz criterion	10.3905
Log likelihood	-815.7869		Hannan-Quinn criterion	10.36748
F-statistic	2.048531		Durbin-Watson statistics	1.654745
P value (*F*-statistic)	0.154353			

From the Table 1, it can be statistically checked whether the given time series data is stationary or non stationary. The observed t-statistic value is -1.431269 and its corresponding p - value or probability value is 0.5657, which is greater than 0.05 and is highly insignificant. The t - statistics value -1.431269 is less than the value of confidence interval values at 1% (-3.471987), 5% (-2.879727), and 10% (-2.576546). In absolute terms, the t - statistics value must be greater than the confidence interval values at 1%, 5%, and 10% levels. But the t - statistic value is not significant as per the assumption Augmented Dickey Fuller test. Therefore, the null hypothesis (H0) is rejected statistically. Therefore, the given time series data needs the first order difference to make the time series stationary.

The White Noise assumption of the proposed ARIMA model can be tested through Table 2. White noise describes the assumption that each element of the time series data is randomly drawn from a population with zero mean and constant variance and indicates whether the residuals are uncorrelated. It can be seen in the Table 2 that the spikes of ACF (autocorrelation function) and PACF (partial autocorrelation function) decrease gradually or have seasonality effect, and have the problem of autocorrelation. The very high value of autocorrelation coefficient proves the existence of autocorrelation among the residuals. Therefore, residuals do not satisfy the white noise assumption. The last lag Q statistics value is 3054.1 and its corresponding p value/probability value is 0.000, which is highly significant. Therefore, the null hypothesis (H0) is rejected.

It can be concluded from the Figure 2 that after taking the first order difference of the original time series data,

Table 2. Results of Autocorrelation Test for the Original Gold Price Time Series

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.986	0.986	157.48	0.000
		2	0.971	-0.046	311.11	0.000
		3	0.956	0.002	461.00	0.000
		4	0.940	-0.036	606.92	0.000
		5	0.925	0.013	749.06	0.000
		6	0.909	-0.013	887.43	0.000
		7	0.893	-0.040	1021.8	0.000
		8	0.877	0.003	1152.2	0.000
		9	0.862	0.011	1279.0	0.000
		10	0.847	0.023	1402.3	0.000
		11	0.832	-0.043	1522.0	0.000
		12	0.815	-0.075	1637.5	0.000
		13	0.796	-0.040	1748.7	0.000
		14	0.777	-0.044	1855.3	0.000
		15	0.757	-0.028	1957.2	0.000
		16	0.737	-0.024	2054.4	0.000
		17	0.715	-0.066	2146.6	0.000
		18	0.693	-0.034	2233.7	0.000
		19	0.670	-0.003	2315.9	0.000
		20	0.649	0.021	2393.5	0.000
		21	0.627	-0.043	2466.4	0.000
		22	0.604	-0.052	2534.7	0.000
		23	0.580	-0.049	2598.0	0.000
		24	0.556	-0.006	2656.7	0.000
		25	0.532	-0.025	2710.8	0.000
		26	0.508	-0.019	2760.4	0.000
		27	0.483	-0.012	2805.7	0.000
		28	0.458	-0.036	2846.7	0.000
		29	0.434	0.032	2883.8	0.000
		30	0.411	0.004	2917.3	0.000
		31	0.387	-0.016	2947.3	0.000
		32	0.364	-0.021	2974.0	0.000
		33	0.342	0.041	2997.8	0.000
		34	0.321	0.030	3018.9	0.000
		35	0.301	0.017	3037.6	0.000
		36	0.281	-0.015	3054.1	0.000

Figure 2. Graph of Gold Price Series at First Order of Difference (*DY*)

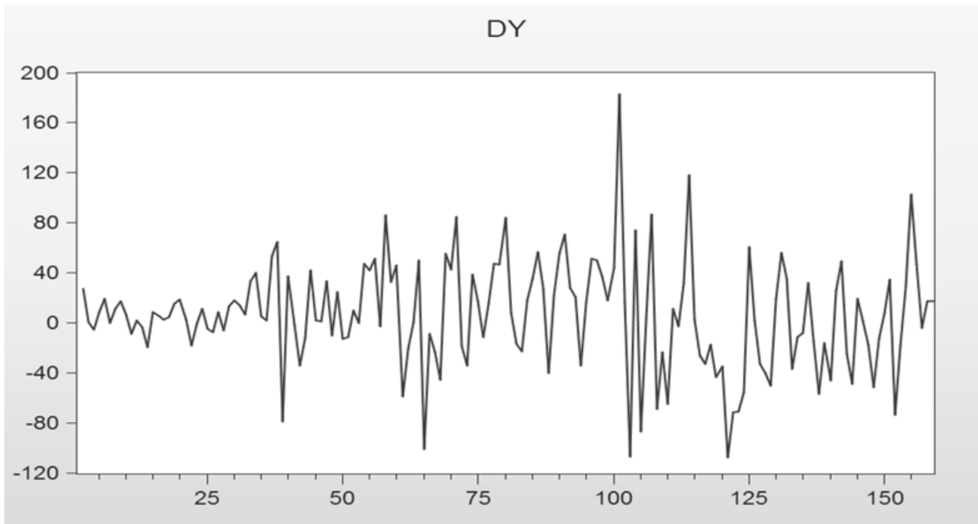


Table 3. Results of Gold Price Series for ADF Test at First Order Differentiated Value of *t*- Statistics

			***t* - Statistic**	***p* - value***
	Augmented Dickey-Fuller test statistic		-10.45919	0.0000
Test Critical Values:		1% level	-3.472259	
		5% level	-2.879846	
		10% level	-2.57661	
*Mackinnon (1996) one side *p* - values.				
Variable	**Coefficient**	**Standard error**	***t*-Statistic**	***p* - value**
DY (-1)	-0.826909	0.079061	-10.45919	0.0000
C	4.8378	3.406814	1.420037	0.1576
R-squared	0.413755		Mean dependent variance	-0.06687
Adjusted *R*-squared	0.409973		Standard Deviation dependent variance	55.04382
Standard Error of regression	42.28093		Akaike information criterion	10.33921
Sum squared residual	277090.1		Schwarz criterion	10.37814
Log likelihood	-809.6277		Hannan-Quinn criterion	10.35502
F-statistic	109.3946		Durbin-Watson statistics	1.978848
Probability (*F*-statistic)	0.0000			

seasonality has been removed and the series is transformed to stationary. The transformed series does not follow any trend or seasonality. Therefore, the null hypothesis (H0) is accepted. Hence, data series becomes suitable to forecast the future selling price of gold by applying ARIMA (*p, q, d*) model by using different values of parameters. This is a hit and trial method in which the values of selected parameters *p, q,* and *d* are chosen on the AIC (Akaike Information Criterion).

The combination of *p, q*, and *d* parameters that has the lowest value is selected as the best model. Therefore, it implies that lower value of AIC has minimum deviation from the actual value of the given time series data. The forecasted value of gold price series is approximately equal to actual value of the data series.

It can be seen from the Table 3 that *t*-statistic value is -10.45919 and its corresponding probability value or

p - value (0.000) is highly significant because it is less than 0.05. The value of t-statistics in absolute terms is 10.45919, which is greater than the confidence level values at 1% (-3.472259), 5% (-2.879846), and 10% (-2.576610). Therefore, the null hypothesis H0 is accepted. The differentiated data series or detrended data series is suitable for model forecasting. After taking the first order of differentiation, the studied gold price time series become stationary.

The first order difference of the original data series of selling gold price has removed the problem of autocorrelation (Table 4). There is no significant pattern left in ACF (autocorrelation function) and PACF (partial autocorrelation function) of the residuals. The coefficient values of ACF and coefficient values of PACF are very small. Therefore, residuals of the selected model are white noise. The Ljung-Box statistics or Q statistics decides whether the null hypothesis is rejected or accepted. Since the last lag value of Q statistics (33.312) and its corresponding probability or p - value (0.597) is greater than 0.05, the null hypothesis (H0) is accepted after taking the first order differentiation. Hence, the model is well specified and adequate to run the ARIMA (p, q, d).

The Table 5 depicts the value of different parameters of autoregressive (p) and moving average (q) of the ARIMA model. ARIMA (1, 1, 2) is the best suitable model for gold price forecasting as shown in the Table 5. The model has the minimum value of AIC (Akaike information criterion), that is, 3.34738 and the lowest value of S.E. Regression (standard error of regression) is 4.32118. ARIMA (1, 1, 2) is preferred as the best model for gold price

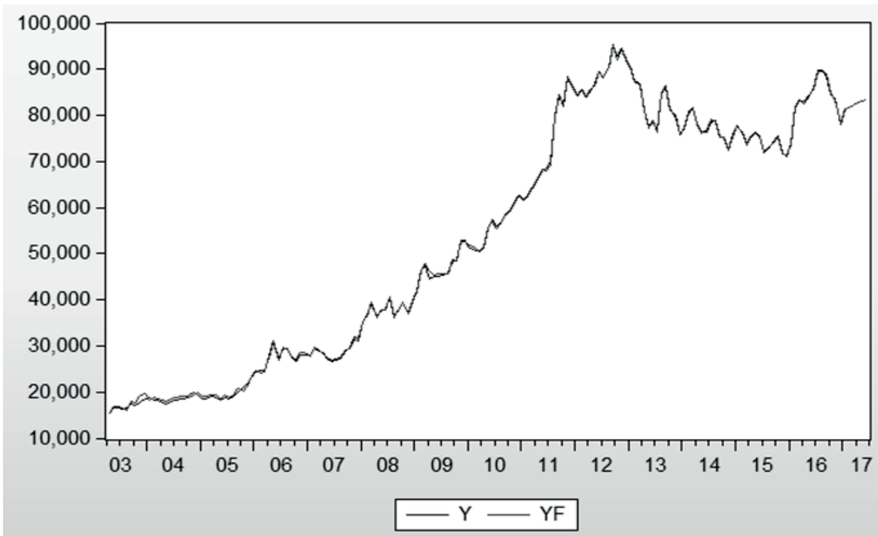
Table 4. Results of First Order Differentiation for Autocorrelation of Residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.173	0.173	4.8204	0.028
		2	-0.024	-0.055	4.9116	0.086
		3	0.043	0.059	5.2171	0.157
		4	-0.005	-0.025	5.2206	0.265
		5	0.139	0.154	8.3982	0.136
		6	0.108	0.054	10.351	0.111
		7	-0.037	-0.053	10.578	0.158
		8	-0.107	-0.105	12.518	0.130
		9	-0.054	-0.025	13.020	0.162
		10	0.057	0.057	13.585	0.193
		11	0.171	0.146	18.591	0.069
		12	0.021	-0.027	18.666	0.097
		13	0.022	0.066	18.751	0.131
		14	0.060	0.057	19.377	0.151
		15	0.042	0.022	19.693	0.184
		16	0.103	0.031	21.565	0.158
		17	0.047	-0.010	21.956	0.186
		18	0.036	0.050	22.192	0.224
		19	-0.051	-0.062	22.659	0.253
		20	0.003	0.026	22.661	0.306
		21	0.030	-0.008	22.827	0.353
		22	0.034	0.026	23.036	0.400
		23	-0.014	-0.028	23.076	0.456
		24	0.028	0.051	23.220	0.507
		25	-0.044	-0.075	23.591	0.543
		26	-0.014	0.003	23.630	0.597
		27	0.016	-0.038	23.682	0.648
		28	-0.065	-0.070	24.507	0.655
		29	0.002	0.005	24.508	0.704
		30	0.021	0.037	24.595	0.744
		31	-0.051	-0.059	25.109	0.763
		32	-0.117	-0.123	27.859	0.676
		33	-0.062	-0.027	28.625	0.685
		34	-0.096	-0.096	30.485	0.641
		35	0.033	0.064	30.704	0.676
		36	-0.112	-0.162	33.312	0.597

Table 5. Statistical Results for ARIMA Models for Different Parameters

ARIMA	AIC	Adjusted R^2	S.E. Regression
(1,0,0)	7.35173	0.810017	9.54826
(1,0,1)	6.33056	0.860286	7.96927
(2,0,0)	8.19800	0.826536	8.95742
(0,0,1)	7.67163	0.726402	10.7721
(0,0,2)	8.69662	0.719478	13.5859
(1,1,0)	8.33921	0.02378	9.28093
(0,1,0)	7.35212	0.0000	9.69010
(0,1,1)	7.33082	0.027190	8.10574
(1,1,2)	**3.34738**	**0.881879**	**4.32118**
(2,1,0)	7.37555	0.85927	11.05465
(2,1,2)	8.38826	0.812381	12.19259

Figure 3. Plot of Forecasted Gold Prices and Actual Gold Prices



forecasting after putting the different values of autoregressive (p) and moving average (q) parameters in E-views.

The Figure 3 depicts the plot of forecasted and actual gold price, where *YF* represents forecasted values of gold selling prices made by the ARIMA model and *Y* represents the actual data forecast of gold selling price. On the X axis, time period is shown in years and on the *Y* axis, gold prices are shown in ₹/oz. From the Figure 3, it is clearly visible that both forecasted gold selling price or actual gold selling price lines are very close to each other. Therefore, the applied ARIMA (1, 1, 2) model is the best fit model to forecast short term gold selling price. The standard error of estimate of ARIMA (1, 1, 2) is 4.32118, which is less than 10%. This statistical measure indicates that the forecasting inaccuracy of gold selling prices is low.

The Table 6 shows that the forecasted value of gold price for the coming five months follows an increasing trend. The values of gold prices in rupees per ounce are shown for the five months Feb - June 2017. The forecasting of gold prices using ARIMA model with different parametric values of p, q, and d under the study are similar to the study results of Nochai and Nochai (2006) who forecasted palm oil prices by applying ARIMA

Table 6. Forecasted Values of Gold Selling Price (₹/Oz)

Feb-17	81644.77
Mar-17	82143.39
Apr-17	82937.56
May-17	83132.33
Jun-17	83425.73

model. Forecasting significance of ARIMA model is also supported by the results of Anand and Dharnidharka (2012). The Ljung-Box statistics' findings are supported by the results of Khan (2013). ARIMA is the best fit model to predict future prices as also supported by Khaemasunun (2014). The study conducted by Deepika, Nambiar, and Rajkumar (2012) forecasted the future gold prices using ARIMA model and found it significant because quarterly data had been taken for the study instead of daily and monthly data. Murthy et al. (2012) found that geometrical random walk model for gold price forecasting was better than ARIMA models. Abdullah (2012) forecasted gold bullion prices by applying the ARIMA model in the short term. Guha and Bandyopadhyay (2016) forecasted gold prices in India by using ARIMA model with different parameters. The study of Ali et al. (2016) also supported the findings of the study.

Research Implications

The study has implications for investors, policy makers, and stock market analysts. Investors and stock market analysts can forecast gold prices and take their positions accordingly. As a policy maker, the government can change import duty to curb gold demand so that the controllable level of current account deficit can be maintained. As an investor, the government can take short or long trade positions accordingly through gold exchange traded funds because the Government of India has only 6% foreign exchange reserves in gold. Reserves of gold can be increased by taking such decision. The outcome of the study may be used by investors in their portfolio construction and time to time portfolio revision by including gold. Investors can diversify their gold investments by purchasing physical gold, gold exchange traded funds, gold mining stocks, gold futures, and gold savings account to enhance their capital gains over time, which is more than the inflation rate prevailing at that time. Gold exchange traded funds offer investors to buy gold in paper form instead of physical form, and it may open new dimensions of growth for the mutual fund industry, and investors can easily buy or sell gold ETFs (Ranjani, 2008).

Conclusion

ARIMA (1, 1, 2) was selected from rest of the different model parameters because it represents the best fit model statistics. The statistical values of ARIMA (1, 1, 2) model as per the results of AIC (Akaike information criterion) is 3.34738 and S.E. regression (standard error of regression) is 4.32118, and both the values are significant. Although the ARIMA model is a traditional approach to forecast series data, but it has importance in this era too. This is beneficial for investors if they predict future gold prices. Investors can reduce their risk and improve the return performance of their financial portfolios by doing timely adjustment. The limitation of ARIMA model is that it forecasts the immediate future of time-series data, but the investors' horizon of investment is for long term. Still, ARIMA model has its own significance.

Limitations of the Study and Scope for Future Research

Although the study has covered the broader aspect of the research, still some limitations exist. Instead of monthly data, if daily data were considered, the results would have been relatively better. Some advanced complex computer and mathematical techniques like neural network analysis and hybrid ARIMA model are available to predict more accurate future gold prices for which latest statistical software is required, which is not within the reach of all government-funded universities. Therefore, the best available technique has been used, that is, the Box-Jenkins ARIMA model. Studies in the future can use these tools to predict the prices of gold. Investors and commodity traders forecast demand and prices of various commodities and make a huge profit. Similarly, the Central government can forecast the prices of various commodities and can help farmers in the procurement of their crops and at last, the government can sell the procured crops in the futures market as the traders are doing it. This area can be explored in future studies.

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