Forecasting Gold Prices Using Geometric Random Walk Growth Model

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INTRODUCTION

Gold is characterized as a precious item having intrinsic resale value, accumulation, especially as a store value of money, is considered to be an important commodity among all tradeable commodities, having its unique importance in every society of the Indian economy. Investors, households, general merchants and business personnel plan for the purchase of gold on part of savings, investments and liquidity business needs. Primary reasons for investors to own gold as an investment option can be categorized into many ways. Investors use Gold as an investment option hedge against inflation and currency depreciation. In the present-day market scenario, gold is the best hedge against the declining dollar currency. From the macroeconomic point of view, gold can be seen as a safe haven, especially in times of geo political, financial market instability, and stable and unstable money supplies. Fundamentals of supply and demand factors of gold cause variations in gold prices, inflation and other commodity prices. Stock market investors always see gold as a portfolio diversifier to distribute the investment risk. Analysis of gold prices gives rise to observed trends of depressions and booms in the market, inflation and deflation situations, and stable and unstable money supplies. Conventional wisdom says that when we observe high gold prices, then we may also have high inflation or instability in the money supply. By carefully analyzing the trends in gold prices, it is possible to forecast future gold prices. The efficient and unbiased forecast on future gold prices may allow policy makers to have some predictions about the state of the economy on a macro level, and it is useful and important information for all stakeholders in the economy.

LITERATURE REVIEW

Research studies on gold price forecasting suggested that ARIMA models outperformed all other types of models in accuracy and validity. Research work in the early 1990s done by Selvanathan concentrated on assessing the accuracy of the gold price forecast. A comparison between the forecasted London daily gold price from the Economic Research Centre (ERC) and ARIMA model (Selvanathan,1991) proved that only simple ARIMA is a low-cost and effective enough model to predict gold prices, and the ARIMA model performed slightly better than the ERC model. A comparison among three forecasting methods - Holt's forecasting method, Box-Jenkins, and Regression method in the forecasting of daily jewellery gold prices (Panichkitkosolkul, 2006) showed that the Box-Jenkins method is the most suitable method with the lowest Mean Absolute Percent Error (MAPE), and the next suitable forecasting model is ARIMA (0,2,1). A study on forecasting the short term gold futures prices using ARIMA models (Rajib and Bhuwania, 2005) highlighted the use of alternative ARIMA models in predicting short term gold futures. A comparative study on the application of ARIMA and GARCH Models to forecast the Gold Futures Prices (Hetamsaria and Maity ,2007) for a short term and long term highlighted the forecast accuracy of ARIMA models. Research studies using the economic factors in studying the gold prices and its forecasting highlighted the application of various models, including ARIMA and GARCH models. Neely (2004) in his study of consistency with other markets implied volatility as a biased predictor of the realized volatility of gold futures. No existing explanation—including a price of volatility

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risk— can completely explain the bias, but much of this apparent bias can be explained by persistence and estimation error in implied volatility. Statistical criteria rejected the hypothesis that implied volatility is informational efficient with respect to econometric forecasts. However, delta hedging exercises indicate that such econometric forecasts have no incremental economic value. Thus, statistical measures of bias and information efficiency are misleading measures of the information content of option prices. Kutan and Aksoy (2004) used daily data to examine the impact of Consumer Price Index (CPI) releases on gold market returns. Given that Turkey's inflation rate fluctuated enormously during the beginning of the 21st century, the article examined gold as an inflation hedge for an emerging market. The authors' primarily hypothesis was that the arrival of public information exerts a limited effect on the gold return in Turkey. With the GARCH model, they captured the time-varying volatility of gold returns, which is not directly or greatly influenced by the arrival of public information. Though the GARCH model was simplified to GARCH (1,1) without explaining the mechanics for the parameters' setting, this piece of analysis made sense, especially for risk management strategies for gold investment. Ramaprasad et al. (2004) conducted an analysis of gold futures between 1990 and 2000 to examine how information flows affect the futures price change and trading volume. The daily data enabled the authors to fit appropriate AR-GARCH models to both the price change and the volume series. Unlike agricultural and oil futures, the variance of the price change has limited causal effect on the variance of price change, leading to a sequential information linkage. And it is implied that gold investment takes place when equity markets underperform. Such join dynamics of price changes and contract volume provide thorough extended traditional models to test information flow hypothesis based on causality in both mean and variance. Mills (2005) found out that gold serves as a hedge against fluctuation in the foreign exchange value of the dollar. The conditional error variance equation was found to be the best modeled as an EGARCH (1, 2) process with Student s t-distributed innovation. He also declared that 'good news' (an unanticipated increase in the price of gold) will have a greater impact on the conditional error variance, and hence the volatility of gold, than 'bad news' (an unanticipated fall in price). Wararit's (2006) idea that Box and Jenkin's ARIMA model has predictability in Gold Price is accepted in many countries, including Thailand. In Australia, the comparison between the forecasted London daily gold price from the Economic Research Centre (ERCP) and ARIMA model was done. The paper claimed and proved that only simple ARIMA is low-cost and effective enough to predict gold prices. Jitprapan's (2006) paper studied the monthly prices' data starting from Jan 1, 1998 to October 30, 2005. The results were found from Multiple Regression - that fours factors significantly affected the change of Thai gold price - which were World Gold prices, US-Thai exchange rate, Consumer Price Index and (9/11) terrorism in the United States. Volkan Alptekin et al. (2010) empirically investigated the volatility of gold prices. Initially, the natural logarithm of the gold market index had been taken in hand to be adjusted in order to avoid the instabilities due to potential fluctuations. Modeling took place using the best ARIMA method by the help of some diagnostic tests. According to the results of the study, the time series of gold prices was volatile and the volatility was eliminated after modeling it using the GARCH (2,1) model.

DATA & METHODOLOGY

This study covers the period from 1971 to 2010 of monthly average gold price time series in Indian rupees per ounce taken from the source of global insight of the World Gold Council according to the London pm fix. For forecasting the gold prices, auto regressive integrated moving average (ARIMA) model was used, which is also known as the Box-Jenkins methodology, based on the probabilistic properties of the time series on their own on the notion of *"let data speak for itself "*. The applicability of ARIMA models requires the time series to be either stationary or non - stationary after one or more differencing. Using the stationary characteristics of time series, the identified statistical model generated from the data provides valid basis for forecasting. In this study, the gold price data was converted into its log form for suitably applying the geometric random walk model. The variable gold price in the log level form was tested for stationary using time series graphs, auto correlation function, the p-value of Q statistic developed by Box and Pierce, and ADF statistics. After the verification of non stationary, the data variable was converted to stationary by a suitable number of differencing. After suitable differencing, the differenced gold price variable was tested for stationary by using the ADF and KPSS statistics. After confirming the stationary, the geometric random walk ARIMA model was tested on the gold price variable by verifying the forecasting measures for estimation and the validation period. After experimenting with all types of ARIMA models on gold price, it was found that the geometric random walk ARIMA model is suitably the best in determining the future gold prices.

Application of the random walk model to the log form of the study variable implies that the forecast for the next period value of the original series will be equivalent to the previous period's value, plus a constant percentage increase. Symbolically,

$$\text{Log } Y(t) = \text{Log}(Y(t-1)) + \alpha$$

Where,

Log is the natural logarithm to the base of exponential (e), and the constant term α is the average monthly change in the variable Log (Y), which is approximately the average monthly percentage change in Y. Doing Exponentiation on both sides of the preceding equation, and using the fact that exponential of x is approximately equal to 1+x for small x, we obtain:

$$Y(t) = Y(t-1)(\text{Exp}(\alpha)) \sim Y(t-1)(1+\alpha)$$

This forecasting model is known as the geometric random walk model, commonly referred to as the ARIMA model with one non seasonal difference and a constant term (random-walk-with-growth model in conjunction with a log transformation). This model assumes that gold price returns in different periods are statistically, independently and identically distributed. The only parameters to estimate are the average period-to-period return (the constant term in the ARIMA (0, 1, 0) model) and the volatility (white-noise noise standard deviation in the ARIMA (0, 1, 0) model). In this empirical study, the total time period was divided into three parts - one was the estimation period, the other was the validation period, and beyond the study period was the period of forecasting for a short range. The data in the estimation period were used to help select the model and to estimate its parameters. The data in the validation period were held out during parameter estimation, and if the data have not been badly over fitted, the error measures in the validation period should be similar to those in the estimation period, although they are often at least slightly larger. Holding data out for validation purposes is probably the single most important diagnostic test of a model, as it gives the best indication of accuracy that can be expected when forecasting the future. Forecasts into the future are "true" forecasts that are made for time periods beyond the end of the available data. For a model which is purely extrapolative in nature, i.e., which forecasts a time series entirely from its own history, it is possible to extend the forecasts into an arbitrary number of periods into the future by "bootstrapping" the model, and calculating confidence intervals for the forecasts. The 95% confidence interval is roughly equal to the forecast plus-or-minus two times the estimated standard deviation of the forecast error at each period. The confidence intervals typically widen as the forecast horizon increases due to the expected build-up of error in the bootstrapping process. In this study, the period from January 1971 to December 1995 (300 observations) was taken for the estimation period. The period from January 1996 to October 2010 (178 observations) was taken for the validation period. After verifying the forecasting measures - Mean Error, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error, Mean Percentage Error, Mean Absolute Percentage Error and Theil's U for estimation and validation periods, the whole data was used in the forecasting for a short-range period from November 2010 to December 2014.

EMPIRICAL ANALYSIS

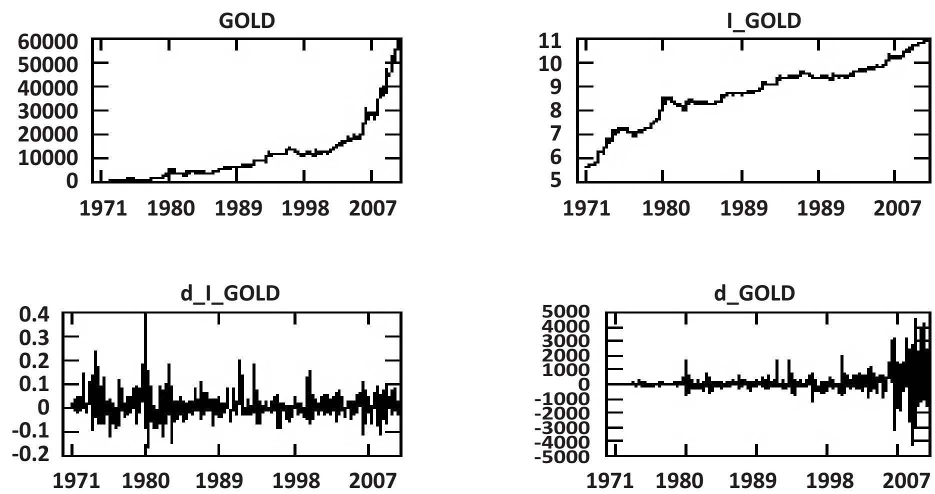
Notations used:

GOLD = Monthly Gold Price ; l_GOLD = Log Monthly Gold Price ; d_GOLD = First Difference of Gold Price ; d_l_GOLD = First Difference of Log Monthly Gold Price

TREND AND LOG TRANSFORMATION

The Figure 1 of gold price data clearly shows irregular exponential growth over the study period. Therefore, after taking the first difference of the gold price, it can be seen that the variations in the gold prices increases with time, depicting heteroskedasticity in the series, and suggesting that random growth take place in percentage terms rather than in absolute terms. It is ,therefore, to linearize the exponential growth and to stabilize the variance that the gold price data is converted into its log form using natural logarithmic transformation. After taking the log form, the gold price data shows linear growth pattern and variance of fluctuations are also comparatively uniform with the original series. The stabilization of the variance is confirmed by the first difference of log transformation of gold price as shown in the Figure 1. The first difference of the logarithm is essentially the percentage difference in the original series, so the plotted graph shows the monthly percentage return on the gold price. The stationary and random

Figure 1 : Trends of Gold Prices From January 1971 to October 2010



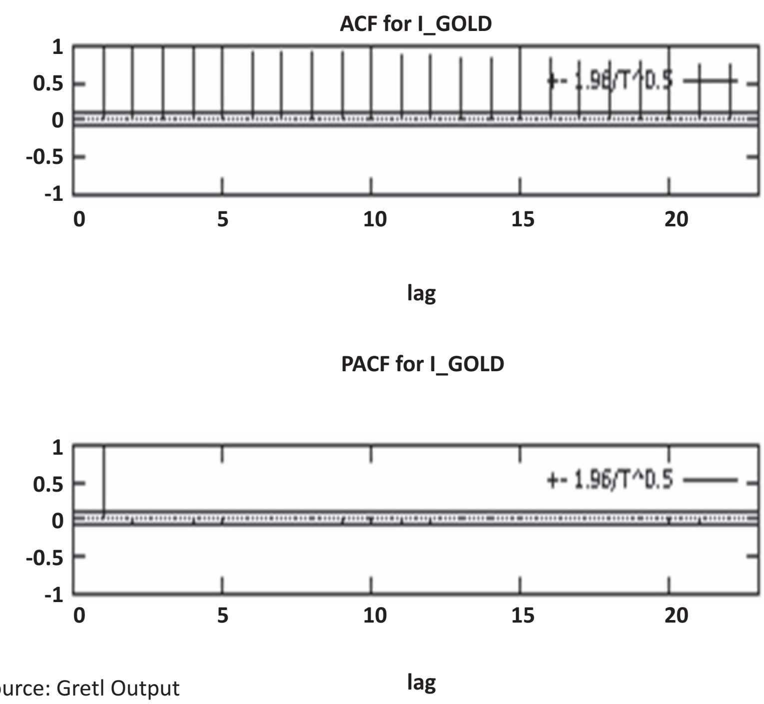
Source: Gretl Output

appearance of this graph suggests that the random walk model is appropriate for the logged series, and it should include a constant term (i.e., positive growth) to account for the trend in the original series.

NON STATIONARY

The gold price data is transformed into its log form and tested for non stationary using correlogram and auto correlation function. The results of the correlogram are indicative for non stationary; the Q statistic p value shows the evidence of non stationary in log level of gold price. The results are displayed in the Figure 2 and Table 1. Further, the

Figure 2: Correlogram of Log Gold Price For Testing Non Stationary



Source: Gretl Output

Table 1 : Autocorrelation Function For l_GOLD Testing For Non Stationary				
LAG	ACF	PACF	Q-stat.	[p-value]
1	0.9889 ***	0.9889 ***	470.3665	[0.000]
2	0.9774 ***	-0.0196	930.8859	[0.000]
3	0.9662 ***	0.0013	1381.7848	[0.000]
4	0.9549 ***	-0.0074	1823.1156	[0.000]
5	0.9435 ***	-0.0082	2254.9116	[0.000]
6	0.9322 ***	-0.0023	2677.3283	[0.000]
7	0.9213 ***	0.0126	3090.8193	[0.000]
8	0.9105 ***	-0.0053	3495.4785	[0.000]
9	0.8992 ***	-0.0244	3891.0159	[0.000]
10	0.8877 ***	-0.0154	4277.3257	[0.000]
11	0.8760 ***	-0.0160	4654.3112	[0.000]
12	0.8639 ***	-0.0199	5021.8055	[0.000]
13	0.8522 ***	0.0066	5380.1402	[0.000]
14	0.8408 ***	0.0082	5729.6887	[0.000]
15	0.8296 ***	0.0048	6070.7572	[0.000]
16	0.8185 ***	-0.0033	6403.4917	[0.000]
17	0.8078 ***	0.0088	6728.2457	[0.000]
18	0.7976 ***	0.0175	7045.5208	[0.000]
19	0.7879 ***	0.0182	7355.7960	[0.000]
20	0.7780 ***	-0.0133	7658.9842	[0.000]
21	0.7678 ***	-0.0168	7954.9499	[0.000]
22	0.7580 ***	0.0112	8244.0559	[0.000]
Source: Gretl Output				

non stationary is verified through the Augmented Dicky Fuller (ADF) test in which the null hypothesis is that the series is non stationary in terms of the unit root hypothesis as shown in the Table 2.

Table 2 : ADF Test Statistics For Non Stationary		
Tests for Non Stationary: Augmented Dickey-Fuller test for l_GOLD Sample size 476 Unit-root null hypothesis: a = 1		
Variables (In log level form)	Test	ADF Test-P Values
l_GOLD	without constant	0.9999
	with constant	0.3469
	with constant and trend	0.121
Source: Gretl Output		

STATIONARY

For foresting purpose, the time-series data should be in stationary, after confirming the non stationary in log level form, the first difference of log gold price is checked for stationary through the use of ADF test for unit root (non stationary) and KPSS statistics. The KPSS (Kwiatkowski, Phillips, Schmidt and Shin, 1992) is a unit root test in which the hypothesis is opposite to that in the ADF test: under the null, the series in question is stationary; the alternative is that the series is I(1). If the calculated KPSS is less than the critical value at the given level of significance (usually 5%), then we accept the null hypothesis of stationary. The resultant p -values of ADF and critical values of KPSS statistics show significant evidence of stationary for the first difference of log gold price, and the results are

Table 3 : Test For Stationary - ADF & KPSS Statistics							
Tests for Stationary: ADF & KPSS							
Sample size 475							
For ADF Test: Unit-root null hypothesis: a = 1							
Variables	Test	ADF Test-P Values	KPSS Statistic (H0: Series is Stationary)				
			Calculated Values	Critical Values			
				10%	5%	2.5%	1%
d_l_GOLD	without constant	0.00000132	0.247579	0.347	0.463	0.574	0.739
	with constant	0.00000122					
	with constant and trend	0.000000213					
Source: Gretl Output							

provided in the Table 3.

GEOMETRIC RANDOM WALK GROWTH MODEL (ARIMA (0, 1, 0))

In ARIMA models, it is assumed that the data series determines its own path by considering the other factors' impact like inflation, interest rates, etc. built within the dataset of the variable. For this forecasting study, three ARIMA (0,1,0) models were developed, one for the estimation period from January 1971 to December 1995, one for the validation period from January 1996 to October 2010, and one for the whole time period from January 1971 to October 2010.

Table 4: ARIMA (0, 1, 0) Model For The Estimation Period 1971:02-1995:12 (T = 299)					
Model 1: ARIMA, using observations 1971:02-1995:12 (T = 299)					
Dependent variable: (1-L) l_GOLD					
Standard errors based on Hessian					
	Coefficient	Std. Error	z	p-value	
const	0.012923	0.0032532	3.9724	0.00007	***
Mean dependent variable	0.012923	S.D. dependent var	0.056351		
Mean of innovations	1.62e-07	S.D. of innovations	0.056257		
Source: Gretl Output					

❖ **For The Estimation Period :** The constant term (0.012923) represents the average percentage return from one month to the next month's purchasing of gold. This means that about 1.2923 percent per month. The standard deviation of innovations (0. 056257) is the standard deviation of the monthly percentage changes, which measures the volatility of 5.6257% returns in purchasing of gold per month (Table 4).

Table 5: ARIMA (0, 1, 0) Model For The Validation Period 1996:01-2010:10 (T = 178)					
Model 2: ARIMA, using observations 1996:01-2010:10 (T = 178)					
Dependent variable: (1-L) l_GOLD					
Standard errors based on Hessian					
	Coefficient	Std. Error	z	p-value	
const	0.00832734	0.00289357	2.8779	0.00400	***
Mean dependent var	0.008327	S.D. dependent var	0.038714		
Mean of innovations	0.000013	S.D. of innovations	0.038605		
Source: Gretl Output					

❖ **For The Validation Period :** In the total sample data, about 37% of the data was used for the validation period that gives the accuracy of using the model for forecasting. It is noted that holding data out for validation purposes is probably the single most important diagnostic test of a model; it gives the best indication of the accuracy that can be expected when forecasting the future. For the validation period, the constant term (0.00832734) represents the average percentage return from one month to the next month's purchasing of gold. This means about 0.8327 percent per month. The standard deviation of innovations (0.038605) is the standard deviation of the monthly percentage changes, which measures the volatility of 3.8605 % returns in purchasing of gold per month (Table 5).

❖ **Forecasting:** The forecasting measures for estimation and validity period were compared to check the accuracy of the ARIMA (0, 1, 0) model for forecasting the future gold prices. The Table 6 presents a comparison between the forecasting measures of the estimation and validation period as a diagnostic test for using the model for forecasting.

Table 6 : Forecasting Measures of Estimation And The Validation Period

Forecasting Measures	Estimation Period 1971:01 - 1995:12	Validation Period 1996:01 - 2010:10
Mean Error	0.0000132	0.0000125
Mean Squared Error (MSE)	0.0031648	0.0014903
Root Mean Squared Error (RMSE)	0.056257	0.038605
Mean Absolute Error (MAE)	0.037662	0.028968
Mean Percentage Error (MPE)	0.0086119	-0.0038059
Mean Absolute Percentage Error (MAPE)	0.48008	0.29146
Theil's U	0.99742	0.98093
Source: Gretl Output		

It can be seen that all forecasting measures in the validation period are comparatively less than the estimation period, which implies that the ARIMA (0, 1, 0) model is suitable for forecasting future gold prices. It is noted that because of the impact of other factors like inflation, interest rate and compound growth, etc., MSE and MPE are not directly comparable between the estimation and validation period, but the MAPE is comparable. However, all the forecasting measures for the validation period are less than that of the estimation period (Table 6).

❖ **Forecasting Model:** Finally, the entire data is used in the geometric random walk growth model for forecasting the future gold prices for a short-range time period till December 2014. The following is the final ARIMA (0, 1, 0) model used in forecasting (Table 7).

Table 7 : ARIMA (0,1,0) Model For Forecasting 1971:02-2010:10 (T = 477)

Final Model: ARIMA, using observations 1971:02-2010:10 (T = 477)

Dependent variable: (1-L) l_GOLD

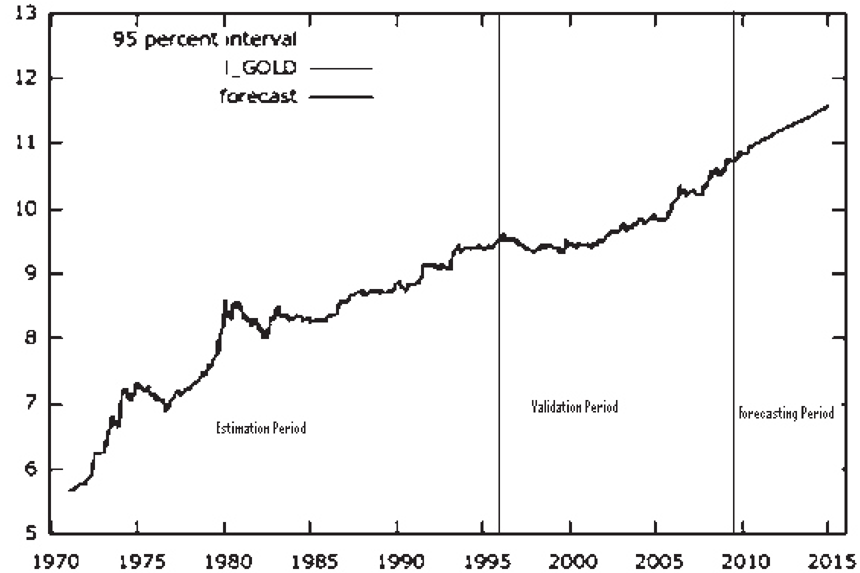
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
Const	0.0112081	0.00230976	4.8525	<0.00001	***

Mean dependent variable	0.011208	S.D. dependent var	0.050500
Mean of innovations	1.40e-07	S.D. of innovations	0.050447
Source: Gretl Output			

For the final model, the constant term (0.0112081) represents the average percentage return from one month to the next month's purchasing of gold. This means that about 1.12 percent per month. The standard deviation of the monthly percentage changes measures the volatility of 5.04 % returns in purchasing of gold per month (Table 7). The Figure 3 shows the sample forecasting in gold prices until December 2014. The more up to date sample used, the more reliable is the forecasting. The Figure 3 forecast, fitted by the model ARIMA (0, 1, 0) is based on the complete observations of the data sample, all the data is used in generating the forecast. As new data became available, it was added to the dataset

Figure 3: Forecasting Graph At 95% Confidence level



Source: Gretl Output

in generating the forecast. The 95% confidence interval shows that the forecast is within the limits, it is always recommendable to use confidence limits in addition to the point forecast. Further, the applicability of the forecast is tested for a short period by taking real-time data up to five months. Except in abnormal conditions, the forecasts are reasonably good and within the confidence limits. The following section gives a glimpse of short run forecasting within 95% and 99% confidence limits.

Table : 8 Forecast Justification At 99% Confidence Level (* Good Forecast)

Time	prediction	99% interval	GOLD Forecast	ORIGINAL	LOWER BOUND	UPPERBOUND
2010:11:00	11.0068	(10.8767, 11.1369)	60282.67	61638.00188	52928.65	68658.48
2010:12:00	11.018	(10.8340, 11.2020)	60961.63	62781.72138	50716.17	73276.85
2011:01:00	11.0292	(10.8039, 11.2545)	61648.24*	61660.93	49212.36	77226.66
2011:02:00	11.0404	(10.7803, 11.3006)	62342.58*	62356.52775	48064.54	80870.15
2011:03:00	11.0516	(10.7608, 11.3425)	63044.75	64040.36277	47136.36	84330.59

Source: Gretl Output

Table : 9 Forecast Justification At 95% Confidence Level (* Good Forecast)

Time	prediction	95% interval	GOLD	ORIGINAL	LOWER BOUND	UPPERBOUND
2010:11:00	11.0068	(10.9079, 11.1057)	60282.67	61638.00188	54606.05	66549.413
2010:12:00	11.018	(10.8782, 11.1578)	60961.63	62781.72138	53008.1	70108.548
2011:01:00	11.0292	(10.8580, 11.2005)	61648.24*	61660.93281	51948.08	73167.016
2011:02:00	11.0404	(10.8427, 11.2382)	62342.58*	62356.52775	51159.32	75978.068
2011:03:00	11.0516	(10.8305, 11.2727)	63044.75	64040.36277	50538.97	78645.052

Source: Gretl Output

❖ **Forecast Justification :** The justification of using ARIMA (0, 1, 0) at 99% and at 95% is clear from the Tables 8 and 9. Except in extremely abnormal conditions, ARIMA (0, 1, 0) has proven to be a good tool for forecasting future gold prices. The higher the confidence level, the broader is the range between the lower and the upper bound. Depending on the confidence coefficient, one can test the accuracy of the forecast in terms of lower and upper bounds. Thus, the geometric random walk growth model comes in handy in determining the future gold prices.

CONCLUSION

The data variable gold price is non stationary in both - the levels form and log level form, but after the first difference, the gold prices becomes stationary and suitable for gold prices forecasting. After testing the various models, finally, the ARIMA (0, 1, 0) was found to be the most suitable for forecasting. The irregular growth in gold prices is well captured by geometric random walk with growth model. The average percentage returns from one month to next month gold purchasing is about 1.12 percent per month. The standard deviation of the monthly percentage changes measures the volatility of 5.04 % returns in purchasing of gold per month. The future prediction of gold prices are well within the confidence limits, suggesting that the geometric random walk with growth model is an ideal model for forecasting random growth nature of gold price series. The reader can see and verify the applicability and accuracy of this method for a future period. Except in extreme abnormal conditions of macroeconomic factors, the ARIMA (0,1,0) model is an excellent model for forecasting gold prices.

POLICY IMPLICATIONS

The study of predictability or forecasting has a direct impact on business policy making in particular, for a commodity like gold, which is used as a hedge against inflation, as an investment avenue, as a cumulative stock value, etc., and attracts the attention of various stakeholders like households, retail and corporate investors, government regulators and business organizations. Forecasting of future gold prices helps investors to buy and sell their gold stocks in gold futures derivative trading from time to time. Retail and corporate investors may take the benefit of forecasting, and accordingly, may build their portfolio of investments. The Government and regulators may have a clear understanding of the dynamics of commodity prices, particularly gold, to determine the fluctuations in other commodity prices, which are closely associated with gold.

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