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FORECASTING GOLD PRICES IN SRI LANKA USING GENERALIZED AUTOREGRESSIVE CONDITIONAL HETEROSKEDASTICITY APPROACH

N.A.M.R.Senaviratna[1], T.M.J.A.Cooray[2]

[1]Lecturer, Department of Mathematics, The Open University of Sri Lanka

[2]Senior Lecturer, Department of Mathematics, University of Moratuwa, Sri Lanka

ABSTRACT

Gold has been the most valuable commodity around the world as a safe return investment due to its exceptional properties. It is useful to study the behavior of gold prices and develop a suitable model to forecast gold prices precisely. The objective of this study is to develop a model to forecast daily gold prices in Sri Lanka using Time Series analysis. In this study, daily gold prices per gram (LKR) were used from 02nd January 2007 to 06th January 2017 of 5-day-per-week frequencies which consists of 2585 observations. Among these observations 2580 observations were used for modeling and 5 observations were used to validate the model. EVIEWS software is used to analyze the data. First Box-Jenkins Autoregressive Moving Average (ARMA) models were tried. Even though models were significant, model assumptions were not satisfied. Thereafter Vector Auto Regressive (VAR) model was tried by using Inflation rate, Exchange rate, Narrow money supply, Crude oil price, All share price index as exogenous variables. However, those variables didn't have Granger Causality with daily gold price. Thus, VAR model was failed to forecast daily gold price. Next Generalized Autoregressive Conditional Heteroskedasticity (GARCH) approach was tried as the presence of significant ARCH effect in the series. Various GARCH models such as Exponential GARCH (EGARCH), Power GARCH (PGARCH), Component ARCH (C-ARCH), Glosten, Jagannathan, and Runkle GARCH (GJR GARCH) were tried under normal distribution. Augmented Dickey-Fuller test is used to check the stationary condition of the *series. Diagnostic tests are carried out using Jarque-Bera test, Breusch-Godfrey LM test and White's general test. Mean Absolute Percentage Error (MAPE) value was used to validate the fitted model. AR(1)-PGARCH(2,1) was found to be the optimal model to forecast the daily gold prices in Sri Lanka as this model comply with all assumptions of GARCH model and MAPE value is 0.57%.*

KEYWORDS - Forecast, Gold Price, Time Series Analysis, GARCH, PGARCH

INTRODUCTION

Gold has been the most attractive and valuable commodity around the world as a safe return investment due to its unique properties. In today world, like many commodities, the price of gold is driven by supply and demand. Due to high demand and limitation supply, the prices of gold are prominently increasing in this era [Shahriar Shafiee and Erkan Topal, 2010]. Therefore, it is required to develop a model that reflects the pattern of the gold price movement since it becomes very significant to investors, policy makers, international portfolio managers to assess future inflation, to estimate demand for jewellery and to assess the future movement of the exchange rate. Then they can take necessary actions to prevent dangers which are leading to financial damages and bankruptcy.

Various statistical models to forecast gold prices are available in the literatures such as Autoregressive Integrated Moving Average (ARIMA) (Pitigalaarachchi et al., 2016, Davis et al., 2014, Ali Khan, 2013), Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family models (Mahalingam et al., 2015, Gencer and Musoglu, 2014, Trück and Liang, 2012, Ping et al., 2013, Sopipan et al., 2012, Kumari and Tan, 2014), Hybrid models of ARIMA and GARCH (Yaziz et al., 2013, Ahmad et al., 2015).

The objective of this study is to develop a model to forecast daily gold prices in Sri Lanka using time series analysis.

MATERIALS AND METHODS

Secondary Data

In this study daily gold prices per gram (LKR) were used from 02nd January 2007 to 06th January 2017 of 5-day-per-week frequencies which consists of 2585 observations. Among these observations 2580 observations were used for modeling and 5 observations were used to validate the model. EVIEWS software is used to analyze the data.

Autoregressive Moving Average - ARMA(p ,q) Model

The autoregressive AR(p) model is defined as

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + ... + \alpha_p Y_{t-p} + e_t \quad (1)$$

Y_t is a linear function of p lagged values.

The moving average MA(q) model is defined as

$$Y_t = e_t + \beta_1 e_{t-1} + \beta_2 e_{t-2} + ... + \beta_q e_{t-q} \quad (2)$$

Y_t is a moving average of past shocks to the process.

ARMA(p ,q) model is the combination of AR(p) and MA(q) models. It can be defined as

$$Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + ... + \alpha_p Y_{t-p} + \beta_1 e_{t-1} + \beta_2 e_{t-2} + ... + \beta_q e_{t-q} + e_t \quad (3)$$

where $e_t \sim iidN\left(0, \sigma^2\right)$

Gaussian Auto Regressive Conditional Heteroscedasticity Model (GARCH)

GARCH models are specifically designed to model and forecast conditional variances. The variance of the dependent variable is modeled as a function of past values of the dependent variable and independent or exogenous variables.

GARCH(1, 1) model:

$$\begin{aligned} u_t &= \sigma_t \in_t, \qquad \in_t \sim IID(0,1) \\ \sigma_t^2 &= \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 \end{aligned} \quad (4)$$

Power GARCH (PGARCH) model

The basic GARCH model can be also extended to allow for leverage effects. This is made possible by treating the basic GARCH model as a special case of the PGARCH model proposed by Ding (1993):

$$\sigma_t^\delta = \omega + \sum_{i=1}^{p} \alpha_i \left(|u_{t-i}| - \eta_i u_{t-i} \right)^\delta + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^\delta \quad (5)$$

$$where\ \delta > 0, \quad \eta_i \le 1 \text{ for i} = 1,...,\text{r}, \quad \eta_\text{i} = 0 \text{ for i} > \text{r and r} \le \text{p}.$$

Augmented Dickey- Fuller (ADF) test

The ADF test is a statistical procedure that examines for the presence of unit roots in time series data. It tests the null hypothesis that a time series is I (1) against the alternative that it is I(0).

Jarque-Bera Test

Jarque–Bera test is a goodness-of-fit test of whether sample data have the skewness and kurtosis matching a normal distribution. The Jarque-Bera test statistic is defined as:

$$\frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \quad (6)$$

with *S, K,* and *N* denoting the sample skewness, the sample kurtosis, and the sample size, respectively.

Breusch-Godfrey Serial Correlation Lugrange Multiplier (LM) Test

BG LM test is used to test the serial correlation among error terms of a model. The null hypothesis of the BG LM Test is that there is no serial correlation among residuals up to the specified number of lags.

White Heteroscedasticity Test

White Heteroscedasticity test is used to check constant variance of error terms. The null hypothesis of the White Test is that there is no heteroscedasticity.

Mean Absolute Percentage Error (MAPE)

MAPE is the most common measure of forecast error. It is a measure of prediction accuracy of a forecasting method in statistics. It usually expresses accuracy as a percentage, and is defined by the formula:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{X_t - \hat{X}_t}{X_t}\right| \times 100 \quad (7)$$

; where X_t - Actual value

$\hat{X}_t$ - Fitted value

n - Sample size

Given a set of candidate models for the data, the preferred model is the one with the minimum MAPE value.

RESULTS AND DISCUSSION

This section describes the results of this research study. Data analysis and outputs of statistical tests which are used to analyze the data are discussed under this section.

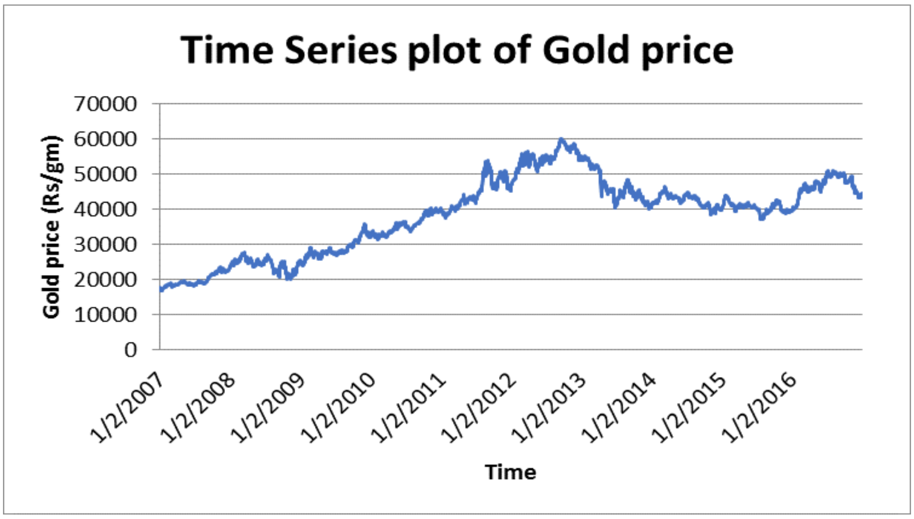

Figure 1: Graphical representation of Gold prices in Sri Lanka

According to Figure 1 it can be seen that the gold price series does not vary in a fixed level which indicates that the series is non-stationary in both mean and variance, as well as exhibits non-seasonal trend. It also illustrates an upward trend of gold price up to 2013 and thereafter downward trend.

Descriptive Statistics of gold price series

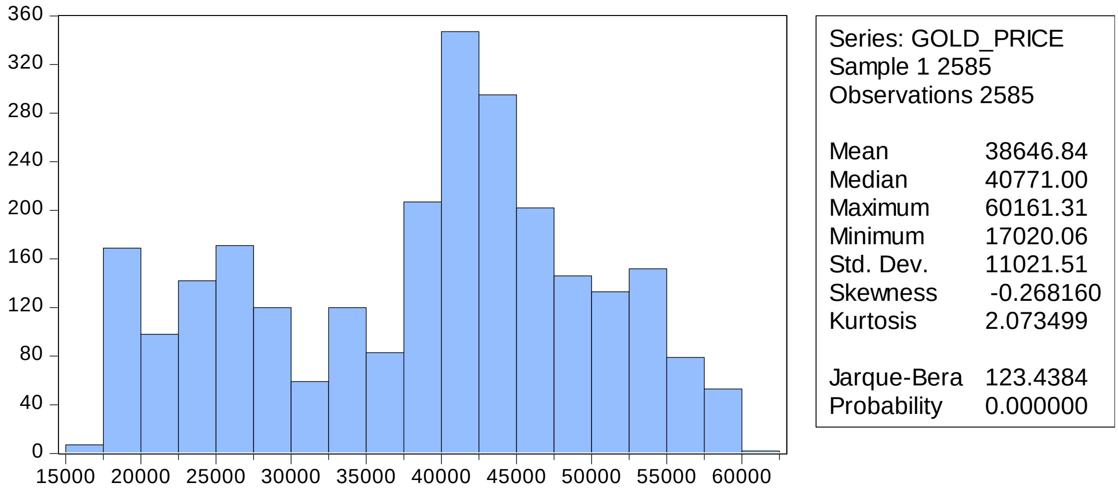

Figure 2: Summary of Descriptive Statistics

Figure 2 shows that summary of descriptive statistics of the gold price series. The gold prices have a standard deviation of 11021 indicating that data fluctuation is very high. The skewness of -0.27 shows that the series is negatively skewed. In terms of kurtosis (2.07), gold price series have a low and broad peak and shorter and thinner tails than a normal distribution. Both skewness and kurtosis of gold price show the departure from the normality. P value of Jarque-Bera test indicates that the gold price series is not normally distributed.

Therefore, Box-Cox transformation is used to transform data into normality and to obtain constant variance. It suggests log transformation is suitable for data. Hence log transformation of gold price series is used for further analysis.

Thereafter stationarity of the log transformation of gold prices is tested using Augmented Dickey-Fuller (ADF) unit root test and results are displayed in Table 1.

Table 1: Results of Augmented Dickey-Fuller unit root test

Log series	p value
original series	0.2016
First difference	0.0001

According to Table 1, results of ADF test depict that first difference of log transformation of gold prices is stationary ($p<0.05$). Then several models of ARMA including combination of AR(1), AR(2), MA(1), MA(2) terms based on observing the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) were tried. However, although model parameters of some models are significant, model assumptions are not satisfied. Then Vector Auto Regressive (VAR) model was tried by using Inflation rate, Exchange rate, Narrow money supply, Crude oil price, All share price index as exogenous variables. However those variables didn't have Granger Causality with daily gold price. Therefore, VAR model was failed to forecast daily gold price in Sri Lanka. Next ARCH LM test is applied to check whether there is an arch effect in log gold price series and results are illustrated in Table 2.

Table 2: Heteroscedasticity Test (ARCH LM test)

F-statistic	544784.8	Prob. F(1,2582)	0.0000
Obs*R-squared	2571.811	Prob. Chi-Square(1)	0.0000

ARCH test results shown in Table 2 strongly suggests the presence of ARCH effect in the series. Therefore, it can be concluded that the gold price series has arch effects. In order to examine possible ARCH and GARCH terms, the plot of ACF and PACF of the squared residuals are plotted and displayed in Figure 3.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.094	0.094	22.949	0.000
		2	0.046	0.037	28.403	0.000
		3	0.067	0.060	40.050	0.000
		4	0.104	0.093	68.319	0.000
		5	0.064	0.043	78.774	0.000
		6	0.139	0.123	129.20	0.000
		7	0.044	0.009	134.12	0.000
		8	0.142	0.121	186.71	0.000
		9	0.100	0.060	212.61	0.000
		10	0.036	-0.007	216.07	0.000
		11	0.099	0.072	241.71	0.000
		12	0.076	0.019	256.76	0.000
		13	0.103	0.071	284.55	0.000
		14	0.072	0.016	298.14	0.000
		15	0.031	-0.017	300.64	0.000
		16	0.050	0.012	307.14	0.000
		17	0.189	0.137	400.19	0.000
		18	0.053	0.003	407.57	0.000
		19	0.051	0.003	414.36	0.000
		20	0.032	-0.018	417.00	0.000
		21	0.109	0.061	447.85	0.000
		22	0.118	0.072	484.37	0.000
		23	0.086	0.024	503.59	0.000
		24	0.073	0.039	517.60	0.000
		25	0.135	0.066	565.49	0.000
		26	0.070	0.012	578.32	0.000
		27	0.036	-0.012	581.72	0.000
		28	0.059	0.000	590.77	0.000
		29	0.048	-0.014	596.89	0.000
		30	0.090	0.019	617.91	0.000
		31	0.057	-0.006	626.38	0.000
		32	0.072	0.034	639.92	0.000
		33	0.012	-0.049	640.31	0.000
		34	0.092	0.023	662.40	0.000
		35	0.056	0.008	670.55	0.000
		36	0.093	0.044	693.00	0.000

Figure 3: Correlogram of squared residuals

It can be seen that the AC and PAC of residual squares are significant at lag 1 and some higher order lags. However, it is decided that not to go for higher order of GARCH models. Thus, it is considered GARCH(0,1), GARCH(1,0), GARCH (1,1), GARCH(2,1), GARCH(2,2), GARCH(1,2), GARCH(2,0) and GARCH(0,2) models. Furthermore, variants of GARCH models such as Exponential GARCH (EGARCH), Power GARCH (PGARCH), Component ARCH (C-ARCH), Glosten, Jagannathan, and Runkle GARCH (GJR GARCH) are also considered under normal distribution in modeling log gold price series for the above terms. However, model assumptions are satisfied only AR(1)- PGARCH(2,1) model and results are displayed in Table 3.

Results of AR(1)-PGARCH (2,1) Model

The parameter coefficients on the dependent variable of the log (gold price) series were obtained and the results are tabulated in Table 3.

Table 3: Results of AR(1)-PGARCH (2,1) Model

@SQRT(GARCH)^C(8) = C(3)+ C(4)*(ABS(RESID(-1)) -C(5)* (RESID(-1)) ^C(8) + C(6)* ABS(RESID(-2)) ^C(8) + C(7)* @SQRT(GARCH(-1)) ^C(8)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.015850	0.006775	2.339458	0.0193
LNGP(-1)	0.998531	0.000644	1551.673	0.0000
	Variance Equation			
C(3)	1.10E-06	1.01E-06	1.089012	0.2761
C(4)	0.089691	0.014323	6.262154	0.0000
C(5)	-0.028392	0.017327	-1.638622	0.1013
C(6)	-0.048716	0.012463	-3.908831	0.0001
C(7)	0.947937	0.006040	156.9518	0.0000
C(8)	2.072863	0.193281	10.72462	0.0000
R-squared	0.998513	Mean dependent var	10.51535	
Adjusted R-squared	0.998509	S.D. dependent var	0.319810	
S.E. of regression	0.012348	Akaike info criterion	-6.110962	
Sum squared resid	0.392753	Schwarz criterion	-6.092829	
Log likelihood	7903.364	Hannan-Quinn criter.	-6.104390	
F-statistic	247166.9	Durbin-Watson stat	2.012958	
Prob(F-statistic)	0.000000			

Even though some coefficients of parameter estimates of the model are not significant, since they are jointly significant we cannot remove them from the model. Diagnostic test results for the model are illustrated in following tables.

Table 4: Results for testing heteroscedasticity of residuals

Heteroskedasticity Test: White			
F-statistic	0.791452	Prob. F(1,2582)	0.3737
Obs*R-squared	0.791822	Prob. Chi-Square(1)	0.3735

Table 4 illustrates results for testing heteroscedasticity of the residuals. Probability of observed R-squared (0.3735) is greater than 0.05 in Table 4. It reveals that there is no Heteroskedasticity in this model at 5% level of significance.

Table 5: Results of testing correlation of residuals

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	1.112823	Prob. F(2,35)	0.3400
Obs*R-squared	2.331730	Prob. Chi-Square(2)	0.3117

Table 5 shows results for testing correlation of residuals. It exhibits that residuals are not serially correlated at 5% level of significance since probability of Observed R-Squared(0.3117) is greater than 0.05.

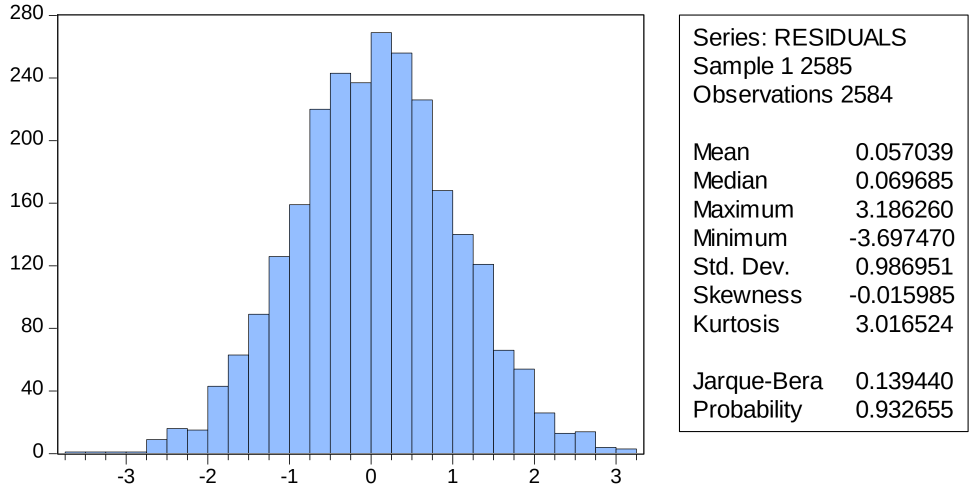

Figure 4: Test of normality of errors

Skewness and kurtosis values of residuals shown in Figure 4 are closer to 0 and 3 respectively. P value of Jarque-Bera test (0.93) is greater than 0.05. Based on these results, it can be concluded that residuals are normally distributed with 5% level of significance. After the model estimation and residual analysis it can be concluded that identified model is suitable for further analysis and forecasting.

The comparison of forecast values and observed values for the period from January 02nd 2017 to January 06th 2017 (out of sample) is shown in Table 6. It indicates that MAPE (0.57%) is lower for the selected model. Therefore, it can be concluded that AR(1)-PGARCH(2,1) is a suitable model to forecast daily gold prices in Sri Lanka.

Table 6: Forecasting performance of the model

Date	Observed value	Forecasted value AR(1)-PGARCH(2,1)
02.01.2017	44431.68	44748.40
03.01.2017	44697.09	44445.59
04.01.2017	44718.89	44711.08
05.01.2017	45248.94	44732.89
06.012017	45447.68	45263.10
MAPE		0.5679%

From Table 3, for the conditional mean equation, the coefficient for the constant parameter was found as μ = 0.01585 (p = 0.0193) and the coefficient for the AR (1) parameter was ϕ_1=0.998531 (p = 0.000) while for the conditional variance equation, the coefficients for the parameters were α_0= 0.000001, α_1= 0.089691, γ_1= -0.028392 , α_2 = -0.048716 and β_1= 0.947937. Coefficient of AR(1) parameter defines the previous month's log (gold price). High value of this coefficient means that change in the gold price of current month is affected by 99.85% of the change in the gold price of previous month. A high value of β_1 means that volatility is persistent and it takes a long time to change. A high value of α_1 means that volatility is spiky and quick to react to the market movements (Dowd, 2002). The sum of ARCH coefficients of the identified model is close to one (0.000001+ 0.089691-0.028392 - 0.048716 + 0.947937) indicating that volatility shocks are quite persistent. This further implies that shocks to the conditional variance will be highly persistent indicating that large changes in price tend to be followed by large changes and small changes tend to be followed by small changes. These results are often observed in high frequency financial data. It can also be seen that both R^2 and adjusted R^2 values are almost equal. The model is able to explain nearly 99% of the observed variability. The AR(1)−PGARCH (2,1) model can be written into conditional mean and conditional variance equations as follows;

$$\log y_t = 0.01585 + 0.998531 \log y_{t-1} + u_t$$

$$\sigma_t = 0.000001 + 0.089691|u_{t-1}| - 0.048716|u_{t-2}| - 0.028392u_{t-1} + 0.947937\sigma_{t-1}$$

CONCLUSION

This study was undertaken to forecast daily gold price in Sri Lanka using Time Series Analysis. First Box-Jenkins ARMA models were tried. Even though models were significant, model assumptions (residuals) were not satisfied. Then Vector Auto Regressive (VAR) model was tried by using Inflation rate, Exchange rate, Narrow money supply, Crude oil price, All share price index as exogenous variables. However those variables didn't have Granger Causality with daily gold price. Therefore, VAR model was failed to forecast daily gold price in Sri Lanka. Next ARCH LM test is applied to check whether there is an arch effect in log gold price series and it strongly suggests the presence of ARCH effect in the series. Then various GARCH models such as EGARCH, PGARCH, C-ARCH, GJR-GARCH models were tried under normal distribution. Of such GARCH families AR (1) −PGARCH (2,1) was selected as the optimal model. The estimated parameters of the AR(1)-PGARCH (2,1) model, the coefficients of AR(ϕ_1), (ARCH (α_1, α_2) and GARCH (β_1) in the conditional variance equation are statistically significant and MAPE value is 0.57%. The developed GARCH model can be used to forecast future gold prices.

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