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Enhancing Gold Price Forecasting: A Study On Optimal Model Selection

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Abstract:
The study of gold price predictions has garnered significant attention due to the metal's historical and economic importance. Accurate forecasting of gold prices is crucial for investors, policymakers, and economists to make informed decisions. Previous research has utilized various time series techniques to predict gold prices, with mixed results in terms of accuracy and reliability. Despite extensive studies, there is still a lack of consensus on the most effective model for long-term gold price forecasting. By identifying the best fit model for gold price predictions, this research aims to contribute to more precise and reliable forecasting methods.

The research aims to identify the most effective model for long-term gold price forecasting, addressing the current lack of consensus in this area. It then reviews previous studies that have employed various time series techniques for gold price forecasting, noting their mixed results in terms of accuracy and reliability.

The findings of this research are expected to contribute to the development of more precise and reliable gold price forecasting methods. It is hypothesized that the ARIMA (0, 2, 1) model will provide the lowest RMSE and AIC values, making it the best fit for forecasting gold prices. By identifying the best fit model, the study aims to provide valuable insights for financial decision-making and economic planning. The results may have significant implications for investment strategies, policy formulation, and economic forecasting related to gold prices.

Keywords: Gold Prices, Time series, Long term Forecasting, ARIMA

Introduction
Gold has historically served as a significant commodity and monetary standard, recognized for its enduring value and multifaceted roles in the global economy. It functions as a store of value, means of exchange, and unit of account, which has led to a well-developed market for gold and its derivatives (Schenk, 2013). Price fluctuations in gold are influenced by macroeconomic variables, such as GDP and exchange rates, highlighting its complex relationship with national economies. Despite the abandonment of the gold standard, gold remains a hedge against inflation and a reliable asset in diversified portfolios, reflecting its unique position among commodities (Bhalerao, 2023).

Gold price forecasting is crucial for investors, policymakers, and economists due to the metal's volatility and its role as a stable store of value. Various models, including ARIMA, VAR, GARCH, and machine learning techniques, have been employed to predict gold prices effectively. For instance, the ARIMA model demonstrated strong predictive capabilities over four months, emphasizing the importance of macroeconomic and geopolitical factors in price movements(Lyu et al., 2024). The VAR model, utilizing a comprehensive dataset, highlighted significant influences from related financial indicators, showcasing its accuracy in capturing market trends(Z. Wang, 2024). Overall, accurate gold price forecasting supports financial stability and informed investment strategies across various sectors(Kong, 2024).

Gold price forecasting is influenced by a multitude of factors, each contributing to the complexity and variability of predictions. Key economic indicators influencing gold price forecasting include inflation rates, interest rates, geopolitical tensions, and overall global economic conditions. Studies highlight that inflation, particularly the Consumer Price Index (CPI), has a strong correlation with gold prices, with correlations reaching up to 0.92 (Kumar et al., 2012). Interest rates also play a critical role, as higher rates typically decrease gold's appeal as a non-yielding asset (K et al., 2024).

Additionally, market indices such as the Dow Jones Industrial Average (DJIA) and the S&P 500 significantly impact gold price trends, with some models indicating they are essential for accurate predictions (Liu & Li, 2017). Other factors include the US dollar index and crude oil prices, which reflect broader economic sentiments and investor behavior, further complicating the forecasting landscape (W. Wang & Xia, 2017).
Gold price forecasting presents significant challenges due to the inherent volatility and complexity of financial markets, influenced by various economic factors and geopolitical events. The non-stationary nature of gold price time series complicates predictions, necessitating advanced modeling techniques such as Long Short-Term Memory (LSTM) networks and hybrid machine learning approaches that incorporate variational mode decomposition (VMD) for improved accuracy (Golubovic et al., 2024). Additionally, external shocks like trade wars and pandemics further exacerbate price fluctuations, making it difficult to establish reliable forecasting models (Yang et al., 2024).

Traditional single models often fail to capture the multifaceted dynamics of the market, prompting the development of innovative frameworks that integrate feature extraction and residual correction methods (Sri Nithya et al., 2024). Moreover, the integration of diverse datasets, including economic indicators and textual data, enhances predictive capabilities, as demonstrated by various machine learning methodologies (Sri Nithya et al., 2024) (Behera et al., 2023). Thus, the complexity of gold price forecasting necessitates a multifaceted approach to improve prediction accuracy and reliability.

Research Methods:
This study aims to address the following research question. What is the most accurate time series model for predicting gold prices in INR/troy ounce? The objective of this study is to determine the best fit forecasting model for gold prices using transformed time series data. Gold Prices are annual closing prices in Indian Rupees per troy ounce as collected from 'world gold council'. The study covers a period of 1980 to 2023 (44 years)

Methods And Scope Of Study:
The objective of the study is "to study the long-run performance of Gold Prices and estimate its forecast" Gold Prices are annual closing prices in Indian Rupees per troy ounce as collected from 'world gold council'. The study covers a period of 1980 to 2023 (44 years)

Results & Discussion:

Gold Prices During The Period Of 1980 To 2023

Figure 1a: time series graph for gold prices (INR) from 1980 to 2023

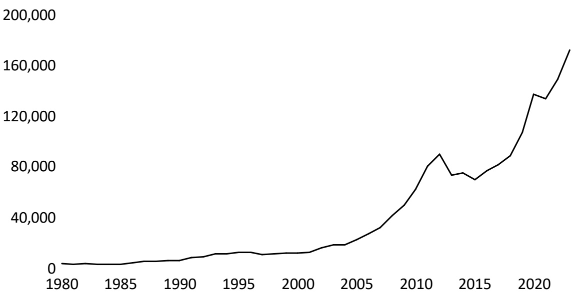


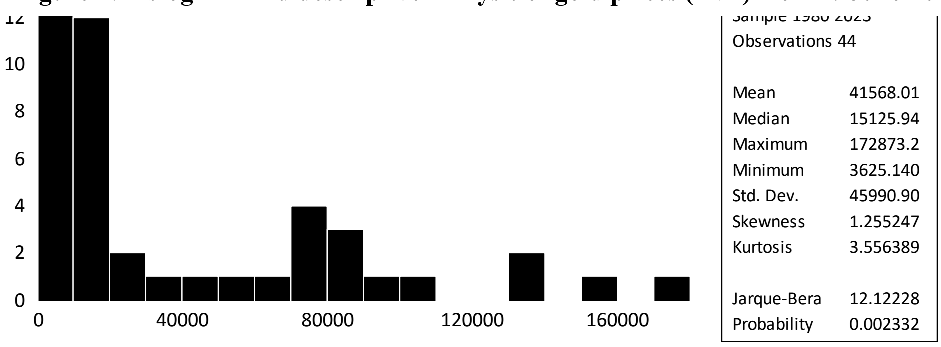
Figure 1b: time series graph for YOY % change in gold prices (INR) from 1980 to 2023

(Source: Authors calculation using eviews software)

The annual closing prices of gold as observed (figure: 1a, b) showed a continuous rise during the period of 1980 to 2023, with a brief correction during the years of 2010-2015. The Year on year % changes were recorded in the range of -20% to +30 % during the period. The annual prices ranged from 3625.140 to 172873.2 during the period of study, forming a mean of 41568.01.

The skewness was recorded at 1.255 indicating slight positive skewness, while kurtosis was recorded at 3.556 indicating that the distribution is heavily tailed. The Jarque-Bera test (12.122) suggests that the distribution may deviate from normality. (Figure: 2)

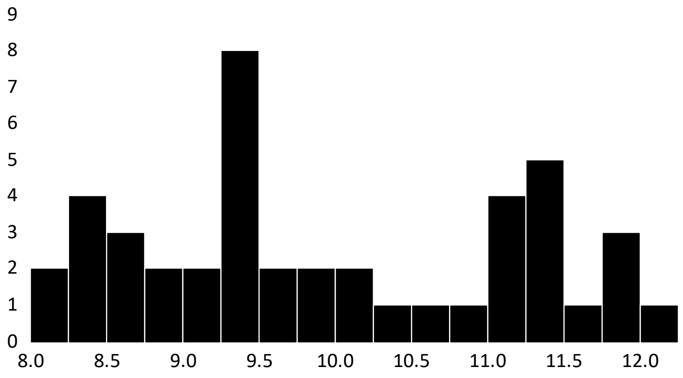
Figure 2: histogram and descriptive analysis of gold prices (INR) from 1980 to 2023



(Source: Authors calculation using eviews software)

To address the issues in skewness and kurtosis, log transformation was applied on the series. Skewness was measured at approximately 0.18, which is slightly asymmetrical, while Kurtosis, was measured at 1.69 indicating tails behavior and peak sharpness. Jarque-Bera statistic was recorded at 3.35. The p-value is approximately 0.1869, which is greater than 0.05, suggesting that there is insufficient evidence to reject the null hypothesis, (the data follow a normal distribution.) and consider that the data are reasonably close to normality. (Figure: 3)

Figure 3: histogram and descriptive analysis of gold prices (LOGINR) from 1980 to 2023



Series: LOGINR	
Sample 1980 2023	
Observations 44	
Mean	9.974733
Median	9.619111
Maximum	12.06031
Minimum	8.195648
Std. Dev.	1.209150
Skewness	0.175770
Kurtosis	1.693844
Jarque-Bera	3.354312
Probability	0.186905

(Source: Authors calculation using eviews software)

Unit Root Test

Augmented (Dickey & Fuller, 1979) and (Philips & Perron, 1988) is used to check unit root for LOGINR. Figure 4a shows the p value of ADF (Augmented Dickey Fuller) test statistic as 0.9910, which is greater than 0.05, hence we fail to accept the null hypothesis at 5% level of significance. This indicates that that the LOGINR series is Non stationery. Subsequently (figure 4b), for the LOGINR series at first difference, whereby the p value of ADF test statistic was recorded as 0.0000, which is less than 0.05, hence the null hypothesis is rejected at 5% level of significance, and can conclude that the gold prices LOGINR are stationery at first difference. Further the R-squared value was measured at 0.49.

Figure 4a: unit root test for LOGINR

Null Hypothesis: LOGINR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.709831	0.9910
Test critical values:	1% level	-3.592462	
	5% level	-2.931404	
	10% level	-2.603944	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LOGINR)
Method: Least Squares
Date: 02/23/24 Time: 17:16
Sample (adjusted): 1981 2023
Included observations: 43 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOGINR(-1)	0.011741	0.016540	0.709831	0.4818
C	-0.032307	0.165311	-0.195433	0.8460

R-squared	0.012140	Mean dependent var	0.084235
Adjusted R-squared	-0.011954	S.D. dependent var	0.125670
S.E. of regression	0.126419	Akaike info criterion	-1.253034
Sum squared resid	0.655253	Schwarz criterion	-1.171118
Log likelihood	28.94023	Hannan-Quinn criter.	-1.222826
F-statistic	0.503861	Durbin-Watson stat	1.662414
Prob(F-statistic)	0.481827		

Figure 4b: unit root test for LOGINR at 1st difference: D (LOGINR

Null Hypothesis: D(LOGINR) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.206687	0.0000
Test critical values:	1% level	-3.596616	
	5% level	-2.933158	
	10% level	-2.604867	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LOGINR,2)
Method: Least Squares
Date: 02/23/24 Time: 17:17
Sample (adjusted): 1982 2023
Included observations: 42 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LOGINR(-1))	-0.892851	0.143853	-6.206687	0.0000
C	0.083133	0.021620	3.845153	0.0004

R-squared	0.490595	Mean dependent var	0.009117
Adjusted R-squared	0.477860	S.D. dependent var	0.161742
S.E. of regression	0.116874	Akaike info criterion	-1.408994
Sum squared resid	0.546381	Schwarz criterion	-1.326248
Log likelihood	31.58888	Hannan-Quinn criter.	-1.378664
F-statistic	38.52296	Durbin-Watson stat	1.862825
Prob(F-statistic)	0.000000		

(Source: Authors calculation using eviews software)

Furthermore, LOG (INR) was transformed using the power transform statistics in statgraphic centurion software to get the optimum level of normality for the series. Box-cox transformation was applied to LOG (INR) series. The transformed variable calculated was: 1 + (LOG (INR) ^-0.3-1)/ (-0.3*9.90351^-1.3). Descriptive statistics for the transformed series is as under:

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Table 1: Summary Statistics for 1 + (LOG (INR) ^-0.3-1)/ (-0.3*9.90351^-1.3)

Count	44
Average	33.6427
Standard deviation	1.19837
Coeff. of variation	3.56205%
Minimum	31.7351
Maximum	35.5587
Range	3.82359
Stnd. skewness	0.0448543
Stnd. kurtosis	-1.76622

(Source: Authors calculation using statgraphics centurion software)

Any statistical test involving the standard deviation would likely be invalidated if the values of standardized skewness and standardized kurtosis fell outside the range of -2 to +2. The standardized skewness number in this instance falls within the range predicted by data with a normal distribution. The range predicted by data with a normal distribution encompasses the standardized kurtosis value.

Figure 5: histogram for 1 + (LOG (INR) ^-0.3-1)/ (-0.3*9.90351^-1.3)

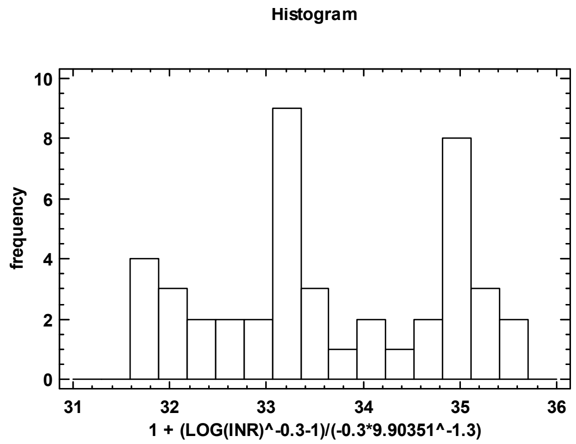
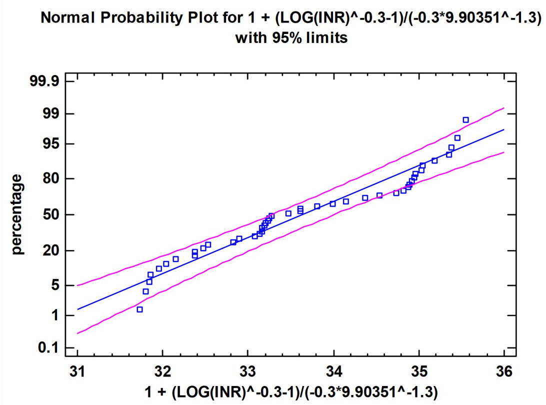


Figure 6: Normal Probability plot for 1 + (LOG (INR) ^-0.3-1)/ (-0.3*9.90351^-1.3)



(Source: Authors calculation using eviews software)

Forecasting Gold Prices

Several models were tested using the transformed series of gold prices in order to identify the best model for gold price forecasting.

Model Comparison

Data variable: 1 + (LOG (INR) ^-0.3-1)/ (-0.3*9.90351^-1.3)
Number of observations = 44

Models

(A) Random walk
(B) Random walk with drift = 0.0818413
(C) Constant mean = 33.6427

(D) Linear trend = 31.5717 + 0.0920448 t
(E) Simple moving average of 2 terms
(F) Simple exponential smoothing with alpha = 0.9999
(G) Brown's linear exp. smoothing with alpha = 0.5722
(H) Holt's linear exp. smoothing with alpha = 0.9999 and beta = 0.0132
(I) ARIMA (0, 2, 1)
(J) ARIMA (0, 2, 2)
(K) ARIMA (1, 2, 1)
(L) ARIMA (2, 2, 1)

Table 2a*: ESTIMATION PERIOD

Model	*RMSE*	*MAE*	*MAPE*	*ME*	*MPE*	*AIC*	*HQC*	*SBIC*
(A)	0.152844	0.124857	0.372082	0.0818413	0.241305	-3.75667	-3.75667	-3.75667
(B)	0.130614	0.101281	0.30386	-1.65242E-16	-.00198713	-4.02556	-4.01052	-3.98501
(C)	1.19837	1.03741	3.08593	1.04967E-14	-0.124192	0.407379	0.422416	0.447928
(D)	0.197679	0.15808	0.470701	9.60848E-15	-.00327932	-3.15132	-3.12124	-3.07022
(E)	0.19114	0.156531	0.463507	0.13163	0.389407	-3.26404	-3.249	-3.22349
(F)	0.152849	0.122024	0.36364	0.0799898	0.235846	-3.71115	-3.69611	-3.6706
(G)	0.138948	0.104097	0.312095	0.00290673	0.00908606	-3.90186	-3.88682	-3.86131
(H)	0.131989	0.0995487	0.298859	-0.00953037	-0.0302297	-3.95916	-3.92908	-3.87806
(I)	**0.118098**	**0.0946616**	**0.282758**	**0.000756157**	**0.0019839**	**-4.22702**	**-4.21198**	**-4.18647**
(J)	0.119538	0.0942814	0.281709	0.00189177	0.00544007	-4.15734	-4.12726	-4.07624
(K)	0.119762	0.0948168	0.283511	0.00207452	0.0061083	-4.15358	-4.12351	-4.07248
(L)	0.11957	0.0896358	0.267465	0.00404801	0.0121704	-4.11134	-4.06623	-3.98969

(Source: Authors calculation using statgraphics centurion software)

Table 2b: ESTIMATION PERIOD

Model	*RMSE*	*RUNS*	*RUNM*	*AUTO*	*MEAN*	*VAR*
(A)	0.152844	OK	OK	OK	OK	OK
(B)	0.130614	OK	OK	OK	OK	OK
(C)	1.19837	***	***	***	***	OK
(D)	0.197679	**	***	***	OK	OK
(E)	0.19114	OK	**	**	OK	OK
(F)	0.152849	OK	OK	OK	OK	OK
(G)	0.138948	OK	OK	OK	OK	OK

(H)	0.131989	OK	OK	OK	OK	OK
(I)	**0.118098**	**OK**	**OK**	**OK**	**OK**	**OK**
(J)	0.119538	OK	OK	OK	OK	OK
(K)	0.119762	OK	OK	OK	OK	OK
(L)	0.11957	OK	OK	OK	OK	OK

(Source: Authors calculation using statgraphics centurion software)

An autoregressive integrated moving average (ARIMA) is the model of choice. This idea states that the best forecast for future data is produced by a parametric model that compares the most recent data value to previous data values and prior noise.
Forecast model selected: ARIMA (0, 2, 1)
Number of forecasts generated: 12
Number of periods withheld for validation: 0

As extracted from Table 2a: ESTIMATION PERIOD – ROW I

	Estimation
Statistic	*Period*
RMSE	0.118098
MAE	0.0946616
MAPE	0.282758
ME	0.000756157
MPE	0.0019839

Arima Model Summary

Table 3: Model summary

Parameter	*Estimate*	*Stnd. Error*	*t*	*P-value*
MA(1)	0.985443	0.0153072	64.3779	0.000000

(Source: Authors calculation using statgraphics centurion software)
Backforecasting: yes
Estimated white noise variance = 0.0178436 with 41 degrees of freedom
Estimated white noise standard deviation = 0.13358

Figure 7: time sequence plot for forecasted values

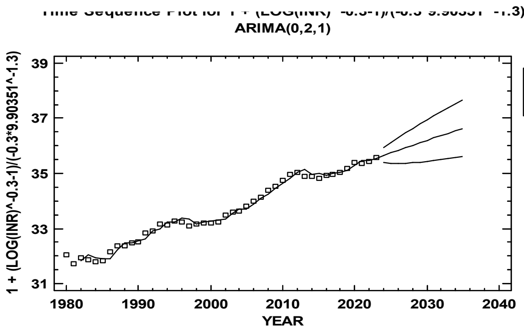
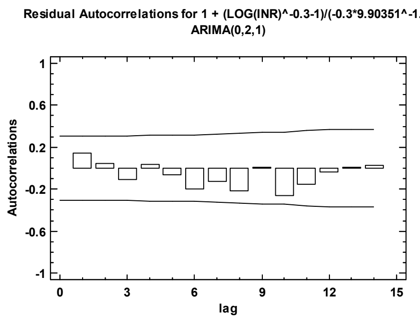


Figure 8: residual autocorrelations



(Source: Authors calculation using statgraphics centurion software)

Table 2 gives the estimates for each models tested and it was found that ARIMA (0, 2, 1) model was the best fit. It reported a lowest RMSE of 0.118 among the models tested which suggests that, on average, the model's predictions deviate by about 0.1181 units from the actual values. ARIMA (0, 2, 1) model resulted in a p-value of 0.000, indicating a strong evidence to reject the null hypothesis, while suggesting that the MA (1) component appears to be significant in model.

Table 4a: Forecast table

Forecast Table for 1 + (LOG (INR) ^-0.3-1)/ (-0.3*9.90351^-1.3) [Model: ARIMA (0, 2, 1)]

Period	*Data*	*Forecast*	*Residual*
1980.0	32.0396		
1981.0	31.7351		
1982.0	31.9564	31.8246	0.131761
1983.0	31.8585	32.0478	-0.189286
1984.0	31.8038	31.9471	-0.143315
1985.0	31.8347	31.8903	-0.0555716
1986.0	32.1509	31.9205	0.230476
1987.0	32.3778	32.24	0.13775
1988.0	32.379	32.4689	-0.0898775
1989.0	32.4714	32.4688	0.00259212
1990.0	32.5269	32.5612	-0.0343185
1991.0	32.8308	32.6162	0.214575
1992.0	32.897	32.9232	-0.0262006
1993.0	33.1576	32.9891	0.168519
1994.0	33.1373	33.2521	-0.114833
1995.0	33.2689	33.2301	0.0388056
1996.0	33.239	33.3623	-0.123323
1997.0	33.0781	33.3306	-0.252479
1998.0	33.1557	33.1661	-0.0104294
1999.0	33.19	33.2434	-0.0534328
2000.0	33.2054	33.277	-0.0715993
2001.0	33.2483	33.2914	-0.0430786
2002.0	33.478	33.3336	0.144334
2003.0	33.6101	33.5654	0.0446381
2004.0	33.615	33.6981	-0.0831796
2005.0	33.8096	33.7018	0.107774
2006.0	33.9929	33.8981	0.0948323
2007.0	34.1454	34.0827	0.0627208
2008.0	34.375	34.2362	0.138839
2009.0	34.5437	34.4678	0.0759372
2010.0	34.7323	34.6376	0.0946864
2011.0	34.9483	34.8275	0.120776
2012.0	35.0427	35.0453	-0.0025734
2013.0	34.8755	35.1397	-0.264192
2014.0	34.8965	34.9686	-0.0721678
2015.0	34.8281	34.9885	-0.160424
2016.0	34.9134	34.9178	-0.00440659
2017.0	34.9642	35.0031	-0.0389564

2018.0	35.0295	35.0533	-0.0238071
2019.0	35.1849	35.1182	0.0666965
2020.0	35.3829	35.2746	0.108229
2021.0	35.3617	35.4742	-0.112461
2022.0	35.4493	35.4514	-0.0021038
2023.0	35.5587	35.5389	0.0198313

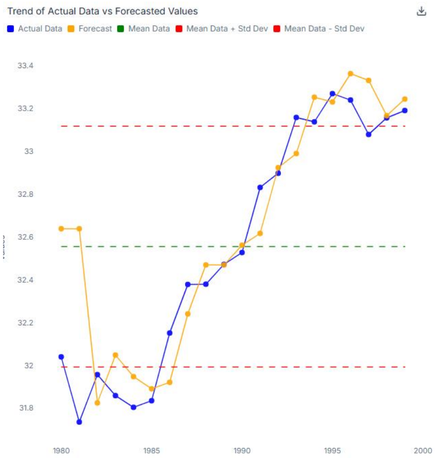
(Source: Authors calculation using statgraphics centurion software)

Table 4b: Forecast table

Period	*Forecast*	*Lower 95.0% Limit*	*Upper 95.0% Limit*
2024.0	35.6487	35.3789	35.9184
2025.0	35.7386	35.3543	36.1229
2026.0	35.8285	35.3544	36.3026
2027.0	35.9184	35.367	36.4698
2028.0	36.0084	35.3874	36.6293
2029.0	36.0983	35.4132	36.7833
2030.0	36.1882	35.443	36.9334
2031.0	36.2781	35.4758	37.0804
2032.0	36.3681	35.5111	37.225
2033.0	36.458	35.5483	37.3677
2034.0	36.5479	35.5872	37.5086
2035.0	36.6378	35.6274	37.6483

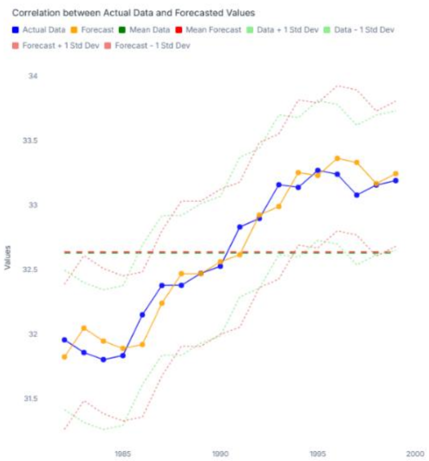
(Source: Authors calculation using statgraphics centurion software)

Figure 09 Trend of actual vs forecast



(source: Author Generated)

Figure 10 Correlation between actual & forecast



(source: Author Generated)

Figure 9 drawn from table 4 a represents a comparison between actual data and forecasted values over time. The actual and forecasted data follow a similar upward trend, indicating that the forecasting model captures the overall pattern well. The values show an initial decline around 1980-1982, followed by a consistent increase from the mid-1980s onwards. The forecasted values closely match the actual data, particularly after 1985, suggesting a good prediction model. However, in the early years (before 1985), there are some deviations where the forecasted values do not align well with the actual data, indicating higher uncertainty. The standard deviation bands (red dashed lines) indicate the range of variability in the actual data. Most of the actual and forecasted data remain within this range, suggesting a stable trend with moderate fluctuations.

This plot shows that the forecasting model performs well in capturing long-term trends, with close alignment between actual and forecasted values after 1985. However, there is some discrepancy in the early years, suggesting potential areas for improvement in short-term predictions. Figure 10 drawn from table 4 b represents a comparison between actual data and forecasted values over time. The actual data and forecasted values are closely aligned, suggesting the model predicts trends well. Some deviation exists, especially in certain periods where actual data diverges from the forecast. The standard deviation bands show the expected range of variability in both actual and forecasted values. The mean values of actual data and forecasts are quite similar, reinforcing the accuracy of the forecasting model. Overall, the plot suggests a good correlation between actual and forecasted values with some fluctuations.

Conclusion

This research focused on identifying the most accurate time series model for predicting gold prices in INR/troy ounce using annual closing price data spanning from 1980 to 2023. After evaluating various models, the ARIMA(0,2,1) model emerged as the most suitable for forecasting gold prices.

The study revealed several key findings, including the non-stationarity of the original gold price data, which necessitated log transformation and Box-Cox transformation to achieve normality. The ARIMA(0,2,1) model demonstrated superior performance compared to other tested models, exhibiting the lowest Root Mean Square Error (RMSE) of 0.118098. The model's forecasts showed strong alignment with actual data, particularly after 1985, indicating its ability to capture long-term trends effectively. Despite its overall strong performance, the model exhibited some discrepancies in early years (pre-1985), suggesting potential for improvement in short-term predictions. The model's reliability is further supported by low Mean Absolute Error (MAE) of 0.0946616 and Mean Absolute Percentage Error (MAPE) of 0.282758. Forecasts generated by the model indicate a continuing upward trend in gold prices through 2035, albeit with increasing confidence intervals. While the ARIMA (0,2,1) model provides a reliable framework for forecasting gold prices in INR/troy ounce, the widening confidence intervals in long-term forecasts highlight growing uncertainty in predictions further into the future.

This study contributes valuable insights to the field of gold price forecasting, particularly for the Indian market, and can assist investors, policymakers, and economists in making informed decisions related to gold investments and economic planning. Future research directions could explore the incorporation of additional economic indicators or the development of hybrid models to enhance short-term prediction accuracy. However, the increasing width of confidence intervals in long-term forecasts suggests growing uncertainty in predictions further into the future. This study contributes to the field of gold price forecasting by identifying an effective model for the Indian market, which can aid investors, policymakers, and economists in decision-making processes related to gold investments and economic planning. Future research could focus on incorporating additional economic indicators or exploring hybrid models to further improve short-term prediction accuracy and reduce forecast uncertainty in the long term.

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