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Forecasting gold price and inflation for India and US: An analysis of ARIMA and Holt Winters models

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Abstract. *Gold is a precious metal and a commodity that is in the spotlight in this new decade. In recent events, gold prices have globally been increasing due to wars, pandemics, and uncertainty in financial markets. We study the gold prices for developing and developed countries i.e., India and the United States (US) based on historical data from 1960 to 2020 and to understand the dynamic advantages of investment on gold in these countries. India and United States are huge markets for gold, and growing affluence is driving growth in demand. We have utilized an autoregressive integrated moving average (ARIMA) and Holt winters statistical models to analyze the trends and produce forecasts of gold price and inflation. We have also empirically investigated and validated the relationship between the gold price and inflation rates. We have concluded that gold is an excellent investment for Indian investors for both short and long-term returns as for the US investors, the gold investment being a part of their portfolio could be a hedge against inflation.*

Keywords: gold price, inflation, India, United States, ARIMA, Holt Winters.

JEL Classification: 62G07, 62C05, 62E20.

1. Introduction

In recent years gold has gained recognition as a hedge against inflation (Huang et al., 2016 and Oloko et al., 2021). The literature in the previous studies showed that gold price affects gold production or mining, import, and exports from country to country (Govett and Govett, 1982; Blose and Shieh, 1995; Blose, 1996), Craig and Rimstidt, 1998; Rockerbie, 1999; Selvanathan and Selvanathan, 1999; and Ghazi et al., 2015) discussed that inflation in Malaysia has no effect on gold price in the country. Hoang et al. (2016) have studied the same considering a few large economies (US, UK, France, China, Japan, and India) and analysed that gold can be a good hedge against inflation for India, the US, and the UK in the short run their approach was through nonlinear autoregressive distributed lags (NARDL) model (Shin et al., 2014). Furthermore, propriety research was conducted by Oxford economics (2011), commissioned by the world gold councils, showed enough evidence that gold has a significant relationship with US inflation.

Several research works conducted to testify gold as a hedge against inflation and on the macroeconomic factors that influence gold price. But no study involves historical data of gold price and rates of inflation. ARIMA model (Hillmer and Tiao, 1982 and Ariyo et al., 2014) is one of the best models to forecast for time series data, and it has been used in many research problems that involve historical data of the subject against time (Box, et al., 1976; Jakaša et al., 2011; Devi et al., 2013; Guha and Bandyopadhyay, 2016).

Hence, this paper is mainly focused on the historical data of the US and India's domestic gold prices and inflation. Additionally, this paper has considered the economical, statistical, and political factors and serves as a good guide for investing in this precious metal. Advancing with studies from previous research, this paper deals with that same question of hedging considering gold but with a comparative study approach. We use statistical techniques and the Box-Jenkins methodology to have a much clearer understanding to make the most optimal investment plan in developing and developed countries.

The remainder of the article is organized in the following manner. The second section demonstrates the inspection of gold and inflation data for the period 1960-2020. The third section analyses results and discussion. And last section elaborates conclusions and suggestions for investment decisions.

2. An inspection of gold and inflation data (1960-2020)

To start with the analysis, we considered the consumer price index (CPI) from 1960-2020 of both countries as a metric of inflation. The raw data of CPI was gathered from World Bank.org (https://data. worldbank.org/indicator/FP.CPI.TOTL.ZG). The gold price data for analysis is the domestic gold prices from 1960-2020 in India and the US which is gathered from Gold Hub (https://www. gold.org/goldhub/data/gold-prices.

To understand at what rate gold prices are increasing we have calculated the annual average growth rate (AAGR) which shows the average increase or decrease in the value of an investment asset, portfolio, or cash flow over a specific period.

Table 1. *AAGR of gold price and CPI*

Country	Gold price	Inflation
India	13%	-10%
US	9%	11%

From Table 1, we observed that AAGR of gold price is thirteen percent in India which is higher than US and the inflation rate in India having the negative growth rate. Further, in the case of US, we observed the interestingly AAGR in inflation and gold price, they have increased with almost similar rates. However, the AAGR is not sufficient to tell whether gold is a good investment or not as AAGR does not take into the consideration of all factors such as volatility and trends.

Hence, a time series plot tells us the past trends of gold prices and inflation rates. Figure 1 and Figure 2 are the time series plots of gold prices and CPI of the two countries.

Figure 1. *Gold price and inflation rate in India*

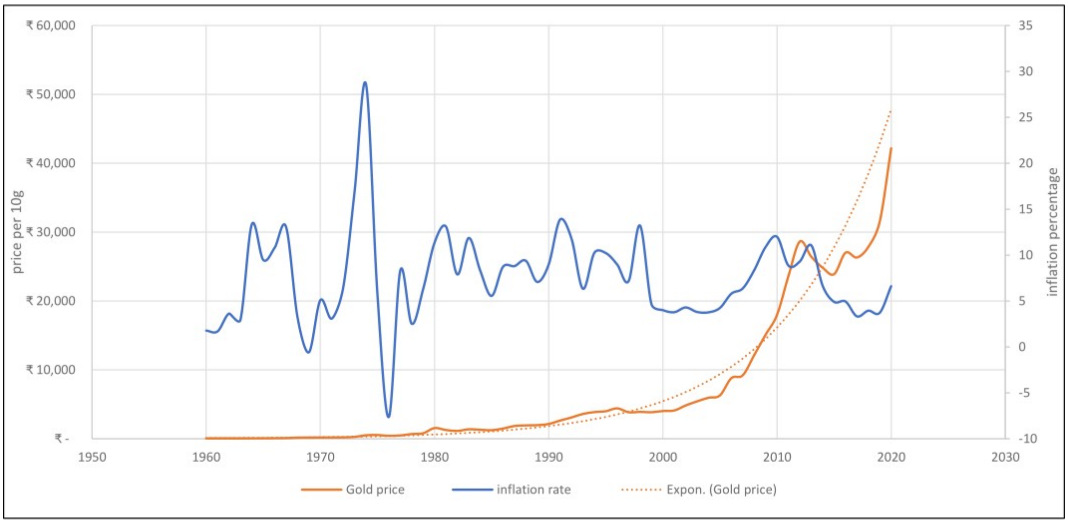


Figure 1 demonstrates the gold price and CPI time series plot for India. We see clearly that gold prices for almost 2 decades had no fluctuation and changes in prices started around 1970. Close to the 2000, the gold price takes a drastic turn. After that the gold price was showing an increasing trend from 2015 to 2020. We observed that the outliers are present in the CPI during the period of 1970-1980. Nevertheless, since 1980, inflation in India has been kept relatively stable even during the 2008 financial crisis. Comparing the gold price and the CPI of India, we do not see much concurrent behavior.

Figure 2. *Gold price and inflation rate in US*

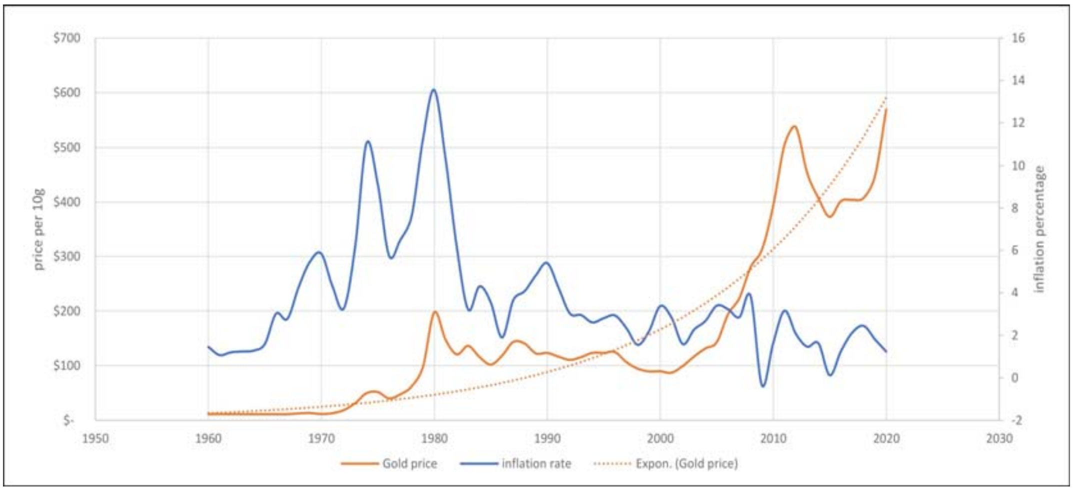


Figure 2 is the gold price and CPI time series plot for the US. Unlike India, we see drastic variation both in the gold price and inflation. Earlier gold prices used to move differently in different countries due to the gold standard. The gold standard is a monetary system in which the value of a country's currency or paper money is closely linked to the value of gold. A gold-standard country establishes a fixed gold price and trades at that price point. In 1971 gold standard was abandoned from US monetary system. For the past two decades, gold prices have been relatively similar throughout the globe which can also be observed in Figure 1 and Figure 2. As we observed in Figure 1 and Figure 2 gold prices from 1960 to 1970 had little to no change in price in both countries. Hence, for further analysis, we have used the gold price data from 1970 onwards.

3. Empirical results and discussion

In this section, we have empirically investigated and validated the relationship between the gold price and inflation. Therefore, we have performed a correlation analysis and the results are shown in Table 2.

Table 2. *Correlation coefficients of gold price and inflation of India and US*

Country	Gold price and inflation	
	correlation coefficients	*p*-value
India	-0.067	0.604
US	-0.285	0.025

The price of gold and inflation has a negative correlation coefficient. From Table 2, we see that gold has a relatively stronger correlation with US inflation. In the following section, we have performed time series analysis to describe our data taking into consideration of its volatility and non-linearity.

Autoregressive integrated moving average model

Time series analysis, often known as trend analysis, is a statistical technique that works with time-series data W.S. Wei (1989). Furthermore, its extending branch is forecasting which is what we desire. Hence, before we start using different modeling processes, checking for the stationarity of the time series data is necessary.

3.1. Augmented Dickey-Fuller (ADF) Test

We use two methods to check for stationarity. 1: using the graphical method or 2: performing a test on the time series data. Now, the graphical methods can be used as an overview to check for stationarity but for a solid affirmation performing a test is the best option. Hence, for this analysis, we have used Augmented Dickey-Fuller (ADF) Test to check the stationarity of the data.

Further, we have performed the ADF which is a unit root test to check for stationarity of the time series data. Unit roots are known to cause unpredictable results in the time series analysis. The ADF test allows for higher-order autoregressive processes and is governed by the model:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t$$

This model is derived from an autoregressive process of 1st order of y_t and $\Delta y_t = y_t - y_{t-1}$, where α is some constant, β is the coefficient on a time trend, δ_i is some coefficient associated with Δy_{t-i} for p number of lags and ε_t is the residuals where, $\varepsilon_t = y_t - \hat{y}_t$. If $\gamma = 0$ which is null hypothesis, then we have a random process. If $\gamma < 0$, then we have a stationary process. The test is performed the same way as a simple linear model test with computed the t-statistic and comparing it with a Dickey-Fuller distribution. Below are the results from performing the ADF test in R software:

Table 3. *ADF p-values before and after difference*

Country	Gold price			Inflation		
	p-values (before)	difference	p-values (after)	p-values (before)	difference	p-values (after)
India	0.96	2	0.01	0.01	0	0.01
US	0.56	1	0.01	0.32	1	0.01

In this test the null hypothesis set as the time series is non-stationary and the alternative is that the time series is stationary. The difference taken in Table 3 is make the time series stationary when the p-value is more than 0.05. Differencing is the transformation of our original time series data (y_t) to a new time series $y_t' = y_t - y_{t-1}$, this is called a first-order difference. Similarly, it can be the second-order difference and so on until the times series is stationary. we see that the p-value is less than 0.05 this suggests that all the time series data is stationary, hence, it can provide good results.

3.2. Model Identification

To determine the process, we need the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots (Box et al., 1976 and Benvenuto, 2020). The autocorrelation function (ACF) is a function which gives us values of autocorrelation of any series with its lagged values. In simple terms, it describes how well the present value of the series is related with its past values. Generally, for time series yt, the ACF for k number of lags is defined as,

$$\rho_k = \frac{Cov(y_t, y_{t+k})}{[Var(y_t)\, Var(y_{t+k})]^{1/2}}$$

For a stationary stochastic or random process of variance σ^2, the previous expression for the ACF reduces to $\rho_k = \frac{Cov(y_t, y_{t+k})}{\sigma^2}$. In time series analysis, The PACF regresses the values of a stationary time series with their own lagged values at all shorter lags. The autocorrelation function, on the other hand, does not regulate the other shorter lags. We have computed all ACF and PACF plots. The ACF and PACF plots show that all the lags, which are represented by the black spikes in the plots, tail-off as the number of lags increase, suggesting an ARMA process (Asad, 2012, Ghazi et al, 2015, Anwar, 2016). Autoregressive moving average (ARMA) is a combination of two processes or models in time series which are the Autoregressive model (AR) and Moving Average model (MA). The Autoregressive model AR(p) refers to the autoregressive model of order p. The AR(p) model is written as,

$$Y_t = c + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \varepsilon_t$$

where, $\varphi_1, \varphi_2 \dots\dots\dots \varphi_p$ are parameters, c is a constant, and the random variable ε_t is white noise error term. Similarly, the Moving-average MA(q) refers to the moving average model of order q:

$$Y_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

where, $\theta_1, \theta_2, \dots\dots, \theta_q$ are the parameters of the model, μ is the expectation of the series, and ε_i are the white noise error terms. Further, the Autoregressive Moving Average ARMA (p, q) refers to the model with p autoregressive terms and q moving-average terms. This model contains the AR (p) and MA (q) models,

$$Y_t = c' + \varepsilon_t + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

Where c' is a constant. Now the ARMA (p, q) is the optimum model for our data that we need to take into account the seasonal differences from Table 3, for which the ARIMA model is clearly understood.

3.3. The Box-Jenkins Model

The autoregressive integrated moving average (ARIMA) model which is also known as the 'BoxJenkins' approach (Box G. and Jenkins G. 1970) utilizes three methods: autoregression, differencing, and moving average. These methods are collectively shown as ARIMA (p, d, q). ARIMA model is widely used for modelling all types of time series data (Box, 1976, As'ad, 2012, Sharma, 2015, Anwar, 2016, Guha and Bandyopadhyay, 2016, Benvenuto et. al, 2020) and is denoted by: ARIMA (p, d, q), where p is the order of the AR (p) , q is the order of the MA(q) and d is the degree of differencing.

The PACF provides the p order or the AR part and ACF provides the q order or the MA part. The values of p and q can be determined by graphical method or else by a R-software. Hence, we have used both methods to select the best models for forecasting of our data. All model computation and statistics are provided in Table 4 in Appendix.

3.4. Diagnostic check

In this study, we have used two statistics to select our ARIMA model; Akaike Information Criterion (AIC) and Mean Absolute Percentage Error (MAPE) values. AIC is an estimator of prediction error and thereby relative quality of statistical models for a given set of data. Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Thus, AIC provides a means for model selection. It is expressed as:

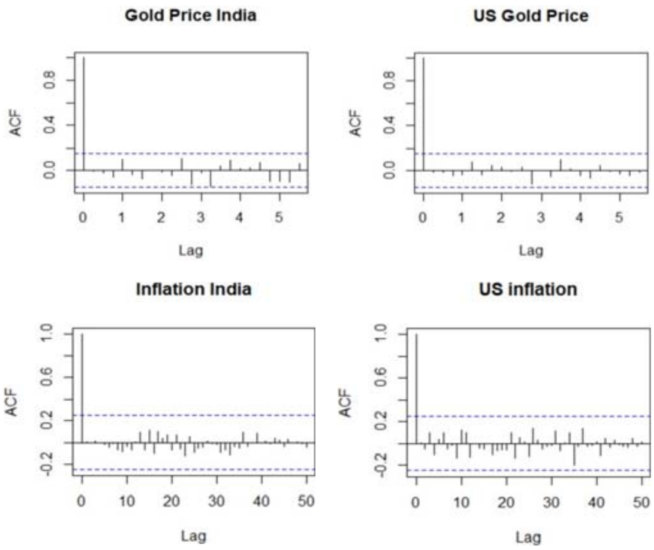
$$AIC = 2k - ln\,\hat{L}$$

Where, k is the number of estimated parameters in the model and $\hat{L}$ is the maximum likelihood of the data. The MAPE is a metric that assesses a forecasting system's accuracy. It is calculated as the average absolute percent error for each minus actual values divided by actual values and are expressed as a percentage. Its expression is as follows:

$$MAPE = \sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right|$$

The data table of AIC and MAPE for all the computed ARIMA model are in the Annexure for reference. Furthermore, residual checking of the ACF plots is very important as it will make sure that the errors are uncorrelated and propose an appropriately fitted model. Following the below residual ACF plots, the spikes stay between the control bands (the blue dotted lines) and as the lags increase, the spikes tail-off to zero suggesting that our ARIMA model is appropriately fitted.

Figure 3. *ACF Plots*



3.5. Forecasting

The best suitable models for Indian gold price and US gold price based on AIC and MAPE are ARIMA (1, 2, 1) and ARIMA (7, 1, 7) respectively. Similarly, the best suitable models for US and Indian inflation are ARIMA (2, 1, 2) and ARIMA (4, 0, 5) respectively. We have used R programming to forecast gold price and inflation. The forecast values of gold prices are presented in the below Figure 4.

Figure 4. *Prediction of Gold price in India and Prediction of Gold price in US*

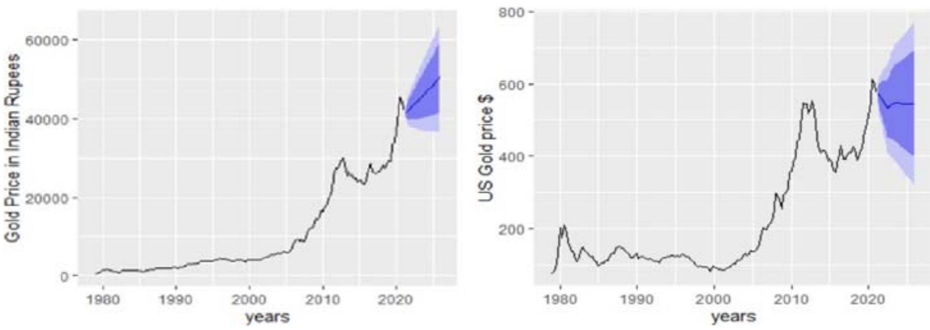
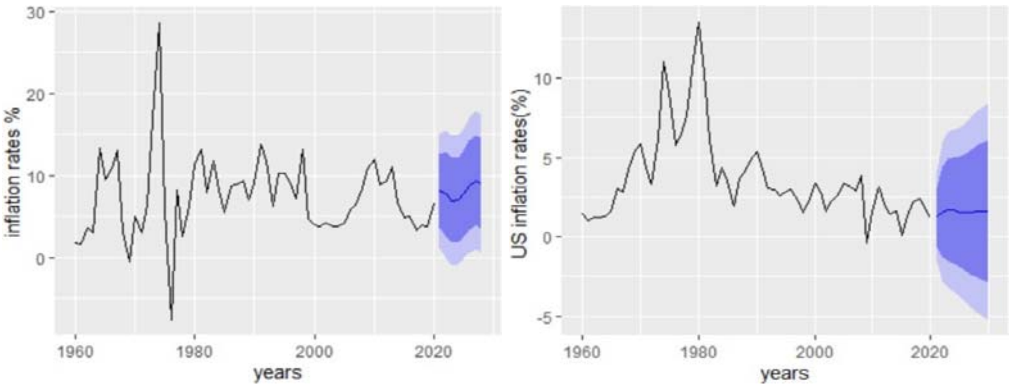


Figure 4 shows the forecast of gold prices giving out very interesting results. The shaded regions are confidence limits. As we observed in the first graph for India, gold prices will keep their steadily increasing trend in the coming years in India. Whereas if we consider the second graph, the is the gold price forecast for US, we see a bulge in the forecast which could be for two reasons. As the US dollar is a more powerful currency against gold and rupees. In simple words, the buying power of the US dollar is stronger than that of the Indian Rupee and gold. We have also forecasted inflation rates which is presented in Figure

5. The forecasted values of ARIMA model for gold prices for India and US are reported in Table 5 and Table 6 in Appendix.

Figure 5. *Prediction of inflation*

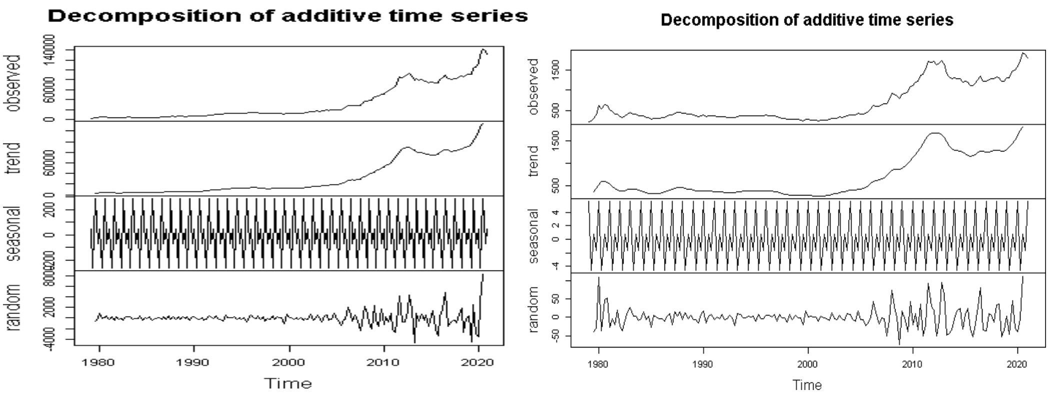


(a) India (b) US

3.6. Forecasting Results of Holt Winters Method

After following the ARIMA model, this study has also utilized the Halt-Winter method for the robustness check of ARIMA forecasting. This method is applicable to forecast the future value of inflation. We have applied this method by using double exponential smoothing for level and trend components. In Halt-Winter Method, firstly, we decompose the time series or separate the observed data into four main components; fitted seasonal factor, growth rate (or trend), level and random factor plot against time (year). The decomposition graphs for the gold prices are given in Figure 6.

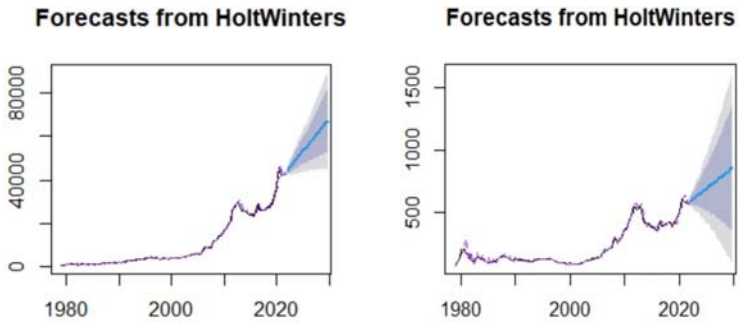
Figure 6. *Decomposition of gold price*



(a) India (b) US

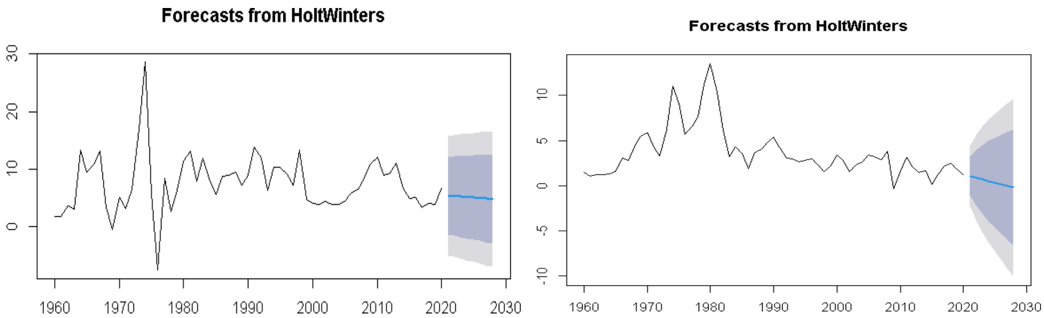
Figures 7 represent the forecast values of gold price of India and US respectively form Holt winters method. The blue line shows the average increase, and the shaded region shows the confidence interval of gold price. It shows the increase pattern in gold price for India and US. After comparing both models (ARIMA and Holts winters), we can conclude that the price should increase in the future in both countries. The forecasted values of Holt Winters model for gold prices for India and US are reported in Table 7 and Table 8 in Appendix.

Figure 7. *Prediction of gold price*



(a) India (b) US

Figure 8. *Prediction of inflation*



(a) India (b) US

Figure 8 represent the forecast values of inflation of India and US respectively form Holt winters method. The forecast of Indian inflation is flat shown by the blue line and for US inflation is on a steady decline. After comparing both the models: ARIMA and Holt winters for forecasting inflation, it is observed that the results are similar for expected inflation with different magnitude in forecasting values.

4. Conclusions

This study has empirically investigated and validated the relationship between the gold price and inflation considering the CPI of a developing and a developed countries i.e., India and the United States. We used ARIMA and Holt winters models to forecast the future gold prices and inflation rates respectively. For Indian investors, we conclude gold as a good hedge against inflation. We conclude that investment on the gold is a very good decision for good returns in both the long and short run. Rather than investing traditionally i. e. buying gold jewelry, exploring other options such as gold bars or coins, gold ETF, sovereign gold bonds, and gold monetization scheme can help to maintain capital returns over time at a pace that exceeds inflation.

Considering the US scenario, we conclude that our analysis shows a relationship between gold price and the US dollar. Hence, the US CPI which is the purchasing power of the US dollar is one of the key driving forces for the fluctuation in gold prices asides for other macroeconomics factors. Further, we can argue that any uncertainty in the US economy increases inflation rates and correspondingly will increase gold prices. From the forecast of US gold price and inflation, their correlation, and observation from the trend curve we conclude that gold can serve as a good hedge against inflation for the US investors also, with less risk and moderate returns.

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Appendix

Table 4. *Computed ARIMA models AIC and MAPE values*

India						US					
Model	Gold		Model	Inflation		Model	Gold		Model	Inflation	
	AIC	MAPE		AIC	MAPE		AIC	MAPE		AIC	MAPE
ARIMA (1,2,1)	2744.81	4.84	ARIMA (0,0,1)	360.26	68.25	ARIMA (1,1,0)	1444.03	5.02	ARIMA (0,1,2)	224.98	71.13
ARIMA (2,2,1)	2832.35	1654.71	ARIMA (2,0,1)	363.49	69.89	ARIMA (7,1,7)	1446.70	5.20	ARIMA (2,1,2)	226.47	72.80
ARIMA (3,2,4)	2763.52	917.30	ARIMA (4,0,5)	365.49	60.66	ARIMA (1,1,1)	1444.62	5.00			
ARIMA (1,2,0)	2999.44	1077.36									

Table 5. *Forecasts: Gold Price (in INR) using ARIMA (1,2,1)*

Year	Quarter	Point Forecast	Confidence Interval	
			80% CI	95% CI
2022	Q1	43835.80	(42709.84,44961.76)	(42113.79,45557.81)
	Q2	44391.85	(42543.59,46240.10)	(41565.18,47218.51)
	Q3	44943.62	(42504.30,47382.93)	(41213.01,48674.23)
	Q4	45494.23	(42543.56,48444.89)	(40981.58,50006.88)
2023	Q1	46044.52	(42632.83,49456.21)	(40826.79,51262.25)
	Q2	46594.73	(42755.41,50434.05)	(40723.00,52466.46)
	Q3	47144.92	(42901.20,51388.63)	(40654.72,53635.11)
	Q4	47695.10	(43063.79,52326.40)	(40612.12,54778.07)
2024	Q1	48245.27	(43238.86,53251.69)	(40588.62,55901.93)
	Q2	48795.45	(43423.40,54167.50)	(40579.61,57011.30)
	Q3	49345.63	(43615.22,55076.03)	(40581.73,58109.53)
	Q4	49895.81	(43812.69,55978.92)	(40592.48,59199.13)
2025	Q1	50445.98	(44014.52,56877.44)	(40609.92,60282.05)
	Q2	50996.16	(44219.74,57772.58)	(40632.52,61359.80)
	Q3	51546.34	(44427.53,58665.14)	(40659.07,62433.61)
	Q4	52096.52	(44637.26,59555.77)	(40688.58,63504.46)
2026	Q1	52646.69	(44848.40,60444.99)	(40720.23,64573.16)
	Q2	53196.87	(45060.49,61333.25)	(40753.35,65640.39)
	Q3	53747.05	(45273.17,62220.93)	(40787.37,66706.73)
	Q4	54297.23	(45486.12,63108.33)	(40821.80,67772.65)

Note: INR indicates Indian Rupees.

Table 6. *Forecasts: Gold Price (in $) using ARIMA (7,1,7)*

Year	Quarter	Point Forecast	Confidence Interval	
			80% CI	95% CI
2022	Q1	583.38	(526.83, 639.93)	(496.89, 669.87)
	Q2	569.63	(504.19, 635.07)	(469.55, 669.72)
	Q3	562.52	(488.36, 636.68)	(449.10, 675.94)
	Q4	572.87	(489.65, 656.10)	(445.60, 700.15)
2023	Q1	582.38	(490.69, 674.07)	(442.16, 722.61)
	Q2	575.11	(476.19, 674.02)	(423.83, 726.38)
	Q3	563.78	(458.23, 669.34)	(402.35, 725.21)
	Q4	567.18	(454.77, 679.60)	(395.25, 739.11)
2024	Q1	578.73	(459.44, 698.02)	(396.30, 761.17)
	Q2	578.82	(453.38, 704.26)	(386.97, 770.67)
	Q3	567.93	(436.99, 698.88)	(367.67, 768.19)
	Q4	564.65	(428.20, 701.10)	(355.97, 773.33)
2025	Q1	573.91	(431.75, 716.07)	(356.50, 791.32)
	Q2	579.67	(432.09, 727.25)	(353.97, 805.37)
	Q3	572.62	(420.18, 725.06)	(339.49, 805.76)
	Q4	565.15	(408.04, 722.26)	(324.87, 805.43)
2026	Q1	569.60	(407.6, 731.57)	(321.88, 817.31)
	Q2	575.41	(439.60,711.22)	(367.71,783.11)
	Q3	573.97	(434.18,713.75)	(360.19,787.74)
	Q4	566.12	(422.20,710.04)	(346.01,786.22)

Table 7. *Forecasts: Gold Price (in INR) using Holt Winters*

Year	Quarter	Point Forecast	Confidence Interval	
			80% CI	95% CI
2022	Q1	44176.24	(42976.85, 45375.64)	(42341.92, 46010.56)
	Q2	44941.88	(43214.46, 46669.30)	(42300.03, 47583.73)
	Q3	45790.50	(43612.42, 47968.57)	(42459.42, 49121.58)
	Q4	46201.42	(43606.68, 48796.15)	(42233.12, 50169.72)
2023	Q1	47113.64	(44099.64, 50127.64)	(42504.12, 51723.16)
	Q2	47879.28	(44477.53, 51281.02)	(42676.76, 53081.79)
	Q3	48727.90	(44942.40, 52513.39)	(42938.49, 54517.30)
	Q4	49138.81	(44970.79, 53306.84)	(42764.37, 55513.26)
2024	Q1	50051.04	(45483.74, 54618.34)	(43065.96, 57036.12)
	Q2	50816.67	(45865.58, 55767.77)	(43244.63, 58388.72)
	Q3	51665.29	(46327.44, 57003.15)	(43501.75, 59828.84)
	Q4	52076.21	(46348.01, 57804.41)	(43315.69, 60836.73)
2025	Q1	52988.43	(46851.70, 59125.17)	(43603.11, 62373.76)
	Q2	53754.07	(47219.45 ,60288.69)	(43760.22, 63747.91)
	Q3	54602.69	(47665.46, 61539.92)	(43993.11, 65212.27)
	Q4	55013.61	(47668.88, 62358.33)	(43780.81, 66246.40)
2026	Q1	55925.83	(48155.70, 63695.96)	(136593.6, 234241.6)
	Q2	56691.47	(48504.36, 64878.57)	(44042.44, 67809.22)
	Q3	57540.08	(48930.77, 66149.40)	(44170.37, 69212.56)
	Q4	57951.00	(48914.21, 66987.79)	(44373.28 ,70706.89)

Table 8. *Forecasts: Gold Price ($) using Holt Winters*

Year	Quarter	Point Forecast	Confidence Interval	
			80% CI	95% CI
2022	Q1	591.5152	(562.7499 , 620.2806)	(547.52244, 635.5080)
	Q2	605.6932	(565.3176, 646.0687)	(543.94410, 667.4422)
	Q3	616.4999	(564.9567, 668.0432)	(537.67138, 695.3285)
	Q4	611.3027	(548.5773, 674.0282)	(515.37242, 707.2330)
2023	Q1	625.6480	(549.2624, 702.0335)	(508.82637, 742.4695)
	Q2	639.8259	(552.0906, 727.5612)	(505.64636, 774.0054)
	Q3	650.6327	(551.1646, 750.1008)	(498.50931, 802.7560)
	Q4	645.4354	(533.8491, 757.0218)	(474.77889, 816.0920)
2024	Q1	659.7807	(533.8273, 785.7341)	(467.15159, 852.4098)
	Q2	673.9586	(535.2985, 812.6188)	(461.89619, 886.0210)
	Q3	684.7654	(533.0003, 836.5305)	(452.66074, 916.8700)
	Q4	679.5682	(514.3116, 844.8247)	(426.83010, 932.3062)
2025	Q1	693.9134	(513.1522, 874.6746)	(417.46297, 970.3638)
	Q2	708.0913	(513.2162, 902.9665)	(410.05554 ,1006.1271)
	Q3	718.8981	(509.5383, 928.2580)	(398.70986, 1039.0864)
	Q4	713.7009	(489.4961, 937.9057)	(370.80928, 1056.5925)
2026	Q1	728.0461	(487.1634, 968.9288)	(359.64780, 1096.4444)
	Q2	742.2241	(485.8939, 998.5542)	(350.20088, 1134.2472)
	Q3	753.0308	(480.9109, 1025.1508)	(336.85924, 1169.2024)
	Q4	747.8336	(459.5901, 1036.0771)	(307.00320, 1188.6640)