

A statistical Study of Price of Gold

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ABSTRACT

Gold has long been considered one of the most precious metals, and its value has been used as the standard for many currencies (known as the gold standard) in history. Ancient India accumulated gold through trade of Indian spices with Roman Empire and by gold mining operations, predominantly in the regions of Hatti and Kolar of modern-day Karnataka.

1. There has been drastic increase in the prices of gold since 2001. Gold prices have been increased by 90% during last 10 years.
2. The Bank of India has one of the largest stores of gold in the world. India is the second largest consumer of gold in the world and is one of the most reliable drivers of global demand. Gold accounts for nearly 5.5% of the total foreign reserve holdings of India. India's festival and wedding season, which runs from October to December, has historically been a huge boon to gold trade.
3. Gold has always been used as a monetary standard. Gold has a profound impact on the value of world currencies. Even though the gold standard has been abandoned, gold as a commodity can act as a substitute for fiat currencies and be used as an effective hedge against inflation. There is no doubt that gold will continue to play an integral role in the foreign exchange markets.

Gold consumption observed a sharp acceleration during the 1990s amidst liberalization of gold import policy, strong economic growth and favourable movements in gold prices.

Gold is now being used as an alternative for dollar since its collapse. Monetary and Non-Monetary demand for gold is steeply rising. It has been demanded by individual buyer, institutional buyer as well as the Countries too.

INTRODUCTION

We started with the literature review of the previous researches on the effect of inflation, silver price, USA dollar trade, personal disposable income, crude oil price, interest rate with gold price. The theoretical or conceptual framework was presented at the following part, identified the network relationships between the variables.

Factors Affecting Gold Prices: A Theoretical Background

1. EXCHANGE RATE:

An exchange rate is the price of nation's currency in terms of another currency. As a rule, when the value of the dollar increases relative to other currencies around the world, the price of gold tends to fall in U.S. dollar terms, it is because gold becomes more expensive in other currencies. Exchange value of US Dollar is an important factor in determining the gold price in India. The appreciation or depreciation of US dollar creates fluctuations in gold price.

$$\text{Exchange Rate (for INDIA)} = \frac{\text{INR}}{\text{USD}}$$

2. CONSUMER PRICE INDEX (INFLATION)

Inflation is defined as a sustained increase in the price of goods and services. Over time, it erodes the value of a nation's currency. In other words, it erodes purchasing power. According to empirical findings, highly positive correlation is found between Gold Prices and CPI rate of our country; however, there is a short-term relationship between inflation and gold prices.

$$\text{CPI} = \frac{\text{current price}}{\text{old price}} \times 100$$

3. BSE SENSEX (BOMBAY STOCK EXCHANGE):

Sensex=Sensitive Index.

Index is a statistical aggregate that measures change. BSE SENSEX is the market weighted stock index of top 30 companies. . Sensex is composed of 30 of the largest and most actively traded stocks on the BSE, providing an accurate gauge of the overall growth, development of particular industries, and booms and busts of the Indian economy. There is an inverse relationship between Gold Prices and Sensex.

$$\text{BSE SENSEX} = \frac{\text{Free float market capitalization of 30 companies}}{\text{Index Divisor}}$$

4. PERSONAL DISPOSABLE INCOME:

Personal Disposable Income (PDI) is the amount of money that households have available for spending and saving after income taxes have been accounted for. According to a report by the World Gold Council, annual data from 1990 to 2015, gold demand is seen to rise with income levels. For a 1 percent increase in income per capita gold demand rises by 1 percent and for a 1 percent increase in prices, the demand for gold deters by 0.5 percent. .Therefore, we can conclude that a higher demand will drive up gold prices by a higher margin.

$$\text{PDI} = \text{PERSONAL INCOME} - \text{PERSONAL CURRENT TAXES}$$

5. INTEREST RATES:

Generally, real interest rates are negatively correlated with the price of gold. i.e. it is relatively expensive to hold gold in the portfolio when real interest rates are high, and relatively cheap when real interest rates are low. Thus, the higher the interest rates are, the higher are carrying costs. However, the relationship is not linear. Gold prices tend to increase significantly only during the periods of negative real interest rates.

$$\text{INTEREST RATE} \propto \frac{1}{\text{GOLD PRICE}}$$

6. CRUDE OIL PRICES :

Crude oil is among the eight core industries in India and plays a major role in influencing decision making for all the other important sections of the economy. Crude oil prices can be used as a reliable proxy

of movements in gold prices since the two have a strong direct relationship. This is because, like oil, gold too is mined from the ground, is standardized and interchangeable. Due to the fact that, energy is the dominant production cost for gold.

7. SILVER PRICES:

Gold and Silver prices are correlated to other commodity prices like, global oil benchmark, global inflation. Silver prices appreciate with trade and growth imbalances against the US. Silver prices rise with falling real interest rates. Prices of both, rise together with economic improvements in emerging markets. Thus, silver and gold prices establish a direct relationship.

Thus, these 7 factors mainly affect the prices of gold.

SOFTWARE USED

- MS-excel:
- R-package:

STATISTICAL TOOLS USED:

- Simple Linear Regression Analysis
- Artificial Neural Networks
- Time Series Analysis

Data collection

For studying about this topic particularly for India, we took help of the government sites, we referred secondary data. We have collected this secondary type of data from the website of Reserve Bank of India (RBI). The Reserve Bank of India is India’s central bank which controls the issue and supply of the Indian rupee. RBI is the regulator of entire banking in India. We have used Handbook Of Statistics (HBS) which disseminates time series data on various economic and financial indicators relating to the Indian Economy.

Yearly Data from year 2000 to 2019 used for Regression Analysis and Artificial Neural Network Modeling

	year	Gold Prices (in thousand rupees per 10 gm)	exchange rate (per U.S dollar)	CPI (in % p.a.)	BSE Index	PDI (in thousand billion rupees)	Interest Rate (in % p.a.)	Crude Oil Prices (in hundred rupees per barrel)	silver price Prices (in rupees per 10 gm)
1	2000-01	4.49483	45.684	3.92	4.27	18.315	9.75	1238.778	78.6839
2	2001-02	4.795228	47.692	4.32	3.332	20.17	8.25	1098.446	74.47193
3	2002-03	5.372766	48.395	3.98	3.206	21.358	5.88	1331.323	79.90528
4	2003-04	5.867071	45.952	3.86	4.492	23.565	5.38	1335.71	87.21896
5	2004-05	6.279673	44.932	3.83	5.741	25.823	6.25	1853.133	106.8082
6	2005-06	7.676048	44.274	4.41	8.279	29.109	6.75	2528.215	118.2881
7	2006-07	9.1268	45.25	6.73	12.277	33.286	8.13	2869.843	190.5657

8	2007-08	10.79595	40.261	6.15	16.569	37.348	8.75	3239.716	194.2745
9	2008-09	13.73814	45.993	9.11	12.366	45.314	8.13	3757.198	212.4757
10	2009-10	16.74764	47.443	12.38	15.585	51.985	7.25	3310.803	253.2069
11	2010-11	21.06953	45.563	10.46	18.605	60.041	8.63	3854.353	372.8954
12	2011-12	26.74995	47.923	8.38	17.423	71.788	8.88	5134.449	573.1092
13	2012-13	29.42491	54.41	10.44	18.202	77.657	8.75	5604.634	576.023
14	2013-14	28.69209	60.502	9.69	20.12	87.685	8.8	6283.448	466.368
15	2014-15	27.24862	61.144	6.26	26.557	96.968	8.38	5065.283	405.5848
16	2015-16	27.84468	65.469	5.66	26.322	107.052	7.15	2997.96	363.181
17	2016-17	29.1651	67.072	4.14	27.338	118.168	6.63	3211.511	427.4831
18	2017-18	29.80033	66.78	3.08	32.397	129.867	6.5	3591.511	390.7218
19	2018-19	32.77538	69.9231	4.82	36.24292	131.842	7.49	4706.244	380.4235

Monthly Data From Year 2000 To 2019 Used For Time Series And Stochastic Process Analysis

month	2000	2001	2002	2003	2004	2005
jan	4508.91	4465.58	4692.69	5752.04	6179.04	6148.6
feb	4706.74	4369.57	4901.04	5771.3	6017.73	6107.5
mar	4541.6	4268.6	4920.21	5432.71	5986.48	6262.2
apr	4460	4267.17	5040.63	5191.6	5915.8	6150.58
may	4473.6	4440.58	5225.8	5560.77	5736.46	6030.38
jun	4521.15	4400.2	5313.2	5509.4	5862.12	6134.23
jul	4529.2	4379.58	5187.5	5362.5	6059.42	6058.26
aug	4516.25	4448.64	5129.2	5462.17	6125.8	6249
sep	4518.13	4631.3	5239.05	5718.4	6170.43	6534.6
oct	4537.61	4687.6	5210.4	5695.19	6360.83	6873.8
nov	4482.69	4603.96	5242.92	5850	6550.83	7167.5
dec	4540.8	4576.46	5443.6	6094.07	6444.62	7585.93

SIMPLE LINEAR REGRESSION

I. GOLD PRICE VS EXCHANGE RATE

MODEL: $Y_g = \beta_0 + \beta_1 * X_e$ Where,

Y_g =gold price X_e =exchange rate

HYPOTHESIS DEVELOPMENT:

$H_0: \beta_1 = 0$ (there is no relation between gold price and exchange) $H_1: \beta_1 \neq 0$ (there is relation between gold price and exchange rate)

TEST CRITERIA:

Reject H_0 if p-value is less than 0.05 or t-statistic is larger than p-value .accept otherwise.

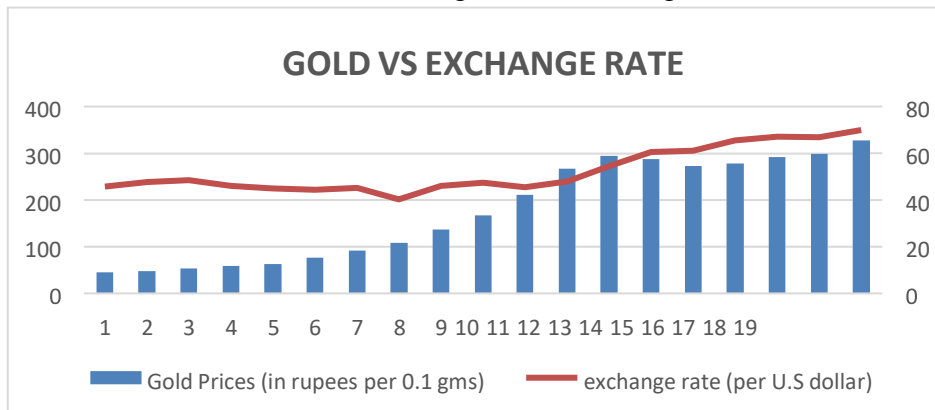
DECISION:

Here, p-value=0.01415<0.05

Reject H_0 ;

Hence, we accept H_1 .

CONCLUSION: There is direct relation between gold and exchange rate.



II. GOLD PRICE VS CRUDE OIL PRICES

MODEL: $Y_g = \beta_0 + \beta_1 * X_{cr}$

Where,

Y_g =gold price

X_{cr} =crude oil prices

HYPOTHESIS DEVELOPMENT:

H0: $\beta_1 = 0$ (there is no relation between gold price and crude oil prices).

H1: $\beta_1 \neq 0$ (there is relation between gold price and crude oil prices).

TEST CRITERIA:

Reject H_0 if p-value is less than 0.05 or t-statistic is larger than p-value. accept otherwise.

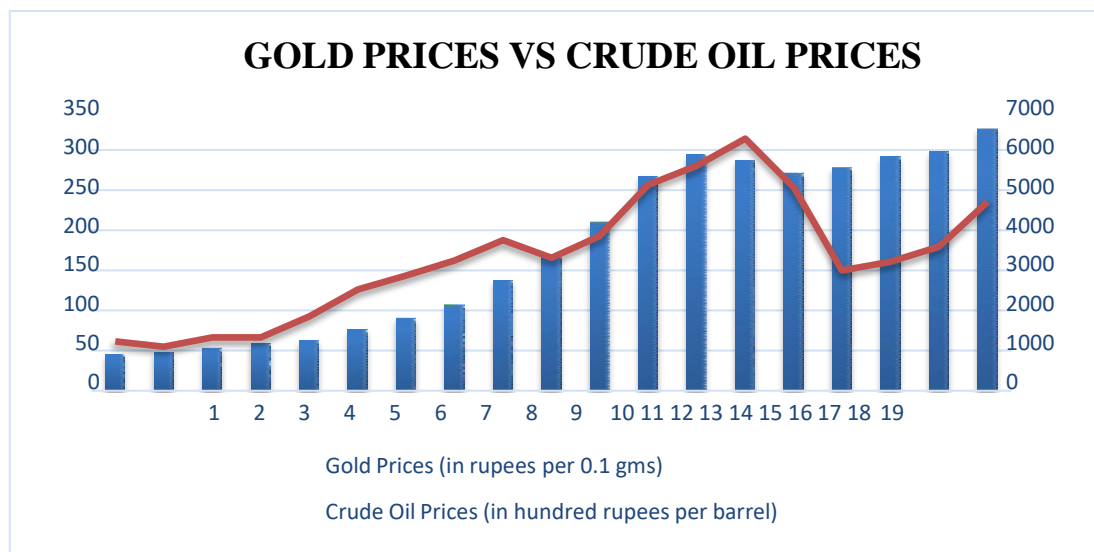
DECISION:

Here, p-value is 0.03503 < 0.05.

reject H_0 ,

Hence accept H_1 .

CONCLUSION: There is relation between gold price and crude oil prices.



III. GOLD PRICE VS BSE

MODEL: $Y_g = \beta_0 + \beta_1 * X_b$

Where,

Y_g : Gold Prices

X_b : BSE Rate

HYPOTHESIS DEVELOPMENT:

H_0 : No relation between gold prices and BSE rate i.e, $B_1 = 0$. H_1 : There is a relation between gold prices and BSE rate.

TEST CRITERIA:

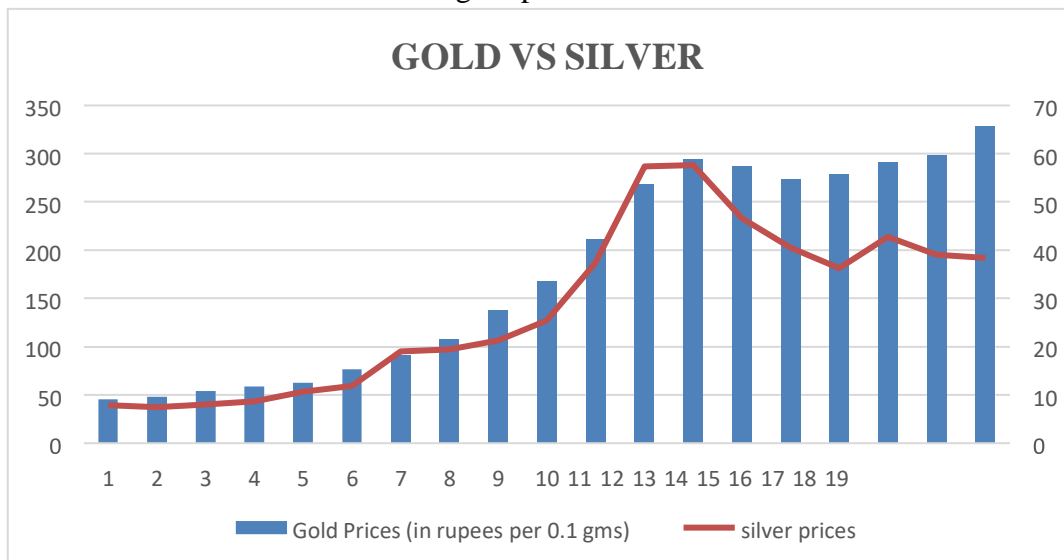
If p-value > 0.05 Accept H_0 .

DECISION:

Here, p-value = 0.001211 < 0.05

Reject H_0 .

CONCLUSION: There is a relation between gold prices and BSE rate.



IV. GOLD PRICE VS SILVER PRICE

MODEL: $Y_g = \beta_0 + \beta_1 * Y_s$

To Test :

H_0 : No relation between gold prices and silver prices i.e $\beta_1 = 0$.

H_1 : There is a relation between gold prices and silver prices.

TEST CRITERION :

If p-value > 0.05

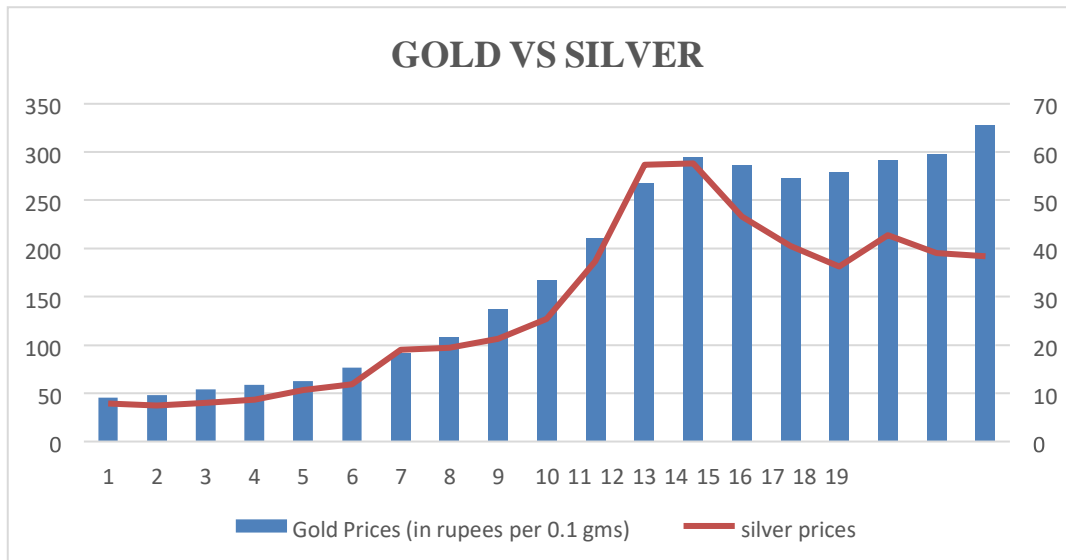
Accept H_0 .

DECISION :

Here , p-value = 0.000950 < 0.05

Reject H_0 .

CONCLUSION : There is a relation between gold prices and silver prices.



Artificial Neural Network (ANN)

Estimation is a process that produces a relationship using examples that have definite consequences and allows you to comment on the new situation through this derivation. As a prediction method, Multi-Layer Neural Network (MLNN), which is an artificial neural network model, was used in this study.

1. The network architecture has an input layer, hidden layer (there can be more than 1) and the output layer. It is also called MLP (Multi Layer Perceptron) because of the multiple layers.
2. The hidden layer can be seen as a “distillation layer” that distills some of the important patterns from the inputs and passes it onto the next layer to see. It makes the network faster and efficient by identifying only the important information from the inputs leaving out the redundant information.

In the study, the MLNN model was used to estimate the gold prices. As input to the model, data sets consisting of input variables (exchange rate, interest rate, CPI, PDI, silver prices, crude oil prices, BSE) were used. In this model, 8 neurons in 2 hidden layers. In this method program attaches weights to different nodes in hidden layer and using back propagation algorithm and predicts the required values of dependent random variable.

R code for fitting of ANN Model

Scaling data (normalization)

```
gp1=(gp-min(gp))/(max(gp)-min(gp));gp1
er1=(er-min(er))/(max(er)-min(er));er1 cpi1=(cpi-min(cpi))/(max(cpi)-min(cpi));cpi1 bse1=(bse-
min(bse))/(max(bse)-min(bse))
pdi1=(pdi-min(pdi))/(max(pdi)-min(pdi))
ir1=(ir-min(ir))/(max(ir)-min(ir))
cop1=(cop-min(cop))/(max(cop)-min(cop))
sp1=(sp-min(sp))/(max(sp)-min(sp))
data<-data.frame(gp1,er1,cpi1,bse1,pdi1,ir1,cop1,sp1);data
```

Data partition

```
train_data<-subset(data,t<=14);train_data
test_data<-subset(data,t>14);test_data
```

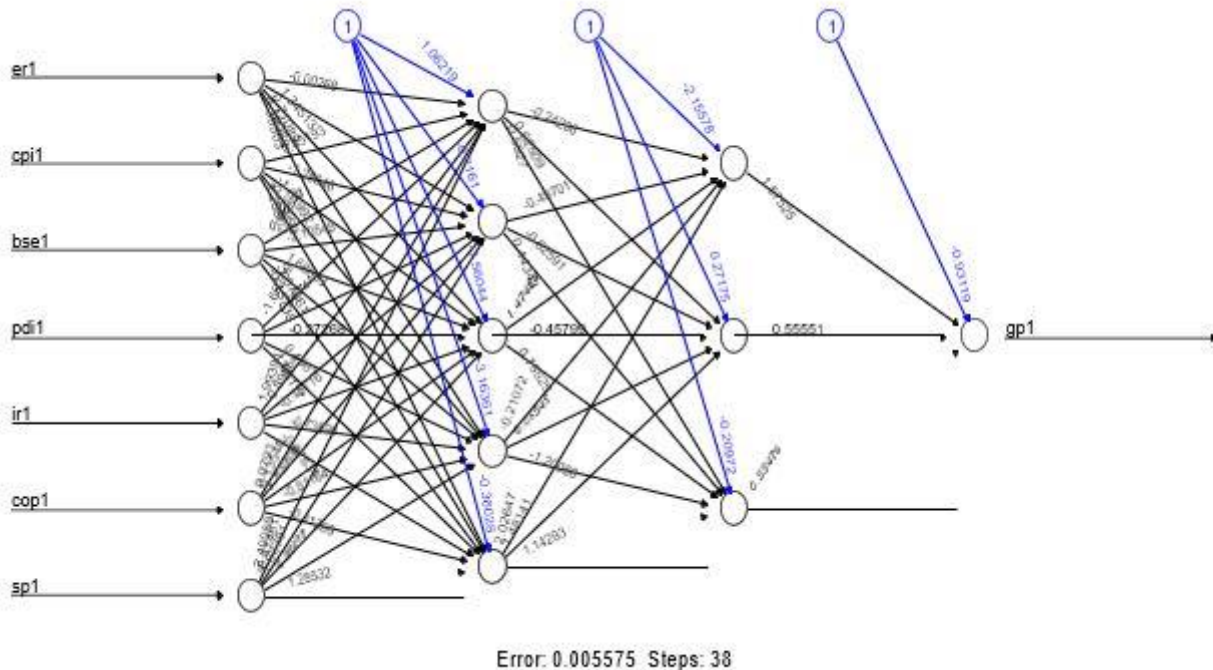
Fitting Of Model

```
library(neuralnet)
allvars<-colnames(data)
predvar<-allvars[!allvars%in%"gp1"]
form<-formula(paste("gp1~",predvar,collapse="+"))
neuralModel<neuralnet(gp1~er1+cpi1+bse1+pdi1+ir1+cop1+sp1,hidden=c(5,4),linear.output=T,
data=train_data)
plot(neuralModel)
```

Prediction

```
pred<-compute(neuralModel,test_data);pred
actual_values<-(pred$net.result)*(max(data1$gp)-min(data1$gp))+min(data1$gp);actual_values
```

NEURAL NETWORK



FORECAST OF GOLD PRICES FROM YEAR 2014 – 15 to 2018 - 19

Year	Test data	Predicted values
2014 – 15	27.24862	27.699
2015 – 16	27.84468	26.992
2016 – 17	29.1651	29.162
2017 – 18	28.90033	29.007
2018 – 19	32.77538	32.060

IME SERIES ANALYSIS

A time series is a series of data points indexed or listed in time order. It can be continuous traceor discrete set of observations. Here we are dealing with observations taken at discrete time periods. By appropriate

choice of origin and scale we can take the time periods to be 1, 2, ...

- **Introduction to Stationarity**

In general, stationarity implies a type of statistical equilibrium or stability in data. A time series is said to be strictly stationary if its properties are not affected by change in time origin. In other words if joint probability distribution of observations $Y_t, Y_{t+1}, \dots, Y_{t+h}$ is exactly same as the joint probability distribution of $Y_{t+k}, Y_{t+k+1}, \dots, Y_{t+h+k}$. A time series is said to be weakly stationary if it has the property that the mean, variance and autocorrelation structure do not change over time.

- **Transformation:**

Transformations are used to stabilize the non-constant variance of a series. Common transformation methods include power transform, square root and log transform.

There are the things which are of interest in time series analysis.

Modelling: We observe the pattern in data and fit a time series model to data. This model depends on unknown parameters which need to be estimated.

Forecasting: On the basis of available observations we predict the further observations with the help of different time series forecasting techniques which suit our data.

STATIONARITY AND NON-STATIONARITY:

A time series is said to be stationary when its behaviour does not change with time. Its mean and variance should be constant. The covariance of i^{th} and $(i+m)^{\text{th}}$ term should not be function of time.

Tests to check Stationarity

1. ADF (Augmented Dickey Fuller) Test

The Dickey Fuller test is one of the most popular statistical tests. It can be used to determine the presence of unit root in the series, and hence help us understand if the series is stationary or not. The null and alternate hypothesis of this test are:

Null Hypothesis: The series has a unit root (value of $a=1$) that is series is stationary.

Alternate Hypothesis: The series has no unit root.

2. KPSS (Kwiatkowski Phillips Schmidt Shin) Test

KPSS is another test for checking the stationarity of a time series. The null and alternate hypothesis for the KPSS test are opposite that of the ADF test, which often creates confusion.

The authors of the KPSS test have defined the null hypothesis as the process is trend stationary, to an alternate hypothesis of a unit root series. Null hypothesis: The process is trend stationary.

Alternate hypothesis: The series has a unit root (series is not stationary)

- **Analysis of data:**

Here for forecasting we have used two techniques:

1. Triple Exponential Smoothing (Holt-winters)
2. ARIMA Modelling

HOLTWINTERS TRIPLE EXPONENTIAL SMOOTHING:

Exponential smoothing is a very popular scheme to produce a smoothed time series. Exponential smoothing assigns exponentially decreasing weights as the observation get older. Recent observations are

given relatively more weights in forecasting than the older observations. It is usually used to make short term forecasts.

Here our data shows trend as well as seasonality hence we use **triple exponential smoothing**.

The basic equations for this method are

$$S_t = \alpha \frac{y_t}{I_{t-L}} + (1-\alpha)(S_{t-1} + b_{t-1})$$

$$b_t = \gamma(S_t - S_{t-1}) + (1-\gamma) b_{t-1}$$

$$I_t = \beta \frac{y_t}{S_t} + (1-\beta) I_{t-L}$$

$$F_{t+m} = (S_t + m * b_t) I_{t-L+m}$$

Where

y is the observation

S is the smoothed observation b is the trend factor

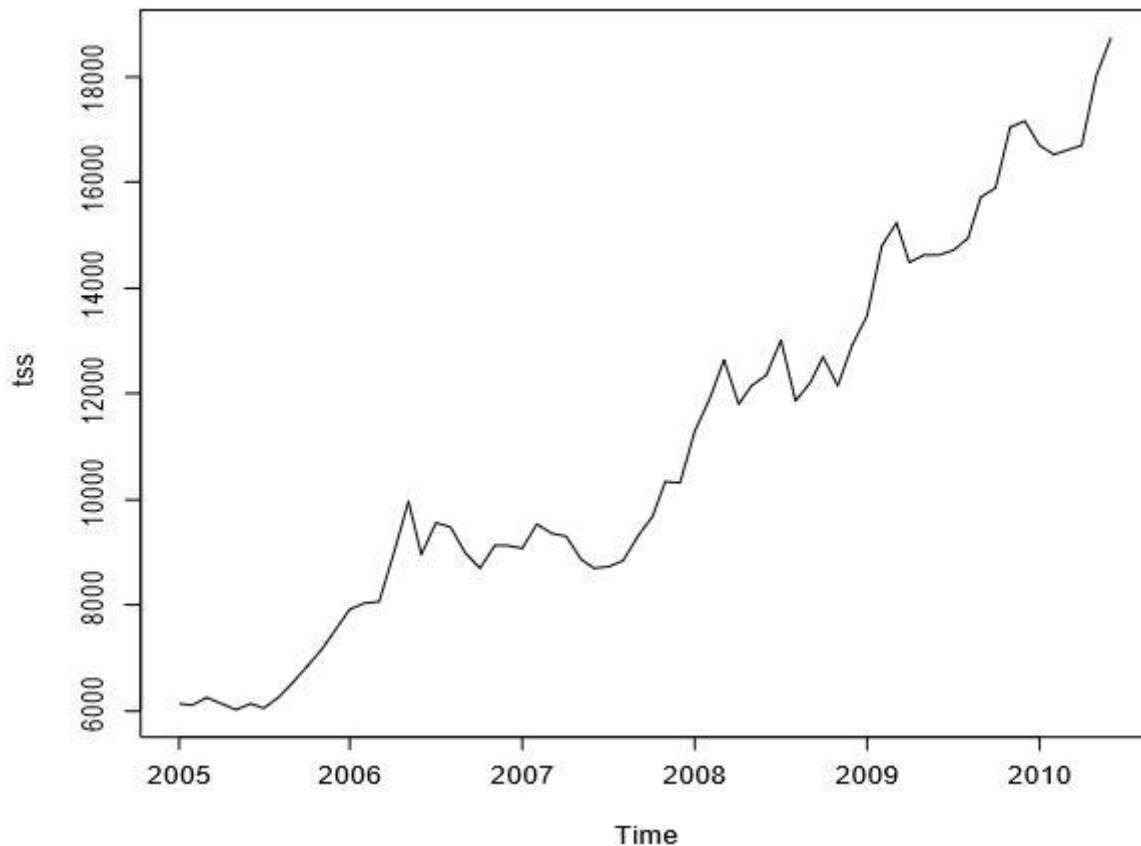
I is the seasonal index

F is the forecast at m periods ahead t is the index denoting a time period

Here we have used monthly data of gold prices. This method is mostly useful in case of short term forecasting. Hence analysis will be done on the data from Jan 2005 to July 2010 and data of next six months will be used for validation of analysis.

The R code:

```
data=read.csv(file.choose(),header=TRUE)
gp=data$price
gp2=gp[61:126]
tss=ts(gp2,frequency=12,start=c(2005,1))
tss
p=plot.ts(tss);p;
```



Decompose Function: the decompose () function is used to decompose the given time series into seasonal, trend and irregular components using moving averages. the function first determines the trend component from data and removes it from series then seasonal figure is computed by averaging. the seasonal figure is then centered. finally the irregular or error component is determined by removing trend and seasonal figure

R code:

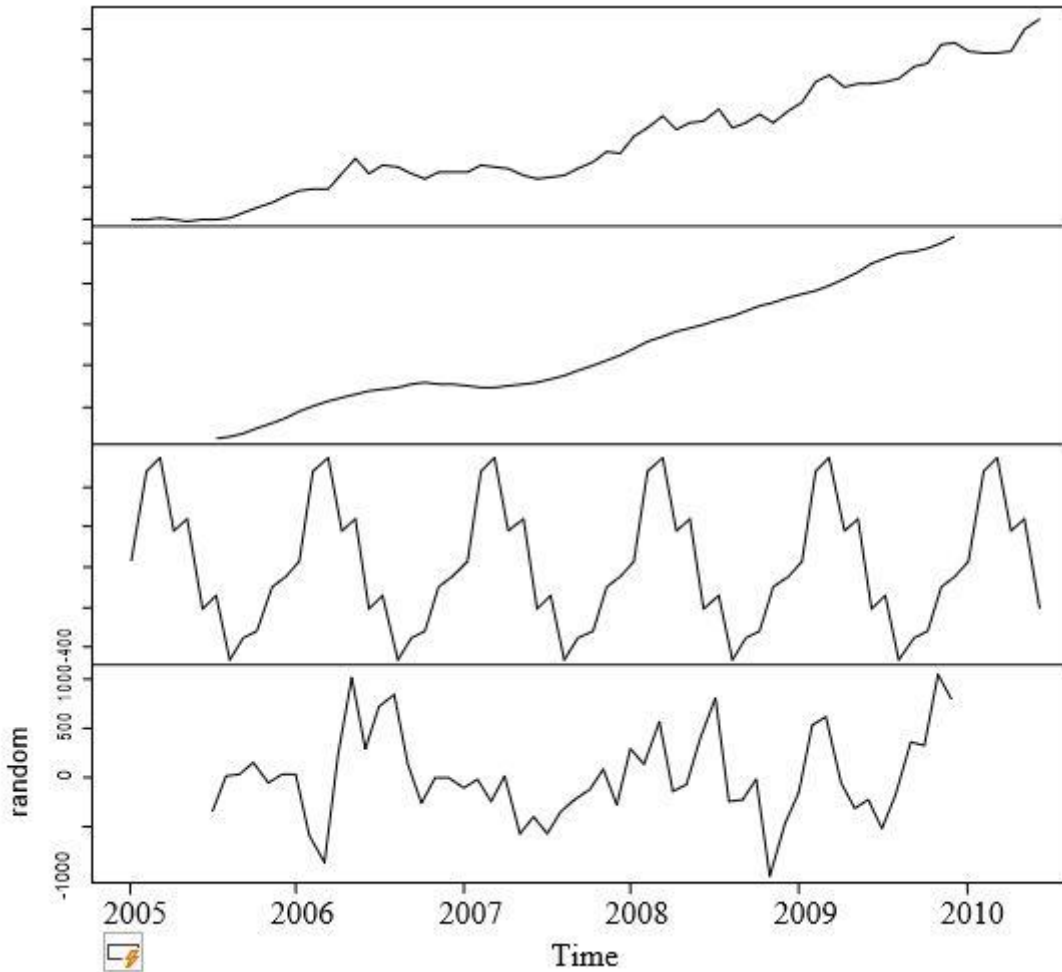
```
tss.dec=decompose(tss)
```

```
tss.dec
```

```
plot(tss.dec)
```

Output:

Decomposition of additive time series



COMENT ON GRAPH: From the graph, we can infer that trend , seasonality is present in the data.

```
R code:
f=HoltWinters(tss)
f
```

Output:

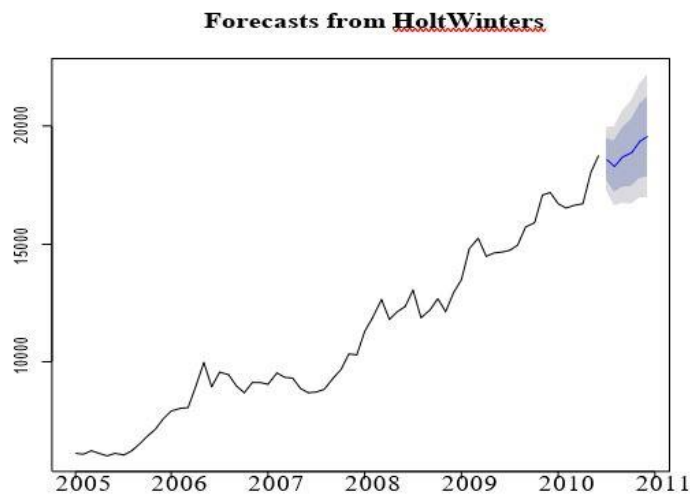
Smoothing parameters:

alpha: 0.7415554					
beta : 0					
gamma: 1					
R code: a=forecast(f,6) summary(a)					

OUTPUT:					
Forecasts:					
Point Forecast		Lo 80	Hi 80	Lo 95	Hi 95
Jul 2010	18614.85	17736.79	19492.92	17271.97	19957.74
Aug 2010	18312.31	17219.16	19405.47	16640.49	19984.14
Sep 2010	18694.00	17421.62	19966.38	16748.06	20639.94
Oct 2010	18905.03	17475.72	20334.34	16719.08	21090.97
Nov 2010	19367.48	17796.84	20938.12	16965.40	21769.57
Dec 2010	19587.62	17887.36	21287.88	16987.29	22187.94

Conclusion: These are the forecasts for six months and also the 80% and 95 % confidence intervals are given in which actual values may lie.

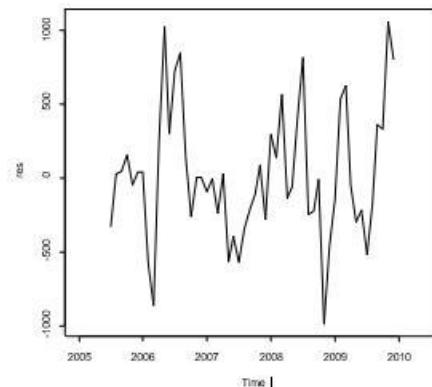
plot(a)



```
res=tss.dec$random
```

```
plot(res)
```

THE RESIDUAL PLOT



Now we check the normality of residuals. Normality of residuals is an assumption of running a linear model. If the residuals are normal means predictions are valid.

R code for checking normality of residuals:

```
res=tss.dec$random  
  
plot(res)  
  
shapiro.test(res)
```

OUTPUT:

Shapiro-Wilk normality test

p-value = 0.2356

As p value is greater than 0.05 we can say that residuals are normally distributed.

Now we check the randomness of residuals by run test. If the residuals are random then it's just the white noise.

The Run test procedure is as follows:

We take median and compare it with each value. The values below median are put as 0 and above values are put as 1. We convert it into vector and run the test.

R code for checking randomness of residuals:

```
r=as.vector(res)  
  
r=r[-c(1,2,3,4,5,6,61,62,63,64,65,66)]  
  
median(r)  
  
r=r-median(r)  
  
q=c(0,1,1,1,0,1,1,0,0,1,1,1,1,1,0,1,1,0,1,0,1,0,0,0,0,0,0,1,0,1,1,1,0,0,1,1,0,0,0,0,0,1,1,0,0,0,0,  
0,1,1,1,1)  
  
q=as.factor(q)  
  
runs.test(q)
```

OUTPUT:

p-value = 0.09923

As the p value is greater than 0.05 we can say that residuals are random.

ARIMA MODELLING

ARIMA stands for *Autoregressive Integrated Moving Average*. This model is fitted to the time series data either to better understand the data or to predict future points in the series.

The AR part of ARIMA indicates that the evolving variable of interest is regressed on its own lagged values. The MA part indicates that the regression error is actually a linear combination of error terms whose values occurred contemporaneously and at various times in the past.

Non seasonal ARIMA Models are generally denoted by ARIMA(p,d,q) where parameters p,d and q are non negative integers.

P= order of autoregressive model

q= order of the moving average model d= degree of differencing

Differencing: In statistics, differencing is the transformation applied to the time series data in order to make it stationary. In order to difference the data, the difference between consecutive observations is computed. Differencing removes the changes in the level of time series, eliminating trend and seasonality and consequently stabilizing the mean of the time series.

Analysis will be done on the data from January 2000 to December 2018 and data of next six months will be used for validation of analysis. Here first we convert our data into timeseries data and we check its stationarity by adf test and kpss test

R code:

```
tss=ts(gp[1:228],frequency=12,start=c(2000,1))  
adf.test(tss)
```

Output:

p-value = 0.6473

```
kpss.test(tss)
```

Output:

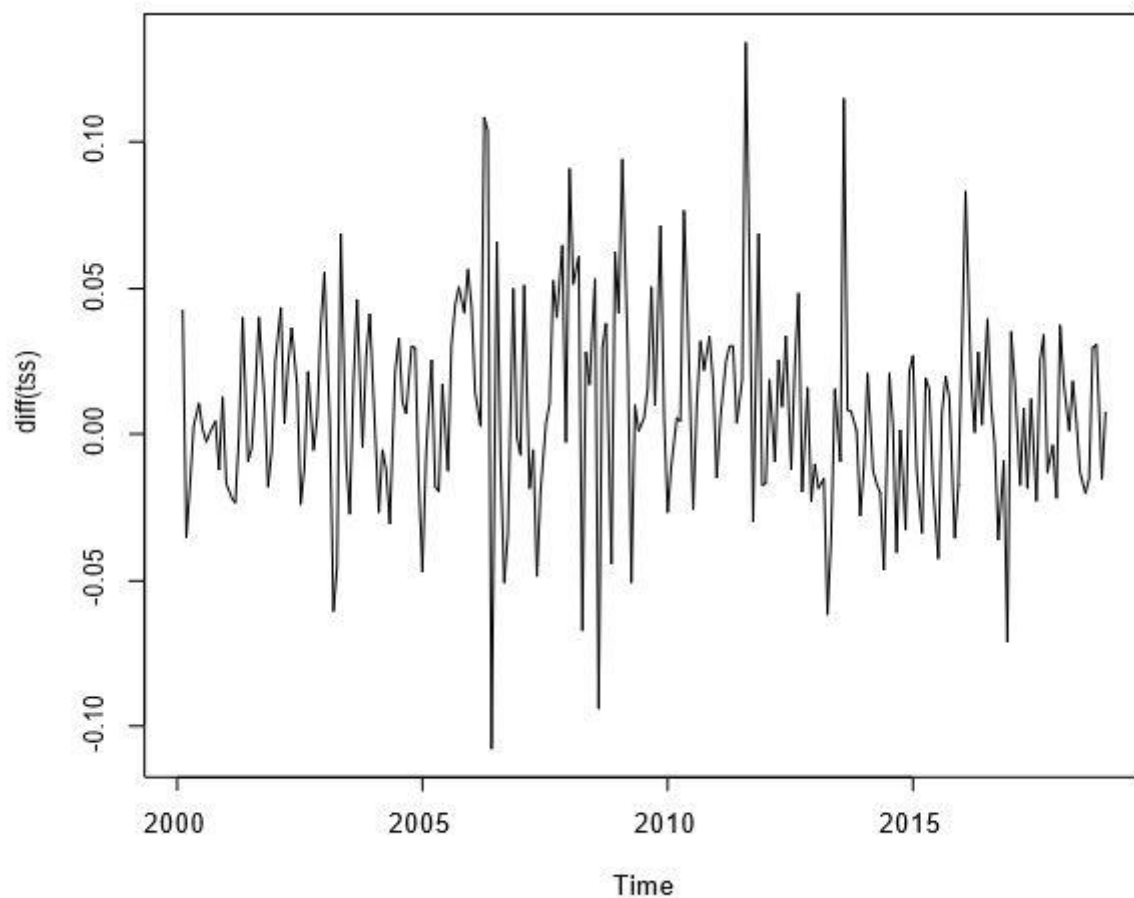
p-value = 0.01

Conclusion: Here for adf test p value is greater than 0.05 and for kpss test p value is less than 0.05 and both indicate non stationarity. To make time series stationary we use log transformation and differencing,

```
tslog=log(gp)  
tslog=log(gp[1:228])  
tss=ts(tslog,frequency=12,start=c(2000,1))  
diff=diff(tss)  
plot.ts(diff(tss))
```

OUTPUT:

Graph showing the differenced time series



Now we check whether the transformed time series is stationary or not

```
adf.test(diff)
```

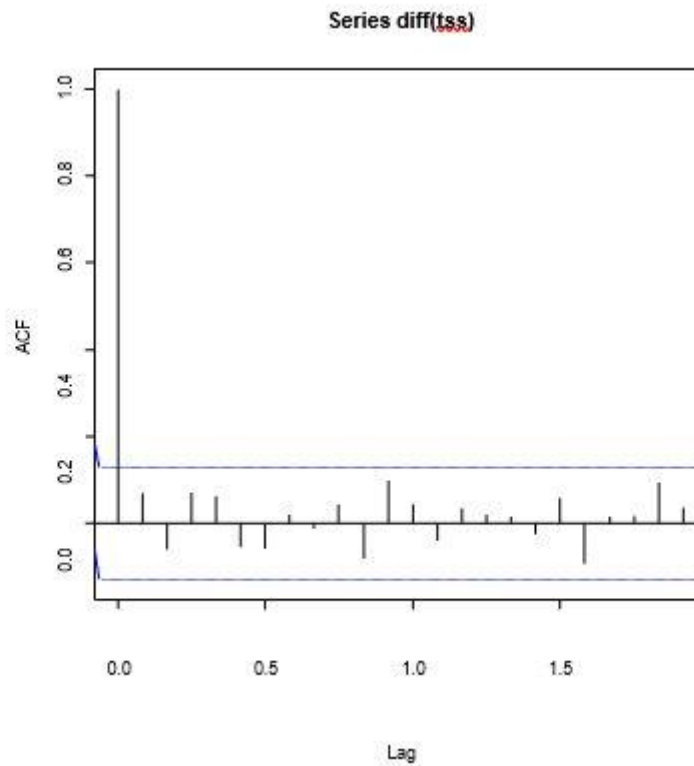
p-value = 0.01

```
kpss.test(diff)
```

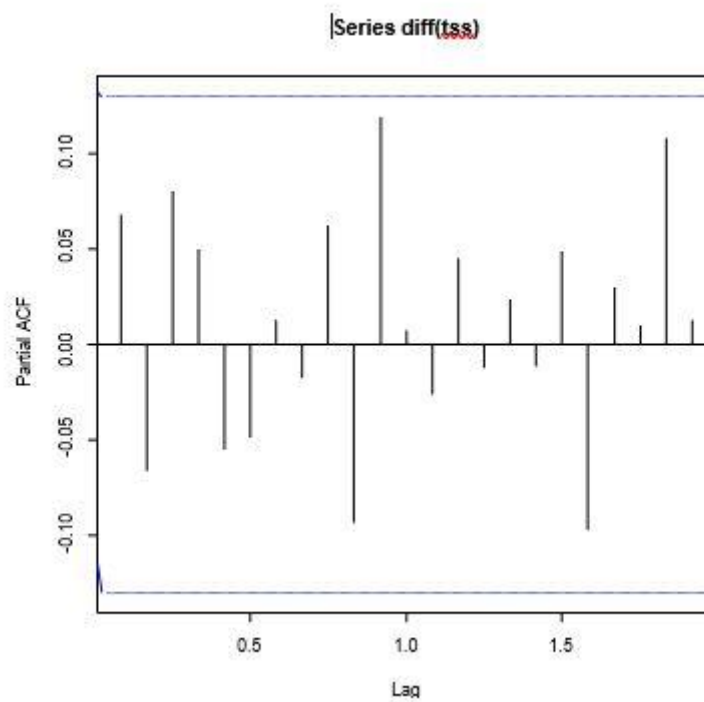
p-value = 0.1

(adf and kpss p values for newly formed time series indicate time series is now stationary. Now as our time series is stationary we can apply Arima model to it)

acf(diff(tss))



pacf(diff(tss))



```
fit=auto.arima(tss)
forecast=forecast(fit,h=6)
fr=as.numeric(forecast$mean);fr;
forecasted_values=exp(fr)
forecasted_values
plot(forecast)
```

Forecasts from ARIMA(0,1,0) with drift



Our best model for our data is ARIMA(0,1,0) which is popularly known as random walk model. Here no AR and MA terms are required in model.

Output:

Actual Values	Forecasted Values
32230	31518
32216	31788
32036	32060
31659	32334
31737	32611
33121	32891

Conclusion:

1. From the graph of decomposed data, we could infer that our time series consists of seasonality, trend and irregular variations.
2. In Holt Winters forecasting, the random or error component of series is normally distributed and completely random. Hence it is a white noise indicating good prediction.
3. Our original time series is non stationary and we convert it to stationary using differencing method on log values.
4. For ARIMA Modelling, the actual and forecasted values have very small difference.
5. For Holt Winters Forecasting, the actual values lie perfectly within given confidence Intervals indicating good prediction.

CONCLUSION

We have made predictions using three techniques time series, stochastic and neural networks. There are some advantages and disadvantages of each technique.

As a primary tool of data analysis we used simple linear regression to analyze the relationship between dependent variable and independent variables.

Due to wide range and different units of dependent variables we couldn't get appropriate predictions by regression. This problem is tackled by method of neural networks. There is no specific method to determine the parameters of ANN model. So by trial and error method we have to find out best parameters that suit our data. Though it is tedious process, outcomes are worth as model learns pattern by itself and predict future forecast.

Method of Neural Networks considers all independent variables. But it is not always feasible to obtain data for each independent variable. Hence by only using dependent variable data we can do forecast by time series.

There are many fluctuations in gold prices due to trend and seasonal factor. Due to presence of seasonality we have used triple exponential smoothing. By this method we can do short term forecasting. Long term predictions do not meet accuracy Hence we use one other method that is ARIMA Modeling. In all the techniques, predictions using neural networks were best.

By keeping an eye on daily prices of Gold, one can decide whether to invest in Gold or Stocks.

It is clear from exploratory analysis that gold prices have increased between year 2000-2019 by nearly 15000.

It is observed that in respect with increase in rate of inflation, there was also rise in price of gold as it is observed that price of dollar affects gold price directly.

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