UNVEILING GOLD PRICE FLUCTUATIONS: A NEURAL NETWORK APPROACH TO MARKET VOLATILITY

S. Subashree, Dr.M.Bhoopal

Doctoral Research Scholar, Part Time, Department of Management Studies, Manonmaniam Sundaranar University, Abishekapatti, Tirunelveli 627012, Tamil Nadu, India.

Assistant Professor, Department of Management Studies, Manonmaniam Sundaranar University, Abishekapatti, Tirunelveli 627012, Tamil Nadu, India.

Abstract

This empirical research study is centred around the utilization of neural networks to forecast gold price volatility with an outstandingly low estimation error of just 0.036. The predictive analysis involves the inclusion of crucial independent variables, such as Crude Oil and silver prices, non-farm payroll data, the Dollar Index, CPI, and the Retail Index. These variables are drawn from a ten-year historical dataset, with great care taken in collecting secondary data from diverse sources, including the Chicago Mercantile Exchange website and official U.S. government platforms that provide payroll insights. The gathered data is then input into a neural network model characterized by a specific architecture featuring two hidden layers, each composed of two neurons. This model is meticulously refined over 25 iterative steps to achieve optimal performance. Notably, the model impressively demonstrates significant success by producing minimal root mean square values when subjected to testing against a dedicated dataset. A remarkable feature of this study is the consistency in error across the predicted variables, which serves to bolster the model's predictive reliability.

Introduction

Studying volatility in gold prices is important as Gold is one of the commodities which is traded at a high rate and has different uses. This is describing gold as a global monetary asset that serves as a reflection of global economic trends. It is actively traded on the spot market and takes various forms, including being held by central banks like the Federal Reserve, utilized as an investment, and even serving as a personal accessory for individuals. It is a costly bullion commodity and seeing its trend of trading, its prices play even a more crucial role. Gold prices are driven by two factors - Volatility and Direction. This research paper is trying to cover the volatility part which has not been discussed extensively.

Most of the researches conducted till date used regression analysis. However, the model's limitation is that it is less accurate. This research wrk is focused on prediction of volatility in the gold prices using artificial intelligence. There would be a reduction in mean error by 25% using Artificial Neural Network (ANN). Artificial Neural networks take into the consideration that a particular variable affects another and forms a network. In this way the root cause of the volatility is captured. Thereby the chances of going wrong is low.

This study will help in knowing about the factors which effects the volatility in the prices of gold and their individual effect on the prices, which in turn will help in better prediction of the prices of gold. All the previous researches were mostly based on regression analysis and discriminant analysis but here we are focusing on usage of Artificial Neural Network for better results.

Any organisation which predicts using a model is not tested on the no. of correct predictions. The intensity of condemn depends on higher wrongly predicted cases. Hence adopting an advanced method would increase the reliability of the organisation. In a market almost where there is perfect competition, the importance of retaining a customer is higher than acquiring a customer. The customers' reliability on the organisation is the accuracy with which the services are delivered. For example, Artificial neural networks (ANN) with 3 layers - 28 financial inputs, 7 hidden neurons and 2 outputs has 71.38% for failed corporates predictions using ANN. However, discriminant analysis and logistic regression achieved 60.12% and 65.29% respectively. Therefore, this research develops a reliable model to predict the volatility in gold prices with utmost accuracy.

Literature Review

Volatility in gold prices is an important point of research and is evident from the number of researches conducted this field. Neural network systems are used to carry forward the research. Volatility in gold prices is due to various reasons but mainly it is affected by macroeconomic factors and partially by other asset markets. Tong-Seng Quah and Bobby Srinivasan [1] states about the usefulness of neural networks. Neural networks have been used earlier in same field like mortgage loan evaluation, bankruptcy prediction.

Xu, X. W. (1998). [2] in "Neural network application in corporate bankruptcy prediction" states that bankruptcy announcements had a significant impact on stock prices. The impact depends on the prior predictions and its expected resolution. Neural networks shows a promising results and correctly identifying the pattern. The capacity of neural network to process large amount of data was underutilized earlier. It is important to choose the right number of variables to avoid over fitting but be accurate. Factor analysis was performed to avoid remove multi-collinearity and processed using neural networks.

Bobby Srinivasan and Tong-Seng Quah [3] states that neural networks are used to pick the top performing stocks in the market and beat the benchmark on a portfolio basis. The P/E ratio is measured to identify if the stock is under or overvalued.

Alici [4] shows that Artificial neural networks(ANN) with 3 layers - 28 financial inputs, 7 hidden neurons and 2 outputs has 71.38% for failed corporates predictions using ANN. However discriminant analysis and logistic regression achieved 60.12% and 65.29% only.

P.Hemavathy [5] states that Gold prices doesn't comply with law of demand and studied the volatility in Gold prices in India using GARCH model. The yellow metal has gained strong momentum even during economic slowdown. The results suggests that even during crisis, rupee depreciation, negative interest rate and bank failures, gold is considered as a safe investment.

Jonathan Andrew Batten and Brian M. Lucey [6] in 'Volatility in the gold futures market" comments on the scholastic nature of the volatility of gold prices. The fluctuating nature of volatility in the gold market aligns with the intricate interplay of price-sensitive information emanating from diverse asset markets, rather than being primarily driven by traders' price discovery activities exclusively within the gold market.

Dirk G. Baur [7] claims that past return shocks of gold and inventory levels also effect volatility in gold prices. Low inventory is likely to render future prices more volatile due to the uncertainty regarding the future supply of the commodity.

Kristjanpoller, W., & Minutolo, M. C. (2015).[8] uses financial variables in addition to the GARCH forecast input. This improves the accuracy of the prediction and ability of financial variable's influence on gold price volatility.

Hasan [9] in his research in emerging market states that the trading activity of gold in emerging markets has surpassed the developed markets during the crisis period in 2008. He tried to link the volatility spill overs in various economies to emerging markets. International investors trying to hedge in gold investments in spot market against the inflation is causing the interdependence.

Girish Karunakaran Nair, Nidhi Choudhary [10] talks about value of yellow metal which is largely determined by supply and demand, without interference from shifts in monetary and corporate policies prevailing in the country.

Jun Cai, Yan-Leung Cheung and Michael C. S. Wong [11] talks about the volatility of Gold Prices with respect to Macro Economics Scheduled Announcements. The factors pointed out are employment reports, gross domestic product (GDP), consumer price index (CPI), Personal income, unanticipated components of U.S. money supply, Producer Price Index (PPI), announcements on gold prices, expected inflation rates, Exchange rates and Appreciation and depreciation of major currencies.

Tong-Seng Quah, Bobby Srinivasan and Hoon-Heng Teh [12] talks about shocks ranging from governmental economic performance statistics released, to news about worldwide turn-moils and social upheavals.

Theory

Fiscor, Steve [1] analyses the impact of occurrence of extraordinary events like Brexit

on the gold price. The article states how the gold prices went up after Brexit referendum was put forth. 'The expectation of the World Gold Council to see sustained and strong inflows into the gold market driven by the intense market uncertainty that faces the global market is cited'. Our research would focus on the impact on volatility in gold prices during such past events. (H1)

Kang, Kiki [2] states in the article that the increase in gold prices with increase in employment opportunities in recent employment data released. A weaker dollar in the last few trading days of 2016 saw gold prices climb off its one year low of $1,124/oz and threaten to break through the $1,200/oz barrier. However, a stronger dollar, driven by a positive US payrolls report, saw some of that gain pared, ANZ Bank said in a note.

Meir, Edward [3] article states the impact on metal prices based on payroll. The high price change was for Aluminium followed by precious metals. However, there is no significant research conducted on the area of volatility in gold prices. Hence our research focus on testing the hypothesis (H2) in the volatility of gold prices in relation to payroll data.

Christner and Dickle [4] found in their paper that there is negative correlation between Gold Prices and USD/EUR and USD/GBP[H4]. It was also noticed that this negative relationship between Gold Prices and USD/EUR and USD/GBP can be observed in annual or long trends.

Most of the previous studies in regards to gold and oil in long-term relationship used traditional time series models, which assumed linear and symmetrical processes. Johansen co integration test and Vector Error Correction model was used to demonstrate asymmetric co- integration relation, confirming the long-term equilibrium between oil and gold price levels.

Previous researches also show that there is significant correlation between gold and oil prices. Gold is basic part of the international reserve portfolio of most countries, including the oil producing countries. When oil price rise, oil exporter's revenues rises, and this may impact the gold price level, provided that gold consists of a significant share of the asset portfolio of oil exporters and oil exporters purchase gold in proportion to their property. In that case, an oil price rise leads to a rise in gold price.

Further past data shows that gold price variations are closely related to silver price variations. Therefore, in the hypothesis (H4) we consider gold price having a positive relation with other commodities.

Hypothesis

H1. There is positive correlation between volatility in gold prices and Consumer Price Index.

H2. There is positive correlation between volatility in gold prices and Retail Sales.

H3. There is a positive relation between volatility in gold prices and non-farm payroll data released in US.

H4. There is a negative relation between Gold prices and Dollar Index.

H5. There is a positive relation between gold prices and other commodity prices.

Proposed Methodology

•Data Collection

The data would be collected from Bloomberg Terminal. We would be considering daily gold prices for past 5 years.

•Data Cleansing:

There is a case that prices of each day are not present, so we would be removing that data.

•Data Analysis

This data is fed as input to SAS enterprise Miner/Rstudio to model it using neural networks.

ISSN PRINT 2319 1775 Online 2320 7876

We would be dividing the data into 2 parts. One for creating model and other one for validation of model.

Results Rcode -

Output:

Rcode
-

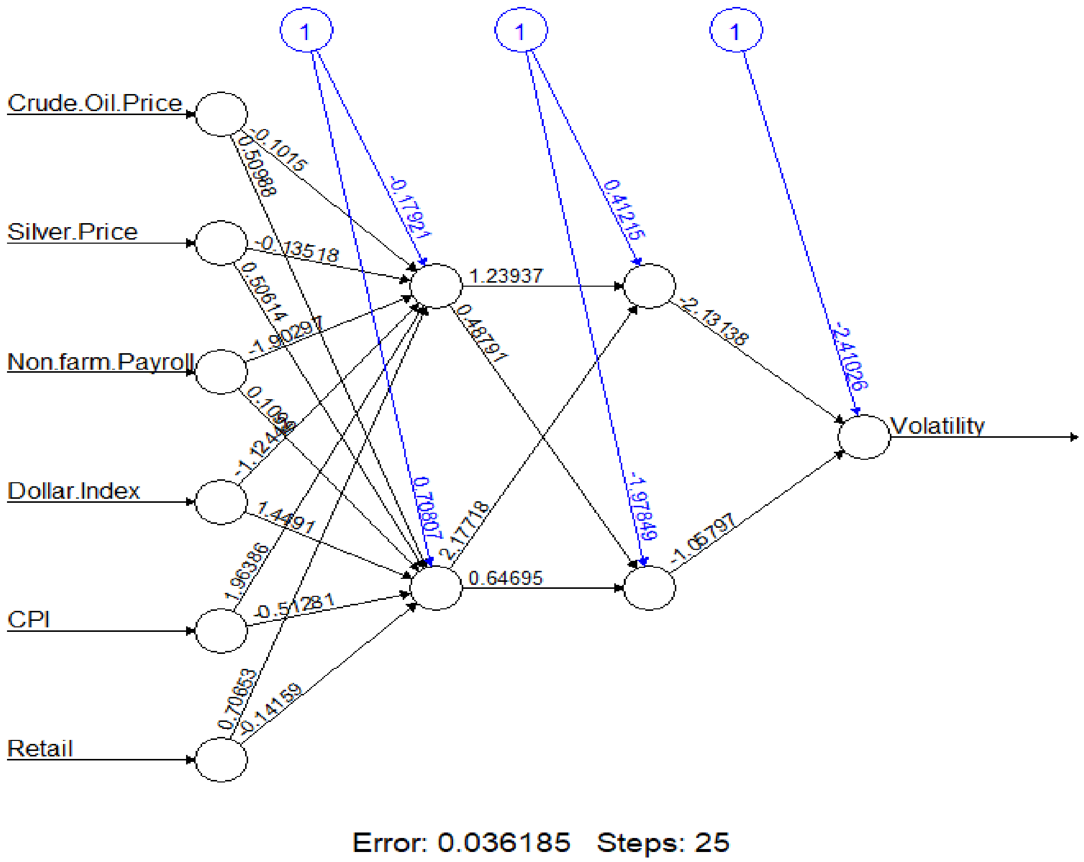
```
#install.packages("neuralnet")
setwd("G:/Empirical")
list.files()
Dataset1<-read.csv("Cleaned data.csv")
Dataset<-Dataset1[,-c(1:4)]
Dataset$EO.Event<-as.factor(Dataset$EO.Event)
summary(Dataset)
set.seed(1)

#Partitioning the Dataset into Train and Test
#install.packages("Rcpp")
library(caret)
train<-createDataPartition(Dataset$Volatility,list = FALSE,times = 1,p=0.5)

Dataset.train<-Dataset[train,]
head(Dataset.train)
Dataset.train1<-scale(Dataset.train[,-2])
head(Dataset.train1)

Dataset.test<-Dataset[-train,]
Dataset.test<-Dataset.test[,-2]
```

```
Dataset.test<-Dataset[-train,]
Dataset.test<-Dataset.test[,-2]
Dataset.test<-scale(Dataset.test)
head(Dataset.test)

#Creating a model on train dataset
library(neuralnet)
Gold.neural<- neuralnet(Volatility~Crude.Oil.Price+Silver.Price
                        +Non.farm.Payroll+Dollar.Index+CPI+Retail,
                        Dataset.train, hidden=c(2,2),
                        lifesign = "minimal",
                        linear.output = FALSE, threshold = 0.1)
summary(Gold.neural)
plot(Gold.neural)

PredVolatility<-compute(Gold.neural,Dataset.test[,-1])
str(PredVolatility$net.result)

#Testing the model for accurracy

# Calculate Root Mean Square Error (RMSE)
head(Dataset.test[,1])
RMSE.NN = (sum((PredVolatility$net.result - Dataset.test[,1])^2) / nrow(Dataset.test)) ^ 0.5
RMSE.NN
```

```
Console G:/Empirical/
> #Creating a model on train dataset
> library(neuralnet)
> Gold.neural<- neuralnet(Volatility~Crude.Oil.Price+Silver.Price
+                         +Non.farm.Payroll+Dollar.Index+CPI+Retail,
+                         Dataset.train, hidden=c(2,2),
+                         lifesign = "minimal",
+                         linear.output = FALSE, threshold = 0.1)
hidden: 2, 2    thresh: 0.1    rep: 1/1    steps:      25       error: 0.03619  time: 0.03 secs
> summary(Gold.neural)
                    Length Class      Mode
call                   7   -none-     call
response            1293   -none-     numeric
covariate           7758   -none-     numeric
model.list             2   -none-     list
err.fct                1   -none-     function
act.fct                1   -none-     function
linear.output          1   -none-     logical
data                   8   data.frame list
net.result             1   -none-     list
weights                1   -none-     list
startweights           1   -none-     list
generalized.weights    1   -none-     list
result.matrix         26   -none-     numeric
> plot(Gold.neural)
>
> PredVolatility<-compute(Gold.neural,Dataset.test[,-1])
> str(PredVolatility$net.result)
 num [1:1293, 1] 0.0125 0.0115 0.0115 0.0115 0.0106 ...
 - attr(*, "dimnames")=List of 2
  ..$ : chr [1:1293] "1" "2" "3" "5" ...
  ..$ : NULL
```

 UGC CARE Listed (Group -I) Journal Volume 11, Iss 13, 2022

Output:



Predicted Gold Price Volatility on Test data set using model

```
>
> #Testing the model for accurracy
>
> # Calculate Root Mean Square Error (RMSE)
> head(Dataset.test[,1])
            1             2             3             5             6             7
-1.0352179633 -0.9755763456 -0.7966514924 -0.6177266393 -0.7966514924 -0.9755763456
> RMSE.NN = (sum((PredVolatility$net.result - Dataset.test[,1])^2) / nrow(Dataset.test)) ^ 0.5
> RMSE.NN
[1] 0.9996282261
> |
```

Discussion

Neural network is a black box. There are 6 input variables namely Crude Oil price, Silver price, Non-farm payroll, Dollar Index, CPI and Retail and these variable determine the volatility in gold prices with 2 hidden layers consisting of 2 neurons each.

The neural network reworks the weights using back propagation mechanism and assigns the weights to get the best fit model with least error. The above plot shows that the estimated error is only 0.036.

The result indicates that the weightages for all the variable are equitable and hence all the variable are equally important. Hence the hypothesis is true and all the variables together is used to predict the volatility of gold price.

The built model is used to predict the volatility of gold prices on the test dataset. The prediction indicates the values are closer to the actual. This shows the reliability on the neural network model. The root mean square error is calculated and the value is close to 1 i.e. minimal.

Error is low and consistent across predicted variables. This model can be used to measure the volatility of gold prices for all scenarios where the given variables are available and any new variables remains unchanged.

References

[1] Tong-Seng, Q., & Srinivasan, B. (2000). Improving accuracy of neural prediction by market segmentation. In *Proceedings of the International Conference on Artificial Intelligence* (Vol. 2, No. 4, pp. 935-937).

[2] Xu, X. W. (1998). *Neural network application in corporate bankruptcy prediction* (Doctoral dissertation).

[3] Quah, T. S., & Srinivasan, B. (2000, June). Utilizing neural networks in stock pickings. In *Proceedings of the International Conference on Artificial Intelligence* (pp. 941-6).

[4] Alici, Y. (1996). *Neural networks in corporate failure prediction* (Doctoral dissertation, University of Exeter).

[5] Hemavathy, P., & Gurusamy, S. (2014). An Empirical Investigation on Exploring the Insight of Gold Price Volatility in India. *International Journal of Business Insights & Transformation*, *8*(1).

[6] Batten, J. A., & Lucey, B. M. (2010). Volatility in the gold futures market. *Applied Economics Letters*, *17*(2), 187-190.

[7] Baur, D. G. (2012). Asymmetric volatility in the gold market. *The Journal of Alternative Investments*, *14*(4), 26.

[8] Kristjanpoller, W., & Minutolo, M. C. (2015). Gold price volatility: A forecasting approach using the Artificial Neural Network–GARCH model. *Expert systems with applications*, *42*(20), 7245-7251.

[9] Baklaci, H. F., Süer, Ö., & Yelkenci, T. (2016). Volatility linkages among gold futures in emerging markets. *Emerging Markets Finance and Trade*, *52*(1), 1-9.

[10] Nair, G. K., Choudhary, N., & Purohit, H. (2015). The relationship between gold prices and exchange value of US Dollar in India. *EMAJ: Emerging Markets Journal*, *5*(1), 17-25.

[11] Cai, J., Cheung, Y. L., & Wong, M. C. (2001). What moves the gold market?. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, *21*(3), 257-278.

[12] Tong-Seng, Q., Tan, C. L., Teh, H. H., & Sriniivasan, B. S. (1995). Utilizing a neural logic expert system in currency option trading. *Expert Systems with Applications*, *9*(2), 213-222.