What Drives Precious Metal Returns? – An empirical approach

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Empirical Research Study

1. Introduction

Precious metals are, and have always been, one of the most prized possessions in our world. Ancient civilizations often used rare metals as their primary form of currency; notorious rulers often flaunted their wealth by wearing jewelry made of gold and silver; even today, governments and individuals view precious metals as inherently valuable investments. Why? Although the beauty of these objects is purely subjective, their scarcity is undeniable. It is this property that has allowed precious metals to retain their value for millenia, and it is this property that will allow precious metals to retain their value for years to come. From the perspective of a sophisticated modern investor, however, simply acknowledging this fact is not enough. Today's precious metals markets have proven to be highly volatile. Therefore, although we can reasonably expect metals such as gold, silver, platinum, and palladium to appreciate in the long run, we must also expect high price variance in the short run. This should be good news for a skilled investor; high volatility environments present opportunities for consistent near-term profits. Of course, there is no such thing as a free lunch; high volatility environments also present the potential for consistent near-term losses. In order to seize this opportunity and avoid disaster, investors typically rely on some sort of price return prediction model. Here, we will explore and develop our own model with hopes of determining which financial and economic variables are the most reliable predictors of returns on the following precious metals: gold, silver, platinum, and palladium.

2. Literature Review

In a paper published in 2015, Urquhart examines the returns of gold, silver, and platinum from 1987 to 2014. The study attempts to predict metal returns among different market conditions and shows that over the long haul there is limited predictability but there is variance over the short term. Overall, platinum was the easiest to predict with silver beng the hardest. In another study, *Is Gold a Zero-Beta*

Asset? Analysis of the Investment Potential of Precious Metals(2006) by Zimmerman and McCown, both gold and silver returns were examined. Both were found to be extremely low-risk assets with near-zero betas, and they showed great hedging capabilities against inflation over the long run. Over the short run, they showed high volatility allowing for investor make short term gains. Further reading found in an academic paper*, The Macroeconomic Determinants of Volatility in Precious Metals Markets*, by Batten, Ciner, and Lucey offers insight into other significant aspects of the precious metals market. Their findings favored the conclusion that identical macroeconomic factors (business cycle, monetary environment and financial market sentiment factors) did not collectively impact the volatility process of the precious metal price series. Additionally, the results found by Batten, Ciner, and Lucey lend credence to the notion that the individual commodities, gold, silver, platinum and palladium, are too distinct to be represented in a single index - they shouldn't be considered a single asset class.

Turning towards the professional sector, we see from a speech given by the managing director of "CPM group" at the extractive industries week event held by the World Bank - that precious metals have some very powerful predictive powers and interesting correlations. In the paper *Do Precious metals shine? An Investment Perspective(2006) by* David Hillier, Paul Draper, and Robert Fauff, they examined the role of gold, silver, and platinum as a hedge. Using daily data from 1976-2004, they found that all three can provide a hedge in periods of abnormal market volatility. They tested the metals at different weights in portfolios with both the buy-and-hold strategy and the switching strategy, and gold showed increased portfolio efficiency with increased weight. Finally, in a professional paper published by JP Morgan, *Gold Set to Shine(2019), they released their forecasts for gold prices moving forward. They surprised most investors because they predict gold prices to increase over the coming years even with the recent rebound of the US dollar. This is because they forecast the two-year treasury yield to be higher than the 10 year yield, which is an inverted yield curve.*

Our research looks to expand on an already massive field. Precious metals have played various roles in society throughout history, and as a result, have had various driving factors in their value. In our research, we are using broad variables rather than ones that pertain specifically with precious metals. Our data has been selected by other researchers as well who are conducting similar research on other assets. This stems from the fact that our x variables were selected on the basis of their relevance to other asset classes. Similar to Batten et al., we look at the precious metals as individuals rather than a single investment class. In terms of external validity, time is a major threat to our model. The relationship of the independent variables are very time sensitive and proximity must be considered when using predictive models.

3. Hypothesis

In order to determine which economic and financial variables have strong predictive power for gold, silver, platinum, and palladium returns, we will analyze stationary time series data. The first step is to determine the optimal number of explanatory variables to include in multivariable regression models for each metal. Next, we will determine which statistically significant explanatory variables have the highest correlation to gold, silver, platinum, and palladium, respectively. Finally, we will examine the economic rationale behind the conclusions drawn from our models in order to determine whether or not they are reasonable. The product of our work will be reliable price return prediction models for the precious metal that we have chosen to analyze.

Amongst the four precious metals evaluated, we hypothesize that gold and silver returns will be heavily impacted by variables such as CPI, unemployment rate, and the ten-year spread over the fed funds rate. As mentioned, both metals have been historically used as safe haven assets for recessions or when currencies are in a general decline. As for platinum and palladium returns, we hypothesize that variables such as NASDAQ index and S&P 500 index will be the best indicators for prediction. Many companies that make up both indexes use platinum and palladium for the production of tech and automotive products. With respect to which metals will have the highest level of predictability, we expect our gold and silver models to outperform our platinum and palladium models in terms of accuracy. Gold and silver have significantly higher levels of popularity in the financial media and the investment world in general than platinum and palladium. Furthermore, the value of gold and silver has been appreciated by society for millennia, while the value of platinum and palladium has only been realized in recent centuries. Thus, the returns of gold and silver are much less susceptible to market noise than the other two metals we are examining

It is important to note that if we are successful in our efforts to create accurate price returns prediction models, a major theoretical assumption of financial markets will be violated. The theory we are referring to is the Efficient Markets Hypothesis

(EMH). The EMH states that financial markets incorporate all available information into asset prices. Under this assumption, it can be posited that no investor will ever be able to consistently achieve returns greater than the market average because that would require the ability to predict the future with accuracy, a practice that most people believe to be impossible. Thus, if we successfully create working price return prediction models, we will be directly challenging conclusions drawn from the very popular EMH, a feat that would be substantial in and of itself.

With regards to statistical theory, we followed CLM assumptions when creating our model. These assumptions are the same as the Gauss Markov assumptions used in multiple regression models. The assumptions are as follows: the data is linear; the data is not perfectly collinear; the error term is zero; homoscedasticity; no serial correlation; normality of errors. For the sample to be liner, no parameter can be exponential. To avoid being collinear, no independent variable can be constant, and they must be a linear combination of another. The error term throughout the entire sample must be zero to ensure it is uncorrelated with the independent variables. For the sample to show homoscedastic, the variance must be constant throughout. To avoid serial correlation, the error term in one period is not correlated to the error in another period. The errors of the sample are independent, and they are identically distributed.

4. Data Description

Before creating our model, we went through an extensive data selection process. Initially we went through the ERS variable dataset folder, which incorporated all X variables submitted by all groups. We decided to exclude any datasets that had yearly or daily data because our Y variables – gold, silver, platinum, and palladium returns – were taken as monthly data. Originally, our y-variables were daily prices, but due to the lack of x-variables taken in daily prices, we decided to switch to monthly data in order to incorporate more X variables. Later on, we calculated the continuously compounded monthly return of each precious metal asset using the monthly prices. We then removed variable datasets that were missing data or posing collinearity issues such as oil prices, oil imports and exports in U.S. dollars, as well as M2 money supply and CPI. In order to convert quarterly data into monthly data – as we did with Real GDP – we took each quarterly datapoint and used them to backfill the missing months. Other limitations that we ran into was that the Euro Stoxx 50 data was taken in terms of Euros. In order to keep our data completely uniform, we took the current U.S. dollar to Euro exchange rate and converted the prices to U.S. dollars. This left us with 12 X variables that include, unemployment rate, oil prices in real dollars, Michigan Consumer Sentiment index, S&P 500 index, NASDAQ index, volatility index, Euro Stoxx 50 in U.S. dollars,10 year spread over fed funds, CPI, U.S. dollar index, average weekly hours of production and nonsupervisory employees(AWHMAN), and real GDP.

In total, we used data from five different sources. Our precious metals prices data was taken from *www.perthmint.com*, an Austrailian website that has historical precious metal prices in Australlian and U.S. dollars dating back to the year 2000. The next five x-variables were taken from *fred.stlouisfed.org*. The first X variable is the 10 year spread and is sourced directly from the Federal Reserve Bank of St.Louis. The second variable is the real GDP which is sourced from U.S. Bureau of Economic Analysis. The third variable is the Michigan Consumer Sentiment which is originally sourced from the University of Michigan. Both CPI and AWHMAN are sourced from U.S. Bureau of Labor Statistics. We took the unemployment rate directly from U.S. Bureau of Labor Statistics website bls.org. Our stock information data for volatility index, S&P500, NASDAQ, and Euro Stoxx 50 were taken from *finance.yahoo.com*. The last two variables, U.S. dollar index and real oil prices, were sourced from *www.macrotrends.net*, which is a website that tracks stock price and other historical economic data.

Overall, we have a total of 236 total observation between all of the variables. It is important to note that our time series data may be affected by economic events that have occurred within the periods of 2000 to 2019. The dot com bubble lasted from 2000 to 2002 and was caused by investments in “dot com” companies based off of internet and website domains. The 2008 financial crisis can be attributed to banks giving out subprime loans to people for housing who had questionable credit and those same banks selling off mortgage backed securities on the stock market.

5. Econometric Model

We began our model-building process by transforming our y-variable data. Our y-variable data originally consisted of gold, silver, platinum, and palladium prices in U.S. dollars; however, we converted them to forward-looking continuously compounded monthly returns by taking the natural log of the next month’s prices divided by the current month’s prices. We opted for forward-looking returns rather than backward-looking because in our analysis we are attempting to use current x-variable data to predict future returns rather than using current x-variable data to explain past returns. Unfortunately, this introduces a look-ahead bias into the model *training* process because we are using data which would not have been known during the period being analyzed to fit our model. The upside to using this kind of data structure is that when using the model to form predictions about the future, no look-ahead bias is present. For example, if you use forward-looking y-variables to train your model, you do not need to input forecasted x-variables in order for the model to make a y-variable prediction for the next period outside of the dataset. This is because the model was trained to use x-variable data from the *present* time period to predict a y-variable for the *future* time period. A linear model trained using x and y variables from the same time periods does not share this characteristic because it is trained to explain *present* y-variable data using *present* x-variable data.

The next step in our model building process was testing our x and y variables for stationarity. We checked for stationarity in our data in two ways. First, we plotted our x and y variables in time series charts and checked the data visually. We wanted to make sure that there was no obvious heteroskedasticity in our data and that the mean remained constant over the entire time series. We observed that every y-variable was already stationary, but every x-variable showed obvious signs of rising variance, increasing means, or both. Unfortunately, simple visual analysis is not enough to confirm whether data is stationary or not. We decided to employ our second method of choice – Dickey-Fuller Tests (DF Tests) – to confirm our suspicions. A DF Test is a statistical test with an alternative hypothesis stating that the data is stationary; thus, if the DF Test returns a P-Value of less than 0.05, one can conclude with a high level of confidence that the data is stationary, and vice-versa. Our DF Tests for the y-variables all yielded P-Values of less than 0.05, and nearly all of our x-variable DF Tests yielded P-Values significantly higher than 0.05. Monthly unemployment rate data yielded a P-Value of 0.0752, which suggests that it is almost stationary because it is close to the statistically significant level of 0.05. However, it failed to pass our visual tests; therefore, we concluded that it – along with all of our other x-variables – was non-stationary.

In order to correct for the lack of stationarity in our x-variables, we decided to difference them. After differencing our x-variables, we once again employed visual analysis and DF Tests check for stationarity. All of our new x-variables showed no signs of increasing mean or variance in the visual tests, and outputted P-Values of less than 0.05 in the DF Tests. We therefore concluded that our differenced x-variables were now stationary. Unfortunately, after differencing our x-variables, we no longer had the predictive data structure that we set out to create: our differenced x-variable data and forward-looking y-variable data were now describing the same time frames. In order to maintain a format in which our model can use x-variable data to explain *future* y-variable data, we had to difference our y-variable data (forward continuously compounded monthly returns). After creating new data-frames containing our differenced y and x variables, we were ready to start constructing our models.

We decided to use the regsubsets function in R to perform forward stepwise selection in order to help determine the optimal x-variables to include in each multivariate linear regression time series model. The optimal number of x-variables for gold, silver, platinum, and palladium were 8, 7, 9, and 6, respectively. After determining this, we plugged in the optimal number of variables for each metal type into more regsubset functions and were then able to determine the specific explanatory variables which would contribute to a higher Adjusted R-squared value. Based off the selected variables, we built multivariate linear regression models for each of the four precious metal returns. Although we now had fully functioning models built according to logical processes, we had no other models to compare their results to; so, before we began analyzing our linear models' outputs, we decided to build one more model per metal.

After extensive research, we decided to utilize the randomForest function to build out multivariate decision tree models. The randomForest model is a type of machine learning model that makes its estimations by combining decisions from a sequence of base models and sums them all into a final, best-fit model at the end of the process. It is important to note that in random forests, all of the base models are created using different subsets of the data. We ran our randomForest models using all of the x-variables in our datasets in order to allow the function to potentially make use of variables that we overlooked in our selection process. We also ran the models using our only our selected variables from our linear regressions to ensure that the function was not able to find a better fit line. After running all of the code and organizing our models, we were ready to analyze our results.

6. Results

As briefly mentioned above, our optimal multivariate linear models for gold, silver, platinum, and palladium had 8, 7, 9, and 6 selected variables, respectively. The selected variables for gold were real oil prices, the S&P 500 index, the Nasdaq index, the VIX, the spread of the 10-year Treasury Bill over the Federal Funds Rate, CPI, real GDP in USD, and the USD Index, which yielded coefficients of 1.209e-03, 2.067e-04, -7.780e-5, -1.1219e-03, 3.251e-02, -2.172e-02, 1.752e-13, and 8.943e-03, respectively. The model had a P-Value of 8.313e-07 and an Adjusted R-Squared of 14.18%. The selected variables for silver were real oil prices, the S&P 500 index, the Nasdaq index, the VIX, the spread of the 10-year Treasury Bill over the Federal Funds Rate, CPI, and the USD Index, which yielded coefficients of 1.723e-03, 2.490e-04, -8.283e-05, -2.880e-03, -2.565e-02, -2.889e-02, and 1.322e-02, respectively. The model had a P-Value of 0.0075 and an Adjusted R-Squared of 5.189%. The selected variables for platinum were the US unemployment rate, real oil prices, the Michigan Consumer Sentiment Index, the S&P 500 index, the Nasdaq index, the VIX, the Euro Stoxx 50 index, CPI, and the USD Index, which yielded coefficients of -2.672e-00, 1.248e-03, -1.653e-04, 5.839e-04, -1.353e-04, -1.736e-03, -1.126e-04, -3.280e-02, and 9.206e-03, respectively. The model had a P-Value of 3.393e-05 and an Adjusted R-Squared of 11.26%. Finally, the selected variables for palladium are the S&P 500 index, the Nasdaq index, the VIX, the Euro Stoxx 50 index, CPI, and the USD Index, which yielded coefficients of 6.975e-04, -2.424e-04, -3.490e-03, -1.071e-04, -1.920e-02, and 1.236e-02, respectively. The model has a P-Value of 0.00197 and an Adjusted R-Squared of 6.23%.

To recap, our multivariate linear regression models for gold, silver, platinum, and palladium resulted in Adjusted R-square values of 14.18%, 5.189%, 11.26%, and 6.23% respectively. The R-squared represents the proportion of the variance for a dependent variable that is explained by the independent variables in a regression model. Since our gold returns model resulted in the highest R-squared, we can conclude that gold is easier to predict based on the explanatory variables included in the model in comparison to the other precious metals. This aligns with our previous hypotheses and literature review as Gold has historically been a metal that is used as not only a safe haven asset but just an overall popular and widely invested-in resource. The relatively higher correlation in our explanatory variables makes sense as shown in behavioral finance theory, individuals will react to the market based off their attempts to predict what they believe to be occurring / what will occur. In an attempt to essentially predict recessions / declines in their economy, the returns on gold will move in parallel to these attempts and changes in the market.

Although we expected our Adjusted R-Squared results to come out in the order of magnitude that they did, our coefficient outputs for our x-variables were surprising. In general, variables such as CPI, S&P 500, Nasdaq, Unemployment rate, and VIX had negative coefficients. This suggests that there is an inverse relationship between these inputs and the returns of precious metals. We hypothesized that CPI would be positively correlated to precious metal prices because research has shown that metals such as gold and silver are great inflation hedges (Zimmerman and McCown, 2006). As for the S&P 500, Nasdaq, Unemployment rate, and VIX, we hypothesized that they would be negatively correlated to precious metal prices because metals are often viewed as legitimate safe-haven assets (Hillier, Draper, Fauff, 2006). There are a couple of reasonable explanations as to why our coefficients do not align with our economic rationale.

The first line of reasoning lies in the *forward* y-variable, *present* x-variable structure of our dataset. Although this structure allows us to build a *predictive* model, it presents challenges in the way one must interpret x-variable coefficients. To better understand how, consider that our model is using x-variable data from a given period to explain y-variable data from the following period. This is an issue with regards to coefficient interpretation because it is possible – or even probable – that x-variables will behave very differently from period to period; thus, even though our (forward) y-variables display nonsensical correlation with our (present) x-variables, it could be the case that – on average – our *forward* x-variables (which is what ultimately determines our forward y-variable values) behave oppositely from the *present* versions of themselves. This suggests that our model may still be capturing our economic rationale correctly, but in an un-intuitive way. The second reason as to why some of our coefficients do not align with our economic rationale may lie in the fact we opted to use some lagging economic indicators such as US unemployment rate data. Lagging indicators are typically not very useful for predictive analysis as they are not an accurate reflection of market expectations for the future; therefore, there correlation to our forward-looking y-variables is intuitive. On the bright side, some of our x-variables did display logical coefficients. For example, we hypothesized that there would be a positive relationship between the USD Index and gold returns because our gold data is priced in USD; thus, any increase in strength in the US Dollar should be reflected in the price of gold. This assumption held up in our model outputs.

Our final step in the analysis of our model results was to compare the quality of the fit of our multivariate linear model to the results of both of our groups of random forest models. To do this, we implemented the use of 4-Fold Cross Validation analysis; however, instead of manually separating our data into four equal sets and averaging the results, we decided to use a preset function called *train* found in the caret library. The train function performs all of the steps of the K-Fold analysis in a few lines of code. The results from our 4-Fold CV analysis was promising. Our multivariable linear model for gold outputted RMSEs of 0.0613, 0.0570, 0.0567, and 0.0596 across the four folds, respectively. Our random forest gold model with all x-variables and our random forest model with only the selected x-variables returned RMSEs that were significantly higher across all folds (they averaged RMSEs of 0.941 and 0.947 across all folds, respectively). Our multivariable linear model for silver outputted RMSEs of 0.093, 0.110, 0.098, and 0.878 across the four folds, respectively. Our random forest silver model with all x-variables and our random forest model with only the selected x-variables returned RMSEs that were significantly higher across all folds (they averaged RMSEs of 1.487 and 1.508 across all folds, respectively). Our multivariable linear model for platinum outputted RMSEs of 0.0775, 0.0799, 0.0822, and 0.0768 across the four folds, respectively. Our random forest platinum model with all x-variables and our random forest model with only the selected x-variables returned RMSEs that were significantly higher across all folds (they averaged RMSEs of 1.291 and 1.324 across all folds, respectively). Finally, our multivariable linear model for palladium outputted RMSEs of 0.135, 0.120, 0.123, and 0.138 across the four folds, respectively. Our random forest palladium model with all x-variables and our random forest model with only the selected x-variables returned RMSEs that were significantly higher across all folds (they averaged RMSEs of 1.961 and 1.994 across all folds, respectively).

7. Conclusion

After carefully reviewing the characteristics of all of our models, we determined that our multivariable linear regression models were the most useful in predicting (in order) gold, silver, platinum, and palladium price returns. The models are referenced in the front of the appendix. Upon examining time series data of these precious metals returns, we have not violated any of the Gauss Markov assumptions. We have ensured of this both in and out sample by k folding our data. We have tested the robustness of our model against a regression and showed RMSE to be lower in proportion. Thus, proving we have created a model that has some predictive power and although containing some bias that is possibly affecting its accuracy it does well within its parameters. Precious metals have some very interesting properties and upon looking at the factors that drive their returns within a predictive time series model we see just how many factors go into its influence.

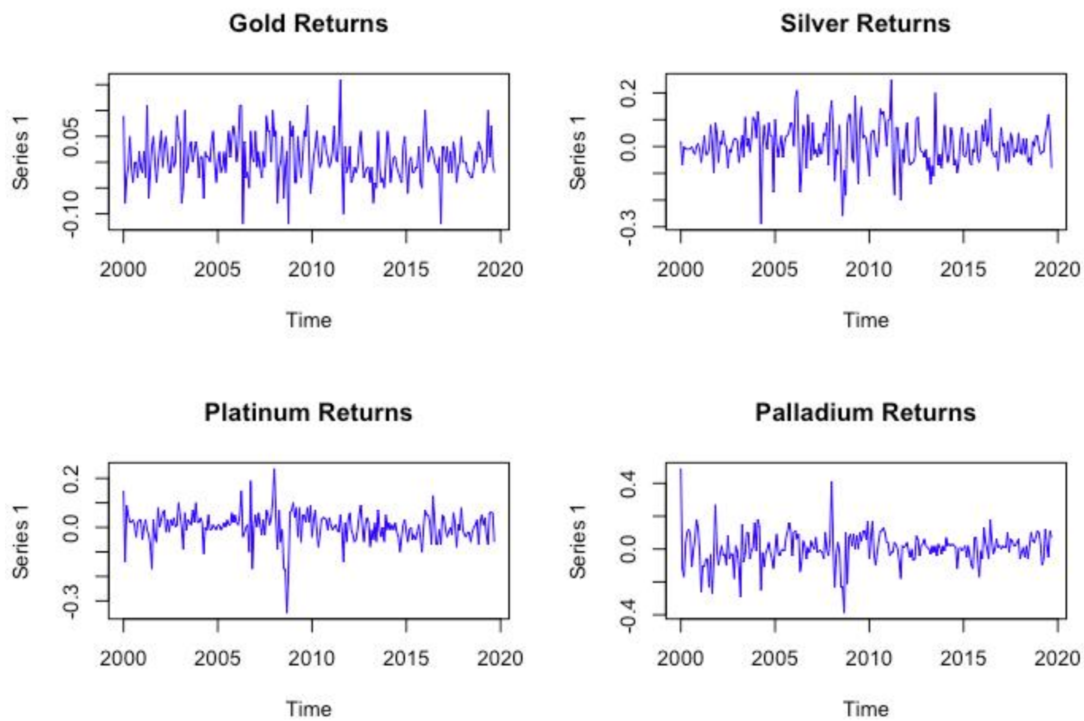
Appendix:

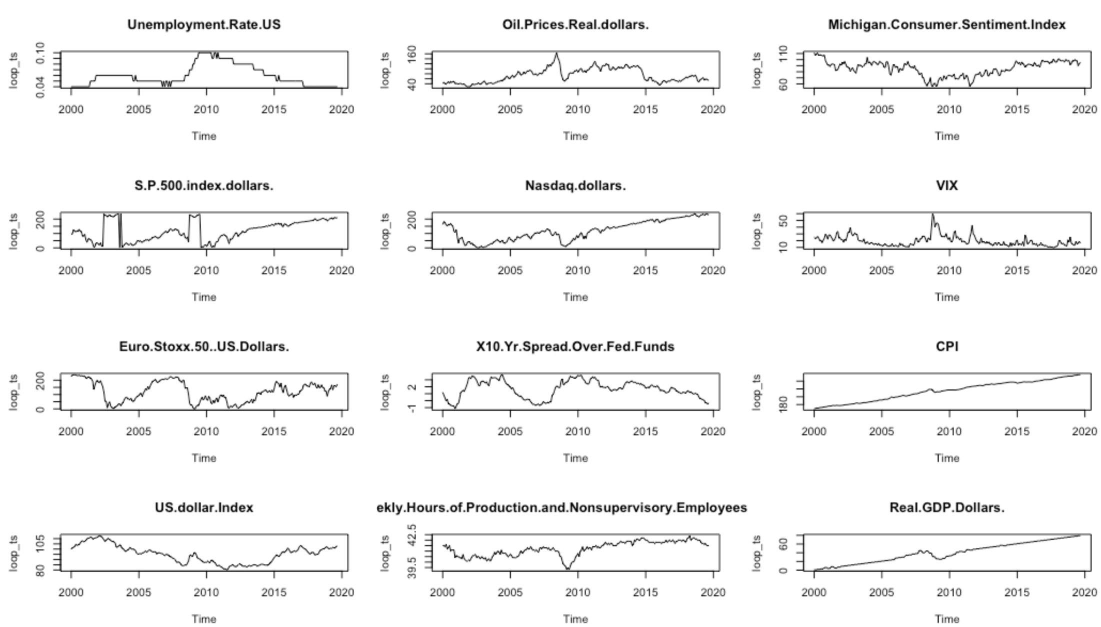
Expected Gold Returns = 3.579e-03 + 1.228e-03(Oil Price) + 2.137e-04(S&P) – 7.741e-05(Nasdaq) – 1.057e-03(VIX) + 3.288e-02(10 Yr. Spread Over Fed Funds) – 2.131e-02(CPI) + 1.418e-13(Real GDP) + 8.520e-03(USD Index) + μ

Expected Silver Returns = 9.463e-03 + 1.723e-03(Oil Price) + 2.490e-04(S&P) - 8.283e-05(Nasdaq) - 2.880e-03(VIX) - 2.565e-02(10 Yr. Spread Over Fed Funds) - 2.889e-02(CPI) + 1.322e-02(USD Index) + μ

Expected Platinum Returns = 8.790e-03 + -2.672e-00(Unemployment Rate) + 1.248e-03(Oil Price) - 1.653e-04(Michigan Consumer Sentiment Index) + 5.839e-04(S&P) - 1.353e-04(Nasdaq) - 1.736e-03(VIX) - 1.126e-04(Euro Stoxx50) - 3.280e-02(CPI) + 9.206e-03(USD Index) + μ

Expected Palladium Returns = 0.004 + 6.975e-04(S&P) - 2.424e-04,(Nasdaq) - 3.490e-03(VIX) - 1.071e-04(Euro Stoxx50) - 1.920e-02(CPI) + 1.236e-02(USD Index) + μ


Gold Returns
Silver Returns
Platinum Returns
Palladium Returns
Series 1
Time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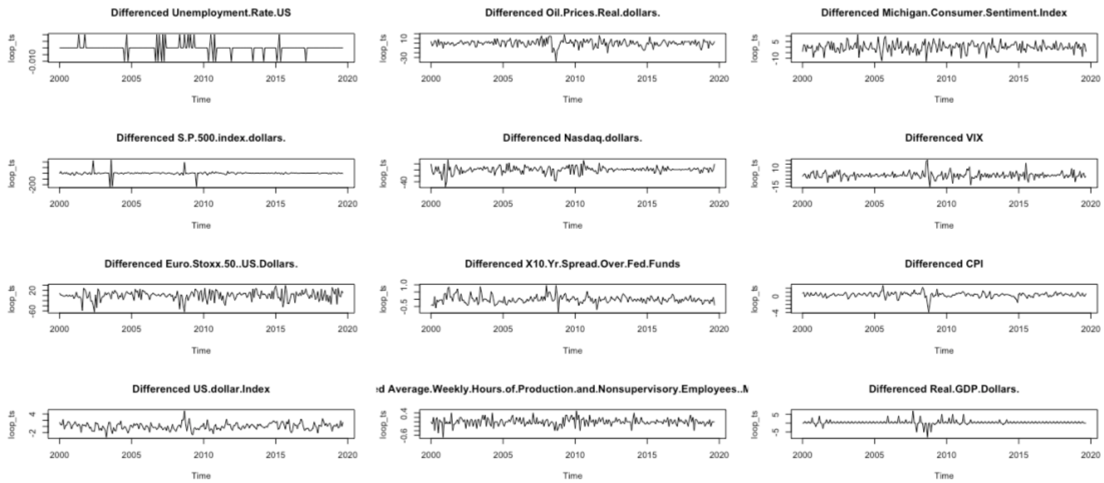
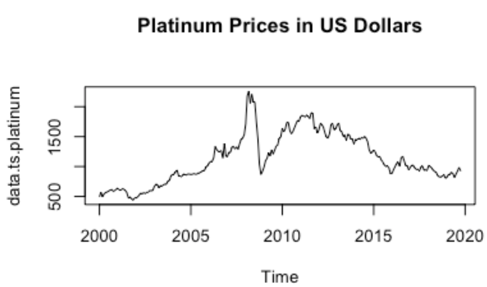
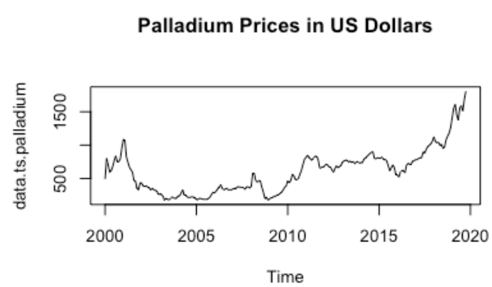
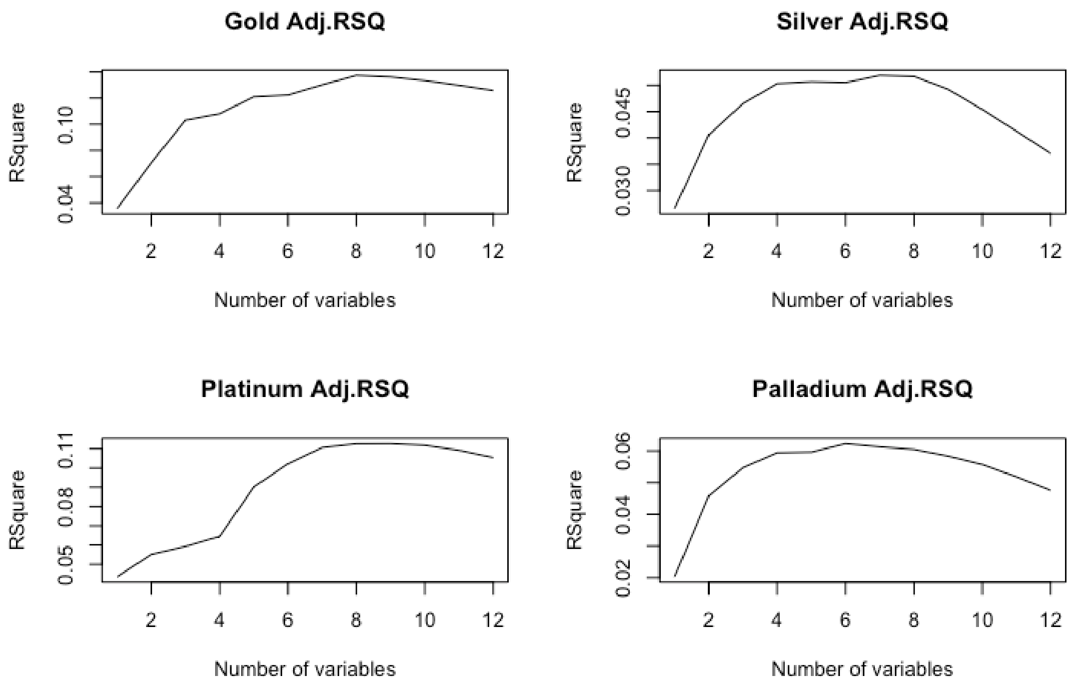






	mean	stdev	MIN	MAX
Gold (US Dollars)	959.21	477.345395	264.55	1,915.55
Gold) look ahead return continuously compounded	0.01	0.04305598329	-0.12	0.16
Silver (US Dollars)	15.69	9.255738445	4.20	48.38
Silver (look ahead return continuously compounded)	0.01	0.07596721746	-0.29	0.25
Platinum(US Dollars)	1,130.71	414.6969931	438.00	2,258.50
Platinum (look ahead return continuously compounded)	0.00	0.06248875021	-0.17	0.24
Palladium(US Dollars)	597.06	320.9930449	175.00	1,807.82
Platinum (look ahead return continuously compounded)	0.01	0.09919341119	-0.39	0.49
Unemployment Rate US	0.06	0.01804880816	0.04	0.10
Oil Prices Real(dollars)	73.15	28.3757175	28.13	164.22
Michigan Consumer Sentiment Index	85.62	12.157751	55.30	111.30
S&P 500 index(dollars)	1,564.38	574.6764293	735.09	3,037.56
Nasdaq(dollars)	3,431.96	1861.864406	1,172.06	8,292.36
VIX	19.54	7.895401679	9.51	59.89
Euro Stoxx 50 (US Dollars)	2,929.34	635.6056546	1,780.39	4,778.33
10 Yr Spread Over Fed Funds	1.66	1.243117138	-1.16	3.72
CPI	214.99	25.25931143	169.30	256.36
US dollar Index	95.26	8.463728615	80.24	112.77
Average Weekly Hours of Production and Nonsupervisory Employees, Manufacturing	41.20	0.6727276517	39.30	42.40
Real GDP(Dollars)	15,811,911,042,016.80	1689241328668	12,924,179,000,000.00	19,112,542,000,000.00



<u>Gold</u>

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Call:
lm(formula = data_gold$data_raw.Gold..look.ahead.return.continuously.compounded ~
    Oil.Prices.Real.dollars. + S.P.500.index.dollars. + Nasdaq.dollars. +
        VIX + X10.Yr.Spread.Over.Fed.Funds + CPI + US.dollar.Index +
        Real.GDP.Dollars., data = data_gold)

Residuals:
      Min        1Q    Median        3Q       Max
-0.199339 -0.023978  0.000177  0.033769  0.150222

Coefficients:
                               Estimate Std. Error t value Pr(>|t|)
(Intercept)                   3.579e-03  4.515e-03   0.793 0.428811
Oil.Prices.Real.dollars.      1.228e-03  6.273e-04   1.958 0.051493 .
S.P.500.index.dollars.        2.137e-04  1.252e-04   1.707 0.089171 .
Nasdaq.dollars.              -7.741e-05  3.172e-05  -2.441 0.015416 *
VIX                          -1.057e-03  1.204e-03  -0.878 0.380938
X10.Yr.Spread.Over.Fed.Funds  3.288e-02  1.441e-02   2.282 0.023418 *
CPI                          -2.131e-02  6.353e-03  -3.354 0.000935 ***
US.dollar.Index               8.520e-03  3.604e-03   2.364 0.018923 *
Real.GDP.Dollars.             1.418e-13  5.299e-14   2.675 0.008011 **
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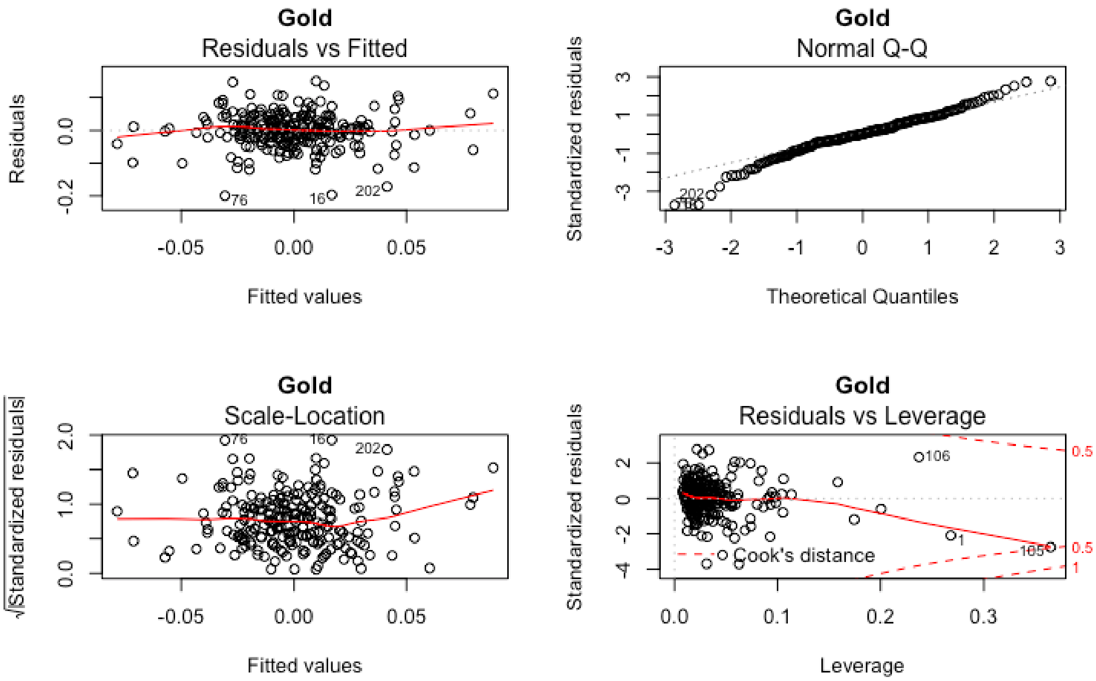
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.05472 on 227 degrees of freedom
Multiple R-squared:  0.1668,    Adjusted R-squared:  0.1374
F-statistic:  5.68 on 8 and 227 DF,  p-value: 1.381e-06
```



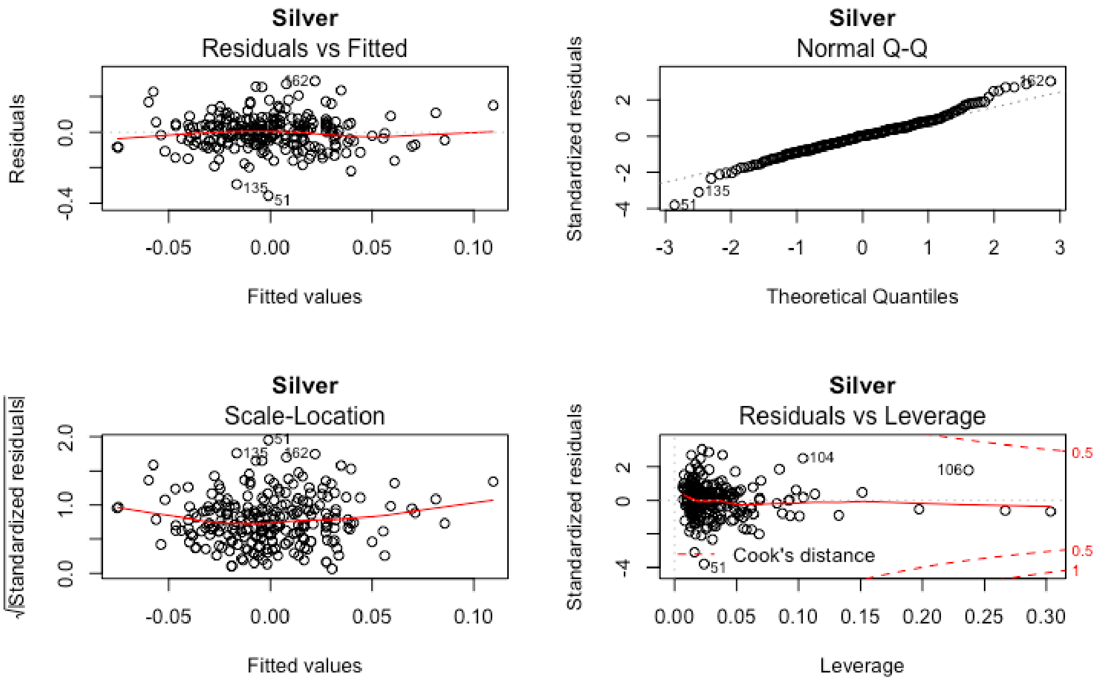
Silver

```
Call:
lm(formula = data_silver$data_raw.Silver..look.ahead.return.continuously.compounded. ~
    Oil.Prices.Real.dollars. + S.P.500.index.dollars. + Nasdaq.dollars. +
        VIX + X10.Yr.Spread.Over.Fed.Funds + CPI + US.dollar.Index,
    data = data_silver)

Residuals:
     Min       1Q   Median       3Q      Max
-0.35895 -0.05558  0.00337  0.04809  0.28805

Coefficients:
                              Estimate Std. Error t value Pr(>|t|)
(Intercept)                  9.463e-03  7.456e-03   1.269  0.20566
Oil.Prices.Real.dollars.     1.723e-03  1.074e-03   1.604  0.11010
S.P.500.index.dollars.       2.490e-04  2.154e-04   1.156  0.24900
Nasdaq.dollars.             -8.283e-05  5.467e-05  -1.515  0.13114
VIX                         -2.880e-03  2.102e-03  -1.370  0.17190
X10.Yr.Spread.Over.Fed.Funds -2.565e-02  2.492e-02  -1.029  0.30449
CPI                         -2.889e-02  1.107e-02  -2.609  0.00967 **
US.dollar.Index              1.322e-02  6.292e-03   2.101  0.03677 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.09555 on 228 degrees of freedom
Multiple R-squared:  0.08013,	Adjusted R-squared:  0.05189
F-statistic: 2.837 on 7 and 228 DF,  p-value: 0.007439
```



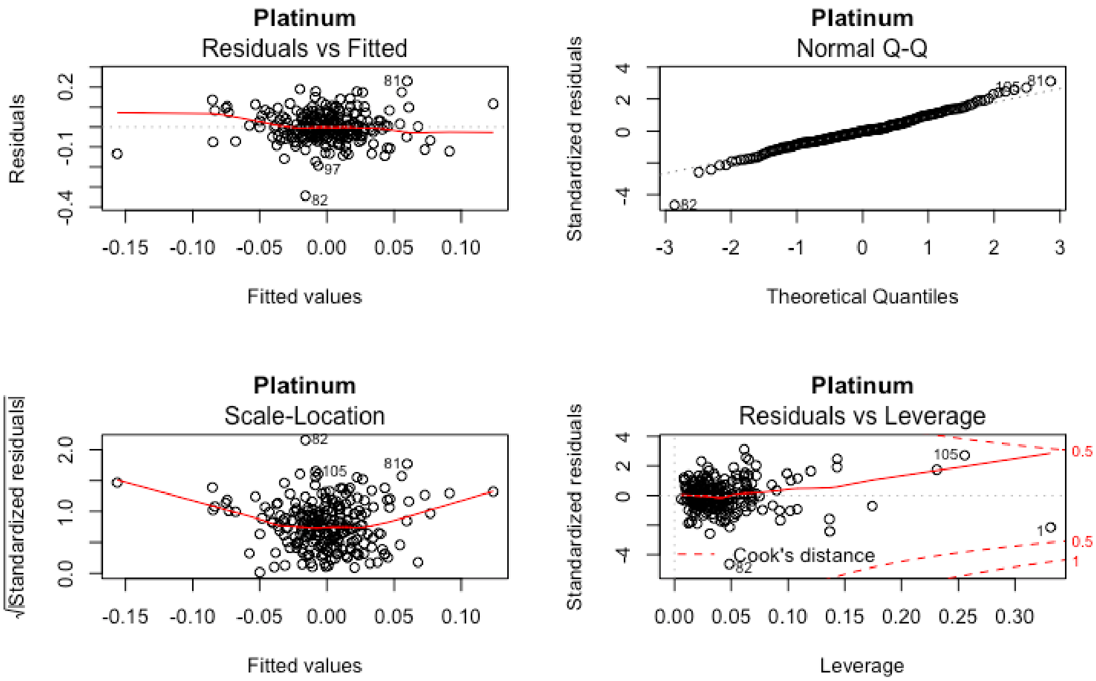
<u>Platinum</u>

```
Call:
lm(formula = data_platinum$data_raw.Platinum..look.ahead.return.continuously.compounded. ~
    Unemployment.Rate.US + Oil.Prices.Real.dollars. + Michigan.Consumer.Sentiment.Index +
        S.P.500.index.dollars. + Nasdaq.dollars. + VIX + Euro.Stoxx.50..US.Dollars. +
        CPI + US.dollar.Index, data = data_platinum)

Residuals:
     Min       1Q   Median       3Q      Max
-0.34405 -0.04537 -0.00070  0.04433  0.23031

Coefficients:
                                    Estimate Std. Error t value Pr(>|t|)
(Intercept)                        8.790e-03  5.953e-03   1.477  0.14116
Unemployment.Rate.US              -2.672e+00  1.426e+00  -1.874  0.06223 .
Oil.Prices.Real.dollars.           1.248e-03  8.514e-04   1.466  0.14414
Michigan.Consumer.Sentiment.Index -1.654e-03  1.300e-03  -1.273  0.20443
S.P.500.index.dollars.             5.839e-04  1.832e-04   3.187  0.00164 **
Nasdaq.dollars.                   -1.353e-04  4.402e-05  -3.074  0.00237 **
VIX                               -1.736e-03  1.724e-03  -1.007  0.31490
Euro.Stoxx.50..US.Dollars.        -1.126e-04  5.209e-05  -2.161  0.03171 *
CPI                               -3.280e-02  8.838e-03  -3.711  0.00026 ***
US.dollar.Index                    9.206e-03  4.893e-03   1.881  0.06122 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.07605 on 226 degrees of freedom
Multiple R-squared:  0.1466,	Adjusted R-squared:  0.1126
F-statistic: 4.315 on 9 and 226 DF,  p-value: 3.393e-05
```



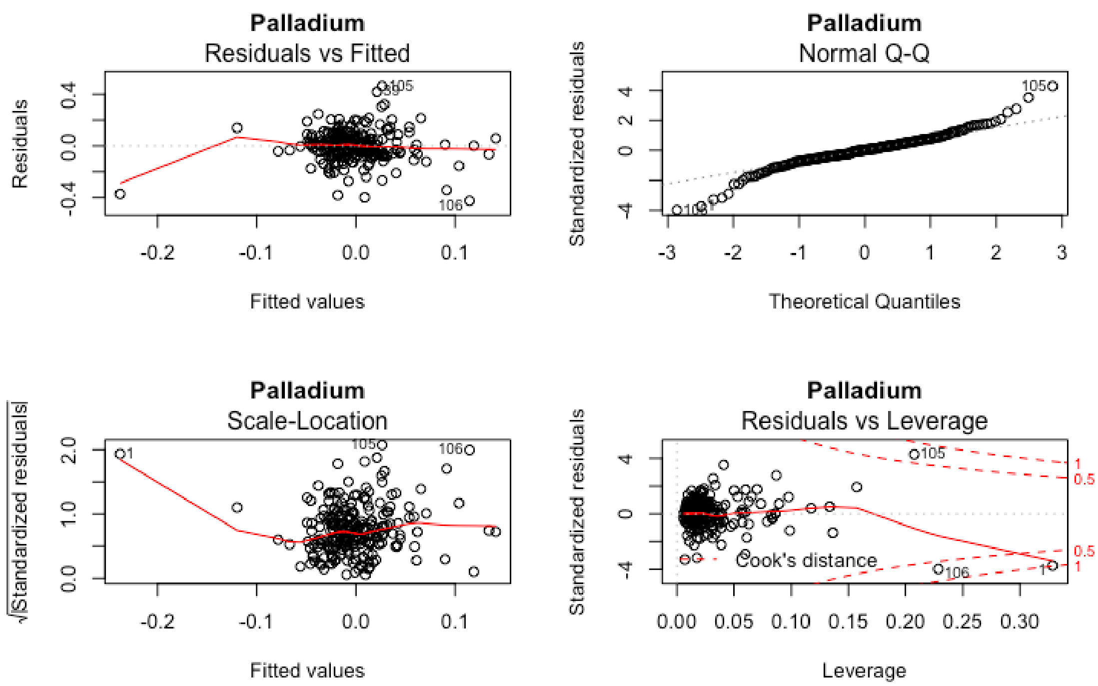
Palladium

```
Call:
lm(formula = data_palladium$data_raw.Palladium..look.ahead.return.continuously.compounded. ~
    S.P.500.index.dollars. + Nasdaq.dollars. + VIX + Euro.Stoxx.50..US.Dollars. +
        CPI + US.dollar.Index, data = data_palladium)

Residuals:
     Min       1Q   Median       3Q      Max
-0.42439 -0.05833  0.00279  0.06325  0.46355

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                 4.059e-03  9.343e-03   0.434   0.6644
S.P.500.index.dollars.      6.975e-04  2.890e-04   2.414   0.0166 *
Nasdaq.dollars.            -2.424e-04  6.965e-05  -3.480   0.0006 ***
VIX                        -3.490e-03  2.707e-03  -1.289   0.1987
Euro.Stoxx.50..US.Dollars. -1.071e-04  8.211e-05  -1.305   0.1934
CPI                        -1.920e-02  1.326e-02  -1.448   0.1490
US.dollar.Index             1.236e-02  7.581e-03   1.631   0.1043
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1214 on 229 degrees of freedom
Multiple R-squared:  0.08624,    Adjusted R-squared:  0.0623
F-statistic: 3.602 on 6 and 229 DF,  p-value: 0.001967
```


Palladium
Residuals vs Fitted
Residuals
Fitted values
Palladium
Normal Q-Q
Standardized residuals
Theoretical Quantiles
Palladium
Scale-Location
√|Standardized residuals|
Fitted values
Palladium
Residuals vs Leverage
Standardized residuals
Cook's distance
Leverage

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