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Oil and gold price on economy prices

Econometrics final project

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Abstract

Nowadays, one of the most challenging issues for investors is to understand the interrelationships between financial markets and commodities.

The purpose of this analysis is to define whether changes in the prices of oil and gold and their volatilities have a relevant effect on the stock market price. In order to carry out this task, we selected four indexes representing the principal commodities' price and volatility, and one representing the US financial market.

After trying different models and techniques, we attained the conclusion that the market is indeed correlated with the chosen goods. In particular, we showed that the evolution of the financial index is driven by the price and volatility of commodities, both at present time and past values.

Keywords: gold, oil, SP500, autoregressive distributed lag,
autocorrelation, stationarity

Contents

Introduction

The impact of oil and gold prices on financial operations and other sectors of the US economy is significant. This impact can be seen easily in consumption, industrial production, and investment in both the real and financial sectors, where oil and gold price volatility affect stock prices and has repercussions in the US capital market, as well as indirectly in inflation and unemployment.

Geopolitical and weather-related factors influence crude oil prices, causing unanticipated adjustments in supply and demand and causing price volatility. Because of their reliance on oil and oil products, industrial producers and consumers are at risk; they are unable to deliver their goods and services at a reasonable price. Because the value of a commodity is dependent on a contingent claim that is affected by volatility, it also influences derivative markets.

Gold is a precious metal that is both a commodity and a monetary asset. It functions as a source of wealth, a unit of value, and a highly liquid investment vehicle. It has traditionally served as an inflation indicator, a hedge against inflation, an essential asset in portfolio allocation, and a role in crises, as it generates a hedge to diversify the increasing risk in the market during crises.

Despite the importance of gold for currency hedging and trading, gold price volatility can have a deleterious impact on financial markets, because higher gold price volatility means riskier investments, while lower gold price volatility means safer investments. An increase in gold volatility serves as a warning to gold investors and producers, exposing them to danger. As a result, understanding gold price volatility helps us better comprehend financial markets.

The stock price is influenced by macroeconomic factors such as gold and crude oil prices, as well as gold and oil price volatility. The purpose of this article is to investigate the long-term link between them and the SP500 index.

1 | Literature Review

Many researches have been conducted on the relationship between the price of oil, gold, and macroeconomic variables. On the other hand, only a few research have looked at the relationship between oil prices, gold prices, and financial markets.

Oil plays an essential role in the US economy, and volatility in oil prices cause stock values to fluctuate (Hamilton, 1983). Oil price and stock price are contemporaneously associated in an efficient market: if oil price rises, stock prices of companies that use oil in their operations will fall (Gilbert, 1984). In an inefficient market, instead, changes in oil price would adapt with the lag of changes in stock price (Mork et al., 1994).

Jones and Kaul (1996) concluded that the price of oil had no effect on real stock returns from 1947 to 1991 in a study. Ciner (2001) uses the non-linear connection to highlight the impact of oil price on real stock returns; he discovered that crude oil price volatility affects stock index returns. Papapetrou (2001) used a multivariate VAR model to investigate the relationship between oil price, real stock price, real economic activity, and interest rates in Greece.

Cai et al. (2001) investigated the relationships between GDP, inflation, and gold price volatility, arguing that GDP and inflation have a significant impact on gold price returns volatility. Gold, according to Capie et al. (2005), is a hedge against foreign exchange volatility. Baur and McDermott (2010) investigated the impact of gold prices on financial markets from 1979 to 2009, finding that gold functions as a hedge and a safe haven in the stock markets of the United States and most European countries. Mensi et al. (2013) looked at the correlations and volatility transmission in commodities including gold, oil, and the stock market. The findings of their research demonstrated that the SP500 price has an impact on gold and oil price volatility. Using the Granger test, Bhunia (2013) investigated the relationship between domestic gold price and stock price return and discovered bidirectional causality between gold price and stock price return. For the period 2004-2011, Arouri et al. (2015) used the VAR-GARCH model to explore the influence of gold price volatility on stock market returns in China; their findings showed that gold price volatility had a significant impact on China's stock market return.

2 | Data

We chose five variables to define our model: as independent variables, the price of gold, the price of oil and their volatilities, while as our dependent variable we opted for a financial index to represent the market and the economy.

Exploiting the code seen during the lessons, we managed to trace back and download the historical data of the chosen five series, represented by five indexes:

- CL = F, index of the oil price, in dollars/barrel;
- GC = F, index of the gold price, in dollars/ounce;
- OVX, oil volatility index;
- GVZ, gold volatility index;
- GSPC, the US market index (SP500), representing the economy.

All the data were downloaded from the Yahoo Finance database.

Since the volatility's data are available starting only from the year 2008, we decided to let our series begin from that date. The sampling period begins on June 3rd, 2008, and it ends on April 25th, 2022. The dimension of this sample is 3499, but we discovered that two variables presented missing values: as a matter of fact, gold only had 3497 observations, while oil 3498. At this point, to overcome this issue, between different solutions we decided to interpolate the prices to fill the empty observations: this way we managed not to decrease the number of measurements, keeping it to 3499. In detail, the interpolation result was obtained summing the previous and the following values, and then dividing it for two. Even though the operation was quite trivial, it allowed us to maintain consistency in our data. A final consideration on the chosen sampling period: given the wideness of our time-window, we are able to better analyze the reaction of the indexes with respect to major political-financial-social events, like the crisis of 2008, the pandemic emergency in 2020 and the recent war between Russia and Ukraine. Below, we present the main plots of these data, and some interesting comments.

2.1. Gold and gold volatility

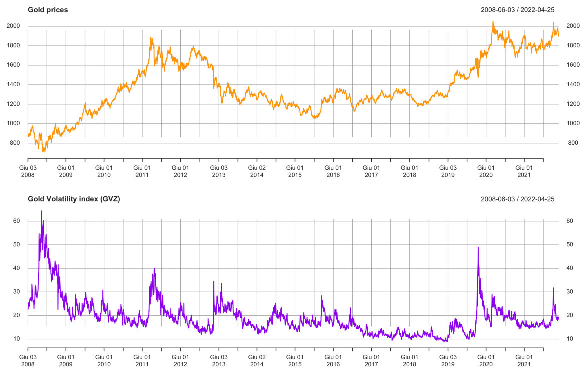

Figure 2.1: Plot of gold and gold volatility prices.

It is a truth universally acknowledged that gold works as a hedge against inflation, especially during periods of uncertainty and crisis.

In our case, we noticed that this rule is confirmed. As a matter of fact, it can be easily seen that the graph of gold price is mostly increasing, and this can be explained with the difficult times we are living since the financial crisis of 2008 and the consequent inflation. Moreover, signals of an economic recovery were testified by the decreasing trend between 2012 and 2015, but they vanished with the arising of the pandemic situation.

Following this argument, we see that the maximum value assumed by the gold price can be associated to the most critical period of all, spring 2020, during which all the Americans were living the lockdown situation.

Lastly, we observed that the two peaks of the gold volatility index were in 2008 and in 2020, during the financial and the socio-economic crisis. Again, this explains how gold is seen as a hedge against inflation and political emergencies: the more people traded gold in those periods, the more the volatility arose.

2.2. Oil and oil volatility

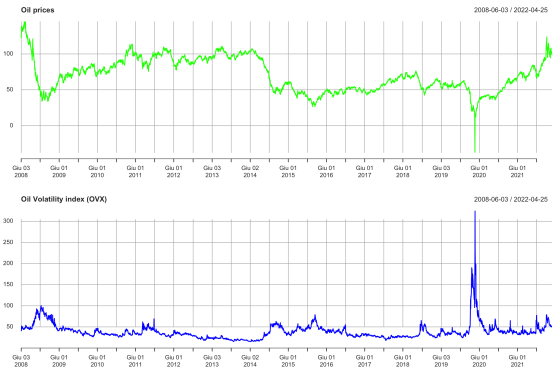

Figure 2.2: Plot of oil and oil volatility prices.

Similarly to what we observed with the gold price, oil price is influenced by the economical wealth of the market. Indeed, the peak was reached in July 2008 (145,29$); then, after the the financial breakdown of Lehman Brothers in September 2008, and the consequent crisis, oil started losing value, until reaching the low points of November 2008 (49,62$) and December 2008 (33,27$).

Another extremely rare event can be found on April 20th 2020, when it happened that the oil price went negative for a day. This time, the reasons were different, more practical: due to the pandemic emergency and the lockdown measures, people were not allowed to leave their homes unless in case of emergency and very specific situations; in this scenario, oil was not consumed, nor for traveling nor for manufacturing reasons, and consequently it was not purchased. This caused its price to go down and down, until reaching negative values for one day.

In this case, it is observable the volatility oscillates around a constant value, except for the peak of spring 2020, in contemporary with the above-described events.

An important remark is that, later, when we are going to apply logarithms to our series, we need to deal with the negative value of oil on April 20th 2020. Our solution will be to again compute interpolation between the value of April 19th and the one of 21st. The final result will be a price of 14,14$, very low as well, and so acceptable for our purpose.

2.3. SP500

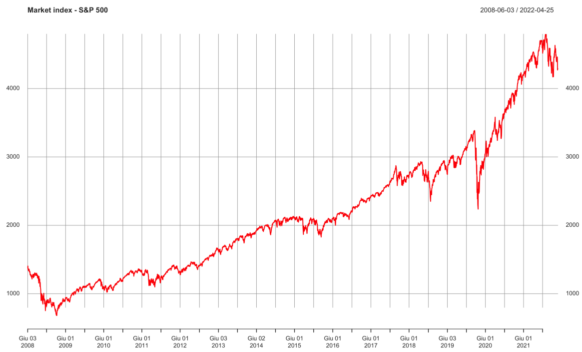

Figure 2.3: Plot of SP500 price.

The graph of the market index is clearly increasing, sign that, after the first years of initial shock due to the financial crisis and damages of 2008, the economy started recovering and is now living a thriving phasis.

Again, we can comment on the temporary crash of spring 2020, where the Corona Virus negatively affected the life of people and the growth of economy. This was a period of general recession for most of the businesses and companies, except for some isolated cases (Netflix and Amazon).

2.4. Correlation between variables

The strongest correlation is the one between gold price and market index: we notice that they are positively correlated and a possible explanation could be that when the market grows, the prices arises (basic economical law of offer and demand) and so, to hedge against inflation, gold is seen as an asset in which investing. Another strong positive correlation is the one between oil price volatility and gold price volatility.

Significant negative correlations are the one between oil and SP and the one between gold price volatility and SP. The first one is obvious: when the price of oil increases, logistic and manufacturing industries suffer higher costs, and so the economy is affected. The second one is clear thinking about the definition of volatility: when the market experiences crisis and turbulences, the prices change significantly, and so the volatility increases.

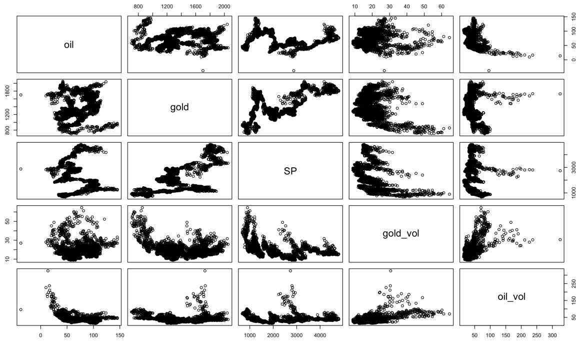

Figure 2.4: Pairs of the variables

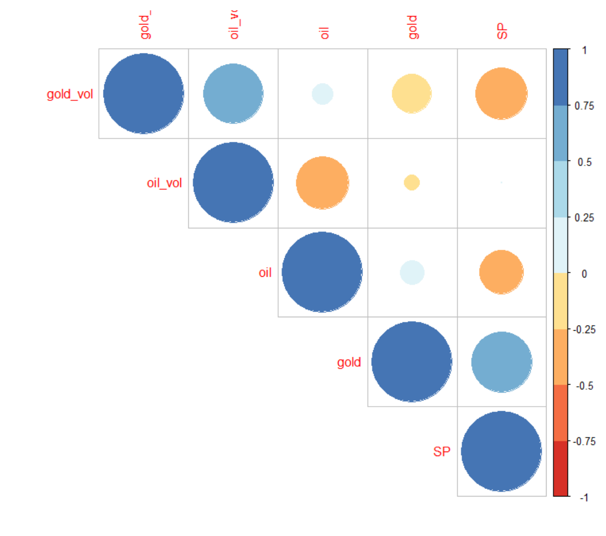

Figure 2.5: Corrplot of the variables

2.5. Main statistics

	oil	gold	SP	gold_vol	oil_vol
nbr.val	3499.00	3499.00	3499.00	3499.00	3499.00
nbr.na	0.00	0.00	0.00	0.00	0.00
min	-37.63	704.90	676.53	8.88	14.50
max	145.29	2051.50	4796.56	64.53	325.15
range	182.92	1346.60	4120.03	55.65	310.65
median	68.21	1306.30	2038.25	17.52	34.94
mean	70.51	1374.11	2166.60	19.01	38.92
var	543.59	80030.98	965957.97	54.39	365.76
std.dev	23.31	282.90	982.83	7.37	19.12

Figure 2.6: Relevant descriptive statistics of the variables

After adjusting the data, we have five series of the same dimension (3499), and no NA values. Again, we highlight the negative value assumed as a minimum for the oil price.

3 | Methodology

3.1. Stationarity

At this point, our objective is to verify whereas the series we have are stationary. The purpose is to be able to construct reliable models, using traditional (non-robust) statistics.

First, from the graphs, we noticed that oil and gold have non-stationary behaviors and so we proceeded to analyze them with an idoneous test, Augmented Dickey Fuller test. This procedure verifies if there is enough statistical evidence to accept the null hypothesis of non-stationarity, or to refuse it in favor of the stationarity condition. After performing the ADF test, we obtained an high level of p-value for both variables (gold: 0.69, oil: 0.34) and therefore we confirmed our initial idea: the series are non-stationary.

In this perspective, we initially applied the logarithm to the variables, obtaining a better result in the ADF test (0.59 and 0.27): still not stationary.

Finally, we were able to solve this issue by defining new variables as the series of the differences between two consecutive values of the previous time series. This expedient allows us to make the series of the logarithms stationary. The p-value of the ADF test is 0.01 for both the series of differences of the logarithms of oil and gold prices: we have indeed statistical evidence to refuse H0. One important remark is that, when we defined the differences, the first value of the series was always NA. Coherently with this observation, we will then remove the first value of the other series too, to maintain the same dimension.

Furthermore, also the volatilities of gold price and oil price have a similar behavior: according to ADF test, they are both stationary. Anyway, we decided to apply the logarithm transformation also to them, in order to maintain internal consistency between the order of our variables.

Lastly, we checked the stationarity of the SP500: the ADF gives us a p-value of 0.29, so there is not enough evidence to refuse the non-stationarity hypothesis. For this reason, we exploit again the logarithm function, obtaining a final stationary series.

The results of this procedure are the following modified and stationary series:

- Differences of the logarithm of oil prices;
- Differences of the logarithm of gold prices;
- Logarithm of oil price volatility;
- Logarithm of gold price volatility;
- Logarithm of SP500 value.

Later we will run some deeper analysis on autocorrelation, and we will arrive to the conclusion that our final model will be composed of the previous variables, with the exception that also the series of the logarithms of SP500 will present the differences.

The following are the plots of the stationary series we will use in our final model

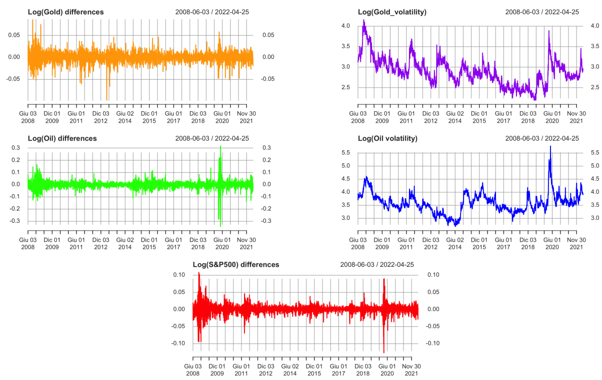

Figure 3.1: Stationary series for our final model

3.2. Heteroscedasticity

Once defined our series and made them stationary, we started to construct some models, increasing every time the level of complexity, trying to obtain more explicative and acceptable results.

Before explaining our main models, a general consideration: on each of them we performed the Breusch Pagan Test to verify if there was heteroscedasticity or not. What we found was that they all presented heteroskedastic residuals. To this matter, on the simplest model, the one with the lowest number of variables, we tried to manually correct this problem: by using the Feasible Generalized Least Squares method (FGLS), we attempted to make the residuals homoscedastic, without any success. Also other methods gave the same results. Eventually, our models will be heteroscedastic. Nevertheless, we tried plotting the residuals' distribution of our final model, in order to see if a pattern is present on the cloud, representing heteroscedasticity.

4 | Results

4.1. First Model: stationary series

We start by assembling the simplest possible model, based on the five stationary series we got in the previous passages, with the logarithm of SP500 as response variable. To do so, we exploit the function "lm", which creates a linear model using the given inputs.

$$\texttt{log(SP500)}_i = \beta_0 + \beta_1 \Delta\texttt{log(oil)}_i + \beta_2 \Delta\texttt{log(gold)}_i + \beta_3 \texttt{log(gold\_vol)}_i + \beta_4 \texttt{log(oil\_vol)}_i + \epsilon_i$$

4.1.1. Summary of the model and comments

```
Call:
lm(formula = SP_log ~ d_oil_log + d_gold_log + oil_vol_log +
    gold_vol_log)

Residuals:
     Min       1Q   Median       3Q      Max
-0.94581 -0.24909 -0.04208  0.18481  1.05028

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)   9.02375    0.06305 143.117   <2e-16 ***
d_oil_log    -0.05279    0.20941  -0.252   0.8010
d_gold_log   -0.95142    0.54253  -1.754   0.0796 .
oil_vol_log   0.39065    0.01924  20.304   <2e-16 ***
gold_vol_log -0.98527    0.02169 -45.415   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3569 on 3493 degrees of freedom
Multiple R-squared:  0.3749,    Adjusted R-squared:  0.3742
F-statistic: 523.8 on 4 and 3493 DF,  p-value: < 2.2e-16
```

Figure 4.1: Summary of the model

We immediately notice that R^2 is acceptable but, on the other hand, two out of four covariates are not significative, giving us the possibility to remove them. Nevertheless, the F-Statistic has a very low p-value telling us that the model has at least one significant regressor. From the estimates we can infer that an increment in oil_vol_log has a positive effect on the market, while the opposite happens for gold_vol_log. Regarding autocorrelation, we conducted a Durbin-Watson test obtaining a very low p-value ($<2.2e^{-16}$) which leads us to prove the presence of autocorrelation. The same p-value occurred while performing Breusch-Pagan test, that gives us a high test statistic value of 158.78, representing heteroscedasticity.

4.2. Second Model: Response variable as differences

Trying to adjust the auto-correlation problem found in the previous step, we created another model, this time applying the expedient of the differences also to the response variable.

$$\Delta\texttt{log(SP500)}_i = \beta_0 + \beta_1\Delta\texttt{log(oil)}_i + \beta_2\Delta\texttt{log(gold)}_i + \beta_3\texttt{log(gold\_vol)}_i + \beta_4\texttt{log(oil\_vol)}_i + \epsilon_i$$

4.2.1. Summary of the model and comments

```
Call:
lm(formula = d_SP_log ~ d_oil_log + d_gold_log + oil_vol_log +
    gold_vol_log)

Residuals:
      Min        1Q    Median        3Q       Max
-0.119025 -0.004495  0.000210  0.005249  0.106303

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.0068386  0.0022598   3.026  0.00249 **
d_oil_log     0.0845179  0.0075053  11.261  < 2e-16 ***
d_gold_log   -0.0595568  0.0194443  -3.063  0.00221 **
oil_vol_log  -0.0009601  0.0006896  -1.392  0.16392
gold_vol_log -0.0010590  0.0007775  -1.362  0.17331
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.01279 on 3493 degrees of freedom
Multiple R-squared:  0.03825,	Adjusted R-squared:  0.03715
F-statistic: 34.73 on 4 and 3493 DF,  p-value: < 2.2e-16
```

Figure 4.2: Summary of the model

In this second case, the R^2 obtained is really low (0.037), telling us that this model has a very poor explanatory ability. We also notice that the two volatility variables are not significative. As expected, Durbin-Watson test's results are a high p-value and a DW Statistic equal to 2.3338, corresponding to a model with no autocorrelation. On the other hand, BP test has the same p-value of the first model, so heteroscedasticity is still present.

4.3. Third Model: Autoregressive distributed lag model

In this case, we exploited the function “auto_ardl” to create an AutoRegressive Distributed Lag model, giving us the possibility to lag our variables. This function enables us to set a maximum order of lag for each variable and then returns the best model possible minimizing AIC (Akaike Information Criterion). By doing this, we penalize models with high lag orders, to maintain a good enough model without overcomplicating it. In this case we use the same variables used in the first model but with a different function, adding lag.

	d_SP_log	d_oil_log	d_gold_log	oil_vol_log	gold_vol_log	AIC
1	1	0	3	2	1	-21237.13
2	1	0	3	3	1	-21236.28
3	1	0	3	2	2	-21235.76
4	1	0	2	2	1	-21234.70
5	1	0	2	2	2	-21233.44
6	1	0	2	1	1	-21216.77
7	1	0	1	1	1	-21208.97
8	1	1	1	1	1	-21208.36

Figure 4.3: AIC of each model, the lower the better

The corresponding best model according to the AIC is:

$$\begin{aligned}\texttt{log(SP500)}_i = {} & \beta_0 + \beta_1\Delta\texttt{log(oil)}_i + \beta_2\Delta\texttt{log(gold)}_i + \beta_3\texttt{log(gold\_vol)}_i + \beta_4\texttt{log(oil\_vol)}_i \\ & + \beta_5\texttt{L(log(SP500),1)}_i + \beta_6\texttt{L(}\Delta\texttt{log(gold),1)}_i + \beta_7\texttt{L(}\Delta\texttt{log(gold),2)}_i \\ & + \beta_8\texttt{L(log(gold\_vol),1)}_i + \beta_9\texttt{L(log(gold\_vol),2)}_i + \beta_{10}\texttt{L(log(oil\_vol),1)}_i \\ & + \beta_{11}\texttt{L(log(oil\_vol),2)}_i + \epsilon_i\end{aligned}$$

We observe that the "L(x,k)" in the model means that the variable "x" is lagged "k" times.

4.3.1. Summary of the model and comments

```
Coefficients:
                     Estimate Std. Error  t value Pr(>|t|)    
(Intercept)         0.0064418  0.0054902    1.173 0.240744    
L(SP_log, 1)        0.9996859  0.0005619 1779.041  < 2e-16 ***
d_oil_log           0.0543921  0.0070696    7.694 1.85e-14 ***
d_gold_log         -0.0635017  0.0179337   -3.541 0.000404 ***
L(d_gold_log, 1)    0.0370501  0.0177102    2.092 0.036509 *  
L(d_gold_log, 2)    0.0591472  0.0177362    3.335 0.000862 ***
oil_vol_log        -0.0580749  0.0035871  -16.190  < 2e-16 ***
L(oil_vol_log, 1)   0.0524725  0.0048279   10.869  < 2e-16 ***
L(oil_vol_log, 2)   0.0052546  0.0035415    1.484 0.137977    
gold_vol_log       -0.0512059  0.0037945  -13.495  < 2e-16 ***
L(gold_vol_log, 1)  0.0631057  0.0050911   12.395  < 2e-16 ***
L(gold_vol_log, 2) -0.0127647  0.0037984   -3.361 0.000786 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.01178 on 3484 degrees of freedom
Multiple R-squared:  0.9993,	Adjusted R-squared:  0.9993 
F-statistic: 4.659e+05 on 11 and 3484 DF,  p-value: < 2.2e-16
```

Figure 4.4: Summary of the model

We notice an extremely high R^2, which is a clear sign of overfitting, meaning that our model describes very well the data we have but is not flexible enough to be applied with new observations. This is caused by the presence of the one-time lagged Log(SP500), in fact its beta is much bigger than the other variables' estimates. Moreover, we arrived to the same conclusion by simply creating an autoregressive model of order one, with just log(SP500) as response and its one-time lag as regressor, which still has a R^2 of around 0.99, essentially proving the other variables to be useless.

Nearly all variables are significative and autocorrelation problem is solved thanks to the addition of lag, as confirmed by DW test. Even in this case, BP test's results lead us to heteroscedasticity.

4.4. Fourth Model: ARDL with response variable as differences

Finally, we continued to apply the "auto_ardl" function but using the differences of log(SP500) as the response variable, trying to obtain a more reasonable model, again minimizing the AIC.

$$\begin{aligned}\Delta\texttt{log(SP500)}_i = {} & \beta_0 + \beta_1\Delta\texttt{log(oil)}_i + \beta_2\Delta\texttt{log(gold)}_i + \beta_3\texttt{log(gold\_vol)}_i + \beta_4\texttt{log(oil\_vol)}_i \\ & + \beta_5\texttt{L}(\Delta\texttt{log(SP500)}, 1)_i + \beta_6\texttt{L}(\Delta\texttt{log(gold)}, 1)_i + \beta_7\texttt{L}(\Delta\texttt{log(gold)}, 2)_i \\ & + \beta_8\texttt{L}(\Delta\texttt{log(gold)}, 3)_i + \beta_9\texttt{L}(\texttt{log(gold\_vol)}, 1)_i + \beta_{10}\texttt{L}(\texttt{log(oil\_vol)}, 1)_i \\ & + \beta_{11}\texttt{L}(\texttt{log(oil\_vol)}, 2)_i + \epsilon_i\end{aligned}$$

4.4.1. Summary of the model and comments

```
Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)         0.004381   0.002057   2.130 0.033272 *
L(d_SP_log, 1)     -0.183479   0.016142 -11.366  < 2e-16 ***
d_oil_log           0.060987   0.006977   8.742  < 2e-16 ***
d_gold_log         -0.054489   0.017639  -3.089 0.002023 **
L(d_gold_log, 1)    0.030692   0.017403   1.764 0.077885 .
L(d_gold_log, 2)    0.065938   0.017388   3.792 0.000152 ***
L(d_gold_log, 3)    0.054187   0.017403   3.114 0.001863 **
oil_vol_log        -0.058409   0.003529 -16.549  < 2e-16 ***
L(oil_vol_log, 1)   0.041959   0.004819   8.707  < 2e-16 ***
L(oil_vol_log, 2)   0.015760   0.003565   4.421 1.01e-05 ***
gold_vol_log       -0.052384   0.003711 -14.116  < 2e-16 ***
L(gold_vol_log, 1)  0.051850   0.003713  13.963  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.01157 on 3483 degrees of freedom
Multiple R-squared:  0.2132,    Adjusted R-squared:  0.2107
F-statistic: 85.78 on 11 and 3483 DF,  p-value: < 2.2e-16
```

Figure 4.5: Summary of the model

We obtain an acceptable value of R^2, especially considering the complexity of our setting. All the variables are significative, except for d_gold_log at time t-1, and most of them have a positive influence on the response since their betas are greater than zero. On the other hand, an increment of one unit of the response at time t-1 (L(d_SP_log,1)), corresponds to a decrease of 0.18 in our response. Since the DW test's p-value is equal to 0.601, this last model does not have autocorrelation.

After running the usual BP test, our heteroscedasticity problem still remains and, in order to understand more about it, we decided to look at the Residuals vs Fitted plot.

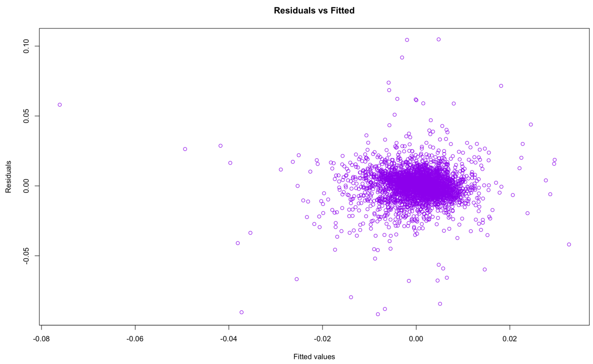

Figure 4.6: Cloud of the residuals of the model

As we can see from the graph the cloud does not present any particular pattern and most of our observations are concentrated with the exception of some outliers. At the end of the day, we can say that the homoscedasticity assumption can be considered respected for our model. This analysis was conducted only on this model since it is the one we will use for our final considerations and inferences.

5 | Conclusions

Oil and gold prices, as well as price volatility, have a significant impact on US economic and financial activities.

On the US SP500 stock market price index, this paper analyzed the relationship between oil price, gold price, gold price volatility index, and oil price volatility index.

Testing different models, we arrived at the conclusion that differences in the price and volatilities of the given commodities influence the market differently depending on whether one analyzes current or historical values.

In particular, positive changes in volatilities and gold price have a present negative effect on the response of the market, while lagged values lead to concordant variations of the SP index. Moreover, oil has always a positive correlation with the market.

The extension of this study, considering the low-medium level of explicated variability of the final model ($R^2 = 0.21$), could be to investigate which other factors may improve the explication of the evolution of the market. Eventually, one could also look at the impact of the mentioned variables on each of the SP500 stock market sectors, such as industry, energy, and transportation, to come up with a very comprehensive and useful policy recommendation.

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