BitCoin Price VAR Forecast Using Main Driving Factors and Ethereum

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Abstract

The recent news about the dropping price of BitCoins has drawn lots of attention from the public. As the most popular digital currency in the world, BitCoins have attracted many of the investors or general public to invest their money. Also knowing that some economists are criticizing the high bubble existing in the digital currencies, I then started to exam the what are the potential significant main factors in determine the future price value of the BitCoins. This paper contributed to this discussion by using the VAR model and the selected factors to forecast the future price of BitCoins. The main influential factors include not only the macro-economy factors but also the characteristic factors correlated with the BitCoin itself. Besides those, I examined the correlation between the BitCoin price and the Ethereum (another popular digital currency) related data, which is new to the referenced papers.

Keywords

BitCoin, Ethereum, Gold, Dow Jones

Introduction

As most popular and widely used digital currency in the world, BitCoin has attracted the attention of many of the investors. Looking back to 2017, BitCoin has increased its price in an unbelievable way from 996.16 USD per BitCoin to 17,060.55 USD per BitCoin. After reaching it's peak at the end of the 2017, BitCoin rapidly dropped it's price to 3,847.03 USD within one year. And it is still dropping in a fast speed at the end of 2018 as shown in Graph 1. A currency with such a large price volatility is not usual and attracts people's attention. And such price behavior has suggested that there must be some special factors which is different from the traditional currencies that determine the price of the BitCoin.

Many researchers have already studied the main drivers of BitCoin or BitCoin price formation. In the paper "What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis" Ladislav Kristoufek (2015), he has performed Wavelet Coherence Analysis to test the correlation between the individual factors with the Bitcoin Price. And he found that the transaction, supply, hash rate and searching record on the internet (interest or attractiveness of Bitcoin), financial stress index and gold price are correlated with the Bitcoin Price. But He looked at the correlation between the factors and Bitcoin Price individually. But There can be interaction among the factors themselves. When looking at the impact of the multiple factors simultaneously, the results can be different and no longer be true.

In the paper of "The economics of BitCoin Price formation", Ciaian, rajcaniova and Kancs are the researchers first ever considering both the traditional determinants of currency prices such as market force (demand and supply) and digital currency-specific factors, for example attractiveness, along with the global macroeconomic, financial development and the interactions.

In this paper, I examined the correlation between the BitCoin price and the Ethereum (the second most popular digital currency) related data. Considering the economic theory of substitutional good and complementary good, the relation between BitCoin and Ethereum then becomes suspicious. And also, the previous study found that the BitCoin price is correlated with some of the stock index. Those data are traded during Monday to Friday in a repeated way. So, I also included a seasonality effect into the forecast model. Those are new extensions compared to the referenced papers.

Model

The model I used to forecast the future BitCoin price was an extended standard VAR model. In order to inspect any time trend and seasonality effects in the data, I included a trend term and seasonality term into the model:

$$\mathrm{y_t} = \alpha + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \beta_0 t + \beta_1 s_1 + \beta_2 s_2 + \beta_3 s_3 + \beta_4 s_4 + \epsilon_t$$

where p is the optimal lag of the VAR model, and alpha is a constant term, s_1, s_2, s_3, s_4 represent the seasonality effect of Monday to Thursday compared to Friday. t is the time trend. And $\mathrm{y_t}$ is the 13 by 1 vectors, and each element of the vector contains all the historical 834 data points from 2015-08-10 to 2018-11-30, excluding the weekend:

$$y_t = (y_{t_{Btc}}, y_{t_{eth}}, y_{t_{add}}, y_{t_{cny-usd}}, y_{t_{diff}}, y_{t_{dow}}, y_{t_{gold}}, y_{t_{harsh}}, y_{t_{revenue}}, y_{t_{total}}, y_{t_{trans}}, y_{t_{bview}}, y_{t_{eview}})$$

Where y_t is the vector of the return data base on the daily level:

$y_{t_{Btc}}$ is the time series of the price value of BitCoin in USD/BitCoin.

$y_{t_{eth}}$ is the time series of the price value of Ethereum in USD/Ethereum.

$y_{t_{add}}$ is the time series of the number of the unique BitCoin addresses used per day.

$y_{t_{cny-usd}}$ is the time series of the exchange rate of CNY/USD.

$y_{t_{diff}}$ is the time series of the mining difficulty (a measure of how difficult it is to find a hash below a given target).

$y_{t_{dow}}$ is the time series of Dow Jones index.

$y_{t_{gold}}$ is the time series of the price of the gold in USD.

$y_{t_{harsh}}$ is the time series of the harsh rate.

$y_{t_{revenue}}$ is the time series of the total miner revenue in USD.

$y_{t_{total}}$ is the time series of the total number of BitCoin been mined in the pool.

$y_{t_{trans}}$ is the time series of the total transaction volume in USD.

$y_{t_{bview}}$ is the time series of volume of daily BitCoin views on Wikipedia.

$y_{t_{eview}}$ is the time series of volume of daily Ethereum views on Wikipedia.

And each ϕ_j is a 13 by 13 matrix for j = 1, …, p, representing the coefficients of the past lags. I also included the second largest digital coin --- Ethereum to detect the potential influence of it to BitCoin. I expect that there can be some correlation between them. And they can be in a relation of either complementary, supplementary or even neutral. I suspect the views of BitCoin and Ethereum, so does some macro-economy factors like gold price and Dow Jones index can influence the price of the digital coins as former researchers suspected. And the rest of the regressors of the model are the related characteristics of the BitCoin itself that were tested for having a significant relationship with BitCoin in the previous literatures.

Data and Empirical Analysis

Data

For traditional determinants of the currencies, I followed a similarly approach as Ciaian et al (2016) suggested in the paper: In order to capture the price relationship driven by the market forces of BitCoin supply and demand, I used total number of BitCoins been mined to represent the total amount of

BitCoin in the market, which is the supply quantity of BitCoin. Then I used number of unique BitCoin transaction per day and number of unique BitCoin addresses used per day to track the information of market size. In addition to his method, also common in most of the financial markets that the volume of the transaction plays an important rule. So, the volume of transaction per day of BitCoin was also included in the model.

Besides that, Kristoufek also suggested that the BitCoin price is correlated with some macro-financial data. While Ciaian et al followed van Wijk (2013) choosing oil price and Dow Jones Index for analyzing, I chose Dow Jones stock index and gold price. To measure the price level of global economy, Ciaian et al used exchange rate between USD and Euro extracted from Federal Reserve System. However, I decided to use the exchange rate between the Chinese Yuan CNY and US dollar USD. The reason was that I was analyzing the data from end of the 2015 to end of the 2018. And China had become the second largest economy compared to US in the world. And recent political and economical event about trade war and new policies of US against China may let the exchange rate between USD and CNY play a more significant role in suggesting global economy level. Due to using the BitCoin prices I used is measured in USD, the value of USD may strongly influence the BitCoin price. And suggested by Ciaian et al (2016), the appreciation of USD against foreign currency may also lead to appreciation of USD against BitCoin and Ethereum. And Kristoufek (2013) suggested that the attractiveness of BitCoin had strong correlation with the price, I chose volumes of daily BitCoin views and Ethereum views on Wikipedia. However, the Google searches of BitCoin and Ethereum are not available in a daily level, so I didn't use them.

There are also some other types of digital currencies compared to BitCoin, for example, BitCoin Cash. However, most of them are just been invented within one year or even within three months to December 2018. Using such kinds of digital currencies may not give us enough degree of freedom. And the price of Ethereum is available from July the 2015. Three years data should leave enough degree of freedom for us. So, in order to capture the effect among the different currencies on their prices, I decided to use Ethereum.

All the data above were extracted from quandl.com, except for the exchange rate between USD and CNY was from Federal Reserve System.

In order to perform the multiple time series forecast at the same scale, I cleaned the data to get rid of the weekends, since digital currency markets opens 7 days a week while stock markets open only from Monday to Friday. The starting date of the data is from August 10th, 2015 to November 30th, 2018. Since I was using VAR model, the coefficient matrices should take care of the interaction of my other potential influential factors of BitCoin. And For each time series in y_t, I performed Ordinary Least Square to estimate the coefficient matrices.

Empirical Analysis

Data Transformation

I first transformed all the data to continuous compounded return by taking the log for the data and then difference once. By doing such we should expect the data now are stationary, and BitCoin and Ehtereum returns are shown in Gragh 2. By performing ADF tests, all the return data are stationary at a confidence level of 90%.

Model Selection with Granger Causality Test

Then, using OLS estimation, I first ran 13 regressions for each of my return data in $\mathrm{y_t}$. Basing on AIC and HQ these two information criteria, the optimal lag value was 5 from both of them.

$$\mathrm{y_t} = (y_{t_{Btc}}, y_{t_{eth}}, y_{t_{add}}, y_{t_{cny-usd}}, y_{t_{diff}}, y_{t_{dow}}, y_{t_{gold}}, y_{t_{harsh}}, y_{t_{revenue}}, y_{t_{total}}, y_{t_{trans}}, y_{t_{bview}}, y_{t_{eview}})$$

$$\widehat{y_t}' = \widehat{\phi_1} y'_{t-1} + \cdots + \widehat{\phi_6} y'_{t-6} - 0.001794t + 3.862s_1$$
$$+0.1486s_2 + 0.05879s_3 - 0.5399s_4 \qquad (1)$$

The detailed estimation results of the return of BitCoin were summarized in the R Output 1.

As we can see from the R Output 1 that many of the regressors in the model we specified above does not have significant impact on the return of BitCoin. So, I did the Granger Causality Test for each of the regressors if Granger Cause the other 12 variables in the model. The null hypothesis is the regressor that we are testing do not Granger-Cause all the other variables. Then I delete the regressor whose p-value is the biggest and greater than 0.2 in Grander Causality Tests on after one. Repeating the above steps, I found the re-estimated results are as follows with the optimal lag of 6:

$$\mathrm{y_t} = (y_{t_{Btc}}, y_{t_{eth}}, y_{t_{add}}, y_{t_{dow}}, y_{t_{gold}}, y_{t_{harsh}}, y_{t_{revenue}}, y_{t_{total}}, y_{t_{trans}}, y_{t_{eview}})$$

$$\widehat{y_t}' = 1.807 + \widehat{\phi_1} y'_{t-1} + \cdots + \widehat{\phi_6} y'_{t-6} + 0.001809t +$$
$$0.1705s_1 + 0.1278s_2 + 0.04961s_3 + 0.6623s_4 \qquad (2)$$

The detailed estimation results of the return of BitCoin are summarized in the R Ouput 2.

Now at the 80% confidence level, $y_{t_{eth}}, y_{t_{add}}, y_{t_{dow}}, y_{t_{harsh}}, y_{t_{revenue}}, y_{t_{total}}, y_{t_{trans}}$ and $y_{t_{eview}}$ all Grander - Cause the other regressors. However, under the null hypothesis that the deterministic term of the model is 0, the constant, trend and seasonality terms were still redundant judging from the p-value of the t-test. I, then, selected the best model by subtracting any of the constant, trend and seasonality term whose p-value was bigger than 0.2 one by one, starting from a VAR model without constant term first. Finally, keeping an 80% confidence level on the Granger – Causality Tests, the best model I finally obtained didn’t have any constant or deterministic term:

$$\mathrm{y_t} = (y_{t_{Btc}}, y_{t_{eth}}, y_{t_{add}}, y_{t_{dow}}, y_{t_{gold}}, y_{t_{harsh}}, y_{t_{revenue}}, y_{t_{total}}, y_{t_{trans}}, y_{t_{eview}})$$

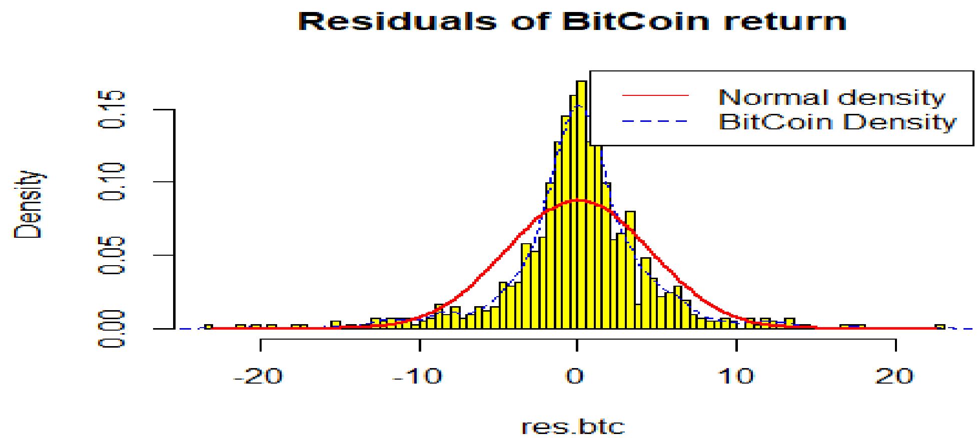
$$\widehat{y_t}' = \widehat{\phi_1} y'_{t-1} + \cdots + \widehat{\phi_6} y'_{t-6} \qquad (3)$$

And the estimated parameters were summarized in R Output 3.

Normality Test

However, the normality assumption on the residuals of the VAR model doesn’t seem to be a good assumption.

```
##  Jarque Bera Test
##
## data:  res.btc H0: The residuals do not follow a Normal Distribution.
## X-squared = 728.34, df = 2, p-value < 2.2e-16, Fails H0.
```



I performed Jarque-Bera Test on the residuals of the model (3), and it failed the null hypothesis that the residuals of the regression of BitCoin return are following a normal distribution.

I found the skewness of the residuals of BitCoin return is -0.41, which means that residuals are almost symmetric but a little bit left skewed. And the kurtosis of BitCoin return is 7.51, which is way bigger than the kurtosis of a normal distribution which is 3. Residuals are quite centred around 0.

But that may not be a big problem, if the forecast ability of the model is not influenced.

Parameters Analysis

Despite above, I still found that there are some results quite interesting:

According to R Output 3, first of all, I found the return, or we call the log different, of Ethereum, unique address used per day, Dow Jones, gold, harsh rate, miner revenue, total BitCoin been mined, total transaction of BitCoin per day and views of Ethereum on Wikipedia all Granger – Cause the return of BitCoin.

As I clarified before, since I got rid of the data points on the weekend, the trading days or the lags we will consider about are only from Monday to Friday.

Bearing that in mind, the results show that, at 90% confidence level, most of the significant impacts of the factors on the BitCoin return happens at the lag of 3 and 6, except for return of Dow Jones Index has a significant positive marginal impact on the BitCoin return at lag of 1:

An unit increase of return of Dow Jones Index 1 trading day before will increase the today's return of BitCoin by 0.02 at a confidence level of 98%.

Ethereum most of the time behaves as a substitutional goods to BitCoin, since it has negative coefficients at lag 1,2,4,5,6. However, at the lag of 3, which is 3 trading days before, it has a 0.055 positive marginal impact on the BitCoin return at a confidence level of 98%. But at the lag of 6, it has a (-0.04862) negative marginal impact on the BitCoin return at a confidence level of 97%.

Miner Revenue also plays an important role in influencing the BitCoin return. An unit increase of miner revenue 3 trading days before will increase the return of BitCoin by 0.1 at a confidence level of 97%.

An unit increase of BitCoin return itself 3 trading days ago will have a (-0.1119) negative impact on today's BitCoin return at a confidence level of 95%.

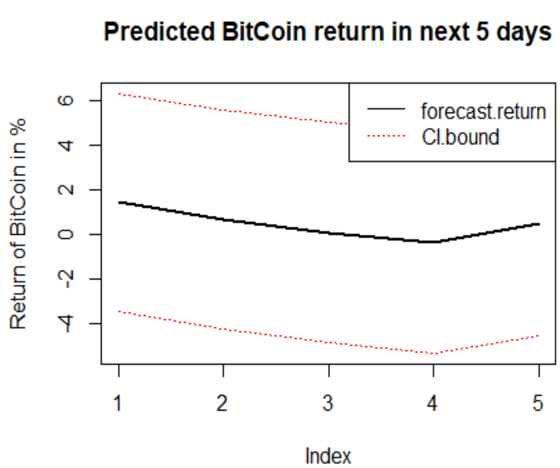
And an unit increase of harsh rate return 3 trading days ago also has a (-0.075) negative impact on today's BitCoin return at a confidence level of 91%.

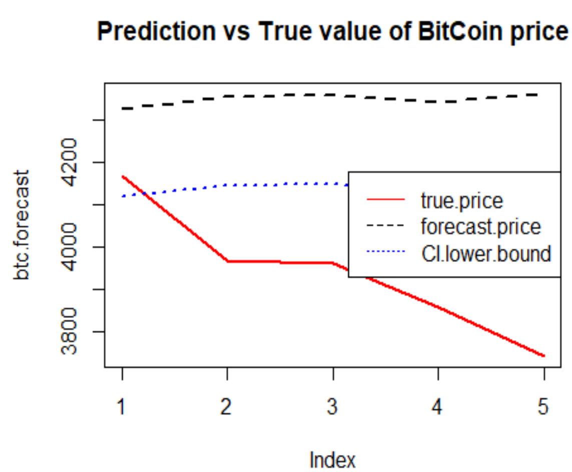
Looking at the influential factors 6 trading days ago, the unit increase of gold return will increase the return of BitCoin by 0.375 at a confidence level of 92%.

Except for Ethereum, the return of views of Ethereum that statised from Wikipedia and unique BitCoin mining address used per day 6 trading days ago also have negative impacts on BitCoin return today: An unit increase of views of Ethereum will decrease BitCoin return by (-0.01853) at a confidence level of 95%. And a unit increase of the address used 6 trading days ago will decrease today's BitCoin return by (-0.04862) at a confidence level of 91%.

Forecasting

The forecasted returns and price values are shown below:





The forecasting results were derived using rolling window method. I did a 5-day forecast on a confidence level of 70%. We can see that the forecasted returns are close to zero. We should also expect that the mean of the forecasted BitCoin prices should also remain in an approximate same level. However, I observed a downward trend of the true BiCoin price from December 2nd, 2018 to December

7th, 2018. And the trend is too strong that drops outside the confidence interval. This may suggest that there are some other factors that the model haven't included in. But noticing the one step ahead forecast draws a fine estimate, which may suggest us to forecast the tomorrow's price by re-estimate the model everytime we get a new data point if using this model.

Conclusion and Future Research

In this paper, I have used the extended VAR model to forecast the BitCoin price. I found the factors usually have a significant impact on the BitCoin return at lag 3 and 6, except for the Dow Jones Index have a significant positive impact at lag of 1. Ethereum price at most of the lags moves in a opposite direction compared to BitCoin price. The rise in the return of Ethereum can have a negative effect on return of BitCoin. But the significance of this finding is not strong. Minor revenue and gold price have significant positive impact on BitCoin return at lag of 3 and 6 correspondingly. And the rest of the factors have a significant impact at lag 3 or 6 either positively or negatively.

The forecast result is only reasonable 1 step ahead the present. From the forecasted result, we expect the returns are around zero. However, recently the true returns are much less than zero leading the true BitCoin price decreasing rapidly. This recent behavior of BitCoin return is quite different from the historical data whose residuals are centred around 0. There must be some other factors that the model doesn't include while determine the BitCoin price crucially. And researchers should keep finding the potential significant factors that formalize the BitCoin price.

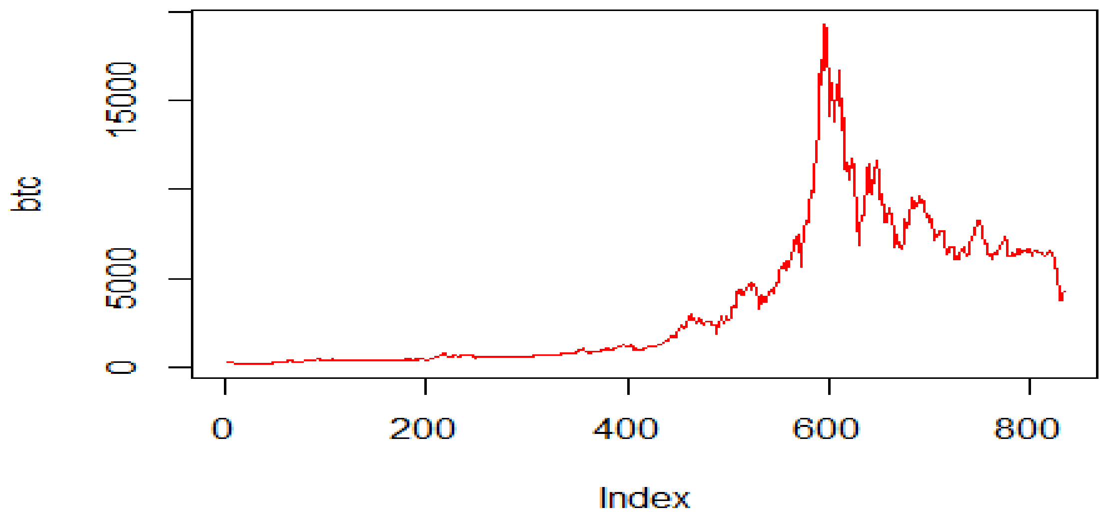
References

Ladislav Kristoufek, 2015. What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis. PLos ONE 10(4): e0123923. doi: 10.1371/journal.pone.0123923.

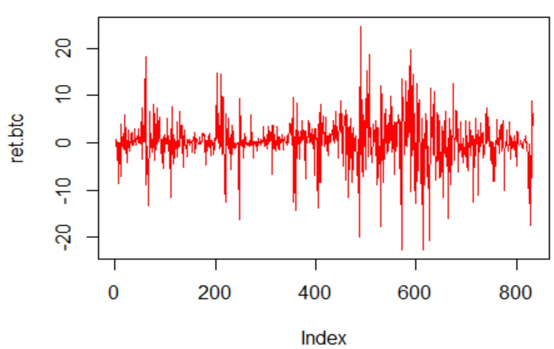
Ciaian P., Rajcaniova M.& Kancs A(2016). The economics of BitCoin price formation, Applied Economics, 48:19, 1799-1815, DOI: 10.1080/00036846.2015.1109038.

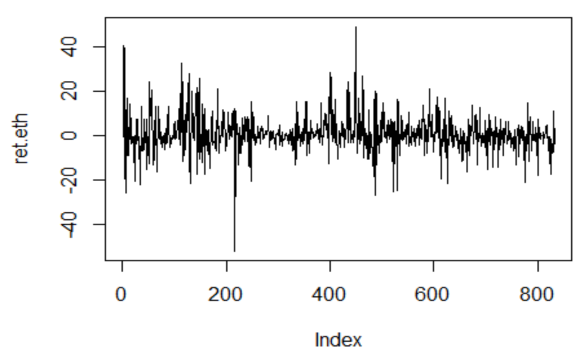
Appendix

Graph 1



Graph 2





R Output 1

```
## Residuals:
##      Min       1Q   Median       3Q      Max 
## -22.7590  -1.7135   0.1442   2.0244  20.6499 
## 
## Coefficients:
##                           Estimate Std. Error t value Pr(>|t|)   
## ret.btc.l1               2.363e-02  5.633e-02   0.420  0.67495   
## ret.eth.l1              -8.716e-03  2.355e-02  -0.370  0.71141   
## ret.address.l1           1.321e-02  2.050e-02   0.644  0.51953   
## ret.cny_usd.l1           4.537e-01  8.255e-01   0.550  0.58275   
## ret.difficulty.l1       -1.549e-01  8.235e-02  -1.881  0.06030 . 
## ret.dow_jones.l1         2.074e-02  7.917e-03   2.619  0.00898 **
## ret.gold.l1              1.463e-01  2.289e-01   0.639  0.52282   
## ret.harsh_rate.l1        3.083e-02  4.192e-02   0.735  0.46226   
## ret.revenue.l1          -1.515e-02  4.408e-02  -0.344  0.73117   
## ret.total_btc.l1        -1.440e+01  3.391e+01  -0.425  0.67129   
## ret.total_transaction.l1  2.473e+00  4.582e+00   0.540  0.58954   
## ret.views_btc.l1         8.873e-03  8.377e-03   1.059  0.28985   
## ret.views_eth.l1         4.060e-03  9.088e-03   0.447  0.65519   
## ret.btc.l2               4.465e-02  5.845e-02   0.764  0.44515   
## ret.eth.l2              -1.665e-03  2.339e-02  -0.071  0.94326   
## ret.address.l2           3.723e-02  2.404e-02   1.549  0.12181   
## ret.cny_usd.l2           8.751e-01  8.193e-01   1.068  0.28579   
## ret.difficulty.l2       -1.216e-02  8.229e-02  -0.148  0.88252   
## ret.dow_jones.l2        -5.047e-03  8.025e-03  -0.629  0.52963   
## ret.gold.l2             -3.387e-02  2.280e-01  -0.149  0.88192   
## ret.harsh_rate.l2        3.041e-02  4.552e-02   0.668  0.50436   
## ret.revenue.l2          -2.564e-02  4.623e-02  -0.555  0.57929   
## ret.total_btc.l2        -6.968e+00  3.314e+01  -0.210  0.83352   
## ret.total_transaction.l2  9.183e-01  4.494e+00   0.204  0.83813   
## ret.views_btc.l2         2.734e-04  8.718e-03   0.031  0.97499   
## ret.views_eth.l2         3.978e-03  9.399e-03   0.423  0.67222   
## ret.btc.l3              -7.632e-02  6.047e-02  -1.262  0.20728   
## ret.eth.l3               4.981e-02  2.335e-02   2.133  0.03322 * 
## ret.address.l3           1.924e-02  2.493e-02   0.772  0.44055   
## ret.cny_usd.l3          -6.809e-01  8.164e-01  -0.834  0.40452   
## ret.difficulty.l3        6.086e-02  8.246e-02   0.738  0.46073   
## ret.dow_jones.l3        -3.355e-03  8.054e-03  -0.417  0.67715   
## ret.gold.l3             -8.607e-02  2.278e-01  -0.378  0.70563   
## ret.harsh_rate.l3       -4.344e-02  4.654e-02  -0.933  0.35096   
## ret.revenue.l3           7.587e-02  4.711e-02   1.610  0.10771   
## ret.total_btc.l3        -4.950e+01  3.294e+01  -1.503  0.13330   
## ret.total_transaction.l3  2.307e+00  4.443e+00   0.519  0.60378   
## ret.views_btc.l3         3.652e-03  8.783e-03   0.416  0.67767   
## ret.views_eth.l3         7.864e-03  9.413e-03   0.835  0.40377   
## ret.btc.l4               3.834e-02  6.021e-02   0.637  0.52454   
```

```
## ret.eth.l4               -2.328e-02  2.319e-02  -1.004  0.31564
## ret.address.l4            1.427e-02  2.366e-02   0.603  0.54653
## ret.cny_usd.l4           -1.195e-01  8.060e-01  -0.148  0.88220
## ret.difficulty.l4         7.816e-02  7.978e-02   0.980  0.32756
## ret.dow_jones.l4          3.959e-03  8.009e-03   0.494  0.62124
## ret.gold.l4              -1.219e-01  2.272e-01  -0.537  0.59165
## ret.harsh_rate.l4         5.088e-02  4.637e-02   1.097  0.27291
## ret.revenue.l4           -1.354e-03  4.663e-02  -0.029  0.97685
## ret.total_btc.l4          5.150e+00  3.314e+01   0.155  0.87654
## ret.total_transaction.l4 -1.352e+00  4.441e+00  -0.305  0.76083
## ret.views_btc.l4          3.545e-03  8.701e-03   0.407  0.68378
## ret.views_eth.l4          2.370e-03  9.417e-03   0.252  0.80134
## ret.btc.l5               -5.403e-02  5.882e-02  -0.919  0.35855
## ret.eth.l5                3.676e-03  2.283e-02   0.161  0.87210
## ret.address.l5            2.423e-03  1.999e-02   0.121  0.90356
## ret.cny_usd.l5            7.978e-02  7.684e-01   0.104  0.91733
## ret.difficulty.l5         2.118e-02  7.668e-02   0.276  0.78247
## ret.dow_jones.l5          2.110e-03  7.939e-03   0.266  0.79051
## ret.gold.l5              -6.807e-02  2.236e-01  -0.304  0.76086
## ret.harsh_rate.l5        -6.910e-03  4.480e-02  -0.154  0.87748
## ret.revenue.l5            3.520e-02  4.544e-02   0.775  0.43875
## ret.total_btc.l5          3.707e+01  3.406e+01   1.088  0.27673
## ret.total_transaction.l5 -5.345e+00  4.547e+00  -1.176  0.24013
## ret.views_btc.l5          2.426e-03  8.393e-03   0.289  0.77264
## ret.views_eth.l5         -2.900e-03  9.292e-03  -0.312  0.75502
## const                     1.840e+00  1.699e+00   1.083  0.27921
## trend                    -1.794e-03  1.580e-03  -1.136  0.25634
## sd1                       3.862e-01  5.478e-01   0.705  0.48099
## sd2                       1.486e-01  5.502e-01   0.270  0.78723
## sd3                       5.879e-02  5.502e-01   0.107  0.91495
## sd4                      -5.399e-01  5.496e-01  -0.982  0.32619
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.753 on 757 degrees of freedom
## Multiple R-squared:  0.06564,    Adjusted R-squared:  -0.02076
## F-statistic: 0.7597 on 70 and 757 DF,  p-value: 0.9261
```

R Output 2

```
## Call:
## lm(formula = y ~ -1 + ., data = datamat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -23.1802  -1.6392   0.0931   1.9496  22.4356
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## ret.btc.l1                 1.628e-02  5.569e-02   0.292   0.7701
## ret.eth.l1                -9.700e-03  2.343e-02  -0.414   0.6790
## ret.address.l1             1.838e-02  2.135e-02   0.861   0.3895
## ret.dow_jones.l1           1.994e-02  7.843e-03   2.543   0.0112 *
## ret.gold.l1                1.014e-01  2.114e-01   0.480   0.6317
## ret.harsh_rate.l1          1.046e-02  4.111e-02   0.255   0.7991
## ret.revenue.l1            -9.318e-04  4.342e-02  -0.021   0.9829
## ret.total_btc.l1           1.679e+00  4.601e+01   0.036   0.9709
## ret.total_transaction.l1  1.526e+00  6.053e+00   0.252   0.8010
## ret.views_eth.l1           3.618e-03  8.938e-03   0.405   0.6857
## ret.btc.l2                 2.669e-02  5.679e-02   0.470   0.6385
## ret.eth.l2                -4.522e-03  2.358e-02  -0.192   0.8480
## ret.address.l2             3.314e-02  2.566e-02   1.291   0.1970
## ret.dow_jones.l2          -3.717e-03  7.917e-03  -0.470   0.6388
## ret.gold.l2               -1.774e-01  2.116e-01  -0.838   0.4021
## ret.harsh_rate.l2          2.448e-03  4.346e-02   0.056   0.9551
## ret.revenue.l2            -2.451e-03  4.495e-02  -0.055   0.9565
## ret.total_btc.l2          -1.039e+01  3.368e+01  -0.309   0.7578
## ret.total_transaction.l2  2.157e+00  4.584e+00   0.471   0.6380
## ret.views_eth.l2           5.204e-03  9.023e-03   0.577   0.5642
## ret.btc.l3                -1.047e-01  5.658e-02  -1.851   0.0646 .
## ret.eth.l3                 5.436e-02  2.311e-02   2.352   0.0189 *
## ret.address.l3             1.770e-02  2.729e-02   0.649   0.5167
## ret.dow_jones.l3          -2.417e-04  7.863e-03  -0.031   0.9755
## ret.gold.l3               -7.293e-03  2.111e-01  -0.035   0.9724
## ret.harsh_rate.l3         -6.988e-02  4.385e-02  -1.594   0.1114
## ret.revenue.l3             9.844e-02  4.363e-02   2.256   0.0243 *
## ret.total_btc.l3          -4.099e+01  3.280e+01  -1.250   0.2118
## ret.total_transaction.l3  1.935e+00  4.438e+00   0.436   0.6629
## ret.views_eth.l3           4.549e-03  9.125e-03   0.499   0.6183
## ret.btc.l4                 5.244e-02  5.697e-02   0.920   0.3576
## ret.eth.l4                -1.998e-02  2.323e-02  -0.860   0.3899
## ret.address.l4             6.242e-03  2.681e-02   0.233   0.8160
## ret.dow_jones.l4           5.043e-03  7.819e-03   0.645   0.5192
## ret.gold.l4               -1.477e-01  2.111e-01  -0.699   0.4845
## ret.harsh_rate.l4          5.530e-02  4.371e-02   1.265   0.2063
## ret.revenue.l4            -6.621e-03  4.371e-02  -0.151   0.8796
## ret.total_btc.l4          -2.504e+00  3.271e+01  -0.077   0.9390
## ret.total_transaction.l4 -1.042e+00  4.401e+00  -0.237   0.8130
## ret.views_eth.l4           8.254e-04  9.144e-03   0.090   0.9281
## ret.btc.l5                -4.363e-02  5.653e-02  -0.772   0.4404
```

```
## ret.eth.l5                1.056e-02  2.313e-02   0.457   0.6481
## ret.address.l5           -1.081e-02  2.531e-02  -0.427   0.6694
## ret.dow_jones.l5          5.307e-04  7.808e-03   0.068   0.9458
## ret.gold.l5              -1.881e-02  2.103e-01  -0.089   0.9287
## ret.harsh_rate.l5         1.507e-03  4.342e-02   0.035   0.9723
## ret.revenue.l5            2.774e-02  4.307e-02   0.644   0.5197
## ret.total_btc.l5          3.500e+01  3.367e+01   1.039   0.2989
## ret.total_transaction.l5 -5.872e+00  4.503e+00  -1.304   0.1926
## ret.views_eth.l5         -6.159e-03  9.118e-03  -0.675   0.4996
## ret.btc.l6                9.132e-03  5.556e-02   0.164   0.8695
## ret.eth.l6               -4.878e-02  2.256e-02  -2.162   0.0309 *
## ret.address.l6           -3.395e-02  1.991e-02  -1.706   0.0885 .
## ret.dow_jones.l6          5.703e-03  7.772e-03   0.734   0.4633
## ret.gold.l6               3.825e-01  2.097e-01   1.824   0.0686 .
## ret.harsh_rate.l6        -1.055e-02  4.210e-02  -0.251   0.8022
## ret.revenue.l6            2.244e-02  4.211e-02   0.533   0.5942
## ret.total_btc.l6         -1.876e+01  4.565e+01  -0.411   0.6811
## ret.total_transaction.l6  1.743e+00  6.002e+00   0.290   0.7716
## ret.views_eth.l6         -1.813e-02  9.145e-03  -1.982   0.0478 *
## const                     1.798e+00  1.757e+00   1.024   0.3063
## trend                    -1.791e-03  1.615e-03  -1.109   0.2679
## sd1                       1.720e-01  5.502e-01   0.313   0.7547
## sd2                       1.600e-01  5.478e-01   0.292   0.7703
## sd3                      -9.482e-02  5.478e-01  -0.173   0.8626
## sd4                      -6.655e-01  5.457e-01  -1.220   0.2230
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.715 on 761 degrees of freedom
## Multiple R-squared:  0.07567,    Adjusted R-squared:  -0.003282
## F-statistic: 0.9584 on 65 and 761 DF,  p-value: 0.5711
```

R Output 3

```
## Residuals:
```

```
##      Min       1Q   Median       3Q      Max 
## -23.0122  -1.7135   0.0936   1.9036  22.8144 
## 
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)  
## ret.btc.l1                 1.713e-02  5.551e-02   0.309   0.7577  
## ret.eth.l1                -1.108e-02  2.325e-02  -0.477   0.6338  
## ret.address.l1             1.973e-02  2.117e-02   0.932   0.3517  
## ret.dow_jones.l1           1.905e-02  7.800e-03   2.442   0.0148 *
## ret.gold.l1                7.357e-02  2.102e-01   0.350   0.7265  
## ret.harsh_rate.l1          7.933e-03  4.091e-02   0.194   0.8463  
## ret.revenue.l1             8.683e-04  4.325e-02   0.020   0.9840  
## ret.total_btc.l1          -2.106e+00  4.585e+01  -0.046   0.9634  
## ret.total_transaction.l1  2.866e+00  6.004e+00   0.477   0.6332  
## ret.views_eth.l1           2.961e-03  8.886e-03   0.333   0.7391  
## ret.btc.l2                 2.132e-02  5.661e-02   0.377   0.7066  
## ret.eth.l2                -2.798e-03  2.339e-02  -0.120   0.9048  
## ret.address.l2             3.514e-02  2.547e-02   1.380   0.1680  
## ret.dow_jones.l2          -4.199e-03  7.872e-03  -0.533   0.5939  
## ret.gold.l2               -1.896e-01  2.106e-01  -0.900   0.3682  
## ret.harsh_rate.l2         -2.162e-03  4.326e-02  -0.050   0.9602  
## ret.revenue.l2             1.637e-04  4.483e-02   0.004   0.9971  
## ret.total_btc.l2          -8.503e+00  3.329e+01  -0.255   0.7985  
## ret.total_transaction.l2  3.349e+00  4.439e+00   0.754   0.4509  
## ret.views_eth.l2           4.579e-03  8.988e-03   0.509   0.6106  
## ret.btc.l3                -1.119e-01  5.634e-02  -1.985   0.0475 *
## ret.eth.l3                 5.501e-02  2.293e-02   2.399   0.0167 *
## ret.address.l3             2.169e-02  2.709e-02   0.800   0.4237  
## ret.dow_jones.l3           3.428e-04  7.819e-03   0.044   0.9650  
## ret.gold.l3                4.773e-03  2.102e-01   0.023   0.9819  
## ret.harsh_rate.l3         -7.515e-02  4.368e-02  -1.720   0.0858 .
## ret.revenue.l3             1.004e-01  4.351e-02   2.307   0.0213 *
## ret.total_btc.l3          -3.152e+01  3.236e+01  -0.974   0.3303  
## ret.total_transaction.l3  2.106e+00  4.297e+00   0.490   0.6242  
## ret.views_eth.l3           3.447e-03  9.093e-03   0.379   0.7047  
## ret.btc.l4                 5.180e-02  5.670e-02   0.914   0.3612  
## ret.eth.l4                -1.994e-02  2.304e-02  -0.865   0.3871  
## ret.address.l4             1.043e-02  2.669e-02   0.391   0.6962  
## ret.dow_jones.l4           5.274e-03  7.782e-03   0.678   0.4982  
## ret.gold.l4               -1.527e-01  2.102e-01  -0.726   0.4679  
## ret.harsh_rate.l4          5.250e-02  4.356e-02   1.205   0.2285  
## ret.revenue.l4            -7.721e-03  4.359e-02  -0.177   0.8595  
## ret.total_btc.l4           4.754e+00  3.222e+01   0.148   0.8828  
## ret.total_transaction.l4 -8.823e-01  4.279e+00  -0.206   0.8367  
## ret.views_eth.l4           5.639e-04  9.112e-03   0.062   0.9507  
## ret.btc.l5                -4.013e-02  5.630e-02  -0.713   0.4762  
```

```
## ret.eth.l5                  7.590e-03  2.299e-02   0.330   0.7414
## ret.address.l5             -1.166e-02  2.523e-02  -0.462   0.6442
## ret.dow_jones.l5           -5.036e-04  7.768e-03  -0.065   0.9483
## ret.gold.l5                -2.720e-02  2.095e-01  -0.130   0.8967
## ret.harsh_rate.l5           8.201e-04  4.326e-02   0.019   0.9849
## ret.revenue.l5              2.846e-02  4.295e-02   0.663   0.5078
## ret.total_btc.l5            3.589e+01  3.323e+01   1.080   0.2805
## ret.total_transaction.l5 -5.260e+00  4.392e+00  -1.198   0.2314
## ret.views_eth.l5           -6.227e-03  9.091e-03  -0.685   0.4936
## ret.btc.l6                  9.378e-03  5.538e-02   0.169   0.8656
## ret.eth.l6                 -4.862e-02  2.244e-02  -2.166   0.0306 *
## ret.address.l6             -3.409e-02  1.980e-02  -1.722   0.0855 .
## ret.dow_jones.l6            4.722e-03  7.732e-03   0.611   0.5415
## ret.gold.l6                 3.750e-01  2.092e-01   1.792   0.0735 .
## ret.harsh_rate.l6          -1.055e-02  4.197e-02  -0.251   0.8016
## ret.revenue.l6              2.171e-02  4.194e-02   0.518   0.6049
## ret.total_btc.l6           -2.087e+01  4.547e+01  -0.459   0.6464
## ret.total_transaction.l6  2.470e+00  5.971e+00   0.414   0.6792
## ret.views_eth.l6           -1.853e-02  9.107e-03  -2.035   0.0422 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.71 on 767 degrees of freedom
## Multiple R-squared:  0.07512,    Adjusted R-squared:  0.002771
## F-statistic: 1.038 on 60 and 767 DF,  p-value: 0.4001
```

Granger Causality Test

```
##  Granger causality H0: ret.eth do not Granger-cause ret.btc
##  ret.address ret.dow_jones ret.gold ret.harsh_rate ret.revenue
##  ret.total_btc ret.total_transaction ret.views_eth
##
## data:  VAR object ret.btc_VAR4.2.2
## F-Test = 1.7568, df1 = 54, df2 = 7670, p-value = 0.0005294
```

```
##  Granger causality H0: ret.address do not Granger-cause ret.btc
##  ret.eth ret.dow_jones ret.gold ret.harsh_rate ret.revenue
##  ret.total_btc ret.total_transaction ret.views_eth
##
## data:  VAR object ret.btc_VAR4.2.2
## F-Test = 2.036, df1 = 54, df2 = 7670, p-value = 1.199e-05
```

```
##  Granger causality H0: ret.dow_jones do not Granger-cause ret.btc
##  ret.eth ret.address ret.gold ret.harsh_rate ret.revenue
```

```
##  ret.total_btc ret.total_transaction ret.views_eth
##
## data:  VAR object ret.btc_VAR4.2.2
## F-Test = 1.4003, df1 = 54, df2 = 7670, p-value = 0.02827


##  Granger causality H0: ret.gold do not Granger-cause ret.btc
##  ret.eth ret.address ret.dow_jones ret.harsh_rate ret.revenue
##  ret.total_btc ret.total_transaction ret.views_eth
##
## data:  VAR object ret.btc_VAR4.2.2
## F-Test = 1.1884, df1 = 54, df2 = 7670, p-value = 0.163


##  Granger causality H0: ret.harsh_rate do not Granger-cause ret.btc
##  ret.eth ret.address ret.dow_jones ret.gold ret.revenue
##  ret.total_btc ret.total_transaction ret.views_eth
##
## data:  VAR object ret.btc_VAR4.2.2
## F-Test = 2.6892, df1 = 54, df2 = 7670, p-value = 3.605e-10


##  Granger causality H0: ret.revenue do not Granger-cause ret.btc
##  ret.eth ret.address ret.dow_jones ret.gold ret.harsh_rate
##  ret.total_btc ret.total_transaction ret.views_eth
##
## data:  VAR object ret.btc_VAR4.2.2
## F-Test = 2.2368, df1 = 54, df2 = 7670, p-value = 5.954e-07


##  Granger causality H0: ret.total_btc do not Granger-cause ret.btc
##  ret.eth ret.address ret.dow_jones ret.gold ret.harsh_rate
##  ret.revenue ret.total_transaction ret.views_eth
##
## data:  VAR object ret.btc_VAR4.2.2
## F-Test = 1.1542, df1 = 54, df2 = 7670, p-value = 0.2052


##  Granger causality H0: ret.total_transaction do not Granger-cause
##  ret.btc ret.eth ret.address ret.dow_jones ret.gold ret.harsh_rate
##  ret.revenue ret.total_btc ret.views_eth
##
## data:  VAR object ret.btc_VAR4.2.2
## F-Test = 1.3634, df1 = 54, df2 = 7670, p-value = 0.03984


##  Granger causality H0: ret.views_eth do not Granger-cause ret.btc
##  ret.eth ret.address ret.dow_jones ret.gold ret.harsh_rate
##  ret.revenue ret.total_btc ret.total_transaction
##
```

```
## data:  VAR object ret.btc_VAR4.2.2
## F-Test = 1.6525, df1 = 54, df2 = 7670, p-value = 0.001899
```