The Rise of Chinese Cryptocurrency: Measuring Event Driven Returns Due to Information Disclosure

J.P. Janko

April 23, 2020

Introduction

With the recent advances of fintech and lack of physical backing of fiat currencies, the notion of a global digital currency has drawn considerable attention. Although the idea of a cryptocurrency has almost become ubiquitous in the global lexicon, few heads of states have publicly stated support of blockchain technology and regulation of the trading of the numerous existing cryptocurrencies remains in a nascent stage. The fight over digital sovereignty remains important for governments, investors, and academics alike as the adoption has major implications on the capital flows of every country as well as illicit money laundering. This paper will attempt to add to the little existing financial literature in the cryptocurrency domain through investigation of the changes of asset returns in NEO, a Chinese cryptocurrency, relative to other major cryptocurrencies through a case study of a policy statement event.

In a departure from many major heads of state on October 25, 2019, Xi Jinping, the President of the Peoples Republic of China, stated We must take the blockchain as an important breakthrough for independent innovation of core technologies even though the trading of cryptocurrency remains banned in China. In addition, he added We must clarify the main direction, increase investment, focus on a number of key core technologies, and accelerate the development of blockchain technology and industrial innovation. The statements made to the Political Bureau of the Central Committee were interpreted by many news sources as a strong indication of possible Chinese acceptance of cryptocurrencies and blockchain, especially as DCEP (Digital Currency Electronic Payment) nears completion and the country looks to compete with Facebook's Libra. The cryptocurrency NEO, also known as the "Chinese ethereum", is likely to most benefit from the adoption of cryptocurrency by China as it used by Alibaba and Microsoft in China for payments. In the below sections we investigate the incorporation of Xi Jinping's statement into the price of the cryptocurrency through the regression version of the difference in difference technique to measure whether statements on blockchain technology policy in China affected NEO's investment performance relative to other cryptocurrencies, as it is the only coin that is Chinese regulatory compliant.

Data

Python was the language of choice for this analysis. To investigate the above event, my proprietary trading data was downloaded from the author's local server cluster. Data for the following cryptocurrencies: NEO, BTC, ETH, XRP, LTC, XMR were downloaded from 2019-09-15 to 2019-12-04 which is 40 days before and after the event. The particular cryptocurrencies were chosen due to their large market capitalization, which could mitigate the effects of exogenous market manipulation events like "pump and dumps", which are known to occur in many altcoins. Using daily average closing prices from multiple exchanges, cumulative returns time series were constructed for each crypto asset. We calculate the cumulative return of underlying asset i via the following methodology:

$$cr_i = \sum_{t=1}^{n} P_{t+1}/P_t - 1$$

where P refers to the price at time t and cr is the cumlative return

Please see the plot below for a plot the cumlative returns of each time series over the period of interest.

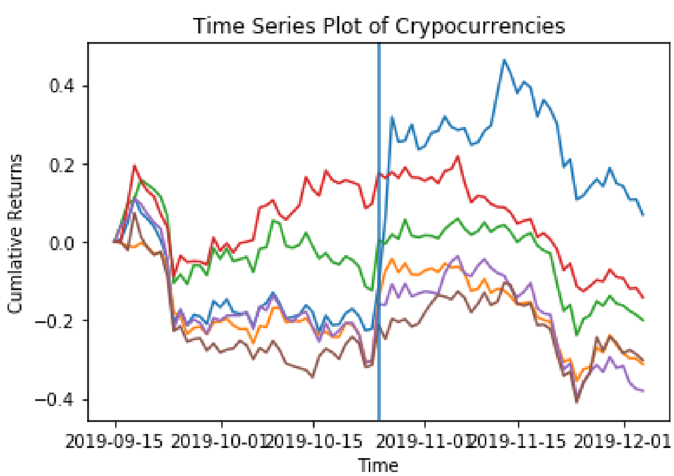


Figure 1: Plot of Cumlative Returns

The individual plots of the z-scores of daily returns over the same time period is constructed to give visual indication that the news on October 25th was an abnormal event. Please note the z-scores were calculated on a insample basis.

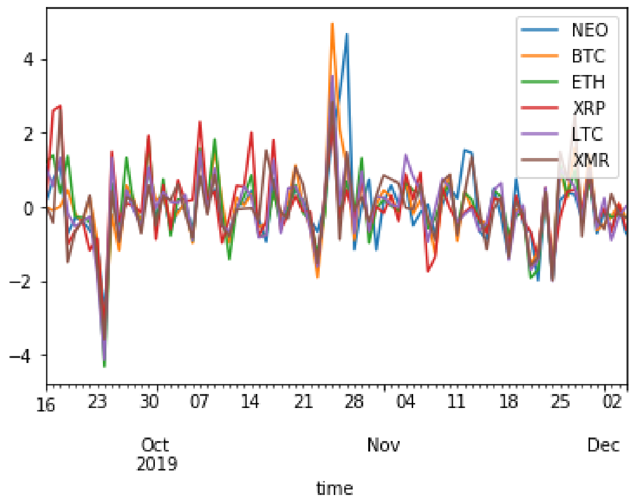


Figure 2: Plot of Z-Score of Daily Returns

time	NEO	BTC	ETH	XRP	LTC	XMR
2019-10-25	1.967057	4.948902	3.353507	2.210548	3.53667	2.822284

Figure 3: Z-Score of Daily Returns on October 25th, 2019

Please see below for a subset of the cumlative return time series for each cryptocurrency.

time	NEO	BTC	ETH	XRP	LTC	XMR
2019-09-15	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
2019-09-16	0.006725	-0.003998	0.044335	0.002684	0.040211	-0.001457
2019-09-17	0.048670	-0.011121	0.096048	0.095992	0.058580	-0.021492
2019-09-18	0.113417	-0.014577	0.108220	0.193928	0.108923	0.073417
2019-09-19	0.074227	-0.003001	0.158890	0.154744	0.096620	0.013321
...	...	...	...	...	...	...
2019-11-30	0.148530	-0.263390	-0.157421	-0.090021	-0.321950	-0.258254
2019-12-01	0.141267	-0.283364	-0.162748	-0.093115	-0.316673	-0.284957
2019-12-02	0.107589	-0.296785	-0.176172	-0.119280	-0.358873	-0.275438
2019-12-03	0.107812	-0.297782	-0.186493	-0.117913	-0.375313	-0.286716
2019-12-04	0.068181	-0.312257	-0.199970	-0.142015	-0.379325	-0.301675

Figure 4: Cumlative Returns DataFrame Subset

Clearly from figure 1, one could hypothesize October 25th was a positive event as cumulative returns spiked on the day of interest. Furthermore, from simple visual inspection, it is easy to see that NEO was a major underperformer relative to the basket of securities before the event, however, after the policy statement, there was a significant performance as investors changed their valuations of the cryptocurrency. NEO was the only positive performer with a cumulative return of 6.8% at the end of the time series. There seems to be a large variance between the performance of each crypto asset indicating that the use of a synthetic control may be needed to meet the parallel trend identification assumption.

Methodology and Results

As already mentioned above, to measure whether NEO changed significantly with the incorporation of this information disclosure relative to other cryptocurrencies, we will use a quasi-experimental approach called difference in difference. By evaluating the data on a daily time frame we will be able to implement a difference in difference where we assume all traders and investors have knowledge of the news event and therefore treatment is not dynamic. It would be safe to assume that major investors would have access to the policy statement within the day, especially since when we live in the day of algorithms trading on machine-readable newsfeeds. Furthermore, we use daily data to reduce noise that would be seen in high-frequency data. Please note that the data source did not have intraday data for NEO at that point in the day and would like to investigate intraday effects in the future.

Obviously, over a long time period changes in idiosyncratic risk due to other events such as COVID change the performance of NEO relative to other digital cryptocurrencies. We hope to mitigate this risk through the use of a smaller time frame of analysis and visual inspection of other possible shocks within the time series and news related headlines during the period. To make sure the event did not induce any compositional changes in market microstructure we were careful to make sure there were no new listings on exchanges through a textual search of news headlines.

We will attempt to estimate the linear conditional expectation function in order to measure the degree of treatment effect. A linear form is consistent with what is found in typical financial academic literature. In line with Angrist's Mostly Harmless Economics (p. 174) we let the regression difference in difference equation follow:

$$Y_{ist} = \alpha + \gamma * t/c_s + \lambda * post_t + \beta * (post * t/c)_{it} + \epsilon_{it}$$

Y_{ist} in the above equation is the outcome variable. Let t/c_s be a dummy variable that is 1 for observations where the symbol of panel data is equal to the treated variable, NEO, and 0 otherwise. $post_t$ is a time dummy that represents the time before and after Xi Jinping's statements on blockchain. ϵ is a stochastic error term. $post_t * t/c_s$ represents the interaction term that is the treatment effect.

We will also investigate the use of a synthetic control group of BTC, ETH, XRP, LTC, XMR to serve as a good counterfactual for post-treatment outcomes that would have been observed for the treated unit in the absence of treatment. This is a saturated model since the conditional mean function $E(Y_{ist}$ takes on the four possible values and parameters. The estimated coefficients from the regression equation have the following interpretation.

$$\alpha = E(Y_{ist}|s = control, t = before)$$

$$\gamma = E(Y_{ist}|s = NEO, t = before) - E(Y_{ist}|s = control, t = before)$$

$$\lambda = E(Y_{ist}|s = control, t = after) - E(Y_{ist}|s = control, t = before)$$

$$\beta = \{E(Y_{ist}|s = NEO, t = after) - E(Y_{ist}|s = NEO, t = before)\} -$$

$$\{E(Y_{ist}|s = control, t = after) - E(Y_{ist}|s = control, t = before)\}$$

To find the optimal weighted average of units of the donor pool, a minimization of the MSE is performed in the pre-treatment period to create a synthetic control which resembles the characteristics of the NEO cryptocurrency. Please note that forming on the control on matching the SSR was done, however, the results changed very little. Similar to Abadie et al (2010), the weights are constrained to be nonegative as well as the weights of control must be equal to one. The minimization algorithm in the scipy package used is a sequential least squares programming algorithm which incorporates the HanPowell quasiNewton method from Kraft (1988). The initial weights assumed in the algorithm were equal weighted.

To help determine whether the synthetic control serves an adequate counterfactual we will employ cross validation in the pre-treatment period with a k-folds algorithm. Approximately 50% of the pre treatment time series was used for the training set with other half used for validation. This is used to make sure the identifying assumption of parallel trends is met. Please see below for output of minimization weights.

```
{'BTC': 0.24867442824567448,
 'ETH': 0.14397259677139704,
 'XRP': 0.07989040365750838,
 'LTC': 0.24250314185876004,
 'XMR': 0.28495942946666014}
```

The insample MSE is 0.0002244, while the out of sample is 0.0003053. Clearly, the insample data set matched the NEO time series pre MSE / post MSE of .73. Graphically it would appear that pre-treatment trajectory of NEO is matched well and the parallel trends assumption is met.

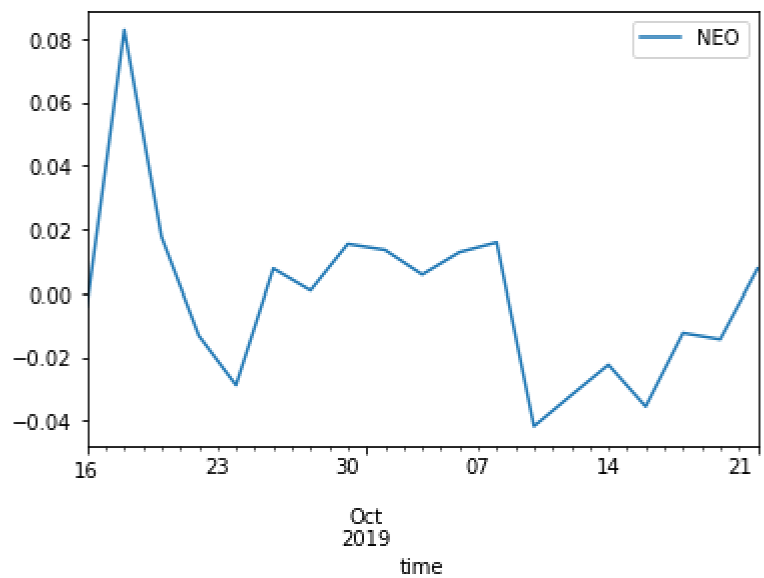


Figure 5: Plot of residual of Validation Set

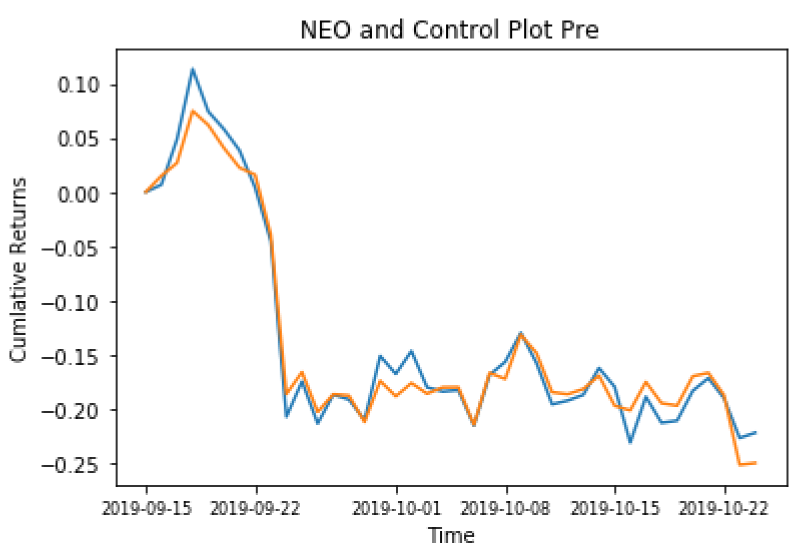


Figure 6: Plot of Control and NEO Time Series Pre-Treatment

After testing the pre-treatment period we will use the weights on the post-treatment to form a full control time series. Please see below for output plots.

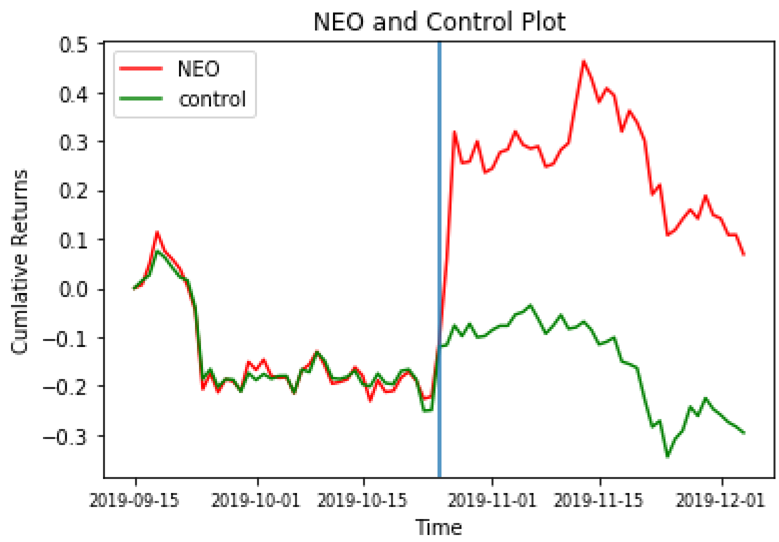


Figure 7:

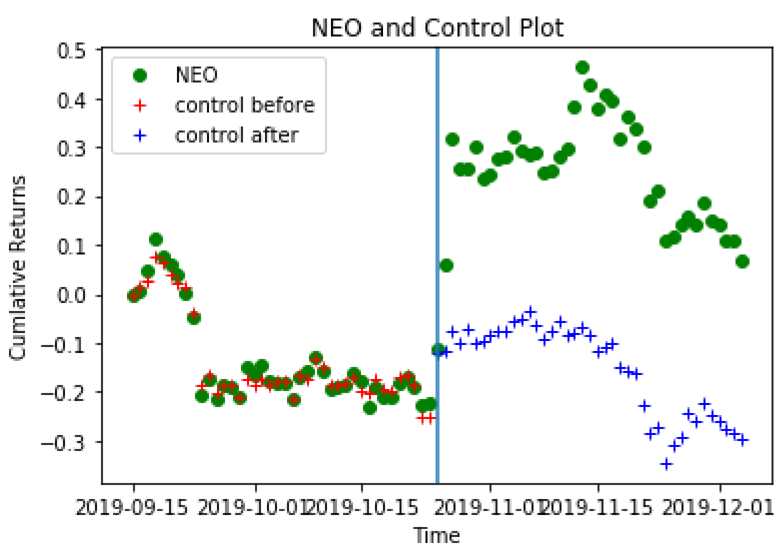


Figure 8:

The regression output of the above implementation is outputted below. In addition, we run the above methodology over different time bandwiths to prove the results to be robust rather overfitting an optimal bandwith window.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                returns   R-squared:                       0.734
Model:                            OLS   Adj. R-squared:                  0.729
Method:                 Least Squares   F-statistic:                     145.6
Date:                Sun, 19 Apr 2020   Prob (F-statistic):           2.91e-45
Time:                        14:24:31   Log-Likelihood:                 133.58
No. Observations:                 162   AIC:                            -259.2
Df Residuals:                     158   BIC:                            -246.8
Df Model:                           3
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
constant       -0.1374      0.017     -8.092      0.000      -0.171      -0.104
t/c             0.0008      0.024      0.033      0.973      -0.047       0.048
post           -0.0619      0.024     -2.591      0.010      -0.109      -0.015
interaction     0.4417      0.034     13.084      0.000       0.375       0.508
==============================================================================
Omnibus:                        0.244   Durbin-Watson:                   0.299
Prob(Omnibus):                  0.885   Jarque-Bera (JB):                0.367
Skew:                           0.080   Prob(JB):                        0.832
Kurtosis:                       2.830   Cond. No.                         6.89
==============================================================================
```

Figure 9: 'Regression Results with 40 day window length'

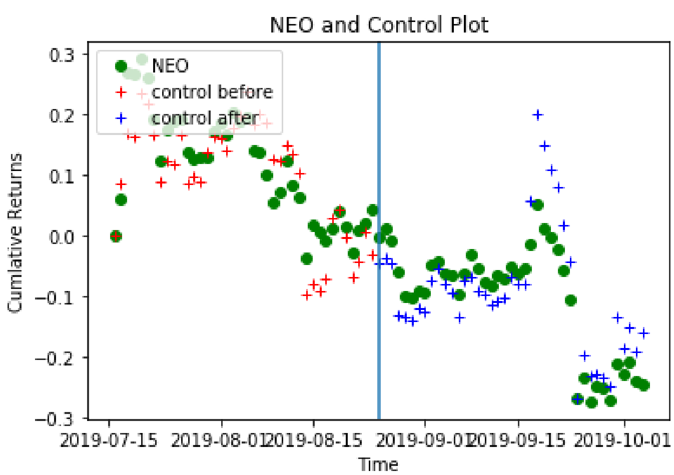
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                returns   R-squared:                       0.903
Model:                            OLS   Adj. R-squared:                  0.899
Method:                 Least Squares   F-statistic:                     241.4
Date:                Mon, 20 Apr 2020   Prob (F-statistic):           2.26e-39
Time:                        19:56:32   Log-Likelihood:                 111.61
No. Observations:                  82   AIC:                            -215.2
Df Residuals:                      78   BIC:                            -205.6
Df Model:                           3
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
constant       -0.0071      0.014     -0.501      0.618      -0.035       0.021
t/c             0.0015      0.020      0.077      0.939      -0.039       0.042
post            0.1031      0.020      5.188      0.000       0.064       0.143
interaction     0.3537      0.028     12.583      0.000       0.298       0.410
==============================================================================
Omnibus:                       78.589   Durbin-Watson:                   0.907
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1168.640
Skew:                          -2.634   Prob(JB):                    1.71e-254
Kurtosis:                      20.728   Cond. No.                         6.93
==============================================================================
```

Figure 10: 'Regression Results with 20 day window length'

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                returns   R-squared:                       0.873
Model:                            OLS   Adj. R-squared:                  0.863
Method:                 Least Squares   F-statistic:                     86.74
Date:                Sun, 19 Apr 2020   Prob (F-statistic):           4.70e-17
Time:                        14:29:29   Log-Likelihood:                 54.363
No. Observations:                  42   AIC:                            -100.7
Df Residuals:                      38   BIC:                            -93.77
Df Model:                           3
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
constant       -0.0195      0.022     -0.884      0.382      -0.064       0.025
t/c            -0.0026      0.031     -0.084      0.933      -0.066       0.060
post            0.1201      0.030      3.944      0.000       0.058       0.182
interaction     0.3023      0.043      7.017      0.000       0.215       0.390
==============================================================================
Omnibus:                       55.525   Durbin-Watson:                   1.198
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              373.963
Skew:                          -3.138   Prob(JB):                     6.24e-82
Kurtosis:                      16.202   Cond. No.                         7.01
==============================================================================
```

Figure 11: 'Regression Results with 10 day window length'

The interaction term of the regression is very significant with a p-value of 0.0 and t-stat of over 13 at 40 day window length give us belief that the treatment is signficant. The results are similar for different time window bandwidths making the interpretation robust. Furthermore I will run a placebo test where I repeat the same process but on August 25, 2019 as the cutoff date. The following results were obtained. As expected the interaction term did not have a strong t-stat value (-.938) and a p-value of .35. There is evidence from this analysis that Xi's statements had a strong positive effect on NEO relative to other major cryptocurrencies.



OLS Regression Results

Dep. Variable:	returns	R-squared:	0.532
Model:	OLS	Adj. R-squared:	0.523
Method:	Least Squares	F-statistic:	59.90
Date:	Sun, 19 Apr 2020	Prob (F-statistic):	6.44e-26
Time:	15:46:38	Log-Likelihood:	151.97
No. Observations:	162	AIC:	-295.9
Df Residuals:	158	BIC:	-283.6
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
constant	0.0952	0.015	6.279	0.000	0.065	0.125
t/c	0.0176	0.021	0.819	0.414	-0.025	0.060
post	-0.1873	0.021	-8.791	0.000	-0.229	-0.145
interaction	-0.0283	0.030	-0.938	0.350	-0.088	0.031

Omnibus:	0.279	Durbin-Watson:	0.334
Prob(Omnibus):	0.870	Jarque-Bera (JB):	0.441
Skew:	-0.023	Prob(JB):	0.802
Kurtosis:	2.748	Cond. No.	6.89

Criticisms of the Research Design and Further Research Potential

The largest criticism of the above model is that there exists confounding factors which explain the increase NEO's performance relative to the synthetic control. Mathematically this can be represented by

$$Y_{ist} = \alpha + \gamma * t/c_s + \lambda * post_t + \beta * (post_t * t/c_s) + X_{it}' * \nu + \epsilon_{it}$$

where X_{it} represents the individual level characteristics as well as other state variables. Many of these factors are not observable, which is considered the standard omitted variable bias problem. There obviously could be unobserved things that could of have caused the change in price. An example of this may be the classic pumps and dump scheme, which is where someone induces momentum ignition in a security by inducing buying or selling pressure. Many of these trades occur on OTC markets or secret chatrooms on encrypted communication sources. Unfortunately, I do not have OTC and chatroom data going back that far to investigate this particular case, however, I hope to do research on this topic in the future and have begun recording such data. For example consider an email that I received from a Chicago broker on March 12, 2020. As you can see from the intraday graph below that this was significantly higher than the current price at the time and that BTC continued to increase in value for the rest of the day. Something similar may have occurred on October 25th, 2019 in NEO which may have caused misspecification the intervention event of study.

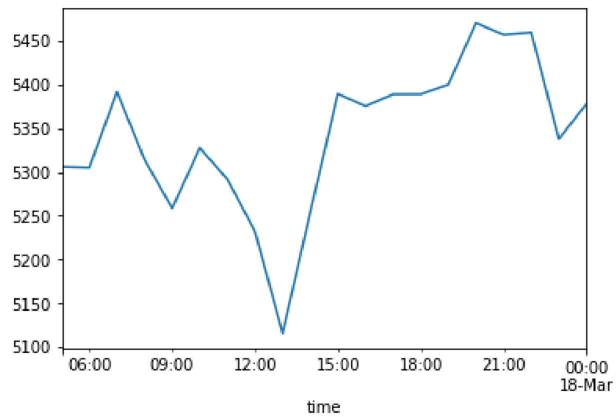


Figure 12:

Besides OTC events, many other factors such as liquidity, size effects due to NEO being an altcoin, increased market fragmentation, non-divisibility of the coin and changes in mining supply would need to be further investigated. Liquidity factors and size effects could be easily controlled for in the regression equation as they are not endogenously defined, which means we are not "over-controlling". The effect of market fragmentation on NEO's performance would need to measure from an instrumental variables approach. For example, one could measure market fragmentation in cryptocurrency through 2SLS. Let the number of exchanges listing be an exogenous instrument to shock firm-level fragmentation. Due to the exclusion restriction principle we must assume the decision to list an exchange is not due to asset level characteristics but only market fragmentation. Thus,

$$fragmentation_{it} = \psi + \eta(\#Exchanges)_t + Controls_{it} + \nu_{it}$$

$$y_{it+1} = \alpha + \beta * fragmentation_{it} + Controls_{it} + \epsilon_{it+1}$$

In addition to the effects above, one may also ask why the research design did not include HFT data. At the time of this event, I did not have access to that type of data in NEO. I believe the above results could be made much stronger by considering intraday changes. I could source this data from former coworkets in industry. A dynamic treatment design may be needed due to the diffusion of news into the prices occurring at different rates due to market participants having different execution capabilities. Looking at this change in policy on a longer time scale does reflect that the textual news does have a long term effect on fundamentals.

One can easily make the argument that the above research could be overfitting. I would tend to agree with this assessment and I am currently building a database of policy statements/social media feeds to build a better understanding of textual sentiment's effects on cryptocurrency performance.

It is self evident that this exact type of research analysis is not exactly the most interesting result in the world, however, there is massive potential to apply this methodology to large number events systematically to answer more interesting questions that contribute to empirical asset literature. In addition, I chose a project like this so that I could have actual results and use my own alternative data source which is not readily available on normal venues like WRDS. In general, there is a disconnect between academics who tend to study asset returns in equilibrium vs practitioners who tend to be more concerned with asset return behavior in the temporal vicinity of events, as handling discontinuities has the largest effect on excess alpha and risk management. It may be an interesting approach to define sentiment from text mining through an event driven approach, which reflects the inherent nature of market makers and traders. You could define events of interests by identifying large discontinuities due to news announcements and running diff in diff tests to confirm significance. Although there exists a growing body of literature on defining sentiment dictionary as in Loughran (2011) there is a lack of research in dictionaries relative to specific sectors of investment such as cryptocurrency. Events like the one studied above may give evidence to that specific need and answer much more important research questions in the search for anomalies in empirical asset pricing.

Code

Listing 1: Python Code used for paper. Please not data methods are omitted

```
# -*- coding: utf-8 -*-
"""
Created on Tue Feb 20 10:04:07 2020

@author: jjandso
"""

import pandas as pd
import numpy as np
from statsmodels import regression
import matplotlib.pyplot as plt
import datetime
from scipy.optimize import minimize


def get_data(symbol):

        #put you server logic to grab data

    return df

def clean_data(df):

    df['returns'] = np.log(df['close']) - np.log(df['close'].shift(1))
    df['vol'] = df['volumeto'] - df['volumefrom']

    df['liquidity'] = df['returns'] / df['vol']

    return df[1:]

def get_between_dates(df, before, after):
    df =df.loc[df.index <= after ]
    df =df.loc[df.index >= before ]
    return df

def k_folds(indices, K):

    for k_fold in range(K):

        training = []
        validation = []

        for i,x in enumerate(indices):
            if i % K != k_fold:
                training.append(x)
            if i % K == k_fold:
                validation.append(x)

    return training, validation

def sum_constraint(inputs):
```

```
    total = 1.0 - np.sum(inputs)
    return total

def minimization_mse(weights,y,x):
    weights = weights / np.sum(weights)
    return np.mean(((y.values-(x * weights).sum(axis=1))**2).values)



if __name__ == "__main__":


    symbols = ['NEO','BTC', 'ETH','XRP','LTC','XMR']

    data_dict = {}

    for x in symbols:
        data_dict[x] = get_data(x)
        data_dict[x] = clean_data(data_dict[x])



    df = pd.DataFrame()
    plot_df = pd.DataFrame()
    #define the inputs
    date_of_interest = pd.Timestamp(2019, 10, 25)
    window = 20

    control_symbols = symbols[1:]
    interest = symbols[0]


    for x in symbols:

        returns = pd.DataFrame(get_between_dates(data_dict[x]['close'],date_of_interest -
\
                        datetime.timedelta(days = window),date_of_interest + \
                        datetime.timedelta(days = window)).sort_index().pct_change().resample('1D'
        volume = pd.DataFrame(get_between_dates(data_dict[x]['vol'],date_of_interest -
\
                            datetime.timedelta(days = window),date_of_interest + \
                                datetime.timedelta(days = window)).sort_index())
        r = returns.copy()
        r.columns = [x]
        returns.columns = ['returns']
        returns['symbol'] = x
        returns['volume'] = volume

        if len(df) == 0:
            df = returns.copy()
            plot_df = r.copy()
        else:
            df=pd.concat([df, returns], axis = 0)
            plot_df = pd.concat([plot_df, r], axis = 1)
    """
    plt.plot(plot_df)
    plt.axvline(x=date_of_interest)
```

```
plt.xlabel('Time')
plt.ylabel('Cumlative Returns')
plt.xticks(fontsize=8)
plt.title('Time Series Plot of Crypocurrencies')
plt.show()
"""

df_copy = df.copy()

z = (((plot_df - plot_df.shift(1))[1:] - (plot_df - plot_df.shift(1))[1:].mean()) \
     / (plot_df - plot_df.shift(1))[1:].std())
"""
z.plot()
"""

z_day = z.loc[z.index == date_of_interest]

controls = {}
for x in symbols:
    controls[x] = df_copy.loc[df_copy['symbol'] == x, 'returns']
controls = pd.DataFrame.from_dict(controls)
pre =  controls.loc[controls.index < date_of_interest - datetime.timedelta(days = 1)]
training, validation = k_folds(pre.index, 2)
training_set = pre.loc[pre.index.isin(training)]
validation_set = pre.loc[pre.index.isin(validation)]


x = pre[control_symbols]
y = pre[interest]

#initially guess equal weights
weights_0 = []
bound_list = []
for i in range(len(x.columns)):
    weights_0.append(1.0/len(x.columns))
    bound_list.append((0.0,1.0))


my_constraints = ({'type': 'eq', "fun": sum_constraint })

result = minimize(minimization_mse, weights_0, method='SLSQP',args = (y,x),bounds=\
                  bound_list,options={'disp': True},constraints=my_constraints)

i = 0
weights_output = {}
for x in control_symbols:
    weights_output[x] = result.x[i]
    i = i +1

out_of_sample = (validation_set[control_symbols] * result.x).sum(axis=1)
out_of_sample.columns = ['NEO']
out_of_sample_mse = minimization_mse(result.x,validation_set[interest],\
                                      validation_set[control_symbols])
validation_resid = validation_set[[interest]] - out_of_sample
print(result.fun / out_of_sample_mse)

iterate = 0
```

```
controls['control'] = 0.0
for x in control_symbols:
    controls['control'] = controls[x] * result.x[iterate] + controls['control']
    iterate = iterate + 1
controls[['control', interest]].plot()

df = pd.DataFrame()
#create a synthetic control column
for x in ['control', interest]:
    returns = pd.DataFrame(controls[x])
    returns.columns = ['returns']
    returns['symbol'] = x

    if len(df) == 0:
        df = returns.copy()
    else:
        df=pd.concat([df, returns], axis = 0)

df['constant'] = 1.0
df['t/c'] = 0
df.loc[df['symbol'] == interest,'t/c'] = 1.0
df['post'] = 0.0
df.loc[df.index >= date_of_interest, 'post'] = 1.
df['date'] = df.index
df = df.reset_index()
df = df.drop(labels = 'time', axis  = 1)
date_dummies = pd.get_dummies(df['date'])
df['interaction'] = df['t/c'] * df['post']

model = regression.linear_model.OLS(df['returns'], \
            pd.concat([df[['constant','t/c', 'post', 'interaction']]], axis =1 ))
results = model.fit()
print(results.summary())


NEO = df.loc[df['symbol']=='NEO'][['returns',\'date']]
NEO_before = df.loc[(df['symbol']=='NEO') & \ (df['date']<date_of_interest)]\
[['returns','date']]
control_before = df.loc[(df['symbol']=='control') &\ (df['date']<date_of_interest)]\
[['returns','date']]\
control_after = df.loc[(df['symbol']=='control') &\ (df['date']>=date_of_interest)]
[['returns','date']]\



#plt.axvline(date_of_interest, 0, .5, label='pyplot vertical line')
"""
#plots the returns before
plt.plot(NEO_before['date'], NEO_before['returns'])
plt.plot(control_before['date'], control_before['returns'])
plt.xticks(fontsize=8)
plt.xlabel('Time')
plt.ylabel('Cumlative Returns')
plt.title('NEO and Control Plot Pre')
"""

"""
```

```
#plots the returns fully
plt.plot(controls['NEO'], 'r',label = 'NEO')
plt.plot(controls['control'], 'g',label = 'control')
plt.xticks(fontsize=8)
plt.xlabel('Time')
plt.axvline(x=date_of_interest)
plt.ylabel('Cumlative Returns')
plt.legend()
plt.title('NEO and Control Plot')
plt.show()
"""
plt.plot(NEO['date'], NEO['returns'],'go',label='NEO')
plt.plot(control_before['date'], control_before['returns'],'r+',label='control_before')
plt.plot(control_after['date'], control_after['returns'],'b+',label='control_after')
plt.legend(loc="upper left")
plt.axvline(x=date_of_interest)
plt.xlabel('Time')
plt.ylabel('Cumlative Returns')
plt.title('NEO and Control Plot')
plt.show()
```

References

[1] Alberto Abadie, Alexis Diamond & Jens Hainmueller (2010) Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of Californias Tobacco Control Program, Journal of the American Statistical Association, 105:490, 493-505, DOI: 10.1198/jasa.2009.ap08746

[2] Angrist, J. D., Pischke, J.-S. (2008). Mostly Harmless Econometrics: An Empiricist's Companion. Princeton University Press. ISBN: 0691120358

[3] John D. Hunter. Matplotlib: A 2D Graphics Environment, Computing in Science & Engineering, 9, 90-95 (2007), DOI:10.1109/MCSE.2007.55 (publisher link)

[4] Kraft D (1988) A software package for sequential quadratic programming. Tech. Rep. DFVLR-FB 88-28, DLR German Aerospace Center Institute for Flight Mechanics, Koln, Germany.

[5] LaLonde, Robert J, 1986. "Evaluating the Econometric Evaluations of Training Programs with Experimental Data," American Economic Review, American Economic Association, vol. 76(4), pages 604-620, September.

[6] Lindo, M. Jason. (2020). Topic 6: DDandFE

[7] Lindo, M. Jason. (2020). Topic 9: Synthetic Control Methods

[8] Loughran, T., & Mcdonald, B. (2011). When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. The Journal of Finance, 66(1), 35-65. Retrieved April 21, 2020, from www.jstor.org/stable/29789771

[9] President Xi Says China Should 'seize Opportunity' To Adopt Blockchain William Foxley - https://www.coindesk.com/president-xi-says-china-should-seize-opportunity-to-adopt-blockchain

[10] Travis E. Oliphant. A guide to NumPy, USA: Trelgol Publishing, (2006).

[11] Wes McKinney. Data Structures for Statistical Computing in Python, Proceedings of the 9th Python in Science Conference, 51-56 (2010) (publisher link)