1_Classification_Hourly_Daily_EDA

November 18, 2022

0.1 # 1. EDA on Hourly/ data

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Description: Performing the EDA on the hourly data

0.1.1 Pre requisites:

1. And add the shortcut of the drive link : https://drive.google.com/drive/folders/1KRMbTR4GNaDGlpBkRi3l to your personal drive.

Files: crypto_data_hour_cleaned_v2.csv – hourly data crypto_data_daily_cleaned_v1.csv – daily data

[ ]:
```
# Connecting to the google drive
from google.colab import drive
drive.mount('/content/drive')
from IPython.display import clear_output
```

```
Mounted at /content/drive
```

[ ]:
```
# packages used in the notebook
import pandas as pd
import warnings
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import plotly.express as px
import statsmodels.graphics.utils as utils
import plotly.graph_objects as go

from plotly.subplots import make_subplots
from plotly.offline import init_notebook_mode
from statsmodels.graphics.tsaplots import _prepare_data_corr_plot, _plot_corr
from statsmodels.tsa.stattools import pacf

warnings.filterwarnings("ignore")
```

Pre Analysis: Intially the analysis was tried to perform on the minute data but the neither colabs(even with pro) or local machines RAM are able be hold the data for processing. We decided to go with hourly data by which we have reduced the data by 60 times.

0.2 Load the dataset

[ ]:
```
# Loading the hourly data
folder_path = '/content/drive/MyDrive/MADS_23_DL_final_project'
hour = pd.read_csv(folder_path + '/data/crypto_data_hour_cleaned_v2.csv')
```

[ ]:
```
hour['Crypto'].value_counts()
```

[ ]:
```
BTC     82960
ETH     57081
LTC     50296
ETC     50296
XMR     50094
XRP     49235
XLM     43605
TRX     43093
ADA     39614
LINK    28458
Name: Crypto, dtype: int64
```

[ ]:
```
# check data types of each column
hour.dtypes
```

[ ]:
```
Open Time             object
Open                 float64
High                 float64
Low                  float64
Close                float64
Volume               float64
train_test            object
Crypto                object
pct_change_1hour     float64
pct_change_2hour     float64
pct_change_1day      float64
dtype: object
```

[ ]:
```
hour.head()
```

[ ]:
```
             Open Time    Open    High     Low   Close   Volume train_test  \
0  2013-04-01 00:00:00  93.155  93.155  93.155  93.155   12.250      Train
1  2013-04-01 01:00:00  93.700  93.790  93.700  93.790   54.120      Train
2  2013-04-01 02:00:00  94.068  94.480  94.000  94.000  205.800      Train
3  2013-04-01 04:00:00  93.550  94.000  93.550  94.000    9.328      Train
4  2013-04-01 05:00:00  94.230  94.230  94.230  94.230    4.826      Train

  Crypto  pct_change_1hour  pct_change_2hour  pct_change_1day
```

```
0     BTC              NaN               NaN              NaN
1     BTC         0.006817               NaN              NaN
2     BTC         0.002239          0.009071              NaN
3     BTC         0.000000          0.002239              NaN
4     BTC         0.002447          0.002447              NaN
```

[ ]:
```
hour.tail(2)
```

[ ]:
```
                  Open Time   Open    High    Low  Close       Volume  \
494730  2022-09-30 22:00:00  27.55  27.641  27.45  27.59  5089.821036
494731  2022-09-30 23:00:00  27.60  27.786  27.57  27.73  4263.484592

       train_test Crypto  pct_change_1hour  pct_change_2hour  pct_change_1day
494730       Test    ETC          0.000000         -0.002531         0.000363
494731       Test    ETC          0.005074          0.005074        -0.002159
```

[ ]:
```
hour['Open Time'] = pd.to_datetime(hour['Open Time'])
```

1 Hour wise summarization

[ ]:
```
# extract hour from the time stamp
hour['hour'] = hour['Open Time'].dt.hour
```

[ ]:
```
# check the number of hours
hour.groupby(['hour']).count()
```

[ ]:
```
      Open Time   Open   High    Low  Close  Volume  train_test  Crypto  \
hour
0         20595  20595  20595  20595  20595   20595       20595   20595
1         20584  20584  20584  20584  20584   20584       20584   20584
2         20579  20579  20579  20579  20579   20579       20579   20579
3         20581  20581  20581  20581  20581   20581       20581   20581
4         20584  20584  20584  20584  20584   20584       20584   20584
5         20582  20582  20582  20582  20582   20582       20582   20582
6         20581  20581  20581  20581  20581   20581       20581   20581
7         20598  20598  20598  20598  20598   20598       20598   20598
8         20594  20594  20594  20594  20594   20594       20594   20594
9         20611  20611  20611  20611  20611   20611       20611   20611
10        20615  20615  20615  20615  20615   20615       20615   20615
11        20624  20624  20624  20624  20624   20624       20624   20624
12        20641  20641  20641  20641  20641   20641       20641   20641
13        20633  20633  20633  20633  20633   20633       20633   20633
14        20640  20640  20640  20640  20640   20640       20640   20640
15        20628  20628  20628  20628  20628   20628       20628   20628
16        20651  20651  20651  20651  20651   20651       20651   20651
17        20645  20645  20645  20645  20645   20645       20645   20645
18        20636  20636  20636  20636  20636   20636       20636   20636
```

```
19        20637  20637  20637  20637  20637   20637        20637   20637
20        20642  20642  20642  20642  20642   20642        20642   20642
21        20624  20624  20624  20624  20624   20624        20624   20624
22        20607  20607  20607  20607  20607   20607        20607   20607
23        20620  20620  20620  20620  20620   20620        20620   20620

      pct_change_1hour  pct_change_2hour  pct_change_1day
hour
0                20594             20594            20593
1                20584             20583            20582
2                20579             20579            20578
3                20581             20581            20581
4                20584             20584            20583
5                20582             20582            20581
6                20581             20581            20580
7                20598             20598            20597
8                20594             20594            20593
9                20611             20611            20610
10               20615             20615            20614
11               20624             20624            20623
12               20641             20641            20640
13               20633             20633            20632
14               20640             20640            20639
15               20628             20628            20627
16               20651             20651            20651
17               20645             20645            20644
18               20636             20636            20635
19               20637             20637            20636
20               20642             20642            20641
21               20624             20624            20623
22               20607             20607            20606
23               20620             20620            20619
```

We trying to undserstand if there are any missing values in termsn of the every hour. The dataset is balanced in terms of the hour although there are a differenece of about -9 for 23rd.

[ ]:
```
hour_group = hour.groupby(['hour']).mean()
```

[ ]:
```
hour_group.head()
```

[ ]:
```
             Open         High          Low        Close        Volume  \
hour
0     1943.387770  1960.747182  1926.154527  1943.444987  3.767053e+06
1     1944.398758  1959.256119  1929.964909  1944.414618  3.316634e+06
2     1944.773672  1957.936126  1930.630557  1943.588471  3.110732e+06
3     1943.189102  1956.489254  1929.177629  1942.299966  3.088448e+06
4     1942.035972  1955.919773  1928.886085  1942.041443  3.070087e+06
```

```
      pct_change_1hour  pct_change_2hour  pct_change_1day
hour
0             0.001612          0.001724         0.016178
1             0.010756          0.012270         0.026648
2            -0.000353         -0.000526         0.015885
3            -0.000349          0.010087         0.014707
4             0.000200         -0.000279         0.015837
```

[ ]:
```
fig = px.line(hour_group,␣
↪y=['pct_change_1hour','pct_change_2hour','pct_change_1day'], x = hour_group.
↪index)

# Show plot
fig.show()
```

[ ]:
```
hour_group.describe()
```

[ ]:
```
              Open         High          Low        Close        Volume  \
count    24.000000    24.000000    24.000000    24.000000  2.400000e+01
mean   1940.925870  1956.152621  1926.027553  1941.028466  3.340634e+06
std       2.054679     1.824004     2.925573     1.942444  3.906647e+05
min    1937.991259  1953.210934  1921.505049  1938.042524  2.874766e+06
25%    1939.257954  1954.963857  1923.684584  1938.998794  3.076614e+06
50%    1940.589269  1955.908268  1926.134864  1940.956667  3.249008e+06
75%    1942.482605  1956.877359  1928.708715  1942.366067  3.528861e+06
max    1944.773672  1960.747182  1930.630557  1944.414618  4.406454e+06

       pct_change_1hour  pct_change_2hour  pct_change_1day
count         24.000000         24.000000        24.000000
mean           0.000780          0.001409         0.015582
std            0.002173          0.003071         0.008121
min           -0.000382         -0.000526         0.004216
25%            0.000112          0.000176         0.012139
50%            0.000270          0.000554         0.015611
75%            0.000646          0.001083         0.018714
max            0.010756          0.012270         0.027469
```

Observation: It is clear fact that as the timeframe is increased (like comparing 30min with 2hours), it can be seen that the volatility(standard deviation) is increase so does the returns(mean value). Our question was which time window to be considered for prediction. And in the next steps based on our final approach we are performing some analysis/tests.

We are considering to use a Time series or classificaion/Regression analaysis as the intial model building process. For Time series we will be doing the correlation/ Partial correlation, Dicky fuller test, KRSS Test etc.

[ ]:
```
```

2 Partial Correlation Analysis for pct_change_1hour

[ ]:
```
# Copied for Florian DL Assignment 6
def plot_pacf_drop(x, ax=None, lags=None, alpha=.05, method='ywunbiased',
              use_vlines=True, title='Partial Autocorrelation', zero=True,
              vlines_kwargs=None, drop_no=0, **kwargs):

    lags_orig=lags
    fig, ax = utils.create_mpl_ax(ax)
    vlines_kwargs = {} if vlines_kwargs is None else vlines_kwargs
    lags, nlags, irregular = _prepare_data_corr_plot(x, lags, zero)
    confint = None
    if alpha is None:
        acf_x = pacf(x, nlags=nlags, alpha=alpha, method=method)
    else:
        acf_x, confint = pacf(x, nlags=nlags, alpha=alpha, method=method)

    if drop_no:
        acf_x = acf_x[drop_no+1:]
        confint = confint[drop_no+1:]
        lags, nlags, irregular = _prepare_data_corr_plot(x, lags_orig-drop_no,␣
↪zero)

    _plot_corr(ax, title, acf_x, confint, lags, False, use_vlines,
               vlines_kwargs, **kwargs)

    return fig
```

[ ]:
```
import matplotlib.pyplot as plt
from statsmodels.graphics.tsaplots import _prepare_data_corr_plot, _plot_corr
import statsmodels.graphics.utils as utils
from statsmodels.tsa.stattools import pacf



for crypto_ in hour['Crypto'].unique():

    plt.figure()
    plot_pacf_drop(hour[hour['Crypto']==crypto_]['pct_change_1hour'].dropna(),␣
↪lags=24,
                   drop_no=3, zero=False, title="Partial Autocorrelation_{}".
↪format(crypto_))

plt.show()
```

```
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```

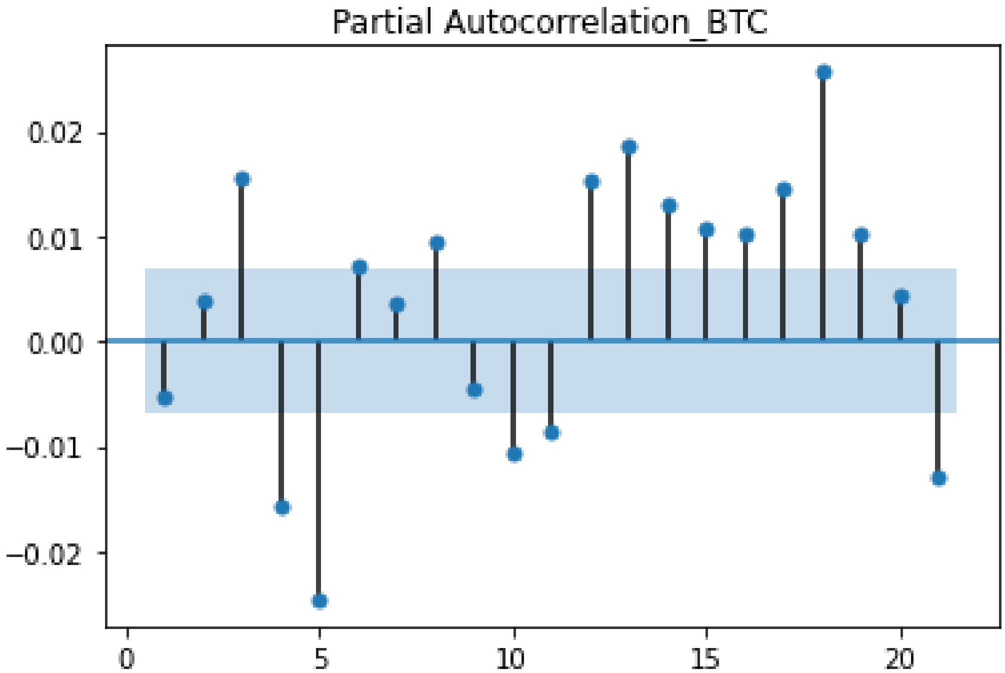

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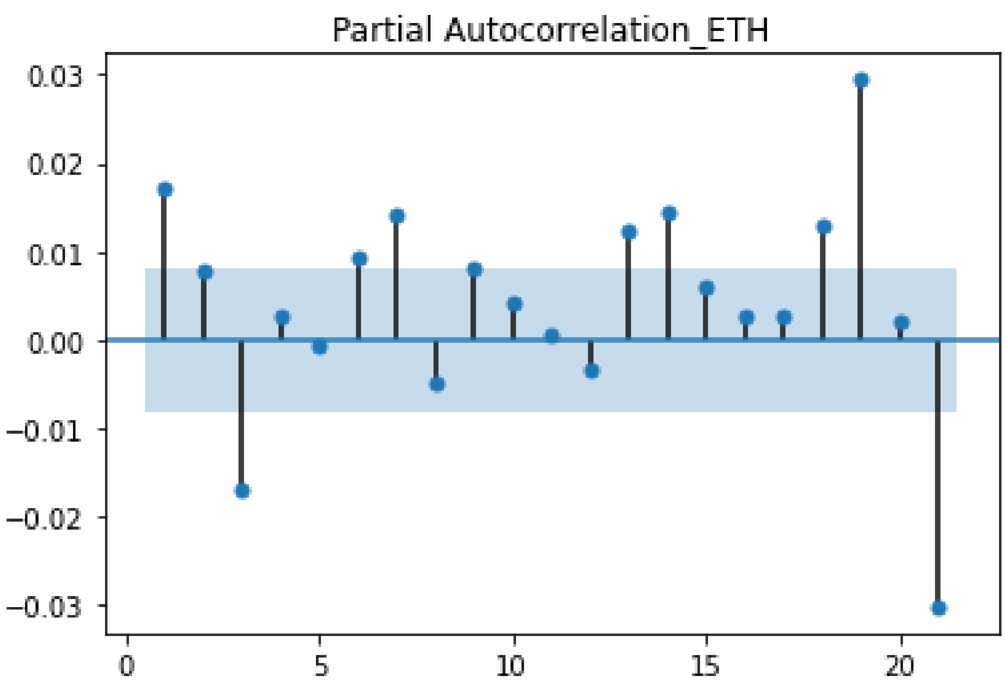

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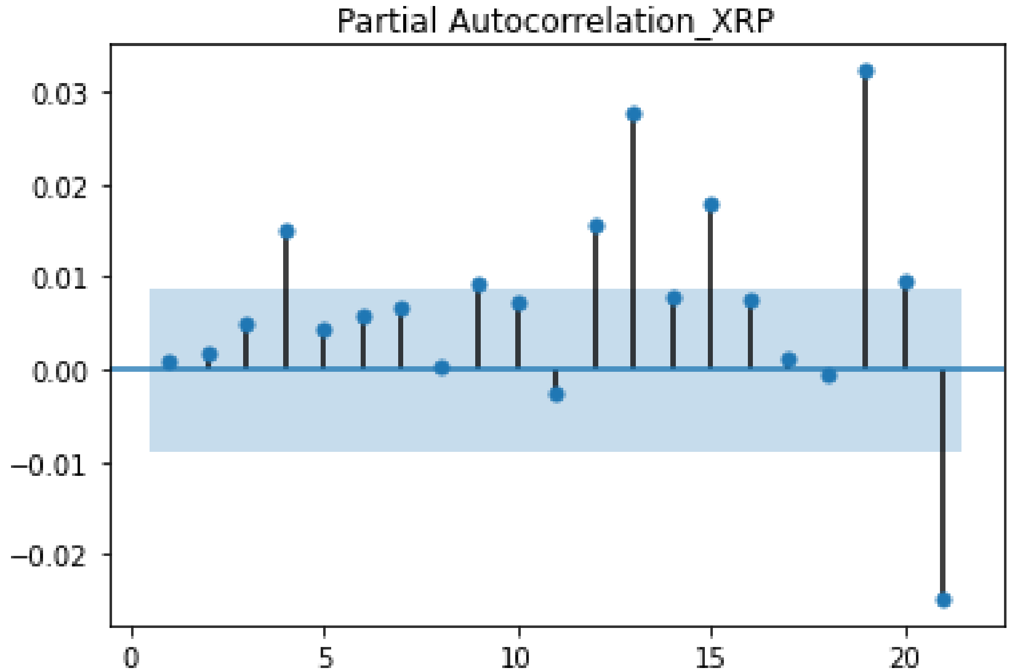

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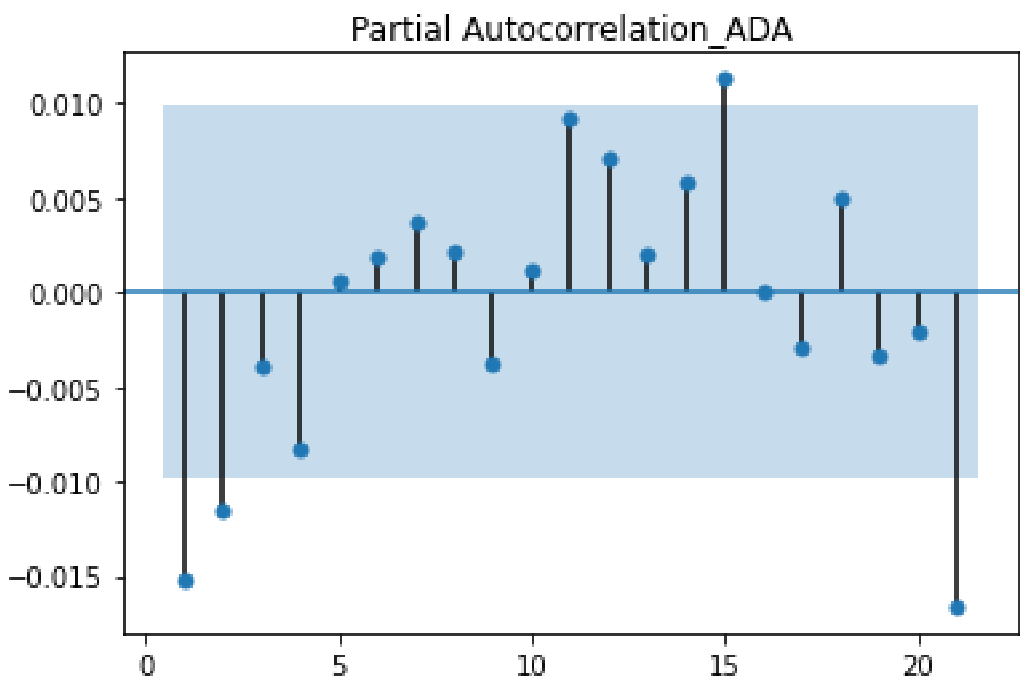

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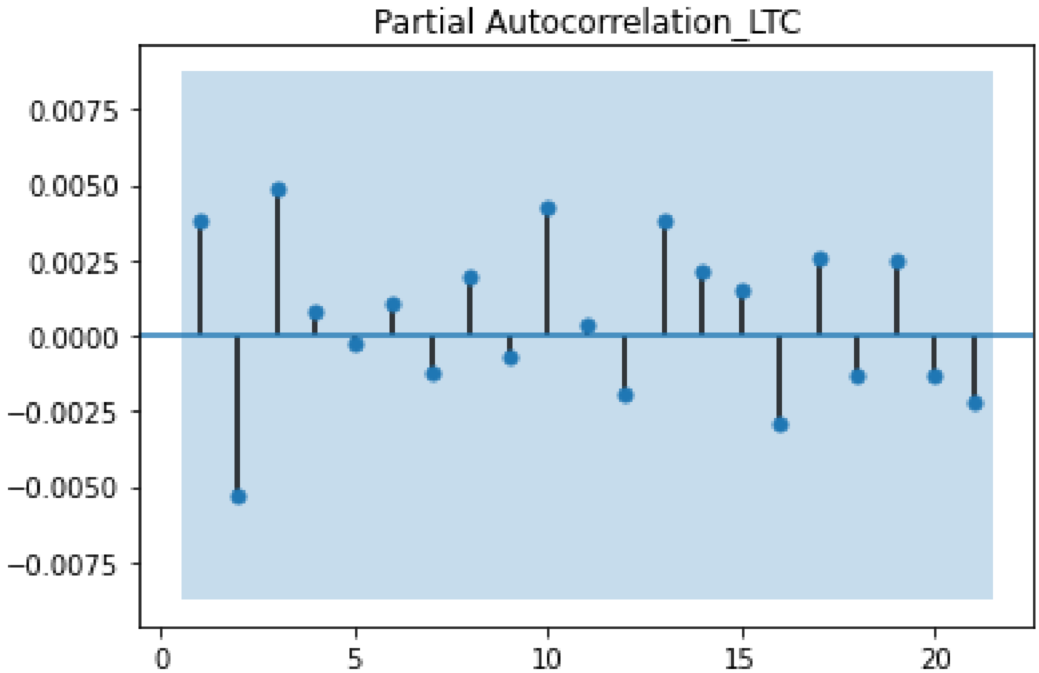

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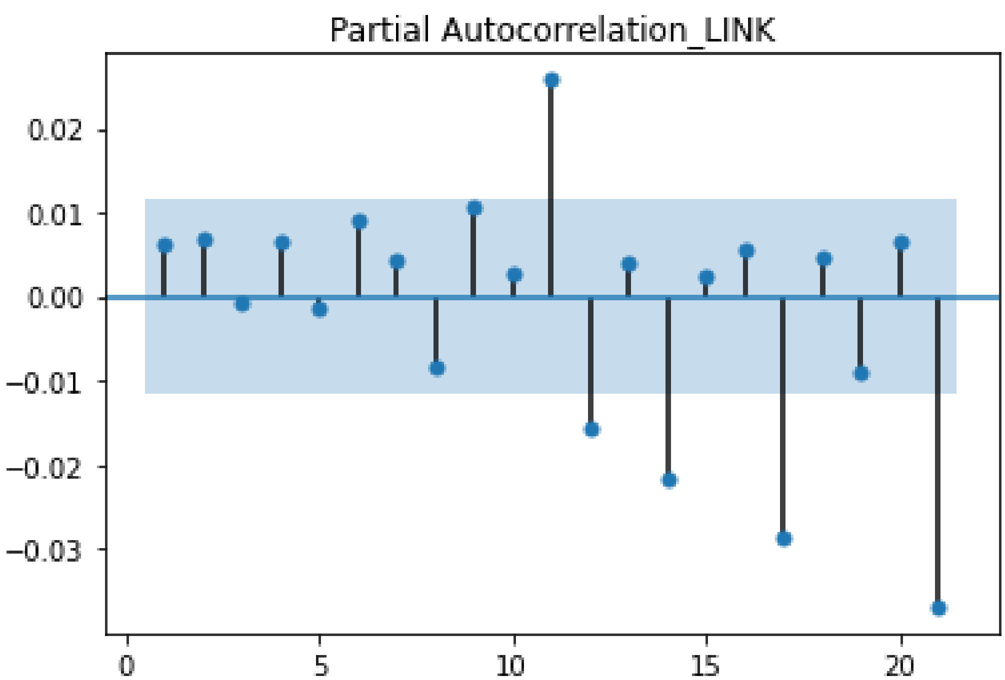

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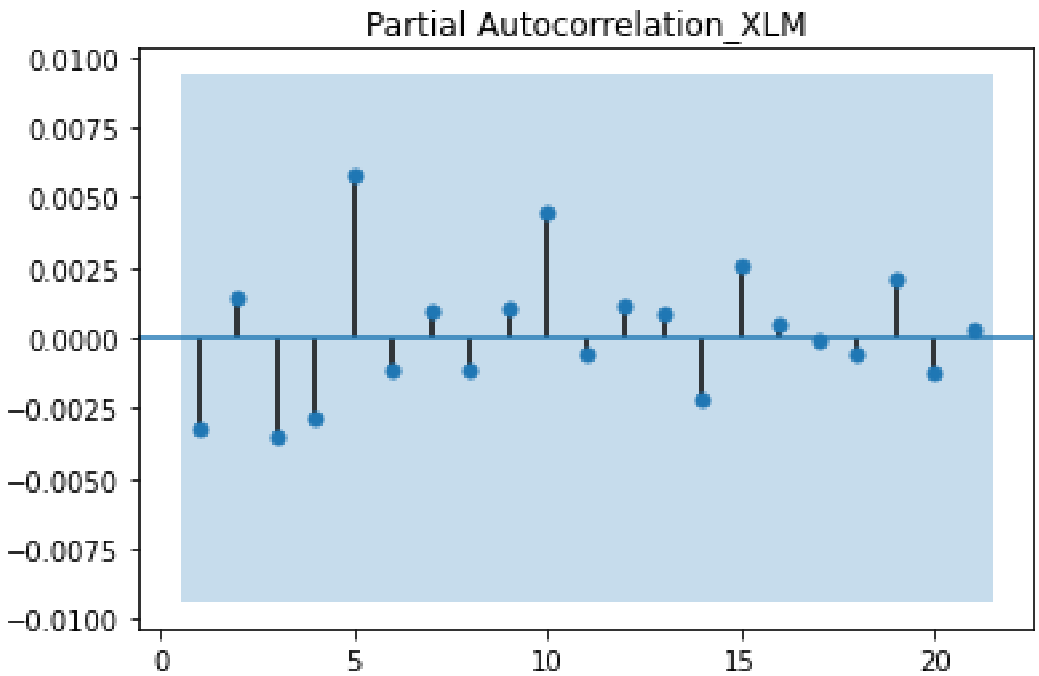

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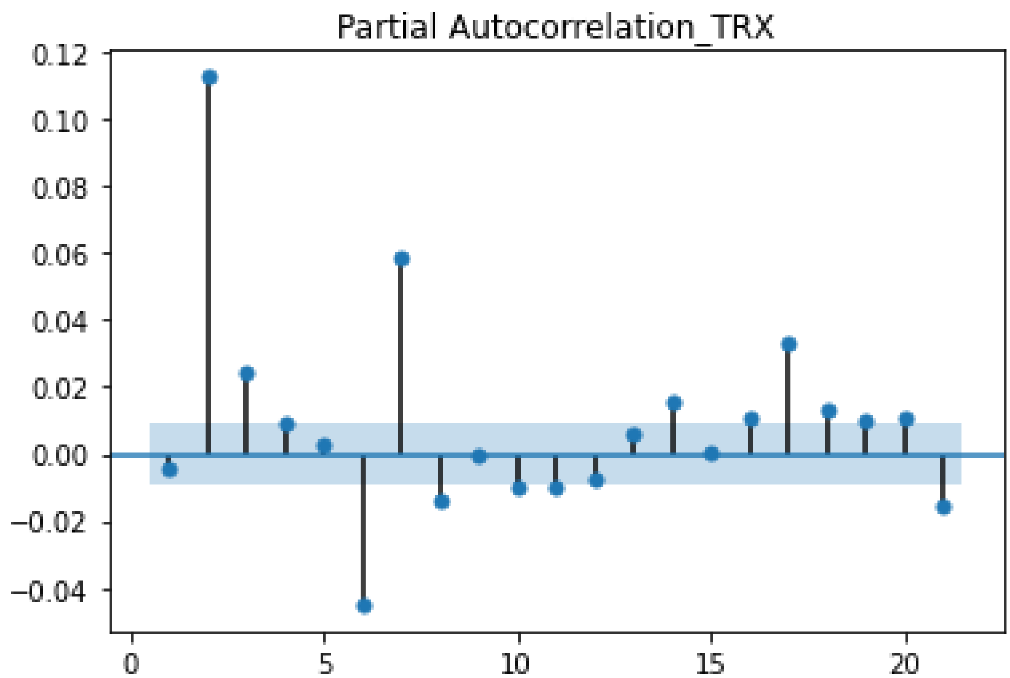


```
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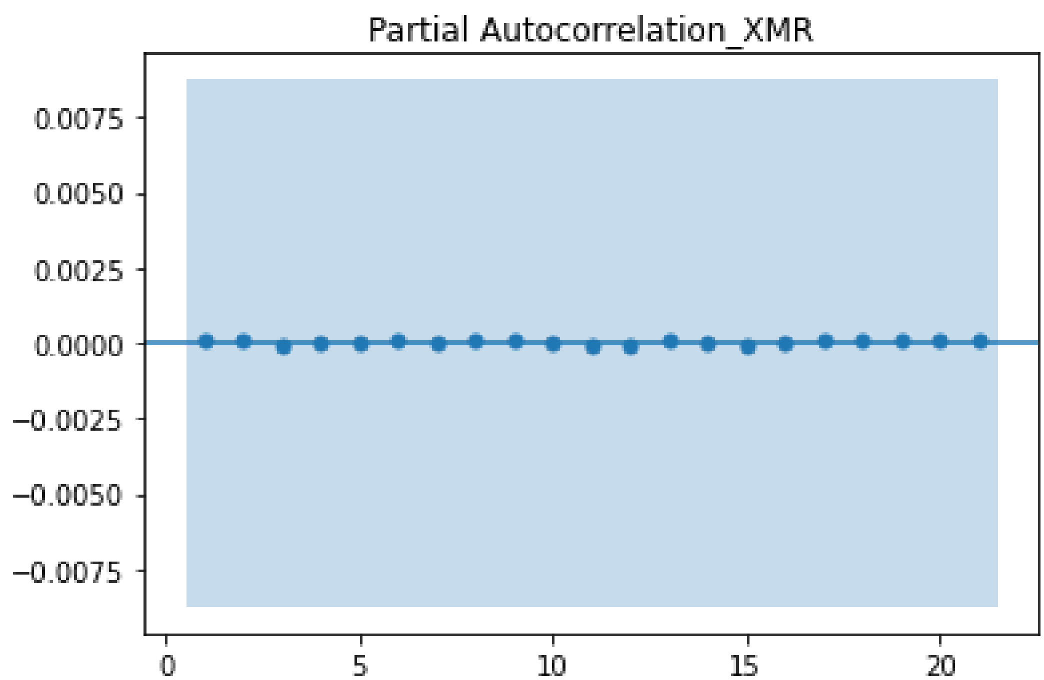

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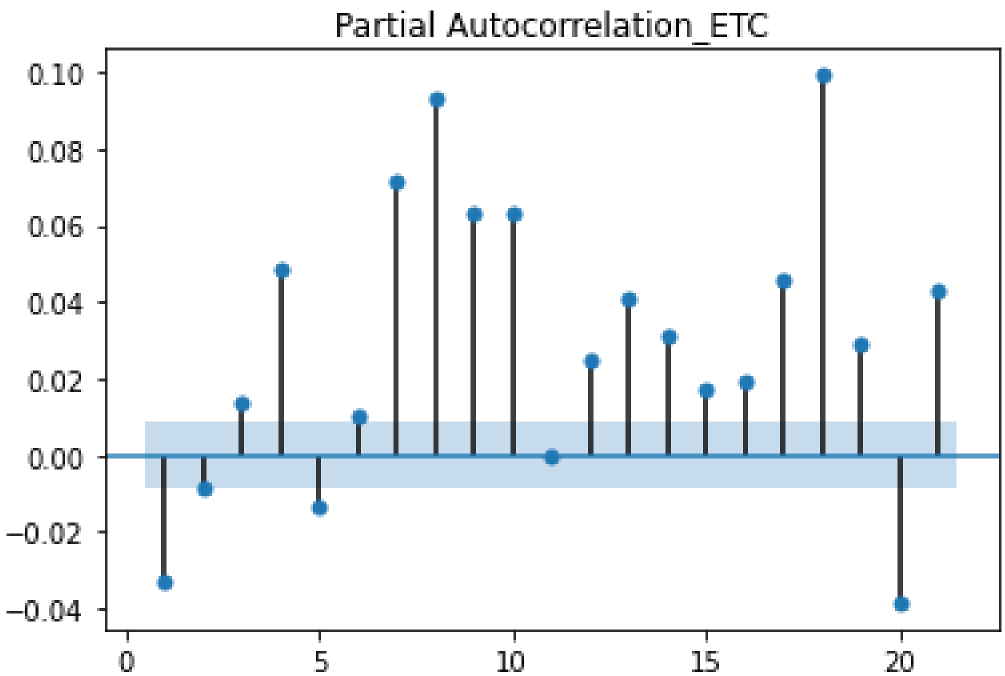


For few cryptro cases we can see there is 2 hourly returns are more significant. One observations is the lag is increased the information coefficents are reducing which indicates that latest or close data points will help predicting returns than less recent values. On comparision the houlry returns looks less significance for the same lag window.

[ ]:

```

```

3 Partial Correlation Analysis for pct_change_2hour

[ ]:

```
from statsmodels.graphics.tsaplots import _prepare_data_corr_plot, _plot_corr
import statsmodels.graphics.utils as utils
from statsmodels.tsa.stattools import pacf

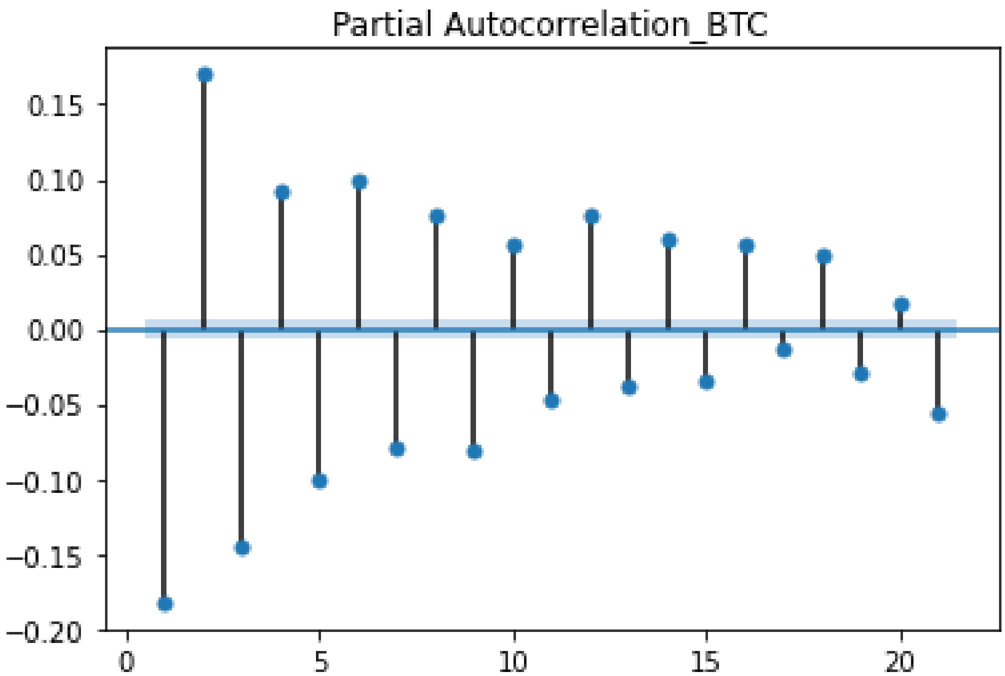


for crypto_ in hour['Crypto'].unique():

    plt.figure()
    plt_pacf_drop(hour[hour['Crypto']==crypto_]['pct_change_2hour'].dropna(),␣
 ↪lags=24,
                   drop_no=3, zero=False, title="Partial Autocorrelation_{}".
 ↪format(crypto_))
```

```
plt.show()
```

<Figure size 432x288 with 0 Axes>



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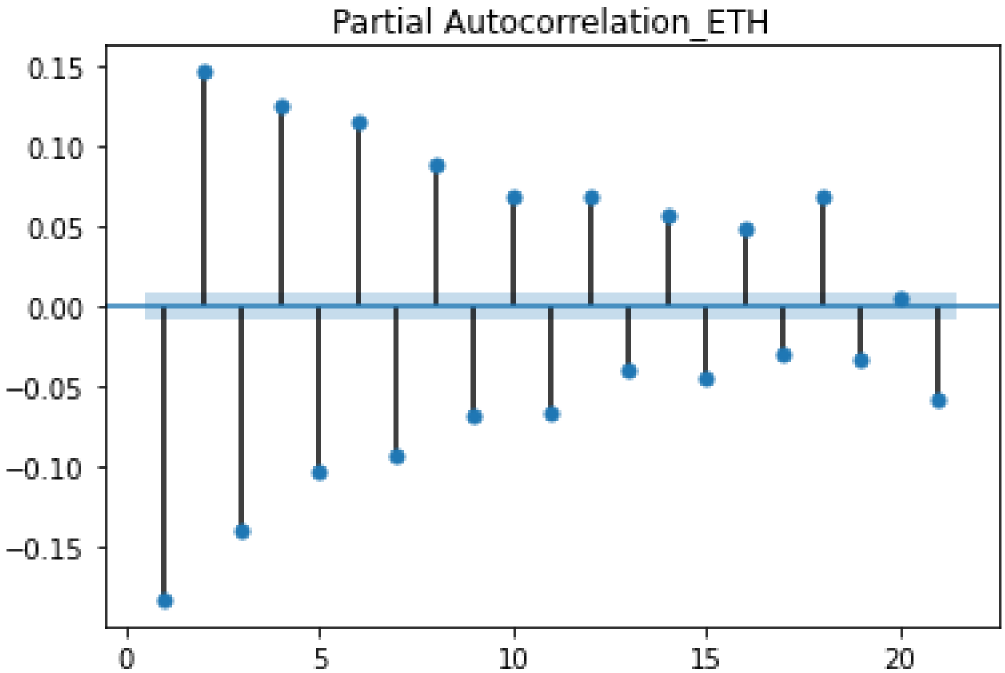

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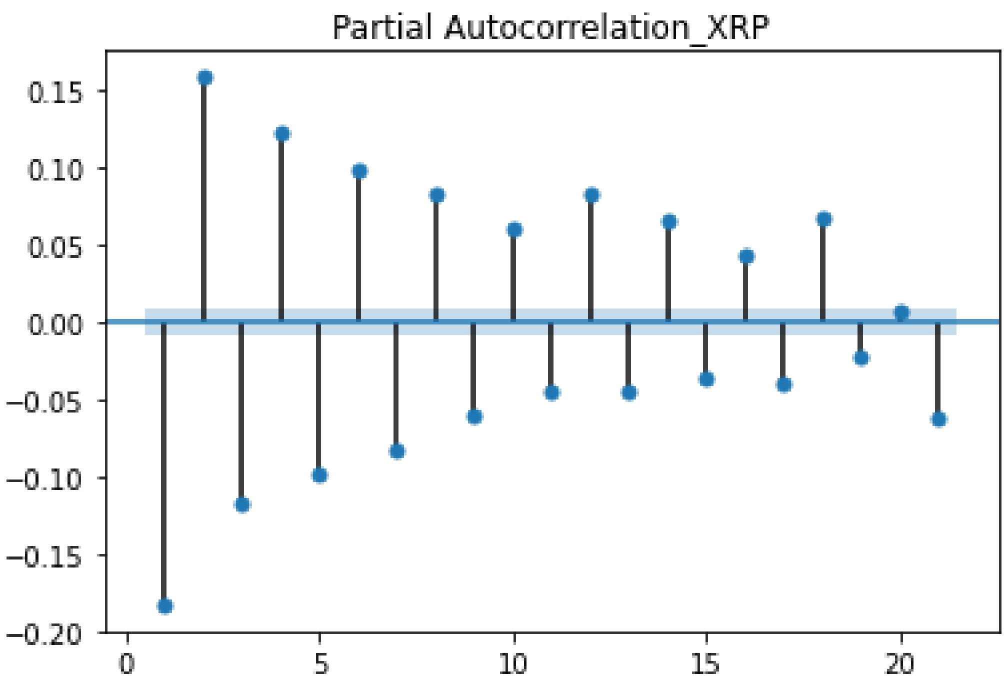

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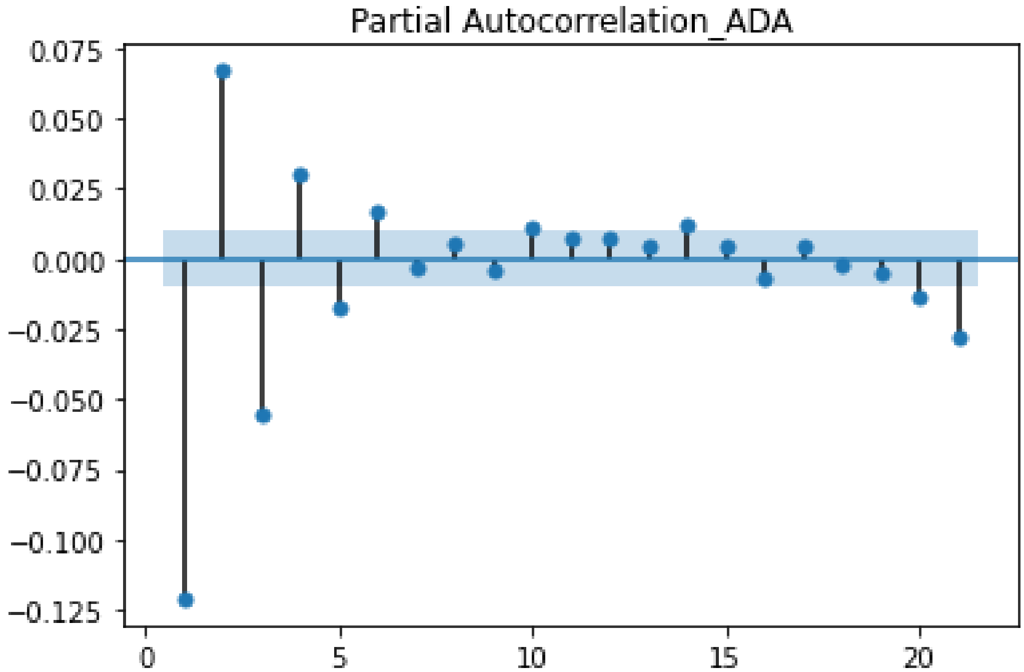

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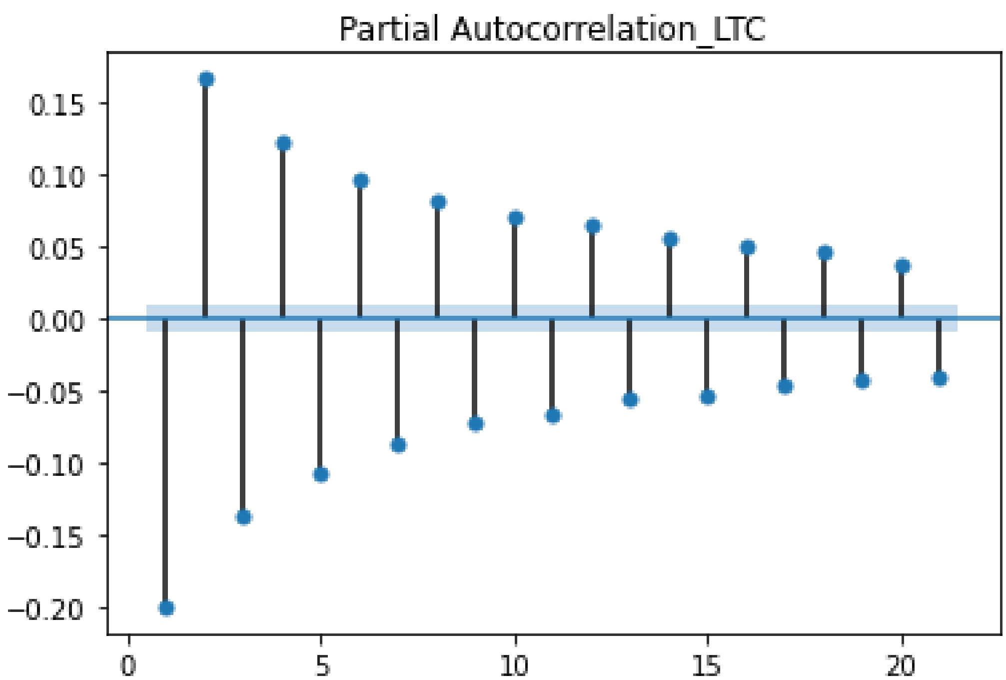

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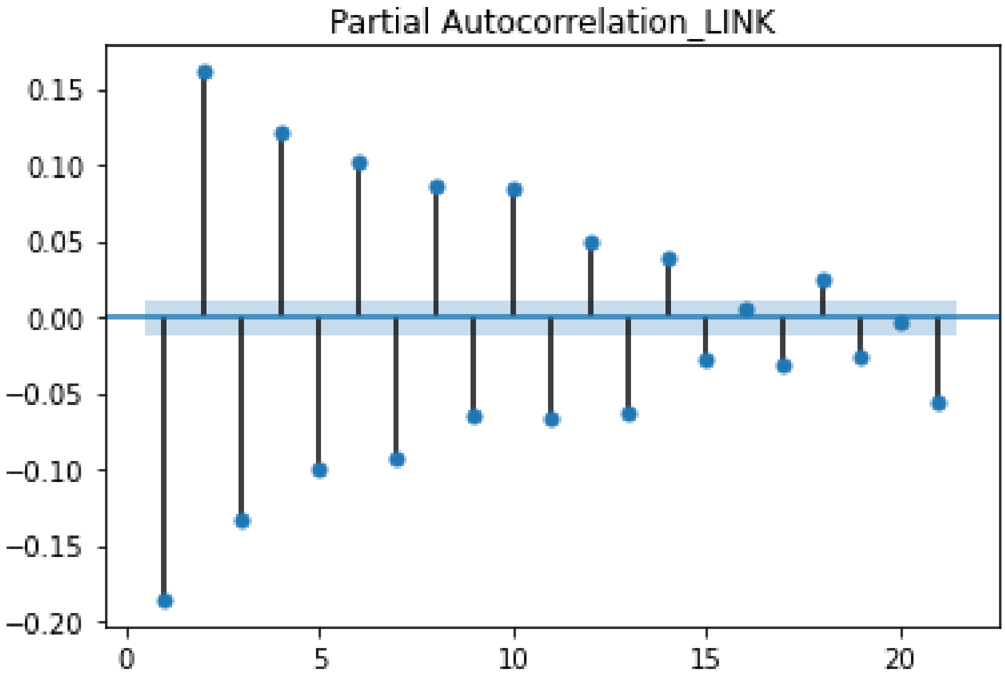

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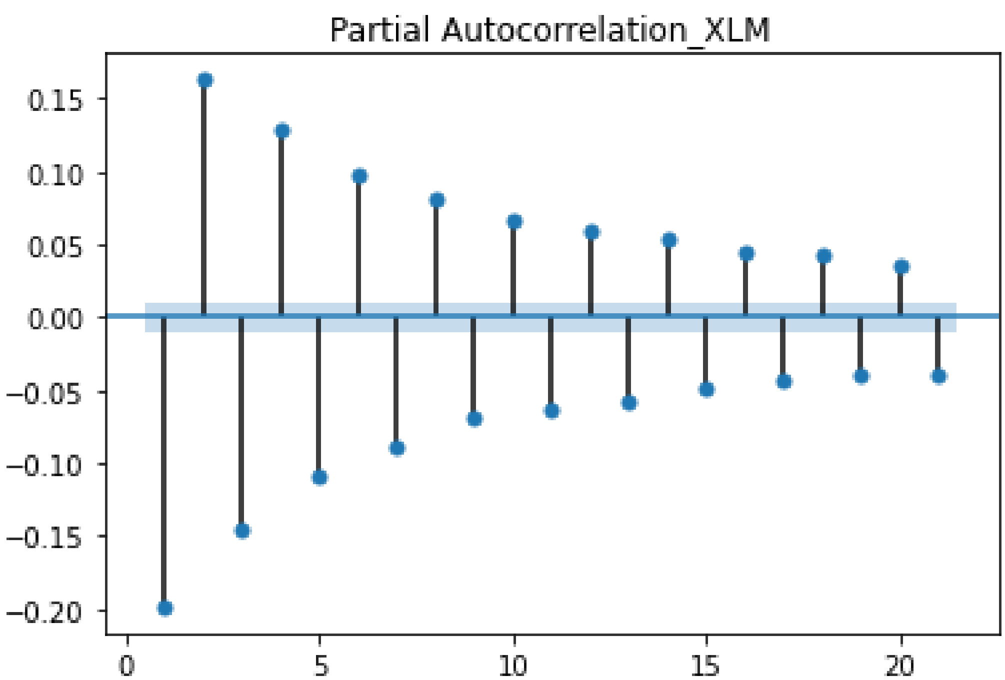

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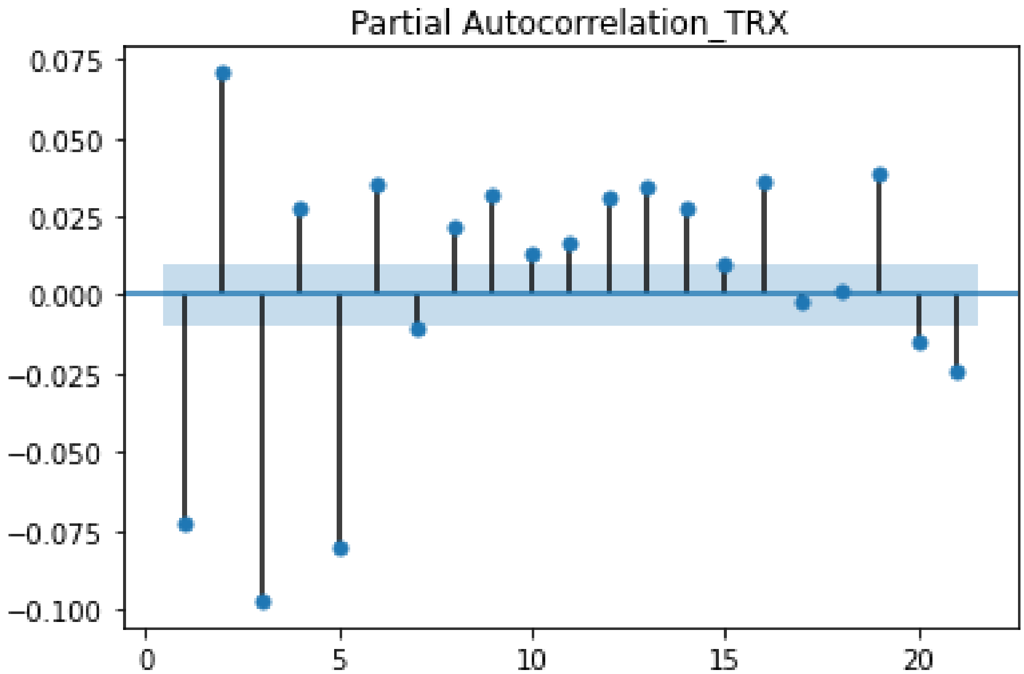

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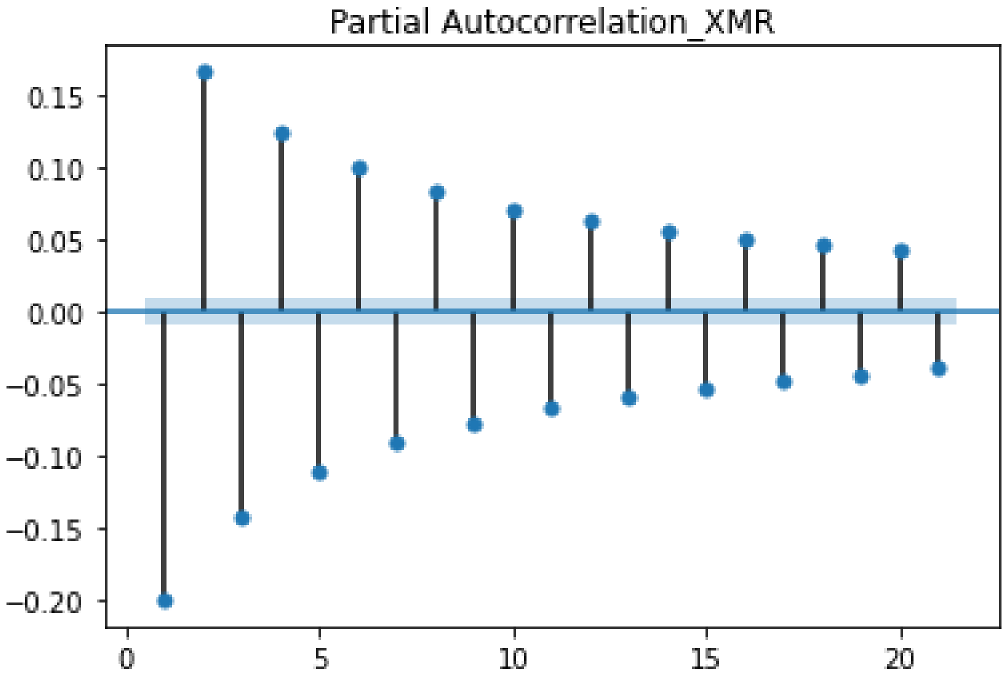

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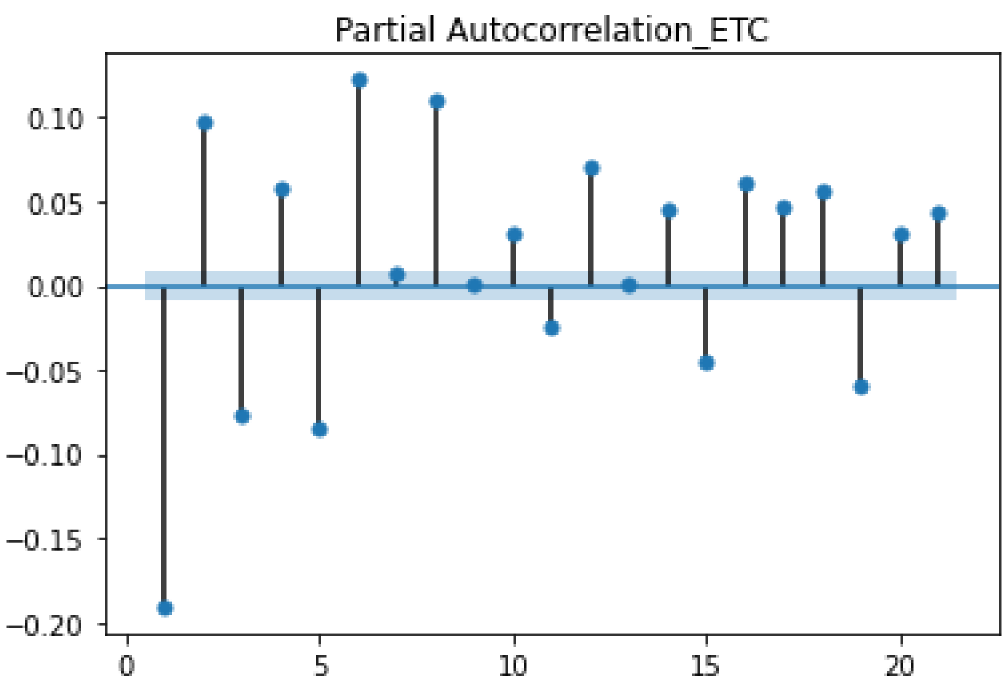

4 Partial Correlation Analysis for pct_change_1day

[ ]:
```
import matplotlib.pyplot as plt
from statsmodels.graphics.tsaplots import _prepare_data_corr_plot, _plot_corr
import statsmodels.graphics.utils as utils
from statsmodels.tsa.stattools import pacf



for crypto_ in hour['Crypto'].unique():

    plt.figure()
    plot_pacf_drop(hour[hour['Crypto']==crypto_]['pct_change_1day'].dropna(),␣
↪lags=50,
                    drop_no=3, zero=False, title="Partial Autocorrelation_{}".
↪format(crypto_))

plt.show()
```

```
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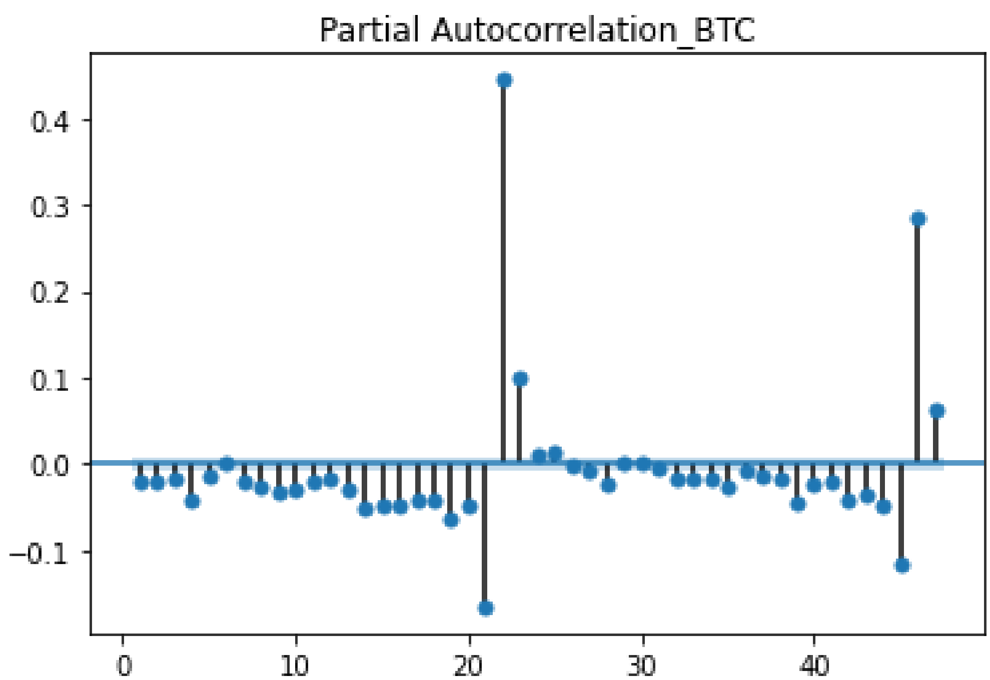


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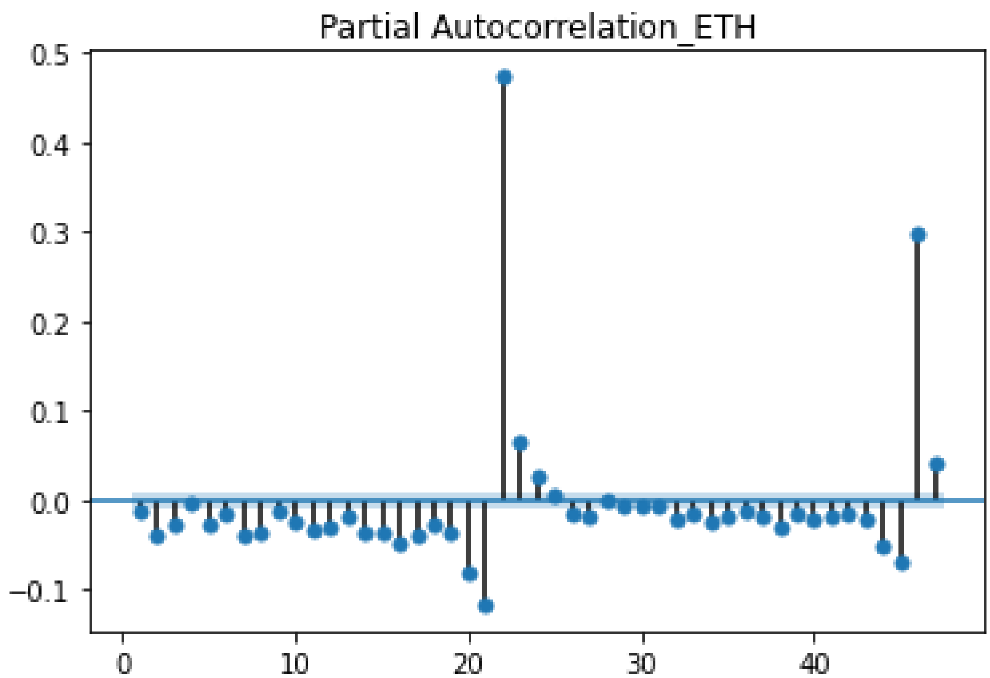

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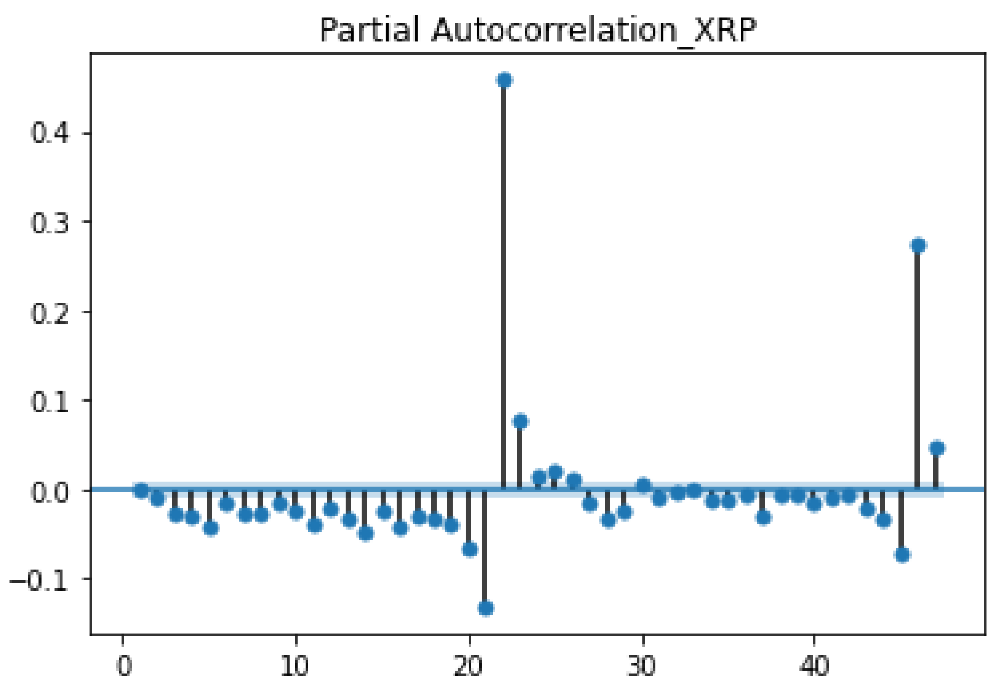

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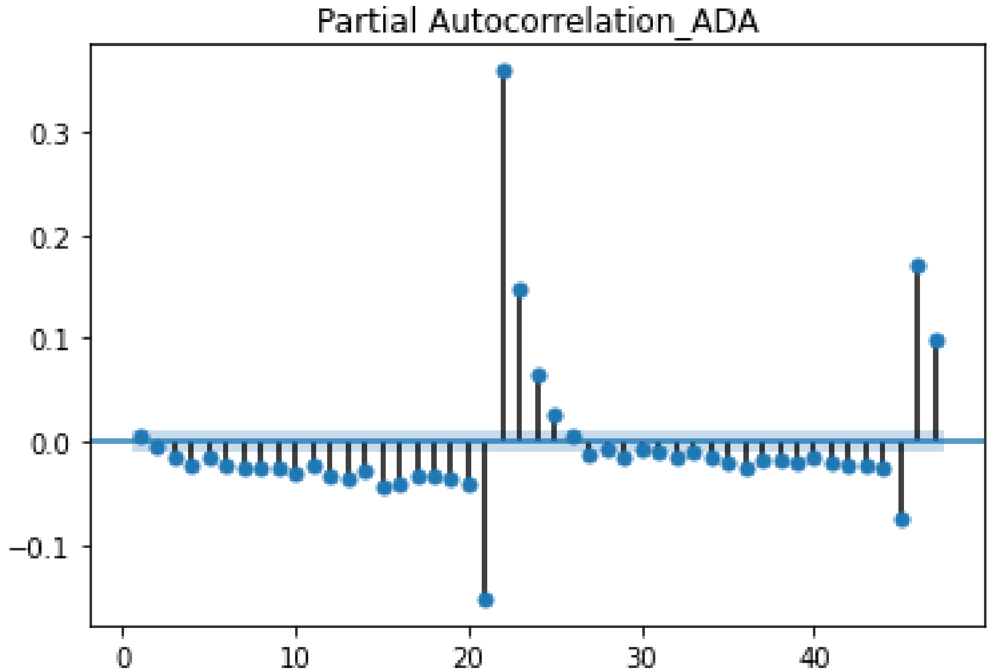

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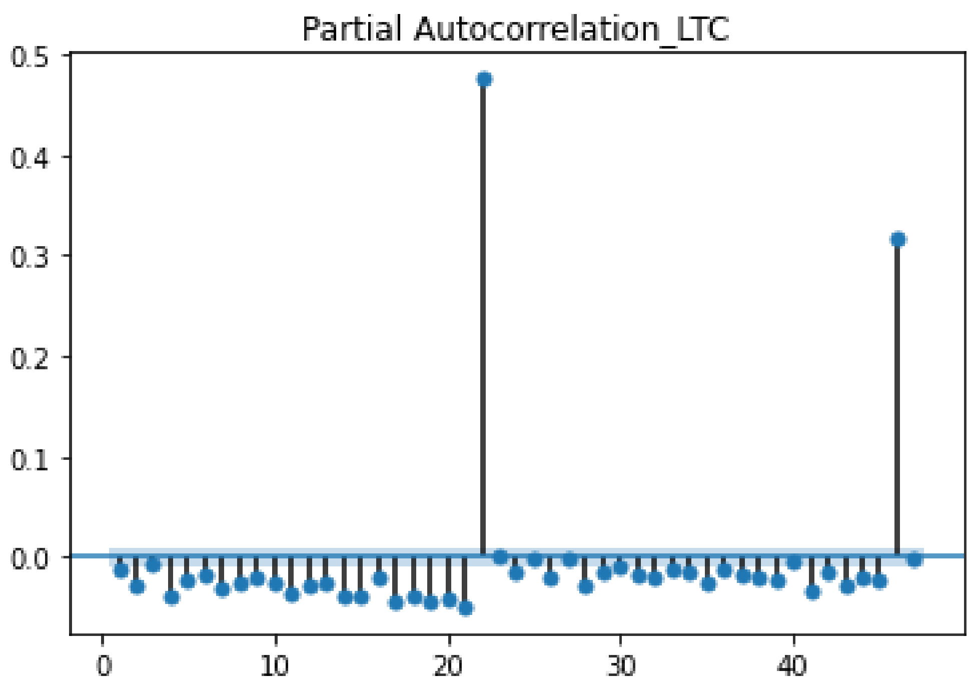

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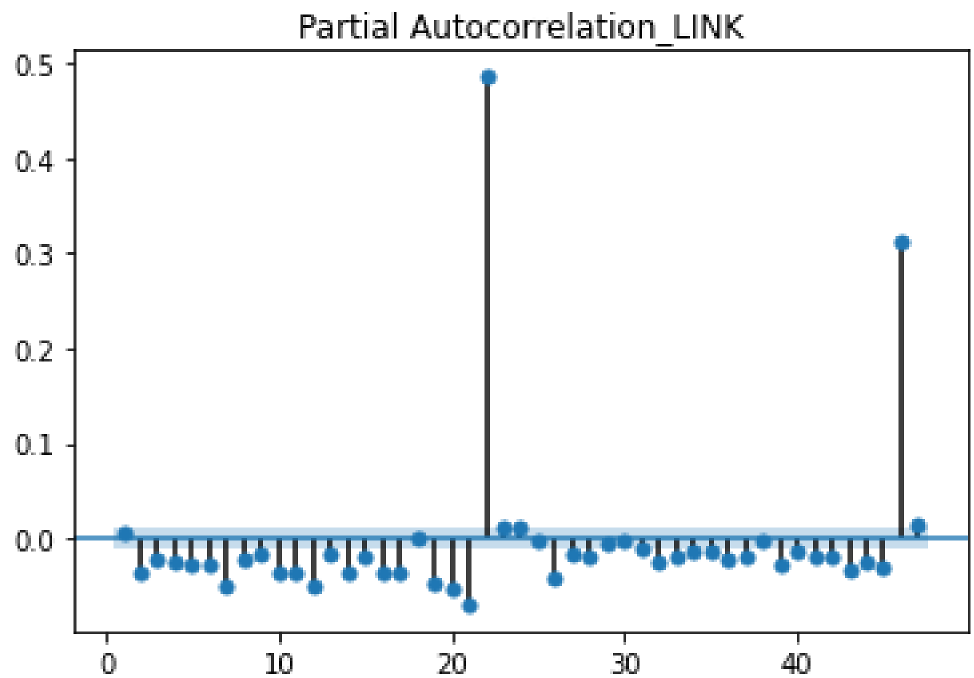

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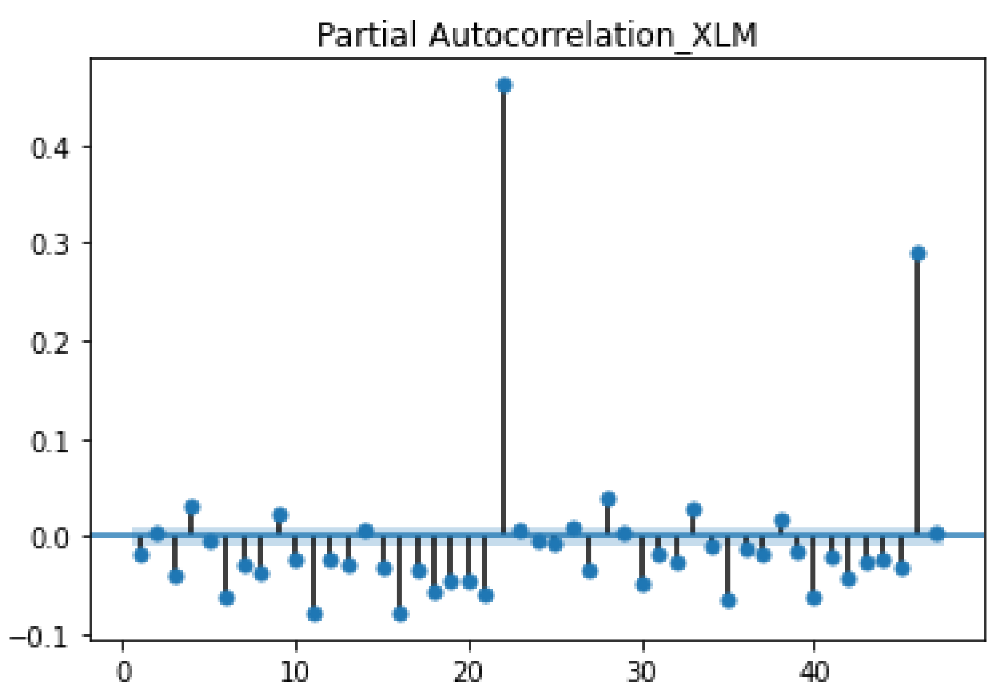

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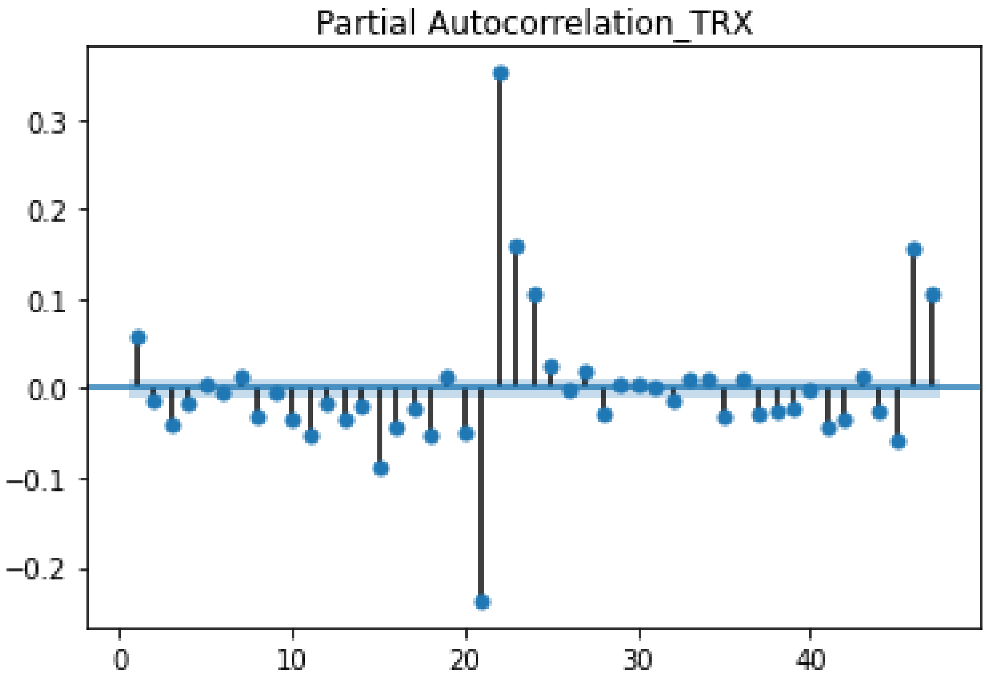

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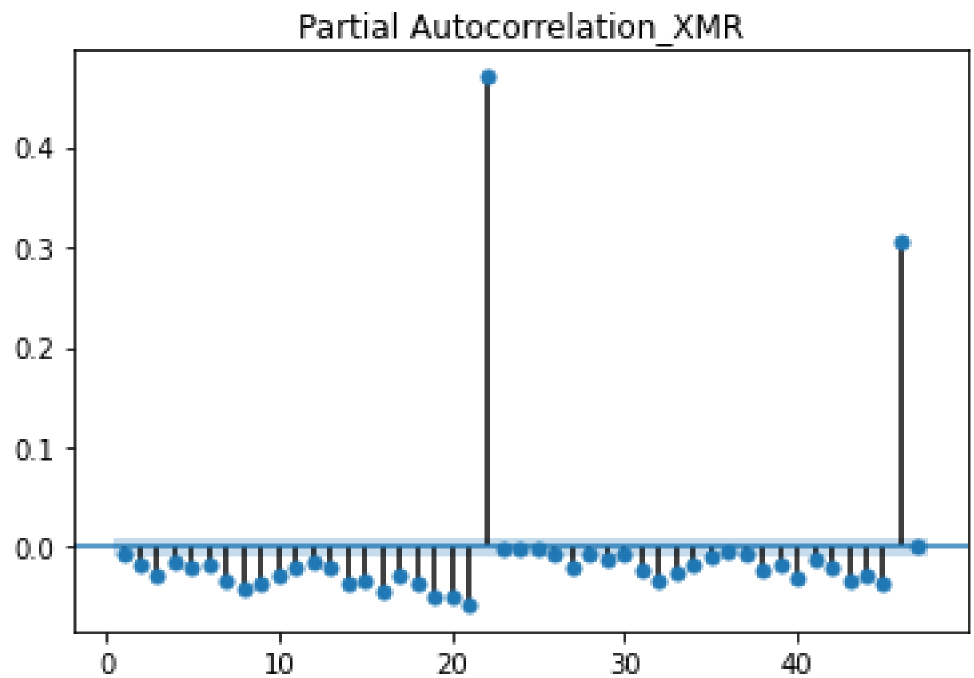
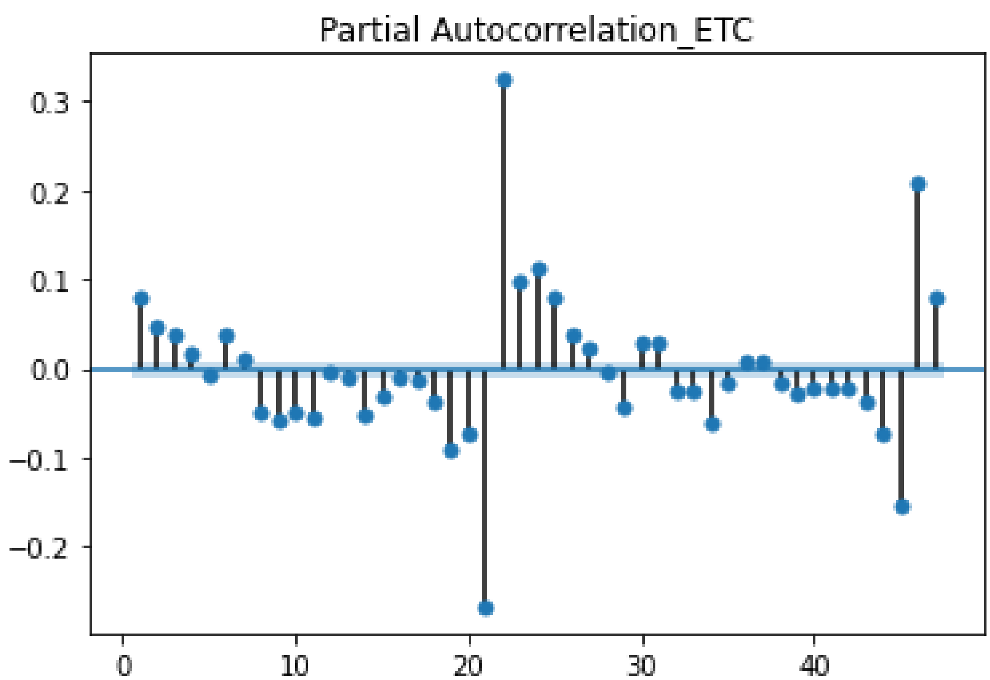


<Figure size 432x288 with 0 Axes>

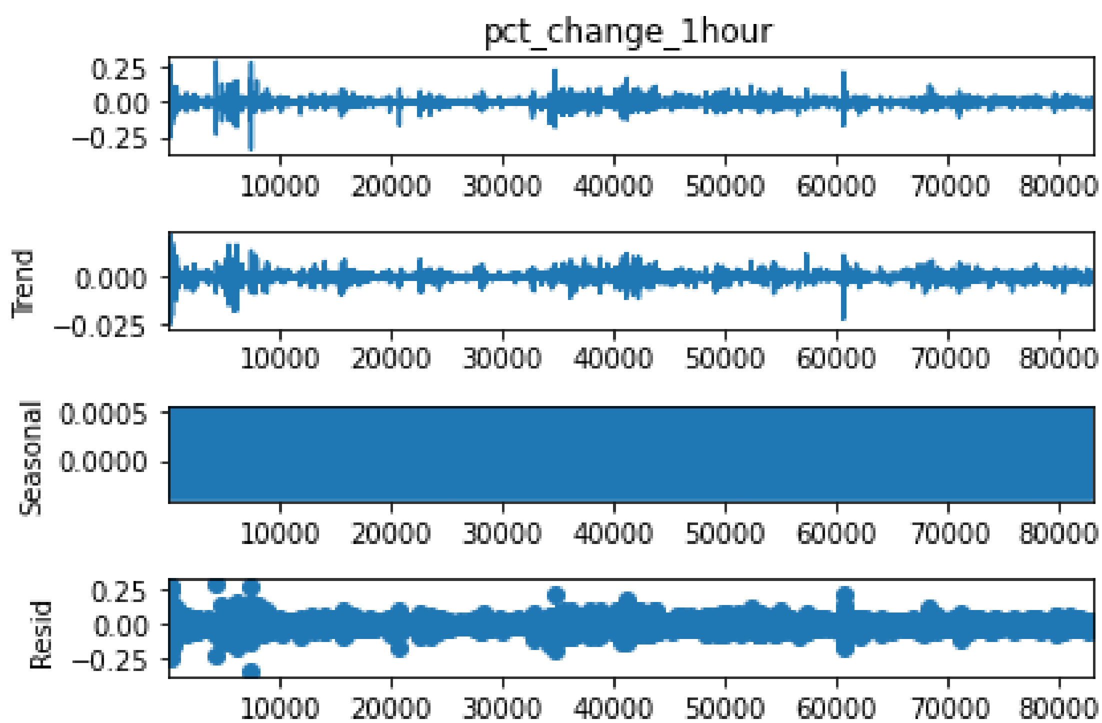


Seems like there's something between 20 and 30 and between 40 and 50 that is correlated with current state

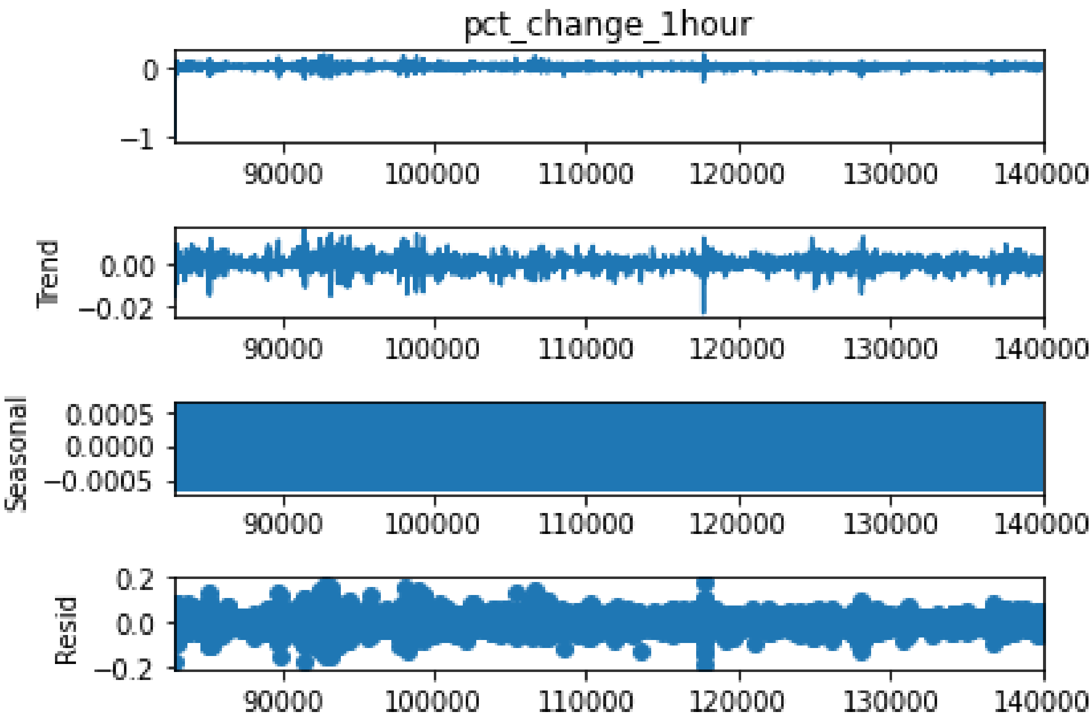
5 Seasonal Decomposition Analysis

[ ]:
```
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.tsatools import freq_to_period
import matplotlib.pyplot as plt
for crypto_ in hour['Crypto'].unique():
  print("Crypto : {}".format(crypto_))
  analysis =␣
 ↪seasonal_decompose(hour[hour['Crypto']==crypto_]["pct_change_1hour"].
 ↪dropna(), freq=freq_to_period('H'))
  analysis.plot()
  plt.show()
```

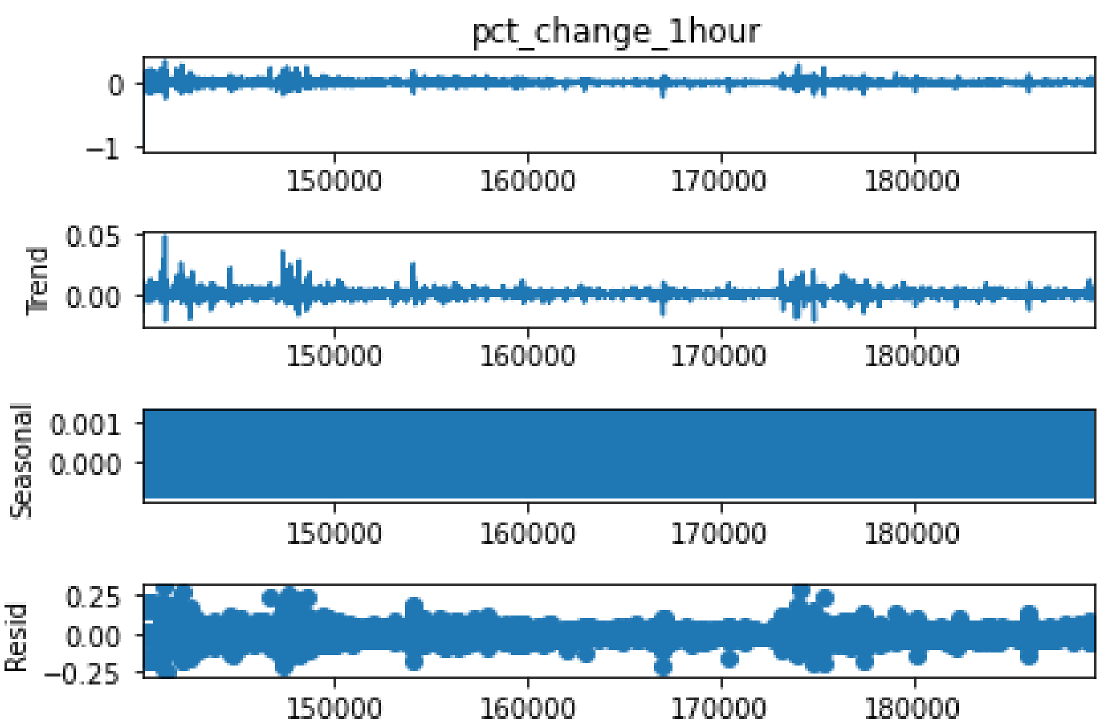
```
Crypto : BTC
```



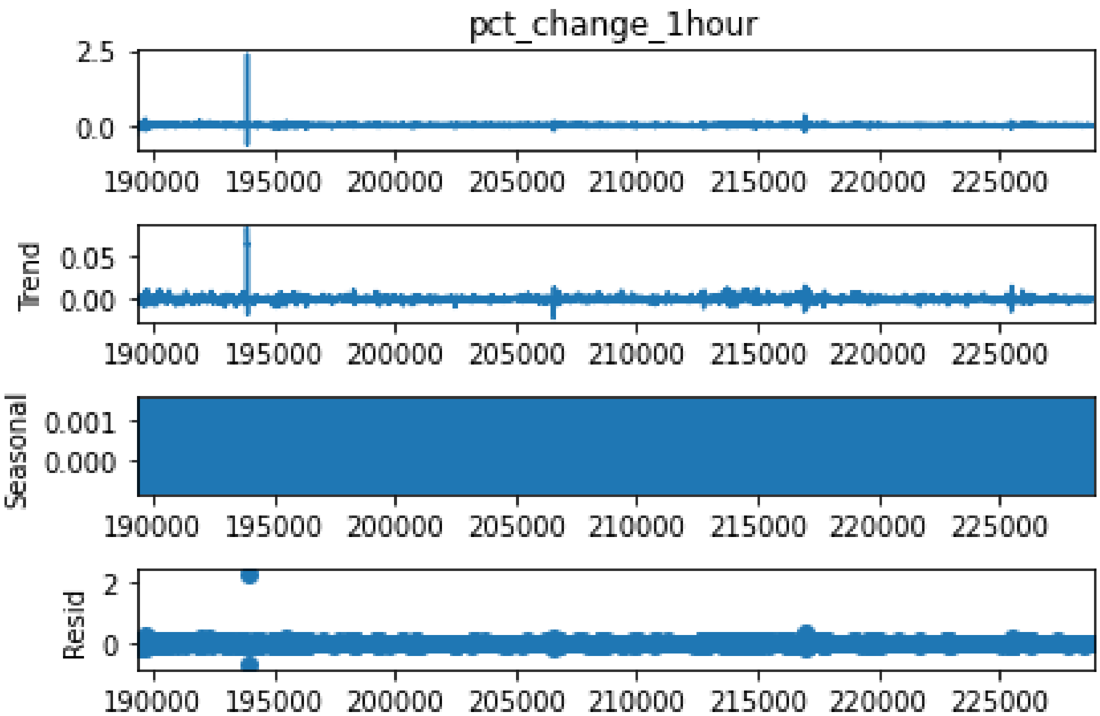

```
Crypto : ETH
```


pct_change_1hour
Trend
Seasonal
Resid
0
−1
0.00
−0.02
0.0005
0.0000
−0.0005
0.2
0.0
−0.2
90000
100000
110000
120000
130000
140000

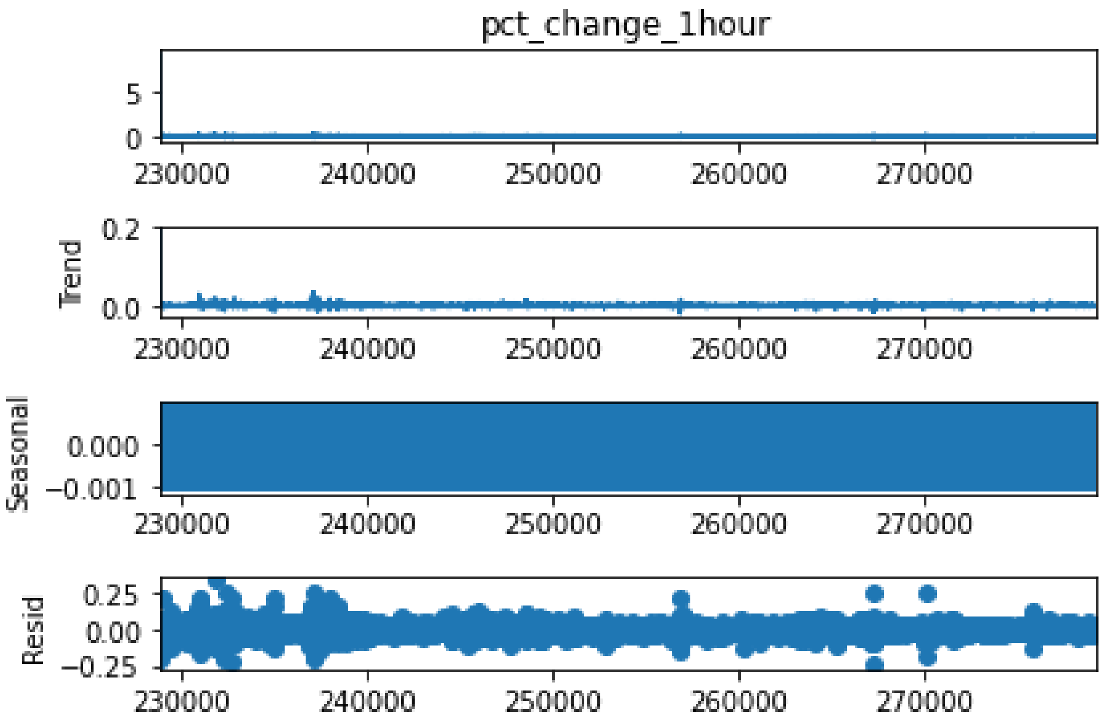
```
Crypto : XRP
```


pct_change_1hour
Trend
Seasonal
Resid
0
−1
0.05
0.00
0.001
0.000
0.25
0.00
−0.25
150000
160000
170000
180000

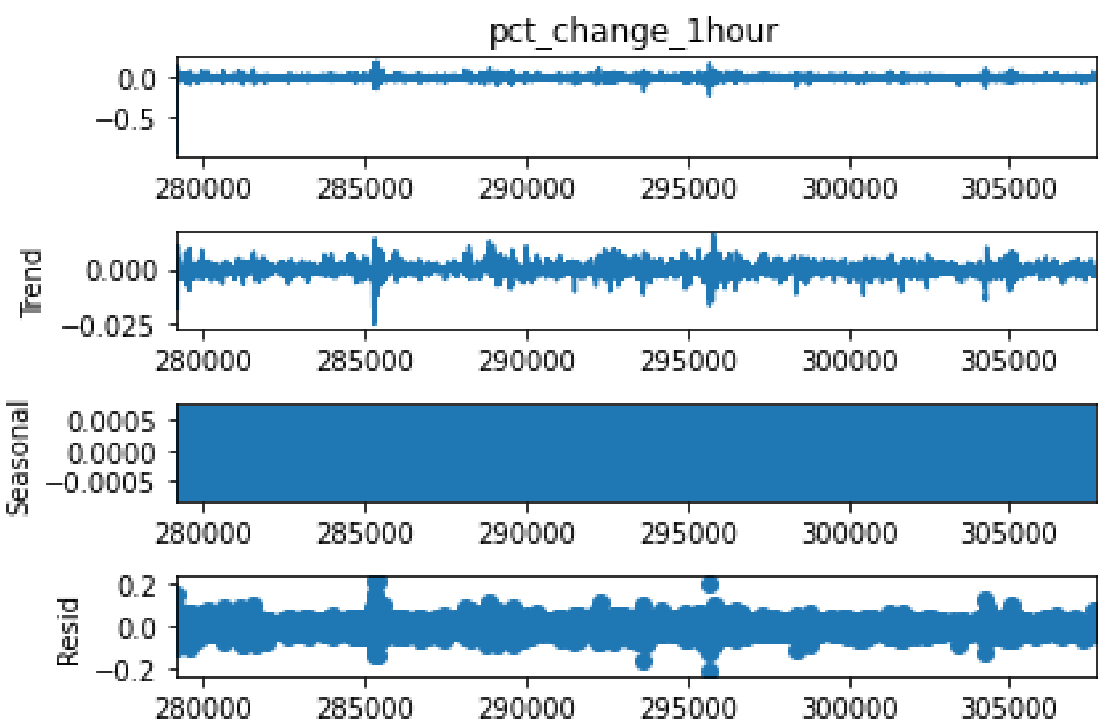
```
Crypto : ADA
```



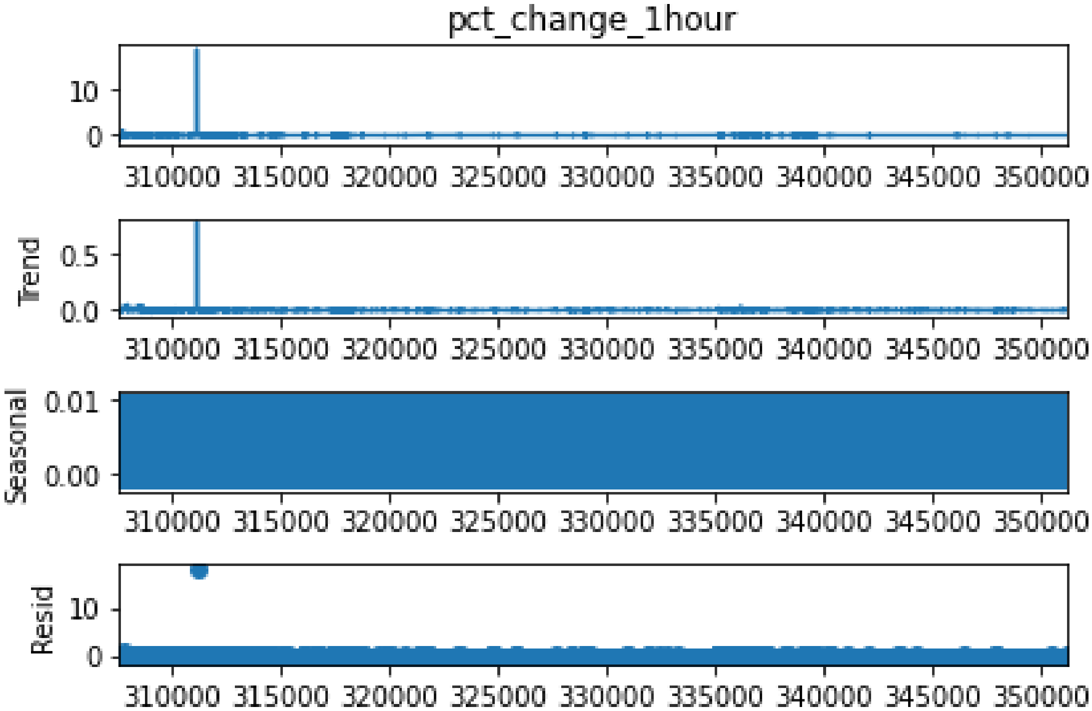

```
Crypto : LTC
```


pct_change_1hour
Trend
Seasonal
Resid

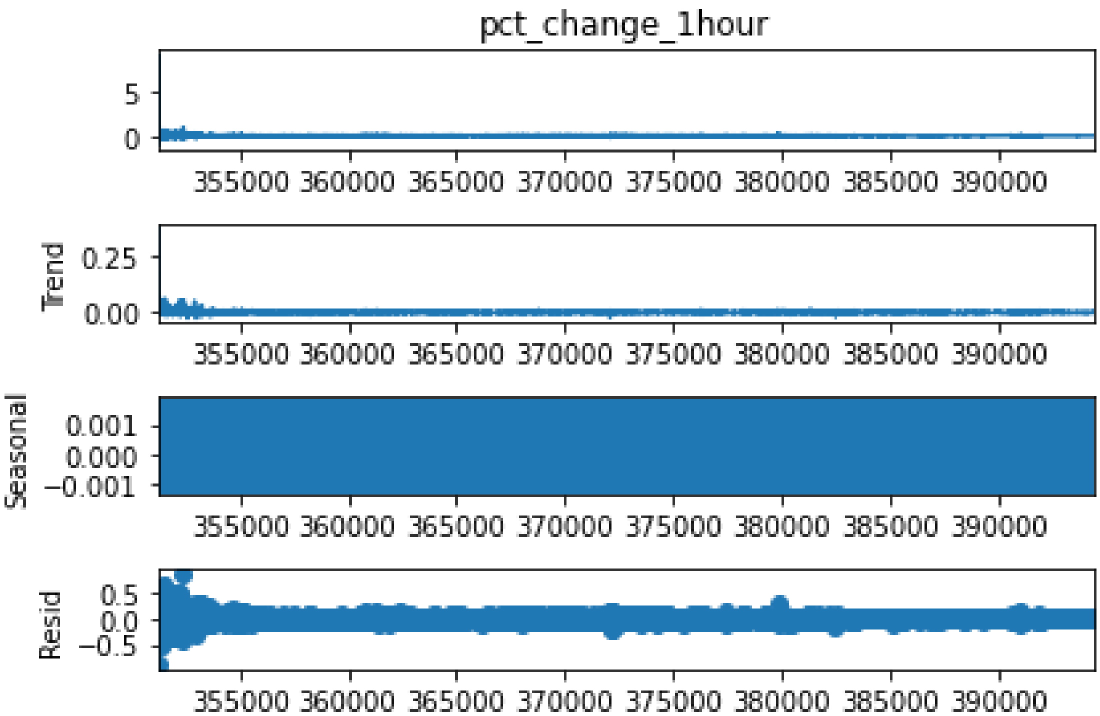
Crypto : LINK


pct_change_1hour
Trend
Seasonal
Resid

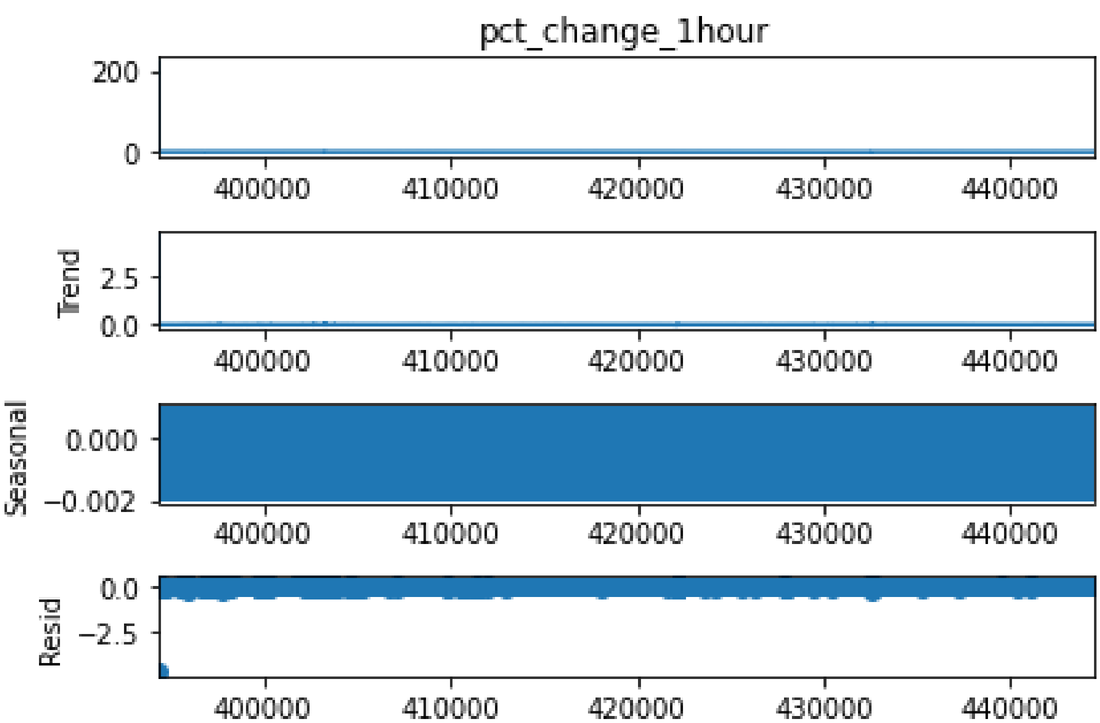
Crypto : XLM



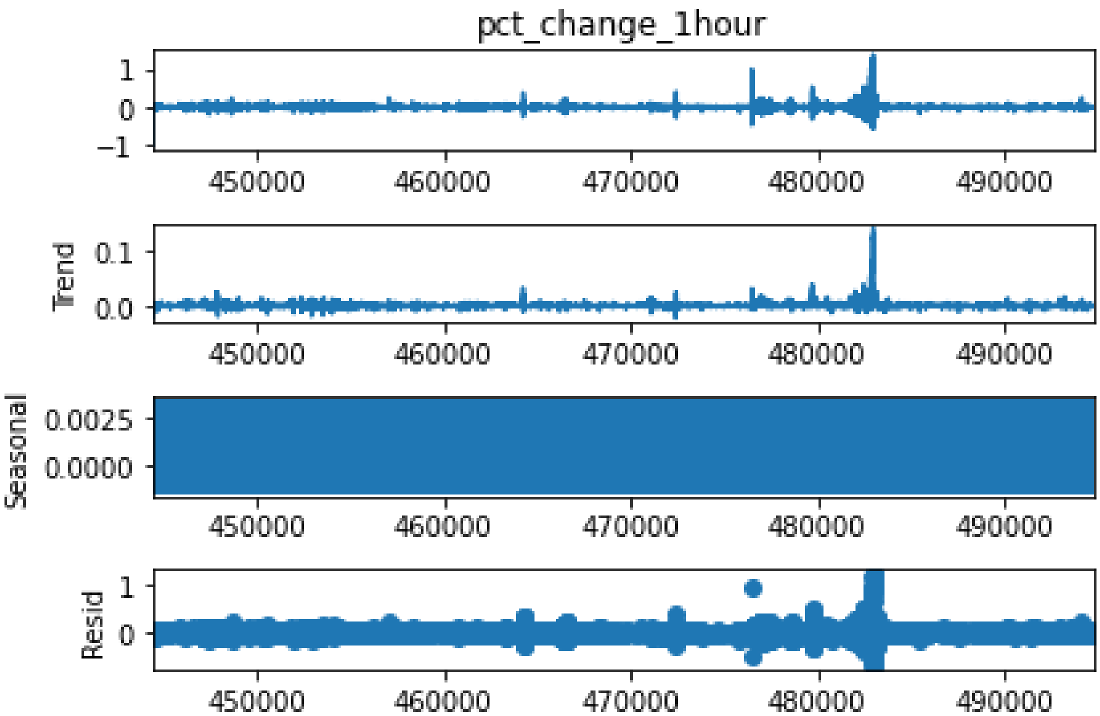
Crypto : TRX


pct_change_1hour
5
0
Trend
0.25
0.00
Seasonal
0.001
0.000
−0.001
Resid
0.5
0.0
−0.5
355000 360000 365000 370000 375000 380000 385000 390000

```
Crypto : XMR
```

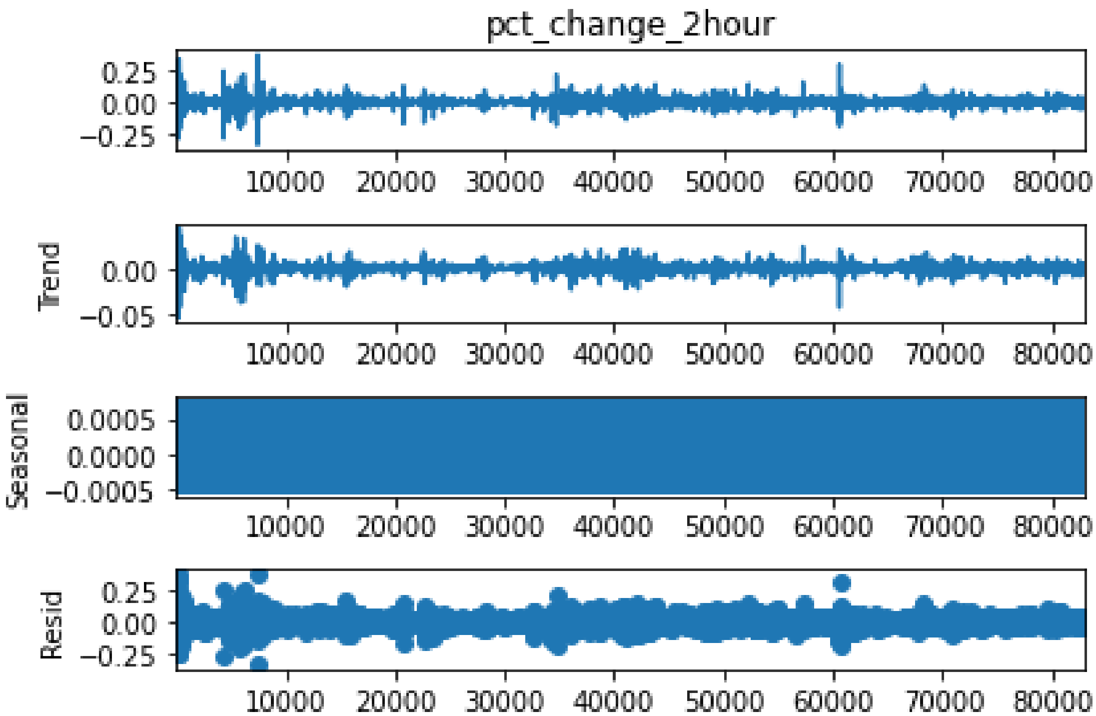

pct_change_1hour
200
0
Trend
2.5
0.0
Seasonal
0.000
−0.002
Resid
0.0
−2.5
400000 410000 420000 430000 440000

Crypto : ETC

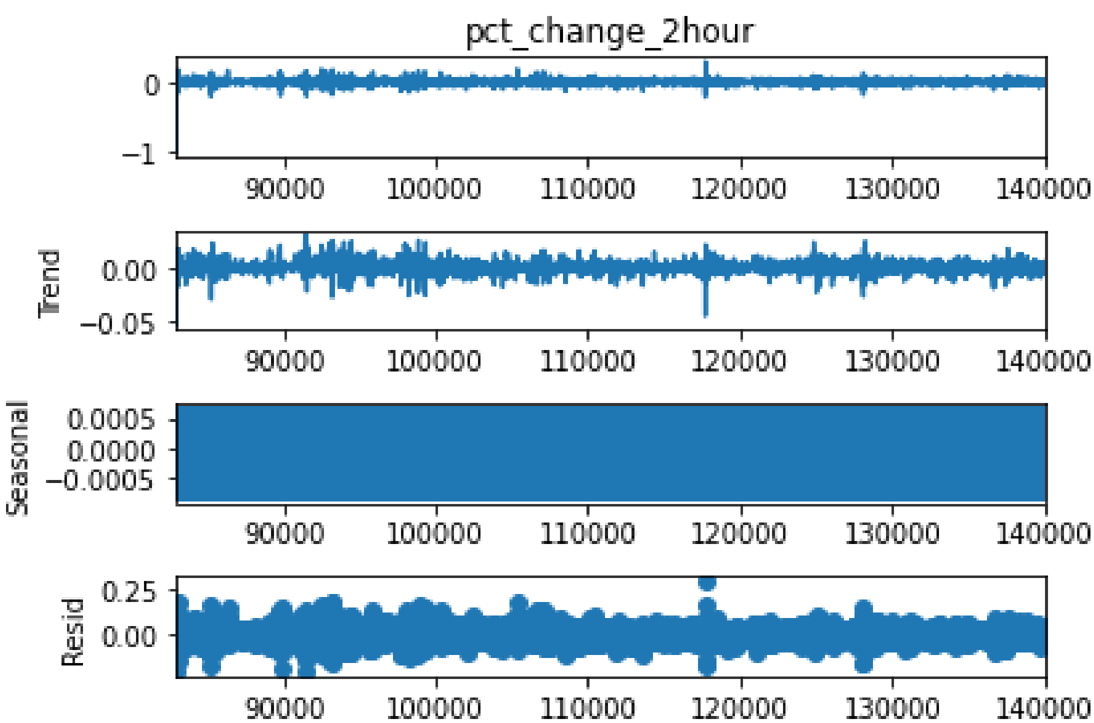



```
[ ]: from statsmodels.tsa.seasonal import seasonal_decompose
     from statsmodels.tsa.tsatools import freq_to_period
     import matplotlib.pyplot as plt
     for crypto_ in hour['Crypto'].unique():
       print("Crypto : {}".format(crypto_))
       analysis =␣
      ↪seasonal_decompose(hour[hour['Crypto']==crypto_]["pct_change_2hour"].
      ↪dropna(), freq=freq_to_period('2H'))

       analysis.plot()
       plt.show()
```

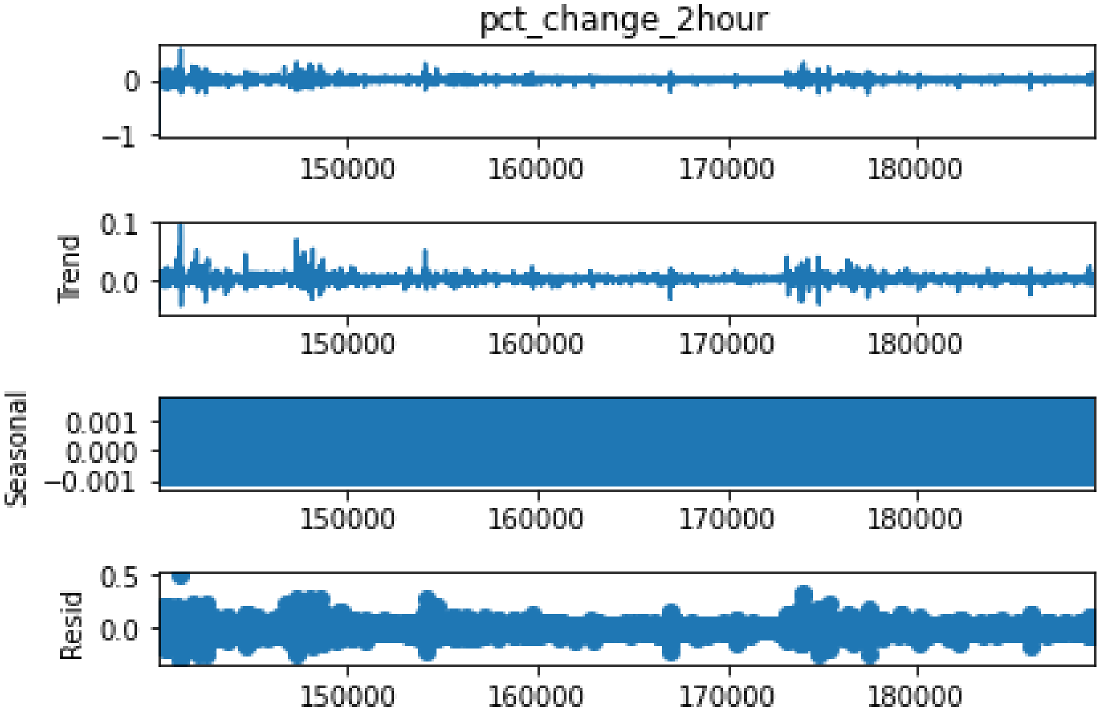
Crypto : BTC


pct_change_2hour
0.25
0.00
−0.25
10000
20000
30000
40000
50000
60000
70000
80000
Trend
0.00
−0.05
Seasonal
0.0005
0.0000
−0.0005
Resid
0.25
0.00
−0.25

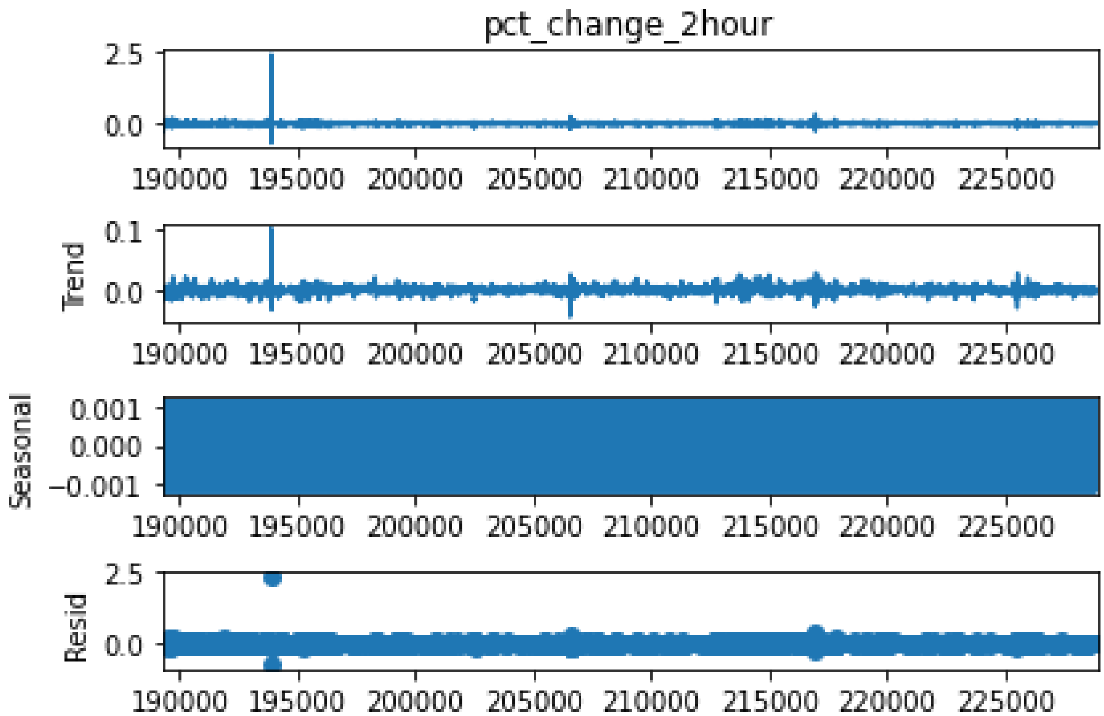
```
Crypto : ETH
```


pct_change_2hour
0
−1
90000
100000
110000
120000
130000
140000
Trend
0.00
−0.05
Seasonal
0.0005
0.0000
−0.0005
Resid
0.25
0.00

Crypto : XRP

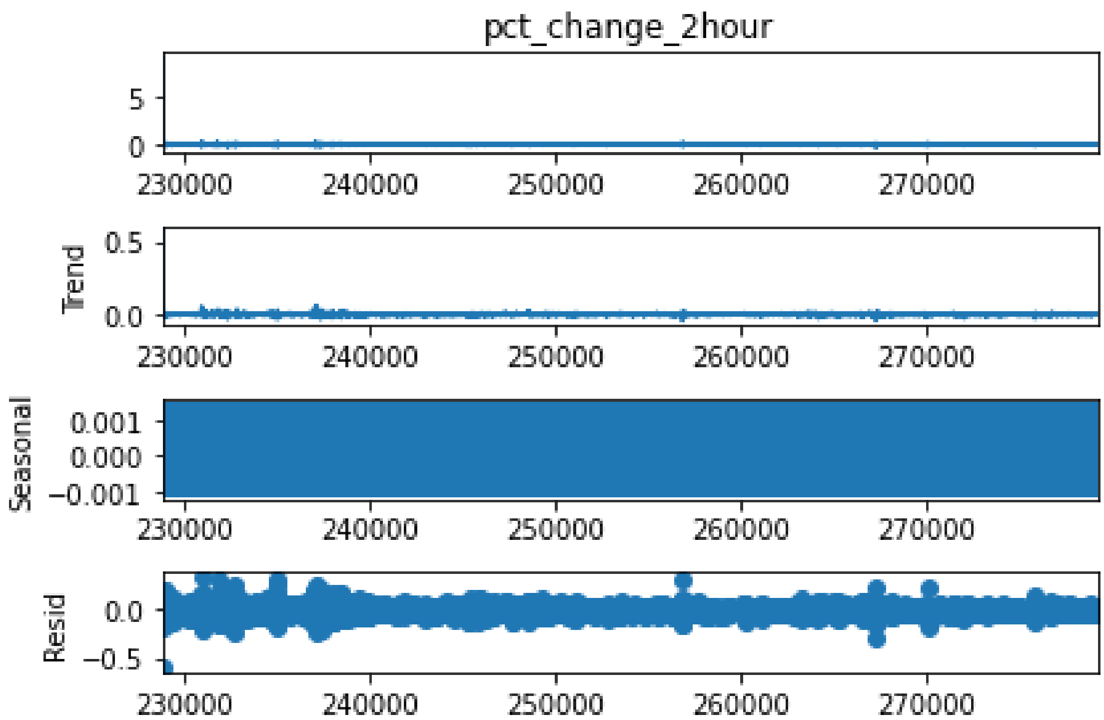


Crypto : ADA



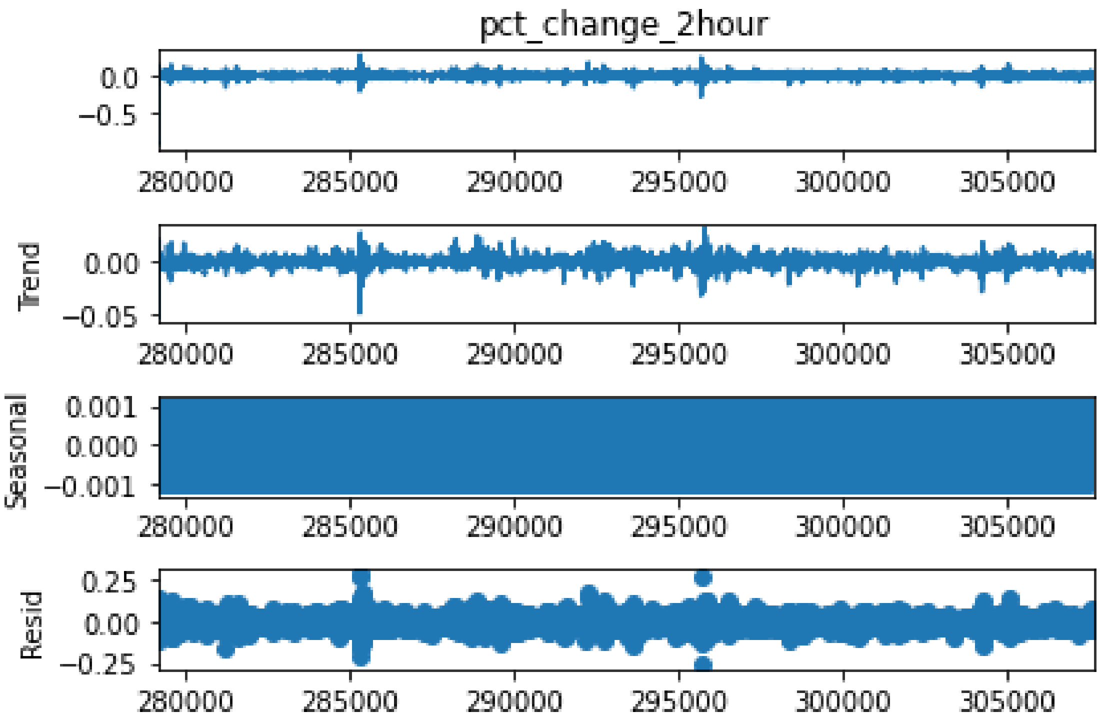
pct_change_2hour
Trend
Seasonal
Resid


```
Crypto : LTC
```

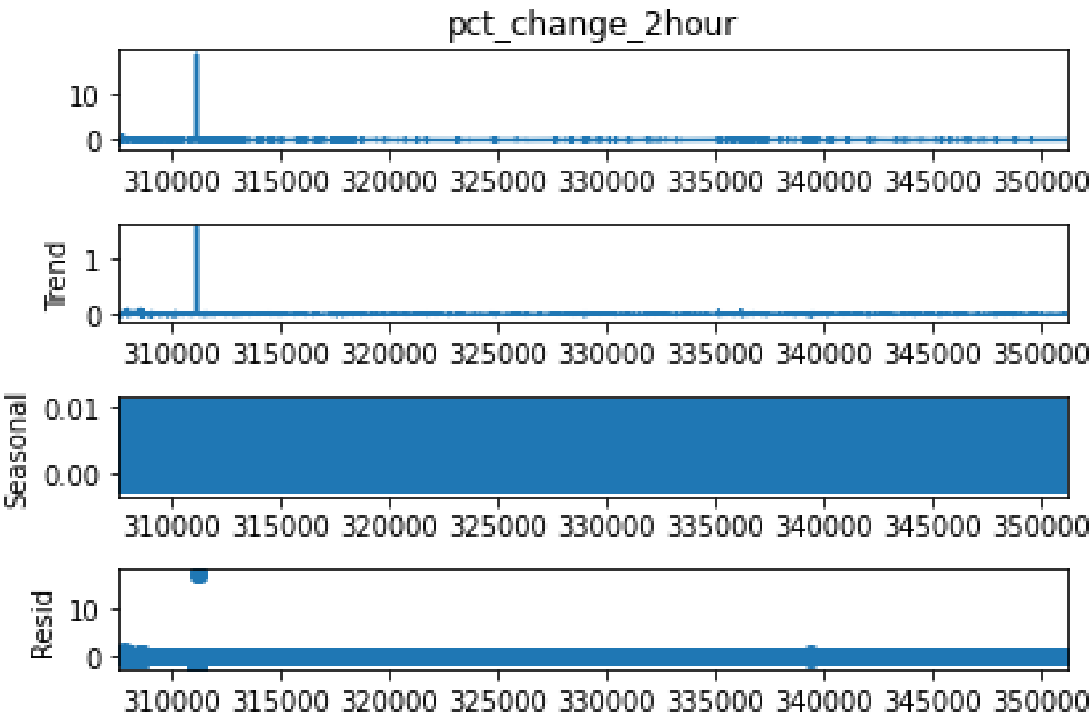


pct_change_2hour
Trend
Seasonal
Resid

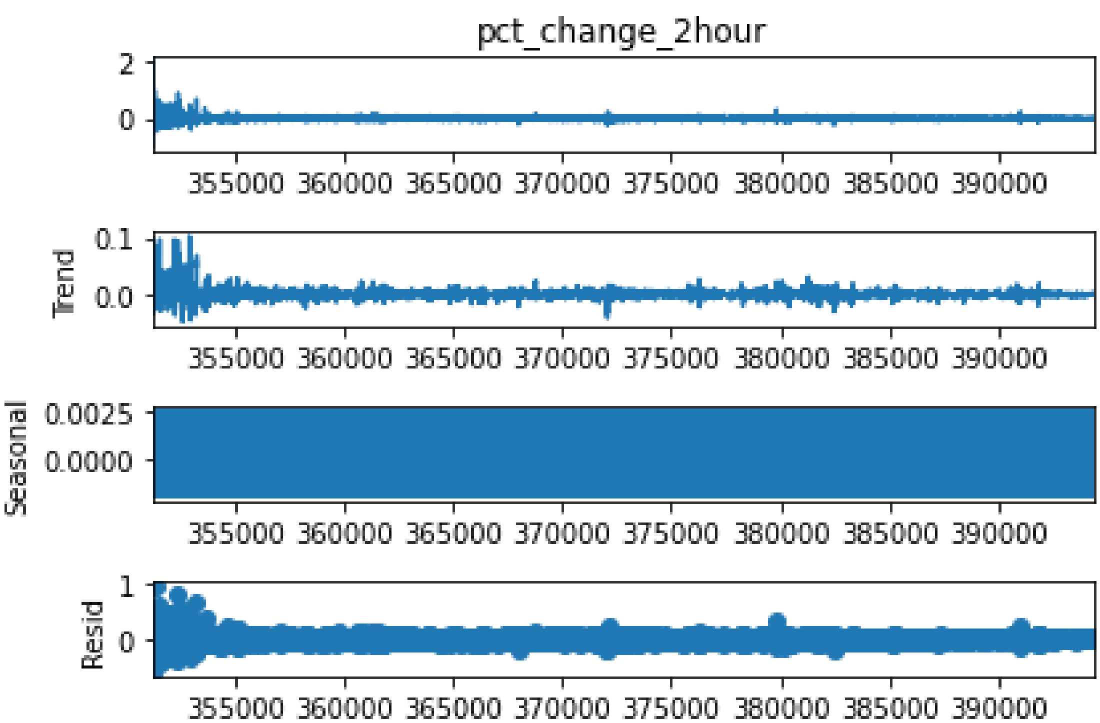
Crypto : LINK



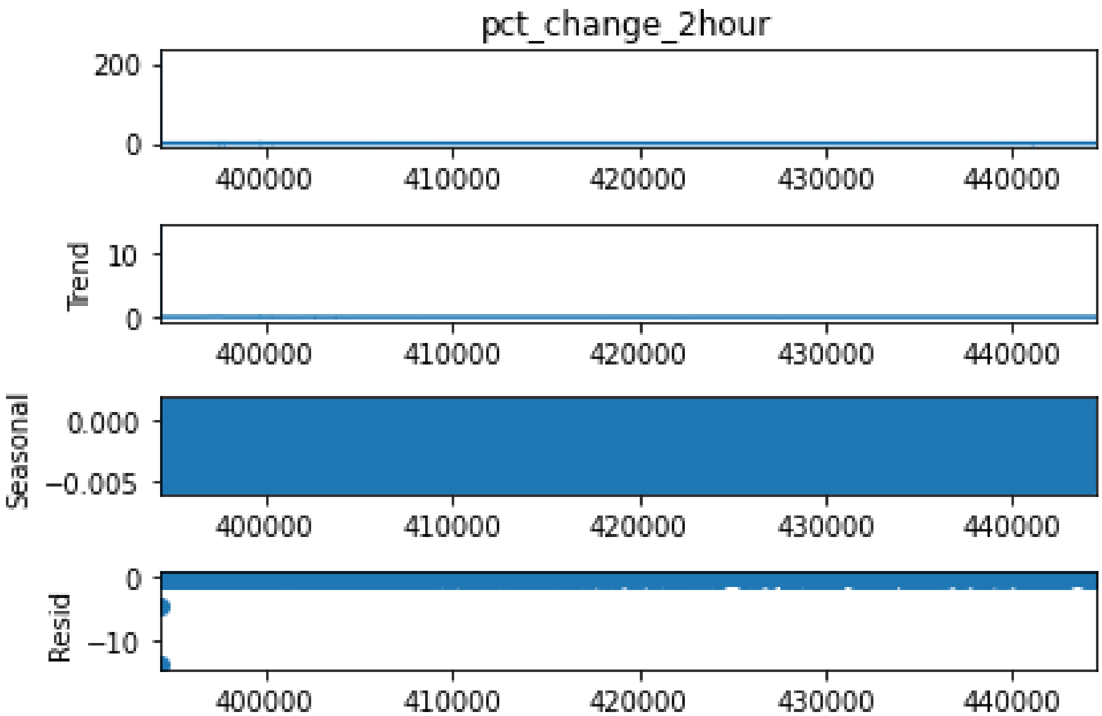
Crypto : XLM


pct_change_2hour
10
0
310000 315000 320000 325000 330000 335000 340000 345000 350000
Trend
1
0
Seasonal
0.01
0.00
Resid
10
0

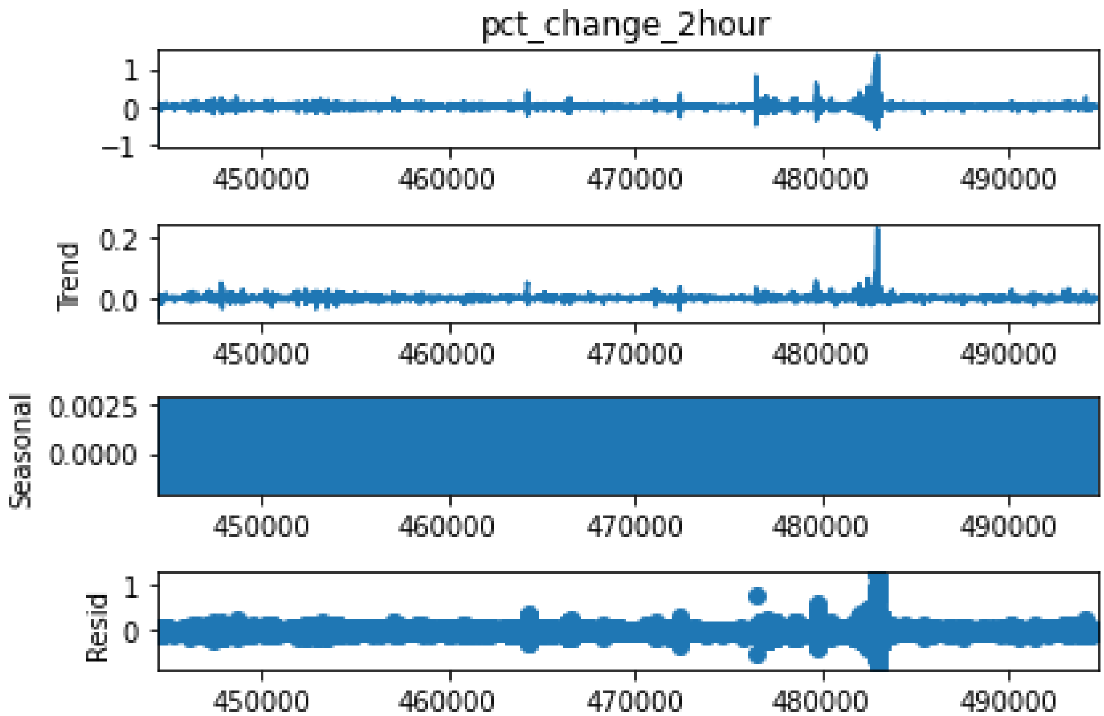
Crypto : TRX


pct_change_2hour
2
0
355000 360000 365000 370000 375000 380000 385000 390000
Trend
0.1
0.0
Seasonal
0.0025
0.0000
Resid
1
0

Crypto : XMR

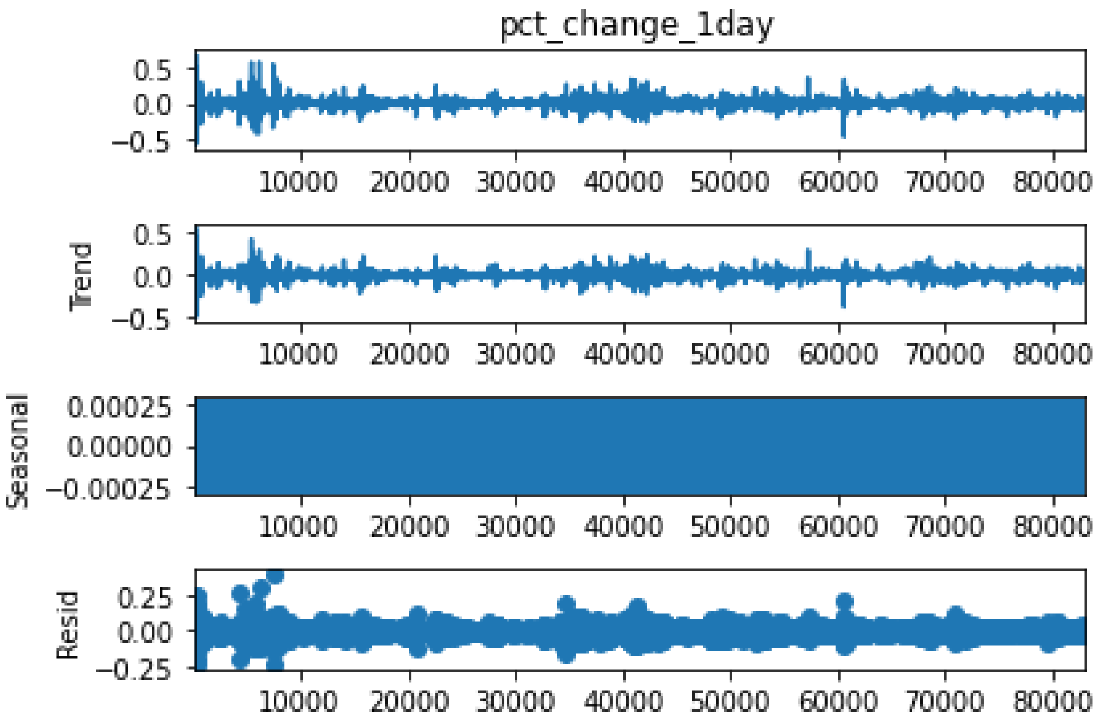


Crypto : ETC

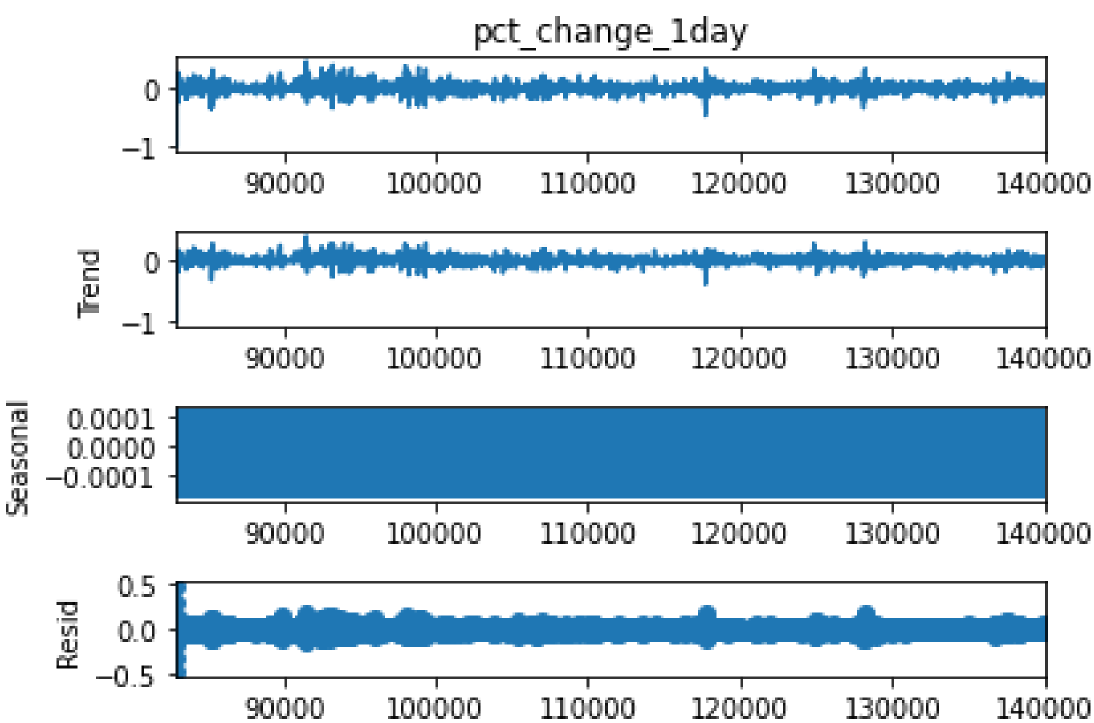


[ ]:
```python
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.tsatools import freq_to_period
import matplotlib.pyplot as plt
for crypto_ in hour['Crypto'].unique():
  print("Crypto : {}".format(crypto_))
  analysis =␣
↪seasonal_decompose(hour[hour['Crypto']==crypto_]["pct_change_1day"].
↪dropna(), freq=freq_to_period('D'))

  analysis.plot()
  plt.show()
```

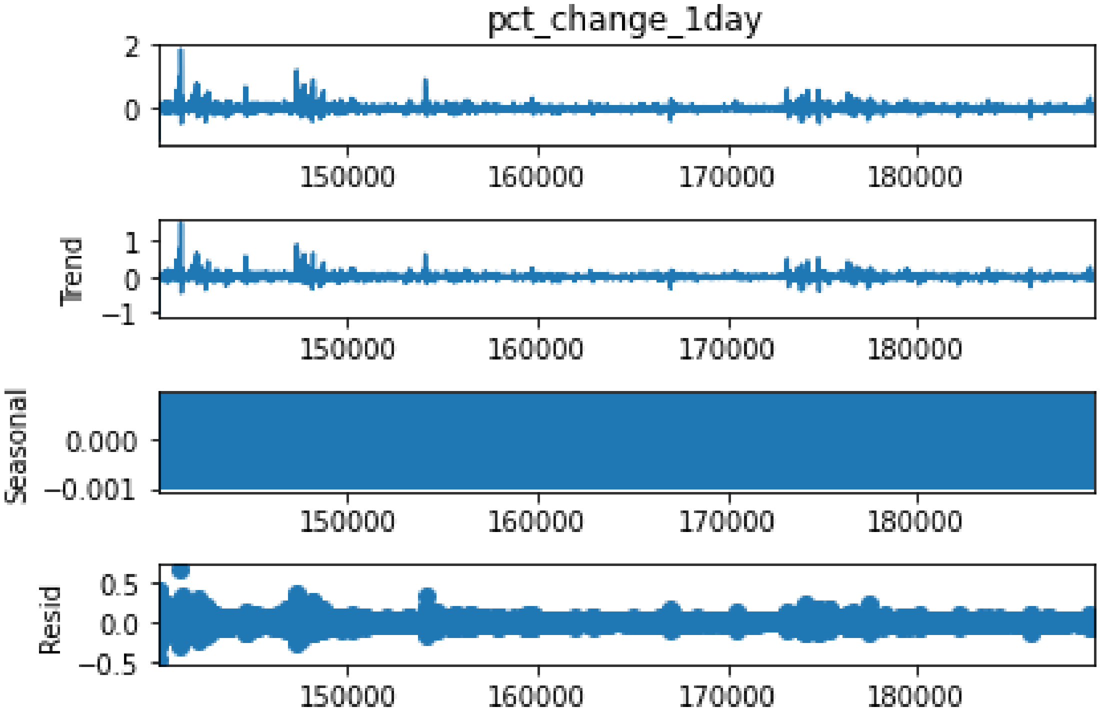
```
Crypto : BTC
```


pct_change_1day
Trend
Seasonal
Resid
0.5
0.0
−0.5
0.00025
0.00000
−0.00025
0.25
0.00
−0.25
10000
20000
30000
40000
50000
60000
70000
80000

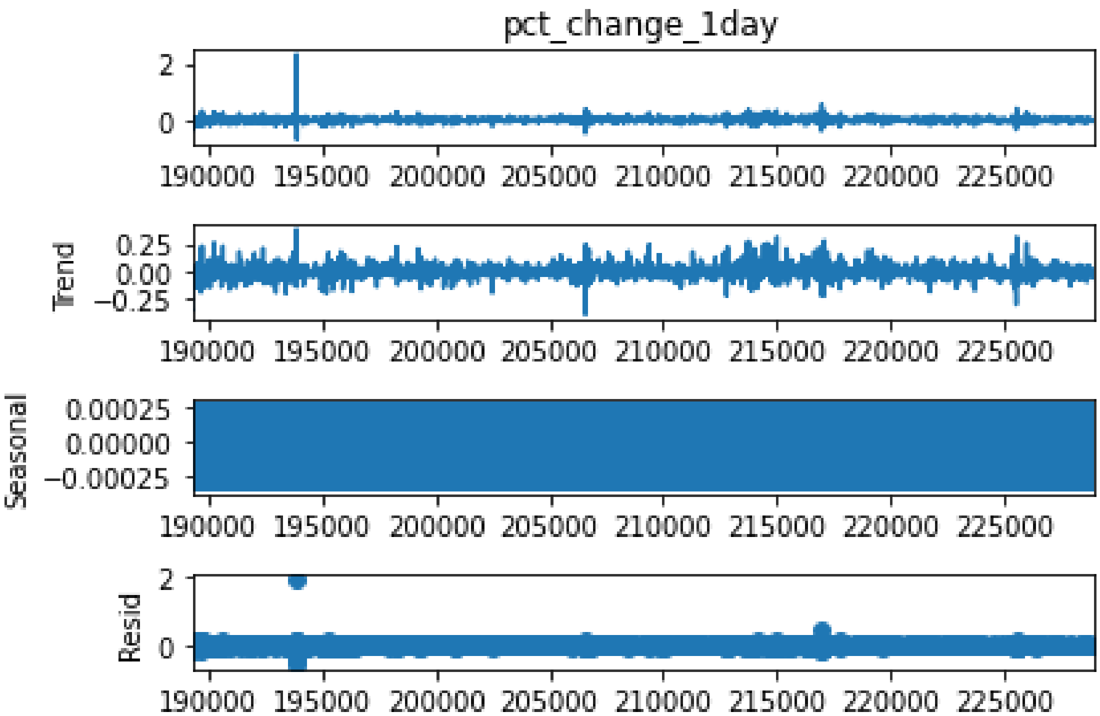
Crypto : ETH


pct_change_1day
Trend
Seasonal
Resid
0
−1
0.0001
0.0000
−0.0001
0.5
0.0
−0.5
90000
100000
110000
120000
130000
140000

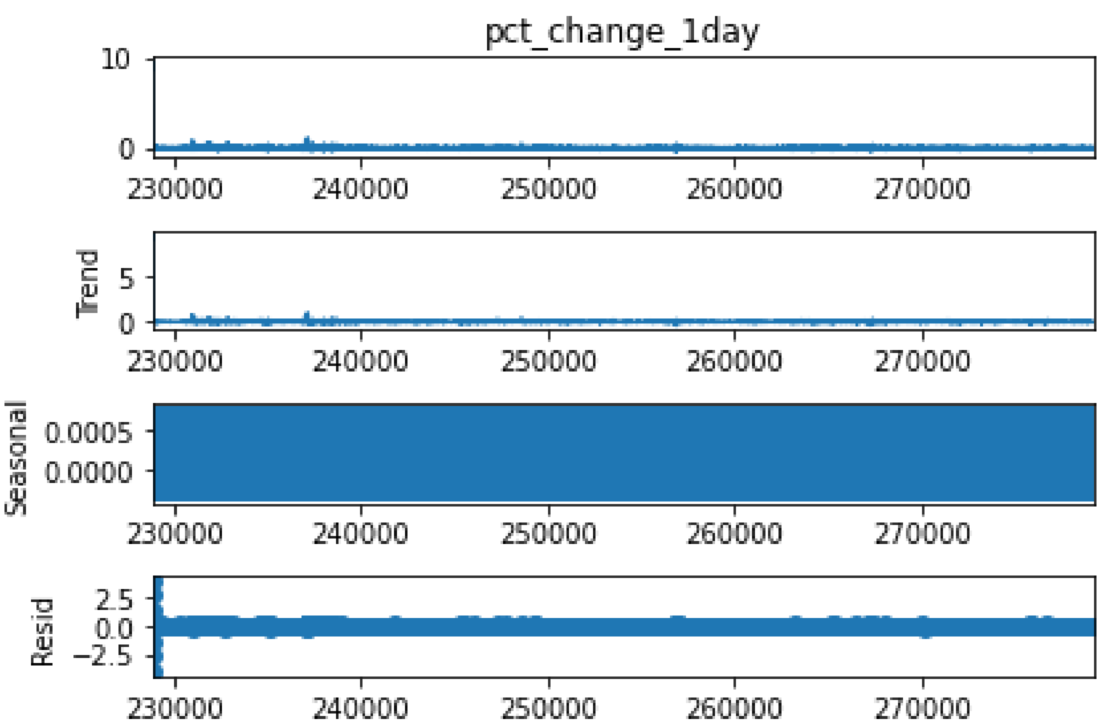
Crypto : XRP



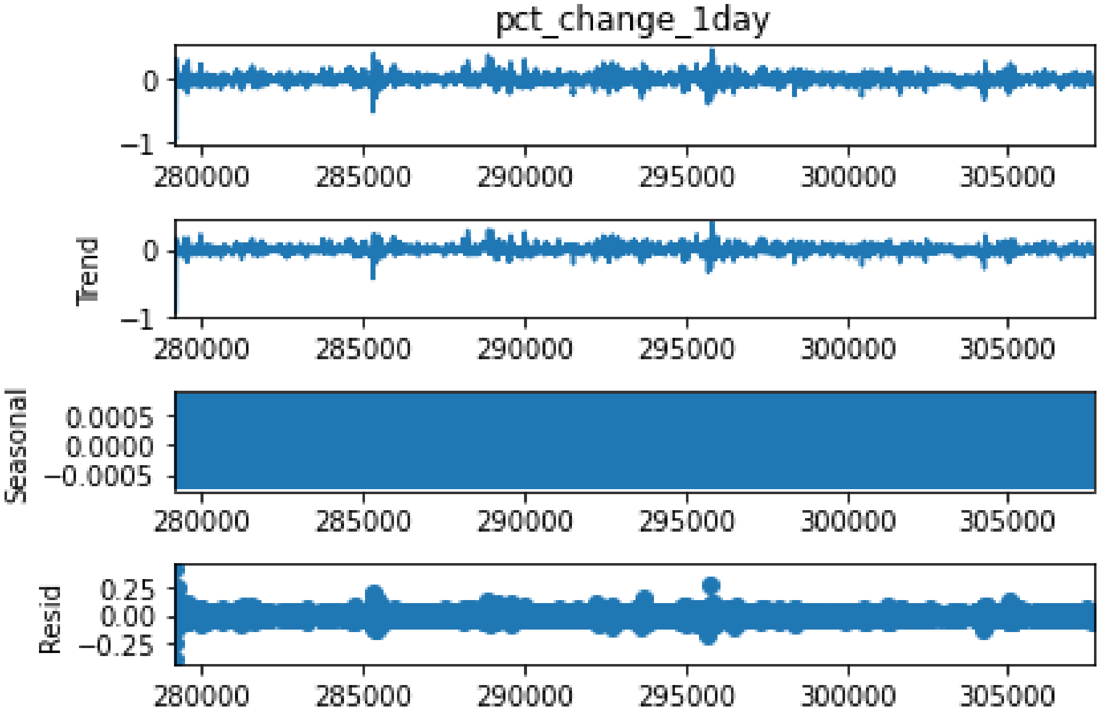
Crypto : ADA


pct_change_1day
2
0
Trend
0.25
0.00
−0.25
Seasonal
0.00025
0.00000
−0.00025
Resid
2
0
190000 195000 200000 205000 210000 215000 220000 225000

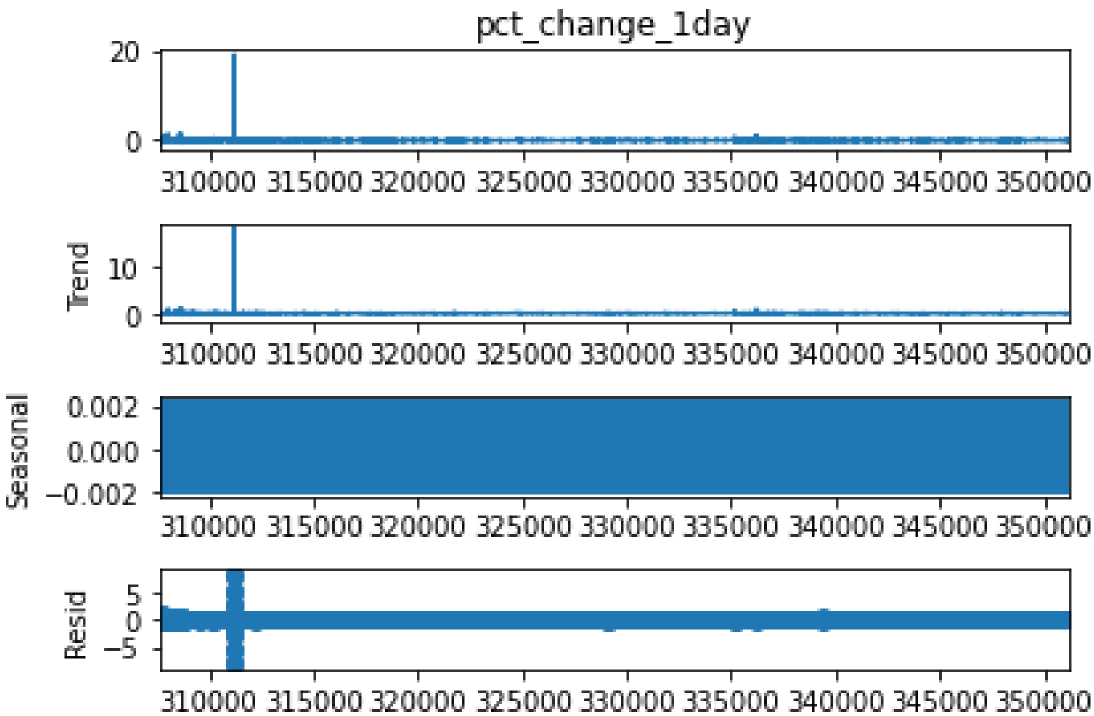
```
Crypto : LTC
```


pct_change_1day
10
0
Trend
5
0
Seasonal
0.0005
0.0000
Resid
2.5
0.0
−2.5
230000 240000 250000 260000 270000

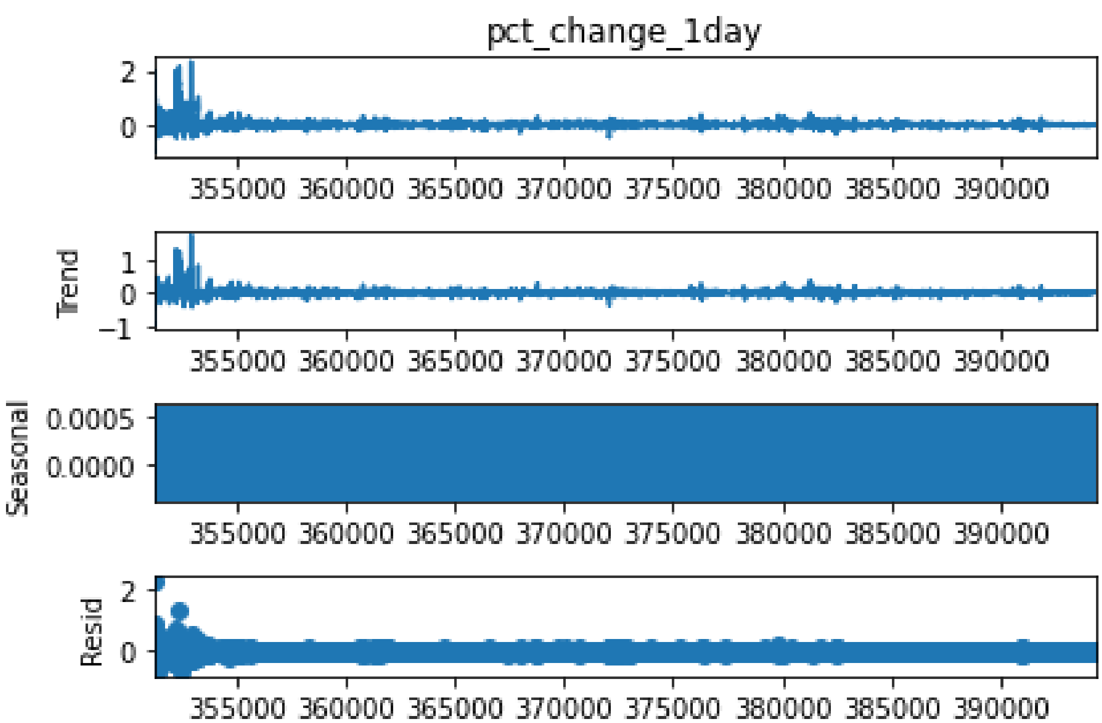
Crypto : LINK



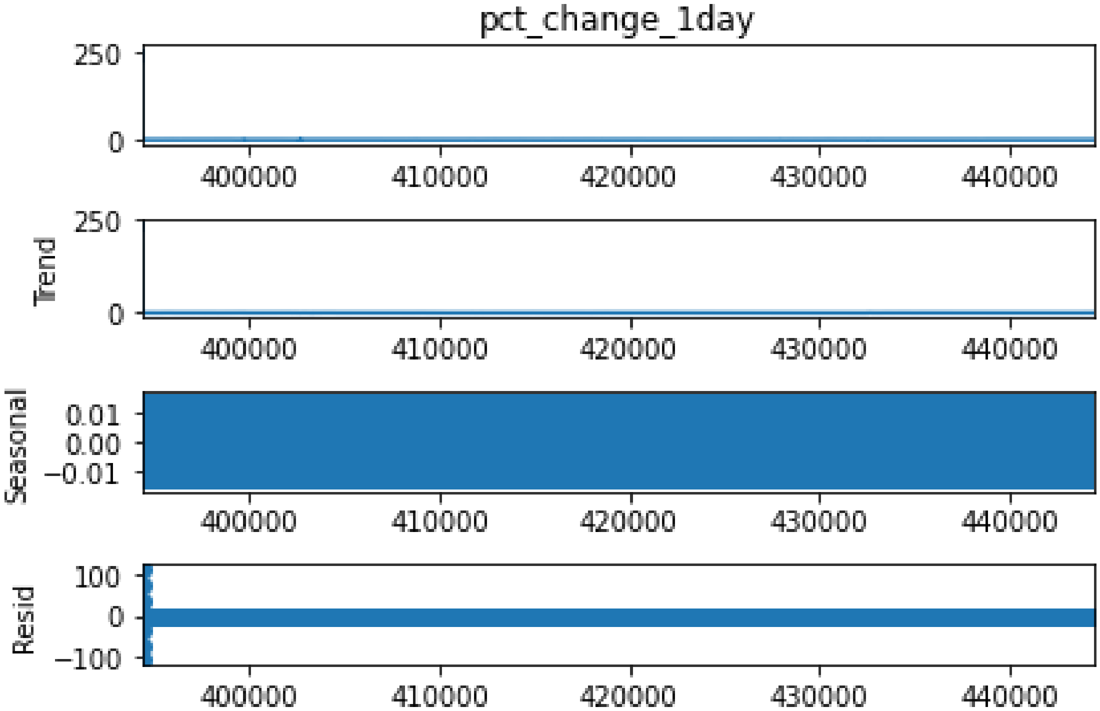
Crypto : XLM


pct_change_1day
Trend
Seasonal
Resid

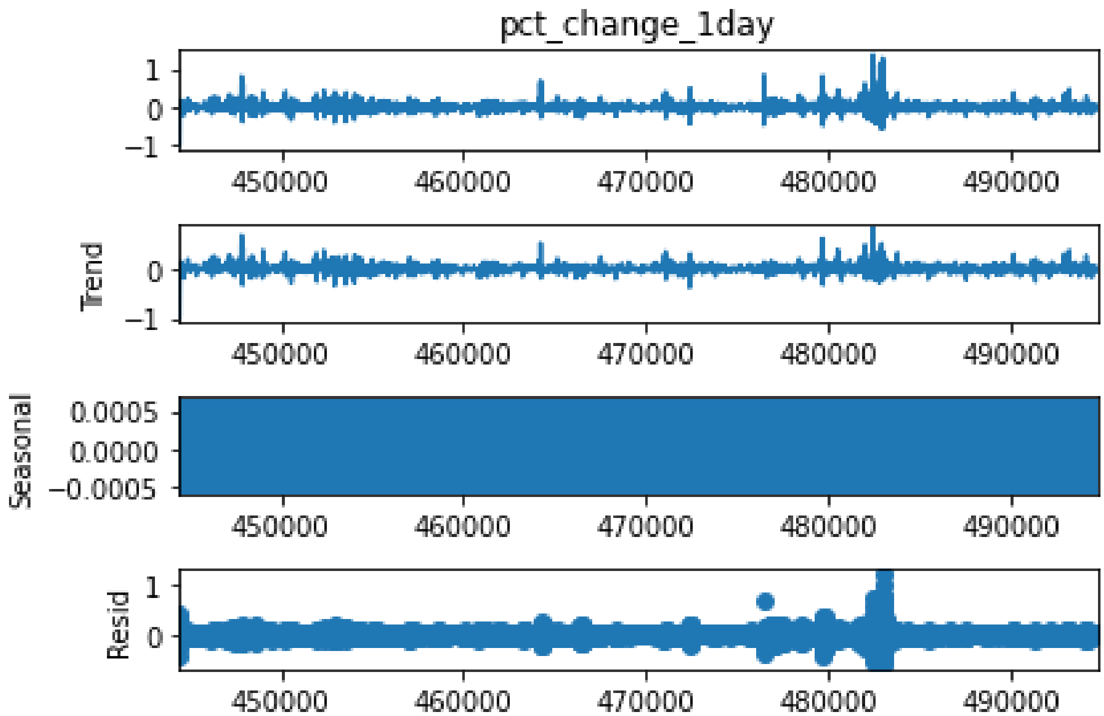
Crypto : TRX


pct_change_1day
Trend
Seasonal
Resid

Crypto : XMR



Crypto : ETC



Observation: In both the cases for all the cyrptos there no particular Trend and seasonality which might give us understanding that Time series models like AR n MA might not be best performing approaches.

[ ]:

6 Questionable ADF test

[ ]:
```
# Function to print out results in customised manner
from statsmodels.tsa.stattools import adfuller
def adf_test(timeseries):
    dftest = adfuller(timeseries, autolag='AIC')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags␣
↪Used','Number of Observations Used'])
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print (dfoutput)


# Call the function and run the test
col = ['pct_change_1day','pct_change_2hour','pct_change_1hour']
coins = hour['Crypto'].unique()
for coin in coins:
```

```python
print('Analysis on {}'.format(coin))
for c in col:
  print('------ result for {} ------'.format(c))
  adf_test(hour[hour['Crypto']==coin][c].dropna())
```

```
Analysis on BTC
------ result for pct_change_1day ------
Test Statistic                    -33.653034
p-value                             0.000000
#Lags Used                         65.000000
Number of Observations Used     82870.000000
Critical Value (1%)                -3.430429
Critical Value (5%)                -2.861575
Critical Value (10%)               -2.566789
dtype: float64
------ result for pct_change_2hour ------
Test Statistic                    -37.399609
p-value                             0.000000
#Lags Used                         63.000000
Number of Observations Used     82894.000000
Critical Value (1%)                -3.430429
Critical Value (5%)                -2.861575
Critical Value (10%)               -2.566789
dtype: float64
------ result for pct_change_1hour ------
Test Statistic                    -37.011265
p-value                             0.000000
#Lags Used                         65.000000
Number of Observations Used     82893.000000
Critical Value (1%)                -3.430429
Critical Value (5%)                -2.861575
Critical Value (10%)               -2.566789
dtype: float64
Analysis on ETH
------ result for pct_change_1day ------
Test Statistic                    -25.112149
p-value                             0.000000
#Lags Used                         54.000000
Number of Observations Used     57026.000000
Critical Value (1%)                -3.430465
Critical Value (5%)                -2.861591
Critical Value (10%)               -2.566797
dtype: float64
------ result for pct_change_2hour ------
Test Statistic                    -30.782409
p-value                             0.000000
#Lags Used                         57.000000
Number of Observations Used     57023.000000
```

```
Critical Value (1%)              -3.430465
Critical Value (5%)              -2.861591
Critical Value (10%)             -2.566797
dtype: float64
------ result for pct_change_1hour ------
Test Statistic                  -32.230784
p-value                           0.000000
#Lags Used                       52.000000
Number of Observations Used   57028.000000
Critical Value (1%)              -3.430465
Critical Value (5%)              -2.861591
Critical Value (10%)             -2.566797
dtype: float64
Analysis on XRP
------ result for pct_change_1day ------
Test Statistic                  -21.415667
p-value                           0.000000
#Lags Used                       57.000000
Number of Observations Used   49177.000000
Critical Value (1%)              -3.430483
Critical Value (5%)              -2.861599
Critical Value (10%)             -2.566801
dtype: float64
------ result for pct_change_2hour ------
Test Statistic                  -26.997775
p-value                           0.000000
#Lags Used                       57.000000
Number of Observations Used   49177.000000
Critical Value (1%)              -3.430483
Critical Value (5%)              -2.861599
Critical Value (10%)             -2.566801
dtype: float64
------ result for pct_change_1hour ------
Test Statistic                  -27.336190
p-value                           0.000000
#Lags Used                       57.000000
Number of Observations Used   49177.000000
Critical Value (1%)              -3.430483
Critical Value (5%)              -2.861599
Critical Value (10%)             -2.566801
dtype: float64
Analysis on ADA
------ result for pct_change_1day ------
Test Statistic                  -20.570407
p-value                           0.000000
#Lags Used                       51.000000
Number of Observations Used   39562.000000
Critical Value (1%)              -3.430515
```

```
Critical Value (5%)              -2.861613
Critical Value (10%)             -2.566809
dtype: float64
------ result for pct_change_2hour ------
Test Statistic                  -40.956310
p-value                           0.000000
#Lags Used                       25.000000
Number of Observations Used   39588.000000
Critical Value (1%)              -3.430515
Critical Value (5%)              -2.861613
Critical Value (10%)             -2.566809
dtype: float64
------ result for pct_change_1hour ------
Test Statistic                  -40.191174
p-value                           0.000000
#Lags Used                       26.000000
Number of Observations Used   39587.000000
Critical Value (1%)              -3.430515
Critical Value (5%)              -2.861613
Critical Value (10%)             -2.566809
dtype: float64
Analysis on LTC
------ result for pct_change_1day ------
Test Statistic                  -27.337883
p-value                           0.000000
#Lags Used                       50.000000
Number of Observations Used   50245.000000
Critical Value (1%)              -3.430480
Critical Value (5%)              -2.861598
Critical Value (10%)             -2.566801
dtype: float64
------ result for pct_change_2hour ------
Test Statistic                  -31.158745
p-value                           0.000000
#Lags Used                       53.000000
Number of Observations Used   50242.000000
Critical Value (1%)              -3.430480
Critical Value (5%)              -2.861598
Critical Value (10%)             -2.566801
dtype: float64
------ result for pct_change_1hour ------
Test Statistic                  -38.112807
p-value                           0.000000
#Lags Used                       36.000000
Number of Observations Used   50259.000000
Critical Value (1%)              -3.430480
Critical Value (5%)              -2.861598
Critical Value (10%)             -2.566801
```

```
dtype: float64
Analysis on LINK
------ result for pct_change_1day ------
Test Statistic                 -1.772342e+01
p-value                         3.460186e-30
#Lags Used                      4.900000e+01
Number of Observations Used     2.840800e+04
Critical Value (1%)            -3.430580e+00
Critical Value (5%)            -2.861642e+00
Critical Value (10%)           -2.566824e+00
dtype: float64
------ result for pct_change_2hour ------
Test Statistic                   -24.027781
p-value                            0.000000
#Lags Used                        50.000000
Number of Observations Used    28407.000000
Critical Value (1%)               -3.430580
Critical Value (5%)               -2.861642
Critical Value (10%)              -2.566824
dtype: float64
------ result for pct_change_1hour ------
Test Statistic                   -29.534843
p-value                            0.000000
#Lags Used                        34.000000
Number of Observations Used    28423.000000
Critical Value (1%)               -3.430580
Critical Value (5%)               -2.861642
Critical Value (10%)              -2.566824
dtype: float64
Analysis on XLM
------ result for pct_change_1day ------
Test Statistic                   -21.071843
p-value                            0.000000
#Lags Used                        55.000000
Number of Observations Used    43549.000000
Critical Value (1%)               -3.430500
Critical Value (5%)               -2.861606
Critical Value (10%)              -2.566805
dtype: float64
------ result for pct_change_2hour ------
Test Statistic                   -27.644639
p-value                            0.000000
#Lags Used                        55.000000
Number of Observations Used    43549.000000
Critical Value (1%)               -3.430500
Critical Value (5%)               -2.861606
Critical Value (10%)              -2.566805
dtype: float64
```

```
------ result for pct_change_1hour ------
Test Statistic                 -211.893190
p-value                           0.000000
#Lags Used                        0.000000
Number of Observations Used   43604.000000
Critical Value (1%)              -3.430500
Critical Value (5%)              -2.861606
Critical Value (10%)             -2.566805
dtype: float64
Analysis on TRX
------ result for pct_change_1day ------
Test Statistic                  -19.315992
p-value                           0.000000
#Lags Used                       55.000000
Number of Observations Used   43037.000000
Critical Value (1%)              -3.430502
Critical Value (5%)              -2.861607
Critical Value (10%)             -2.566806
dtype: float64
------ result for pct_change_2hour ------
Test Statistic                  -25.411362
p-value                           0.000000
#Lags Used                       55.000000
Number of Observations Used   43037.000000
Critical Value (1%)              -3.430502
Critical Value (5%)              -2.861607
Critical Value (10%)             -2.566806
dtype: float64
------ result for pct_change_1hour ------
Test Statistic                  -25.943050
p-value                           0.000000
#Lags Used                       55.000000
Number of Observations Used   43037.000000
Critical Value (1%)              -3.430502
Critical Value (5%)              -2.861607
Critical Value (10%)             -2.566806
dtype: float64
Analysis on XMR
------ result for pct_change_1day ------
Test Statistic                  -28.332150
p-value                           0.000000
#Lags Used                       57.000000
Number of Observations Used   50036.000000
Critical Value (1%)              -3.430481
Critical Value (5%)              -2.861598
Critical Value (10%)             -2.566801
dtype: float64
------ result for pct_change_2hour ------
```

```
Test Statistic                  -33.782414
p-value                           0.000000
#Lags Used                       47.000000
Number of Observations Used   50046.000000
Critical Value (1%)              -3.430481
Critical Value (5%)              -2.861598
Critical Value (10%)             -2.566801
dtype: float64
------ result for pct_change_1hour ------
Test Statistic                  -32.773359
p-value                           0.000000
#Lags Used                       48.000000
Number of Observations Used   50045.000000
Critical Value (1%)              -3.430481
Critical Value (5%)              -2.861598
Critical Value (10%)             -2.566801
dtype: float64
Analysis on ETC
------ result for pct_change_1day ------
Test Statistic                  -23.411194
p-value                           0.000000
#Lags Used                       57.000000
Number of Observations Used   50238.000000
Critical Value (1%)              -3.430480
Critical Value (5%)              -2.861598
Critical Value (10%)             -2.566801
dtype: float64
------ result for pct_change_2hour ------
Test Statistic                  -21.947268
p-value                           0.000000
#Lags Used                       57.000000
Number of Observations Used   50238.000000
Critical Value (1%)              -3.430480
Critical Value (5%)              -2.861598
Critical Value (10%)             -2.566801
dtype: float64
------ result for pct_change_1hour ------
Test Statistic                  -19.095031
p-value                           0.000000
#Lags Used                       56.000000
Number of Observations Used   50239.000000
Critical Value (1%)              -3.430480
Critical Value (5%)              -2.861598
Critical Value (10%)             -2.566801
dtype: float64
```

[ ]:

```

```

7 KPSS test

[ ]:
```
from statsmodels.tsa.stattools import kpss
def kpss_test(timeseries):
    print ('Results of KPSS Test:')
    kpsstest = kpss(timeseries, regression='c', nlags="auto")
    kpss_output = pd.Series(kpsstest[0:3], index=['Test␣
↪Statistic','p-value','#Lags Used'])
    for key,value in kpsstest[3].items():
        kpss_output['Critical Value (%s)'%key] = value
    print (kpss_output)

col = ['pct_change_1day','pct_change_2hour','pct_change_1hour']
coins = hour['Crypto'].unique()
for coin in coins:
  print('Analysis on {}'.format(coin))
  for c in col:
    print('------ result for {} ------'.format(c))
    kpss_test(hour[hour['Crypto']==coin][c].dropna())
```

```
Analysis on BTC
------ result for pct_change_1day ------
Results of KPSS Test:
Test Statistic             0.257743
p-value                    0.100000
#Lags Used               155.000000
Critical Value (10%)       0.347000
Critical Value (5%)        0.463000
Critical Value (2.5%)      0.574000
Critical Value (1%)        0.739000
dtype: float64
------ result for pct_change_2hour ------
Results of KPSS Test:
Test Statistic            0.302831
p-value                   0.100000
#Lags Used               13.000000
Critical Value (10%)      0.347000
Critical Value (5%)       0.463000
Critical Value (2.5%)     0.574000
Critical Value (1%)       0.739000
dtype: float64
------ result for pct_change_1hour ------
Results of KPSS Test:
Test Statistic            0.362251
p-value                   0.093426
#Lags Used               52.000000
Critical Value (10%)      0.347000
Critical Value (5%)       0.463000
```

```
Critical Value (2.5%)     0.574000
Critical Value (1%)       0.739000
dtype: float64
Analysis on ETH
------ result for pct_change_1day ------
Results of KPSS Test:
Test Statistic              0.189878
p-value                     0.100000
#Lags Used                131.000000
Critical Value (10%)        0.347000
Critical Value (5%)         0.463000
Critical Value (2.5%)       0.574000
Critical Value (1%)         0.739000
dtype: float64
------ result for pct_change_2hour ------
Results of KPSS Test:
Test Statistic             0.242877
p-value                    0.100000
#Lags Used                30.000000
Critical Value (10%)       0.347000
Critical Value (5%)        0.463000
Critical Value (2.5%)      0.574000
Critical Value (1%)        0.739000
dtype: float64
------ result for pct_change_1hour ------
Results of KPSS Test:
Test Statistic             0.295735
p-value                    0.100000
#Lags Used                19.000000
Critical Value (10%)       0.347000
Critical Value (5%)        0.463000
Critical Value (2.5%)      0.574000
Critical Value (1%)        0.739000
dtype: float64
Analysis on XRP
------ result for pct_change_1day ------
Results of KPSS Test:
Test Statistic              0.457238
p-value                     0.052484
#Lags Used                125.000000
Critical Value (10%)        0.347000
Critical Value (5%)         0.463000
Critical Value (2.5%)       0.574000
Critical Value (1%)         0.739000
dtype: float64
------ result for pct_change_2hour ------
Results of KPSS Test:
Test Statistic             0.663779
```

```
p-value                  0.016838
#Lags Used              33.000000
Critical Value (10%)     0.347000
Critical Value (5%)      0.463000
Critical Value (2.5%)    0.574000
Critical Value (1%)      0.739000
dtype: float64
------ result for pct_change_1hour ------
Results of KPSS Test:
Test Statistic          0.901509
p-value                 0.010000
#Lags Used              9.000000
Critical Value (10%)    0.347000
Critical Value (5%)     0.463000
Critical Value (2.5%)   0.574000
Critical Value (1%)     0.739000
dtype: float64
Analysis on ADA
------ result for pct_change_1day ------
Results of KPSS Test:
Test Statistic            0.457789
p-value                   0.052246
#Lags Used              109.000000
Critical Value (10%)      0.347000
Critical Value (5%)       0.463000
Critical Value (2.5%)     0.574000
Critical Value (1%)       0.739000
dtype: float64
------ result for pct_change_2hour ------
Results of KPSS Test:
Test Statistic           0.256335
p-value                  0.100000
#Lags Used              14.000000
Critical Value (10%)     0.347000
Critical Value (5%)      0.463000
Critical Value (2.5%)    0.574000
Critical Value (1%)      0.739000
dtype: float64
------ result for pct_change_1hour ------
Results of KPSS Test:
Test Statistic           0.167418
p-value                  0.100000
#Lags Used              40.000000
Critical Value (10%)     0.347000
Critical Value (5%)      0.463000
Critical Value (2.5%)    0.574000
Critical Value (1%)      0.739000
dtype: float64
```

```
Analysis on LTC
------ result for pct_change_1day ------
Results of KPSS Test:
Test Statistic             0.606320
p-value                    0.022062
#Lags Used               125.000000
Critical Value (10%)       0.347000
Critical Value (5%)        0.463000
Critical Value (2.5%)      0.574000
Critical Value (1%)        0.739000
dtype: float64
------ result for pct_change_2hour ------
Results of KPSS Test:
Test Statistic            0.635105
p-value                   0.019445
#Lags Used               26.000000
Critical Value (10%)      0.347000
Critical Value (5%)       0.463000
Critical Value (2.5%)     0.574000
Critical Value (1%)       0.739000
dtype: float64
------ result for pct_change_1hour ------
Results of KPSS Test:
Test Statistic           0.686103
p-value                  0.014809
#Lags Used               2.000000
Critical Value (10%)     0.347000
Critical Value (5%)      0.463000
Critical Value (2.5%)    0.574000
Critical Value (1%)      0.739000
dtype: float64
Analysis on LINK
------ result for pct_change_1day ------
Results of KPSS Test:
Test Statistic            0.220887
p-value                   0.100000
#Lags Used               92.000000
Critical Value (10%)      0.347000
Critical Value (5%)       0.463000
Critical Value (2.5%)     0.574000
Critical Value (1%)       0.739000
dtype: float64
------ result for pct_change_2hour ------
Results of KPSS Test:
Test Statistic            0.196965
p-value                   0.100000
#Lags Used               24.000000
Critical Value (10%)      0.347000
```

```
Critical Value (5%)       0.463000
Critical Value (2.5%)     0.574000
Critical Value (1%)       0.739000
dtype: float64
------ result for pct_change_1hour ------
Results of KPSS Test:
Test Statistic           0.186962
p-value                  0.100000
#Lags Used               2.000000
Critical Value (10%)     0.347000
Critical Value (5%)      0.463000
Critical Value (2.5%)    0.574000
Critical Value (1%)      0.739000
dtype: float64
Analysis on XLM
------ result for pct_change_1day ------
Results of KPSS Test:
Test Statistic             0.340295
p-value                    0.100000
#Lags Used               113.000000
Critical Value (10%)       0.347000
Critical Value (5%)        0.463000
Critical Value (2.5%)      0.574000
Critical Value (1%)        0.739000
dtype: float64
------ result for pct_change_2hour ------
Results of KPSS Test:
Test Statistic            0.395946
p-value                   0.078902
#Lags Used               23.000000
Critical Value (10%)      0.347000
Critical Value (5%)       0.463000
Critical Value (2.5%)     0.574000
Critical Value (1%)       0.739000
dtype: float64
------ result for pct_change_1hour ------
Results of KPSS Test:
Test Statistic           0.450959
p-value                  0.055190
#Lags Used               5.000000
Critical Value (10%)     0.347000
Critical Value (5%)      0.463000
Critical Value (2.5%)    0.574000
Critical Value (1%)      0.739000
dtype: float64
Analysis on TRX
------ result for pct_change_1day ------
Results of KPSS Test:
```

```
Test Statistic            0.366092
p-value                   0.091771
#Lags Used              113.000000
Critical Value (10%)      0.347000
Critical Value (5%)       0.463000
Critical Value (2.5%)     0.574000
Critical Value (1%)       0.739000
dtype: float64
------ result for pct_change_2hour ------
Results of KPSS Test:
Test Statistic           2.151703
p-value                  0.010000
#Lags Used              52.000000
Critical Value (10%)     0.347000
Critical Value (5%)      0.463000
Critical Value (2.5%)    0.574000
Critical Value (1%)      0.739000
dtype: float64
------ result for pct_change_1hour ------
Results of KPSS Test:
Test Statistic           1.647778
p-value                  0.010000
#Lags Used              55.000000
Critical Value (10%)     0.347000
Critical Value (5%)      0.463000
Critical Value (2.5%)    0.574000
Critical Value (1%)      0.739000
dtype: float64
Analysis on XMR
------ result for pct_change_1day ------
Results of KPSS Test:
Test Statistic            0.361726
p-value                   0.093652
#Lags Used              125.000000
Critical Value (10%)      0.347000
Critical Value (5%)       0.463000
Critical Value (2.5%)     0.574000
Critical Value (1%)       0.739000
dtype: float64
------ result for pct_change_2hour ------
Results of KPSS Test:
Test Statistic           0.347308
p-value                  0.099867
#Lags Used              26.000000
Critical Value (10%)     0.347000
Critical Value (5%)      0.463000
Critical Value (2.5%)    0.574000
Critical Value (1%)      0.739000
```

```
dtype: float64
------ result for pct_change_1hour ------
Results of KPSS Test:
Test Statistic           0.342825
p-value                  0.100000
#Lags Used               0.000000
Critical Value (10%)     0.347000
Critical Value (5%)      0.463000
Critical Value (2.5%)    0.574000
Critical Value (1%)      0.739000
dtype: float64
Analysis on ETC
------ result for pct_change_1day ------
Results of KPSS Test:
Test Statistic             0.118971
p-value                    0.100000
#Lags Used               125.000000
Critical Value (10%)       0.347000
Critical Value (5%)        0.463000
Critical Value (2.5%)      0.574000
Critical Value (1%)        0.739000
dtype: float64
------ result for pct_change_2hour ------
Results of KPSS Test:
Test Statistic            0.780167
p-value                   0.010000
#Lags Used               76.000000
Critical Value (10%)      0.347000
Critical Value (5%)       0.463000
Critical Value (2.5%)     0.574000
Critical Value (1%)       0.739000
dtype: float64
------ result for pct_change_1hour ------
Results of KPSS Test:
Test Statistic            1.133902
p-value                   0.010000
#Lags Used               79.000000
Critical Value (10%)      0.347000
Critical Value (5%)       0.463000
Critical Value (2.5%)     0.574000
Critical Value (1%)       0.739000
dtype: float64
```

We have conducted ADF and KPSS tests to understand the stationarity of the sequence. From ADF tets it proved that none of the crypto sequence are have stationarity while KPSS provided that for few crypto(close to 4) the series is stationary.

Finally after the analysis performed we understood that Time series models like ARMA , ARIMA etc might be suitable for this dataset and regualr classificcation can be used

After trying some models we realized it is hard to do hyperparameter tuning on models built with hourly data, so we decided to use daily data.

[ ]:

```

```

8 THIS IS WHAT WE GO FOR: 1 day returns for all coins

[ ]:

```
folder_path = '/content/drive/MyDrive/MADS_23_DL_final_project'
df = pd.read_csv(folder_path + '/data/crypto_data_daily_cleaned_v1.csv')
```

[ ]:

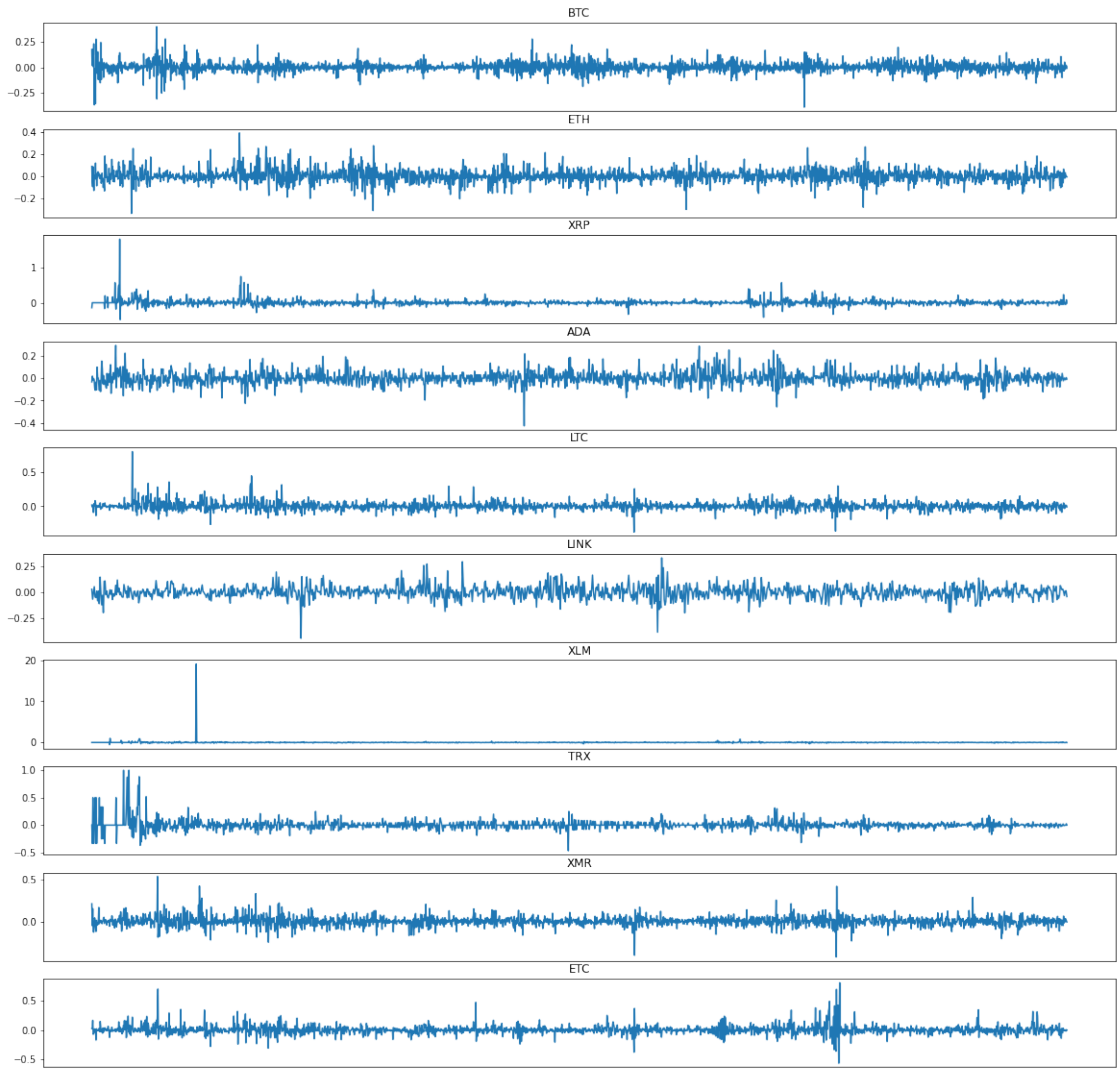
```
def calculate_pct_change(df):
  coins = df.Crypto.unique()
  df_pct_change = pd.DataFrame()
  for coin in coins:
    x = df[df['Crypto']==coin]
    x['pct_change_1day'] = x['Close'].pct_change(1)
    df_pct_change = pd.concat([df_pct_change,x])
  return df_pct_change
```

[ ]:

```
df = calculate_pct_change(df)
```

[ ]:

```
#Plotting 1 day returns for all coins

coins = df['Crypto'].unique()

f,ax = plt.subplots(len(coins),figsize=(20,20))
for i in range(len(coins)):

  ax[i].plot(df.index[df['Crypto']==coins[i]],df.
↪pct_change_1day[df['Crypto']==coins[i]])
  ax[i].title.set_text(coins[i])
  ax[i].set_xticks([])
```



[ ]:

```

```

8.1 Calculating the Market Cap

The basic analysis is to build a Market capital column and extarct the weightage based on the volumn traded.

[ ]:

```
# calculate value of each cryto at certain time points
df['Value'] = df['Close']*df['Volume']

# the sum of values at each time point
sum_at_timepoints = df.groupby('Open Time').sum()['Value']
```

```python
# merge and calculate their weights over the sum at that time
merged_daily = df.merge(sum_at_timepoints, how='left',
                        on='Open Time', suffixes=('_vol', '_vol_sum'))
merged_daily['Weight'] = merged_daily['Value_vol']/merged_daily['Value_vol_sum']
```

[ ]:
```python
merged_daily.head(2).T
```

[ ]:

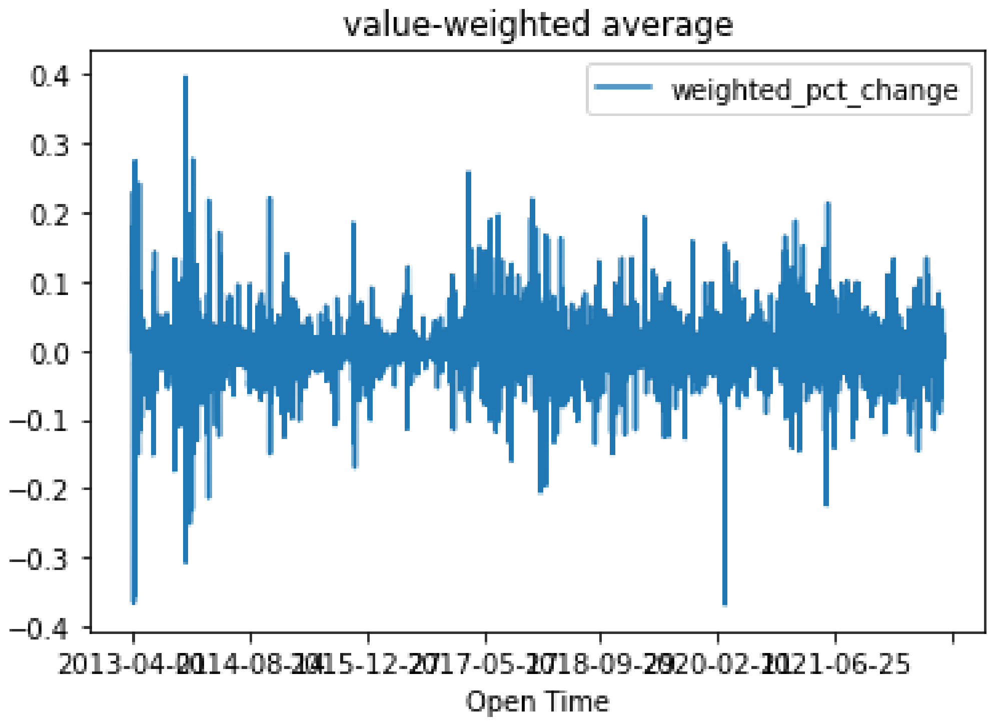
	0	1
Open Time	2013-04-01	2013-04-02
Open	93.155	104.72
High	105.9	127.0
Low	93.155	99.0
Close	104.75	123.016
Volume	11008.524	24187.398
train_test	Train	Train
Crypto	BTC	BTC
pct_change_1day	NaN	0.174377
Value_vol	1153142.889	2975436.952368
Value_vol_sum	1153142.889	2975436.952368
Weight	1.0	1.0

[ ]:
```python

```

8.2 Calculate weighted pct change

[ ]:
```python
# calculate weighted pct change
merged_daily['weighted_pct_change'] =␣
 ↪merged_daily['pct_change_1day']*merged_daily['Weight']

# plot value weighted average over time
time_group2 = merged_daily.groupby('Open Time').sum()
time_group2.plot(y='weighted_pct_change',kind='line',title='value-weighted␣
 ↪average')
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb1845a9fd0>



[ ]:
```
# adding the weighted_pct_change to the final dataframe
daily_v2 = merged_daily.merge(time_group2[['weighted_pct_change']], how='left',
                              on='Open Time' )
```

[ ]:
```
daily_v2.head(2)
```

[ ]:
```
    Open Time     Open   High     Low    Close     Volume train_test Crypto  \
0  2013-04-01   93.155  105.9  93.155  104.750  11008.524      Train    BTC
1  2013-04-02  104.720  127.0  99.000  123.016  24187.398      Train    BTC

   pct_change_1day     Value_vol  Value_vol_sum  Weight  \
0              NaN  1.153143e+06   1.153143e+06     1.0
1         0.174377  2.975437e+06   2.975437e+06     1.0

   weighted_pct_change_x  weighted_pct_change_y
0                    NaN               0.000000
1               0.174377               0.174377
```

8.3 Correlation between the coins - based closed value

Trying to understand how Crytos are inter dependant on each other.

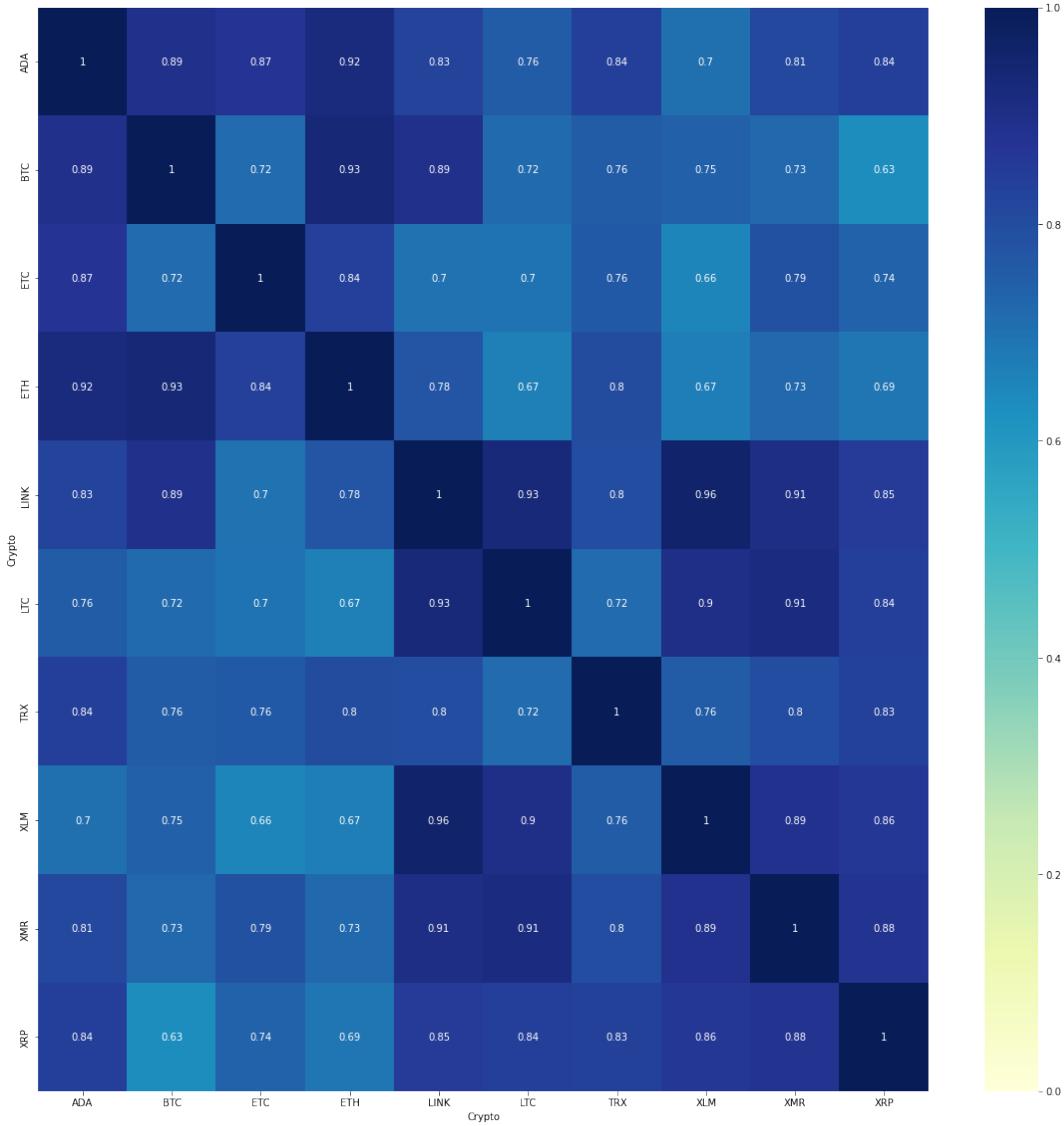
[ ]:
```
#unstacking the coins to understand the correlation between the coins
wide_format = df.groupby(['Open Time', 'Crypto'])['Close'].last().unstack()
```

[ ]:
```
wide_format
```

[ ]:
```
Crypto          ADA        BTC    ETC         ETH   LINK    LTC      TRX  \
Open Time
2013-04-01      NaN    104.750    NaN         NaN    NaN    NaN      NaN
2013-04-02      NaN    123.016    NaN         NaN    NaN    NaN      NaN
2013-04-03      NaN    125.500    NaN         NaN    NaN    NaN      NaN
2013-04-04      NaN    135.632    NaN         NaN    NaN    NaN      NaN
2013-04-05      NaN    142.990    NaN         NaN    NaN    NaN      NaN
…             …        …    …           …    …     …       …
2022-09-26  0.44710  19228.000  28.46  1336.54000  7.943  53.45  0.05961
2022-09-27  0.44120  19077.570  28.13  1327.92000  7.700    NaN      NaN
2022-09-28  0.43606  19400.000  27.63  1337.30000  7.790  53.28  0.05958
2022-09-29  0.43830  19599.590  27.79  1336.04000  7.905  53.95  0.06106
2022-09-30  0.43480  19425.200  27.73  1329.03884  7.584  53.43  0.06104

Crypto          XLM     XMR      XRP
Open Time
2013-04-01      NaN     NaN      NaN
2013-04-02      NaN     NaN      NaN
2013-04-03      NaN     NaN      NaN
2013-04-04      NaN     NaN      NaN
2013-04-05      NaN     NaN      NaN
…             …     …       …
2022-09-26  0.11374  146.02  0.46791
2022-09-27      NaN     NaN      NaN
2022-09-28  0.10814  147.23  0.44890
2022-09-29  0.11532  148.47  0.48605
2022-09-30  0.11455  147.45  0.48024

[3463 rows x 10 columns]
```

Observation: From the data we can clearly see the BTC coin has data from 2013 where as the remaining coins has data from 2016/17.

[ ]:
```
plt.figure(figsize=(20,20))
sns.heatmap(wide_format.corr(),vmin=0, vmax=1, annot=True, cmap="YlGnBu");
```



Observation: Most of the blocks are more blueish which is sign that they are highlight correlated with each others.

[ ]:
```
# Code to print the top coins which are correlate with others
corr_matrix = wide_format.corr()
corr_matrix['BTC'].sort_values(ascending=False)
```

[ ]:
```
Crypto
BTC     1.000000
ETH     0.934804
LINK    0.893931
```

```
ADA      0.891974
TRX      0.756979
XLM      0.745775
XMR      0.725461
LTC      0.722621
ETC      0.715224
XRP      0.634110
Name: BTC, dtype: float64
```

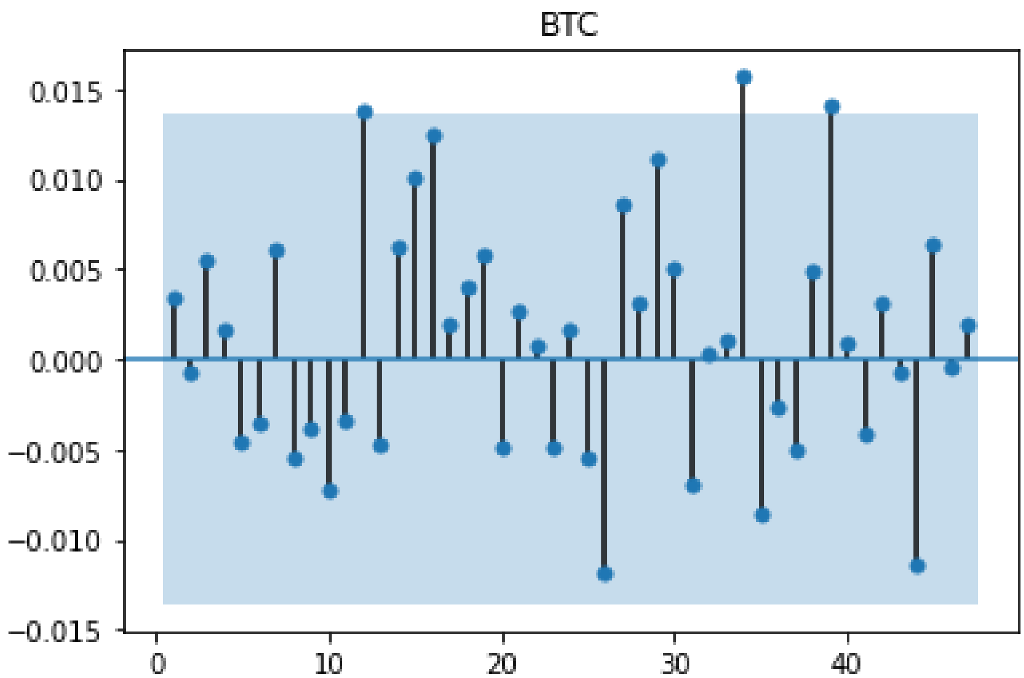
8.4 Closing values comparision amoung the Coins

[ ]:
```python
wide_format = wide_format.reset_index()
```

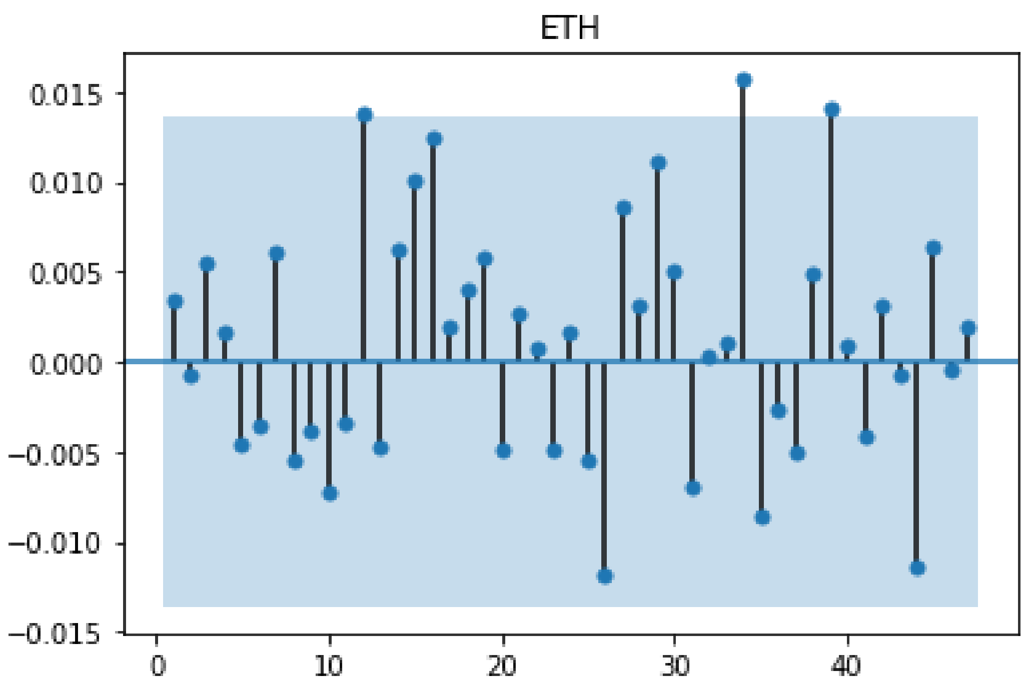
[ ]:
```python
fig = px.line(wide_format, y=wide_format.columns, x = 'Open Time')

# Show plot
fig.show()
```

[ ]:
```python
col = 'pct_change_1day'

coins = daily_v2['Crypto'].unique()
for coin in coins:
    plt.figure()
    plot_pacf_drop(daily_v2[col].dropna(), lags=50, drop_no=3,␣
 ↪zero=False,title=coin)

plt.show()
```

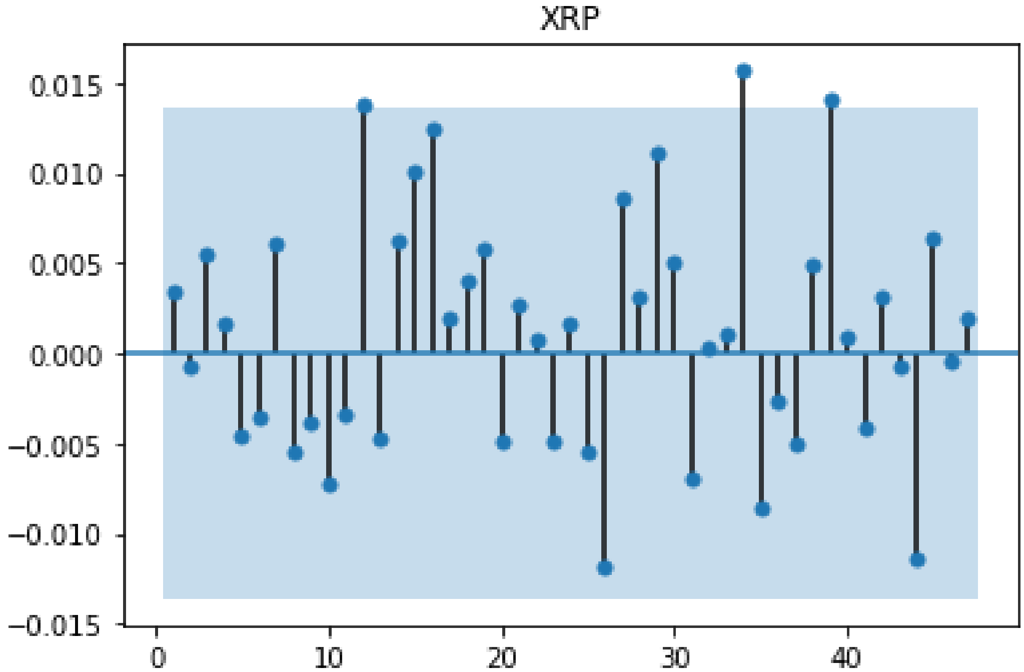
```
<Figure size 432x288 with 0 Axes>
```



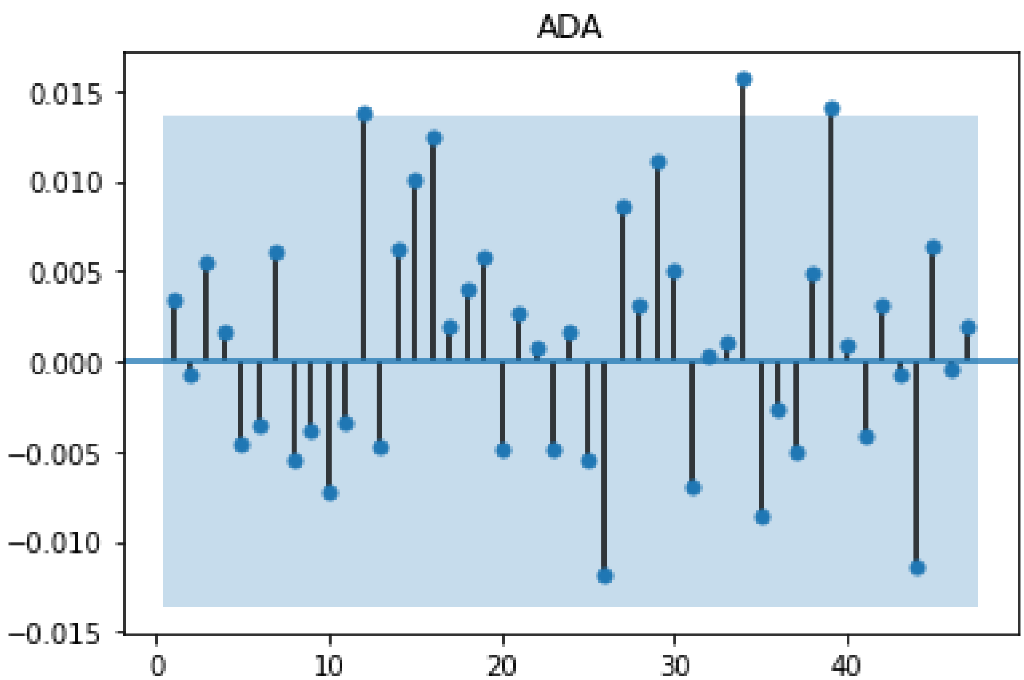
<Figure size 432x288 with 0 Axes>



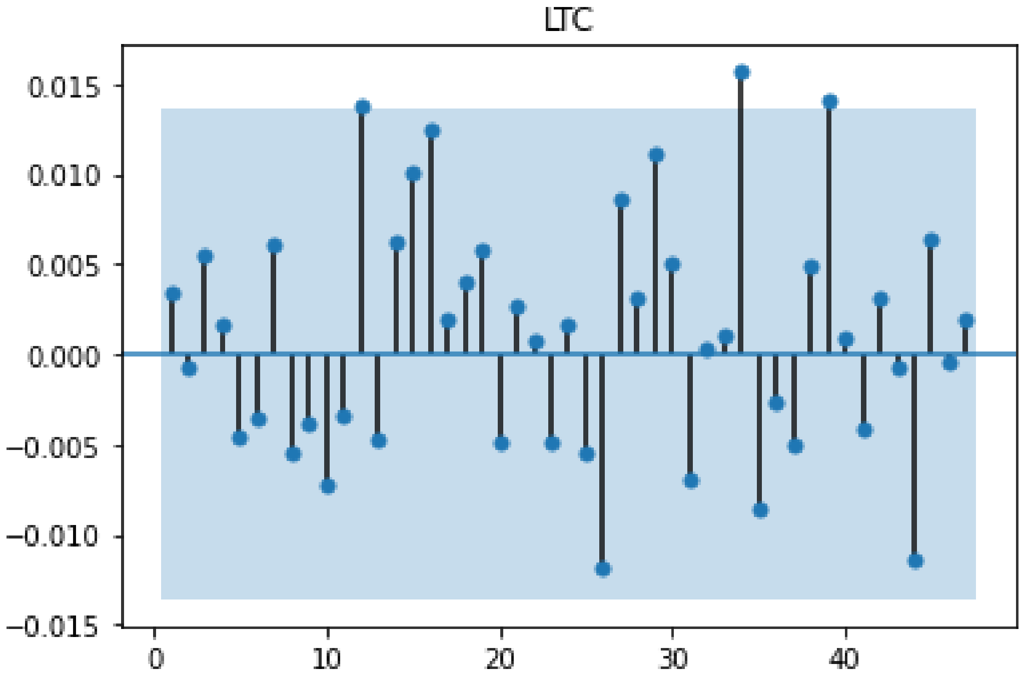
<Figure size 432x288 with 0 Axes>



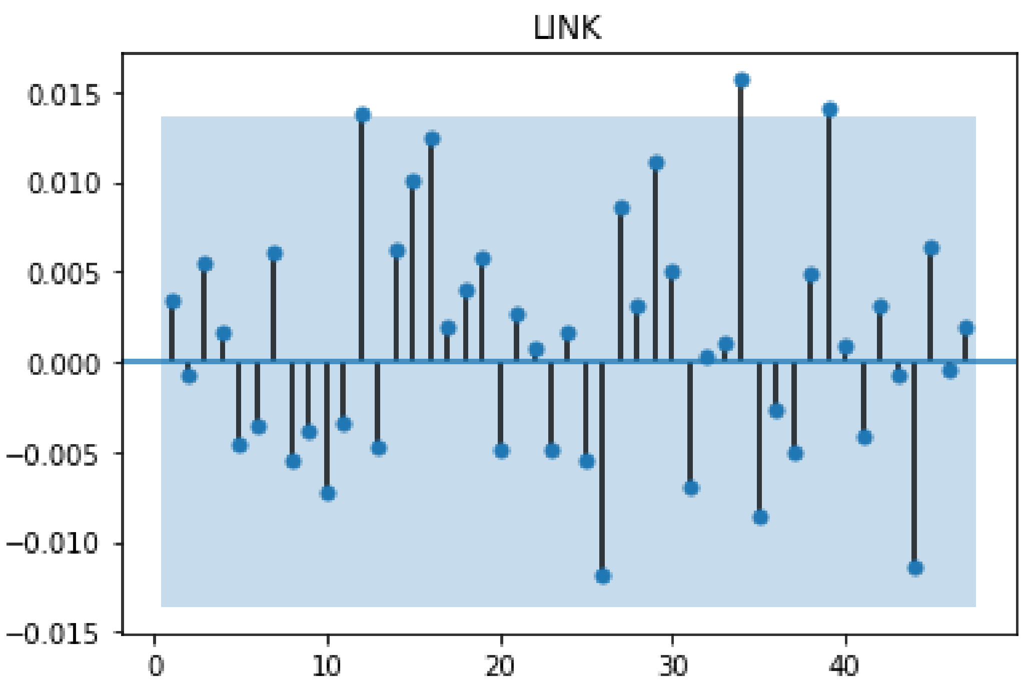
<Figure size 432x288 with 0 Axes>



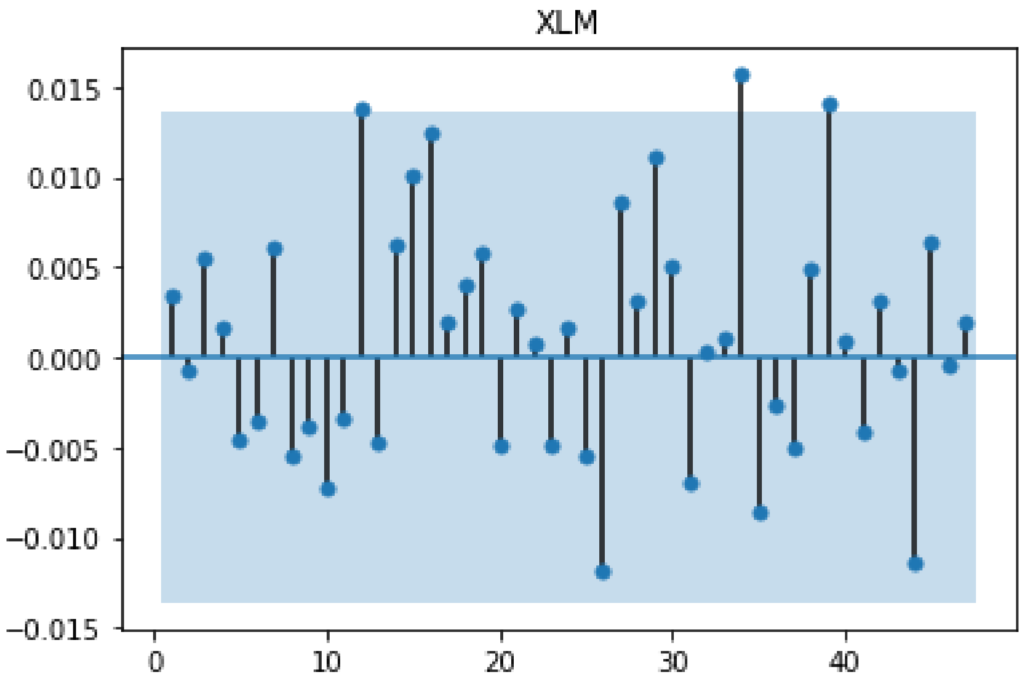
<Figure size 432x288 with 0 Axes>



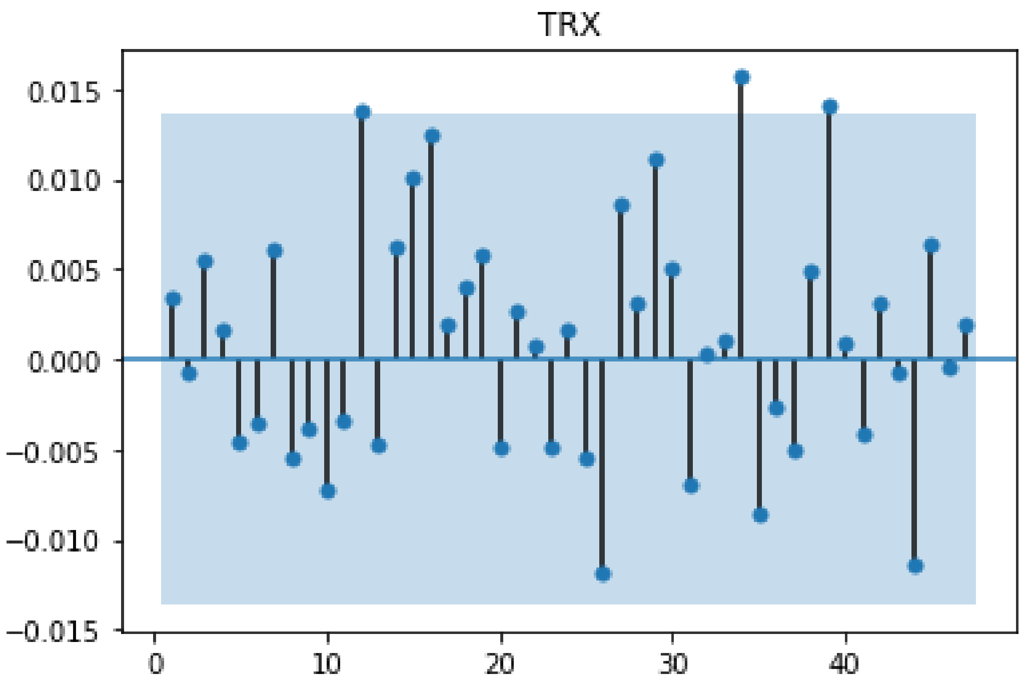
<Figure size 432x288 with 0 Axes>



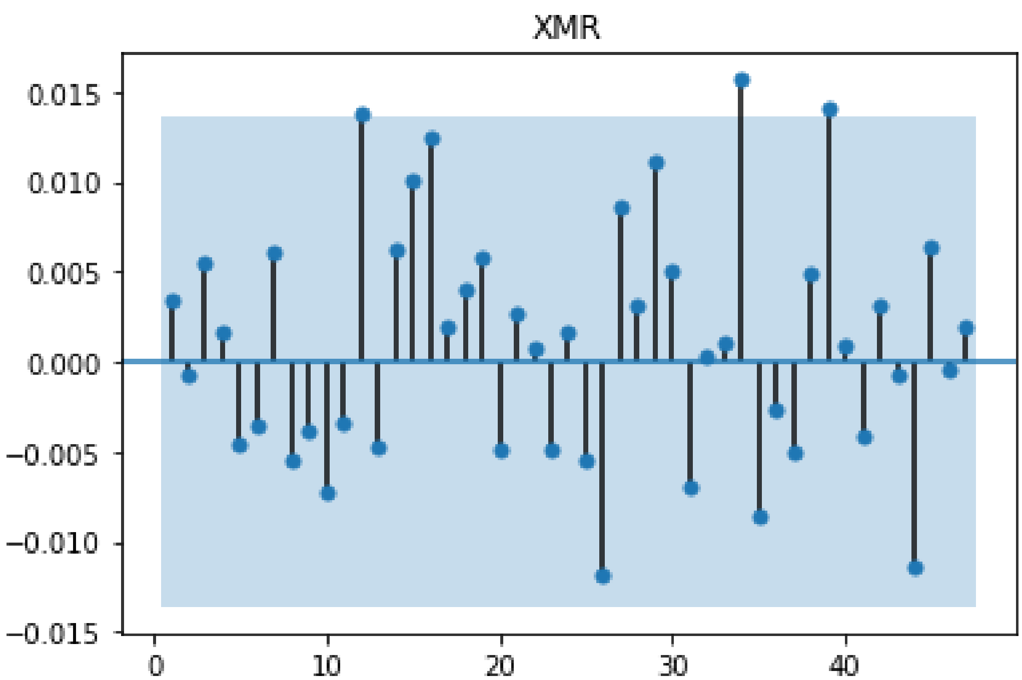
<Figure size 432x288 with 0 Axes>



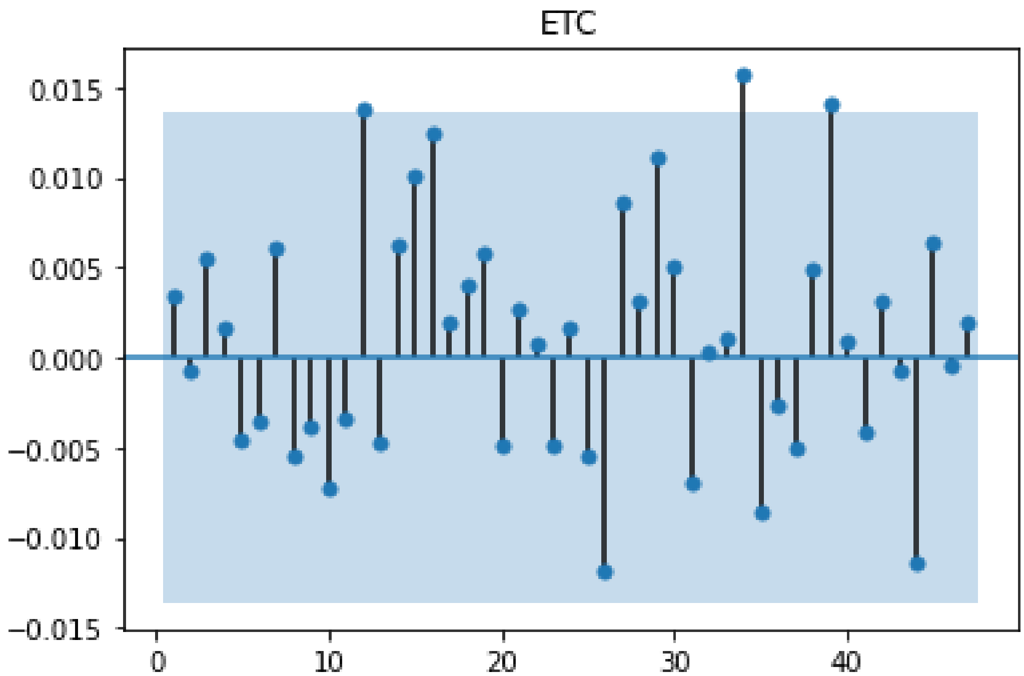
<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



```
<Figure size 432x288 with 0 Axes>
```



The plots are not so informative in this case

[ ]:
```

```

8.5 Defining the Target Variable

We want to follow the classification approach and hence based on the "pct_change_2hour" we are creating 2 classes one class '0' when the returns are negative and '1' When the retruns are postive.

[ ]:
```
def create_target(df):
  market_RoR = 26.89
  market_RoR_1d = market_RoR/365
  df['Target'] = np.where(df['pct_change_1day']>0, 1,0)
  df['Target'] = np.where(df['pct_change_1day']>market_RoR_1d, 2,1)
  df['Target'][df['Target']==1] = np.
 ↪where(df['pct_change_1day'][df['Target']==1]>=0, 1,0)
  return df
```

[ ]:
```
daily_v2 = create_target(daily_v2)
```

[ ]:
```
daily_v2['Target'].value_counts(normalize=True)
```

[ ]:
```
0    0.465005
1    0.452135
2    0.082859
Name: Target, dtype: float64
```

[ ]:
```
daily_v2.drop(['pct_change_1day'], axis=1, inplace=True) # droppping the column␣
↪as we already extracted the target
```

[ ]:
```
daily_v2.shape
```

[ ]:
```
(20746, 15)
```

[ ]:
```

```

8.6 Crypto vs Yearly returns

[ ]:
```
temp = dict(layout=go.Layout(font=dict(family="Franklin Gothic", size=12),␣
↪width=800))
daily_v2['Open Time'] = pd.to_datetime(df['Open Time'])
daily_v2['Year'] = daily_v2['Open Time'].dt.year
last_5_years =  [2018, 2019, 2020, 2021, 2022]

years = {year: pd.DataFrame() for year in last_5_years[::-1]}
for key in years.keys():
    temp_df=daily_v2[daily_v2.Year == key]
    years[key] = temp_df.groupby('Crypto')['Target'].mean().
↪rename("Avg_return_{}".format(key))
temp_df_v2=pd.concat((years[i].to_frame() for i in years.keys()), axis=1)
temp_df_v2=temp_df_v2.sort_values(by="Avg_return_2021")
```

[ ]:
```
fig = make_subplots(rows=1, cols=len(df.columns), shared_yaxes=True)
for i, col in enumerate(temp_df_v2.columns):
    x = temp_df_v2[col]
    mask = x<=0
    fig.add_trace(go.Bar(x=x[mask], y=temp_df_v2.index[mask],orientation='h',
                         text=x[mask], texttemplate='%{text:.
↪2f}%',textposition='auto',
                         hovertemplate='Average Return in %{y} Coins = %{x:.
↪4f}%',
                         marker=dict(color='red', opacity=0.7),name=col[-4:]),
                  row=1, col=i+1)
    fig.add_trace(go.Bar(x=x[~mask], y=temp_df_v2.index[~mask],orientation='h',
                         text=x[~mask], texttemplate='%{text:.2f}%',␣
↪textposition='auto',
                         hovertemplate='Average Return in %{y} Coins = %{x:.
↪4f}%',
                         marker=dict(color='green', opacity=0.7),name=col[-4:]),
```

```
                  row=1, col=i+1)
    fig.update_xaxes(range=(x.min()-.15,x.max()+.15), title='{}'.format(col[-4:
 ↪]),
                     showticklabels=False, row=1, col=i+1)
fig.update_layout(template=temp,title='Yearly Average Returns by Coin',
                  hovermode='closest',margin=dict(l=250,r=50),
                  height=600, width=1000, showlegend=False)
fig.show()
```

8.7 End of the notebook

[ ]:

```

```