MScFE_Capstone_Workbook_M6

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1 Market Timing Strategies using Kalman Filter

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2 Introduction

In this section, I will explore the implementation of a Kalman filter in Python using the library Pykalman to forecast stock prices. The 2 stocks we are targeting are Ethereum and Bitcoin. As discussed in the literature review, research shows that Kalman filters have better outcomes for time series forecasting and can be used with various pricing algorithms, such as Heston, Bates, etc.

[1]:
```
# installation of libraries

!pip install pykalman
!pip install plotly
!pip install statsmodels
```

```
Collecting pykalman
  Downloading pykalman-0.9.7-py2.py3-none-any.whl.metadata (5.5 kB)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages
(from pykalman) (1.26.4)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages
(from pykalman) (1.13.1)
Downloading pykalman-0.9.7-py2.py3-none-any.whl (251 kB)
                         251.6/251.6 kB
3.7 MB/s eta 0:00:00
Installing collected packages: pykalman
Successfully installed pykalman-0.9.7
Requirement already satisfied: plotly in /usr/local/lib/python3.10/dist-packages
(5.24.1)
Requirement already satisfied: tenacity>=6.2.0 in
/usr/local/lib/python3.10/dist-packages (from plotly) (9.0.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-
packages (from plotly) (24.1)
Requirement already satisfied: statsmodels in /usr/local/lib/python3.10/dist-
packages (0.14.4)
Requirement already satisfied: numpy<3,>=1.22.3 in
```

```
/usr/local/lib/python3.10/dist-packages (from statsmodels) (1.26.4)
Requirement already satisfied: scipy!=1.9.2,>=1.8 in
/usr/local/lib/python3.10/dist-packages (from statsmodels) (1.13.1)
Requirement already satisfied: pandas!=2.1.0,>=1.4 in
/usr/local/lib/python3.10/dist-packages (from statsmodels) (2.2.2)
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.10/dist-
packages (from statsmodels) (0.5.6)
Requirement already satisfied: packaging>=21.3 in
/usr/local/lib/python3.10/dist-packages (from statsmodels) (24.1)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.10/dist-packages (from pandas!=2.1.0,>=1.4->statsmodels)
(2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-
packages (from pandas!=2.1.0,>=1.4->statsmodels) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-
packages (from pandas!=2.1.0,>=1.4->statsmodels) (2024.2)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages
(from patsy>=0.5.6->statsmodels) (1.16.0)
```

[2]:
```python
# importing of libraries

import pandas as pd
import yfinance as yf
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.graph_objects as go
import statsmodels.api as sm
```

3 Exploratory Data Analysis

[3]:
```python
# crypto currencies of interest - Bitcoin and Ethereum

stock_list = ['BTC-USD', 'ETH-USD']
```

[4]:
```python
# extracting the stock price for the last 2 years
data = yf.download(stock_list, start='2022-09-01', end='2024-08-31')
data.head()
```

```
[*********************100%***********************]  2 of 2 completed
```

[4]:
```
Price                         Adj Close                        Close  \
Ticker                          BTC-USD      ETH-USD         BTC-USD
Date
2022-09-01 00:00:00+00:00  20127.140625  1586.176758  20127.140625
2022-09-02 00:00:00+00:00  19969.771484  1577.220459  19969.771484
2022-09-03 00:00:00+00:00  19832.087891  1556.872681  19832.087891
2022-09-04 00:00:00+00:00  19986.712891  1577.641602  19986.712891
```

```
2022-09-05 00:00:00+00:00  19812.371094  1617.183228  19812.371094

Price                                          High                \
Ticker                         ETH-USD      BTC-USD      ETH-USD
Date
2022-09-01 00:00:00+00:00  1586.176758  20198.390625  1593.082764
2022-09-02 00:00:00+00:00  1577.220459  20401.568359  1643.183228
2022-09-03 00:00:00+00:00  1556.872681  20037.009766  1579.454346
2022-09-04 00:00:00+00:00  1577.641602  19999.689453  1578.009277
2022-09-05 00:00:00+00:00  1617.183228  20031.160156  1621.661377

Price                               Low                        Open  \
Ticker                          BTC-USD      ETH-USD       BTC-USD
Date
2022-09-01 00:00:00+00:00  19653.968750  1520.188354  20050.498047
2022-09-02 00:00:00+00:00  19814.765625  1551.877930  20126.072266
2022-09-03 00:00:00+00:00  19698.355469  1541.672119  19969.718750
2022-09-04 00:00:00+00:00  19636.816406  1543.698853  19832.470703
2022-09-05 00:00:00+00:00  19673.046875  1559.781860  19988.789062

Price                                       Volume
Ticker                         ETH-USD     BTC-USD      ETH-USD
Date
2022-09-01 00:00:00+00:00  1553.756348  30182031010  16434276817
2022-09-02 00:00:00+00:00  1586.017944  29123998928  17708478709
2022-09-03 00:00:00+00:00  1577.213745  23613051457   9516825994
2022-09-04 00:00:00+00:00  1556.895874  25245861652   8884144998
2022-09-05 00:00:00+00:00  1577.884033  28813460025  13060541168
```

[5]:
```python
data.describe()
```

[5]:
```
Price      Adj Close                    Close                       High  \
Ticker       BTC-USD      ETH-USD       BTC-USD      ETH-USD       BTC-USD
count     730.000000   730.000000    730.000000   730.000000    730.000000
mean    37518.319863  2154.649833  37518.319863  2154.649833  38162.137949
std     17685.270401   760.858790  17685.270401   760.858790  18083.910703
min     15787.284180  1100.169800  15787.284180  1100.169800  16253.047852
25%     23665.855469  1620.496521  23665.855469  1620.496521  24119.581543
50%     29412.204102  1866.100159  29412.204102  1866.100159  29845.836914
75%     55988.014648  2640.965576  55988.014648  2640.965576  57679.622070
max     73083.500000  4066.445068  73083.500000  4066.445068  73750.070312

Price                           Low                         Open              \
Ticker      ETH-USD       BTC-USD      ETH-USD       BTC-USD      ETH-USD
count    730.000000    730.000000   730.000000    730.000000   730.000000
mean    2197.880829  36780.942348  2107.257615  37464.146091  2153.339377
std      781.196683  17220.739292   736.665024  17678.426052   761.057358
```

```
min     1136.442627  15599.046875  1081.138184  15782.300781  1100.107178
25%     1644.864014  23253.754883  1580.678528  23627.717285  1617.854645
50%     1887.949524  29113.966797  1845.784241  29403.917969  1865.844604
75%     2709.429199  54234.083008  2585.498413  55644.687500  2640.590576
max     4092.284180  71334.093750  3936.627197  73079.375000  4066.690430

Price         Volume
Ticker       BTC-USD       ETH-USD
count   7.300000e+02  7.300000e+02
mean    2.494924e+10  1.111478e+10
std     1.410581e+10  6.917282e+09
min     5.331173e+09  2.081626e+09
25%     1.473525e+10  6.289494e+09
50%     2.165289e+10  9.412596e+09
75%     3.145988e+10  1.414162e+10
max     1.189925e+11  6.766813e+10
```

The data shows that open, close, High,low are correlated, we can check this in our plot

[6]:
```
data.corr().style.background_gradient(cmap='coolwarm')
```

[6]:
```
<pandas.io.formats.style.Styler at 0x78ef7d123550>
```

[7]:
```
data.isnull().any()
```

[7]:
```
Price      Ticker
Adj Close  BTC-USD    False
           ETH-USD    False
Close      BTC-USD    False
           ETH-USD    False
High       BTC-USD    False
           ETH-USD    False
Low        BTC-USD    False
           ETH-USD    False
Open       BTC-USD    False
           ETH-USD    False
Volume     BTC-USD    False
           ETH-USD    False
dtype: bool
```

The dataset do not contain any null values

[8]:
```
closing_data = data['Adj Close']['BTC-USD']
closing_data.head()
```

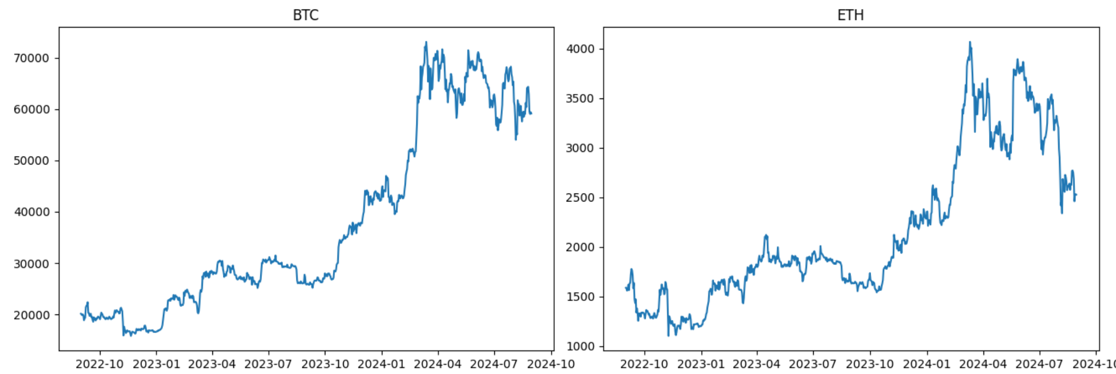
[8]:
```
Date
2022-09-01 00:00:00+00:00    20127.140625
2022-09-02 00:00:00+00:00    19969.771484
```

```
2022-09-03 00:00:00+00:00    19832.087891
2022-09-04 00:00:00+00:00    19986.712891
2022-09-05 00:00:00+00:00    19812.371094
Name: BTC-USD, dtype: float64
```

[9]:
```python
closing_data = data['Adj Close']['ETH-USD']
closing_data.head()
```

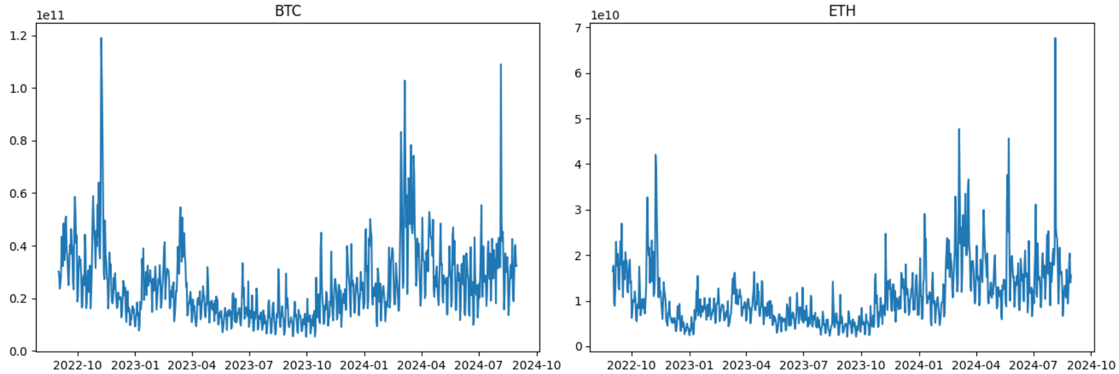
[9]:
```
Date
2022-09-01 00:00:00+00:00    1586.176758
2022-09-02 00:00:00+00:00    1577.220459
2022-09-03 00:00:00+00:00    1556.872681
2022-09-04 00:00:00+00:00    1577.641602
2022-09-05 00:00:00+00:00    1617.183228
Name: ETH-USD, dtype: float64
```

[10]:
```python
fig, axs =plt.subplots(1,2,figsize=(16, 5),gridspec_kw ={'hspace': 0.2,␣
↪'wspace': 0.1})
axs[0].plot(data['Adj Close']['BTC-USD'])
axs[0].set_title('BTC')
axs[1].plot(data['Adj Close']['ETH-USD'])
axs[1].set_title('ETH')
plt.show()
```

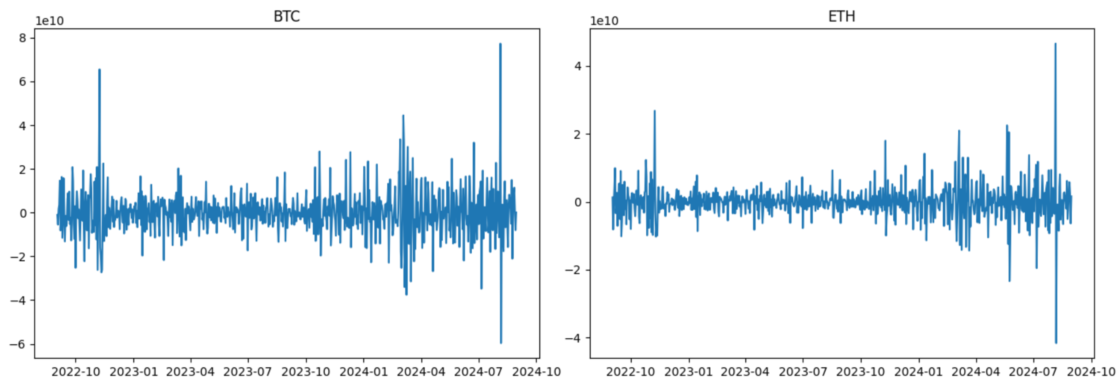


Lets Visualize the Volume for trend, noise and seasonality

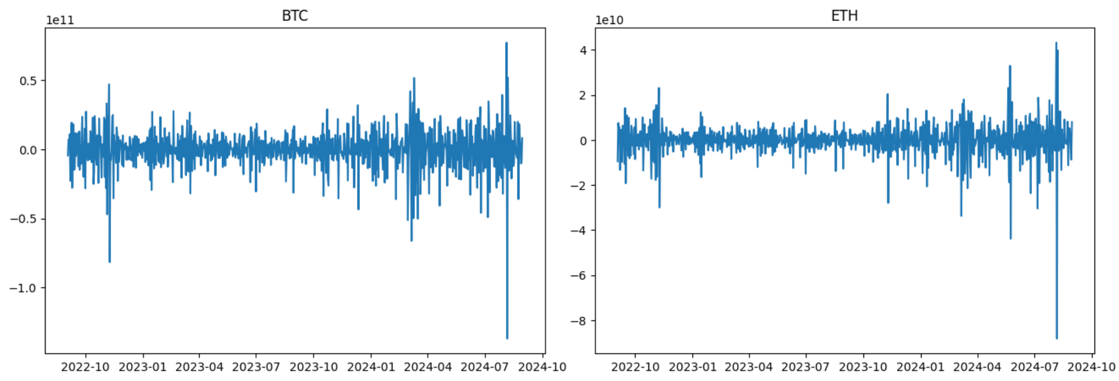
[74]:
```python
fig, axs =plt.subplots(1,2,figsize=(16, 5),gridspec_kw ={'hspace': 0.2,␣
↪'wspace': 0.1})
axs[0].plot(data['Volume']['BTC-USD'])
axs[0].set_title('BTC')
axs[1].plot(data['Volume']['ETH-USD'])
axs[1].set_title('ETH')
plt.show()
```



[81]:
```python
fig, axs =plt.subplots(1,2,figsize=(16, 5),gridspec_kw ={'hspace': 0.2,
↪'wspace': 0.1})
axs[0].plot(data['Volume']['BTC-USD'].diff())
axs[0].set_title('BTC')
axs[1].plot(data['Volume']['ETH-USD'].diff())
axs[1].set_title('ETH')
plt.show()
```

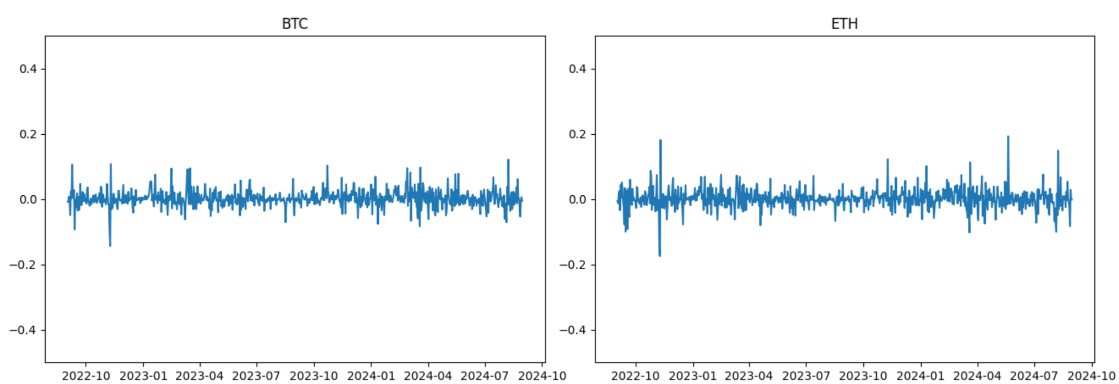


[82]:
```python
fig, axs =plt.subplots(1,2,figsize=(16, 5),gridspec_kw ={'hspace': 0.2,
↪'wspace': 0.1})
axs[0].plot(data['Volume']['BTC-USD'].diff().diff())
axs[0].set_title('BTC')
axs[1].plot(data['Volume']['ETH-USD'].diff().diff())
axs[1].set_title('ETH')
plt.show()
```



[79]:
```
fig, axs = plt.subplots(1,2,figsize=(16,5),gridspec_kw ={'hspace': 0.2, 'wspace': 0.1})
btc = data['Adj Close']['BTC-USD'].pct_change().dropna(axis=0)
axs[0].plot(btc)
axs[0].set_title('BTC')
axs[0].set_ylim([-0.5,0.5])

eth = data['Adj Close']['ETH-USD'].pct_change().dropna(axis=0)
axs[1].plot(eth)
axs[1].set_title('ETH')
axs[1].set_ylim([-0.5,0.5])
```

[79]:
```
(-0.5, 0.5)
```



OHLC plots - Price movements A candle stick plot helps us understand the spread between the prices of the crypto currency from the opening and closing price and identity the periods where they were coninuously on the rise.

[12]:
```
fig = go.Figure(data=[go.Candlestick(x=data.index,
                open=data['Open']['BTC-USD'], high=data['High']['BTC-USD'],
```

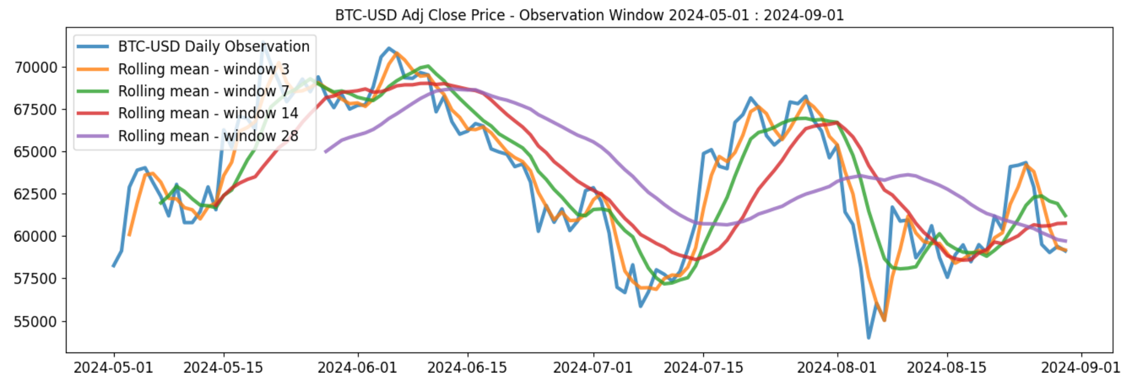
```
                low=data['Low']['BTC-USD'], close=data['Close']['BTC-USD'])
                     ])
fig.update_layout(xaxis_rangeslider_visible=True)
fig.show()
```

[13]:
```
fig = go.Figure(data=[go.Candlestick(x=data.index,
                open=data['Open']['ETH-USD'], high=data['High']['ETH-USD'],
                low=data['Low']['ETH-USD'], close=data['Close']['ETH-USD'])
                     ])
fig.update_layout(xaxis_rangeslider_visible=True)
fig.show()
```

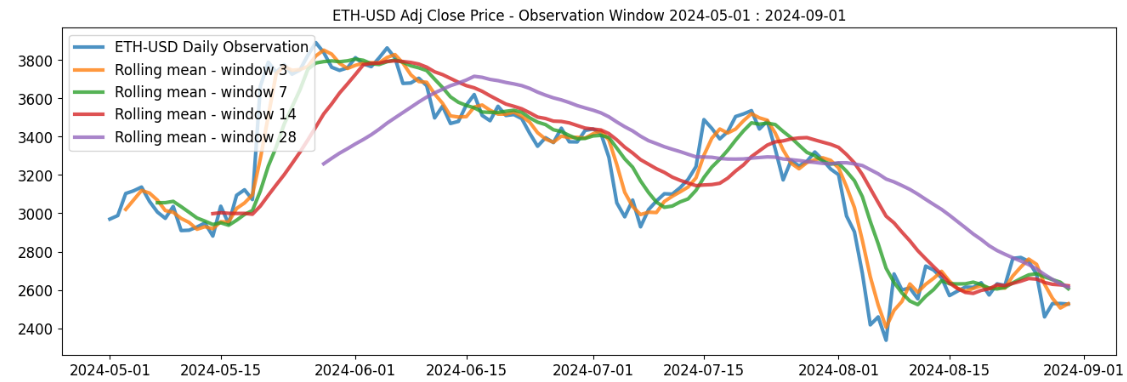
Understanding the Price shocks

We can see how the rolling mean for various intervals looks like for our crypto data, we find that with increasing window size our data gets smoother and allows us to see the trend over which can be used for generating feature engineering. The shorter the window closer it is to the actual stock price and considers the price shocks.

[14]:
```
btc_closing_data = data['Adj Close']['BTC-USD'].loc['2024-05-01':'2024-09-01']
rolling_3d = btc_closing_data.rolling(window=3).mean()
rolling_7d = btc_closing_data.rolling(window=7).mean()
rolling_14d = btc_closing_data.rolling(window=14).mean()
rolling_28d = btc_closing_data.rolling(window=28).mean()


plt.figure(figsize=(16, 5))
plt.plot(btc_closing_data.index, btc_closing_data, lw=3, alpha=0.8,␣
 ↪label='BTC-USD Daily Observation')
plt.plot(btc_closing_data.index, rolling_3d, lw=3, alpha=0.8,label='Rolling␣
 ↪mean - window 3')
plt.plot(btc_closing_data.index, rolling_7d, lw=3, alpha=0.8,label='Rolling␣
 ↪mean - window 7')
plt.plot(btc_closing_data.index, rolling_14d, lw=3, alpha=0.8,label='Rolling␣
 ↪mean - window 14')
plt.plot(btc_closing_data.index, rolling_28d, lw=3, alpha=0.8,label='Rolling␣
 ↪mean - window 28')

plt.title('BTC-USD Adj Close Price - Observation Window 2024-05-01 :␣
 ↪2024-09-01')
plt.tick_params(labelsize=12)
plt.legend(loc='upper left', fontsize=12)
plt.show()
```



[15]:
```python
eth_closing_data = data['Adj Close']['ETH-USD'].loc['2024-05-01':'2024-09-01']
rolling_3d = eth_closing_data.rolling(window=3).mean()
rolling_7d = eth_closing_data.rolling(window=7).mean()
rolling_14d = eth_closing_data.rolling(window=14).mean()
rolling_28d = eth_closing_data.rolling(window=28).mean()


plt.figure(figsize=(16, 5))
plt.plot(eth_closing_data.index, eth_closing_data, lw=3, alpha=0.8,␣
 ↪label='ETH-USD Daily Observation')
plt.plot(eth_closing_data.index, rolling_3d, lw=3, alpha=0.8,label='Rolling␣
 ↪mean - window 3')
plt.plot(eth_closing_data.index, rolling_7d, lw=3, alpha=0.8,label='Rolling␣
 ↪mean - window 7')
plt.plot(eth_closing_data.index, rolling_14d, lw=3, alpha=0.8,label='Rolling␣
 ↪mean - window 14')
plt.plot(eth_closing_data.index, rolling_28d, lw=3, alpha=0.8,label='Rolling␣
 ↪mean - window 28')

plt.title('ETH-USD Adj Close Price - Observation Window 2024-05-01 :␣
 ↪2024-09-01')
plt.tick_params(labelsize=12)
plt.legend(loc='upper left', fontsize=12)
plt.show()
```



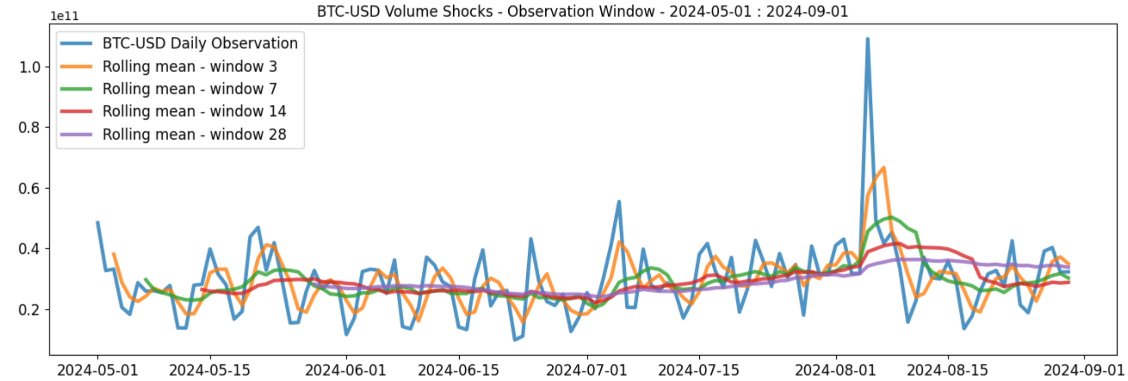
Ethereum rolling means are lot steeper than BTC, in the further sections we will do the causality tests to see autocorrelation.

Understanding the Volume Shocks

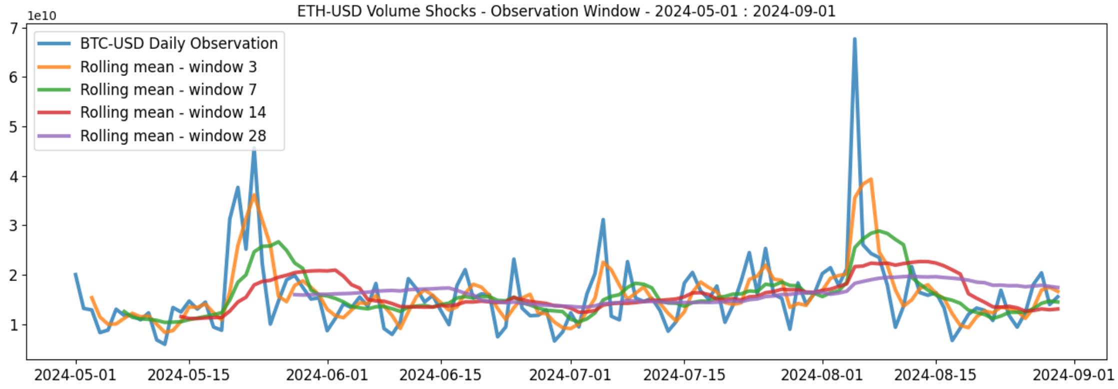
Positive volume shocks can be leveraged to improve returns and it is signifcant for volume based trading in crypto. Trading strategists can buy stocks on a positive volume jump and sell stocks on volume downsides to make profit over a period of time. A shock is defined as the increase or decrease in the volume comapred to the 12-month average. Compared to the rolling mean for 28 days, daily volume shows significant upward spikes compared to downfalls.

[16]:
```
btc_closing_data = data['Volume']['BTC-USD'].loc['2024-05-01':'2024-09-01']
rolling_3d = btc_closing_data.rolling(window=3).mean()
rolling_7d = btc_closing_data.rolling(window=7).mean()
rolling_14d = btc_closing_data.rolling(window=14).mean()
rolling_28d = btc_closing_data.rolling(window=28).mean()



plt.figure(figsize=(16, 5))
plt.plot(btc_closing_data.index, btc_closing_data, lw=3, alpha=0.8,␣
↪label='BTC-USD Daily Observation')
plt.plot(btc_closing_data.index, rolling_3d, lw=3, alpha=0.8,label='Rolling␣
↪mean - window 3')
plt.plot(btc_closing_data.index, rolling_7d, lw=3, alpha=0.8,label='Rolling␣
↪mean - window 7')
plt.plot(btc_closing_data.index, rolling_14d, lw=3, alpha=0.8,label='Rolling␣
↪mean - window 14')
plt.plot(btc_closing_data.index, rolling_28d, lw=3, alpha=0.8,label='Rolling␣
↪mean - window 28')

plt.title('BTC-USD Volume Shocks - Observation Window - 2024-05-01 :␣
↪2024-09-01')
plt.tick_params(labelsize=12)
plt.legend(loc='upper left', fontsize=12)
```

```
plt.show()
```



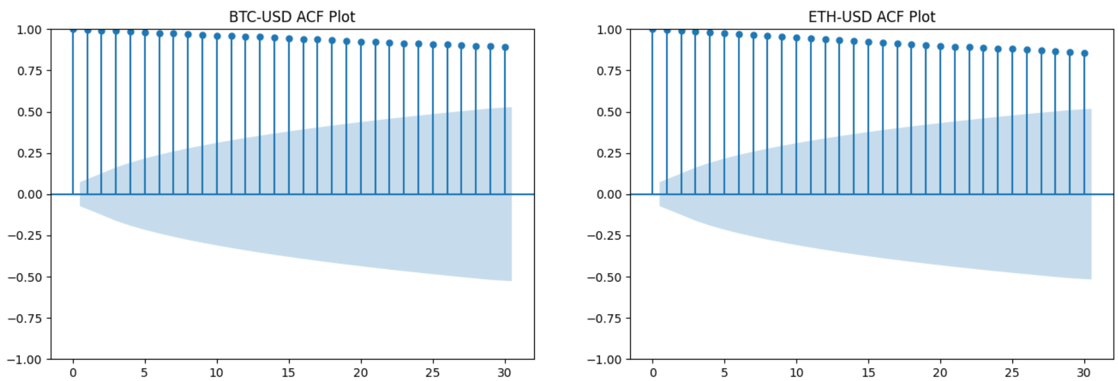
[17]:
```
btc_closing_data = data['Volume']['ETH-USD'].loc['2024-05-01':'2024-09-01']
rolling_3d = btc_closing_data.rolling(window=3).mean()
rolling_7d = btc_closing_data.rolling(window=7).mean()
rolling_14d = btc_closing_data.rolling(window=14).mean()
rolling_28d = btc_closing_data.rolling(window=28).mean()


plt.figure(figsize=(16, 5))
plt.plot(btc_closing_data.index, btc_closing_data, lw=3, alpha=0.8,␣
    ↪label='BTC-USD Daily Observation')
plt.plot(btc_closing_data.index, rolling_3d, lw=3, alpha=0.8,label='Rolling␣
    ↪mean - window 3')
plt.plot(btc_closing_data.index, rolling_7d, lw=3, alpha=0.8,label='Rolling␣
    ↪mean - window 7')
plt.plot(btc_closing_data.index, rolling_14d, lw=3, alpha=0.8,label='Rolling␣
    ↪mean - window 14')
plt.plot(btc_closing_data.index, rolling_28d, lw=3, alpha=0.8,label='Rolling␣
    ↪mean - window 28')

plt.title('ETH-USD Volume Shocks - Observation Window - 2024-05-01 :␣
    ↪2024-09-01')
plt.tick_params(labelsize=12)
plt.legend(loc='upper left', fontsize=12)
plt.show()
```



Check for Autocorrelation and Partial autocorrelation

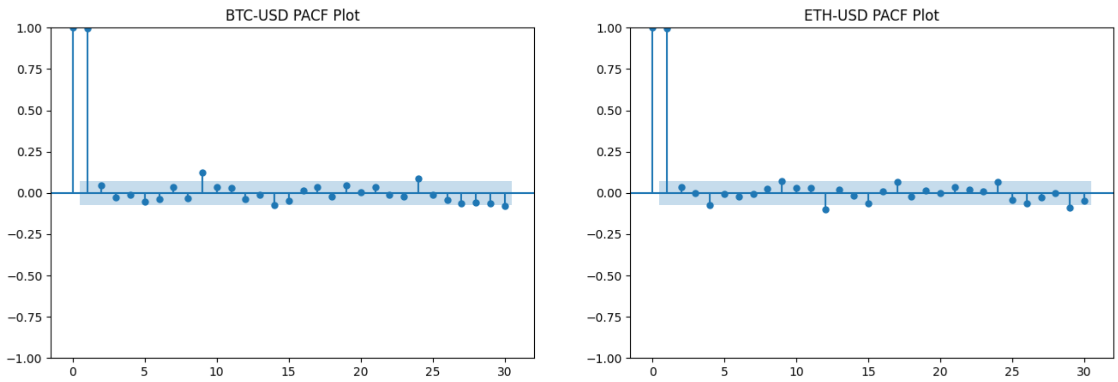
In the below section we can check for ACF and PACF functions for 'Adjusted Closing Price'

[18]:
```
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(16, 5))

btc_data = data['Adj Close']['BTC-USD']
sm.graphics.tsa.plot_acf(btc_data.values.squeeze(), lags=30, ax=ax1,␣
 ↪title="BTC-USD ACF Plot")

eth_data = data['Adj Close']['ETH-USD']
sm.graphics.tsa.plot_acf(eth_data.values.squeeze(), lags=30, ax=ax2,␣
 ↪title="ETH-USD ACF Plot")
plt.show()
```



[19]:
```
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(16, 5))

btc_data = data['Adj Close']['BTC-USD']
sm.graphics.tsa.plot_pacf(btc_data.values.squeeze(), lags=30, ax=ax1,␣
 ↪title="BTC-USD PACF Plot")
```

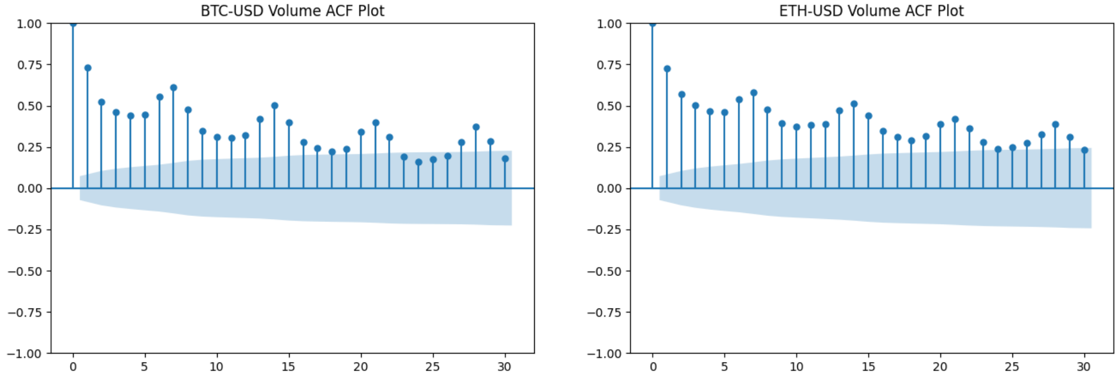
```
eth_data = data['Adj Close']['ETH-USD']
sm.graphics.tsa.plot_pacf(eth_data.values.squeeze(), lags=30, ax=ax2,␣
 ↪title="ETH-USD PACF Plot")
plt.show()
```



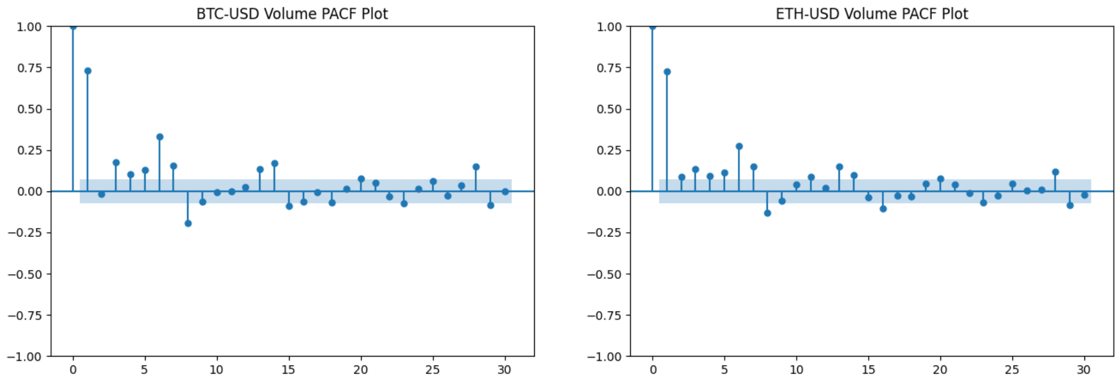
The plot shows significant autocorrelation, the previous value of the currenty determines days closing price. From the PACF plot it is clear that price of certain period of time is correlated than others, say for example price on day 4, 9, 12, 15 etc.

In the next sections we will check for Autocorrelatioins and Partial Autocorrelations for Volume in both crypto currencies.

[20]:
```
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(16, 5))

btc_data = data['Volume']['BTC-USD']
sm.graphics.tsa.plot_acf(btc_data.values.squeeze(), lags=30, ax=ax1,␣
 ↪title="BTC-USD Volume ACF Plot")

eth_data = data['Volume']['ETH-USD']
sm.graphics.tsa.plot_acf(eth_data.values.squeeze(), lags=30, ax=ax2,␣
 ↪title="ETH-USD Volume ACF Plot")
plt.show()
```



[21]:
```
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(16, 5))

btc_data = data['Volume']['BTC-USD']
sm.graphics.tsa.plot_pacf(btc_data.values.squeeze(), lags=30, ax=ax1,␣
 ↪title="BTC-USD Volume PACF Plot")

eth_data = data['Volume']['ETH-USD']
sm.graphics.tsa.plot_pacf(eth_data.values.squeeze(), lags=30, ax=ax2,␣
 ↪title="ETH-USD Volume PACF Plot")
plt.show()
```



4 Statistical Test for Stationarity

In this section we will use ADF test to establish that dataset is stationary. It is a unit-root test for time series.

[72]:
```
from statsmodels.tsa.stattools import adfuller
```

```
print("P-value for AD Fuller test for BTC-USD Adj Close {}".format(adfuller(␣
 ↪data['Adj Close']['BTC-USD'])[1]))
print("P-value for AD Fuller test for ETH-USD Adj Close {}".format(adfuller(␣
 ↪data['Adj Close']['ETH-USD'])[1]))
print("P-value for AD Fuller test for BTC-USD Volume {}".format(adfuller(␣
 ↪data['Volume']['BTC-USD'])[1]))
print("P-value for AD Fuller test for ETH-USD Volume {}".format(adfuller(␣
 ↪data['Volume']['ETH-USD'])[1]))
```

```
P-value for AD Fuller test for BTC-USD Adj Close 0.8759619045006749
P-value for AD Fuller test for ETH-USD Adj Close 0.6087041759596575
P-value for AD Fuller test for BTC-USD Volume 0.011305878023385845
P-value for AD Fuller test for ETH-USD Volume 0.02339000739363443
```

From the AD Fuller test, it can be seen for Adj Close Price the p-value is greater than 0.05 for ETH-USD and BTC-USD, indicating the data series is non-stationary. In the case Volume the p-value is less than 0.05, therefore wwe reject the null hypotheis and the series is stationary. We can see this with Kalman Forecast below for Volume, they do no show any trend.

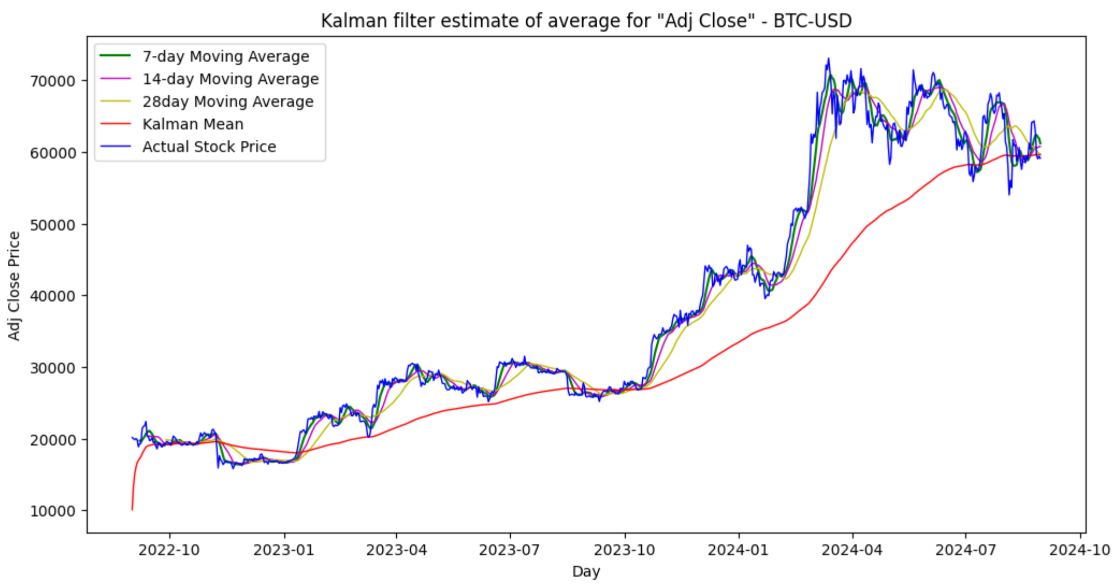
5 Exploring Kalman Filter

Getting started with Kalman Filters for the data, we will be using the algorithms implementation in pykalman. Let us do the Kalman smoothing and filtering methods to remove the trend here. Stock price by nature is very noisy and with an underlying trend. The identification of this trend can be useful in many ways and can also be used as a feature for stock price forecasting using ARIMA, Linear Regression or any other methods.

[22]:
```
# initializing kalman filters

from pykalman import KalmanFilter
import numpy as np


kalmanFilter = KalmanFilter(transition_matrices = [1],
              observation_matrices = [1],
              initial_state_mean = 0,
              initial_state_covariance = 1,
              observation_covariance=1,
              transition_covariance=.0001)
```

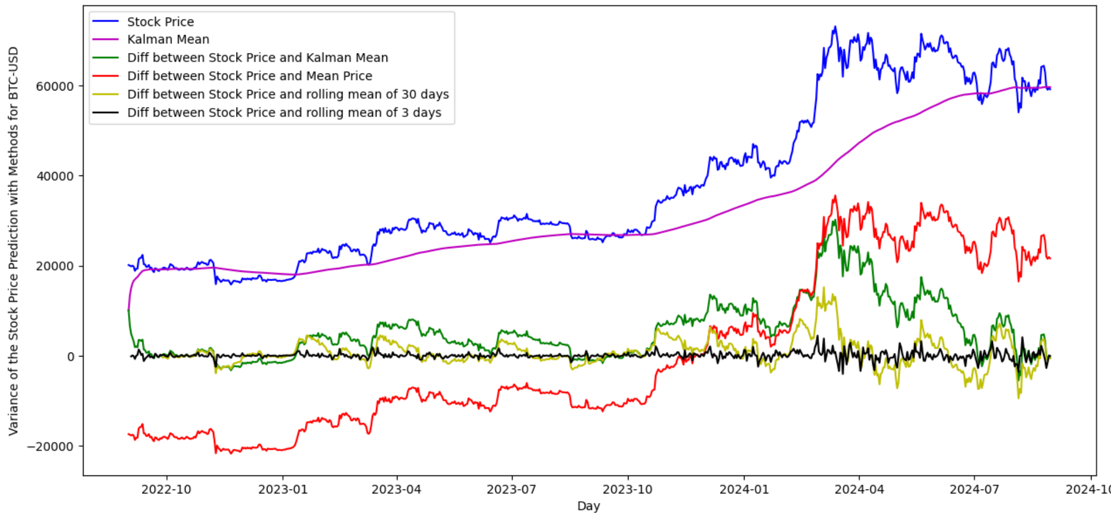
[23]:
```
# using Kalman Filters for BTC-USD

stock_price = data['Adj Close']['BTC-USD']
mean, cov = kalmanFilter.filter(stock_price)
kalman_mean = pd.Series(mean.flatten(), index=stock_price.index)
```

```
rolling_3d = stock_price.rolling(window=3).mean()
rolling_7d = stock_price.rolling(window=7).mean()
rolling_14d = stock_price.rolling(window=14).mean()
rolling_28d = stock_price.rolling(window=28).mean()

plt.figure(figsize=(12,6))
plt.plot(rolling_7d,'-g',lw=1.5)
plt.plot(rolling_14d, 'm', lw=1)
plt.plot(rolling_28d, 'y', lw=1)
plt.plot(kalman_mean, 'r', lw=1)
plt.plot(stock_price, 'b', lw=1)
plt.title('Kalman filter estimate of average for "Adj Close" - BTC-USD')
plt.legend(['7-day Moving Average', '14-day Moving Average', '28day Moving␣
 ↪Average', 'Kalman Mean', 'Actual Stock Price'])
plt.xlabel('Day')
plt.ylabel('Adj Close Price');
```



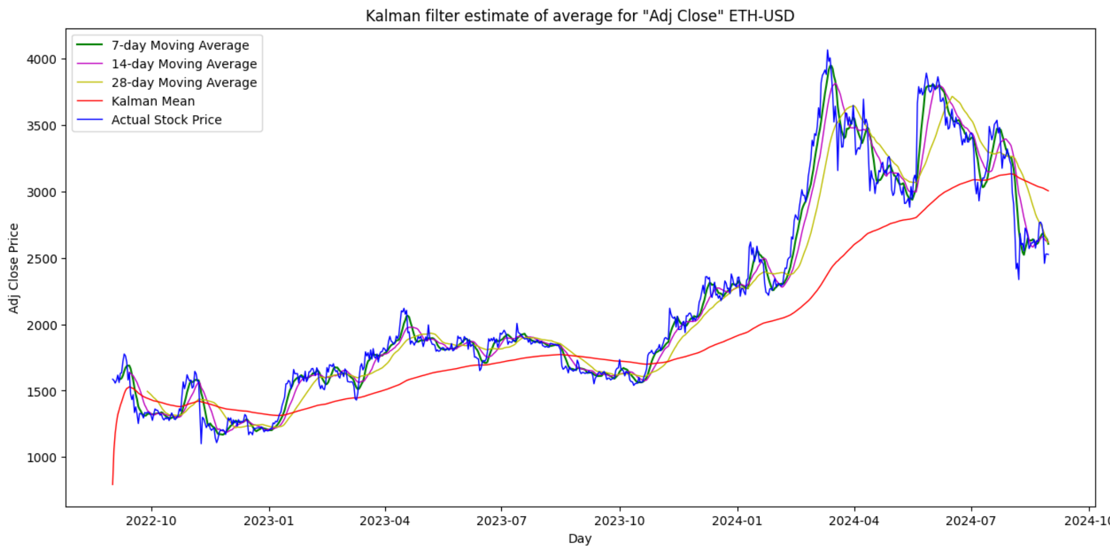
[24]:
```
plt.figure(figsize=(15,7))
plt.plot(stock_price ,'b',lw=1.5)
plt.plot(kalman_mean ,'m',lw=1.5)
plt.plot(stock_price - kalman_mean,'-g',lw=1.5)
plt.plot(stock_price - stock_price.mean() ,'r',lw=1.5)
plt.plot(stock_price - rolling_28d ,'y',lw=1.5)
plt.plot(stock_price - rolling_3d ,'k',lw=1.5)
plt.legend(['Stock Price', 'Kalman Mean', 'Diff between Stock Price and Kalman␣
 ↪Mean', 'Diff between Stock Price and Mean Price',
```

```
            'Diff between Stock Price and rolling mean of 30 days', 'Diff between Stock Price and rolling mean of 3 days'])
plt.xlabel('Day')
plt.ylabel('Variance of the Stock Price Prediction with Methods for BTC-USD');
```



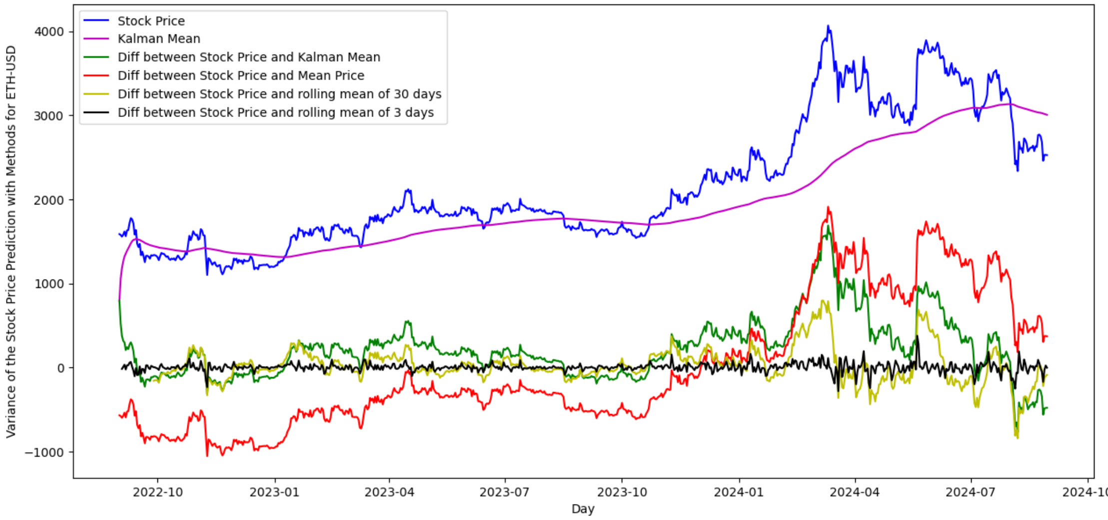
[25]:
```
kalmanFilter = KalmanFilter(transition_matrices = [1],
              observation_matrices = [1],
              initial_state_mean = 0,
              initial_state_covariance = 1,
              observation_covariance=1,
              transition_covariance=.0001)

stock_price = data['Adj Close']['ETH-USD']
mean, cov = kalmanFilter.filter(stock_price)
kalman_mean = pd.Series(mean.flatten(), index=stock_price.index)



rolling_3d = stock_price.rolling(window=3).mean()
rolling_7d = stock_price.rolling(window=7).mean()
rolling_14d = stock_price.rolling(window=14).mean()
rolling_28d = stock_price.rolling(window=28).mean()

plt.figure(figsize=(15,7))
plt.plot(rolling_7d,'-g',lw=1.5)
plt.plot(rolling_14d, 'm', lw=1)
plt.plot(rolling_28d, 'y', lw=1)
plt.plot(kalman_mean, 'r', lw=1)
plt.plot(stock_price, 'b', lw=1)
```

```
plt.title('Kalman filter estimate of average for "Adj Close" ETH-USD')
plt.legend(['7-day Moving Average', '14-day Moving Average', '28-day Moving␣
 ↪Average', 'Kalman Mean', 'Actual Stock Price'])
plt.xlabel('Day')
plt.ylabel('Adj Close Price');
```



From the kalman Filter for Bitcoin it can be seen that it produces much more smooth signal than others and is more generalised than the rolling window prediction. Kalman fiklter helps in separating the noise from the signals and can be used for prediction

[26]:
```
plt.figure(figsize=(15,7))
plt.plot(stock_price ,'b',lw=1.5)
plt.plot(kalman_mean ,'m',lw=1.5)
plt.plot(stock_price - kalman_mean,'-g',lw=1.5)
plt.plot(stock_price - stock_price.mean() ,'r',lw=1.5)
plt.plot(stock_price - rolling_28d ,'y',lw=1.5)
plt.plot(stock_price - rolling_3d ,'k',lw=1.5)

plt.legend(['Stock Price', 'Kalman Mean', 'Diff between Stock Price and Kalman␣
 ↪Mean', 'Diff between Stock Price and Mean Price',  'Diff between Stock Price␣
 ↪and rolling mean of 30 days',
            'Diff between Stock Price and rolling mean of 3 days'])
plt.xlabel('Day')
plt.ylabel('Variance of the Stock Price Prediction with Methods for ETH-USD');
```



Kalman Filters gives a time-evolving mean and shows fluctuations with time than the and difference stays closer to 0 compared to the other steps such as rolling mean and static mean. Such updated mean for each time point could help us manage aggressive trading strategies.

In the below section we will using Kalman Filter update method to do stock price forecasts for each day using the previous data as the prior and will keep on update the price on based on the daily available actual price like a dynamic system.

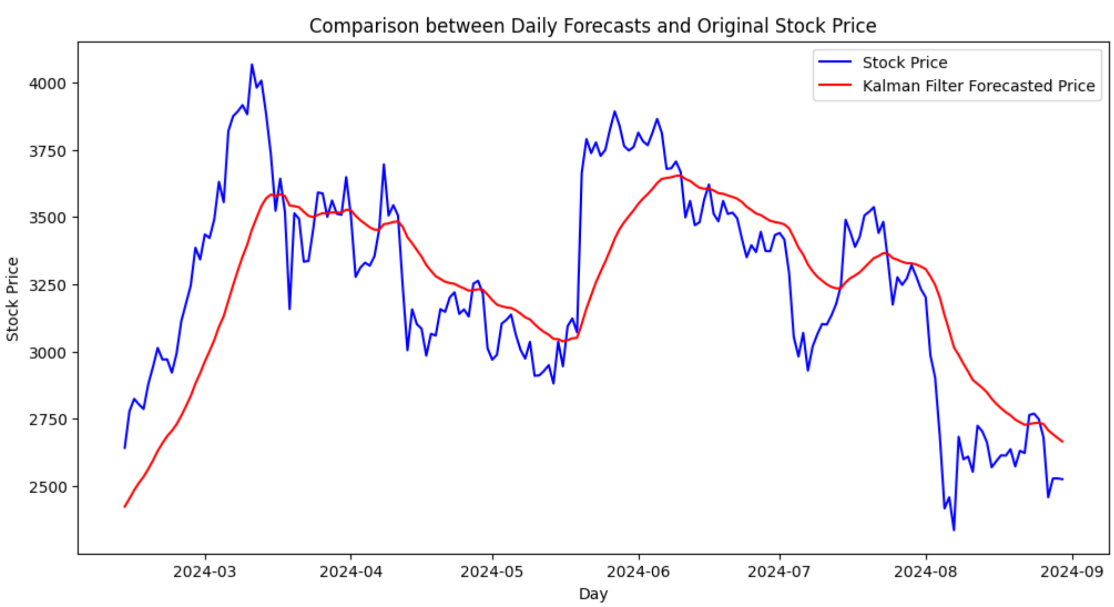
In the below Sections we will forecast Kalman Filter for **ETH-USD** data for various time intervals. We will be using Kalman Filter update on 'Adj Close' column of the time series.

6 Kalman Filter for 'Adj Close'

[27]:
```
kalmanFilter = KalmanFilter(transition_matrices = [1],
                observation_matrices = [1],
                initial_state_mean = 0,
                initial_state_covariance = 1,
                observation_covariance=1,
                transition_covariance=.0001)



# Predicting for ETH-USD
stock_price = data['Adj Close']['ETH-USD']

# Kalman Forecast for Next 100 days
mean, cov = kalmanFilter.em(stock_price[:-200], n_iter=10).smooth(stock_price[:
 ↪-200]) # changed from 10 to 100, after experiment put it back to 10
# mean, cov = kalmanFilter.em(stock_price[1], n_iter=10)

next_means = []
```

```python
next_covs = []
next_mean = mean[-1]
next_cov = cov[-1]
for i in range(200):
  next_mean, next_cov = kalmanFilter.filter_update(next_mean, next_cov, stock_price[-(200 - i * 1)]) # changed from 10 to 100, after experiment put it back to 10
  next_means.append(next_mean[0])
  next_covs.append(next_cov[0])


# replacing the forecasted price for the last 10 days
forecasted_price = pd.DataFrame(data=np.concatenate([stock_price[:-200].values, next_means]),
                   index=stock_price.index)

plt.figure(figsize=(12,6))
plt.plot(stock_price[len(stock_price)-200:] ,'b',lw=1.5)
plt.plot(forecasted_price[len(stock_price)-200:] ,'r',lw=1.5)
plt.legend(['Stock Price', 'Kalman Filter Forecasted Price'])
plt.xlabel('Day')
plt.ylabel('Stock Price')
plt.title('Comparison between Daily Forecasts and Original Stock Price');
```

```
<ipython-input-27-d5d7869a3599>:21: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future
version, integer keys will always be treated as labels (consistent with
DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
```



[28]:

```
from sklearn.metrics import r2_score , mean_absolute_percentage_error,␣
↪mean_squared_error, mean_absolute_error
import math

_y_stock = stock_price[len(stock_price)-200:] # changed from 10 to 100, after␣
↪experiment put it back to 10
kalman_forecast_y = forecasted_price[len(stock_price)-200:] # changed from 10␣
↪to 100, after experiment put it back to 10
print("R square {}".format(r2_score(_y_stock, kalman_forecast_y)))
print("Mean absolute percentage error {}".
↪format(mean_absolute_percentage_error(_y_stock, kalman_forecast_y)))
print("Root Mean Square Error RMSE {}".format(math.
↪sqrt(mean_squared_error(_y_stock, kalman_forecast_y))))
print("Mean absolute error {}".format(mean_absolute_error(_y_stock,␣
↪kalman_forecast_y)))
```

```
R square 0.5331947237800019
Mean absolute percentage error 0.06379022509833535
Root Mean Square Error RMSE 262.8734331675915
Mean absolute error 204.2497629668713
```

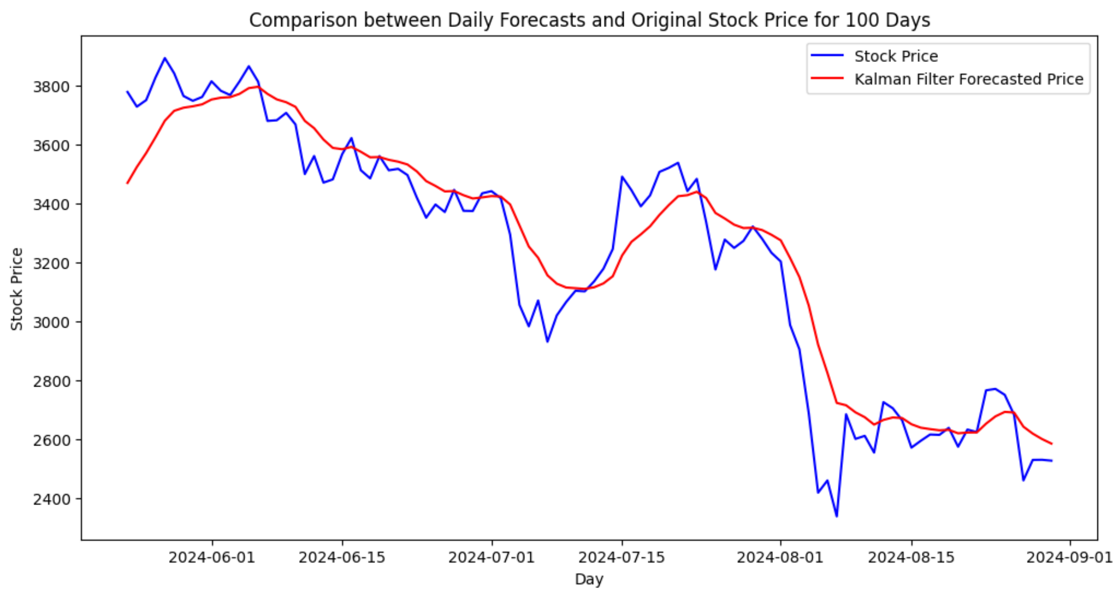
[29]:

```
kalmanFilter = KalmanFilter(transition_matrices = [1],
              observation_matrices = [1],
              initial_state_mean = 0,
              initial_state_covariance = 1,
              observation_covariance=1,
              transition_covariance=.0001)


# Predicting for ETH-USD
stock_price = data['Adj Close']['ETH-USD']

# Kalman Forecast for Next 100 days
mean, cov = kalmanFilter.em(stock_price[:-100], n_iter=10).smooth(stock_price[:
↪-100]) # changed from 10 to 100, after experiment put it back to 10
# mean, cov = kalmanFilter.em(stock_price[1], n_iter=10)

next_means = []
next_covs = []
next_mean = mean[-1]
next_cov = cov[-1]
for i in range(100):
```

```
next_mean, next_cov = kalmanFilter.filter_update(next_mean, next_cov,␣
↪stock_price[-(100 - i * 1)]) # changed from 10 to 100, after experiment put␣
↪it back to 10
 next_means.append(next_mean[0])
 next_covs.append(next_cov[0])
```

```
<ipython-input-29-968bb0fc92b6>:21: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future
version, integer keys will always be treated as labels (consistent with
DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
```

[30]:
```
# replacing the forecasted price for the last 10 days
forecasted_price = pd.DataFrame(data=np.concatenate([stock_price[:-100].values,␣
↪next_means]),
                   index=stock_price.index)

plt.figure(figsize=(12,6))
plt.plot(stock_price[len(stock_price)-100:] ,'b',lw=1.5)
plt.plot(forecasted_price[len(stock_price)-100:] ,'r',lw=1.5)
plt.legend(['Stock Price', 'Kalman Filter Forecasted Price'])
plt.xlabel('Day')
plt.ylabel('Stock Price')
plt.title('Comparison between Daily Forecasts and Original Stock Price for 100␣
↪Days');
```



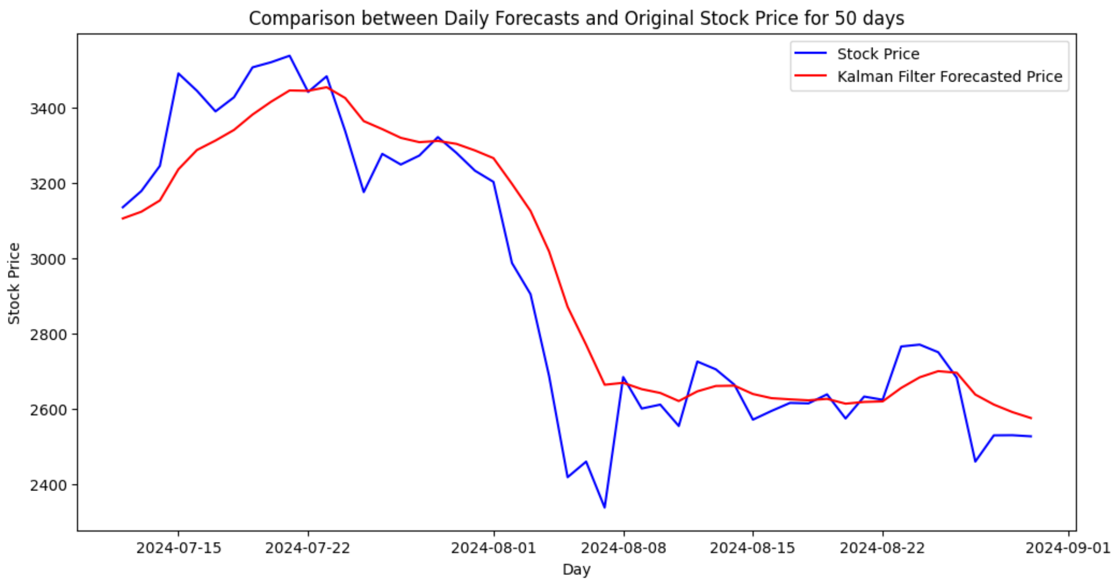
[31]:
```
from sklearn.metrics import r2_score , mean_absolute_percentage_error,␣
↪mean_squared_error, mean_absolute_error
import math

_y_stock = stock_price[len(stock_price)-100:] # changed from 10 to 100, after␣
↪experiment put it back to 10
kalman_forecast_y = forecasted_price[len(stock_price)-100:] # changed from 10␣
↪to 100, after experiment put it back to 10
print("R square {}".format(r2_score(_y_stock, kalman_forecast_y)))
print("Mean absolute percentage error {}".
↪format(mean_absolute_percentage_error(_y_stock, kalman_forecast_y)))
print("Root Mean Square Error RMSE {}".format(math.
↪sqrt(mean_squared_error(_y_stock, kalman_forecast_y))))
print("Mean absolute error {}".format(mean_absolute_error(_y_stock,␣
↪kalman_forecast_y)))
```

```
R square 0.9041106970476439
Mean absolute percentage error 0.031062199149145875
Root Mean Square Error RMSE 134.7597223756434
Mean absolute error 95.2399569958813
```

[32]:
```
kalmanFilter = KalmanFilter(transition_matrices = [1],
              observation_matrices = [1],
              initial_state_mean = 0,
              initial_state_covariance = 1,
              observation_covariance=1,
              transition_covariance=.0001)



# Predicting for ETH-USD
stock_price = data['Adj Close']['ETH-USD']

# Kalman Forecast for Next 100 days
mean, cov = kalmanFilter.em(stock_price[:-50], n_iter=10).smooth(stock_price[:
↪-50]) # changed from 10 to 100, after experiment put it back to 10
# mean, cov = kalmanFilter.em(stock_price[1], n_iter=10)

next_means = []
next_covs = []
next_mean = mean[-1]
next_cov = cov[-1]
for i in range(50):
  next_mean, next_cov = kalmanFilter.filter_update(next_mean, next_cov,␣
↪stock_price[-(50 - i * 1)]) # changed from 10 to 100, after experiment put␣
↪it back to 10
  next_means.append(next_mean[0])
  next_covs.append(next_cov[0])
```

```
# replacing the forecasted price for the last 10 days
forecasted_price = pd.DataFrame(data=np.concatenate([stock_price[:-50].values,
    next_means]),
                    index=stock_price.index)

plt.figure(figsize=(12,6))
plt.plot(stock_price[len(stock_price)-50:] ,'b',lw=1.5)
plt.plot(forecasted_price[len(stock_price)-50:] ,'r',lw=1.5)
plt.legend(['Stock Price', 'Kalman Filter Forecasted Price'])
plt.xlabel('Day')
plt.ylabel('Stock Price')
plt.title('Comparison between Daily Forecasts and Original Stock Price for 50
    days');
```

```
<ipython-input-32-70c97d46fae8>:21: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future
version, integer keys will always be treated as labels (consistent with
DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
```



[33]:
```
from sklearn.metrics import r2_score , mean_absolute_percentage_error,
    mean_squared_error, mean_absolute_error
import math
```

```
_y_stock = stock_price[len(stock_price)-50:] # changed from 10 to 100, after␣
↪experiment put it back to 10
kalman_forecast_y = forecasted_price[len(stock_price)-50:] # changed from 10 to␣
↪100, after experiment put it back to 10
print("R square {}".format(r2_score(_y_stock, kalman_forecast_y)))
print("Mean absolute percentage error {}".
↪format(mean_absolute_percentage_error(_y_stock, kalman_forecast_y)))
print("Root Mean Square Error RMSE {}".format(math.
↪sqrt(mean_squared_error(_y_stock, kalman_forecast_y))))
print("Mean absolute error {}".format(mean_absolute_error(_y_stock,␣
↪kalman_forecast_y)))
```

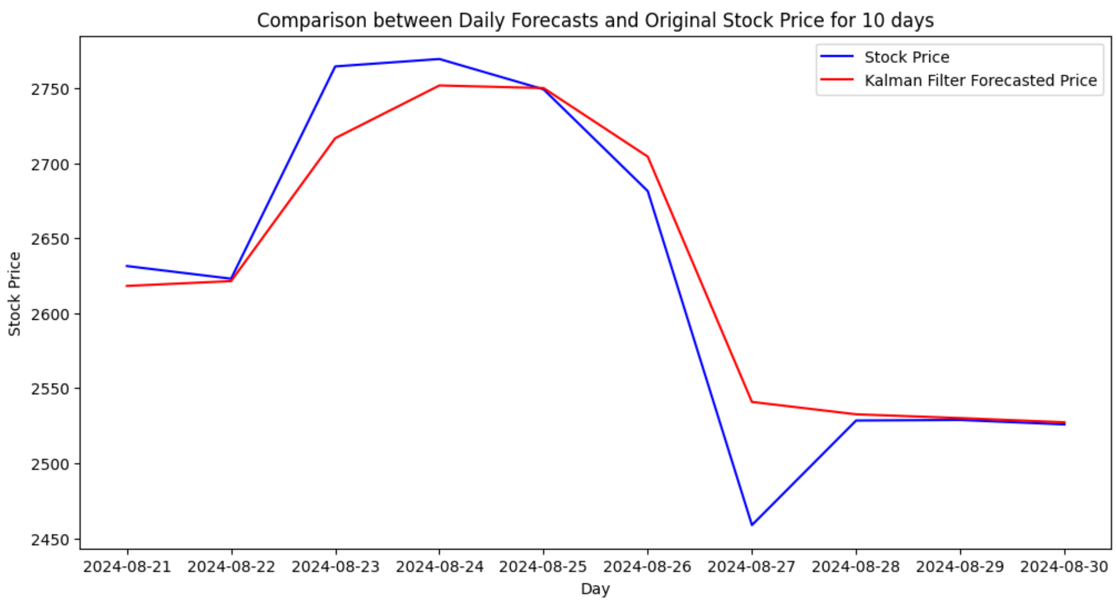
```
R square 0.8698406878436127
Mean absolute percentage error 0.033123361785285604
Root Mean Square Error RMSE 135.19253245722786
Mean absolute error 93.34666907382754
```

[86]:

```
kalmanFilter = KalmanFilter(transition_matrices = [1],
              observation_matrices = [1],
              initial_state_mean = 0,
              initial_state_covariance = 1,
              observation_covariance=1,
              transition_covariance=.01)



# Predicting for ETH-USD
stock_price = data['Adj Close']['ETH-USD']

# Kalman Forecast for Next 100 days
mean, cov = kalmanFilter.em(stock_price[:-10], n_iter=10).smooth(stock_price[:
↪-10]) # changed from 10 to 100, after experiment put it back to 10
# mean, cov = kalmanFilter.em(stock_price[1], n_iter=10)

next_means = []
next_covs = []
next_mean = mean[-1]
next_cov = cov[-1]
for i in range(10):
  next_mean, next_cov = kalmanFilter.filter_update(next_mean, next_cov,␣
↪stock_price[-(10 - i * 1)]) # changed from 10 to 100, after experiment put␣
↪it back to 10
  next_means.append(next_mean[0])
  next_covs.append(next_cov[0])



# replacing the forecasted price for the last 10 days
```

```
forecasted_price = pd.DataFrame(data=np.concatenate([stock_price[:-10].values,␣
↪next_means]),
                  index=stock_price.index)

plt.figure(figsize=(12,6))
plt.plot(stock_price[len(stock_price)-10:] ,'b',lw=1.5)
plt.plot(forecasted_price[len(stock_price)-10:] ,'r',lw=1.5)
plt.legend(['Stock Price', 'Kalman Filter Forecasted Price'])
plt.xlabel('Day')
plt.ylabel('Stock Price')
plt.title('Comparison between Daily Forecasts and Original Stock Price for 10␣
↪days');
```

```
<ipython-input-86-ebbd399fcbf2>:21: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future
version, integer keys will always be treated as labels (consistent with
DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
```



[87]:
```
from sklearn.metrics import r2_score , mean_absolute_percentage_error,␣
↪mean_squared_error, mean_absolute_error
import math

_y_stock = stock_price[len(stock_price)-10:] # changed from 10 to 100, after␣
↪experiment put it back to 10
```

```
kalman_forecast_y = forecasted_price[len(stock_price)-10:] # changed from 10 to␣
↪100, after experiment put it back to 10
print("R square {}".format(r2_score(_y_stock, kalman_forecast_y)))
print("Mean absolute percentage error {}".
↪format(mean_absolute_percentage_error(_y_stock, kalman_forecast_y)))
print("Root Mean Square Error RMSE {}".format(math.
↪sqrt(mean_squared_error(_y_stock, kalman_forecast_y))))
print("Mean absolute error {}".format(mean_absolute_error(_y_stock,␣
↪kalman_forecast_y)))
```

```
R square 0.9124687521208008
Mean absolute percentage error 0.007428851406645756
Root Mean Square Error RMSE 31.72503430765914
Mean absolute error 19.307972955498645
```

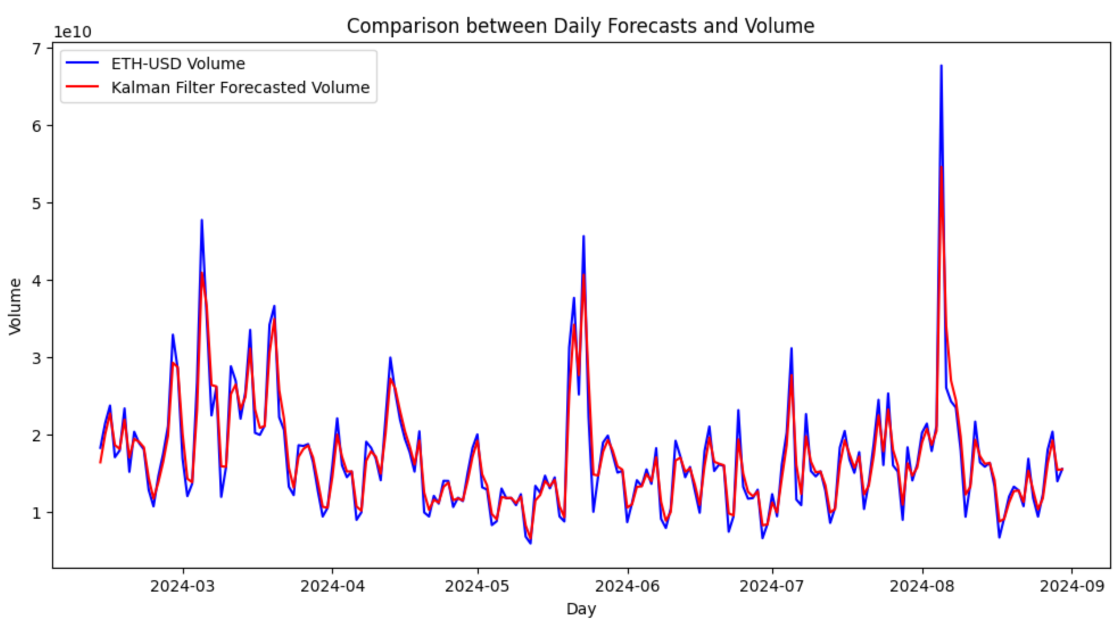
7 Kalman Filter Forecast for Volume

In the below section we will forecast Volume for Ethereum data for 200 days

[88]:
```
kalmanFilter = KalmanFilter(transition_matrices = [1],
              observation_matrices = [1],
              initial_state_mean = 0,
              initial_state_covariance = 1,
              observation_covariance=1,
              transition_covariance=2)


# Predicting for ETH-USD
volume = data['Volume']['ETH-USD']

# Kalman Forecast for Next 100 days
mean, cov = kalmanFilter.em(volume[:-200], n_iter=10).smooth(volume[:-200]) #␣
↪changed from 10 to 100, after experiment put it back to 10
# mean, cov = kalmanFilter.em(stock_price[1], n_iter=10)

next_means = []
next_covs = []
next_mean = mean[-1]
next_cov = cov[-1]
for i in range(200):
  next_mean, next_cov = kalmanFilter.filter_update(next_mean, next_cov,␣
↪volume[-(200 - i * 1)]) # changed from 10 to 100, after experiment put it␣
↪back to 10
  next_means.append(next_mean[0])
  next_covs.append(next_cov[0])
```

```
# replacing the forecasted price for the last 10 days
forecasted_volume = pd.DataFrame(data=np.concatenate([volume[:-200].values,␣
 ↪next_means]),
                  index=volume.index)

plt.figure(figsize=(12,6))
plt.plot(volume[len(volume)-200:] ,'b',lw=1.5)
plt.plot(forecasted_volume[len(volume)-200:] ,'r',lw=1.5)
plt.legend(['ETH-USD Volume', 'Kalman Filter Forecasted Volume'])
plt.xlabel('Day')
plt.ylabel('Volume')
plt.title('Comparison between Daily Forecasts and Volume');
```

```
<ipython-input-88-b19efca3b6aa>:21: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future
version, integer keys will always be treated as labels (consistent with
DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
```



[89]:
```
from sklearn.metrics import r2_score , mean_absolute_percentage_error,␣
 ↪mean_squared_error, mean_absolute_error
import math

_y_volume = volume[len(volume)-200:] # changed from 10 to 100, after experiment␣
 ↪put it back to 10
```

```
kalman_forecast_y = forecasted_volume[len(volume)-200:] # changed from 10 to
 ↪100, after experiment put it back to 10
print("R square {}".format(r2_score(_y_volume, kalman_forecast_y)))
print("Mean absolute percentage error {}".
 ↪format(mean_absolute_percentage_error(_y_volume, kalman_forecast_y)))
print("Root Mean Square Error RMSE {}".format(math.
 ↪sqrt(mean_squared_error(_y_volume, kalman_forecast_y))))
print("Mean absolute error {}".format(mean_absolute_error(_y_volume,
 ↪kalman_forecast_y)))
```

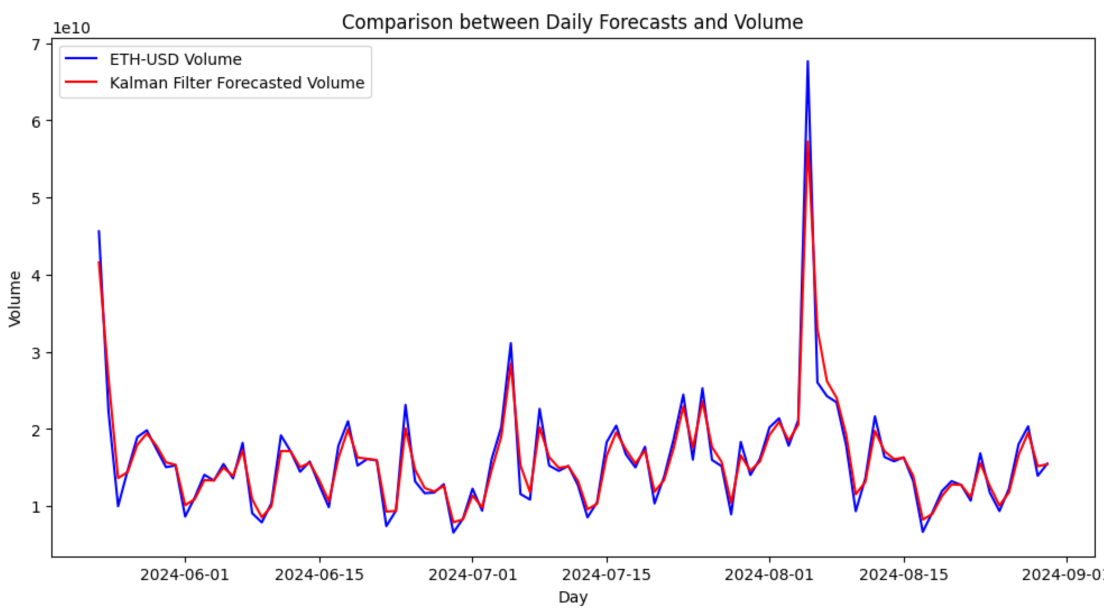
```
R square 0.9286127908117351
Mean absolute percentage error 0.08178317315450043
Root Mean Square Error RMSE 2049202655.6268578
Mean absolute error 1374597299.8002546
```

[83]:

```
kalmanFilter = KalmanFilter(transition_matrices = [1],
              observation_matrices = [1],
              initial_state_mean = 0,
              initial_state_covariance = 1,
              observation_covariance=1,
              transition_covariance=2)


# Predicting for ETH-USD
volume = data['Volume']['ETH-USD']

# Kalman Forecast for Next 100 days
mean, cov = kalmanFilter.em(volume[:-100], n_iter=10).smooth(volume[:-100]) #
 ↪changed from 10 to 100, after experiment put it back to 10
# mean, cov = kalmanFilter.em(stock_price[1], n_iter=10)

next_means = []
next_covs = []
next_mean = mean[-1]
next_cov = cov[-1]
for i in range(100):
  next_mean, next_cov = kalmanFilter.filter_update(next_mean, next_cov,
 ↪volume[-(100 - i * 1)]) # changed from 10 to 100, after experiment put it
 ↪back to 10
  next_means.append(next_mean[0])
  next_covs.append(next_cov[0])


# replacing the forecasted price for the last 10 days
forecasted_volume = pd.DataFrame(data=np.concatenate([volume[:-100].values,
 ↪next_means]),
                  index=volume.index)
```

```
plt.figure(figsize=(12,6))
plt.plot(volume[len(volume)-100:] ,'b',lw=1.5)
plt.plot(forecasted_volume[len(volume)-100:] ,'r',lw=1.5)
plt.legend(['ETH-USD Volume', 'Kalman Filter Forecasted Volume'])
plt.xlabel('Day')
plt.ylabel('Volume')
plt.title('Comparison between Daily Forecasts and Volume');
```

```
<ipython-input-83-cc2dd358d03f>:21: FutureWarning:

Series.__getitem__ treating keys as positions is deprecated. In a future
version, integer keys will always be treated as labels (consistent with
DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
```



[84]:
```
from sklearn.metrics import r2_score , mean_absolute_percentage_error,
    mean_squared_error, mean_absolute_error
import math

_y_volume = volume[len(volume)-100:] # changed from 10 to 100, after experiment
    put it back to 10
kalman_forecast_y = forecasted_volume[len(volume)-100:] # changed from 10 to
    100, after experiment put it back to 10
print("R square {}".format(r2_score(_y_volume, kalman_forecast_y)))
print("Mean absolute percentage error {}".
    format(mean_absolute_percentage_error(_y_volume, kalman_forecast_y)))
```

```python
print("Root Mean Square Error RMSE {}".format(math.
    ↪sqrt(mean_squared_error(_y_volume, kalman_forecast_y))))
print("Mean absolute error {}".format(mean_absolute_error(_y_volume,␣
    ↪kalman_forecast_y)))
```

```
R square 0.9436112773958336
Mean absolute percentage error 0.07167967220019686
Root Mean Square Error RMSE 1813420368.38731
Mean absolute error 1144993804.7182558
```

8 Using Traditional ML for Prediction

In this section we will explore how traditional methods work for stock price prediction. We will be using multivariable regression technique to predict closing price of the stock for the next day. The feature engineering for this model will include column values high, low, open, close, volume to determine the Adjusted close price for the next day.

[40]:
```python
data.head()
```

[40]:
```
Price                          Adj Close                    Close  \
Ticker                           BTC-USD      ETH-USD     BTC-USD
Date
2022-09-01 00:00:00+00:00   20127.140625  1586.176758  20127.140625
2022-09-02 00:00:00+00:00   19969.771484  1577.220459  19969.771484
2022-09-03 00:00:00+00:00   19832.087891  1556.872681  19832.087891
2022-09-04 00:00:00+00:00   19986.712891  1577.641602  19986.712891
2022-09-05 00:00:00+00:00   19812.371094  1617.183228  19812.371094

Price                                            High                \
Ticker                          ETH-USD       BTC-USD      ETH-USD
Date
2022-09-01 00:00:00+00:00   1586.176758  20198.390625  1593.082764
2022-09-02 00:00:00+00:00   1577.220459  20401.568359  1643.183228
2022-09-03 00:00:00+00:00   1556.872681  20037.009766  1579.454346
2022-09-04 00:00:00+00:00   1577.641602  19999.689453  1578.009277
2022-09-05 00:00:00+00:00   1617.183228  20031.160156  1621.661377

Price                                Low                     Open  \
Ticker                           BTC-USD      ETH-USD     BTC-USD
Date
2022-09-01 00:00:00+00:00   19653.968750  1520.188354  20050.498047
2022-09-02 00:00:00+00:00   19814.765625  1551.877930  20126.072266
2022-09-03 00:00:00+00:00   19698.355469  1541.672119  19969.718750
2022-09-04 00:00:00+00:00   19636.816406  1543.698853  19832.470703
2022-09-05 00:00:00+00:00   19673.046875  1559.781860  19988.789062

Price                                                 Volume
```

```
Ticker                          ETH-USD      BTC-USD      ETH-USD
Date
2022-09-01 00:00:00+00:00  1553.756348  30182031010  16434276817
2022-09-02 00:00:00+00:00  1586.017944  29123998928  17708478709
2022-09-03 00:00:00+00:00  1577.213745  23613051457   9516825994
2022-09-04 00:00:00+00:00  1556.895874  25245861652   8884144998
2022-09-05 00:00:00+00:00  1577.884033  28813460025  13060541168
```

[41]:
```
btc_data = {'Open': data['Open']['BTC-USD'],
            'Close': data['Close']['BTC-USD'],
            'High': data['High']['BTC-USD'],
            'Low': data['Low']['BTC-USD'],
            'Volume': data['Low']['BTC-USD'],
            'Adj Close': data['Adj Close']['BTC-USD']
            }

eth_data = {'Open': data['Open']['ETH-USD'],
            'Close': data['Close']['ETH-USD'],
            'High': data['High']['ETH-USD'],
            'Low': data['Low']['ETH-USD'],
            'Volume': data['Low']['ETH-USD'],
            'Adj Close': data['Adj Close']['ETH-USD']
            }

btc_df = pd.DataFrame(btc_data, columns = ['Open', 'Close', 'High', 'Low',␣
 ↪'Volume', 'Adj Close'])
eth_df = pd.DataFrame(eth_data, columns = ['Open', 'Close', 'High', 'Low',␣
 ↪'Volume', 'Adj Close'])
```

[42]:
```
eth_df.head()
```

[42]:
```
                                  Open        Close         High          Low  \
Date
2022-09-01 00:00:00+00:00  1553.756348  1586.176758  1593.082764  1520.188354
2022-09-02 00:00:00+00:00  1586.017944  1577.220459  1643.183228  1551.877930
2022-09-03 00:00:00+00:00  1577.213745  1556.872681  1579.454346  1541.672119
2022-09-04 00:00:00+00:00  1556.895874  1577.641602  1578.009277  1543.698853
2022-09-05 00:00:00+00:00  1577.884033  1617.183228  1621.661377  1559.781860

                                Volume    Adj Close
Date
2022-09-01 00:00:00+00:00  1520.188354  1586.176758
2022-09-02 00:00:00+00:00  1551.877930  1577.220459
2022-09-03 00:00:00+00:00  1541.672119  1556.872681
2022-09-04 00:00:00+00:00  1543.698853  1577.641602
2022-09-05 00:00:00+00:00  1559.781860  1617.183228
```

[43]:
```
eth_df.describe()
```

[43]:

```
              Open        Close         High          Low       Volume  \
count   730.000000   730.000000   730.000000   730.000000   730.000000
mean   2153.339377  2154.649833  2197.880829  2107.257615  2107.257615
std     761.057358   760.858790   781.196683   736.665024   736.665024
min    1100.107178  1100.169800  1136.442627  1081.138184  1081.138184
25%    1617.854645  1620.496521  1644.864014  1580.678528  1580.678528
50%    1865.844604  1866.100159  1887.949524  1845.784241  1845.784241
75%    2640.590576  2640.965576  2709.429199  2585.498413  2585.498413
max    4066.690430  4066.445068  4092.284180  3936.627197  3936.627197

         Adj Close
count   730.000000
mean   2154.649833
std     760.858790
min    1100.169800
25%    1620.496521
50%    1866.100159
75%    2640.965576
max    4066.445068
```

[44]:
```
btc_df.describe()
```

[44]:

```
               Open         Close          High           Low        Volume  \
count    730.000000    730.000000    730.000000    730.000000    730.000000
mean   37464.146091  37518.319863  38162.137949  36780.942348  36780.942348
std    17678.426052  17685.270401  18083.910703  17220.739292  17220.739292
min    15782.300781  15787.284180  16253.047852  15599.046875  15599.046875
25%    23627.717285  23665.855469  24119.581543  23253.754883  23253.754883
50%    29403.917969  29412.204102  29845.836914  29113.966797  29113.966797
75%    55644.687500  55988.014648  57679.622070  54234.083008  54234.083008
max    73079.375000  73083.500000  73750.070312  71334.093750  71334.093750

          Adj Close
count    730.000000
mean   37518.319863
std    17685.270401
min    15787.284180
25%    23665.855469
50%    29412.204102
75%    55988.014648
max    73083.500000
```

[45]:
```
btc_df.head()
```

[45]:
```
                                   Open         Close          High  \
Date
2022-09-01 00:00:00+00:00  20050.498047  20127.140625  20198.390625
2022-09-02 00:00:00+00:00  20126.072266  19969.771484  20401.568359
2022-09-03 00:00:00+00:00  19969.718750  19832.087891  20037.009766
2022-09-04 00:00:00+00:00  19832.470703  19986.712891  19999.689453
2022-09-05 00:00:00+00:00  19988.789062  19812.371094  20031.160156

                                    Low        Volume     Adj Close
Date
2022-09-01 00:00:00+00:00  19653.968750  19653.968750  20127.140625
2022-09-02 00:00:00+00:00  19814.765625  19814.765625  19969.771484
2022-09-03 00:00:00+00:00  19698.355469  19698.355469  19832.087891
2022-09-04 00:00:00+00:00  19636.816406  19636.816406  19986.712891
2022-09-05 00:00:00+00:00  19673.046875  19673.046875  19812.371094
```

[46]:
```python
eth_df['Target'] = eth_df['Adj Close'].shift(-1)
eth_df.dropna(inplace=True)
eth_df.head()
```

[46]:
```
                                  Open        Close         High          Low  \
Date
2022-09-01 00:00:00+00:00  1553.756348  1586.176758  1593.082764  1520.188354
2022-09-02 00:00:00+00:00  1586.017944  1577.220459  1643.183228  1551.877930
2022-09-03 00:00:00+00:00  1577.213745  1556.872681  1579.454346  1541.672119
2022-09-04 00:00:00+00:00  1556.895874  1577.641602  1578.009277  1543.698853
2022-09-05 00:00:00+00:00  1577.884033  1617.183228  1621.661377  1559.781860

                                Volume    Adj Close       Target
Date
2022-09-01 00:00:00+00:00  1520.188354  1586.176758  1577.220459
2022-09-02 00:00:00+00:00  1551.877930  1577.220459  1556.872681
2022-09-03 00:00:00+00:00  1541.672119  1556.872681  1577.641602
2022-09-04 00:00:00+00:00  1543.698853  1577.641602  1617.183228
2022-09-05 00:00:00+00:00  1559.781860  1617.183228  1561.748535
```

[47]:
```python
eth_df.tail()
```

[47]:
```
                                  Open        Close         High          Low  \
Date
2024-08-25 00:00:00+00:00  2769.098145  2749.157715  2793.012939  2736.088867
2024-08-26 00:00:00+00:00  2749.247559  2681.340576  2763.004150  2668.886719
2024-08-27 00:00:00+00:00  2681.622803  2458.726562  2700.152832  2401.175049
2024-08-28 00:00:00+00:00  2458.904785  2528.415527  2553.820068  2422.293701
2024-08-29 00:00:00+00:00  2528.362305  2528.792725  2595.977051  2507.502441

                                Volume    Adj Close       Target
```

```
Date
2024-08-25 00:00:00+00:00  2736.088867  2749.157715  2681.340576
2024-08-26 00:00:00+00:00  2668.886719  2681.340576  2458.726562
2024-08-27 00:00:00+00:00  2401.175049  2458.726562  2528.415527
2024-08-28 00:00:00+00:00  2422.293701  2528.415527  2528.792725
2024-08-29 00:00:00+00:00  2507.502441  2528.792725  2525.822021
```

We can define as the forecast set for the last 10 data points to compare with our Kalman Forecast.

[48]:
```
forecast_set = eth_df[-200:] # validation set
training_set = eth_df[:-200] # changed from 10 to 100, after experiment put it␣
↪back to 10
```

[49]:
```
forecast_set
```

[49]:
```
                                  Open        Close         High          Low  \
Date
2024-02-12 00:00:00+00:00  2507.578857  2658.115967  2663.842773  2473.812012
2024-02-13 00:00:00+00:00  2659.586182  2642.185303  2686.455078  2599.169434
2024-02-14 00:00:00+00:00  2641.685303  2777.902344  2786.893555  2621.025391
2024-02-15 00:00:00+00:00  2777.601318  2824.378906  2865.845459  2764.010498
2024-02-16 00:00:00+00:00  2825.480713  2803.691406  2858.450439  2760.331055
…                                    …            …            …            …
2024-08-25 00:00:00+00:00  2769.098145  2749.157715  2793.012939  2736.088867
2024-08-26 00:00:00+00:00  2749.247559  2681.340576  2763.004150  2668.886719
2024-08-27 00:00:00+00:00  2681.622803  2458.726562  2700.152832  2401.175049
2024-08-28 00:00:00+00:00  2458.904785  2528.415527  2553.820068  2422.293701
2024-08-29 00:00:00+00:00  2528.362305  2528.792725  2595.977051  2507.502441

                                Volume    Adj Close       Target
Date
2024-02-12 00:00:00+00:00  2473.812012  2658.115967  2642.185303
2024-02-13 00:00:00+00:00  2599.169434  2642.185303  2777.902344
2024-02-14 00:00:00+00:00  2621.025391  2777.902344  2824.378906
2024-02-15 00:00:00+00:00  2764.010498  2824.378906  2803.691406
2024-02-16 00:00:00+00:00  2760.331055  2803.691406  2786.672607
…                                    …            …            …
2024-08-25 00:00:00+00:00  2736.088867  2749.157715  2681.340576
2024-08-26 00:00:00+00:00  2668.886719  2681.340576  2458.726562
2024-08-27 00:00:00+00:00  2401.175049  2458.726562  2528.415527
2024-08-28 00:00:00+00:00  2422.293701  2528.415527  2528.792725
2024-08-29 00:00:00+00:00  2507.502441  2528.792725  2525.822021

[200 rows x 7 columns]
```

[50]:
```
# len(X_test)
```

[51]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import preprocessing

X = training_set.drop('Target', axis=1)
y = training_set['Target']


# calling pre-processing for scaling or standardization of the X values
X_scaled = preprocessing.scale(X)

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,␣
↪random_state=42, shuffle=False)


lr = LinearRegression(n_jobs=-1)
lr.fit(X_train, y_train)

score = lr.score(X_test, y_test)
print('The linear regression confidence is {}'.format(score))
```

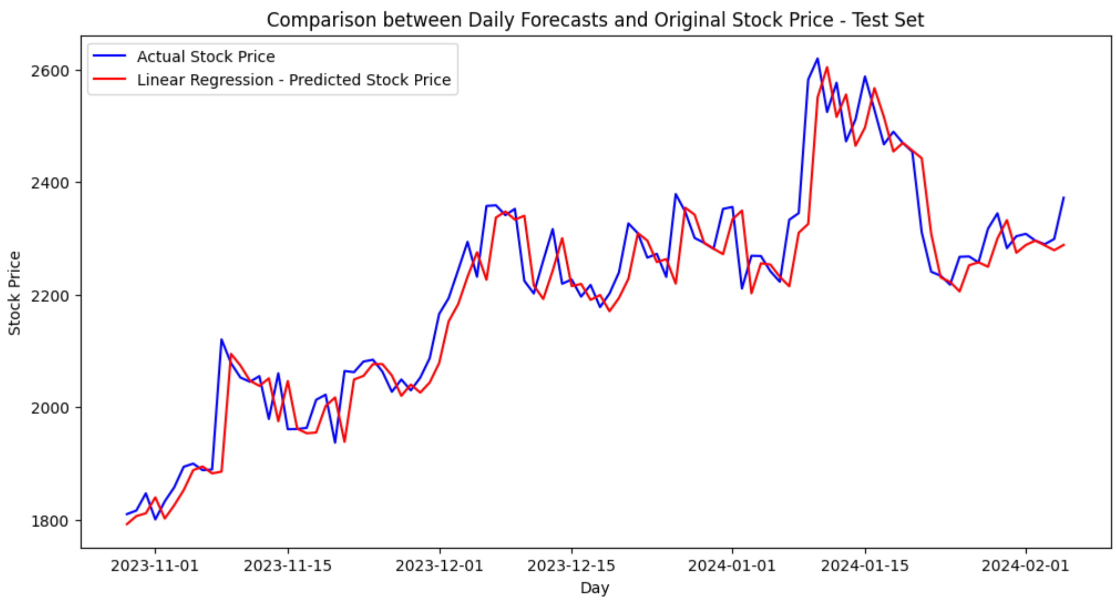
```
The linear regression confidence is 0.8901272092118377
```

[52]:
```
prediction = lr.predict(X_test[:100])

# from sklearn.metrics import r2_score , mean_absolute_percentage_error
# print("R square {}".format(r2_score(y_test, prediction)))
# print("Mean absolute percentage error {}".
↪format(mean_absolute_percentage_error(y_test, prediction)))
```

[53]:
```
from sklearn.metrics import r2_score , mean_absolute_percentage_error,␣
↪mean_squared_error, mean_absolute_error
import math

print("R square {}".format(r2_score(y_test[:100], prediction)))
print("Mean absolute percentage error {}".
↪format(mean_absolute_percentage_error(y_test[:100], prediction)))
print("Root Mean Square Error RMSE {}".format(math.
↪sqrt(mean_squared_error(y_test[:100], prediction))))
print("Mean absolute error {}".format(mean_absolute_error(y_test[:100],␣
↪prediction)))
```

```
R square 0.8852723302985438
Mean absolute percentage error 0.020247466438748578
Root Mean Square Error RMSE 64.68978629963057
Mean absolute error 45.34421937020249
```

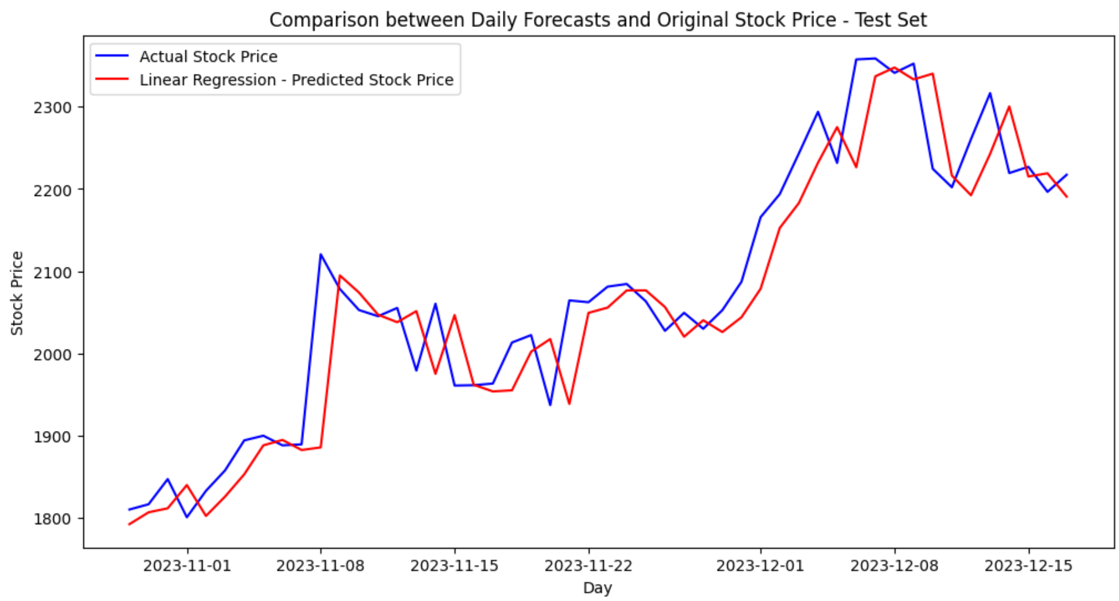
[54]:
```
plt.figure(figsize=(12,6))
plt.plot(y_test[:100] ,'b',lw=1.5)
plt.plot(pd.DataFrame(data=prediction, index=y_test[:100].index) ,'r',lw=1.5)
plt.legend(['Actual Stock Price', 'Linear Regression - Predicted Stock Price'])
plt.xlabel('Day')
plt.ylabel('Stock Price')
plt.title('Comparison between Daily Forecasts and Original Stock Price - Test␣
↪Set');
```



[55]:
```
prediction = lr.predict(X_test[:50])
from sklearn.metrics import r2_score , mean_absolute_percentage_error,␣
↪mean_squared_error, mean_absolute_error
import math

print("R square {}".format(r2_score(y_test[:50], prediction)))
print("Mean absolute percentage error {}".
↪format(mean_absolute_percentage_error(y_test[:50], prediction)))
print("Root Mean Square Error RMSE {}".format(math.
↪sqrt(mean_squared_error(y_test[:50], prediction))))
print("Mean absolute error {}".format(mean_absolute_error(y_test[:50],␣
↪prediction)))
```

```
R square 0.8508220091574861
Mean absolute percentage error 0.02041025364721451
Root Mean Square Error RMSE 60.52601272456529
Mean absolute error 42.913583621540994
```

[56]:
```
plt.figure(figsize=(12,6))
plt.plot(y_test[:50] ,'b',lw=1.5)
plt.plot(pd.DataFrame(data=prediction, index=y_test[:50].index) ,'r',lw=1.5)
plt.legend(['Actual Stock Price', 'Linear Regression - Predicted Stock Price'])
plt.xlabel('Day')
plt.ylabel('Stock Price')
plt.title('Comparison between Daily Forecasts and Original Stock Price - Test␣
↪Set');
```

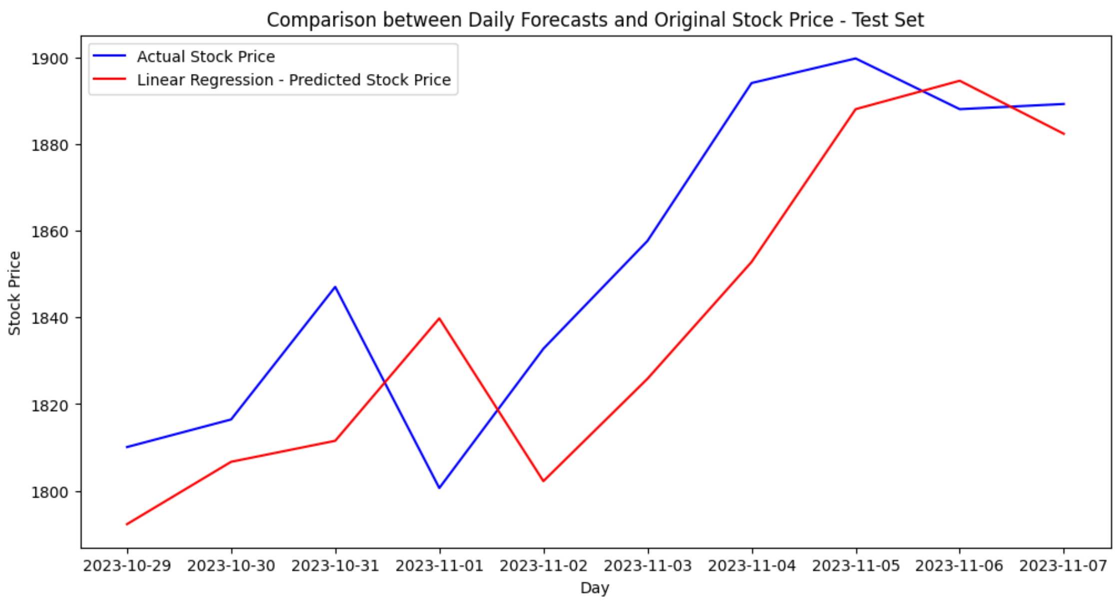


[57]:
```
prediction = lr.predict(X_test[:10])
from sklearn.metrics import r2_score , mean_absolute_percentage_error,␣
↪mean_squared_error, mean_absolute_error
import math

print("R square {}".format(r2_score(y_test[:10], prediction)))
print("Mean absolute percentage error {}".
↪format(mean_absolute_percentage_error(y_test[:10], prediction)))
print("Root Mean Square Error RMSE {}".format(math.
↪sqrt(mean_squared_error(y_test[:10], prediction))))
print("Mean absolute error {}".format(mean_absolute_error(y_test[:10],␣
↪prediction)))
```

```
R square 0.4464668178124982
Mean absolute percentage error 0.012516394619436188
Root Mean Square Error RMSE 26.64129516909742
Mean absolute error 23.124079376954207
```

[58]:

```
plt.figure(figsize=(12,6))
plt.plot(y_test[:10] ,'b',lw=1.5)
plt.plot(pd.DataFrame(data=prediction, index=y_test[:10].index) ,'r',lw=1.5)
plt.legend(['Actual Stock Price', 'Linear Regression - Predicted Stock Price'])
plt.xlabel('Day')
plt.ylabel('Stock Price')
plt.title('Comparison between Daily Forecasts and Original Stock Price - Test␣
↪Set');
```



[58]:

```
```

[59]:

```
# We will not forecast for the next days based on this model
forecast_X = forecast_set.drop('Target', axis=1)
forecast_y = forecast_set['Target']
forecast_pred = lr.predict(preprocessing.scale(forecast_X))
forecast_pred
```

[59]:

```
array([1217.91571333, 1216.1973982 , 1322.02023933, 1370.38365189,
       1354.01390365, 1335.68814119, 1411.43525403, 1469.86042295,
       1523.72327363, 1490.37171101, 1495.12993538, 1457.19613254,
       1509.49103753, 1608.42146148, 1663.69507854, 1726.4507585 ,
       1842.10495806, 1819.31722747, 1885.72513323, 1880.2195351 ,
       1929.57281682, 2044.33892688, 1981.11571383, 2200.08262905,
       2257.88224042, 2281.10149117, 2298.90060741, 2268.37202312,
       2404.52098619, 2347.55004232, 2375.99336318, 2264.35578722,
       2142.2916627 , 1974.17046562, 2051.91177114, 1962.26772122,
       1673.80850231, 1926.04722158, 1939.10137169, 1809.04417871,
```

```
       1808.22907973, 1897.52621746, 2015.49548376, 2022.81446159,
       1952.10872937, 1994.23539975, 1957.02888573, 1955.11849923,
       2062.61473059, 1950.07988573, 1762.85193517, 1781.18522494,
       1802.83978859, 1784.97151683, 1821.82626384, 1899.48239066,
       2093.80131211, 1957.44444349, 1974.22140874, 1954.81716688,
       1731.69851211, 1528.52931917, 1637.63449033, 1611.71757956,
       1588.55291317, 1510.06876242, 1571.25371138, 1559.77248928,
       1646.14150478, 1647.21106359, 1689.83449389, 1705.81581857,
       1645.82738758, 1649.8785952 , 1631.55327097, 1723.95362221,
       1749.32809718, 1699.72533838, 1535.78015099, 1485.16888968,
       1505.33322301, 1600.49484344, 1622.87813586, 1635.15264144,
       1582.33607956, 1533.60429276, 1499.5310146 , 1547.14179316,
       1449.4086738 , 1446.2221755 , 1460.34258199, 1474.4021061 ,
       1422.81302033, 1540.95390057, 1477.77928282, 1591.77010462,
       1624.8116187 , 1584.49700168, 2044.43499103, 2183.46310097,
       2144.73023246, 2173.80887091, 2136.5061315 , 2156.80553927,
       2219.84371267, 2279.66788728, 2234.10786577, 2174.40223398,
       2156.87148163, 2169.70571118, 2208.87095159, 2185.45848431,
       2177.01190551, 2207.41429026, 2250.80190822, 2210.21490447,
       2100.78121042, 2100.79584598, 2119.2508682 , 2088.57290852,
       1947.74702974, 1995.68538769, 1921.2689725 , 1923.06757158,
       1997.02770605, 2044.584827  , 1958.34944967, 1924.36412948,
       1991.52915793, 1959.94648173, 1955.90051719, 1941.5636446 ,
       1881.46883844, 1814.04420361, 1854.42590641, 1834.76857703,
       1895.19029588, 1843.85905331, 1839.82879103, 1884.60458989,
       1899.06525869, 1876.09982191, 1773.59720704, 1580.2533993 ,
       1499.26460873, 1572.85955284, 1467.89462867, 1526.94796516,
       1574.18623187, 1605.31957206, 1609.89494555, 1629.92477652,
       1668.78512425, 1724.66504   , 1919.93513024, 1893.26514808,
       1858.12843421, 1883.82554778, 1943.73890354, 1961.0376562 ,
       1967.95165717, 1900.50979209, 1927.9188702 , 1811.80603737,
       1670.43224362, 1749.31916994, 1731.98801923, 1747.23478852,
       1794.05344506, 1759.3973609 , 1723.31500299, 1684.28041568,
       1518.97829078, 1441.53056507, 1263.16346476, 1014.66780036,
       1064.54911545,  967.379339  , 1229.57357063, 1182.84953281,
       1189.74094249, 1150.66861676, 1273.53733526, 1263.77255521,
       1239.24177516, 1156.93062278, 1174.93204633, 1192.73181538,
       1195.90344294, 1208.21075628, 1164.05984206, 1203.18748243,
       1199.17668029, 1313.6086976 , 1326.00771347, 1309.57842541,
       1253.6660973 , 1068.45111552, 1114.32398562, 1123.44135779])
```

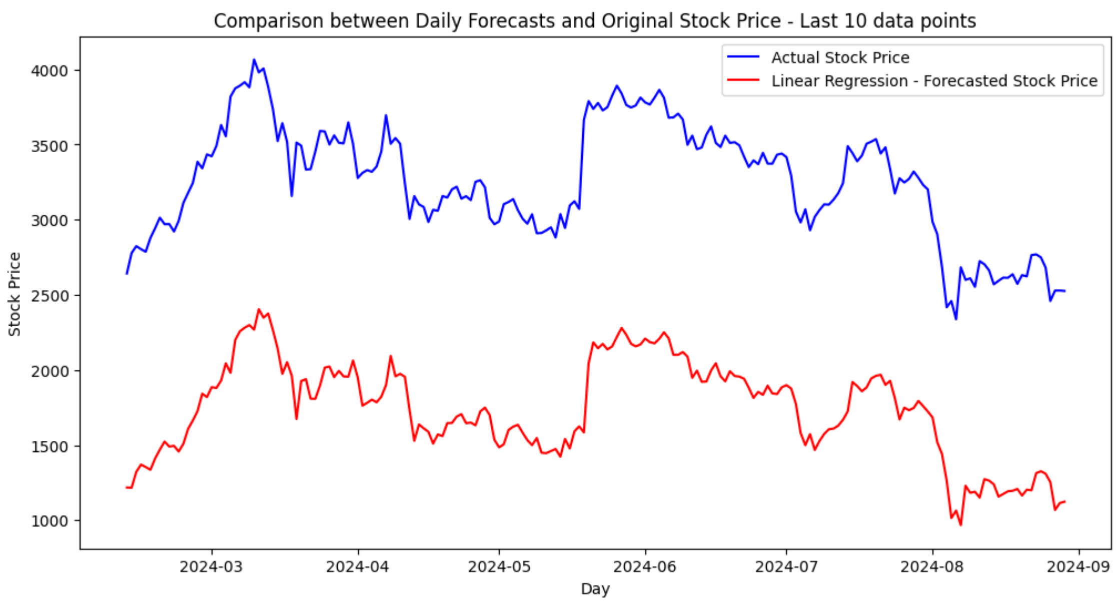
[60]:
```
forecast_y
```

[60]:
```
Date
2024-02-12 00:00:00+00:00    2642.185303
2024-02-13 00:00:00+00:00    2777.902344
2024-02-14 00:00:00+00:00    2824.378906
```

```
2024-02-15 00:00:00+00:00    2803.691406
2024-02-16 00:00:00+00:00    2786.672607
                                 …
2024-08-25 00:00:00+00:00    2681.340576
2024-08-26 00:00:00+00:00    2458.726562
2024-08-27 00:00:00+00:00    2528.415527
2024-08-28 00:00:00+00:00    2528.792725
2024-08-29 00:00:00+00:00    2525.822021
Name: Target, Length: 200, dtype: float64
```

[61]:

```
plt.figure(figsize=(12,6))
plt.plot(forecast_y ,'b',lw=1.5)
plt.plot(pd.DataFrame(data=forecast_pred, index=forecast_y.index) ,'r',lw=1.5)
plt.legend(['Actual Stock Price', 'Linear Regression - Forecasted Stock Price'])
plt.xlabel('Day')
plt.ylabel('Stock Price')
plt.title('Comparison between Daily Forecasts and Original Stock Price - Last␣
↪10 data points');
```



Metrics from LR for the stock price

[62]:

```
from sklearn.metrics import r2_score , mean_absolute_percentage_error,␣
↪mean_squared_error, mean_absolute_error
import math

print("R square {}".format(r2_score(forecast_y, forecast_pred)))
```

```
print("Mean absolute percentage error {}".
 ↪format(mean_absolute_percentage_error(forecast_y, forecast_pred)))
print("Root Mean Square Error RMSE {}".format(math.
 ↪sqrt(mean_squared_error(forecast_y, forecast_pred))))
print("Mean absolute error {}".format(mean_absolute_error(forecast_y,␣
 ↪forecast_pred)))
```

```
R square -14.678373150650259
Mean absolute percentage error 0.470722951756699
Root Mean Square Error RMSE 1523.4539014820086
Mean absolute error 1518.8060010609427
```

Metrics from the Kalman Filter forecast

[63]:
```
_y_stock = stock_price[len(stock_price)-2000:] # changed from 10 to 100, after␣
 ↪experiment put it back to 10
kalman_forecast_y = forecasted_price[len(stock_price)-2000:] # changed from 10␣
 ↪to 100, after experiment put it back to 10
print("R square {}".format(r2_score(_y_stock, kalman_forecast_y)))
print("Mean absolute percentage error MAPE {}".
 ↪format(mean_absolute_percentage_error(_y_stock, kalman_forecast_y)))
print("Root Mean Square Error RMSE {}".format(math.
 ↪sqrt(mean_squared_error(_y_stock, kalman_forecast_y))))
print("Mean absolute error MAE {}".format(mean_absolute_error(_y_stock,␣
 ↪kalman_forecast_y)))
```

```
R square 0.9998118018583926
Mean absolute percentage error MAPE 0.00037247146220583305
Root Mean Square Error RMSE 10.430714570659806
Mean absolute error MAE 0.966728266157691
```

[64]:
```
_y_stock = stock_price[len(stock_price)-500:] # changed from 10 to 100, after␣
 ↪experiment put it back to 10
kalman_forecast_y = forecasted_price[len(stock_price)-500:] # changed from 10␣
 ↪to 100, after experiment put it back to 10
print("R square {}".format(r2_score(_y_stock, kalman_forecast_y)))
print("Mean absolute percentage error MAPE {}".
 ↪format(mean_absolute_percentage_error(_y_stock, kalman_forecast_y)))
print("Root Mean Square Error RMSE {}".format(math.
 ↪sqrt(mean_squared_error(_y_stock, kalman_forecast_y))))
print("Mean absolute error MAE {}".format(mean_absolute_error(_y_stock,␣
 ↪kalman_forecast_y)))
```

```
R square 0.9996946969956958
Mean absolute percentage error MAPE 0.0005438083348205162
Root Mean Square Error RMSE 12.60348036947252
Mean absolute error MAE 1.4114232685902288
```

[65]:
```
_y_stock = stock_price[len(stock_price)-200:] # changed from 10 to 100, after␣
↪experiment put it back to 10
kalman_forecast_y = forecasted_price[len(stock_price)-200:] # changed from 10␣
↪to 100, after experiment put it back to 10
print("R square {}".format(r2_score(_y_stock, kalman_forecast_y)))
print("Mean absolute percentage error MAPE {}".
↪format(mean_absolute_percentage_error(_y_stock, kalman_forecast_y)))
print("Root Mean Square Error RMSE {}".format(math.
↪sqrt(mean_squared_error(_y_stock, kalman_forecast_y))))
print("Mean absolute error MAE {}".format(mean_absolute_error(_y_stock,␣
↪kalman_forecast_y)))
```

```
R square 0.9973173541119791
Mean absolute percentage error MAPE 0.0013595208370512906
Root Mean Square Error RMSE 19.92785220637683
Mean absolute error MAE 3.5285581714755723
```

[66]:
```
_y_stock = stock_price[len(stock_price)-100:] # changed from 10 to 100, after␣
↪experiment put it back to 10
kalman_forecast_y = forecasted_price[len(stock_price)-100:] # changed from 10␣
↪to 100, after experiment put it back to 10
print("R square {}".format(r2_score(_y_stock, kalman_forecast_y)))
print("Mean absolute percentage error MAPE {}".
↪format(mean_absolute_percentage_error(_y_stock, kalman_forecast_y)))
print("Root Mean Square Error RMSE {}".format(math.
↪sqrt(mean_squared_error(_y_stock, kalman_forecast_y))))
print("Mean absolute error MAE {}".format(mean_absolute_error(_y_stock,␣
↪kalman_forecast_y)))
```

```
R square 0.9958062655293043
Mean absolute percentage error MAPE 0.0027190416741025808
Root Mean Square Error RMSE 28.182238859224718
Mean absolute error MAE 7.0571163429511445
```

[67]:
```
_y_stock = stock_price[len(stock_price)-50:] # changed from 10 to 100, after␣
↪experiment put it back to 10
kalman_forecast_y = forecasted_price[len(stock_price)-50:] # changed from 10 to␣
↪100, after experiment put it back to 10
print("R square {}".format(r2_score(_y_stock, kalman_forecast_y)))
print("Mean absolute percentage error MAPE {}".
↪format(mean_absolute_percentage_error(_y_stock, kalman_forecast_y)))
print("Root Mean Square Error RMSE {}".format(math.
↪sqrt(mean_squared_error(_y_stock, kalman_forecast_y))))
print("Mean absolute error MAE {}".format(mean_absolute_error(_y_stock,␣
↪kalman_forecast_y)))
```

```
R square 0.9886877025379025
Mean absolute percentage error MAPE 0.005438083348205162
```

```
Root Mean Square Error RMSE 39.85570441275366
Mean absolute error MAE 14.114232685902289
```

[68]:
```
_y_stock = stock_price[len(stock_price)-10:] # changed from 10 to 100, after␣
 ↪experiment put it back to 10
kalman_forecast_y = forecasted_price[len(stock_price)-10:] # changed from 10 to␣
 ↪100, after experiment put it back to 10
print("R square {}".format(r2_score(_y_stock, kalman_forecast_y)))
print("Mean absolute percentage error MAPE {}".
 ↪format(mean_absolute_percentage_error(_y_stock, kalman_forecast_y)))
print("Root Mean Square Error RMSE {}".format(math.
 ↪sqrt(mean_squared_error(_y_stock, kalman_forecast_y))))
print("Mean absolute error MAE {}".format(mean_absolute_error(_y_stock,␣
 ↪kalman_forecast_y)))
```

```
R square 0.30926748192137554
Mean absolute percentage error MAPE 0.027190416741025812
Root Mean Square Error RMSE 89.12006435805553
Mean absolute error MAE 70.57116342951144
```