1 Import Libraries and Data

In [ ]:

```
# ## This cell is exclusively for checking to see if you are using your GPU as TF's hardware accelerator

%tensorflow_version 2.x
import tensorflow as tf
device_name = tf.test.gpu_device_name()
if device_name != '/device:GPU:0':
  raise SystemError('GPU device not found')
print('Found GPU at: {}'.format(device_name))
```

```
/usr/local/lib/python3.7/dist-packages/requests/__init__.py:91: RequestsDependencyWarning: urllib3 (1.26.5) or chardet (3.0.4) doesn't mat
ch a supported version!
  RequestsDependencyWarning)
```

```
Found GPU at: /device:GPU:0
```

In [ ]:

```python
## If using Google Colab, use this code to upload data file to Google Collab from the local drive

from google.colab import files
uploaded = files.upload()
btc = files.upload()
```

Choose Files No file chosen

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving eth.csv to eth (2).csv
```

Choose Files No file chosen

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving eth.csv to eth (3).csv
```

In [1]:

```python
import pandas as pd
import numpy as np
import math
from sklearn.metrics import mean_squared_error

from statsmodels.tsa.stattools import acf
from statsmodels.tsa.arima_model import ARMA
from statsmodels.tsa.statespace.sarimax import SARIMAX

import matplotlib.pyplot as plt
plt.style.use('dark_background')

import plotly.express as px
import plotly.io as pio
import plotly.graph_objects as go
pio.templates.default = 'plotly_dark'

import statsmodels.api as sm

import warnings
warnings.filterwarnings("ignore")

df = pd.read_csv('data/eth.csv')
df2 = pd.read_csv('data/btc.csv')

print(df.shape)
display(df)

print(df2.shape)
display(df)
```

executed in 5.48s, finished 15:40:24 2021-06-23

(2134, 7)

	Date	Open_	High	Low	Close__	Volume	MarketCap
0	Jun 08, 2021	$2,594.60	$2,620.85	$2,315.55	$2,517.44	$41,909,736,778	$292,557,075,207
1	Jun 07, 2021	$2,713.05	$2,845.19	$2,584.00	$2,590.26	$30,600,111,277	$300,985,400,826
2	Jun 06, 2021	$2,629.75	$2,743.44	$2,616.16	$2,715.09	$25,311,639,414	$315,453,931,558
3	Jun 05, 2021	$2,691.62	$2,817.48	$2,558.23	$2,630.58	$30,496,672,724	$305,598,725,249
4	Jun 04, 2021	$2,857.17	$2,857.17	$2,562.64	$2,688.19	$34,173,841,611	$312,256,566,095
...	...	...	...	...	...	...	...
2129	Aug 10, 2015	$0.71	$0.73	$0.64	$0.71	$405,283	$42,818,364
2130	Aug 09, 2015	$0.71	$0.88	$0.63	$0.7	$532,170	$42,399,574
2131	Aug 08, 2015	$2.79	$2.80	$0.71	$0.75	$674,188	$45,486,894
2132	Aug 07, 2015	$2.83	$3.54	$2.52	$2.77	$164,329	$166,610,555
2133	Jun 09, 2021	$2,510.20	$2,625.07	$2,412.20	$2,608.27	$36,075,832,186	$303,147,462,062

2134 rows × 7 columns

(2978, 7)

	Date	Open_	High	Low	Close__	Volume	MarketCap
0	Jun 08, 2021	$2,594.60	$2,620.85	$2,315.55	$2,517.44	$41,909,736,778	$292,557,075,207
1	Jun 07, 2021	$2,713.05	$2,845.19	$2,584.00	$2,590.26	$30,600,111,277	$300,985,400,826
2	Jun 06, 2021	$2,629.75	$2,743.44	$2,616.16	$2,715.09	$25,311,639,414	$315,453,931,558
3	Jun 05, 2021	$2,691.62	$2,817.48	$2,558.23	$2,630.58	$30,496,672,724	$305,598,725,249
4	Jun 04, 2021	$2,857.17	$2,857.17	$2,562.64	$2,688.19	$34,173,841,611	$312,256,566,095
...	...	...	...	...	...	...	...
2129	Aug 10, 2015	$0.71	$0.73	$0.64	$0.71	$405,283	$42,818,364
2130	Aug 09, 2015	$0.71	$0.88	$0.63	$0.7	$532,170	$42,399,574
2131	Aug 08, 2015	$2.79	$2.80	$0.71	$0.75	$674,188	$45,486,894

	Date	Open_	High	Low	Close__	Volume	MarketCap
2132	Aug 07, 2015	$2.83	$3.54	$2.52	$2.77	$164,329	$166,610,555
2133	Jun 09, 2021	$2,510.20	$2,625.07	$2,412.20	$2,608.27	$36,075,832,186	$303,147,462,062

2134 rows × 7 columns

2 Business Understanding

- Ethereum is a decentralized, open-source blockchain with smart contract functionality. Its adoption in the financial world has grown exponentially over the past few years, and as a result, its price has skyrocketed from being worth less than $1 to over$2000 at the time of writing this page.
- Due to the uncertainty of decentralized finance, or DeFi, the value of Ethereum is highly volatile, which makes the use of traditional forecasting models such as ARIMA difficult

3 Goal/Audience and Data Description

3.1 Goal and Audience

- The goal of this project is to create a model that attempts to accurately predict if the value of Ethereum will go up or down for the next day. If the model predicts a rise, then one unit of Ethereum will be bought. If it predicts a fall, then one unit of Ethereum will be sold.
- The target audience of this project is an investment firm or a retail trader with extensive disposable income.
    - To consistently buy and sell one unit of Ethereum requires a large amount of liquidity, something that most retail investors do not have, hence the specification towards investment firms and the retail investors that fall in the highest percentiles of disposable income/liquidity.

At the end of this project, an evaluation/comparison will be made between the total profit of three different trading strategies by backtesting over the time period of the created test-set:

1. A strategy derived from the best-performing model construcred
2. A Simple Moving Average Model
3. The Buy-and-Hold Strategy

3.2 Data Source

This data was scraped from CoinMarketCap.com using the webscraper Octoparse. The webpages used ajax syntax for the "load page" button, and therfore ajax timeout time needed to be applied in order to properly extract the data. This data is only concerned with Ethereum, and no other coin or blockchain.

3.3 Features

The data includes the following features:

1. Open
2. High
3. Low
4. Close
5. Volume
6. Market Cap

This dataset provides a timeline of Ethereum prices and related data from August 7th, 2015 to June 8th, 2021.

4 Data Preprocessing

4.1 Eth Data

In [2]:

```python
# Convert the 'Date' column to a datetime datatype and set it as the index, then sort the index
df['Date'] = pd.to_datetime(df.Date)
df.set_index(df.Date, inplace=True)
df.drop(df.tail(1).index, inplace=True)
df = df.sort_index()

# Drop the Date column
df = df.drop(columns=['Date'], axis=1)

# Specify columns
cols = list(df.columns)

# Replace the dollar signs and commas with empty character
df[cols] = df[cols].replace({'\$': '', ',': ''}, regex=True)

## Convert all entries to numerical data type
for col in cols:
    df[col] = pd.to_numeric(df[col], errors='coerce')

# Rename the columns with unconventional text in the string
df.rename(columns={'Open_':'Open', 'Close__':'Close'}, inplace=True)

# Find missing values
print(df.isna().sum())

# There are very few missing values, so we will drop all of them
df = df.dropna()

# Check for duplicates in index
print(df.index.duplicated().sum())

# Check for duplicates in columns
print(df.duplicated().sum())
```

```python
# Check how much of the data are duplicates overall
print(df[df.duplicated()==True].shape[0] / df.shape[0])

# There are no duplicates but let's use the drop_duplciates method just as good practice
df = df.drop_duplicates()
print(df.shape)
df.info()
```

executed in 403ms, finished 15:40:27 2021-06-23

```
Open         0
High         0
Low          0
Close        0
Volume       0
MarketCap    0
dtype: int64
0
0
0.0
(2133, 6)
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2133 entries, 2015-08-07 to 2021-06-08
Data columns (total 6 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Open       2133 non-null   float64
 1   High       2133 non-null   float64
 2   Low        2133 non-null   float64
 3   Close      2133 non-null   float64
 4   Volume     2133 non-null   int64  
 5   MarketCap  2133 non-null   int64  
dtypes: float64(4), int64(2)
memory usage: 116.6 KB
```

4.2 Btc Data

In [3]:

```python
# Convert the 'Date' column to a datetime datatype and set it as the index, then sort the index
df2['Date'] = pd.to_datetime(df2.Date)
df2.set_index(df2.Date, inplace=True)
df2.drop(df2.tail(1).index, inplace=True)
df2 = df2.sort_index()

# Drop the Date column
df2 = df2.drop(columns=['Date'], axis=1)

# Specify columns
cols = list(df2.columns)

# Replace the dollar signs and commas with empty character
df2[cols] = df2[cols].replace({'\$': '', ',': ''}, regex=True)

## Convert all entries to numerical data type
for col in cols:
    df2[col] = pd.to_numeric(df2[col], errors='coerce')

# Rename the columns with unconventional text in the string
df2.rename(columns={'Open_':'Open', 'Close__':'Close'}, inplace=True)

# Find missing values
print(df2.isna().sum())

# There are very few missing values, so we will drop all of them
df2 = df2.dropna()

# Check for duplicates in index
print(df2.index.duplicated().sum())

# Check for duplicates in columns
print(df2.duplicated().sum())
```

```python
# Check how much of the data are duplicates overall
print(df2[df2.duplicated()==True].shape[0] / df2.shape[0])

# There are no duplicates but let's use the drop_duplciates method just as good practice
df2 = df2.drop_duplicates()
print(df2.shape)
df2.info()
```

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```
Open         0
High         0
Low          0
Close        0
Volume       0
MarketCap    0
dtype: int64
0
0
0.0
(2977, 6)
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2977 entries, 2013-04-29 to 2021-06-22
Data columns (total 6 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Open       2977 non-null   float64
 1   High       2977 non-null   float64
 2   Low        2977 non-null   float64
 3   Close      2977 non-null   float64
 4   Volume     2977 non-null   int64  
 5   MarketCap  2977 non-null   int64  
dtypes: float64(4), int64(2)
memory usage: 162.8 KB
```

5 EDA

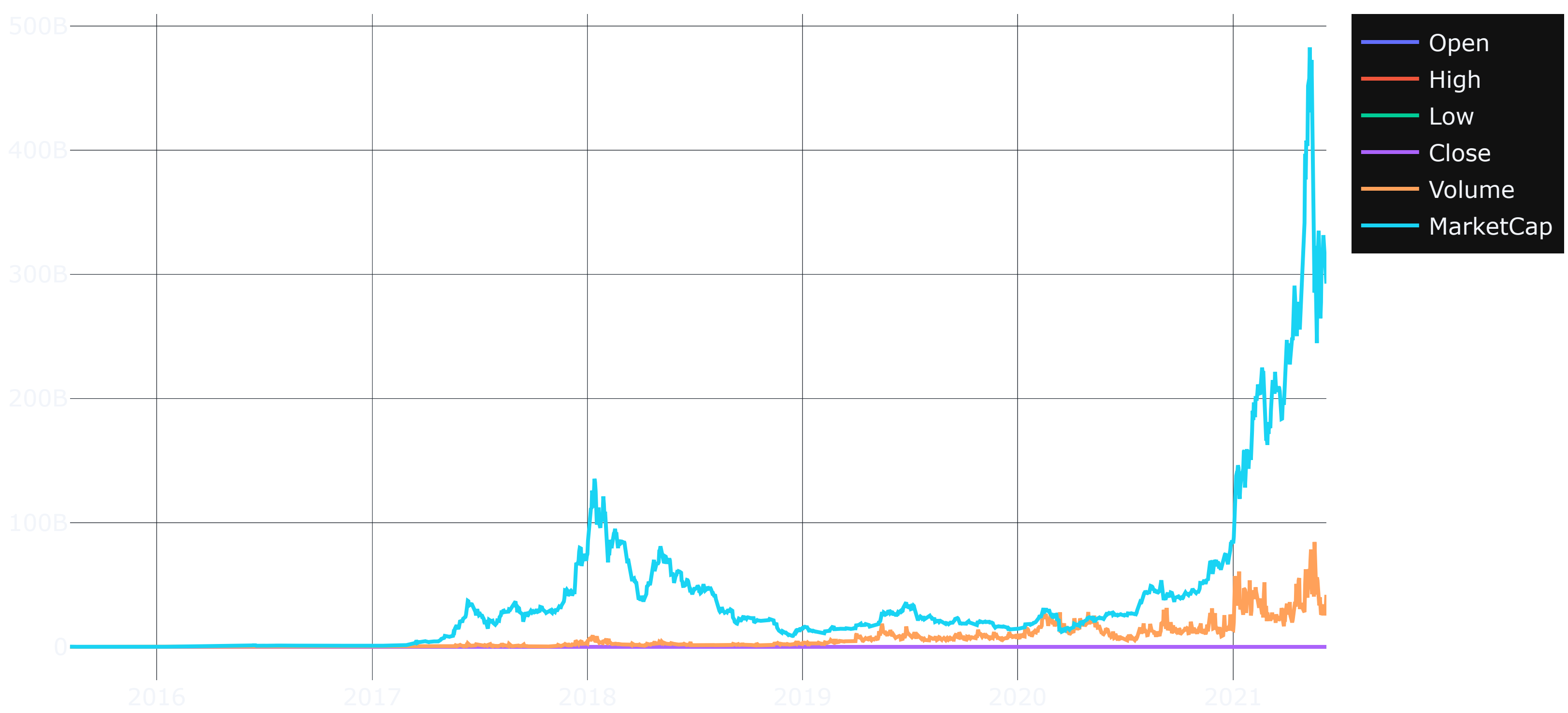
5.0.1 Original Time Series Visualizations

	Let's take a look at the time series.

In [4]:

```
# Create figure
fig = go.Figure()

# Add traces
for c in list(df.columns):
    fig.add_trace(go.Scatter(x=df.index, y=df[c], mode='lines', name=f'{c}'))
fig
```

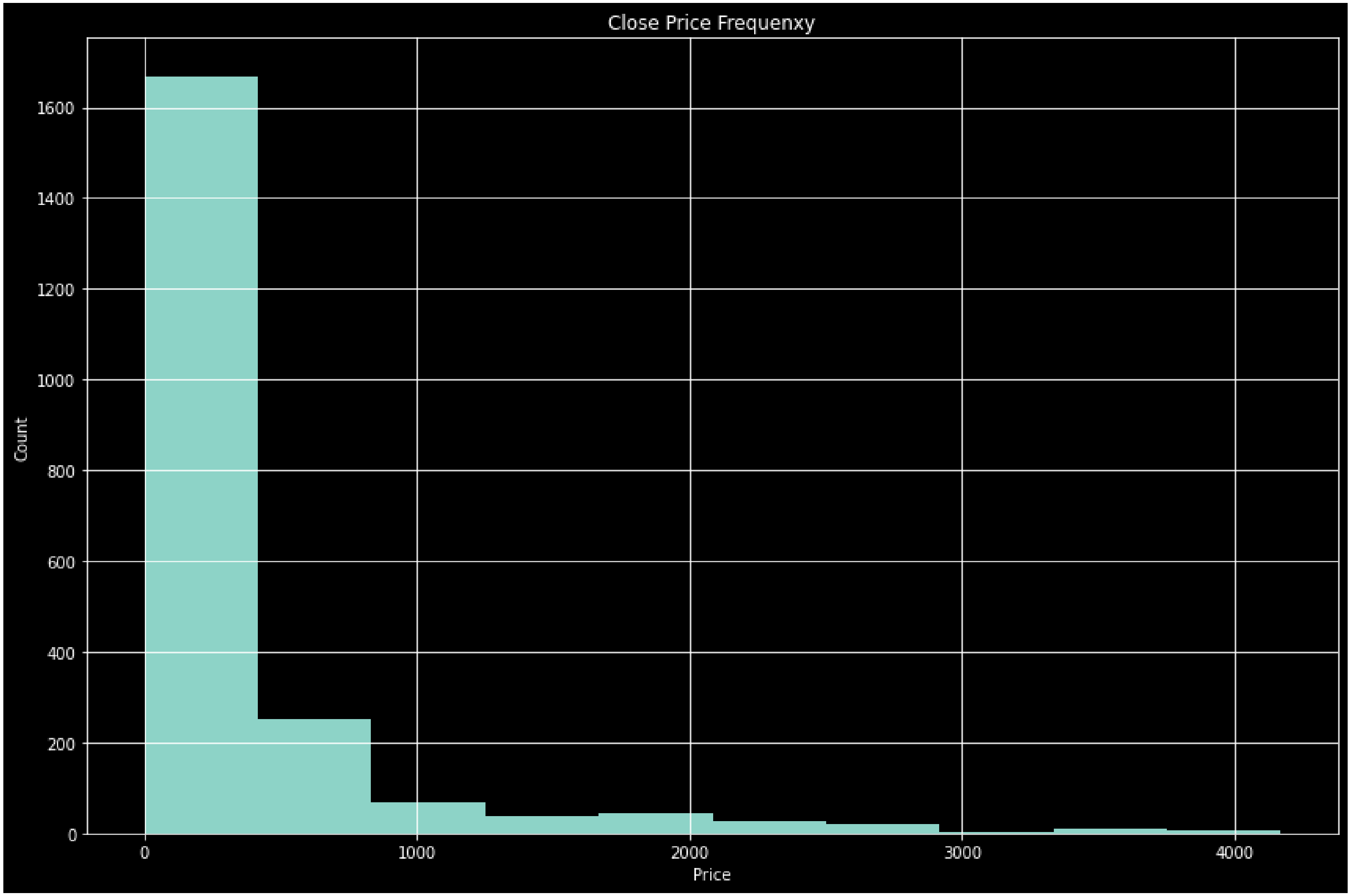
executed in 909ms, finished 15:40:34 2021-06-23



5.0.2 Price Frequency

In [ ]:

```
fig, ax = plt.subplots(figsize=(12,8))
df.hist(column=['Close'], ax=ax)
ax.set_title('Close Price Frequenxy')
ax.set_xlabel('Price')
ax.set_ylabel('Count')
plt.tight_layout()
# plt.savefig('Histograms')
```



Above is a histogram of the frequency of occurences of price value. Their distribution exemplifies the volatility of the asset. The large majority of prices fall between 0 and 1000, however there are low-frequency instances of prices that are 2, 3, and 4 times the max value of that range. This shows that the price spiked and fell, never maintaining a high value for very long at all.

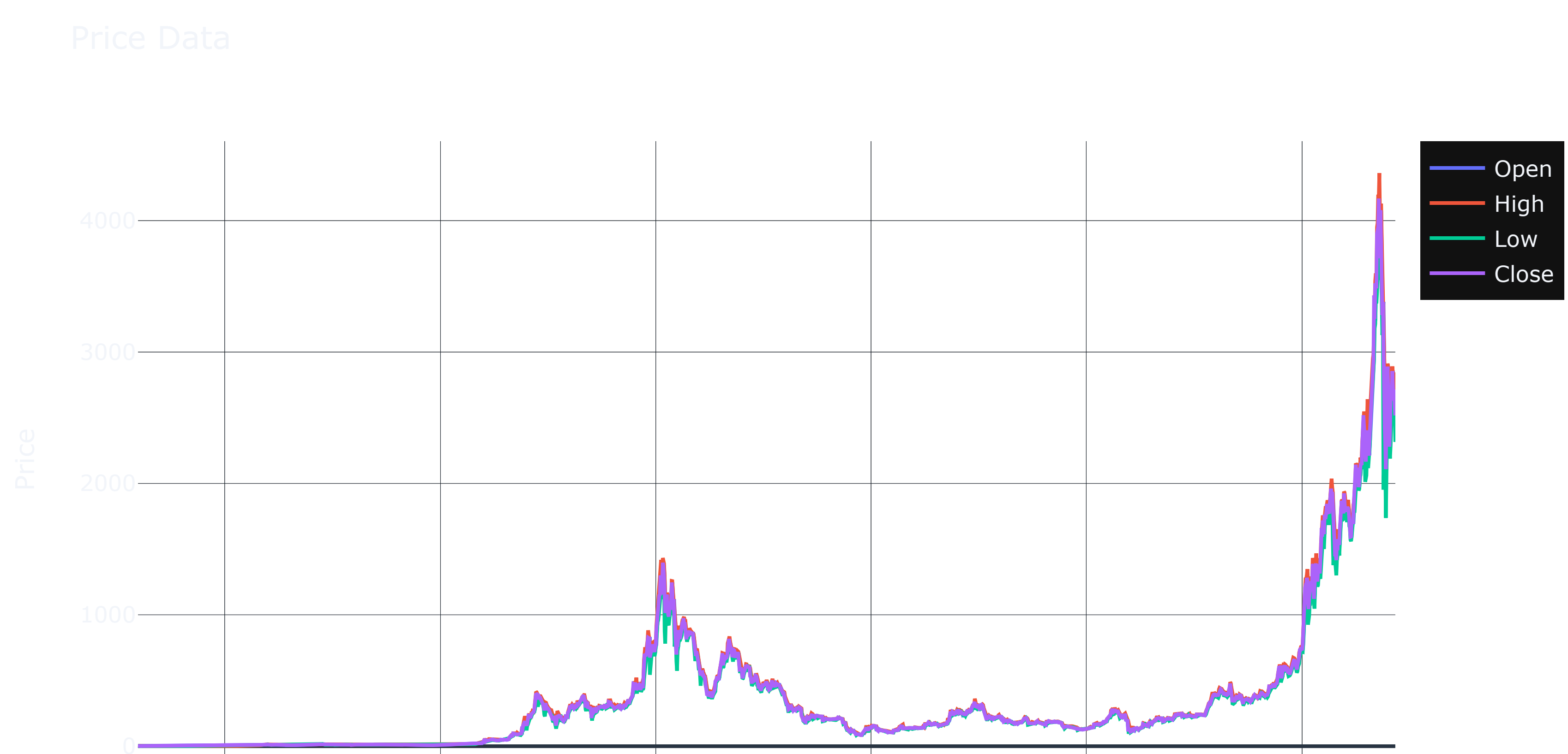
5.0.3 Clean up the Graphs

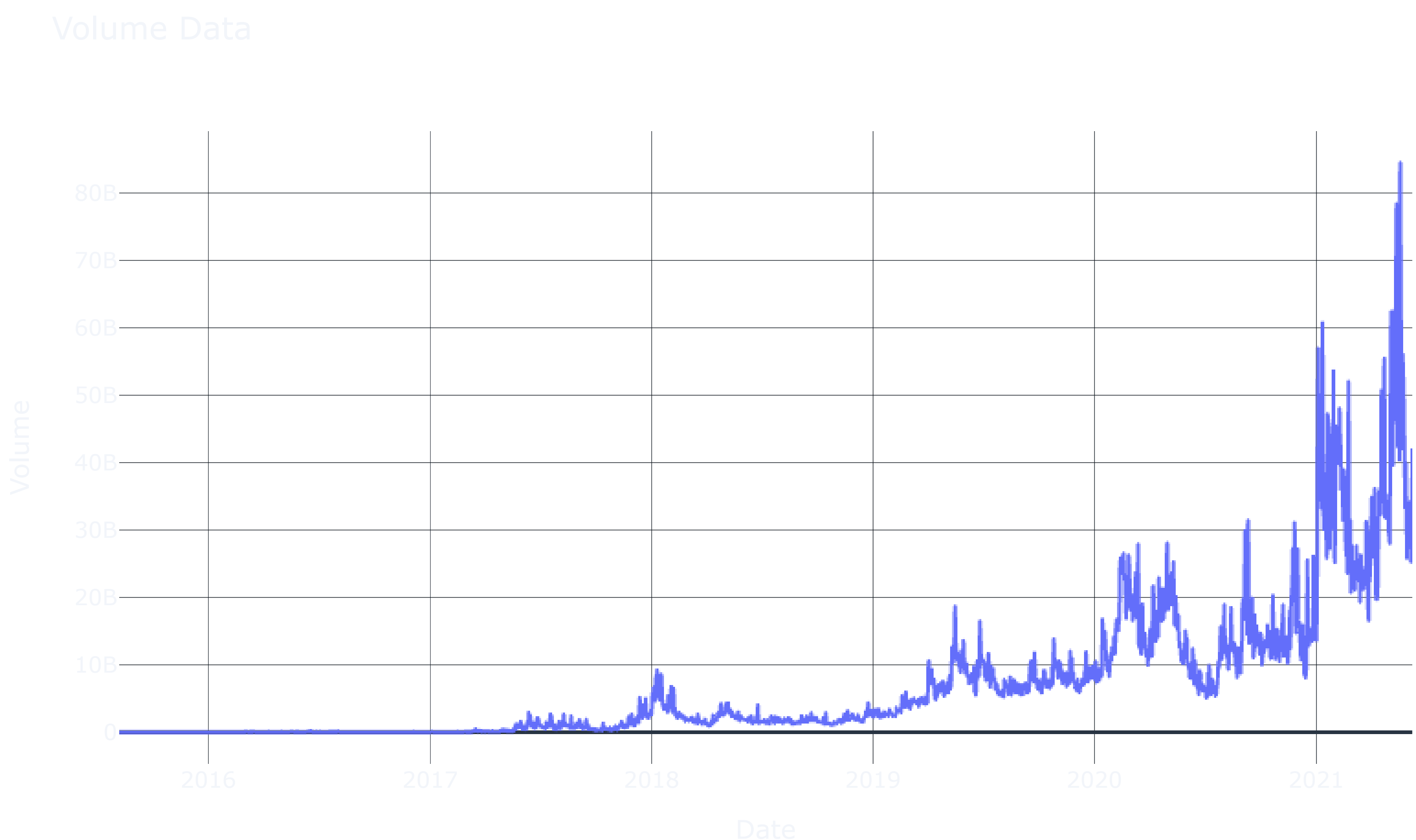
The original time series was very hard to interpret because the volume column has very large numbers that messed with the scale of the graph. In order to remedy this, we will plot the price data and the volume data seperately, and we will resample the Volume data in order

In [5]:

```
# Plot the time series
fig = go.Figure()
col = ['Open', 'High', 'Low', 'Close']

# Add traces
for c in col:
    fig.add_trace(go.Scatter(x=df.index, y=df[c], mode='lines', name=f'{c}'))
fig.update_layout(
title='Price Data',
xaxis_title='Date',
yaxis_title='Price')
fig.show()
display(px.line(data_frame=df, x=df.index, y=df['Volume'], title='Volume Data'))
```

executed in 555ms, finished 15:40:39 2021-06-23





Target Variable

The trends of each series for each price related column (our target) are pretty much identical, so we can choose one of the features as a target variable and stick with that.

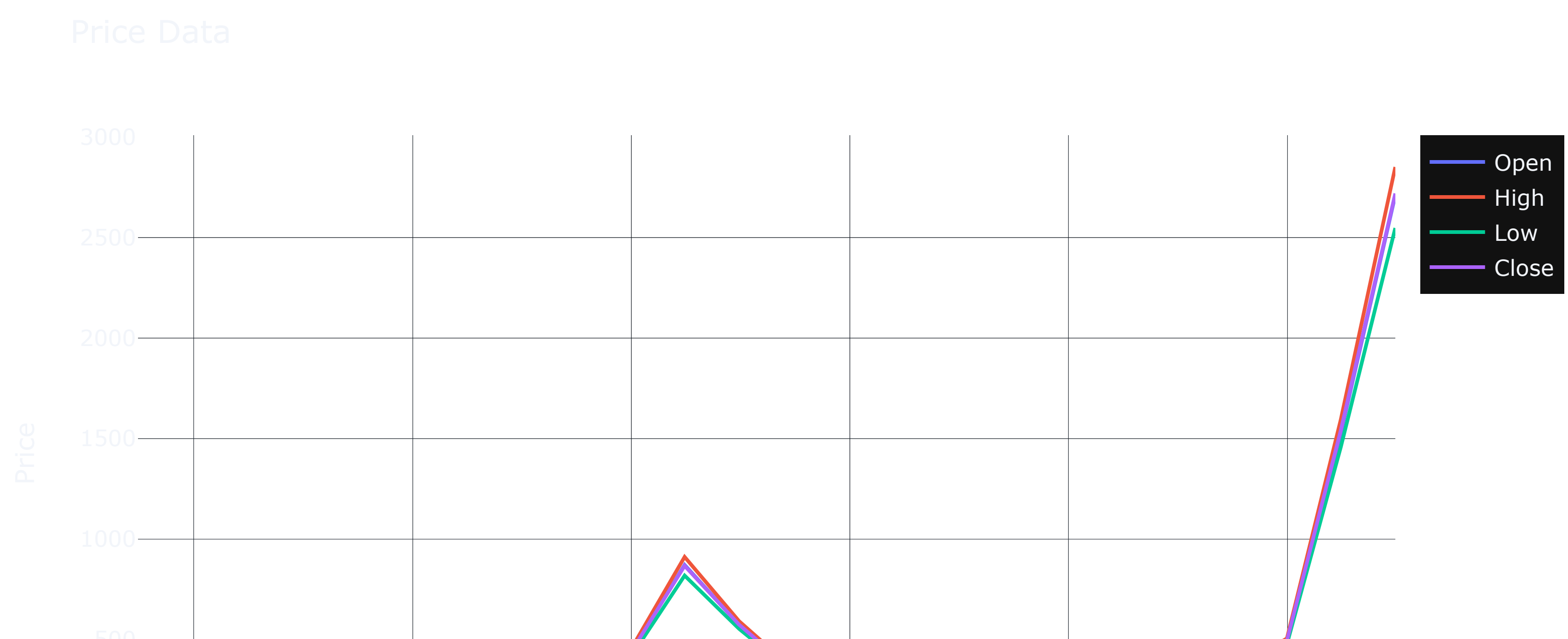
I will be using the "Close" price for Ethereum, which is the price of the asset at the close of normal trading hours at 4pm.

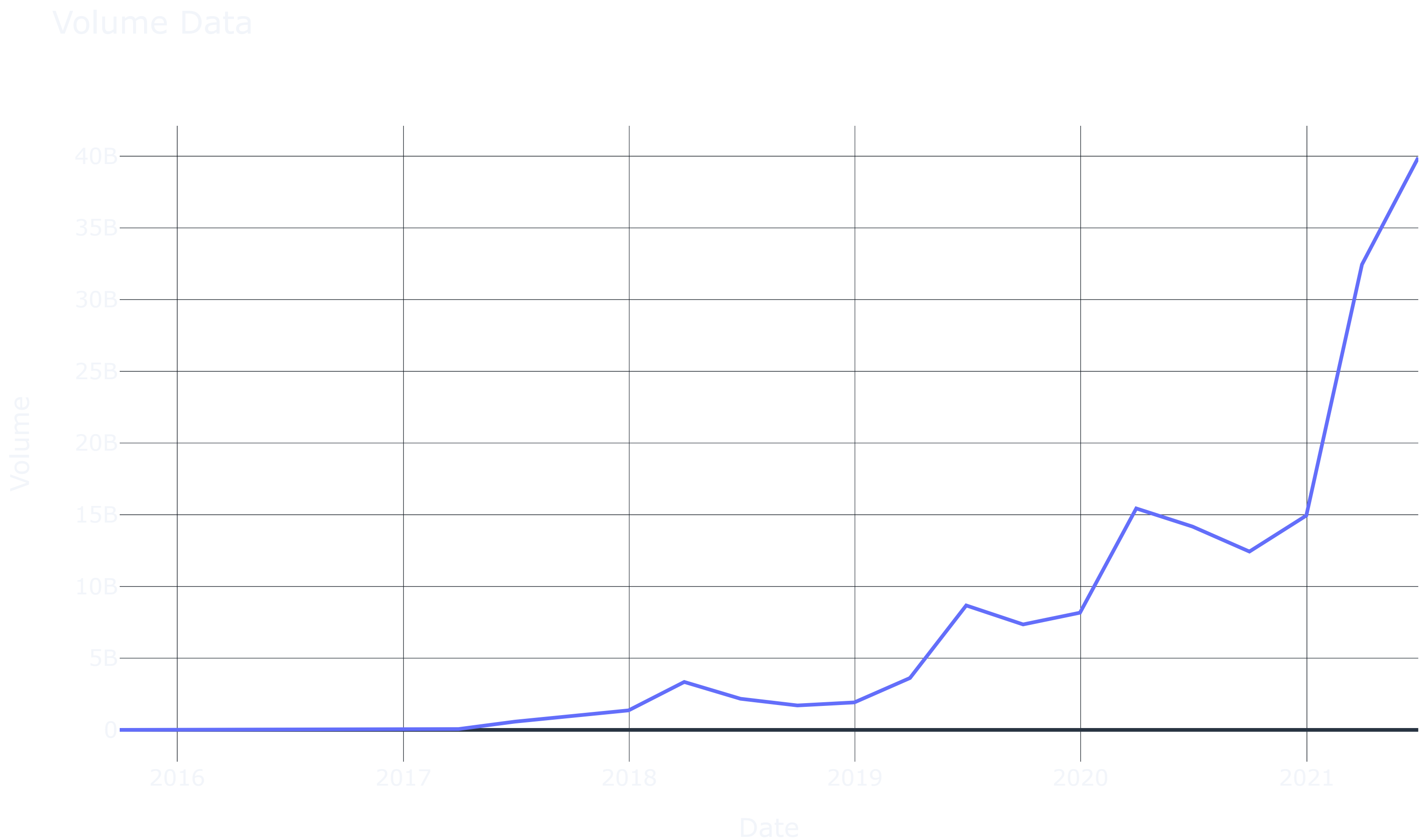
5.0.4 Resample Data (Week, Month, Year)

In [6]:

```
# Create resampled DataFrame for more smooth visualization
quarterly_df = pd.DataFrame(df.resample('Q').mean())

# Plot the time series
fig = go.Figure()
col = ['Open', 'High', 'Low', 'Close']
# Add traces
for c in col:
    fig.add_trace(go.Scatter(x=quarterly_df.index, y=quarterly_df[c], mode='lines', name=f'{c}'))
fig.update_layout(
title='Price Data',
xaxis_title='Date',
yaxis_title='Price')
fig.show()
display(px.line(data_frame=quarterly_df, x=quarterly_df.index, y=quarterly_df['Volume'], title='Volume Data
```

executed in 105ms, finished 15:40:42 2021-06-23



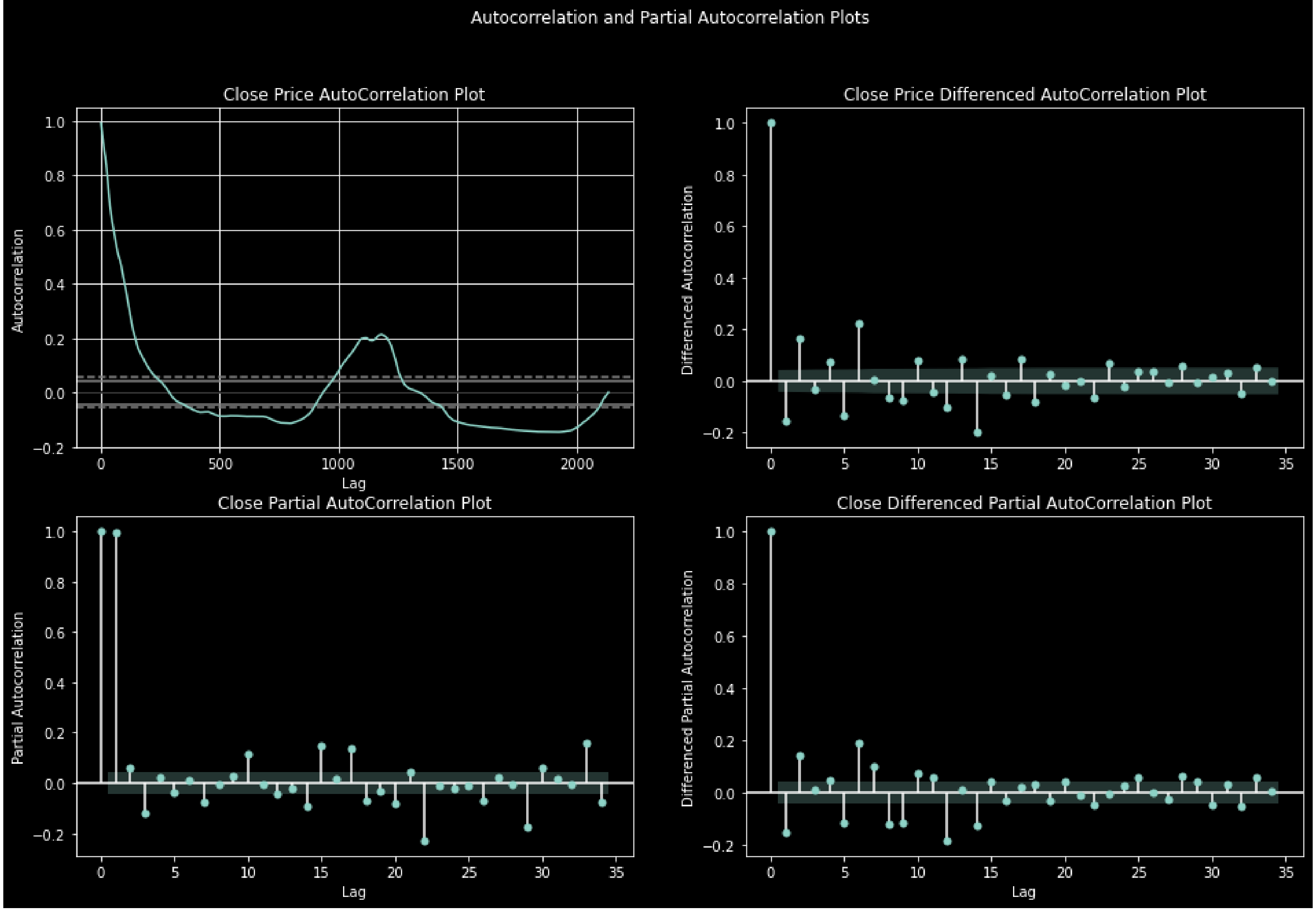


5.0.5 Autocorrelation Plots

In [7]:

```
from pandas.plotting import autocorrelation_plot
from statsmodels.graphics.tsaplots import plot_pacf, plot_acf
fig, ax = plt.subplots(2, 2, figsize=(16, 10))

autocorrelation_plot(df['Close'].dropna(), ax=ax[0][0])
ax[0][0].set_title('Close Price AutoCorrelation Plot')

plot_acf(df['Close'].diff().dropna(), ax=ax[0][1])
ax[0][1].set_title('Close Price Differenced AutoCorrelation Plot')
ax[0][1].set_ylabel('Differenced Autocorrelation')

plot_pacf(df['Close'].dropna(), ax=ax[1][0])
ax[1][0].set_title('Close Partial AutoCorrelation Plot')
ax[1][0].set_xlabel('Lag')
ax[1][0].set_ylabel('Partial Autocorrelation')

plot_pacf(df['Close'].diff().dropna(), ax=ax[1][1])
ax[1][1].set_title('Close Differenced Partial AutoCorrelation Plot')
ax[1][1].set_xlabel('Lag')
ax[1][1].set_ylabel('Differenced Partial Autocorrelation')

plt.suptitle('Autocorrelation and Partial Autocorrelation Plots')
fig.show()
# plt.savefig('acf_plots')
```

executed in 755ms, finished 15:43:31 2021-06-23



5.0.6 Test Stationarity

In [8]:

```python
from statsmodels.tsa.stattools import adfuller

# ADF Test for Non-differenced target variable
result = adfuller(df['Close'], autolag='AIC')
print('NON-DIFFERENCED TARGET VARIABLE')
print(f'ADF Statistic: {result[0]}')
print(f'p-value: {result[1]}')

print(' ')
print(' ')

# ADF Test for Differenced target variable
result = adfuller(df['Close'].diff().dropna(), autolag='AIC')
print('DIFFERENCED TARGET VARIABLE')
print(f'ADF Statistic: {result[0]}')
print(f'p-value: {result[1]}')
```

executed in 417ms, finished 15:43:35 2021-06-23

```
NON-DIFFERENCED TARGET VARIABLE
ADF Statistic: 1.0029061147236595
p-value: 0.9942965169904011


DIFFERENCED TARGET VARIABLE
ADF Statistic: -9.300900887869764
p-value: 1.1132363356594116e-15
```

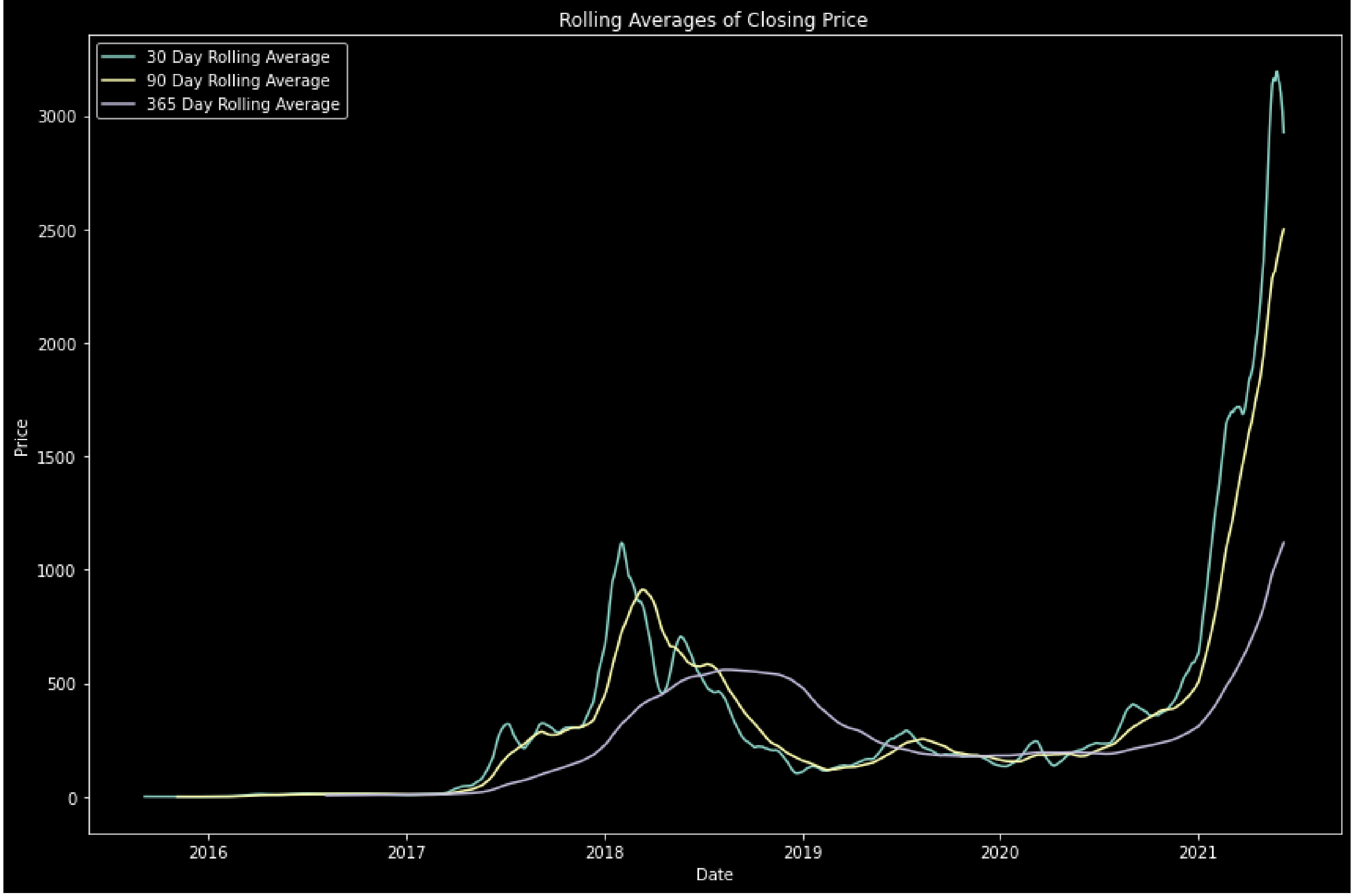
- A first-order difference is enough to stationarize the data

5.0.7 Rolling Averages

In [9]:

```
fig, ax = plt.subplots(figsize=(12,8))
df_30d_rol = df['Close'].rolling(window = 30).mean()
df_90d_rol = df['Close'].rolling(window = 90).mean()
df_365d_rol = df['Close'].rolling(window = 365).mean()
ax.plot(df_30d_rol, label='30 Day Rolling Average')
ax.plot(df_90d_rol, label='90 Day Rolling Average')
ax.plot(df_365d_rol, label='365 Day Rolling Average')
ax.set_xlabel('Date')
ax.set_ylabel('Price')
ax.set_title('Rolling Averages of Closing Price')
plt.legend()
plt.tight_layout()
plt.savefig('rolling_averages')
```

executed in 457ms, finished 15:43:37 2021-06-23


Rolling Averages of Closing Price
30 Day Rolling Average
90 Day Rolling Average
365 Day Rolling Average
Price
3000
2500
2000
1500
1000
500
0
2016
2017
2018
2019
2020
2021
Date

In [ ]:

```
# # Full compiled graph of 30-day, 90-day, and 365-day rolling averages

# fig = go.Figure()



# df_30d_rol = df['Close'].rolling(window = 30).mean()
# df_90d_rol = df['Close'].rolling(window = 90).mean()
# df_365d_rol = df['Close'].rolling(window = 365).mean()
# fig.add_trace(go.Scatter(x=df.index, y=df_30d_rol, mode='lines', name=f'30d Close'))
# fig.add_trace(go.Scatter(x=df.index, y=df_90d_rol, mode='lines', name=f'90d Close'))
# fig.add_trace(go.Scatter(x=df.index, y=df_365d_rol, mode='lines', name=f'365d Close'))

# fig.update_layout(
# title='Price Data',
# xaxis_title='Date',
# yaxis_title='Price',
# legend_title='Legend')
# fig.show()
```

The rolling averages calculated from three different windows (30, 90, 365) provide some more insight to the data. As the window increases in size, the rolling averages' values have very different values during the highly volatile periods of the price of Ethereum. This volatility resulted in each of these periods having wildly different minimum and maximum values, which results in rolling averages that also different by quite a lot. Unsurprisingly, the 30-day and 90-day rolling averages were the most closely related, especially during the first period of steep upwards trend. The prices did not reach magnitude differences during these windows that warranted such a drastic rolling average difference. However, at the end of our time period, the rolling averages end up differing in value by almost $500, which goes to show the extreme volatility that Ethereum experienced during this time period (the most recent months when Ethereum had a meteoric rise). In short summary, the 365-day moving average had the lowest average value because it generalized the most volatility, however its final value was very below the true price. The 30-day moving average had the highest value because it strongly accounted for the high volatility, and its final value was a little higher than the true price (the extreme upper values pulled the average upwards). The 90-day moving average was the closest to the true price, showing that it both accounted for and generalized the volatility the best of the three windows!

5.0.8 Seasonality

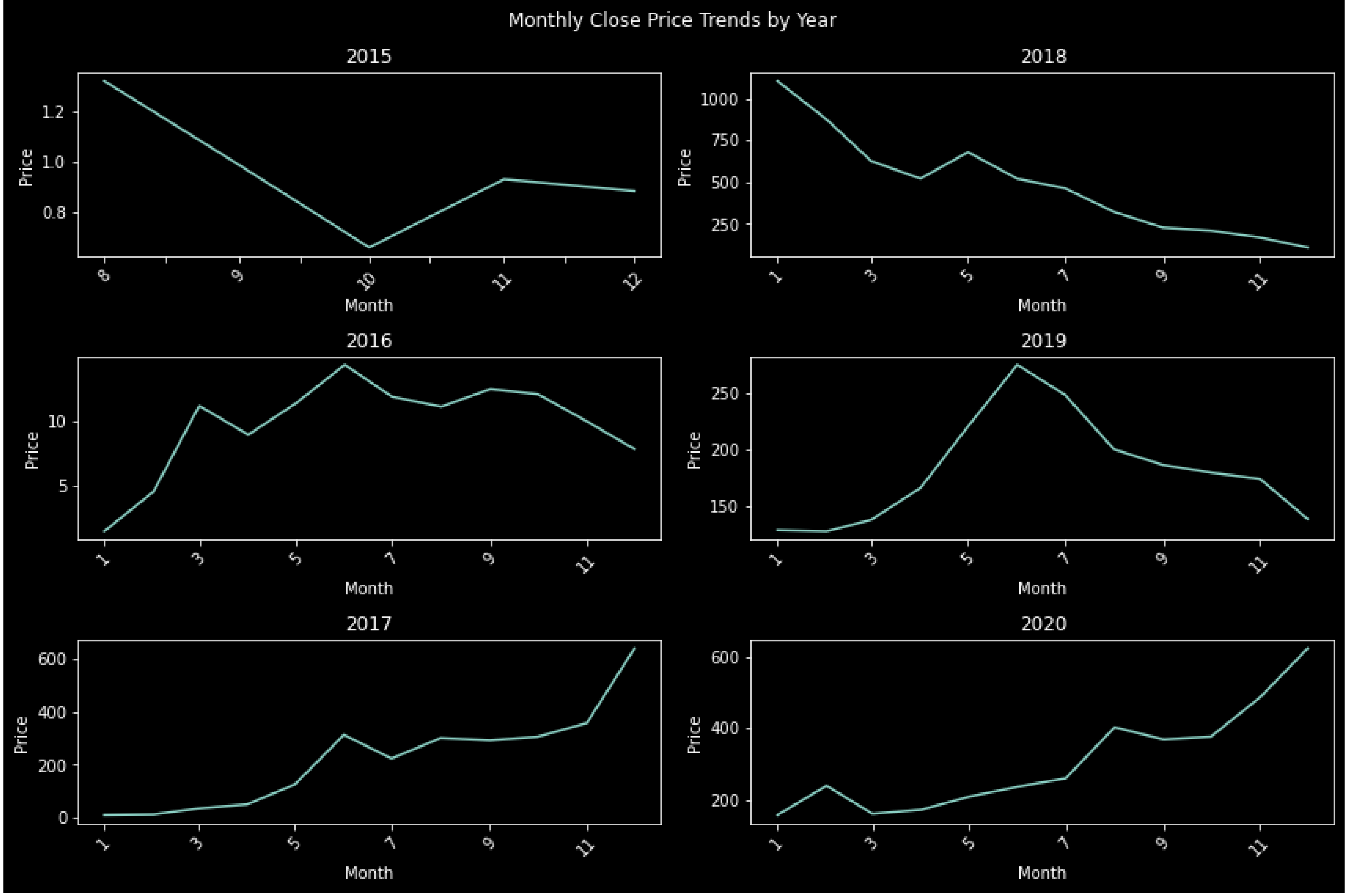
Below are the price trends of Ethereum across all 12 months for each year since 2015. Looking at these price trends, there is no obvious seasonality to be seen, and therefore we will avoid using a SARIMAX model during our modeling process.

In [11]:

```python
# Investigate Monthly Seasonality per Year
plt.style.use('dark_background')

monthly_df = pd.DataFrame(df.resample('MS').mean())
fig, ax = plt.subplots(3,2, figsize=(12, 8))

ax[0][0].plot(monthly_df['Close']['2015'])
ax[0][0].set_title('2015')
ax[0][0].set_xlabel('Month')
ax[0][0].set_ylabel('Price')
ax[0][0].set_xticklabels(labels=['8', '', '9', '', '10', '', '11', '', '12'],rotation=45)

ax[1][0].plot(monthly_df['Close']['2016'])
ax[1][0].set_title('2016')
ax[1][0].set_xlabel('Month')
ax[1][0].set_ylabel('Price')
ax[1][0].set_xticklabels(labels=['1', '3', '5', '7', '9', '11'],rotation=45)

ax[2][0].plot(monthly_df['Close']['2017'])
ax[2][0].set_title('2017')
ax[2][0].set_xlabel('Month')
ax[2][0].set_ylabel('Price')
ax[2][0].set_xticklabels(labels=['1', '3', '5', '7', '9', '11'],rotation=45)

ax[0][1].plot(monthly_df['Close']['2018'])
ax[0][1].set_title('2018')
ax[0][1].set_xlabel('Month')
ax[0][1].set_ylabel('Price')
ax[0][1].set_xticklabels(labels=['1', '3', '5', '7', '9', '11'],rotation=45)

ax[1][1].plot(monthly_df['Close']['2019'])
ax[1][1].set_title('2019')
ax[1][1].set_xlabel('Month')
```

```
ax[1][1].set_ylabel('Price')
ax[1][1].set_xticklabels(labels=['1', '3', '5', '7', '9', '11'],rotation=45)

ax[2][1].plot(monthly_df['Close']['2020'])
ax[2][1].set_title('2020')
ax[2][1].set_xlabel('Month')
ax[2][1].set_ylabel('Price')
ax[2][1].set_xticklabels(labels=['1', '3', '5', '7', '9', '11'],rotation=45)

plt.suptitle('Monthly Close Price Trends by Year')
plt.tight_layout()
plt.savefig('monthly_price_trends')
```

executed in 2.15s, finished 15:44:51 2021-06-23



Because the evidence of seasonality is rather weak and can most certainly be disputed, during the modeling process an ARIMA model with no seasonality inclusion will be test first, followed by a SARIMAX model.

5.0.9 Findings

Ethereum prices follow what is called a "cyclical trend", which means that it has trends however these trends so no specific pattern of repetition. To illustrate this, we can look at two of the graphs, which are both displayed above.

From the year 2015 to the first quarter of 2017, the price of Ethereum remained quite stationary, with a very strong rise starting between March and April, which led to a strong upwards trend that lasted throughout the rest of the year of 2017, bring the price to a maximum value of 826.82 by the end of the year. This constituted a

10,106 percent price increase from the minimum price of 8.17 in the year of 2017, which is by all standards a very strong upwards trend. The volume of trades also followed this trend quite closely, matching the sentiment idea that as an asset shoots up in price, more people attempt to join in on the ride, and hence more trades are made. After the year 2017, the price of Ethereum immediately started a strong downwards trend beginning in January of 2018, and by the end of 2018 the price had settled to a minimum value of 84.30, roughly a 94% drop from its all time high at the very beginning of 2018. Volume for the rest of 2018 remained on average higher than the two years afterwards and the year before because at first people were participating in frequent trades due to the meteoric rise in price, and then people continued to sell their coins over the year as the price tanked. From 2019 to mid-2020, the price once again mostly resumed the stationary trend that it had exemplified from 2015 to about a quarter of the way through 2017, indicating that perhaps people lost interest in the Ethereum block-chain, doubted its potential, or simply moved on to different investments. There was a sharp rise in prise to a little over 250 during 2019, but it just as quickly fell back to close to the minimum value of that year, failing to breakout of its strong downwards trend. The volume from 2019 to mid-2020 would never drop to the levels seen before the coin's meteoric rise, most likely because such a note-worthy event put Ethereum on the map permanently. During 2019, there was a sharp rise and fall in volume that mirrored the trend of the quick rise and fall of price during that year. 2019-2021 would be the period of time when Ethereum would consistently reflect a yearly upwards trend. Volume was higher than its ever been, and the price rose to an unprecedented level of roughly 4000. During this upwards trend, there were several downwards trends that occured during certain months of the years. They seemed to be relatively random, with no predictability in their occurences, highlighting the unstationarity of the price of Ethereum, and also the idea that the price follows a "cyclical trend". There are very clear bull and bear markets, however the trickly part is timing these.

6 Modeling

6.1 Scale the Data

We are going to want to scale the data because of the massive magnitude differences between values. This will most likely improve the accuracy of our forecast

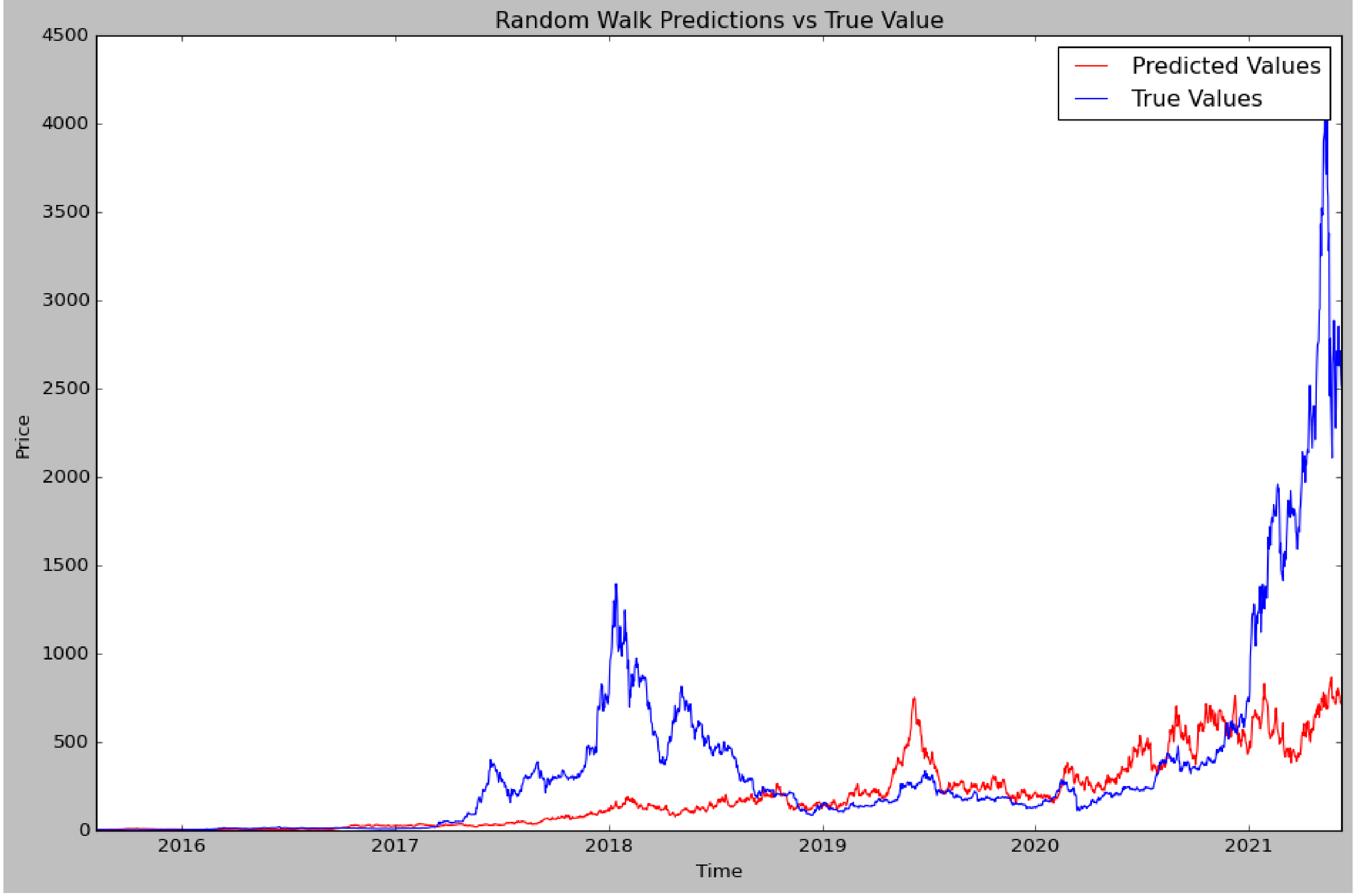
In [6]:
```
from sklearn.preprocessing import MinMaxScaler
ss = MinMaxScaler()
scaled_data = pd.DataFrame(ss.fit_transform(df), columns=df.columns, index=df.index)
```

6.2 Random-Walk

In [ ]:

```python
## Walk
rwdata = pd.DataFrame(df['Close'], columns=['Close'])
rwdata['change'] = df['Close'].pct_change()
mean = rwdata['change'][1:].mean()
sd = rwdata['change'][1:].std()

## Predict
model = {}
model['Prediction'] = [rwdata['Close'][0]]
for time in range(1, len(rwdata)):
    old = model['Prediction'][time -1]
    new_price = old*(1+ mean) + old*sd*np.random.normal(0,1)
    model['Prediction'].append(new_price)

## Plot
rwdf = pd.DataFrame(model, index=rwdata.index)

fig, ax = plt.subplots(figsize=(12,8))
ax.plot(rwdf, label='Predicted Values', color='Red')
ax.plot(rwdata['Close'], label='True Values', color='Blue')

plt.xlabel('Time')
plt.ylabel('Price')
plt.title('Random Walk Predictions vs True Value')
plt.legend()
plt.tight_layout()

rmse = math.sqrt(mean_squared_error(rwdf, rwdata['Close']))
print(f'RMSE = {rmse}')
```

```
RMSE = 493.48776665070574
```



The model was run multiple times, in an attempt to aquire the best possible model for the problem. The best random-walk achieved had an RMSE of 323.097. Since the business strategy we are focusing on is day-trading, it is preferable to have tighter margins of error, because we are not holding for long periods of time and therefore a wrong guess affects our success more strongly.

6.3 ARIMA Model

In [7]:

```
### Train-Test-Split the Non-Scaled Data
y_train = df['Close'][:'2019-06-13']
y_test = df['Close']['2019-06-14':]
x_train = df.index[:1407]
x_test = df.index[1407:]

###
y_train_scaled = scaled_data['Close'][:'2019-06-13']
y_test_scaled = scaled_data['Close']['2019-06-14':]
```

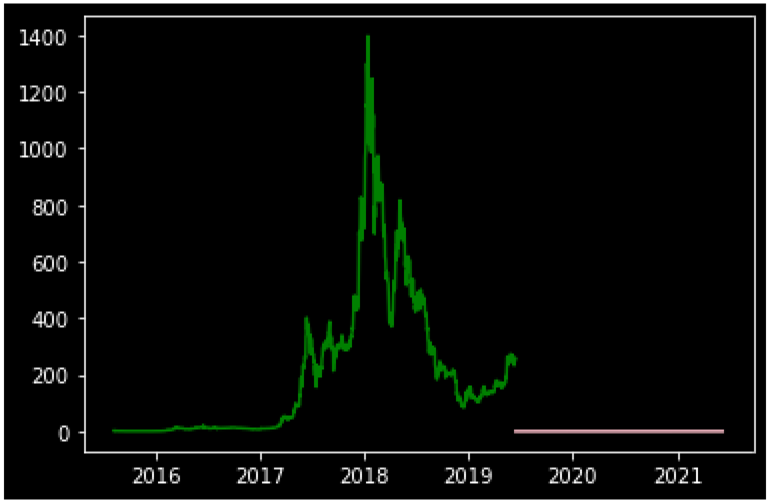
In [8]:

```python
import pmdarima as pm
model = pm.auto_arima(y_train_scaled, start_P=0, d=2, start_q=0, max_p=5, max_d=5, max_q=5,
                      D=1, start_Q=0, max_D=5, max_Q=5, m=12, seasonal=True, error_action='warn',
                      trace=True, supress_warnings=True, stepwise=False)
model.summary()
```

```
 ARIMA(0,2,0)(0,1,0)[12]             : AIC=-8784.166, Time=0.50 sec
 ARIMA(0,2,0)(0,1,1)[12]             : AIC=-9702.335, Time=0.96 sec
 ARIMA(0,2,0)(0,1,2)[12]             : AIC=inf, Time=18.61 sec
 ARIMA(0,2,0)(0,1,3)[12]             : AIC=inf, Time=15.95 sec
 ARIMA(0,2,0)(0,1,4)[12]             : AIC=inf, Time=16.26 sec
 ARIMA(0,2,0)(0,1,5)[12]             : AIC=inf, Time=76.53 sec
 ARIMA(0,2,0)(1,1,0)[12]             : AIC=-9174.729, Time=1.90 sec
 ARIMA(0,2,0)(1,1,1)[12]             : AIC=inf, Time=4.93 sec
 ARIMA(0,2,0)(1,1,2)[12]             : AIC=inf, Time=9.88 sec
 ARIMA(0,2,0)(1,1,3)[12]             : AIC=inf, Time=32.77 sec
 ARIMA(0,2,0)(1,1,4)[12]             : AIC=inf, Time=32.74 sec
 ARIMA(0,2,0)(2,1,0)[12]             : AIC=-9427.726, Time=2.28 sec
 ARIMA(0,2,0)(2,1,1)[12]             : AIC=inf, Time=9.48 sec
 ARIMA(0,2,0)(2,1,2)[12]             : AIC=inf, Time=13.09 sec
 ARIMA(0,2,0)(2,1,3)[12]             : AIC=inf, Time=31.28 sec
 ARIMA(0,2,1)(0,1,0)[12]             : AIC=inf, Time=0.83 sec
 ARIMA(0,2,1)(0,1,1)[12]             : AIC=inf, Time=3.26 sec
 ARIMA(0,2,1)(0,1,2)[12]             : AIC=inf, Time=14.53 sec
 ARIMA(0,2,1)(0,1,3)[12]             : AIC=inf, Time=21.77 sec
 ARIMA(0,2,1)(0,1,4)[12]             : AIC=inf, Time=40.77 sec
 ARIMA(0,2,1)(1,1,0)[12]             : AIC=-9911.095, Time=0.64 sec
 ARIMA(0,2,1)(1,1,1)[12]             : AIC=inf, Time=7.74 sec
 ARIMA(0,2,1)(1,1,2)[12]             : AIC=inf, Time=21.56 sec
 ARIMA(0,2,1)(1,1,3)[12]             : AIC=-10475.454, Time=8.46 sec
```

In [9]:

```
# make your forecasts
prediction = pd.DataFrame(model.predict(n_periods=726), index=y_test.index)
# Visualize the forecasts (blue=train, green=forecasts)
x = np.arange(y_test.shape[0])
plt.plot(y_train, c='green')
plt.plot(prediction, c='pink')
plt.show()

rmse = math.sqrt(mean_squared_error(prediction, y_test))
print(f'RMSE = {rmse}')
```



```
RMSE = 1053.2547788963773
```

The ARIMA model performed poorly for the data provided. This can almost certainly be attributed to the exaggerated volatility of Ethereum prices. The period of time that ARIMA was trained on showed an interesting trend. The price remained low, then spiked to a value that was much higher than before, and just as quickly fell down to a very low value again and remained there for quite some time. In other words, it was relatively stationary, then had a steep upwards trend, a steep downwards trend, and then remained relatively stationary again. The two main determinants of ARIMA predicitons, past values and moving average, are very hard to predict upon because thei values vary by so much.

6.4 Prophet

In [ ]:

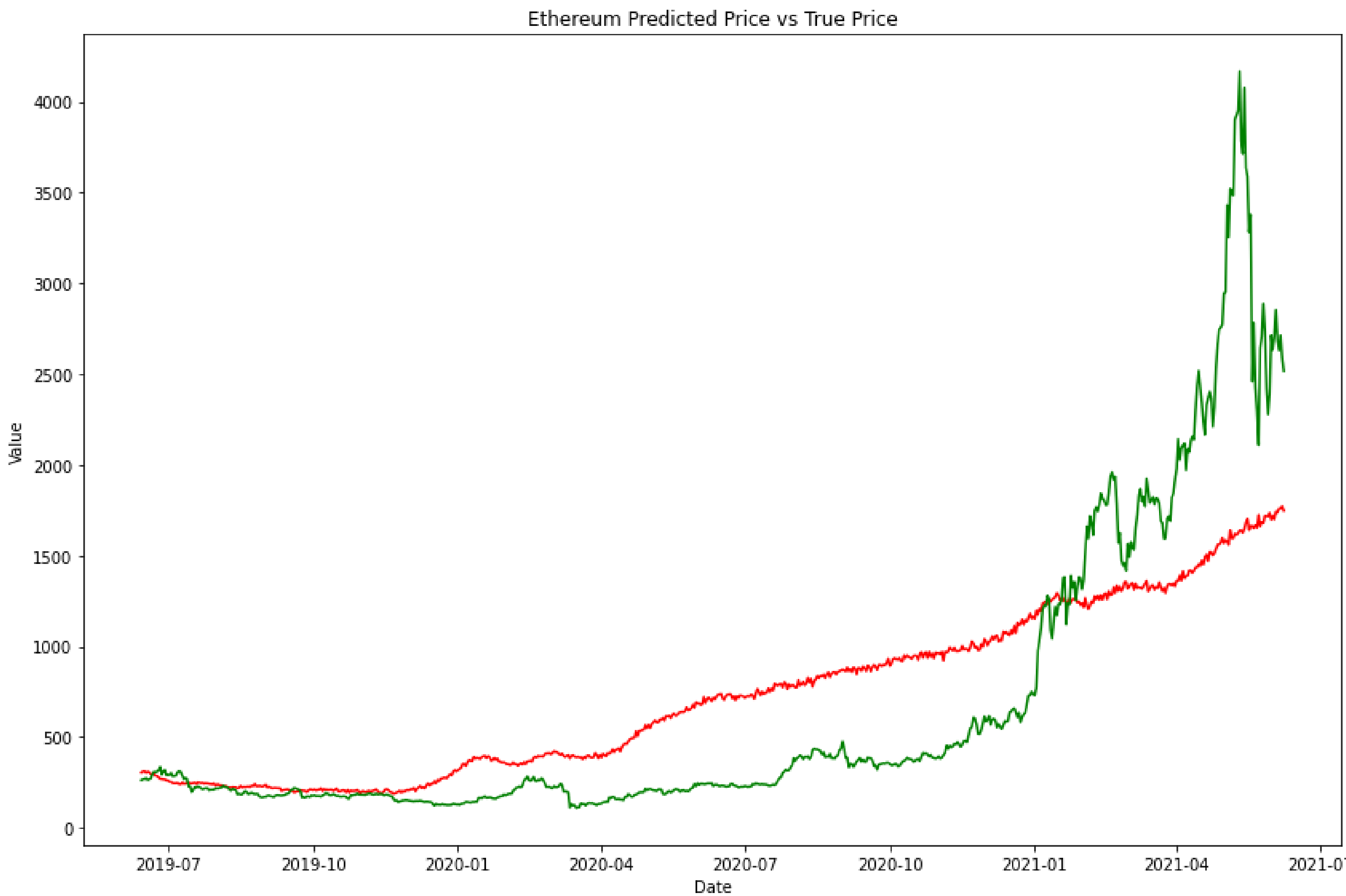
```
### Import Prophet
from fbprophet import Prophet



### Create Prophet compatible DataFrame
data = df.reset_index()[['Date', 'Close', 'Volume', 'MarketCap']].rename(columns={'Date':'ds', 'Close':'y',
data['btc'] = df2['Open'][830:2963].values
### Train-Test-Split the data
train = data[:1407]
test = data[1407:]
```

First, Prophet will be used as a univariate regression model, with the sole determinant variable being our target variable, the "Close" price.

In [ ]:

```python
### Predictions using training data
m = Prophet(daily_seasonality=False)
m.fit(train)
future = m.make_future_dataframe(periods=len(test), freq='D')[1407:]
forecast = m.predict(future)



### Predictions DataFrame
pred = pd.DataFrame(forecast.yhat_upper[-726:])
pred.index=forecast.ds[-726:]
pred

### Test data DataFrame
testplot = pd.DataFrame(test.y)
testplot.index=test.ds

### Plot Test vs Predictions
fig, ax = plt.subplots(figsize=(12, 8))
ax.plot(pred, label='Predictions', color='red')
ax.plot(testplot, label='True', color='green')
ax.set_xlabel('Date')
ax.set_ylabel('Value')
ax.set_title('Ethereum Predicted Price vs True Price')
plt.tight_layout()

### Calculate RMSE
from sklearn.metrics import mean_squared_error
import math
rmse = math.sqrt(mean_squared_error(pred, testplot))

# display(future)
# display(pred)
print(rmse)
```

```
506.81105103489233
```



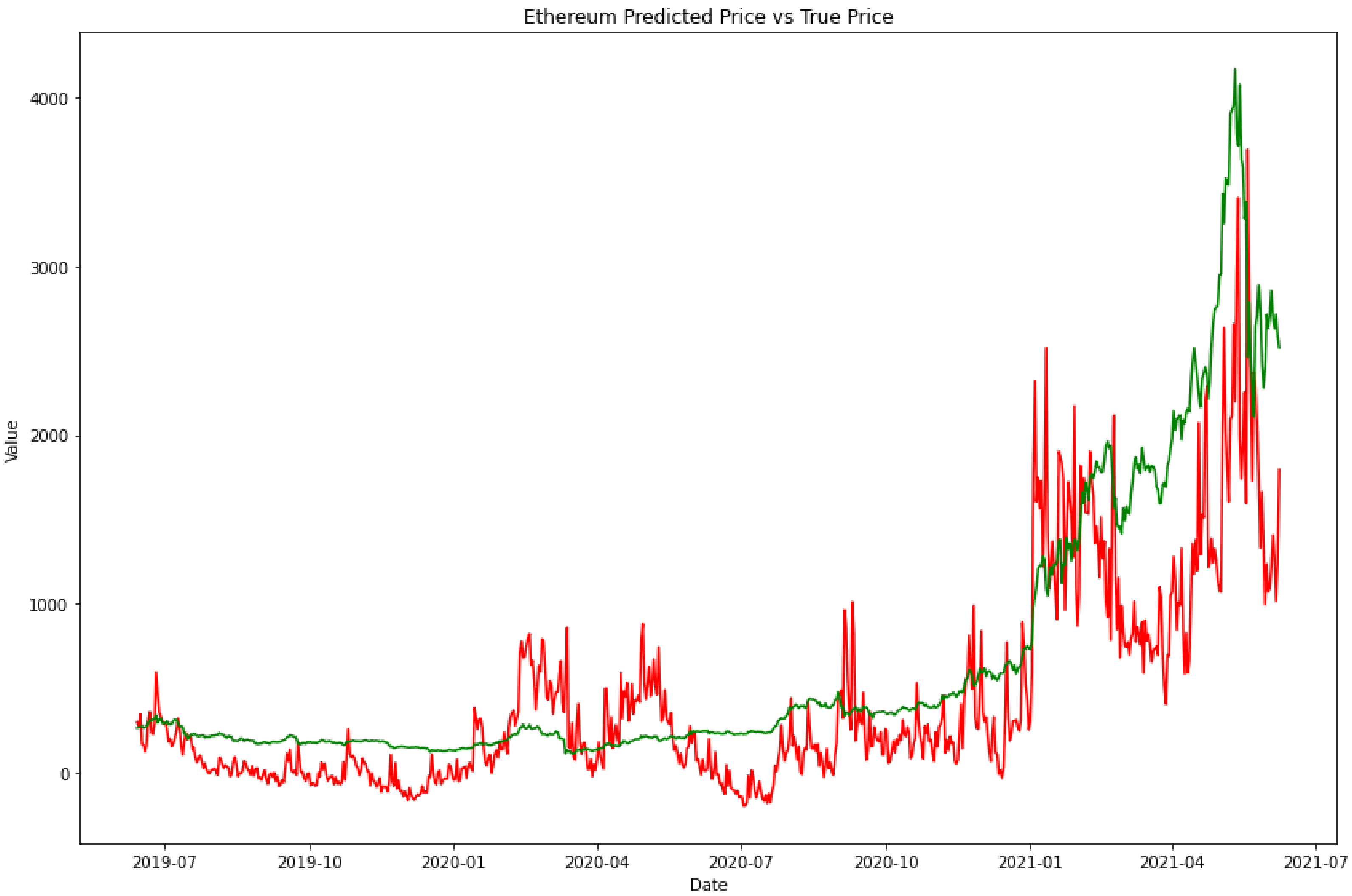
	The univariate model had an RMSE of 505.761 To try and improve this model's performance, a second regressor variable will be added into the model's calculations. This will be the "Volume" data found in the same imported data as the "Close" prices.

In [ ]:

```python
### Predictions using training data
m = Prophet(daily_seasonality=False)
m.add_regressor('Volume')
m.fit(train)
future = m.make_future_dataframe(periods=len(test), freq='D')[1407:]
future['Volume'] = test['Volume'].values
forecast = m.predict(future)


### Predictions DataFrame
pred = pd.DataFrame(forecast.yhat_upper[-726:])
pred.index=forecast.ds[-726:]
pred

### Test data DataFrame
testplot = pd.DataFrame(test.y)
testplot.index=test.ds

### Plot Test vs Predictions
fig, ax = plt.subplots(figsize=(12, 8))
ax.plot(pred, label='Predictions', color='red')
ax.plot(testplot, label='True', color='green')
ax.set_xlabel('Date')
ax.set_ylabel('Value')
ax.set_title('Ethereum Predicted Price vs True Price')
plt.tight_layout()

### Calculate RMSE
from sklearn.metrics import mean_squared_error
import math
rmse = math.sqrt(mean_squared_error(pred, testplot))

# display(future)
```

```python
# display(pred)
print(rmse)
```

```
512.8331167705669
```



The RMSE of the new model was 505.584

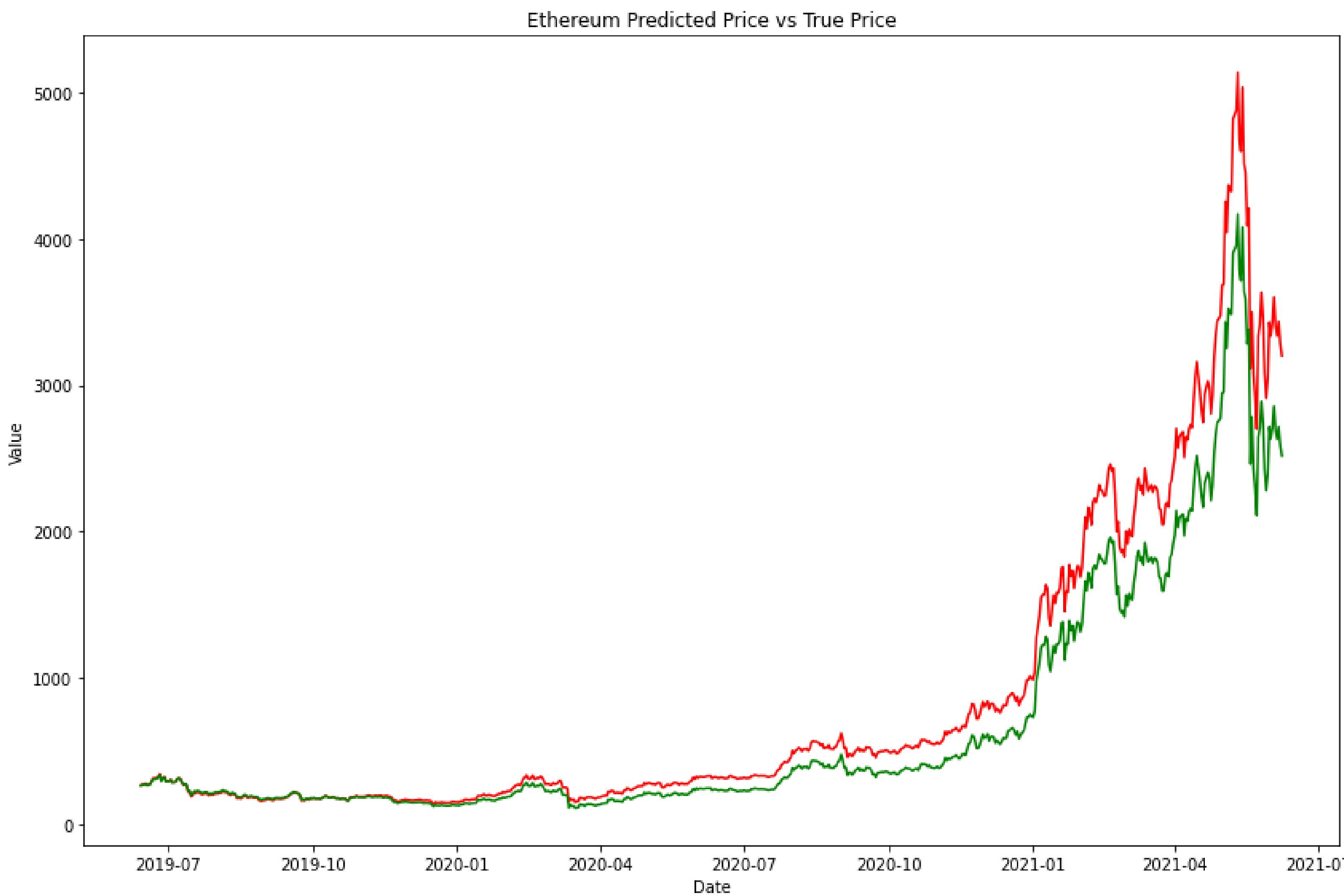
Adding one additional regressor to the model seemed to improve its performance, but only ever so slightly. Let's add one more regressor to see if it can help improve the model. We will use another variable that was found in the imported data that cannot be directly derived from the price; "Market Cap"

In [ ]:

```python
### Predictions using training data
m = Prophet(daily_seasonality=False)
m.add_regressor('Volume')
m.add_regressor('MarketCap')
m.fit(train)
future = m.make_future_dataframe(periods=len(test), freq='D')[1407:]
future['Volume'] = test['Volume'].values
future['MarketCap'] = test['MarketCap'].values
forecast = m.predict(future)



### Predictions DataFrame
pred = pd.DataFrame(forecast.yhat_upper[-726:])
pred.index=forecast.ds[-726:]
pred

### Test data DataFrame
testplot = pd.DataFrame(test.y)
testplot.index=test.ds

### Plot Test vs Predictions
fig, ax = plt.subplots(figsize=(12, 8))
ax.plot(pred, label='Predictions', color='red')
ax.plot(testplot, label='True', color='green')
ax.set_xlabel('Date')
ax.set_ylabel('Value')
ax.set_title('Ethereum Predicted Price vs True Price')
plt.tight_layout()

### Calculate RMSE
from sklearn.metrics import mean_squared_error
import math
rmse = math.sqrt(mean_squared_error(pred, testplot))
```

```python
# display(future)
# display(pred)
print(rmse)
```

```
277.9156730399441
```



The RMSE score for the model with two additional regressor variables was 276.252

Adding a second regressor improved our RMSE metric by a very considerable amount.

This begs the question; "Will adding one or two more regressors improve the model even further?"

Let's find out.

In order to do this, we will have to use new data imported from the same source as the original data used; CoinMarketCap.com

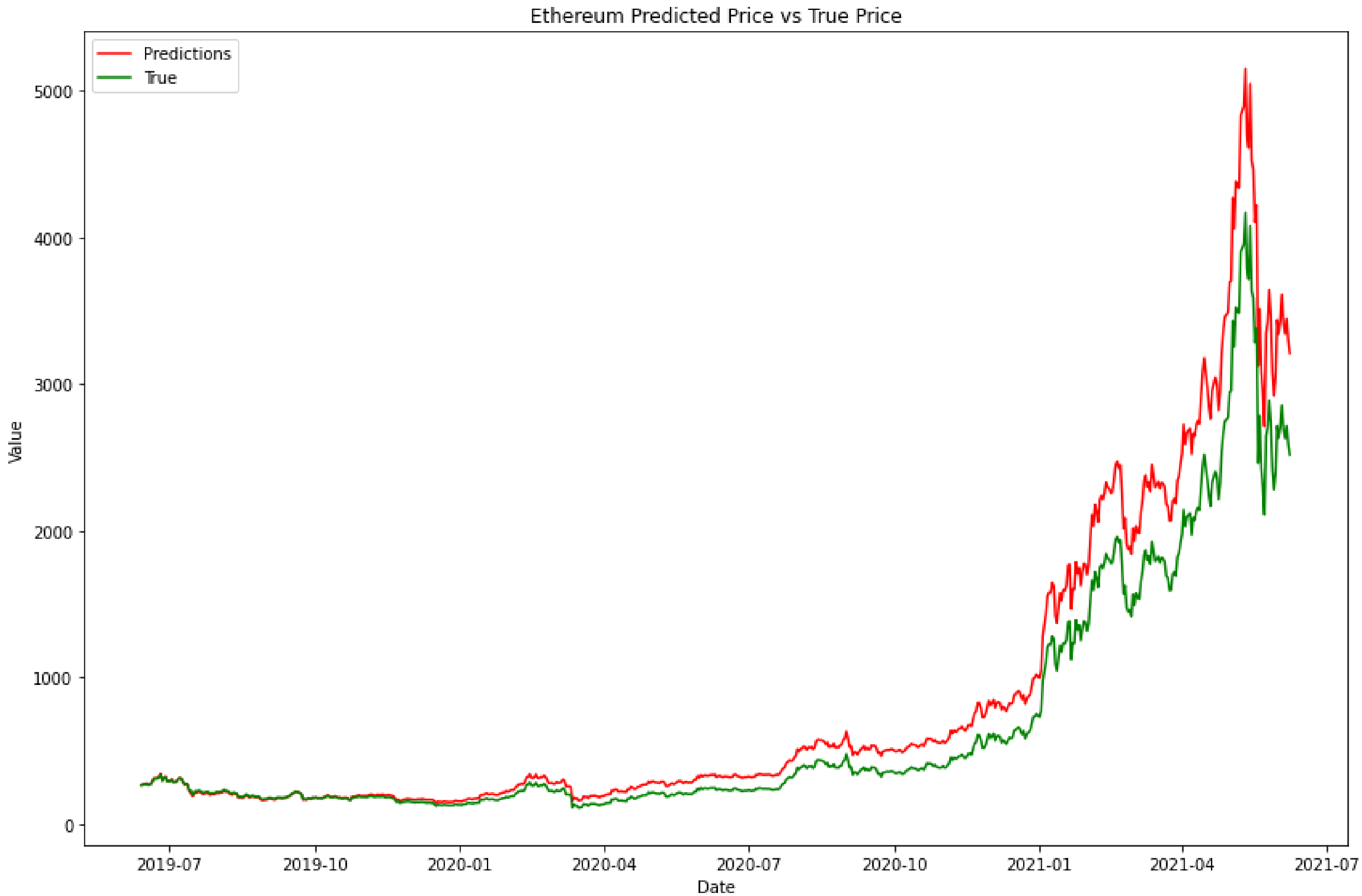
- We will use BitCoin close prices on the corresponding dates as our third regressor variable.

In [ ]:

```python
### Predictions using training data
m = Prophet(daily_seasonality=False)
m.add_regressor('Volume')
m.add_regressor('MarketCap')
m.add_regressor('btc')
m.fit(train)
future = m.make_future_dataframe(periods=len(test), freq='D')[1407:]
future['Volume'] = test['Volume'].values
future['MarketCap'] = test['MarketCap'].values
future['btc'] = test['btc'].values
# future['Bitcoin_Close'] = test['Close']  ### HAVE TO SCRAPE BITCOIN DATA FOR THIS!!!
forecast = m.predict(future)



### Predictions DataFrame
pred = pd.DataFrame(forecast.yhat_upper[-726:])
pred.index=forecast.ds[-726:]
pred

### Test data DataFrame
testplot = pd.DataFrame(test.y)
testplot.index=test.ds

### Plot Test vs Predictions
fig, ax = plt.subplots(figsize=(12, 8))
ax.plot(pred, label='Predictions', color='red')
ax.plot(testplot, label='True', color='green')
ax.set_xlabel('Date')
ax.set_ylabel('Value')
ax.set_title('Ethereum Predicted Price vs True Price')
ax.legend()
plt.tight_layout()
```

```python
### Calculate RMSE
from sklearn.metrics import mean_squared_error
import math
rmse = math.sqrt(mean_squared_error(pred, testplot))

# display(future)
# display(pred)
print(rmse)
```

```
285.5042348688131
```



6.5 Deep Learning

6.5.1 LSTM

In [ ]:
```
data = np.asarray(df['Close']).reshape(-1,1)
```

In [ ]:

```python
# Scale the data
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler(feature_range=(0, 1))
data = scaler.fit_transform(data)

# split into train and test sets
train_size = int(len(data) * 0.6)
test_size = len(data) - train_size

train = data[0:train_size,:]
test = data[train_size:len(data),:]
```

In [ ]:

```python
# Use TimeseriesGenerator to create the samples
from keras.preprocessing.sequence import TimeseriesGenerator
n_input = 90

train_data = TimeseriesGenerator(train, train,
    length=n_input,
    batch_size=128)

test_data = TimeseriesGenerator(test, test,
    length=n_input,
    batch_size=1)
```

In [ ]:

```python
from keras.models import Sequential
from keras.layers import Dense, LSTM
from keras.layers import Dropout
import tensorflow as tf
```

All models will be trained on the training data and then their RSME scores will be calculated using the testing data.

	The first model will contain one LSTM layer, with 256 units and a dropout of 0.2 100 Epochs

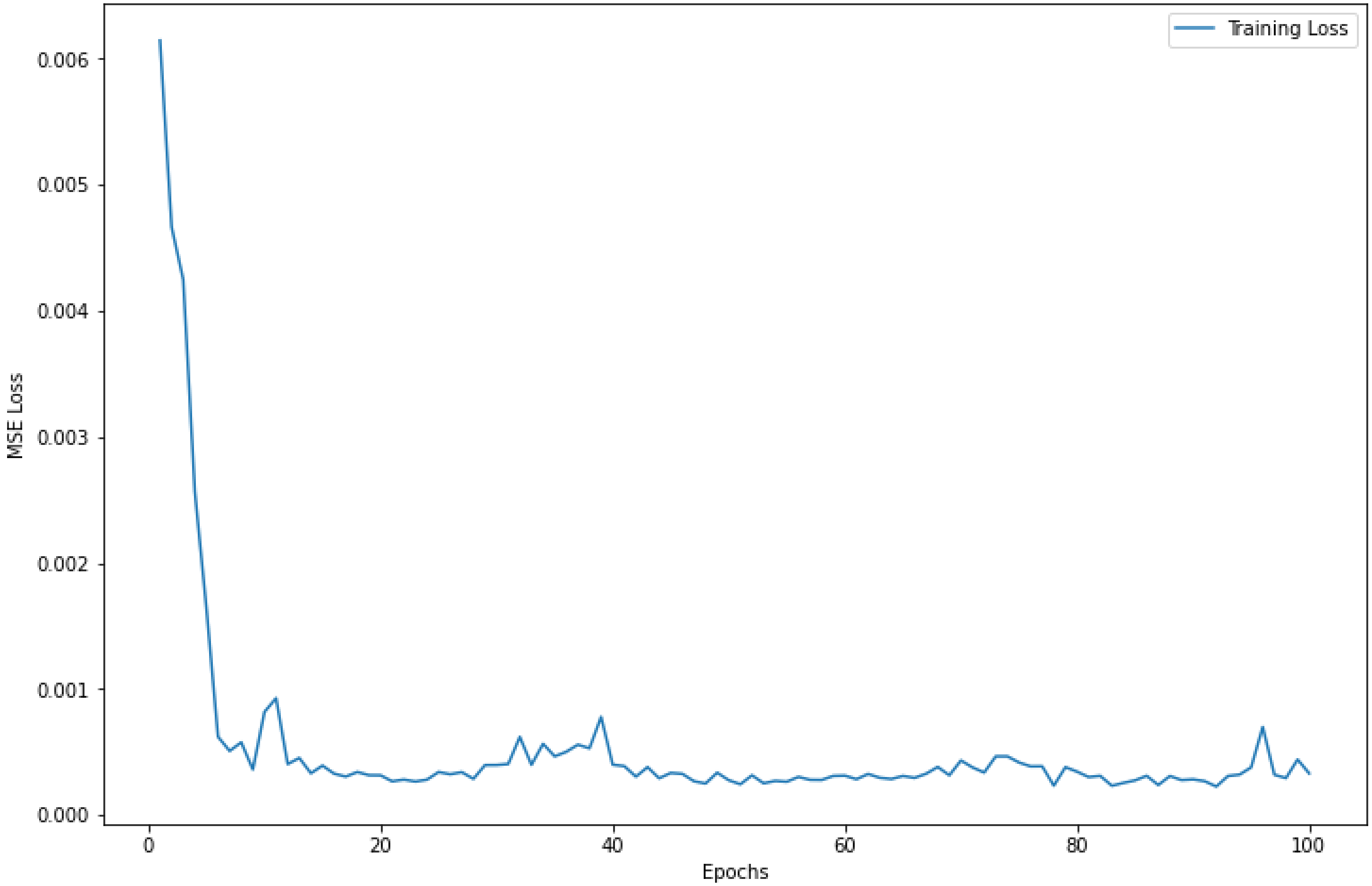
In [ ]:

```
# Model 1

model1 = Sequential()
model1.add(LSTM(256, return_sequences=False,
                input_shape=(10,2), dropout=0.2))
# model1.add(Dropout(0.2))
model1.add(Dense(units=1))

# Compile the model
model1.compile(optimizer='adam', loss='mean_squared_error', metrics=['MeanSquaredError'])

# Summarize the model
model1.summary()
history = model1.fit_generator(train_data, epochs=100, verbose=0)

# Plot loss by epoch
loss = history.history['loss']
epochs = range(1, 101)
plt.figure(figsize=(12,8))
plt.plot(epochs, loss)
plt.legend(['Training Loss'])
plt.xlabel('Epochs')
plt.ylabel('MSE Loss')
plt.show();

# Predict
train_pred = model1.predict_generator(train_data)
test_pred = model1.predict_generator(test_data)

# Inverse the transformation we did earlier so we have the true values of the predictions
train_pred = scaler.inverse_transform(train_pred)
test_pred = scaler.inverse_transform(test_pred)
```

```python
# Helper function
def get_y_from_generator(gen):
    '''
    Get all targets y from a TimeseriesGenerator instance.
    '''
    y = None
    for i in range(len(gen)):
        batch_y = gen[i][1]
        if y is None:
            y = batch_y
        else:
            y = np.append(y, batch_y)
    y = y.reshape((-1,1))
    print(y.shape)
    return y

# Get the y values
train_output = get_y_from_generator(train_data)
test_output = get_y_from_generator(test_data)

# Reverse transform those
train_output = scaler.inverse_transform(train_output)
test_output = scaler.inverse_transform(test_output)


# Plot
fig, ax = plt.subplots(figsize=(12, 8))
ax.plot(test_pred, label='Predictions', color='red')
ax.plot(test_output, label="True Values")
ax.set_xlabel('Date')
ax.set_ylabel('Price')
plt.legend()
ax.set_title('LSTM Model Prediction vs True Values')
plt.tight_layout()
```

```python
plt.savefig('lstm')

# Show predictions and RMSE
rmse_df1 = pd.DataFrame(df['Close'], index=df.index[1369:])
rmse_df1['Pred'] = test_pred
display(rmse_df1)
rmse = math.sqrt(mean_squared_error(rmse_df1['Close'], rmse_df1['Pred']))
print(f'RMSE = {rmse}')
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 256)               265216
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 257
=================================================================
Total params: 265,473
Trainable params: 265,473
Non-trainable params: 0
_________________________________________________________________
```

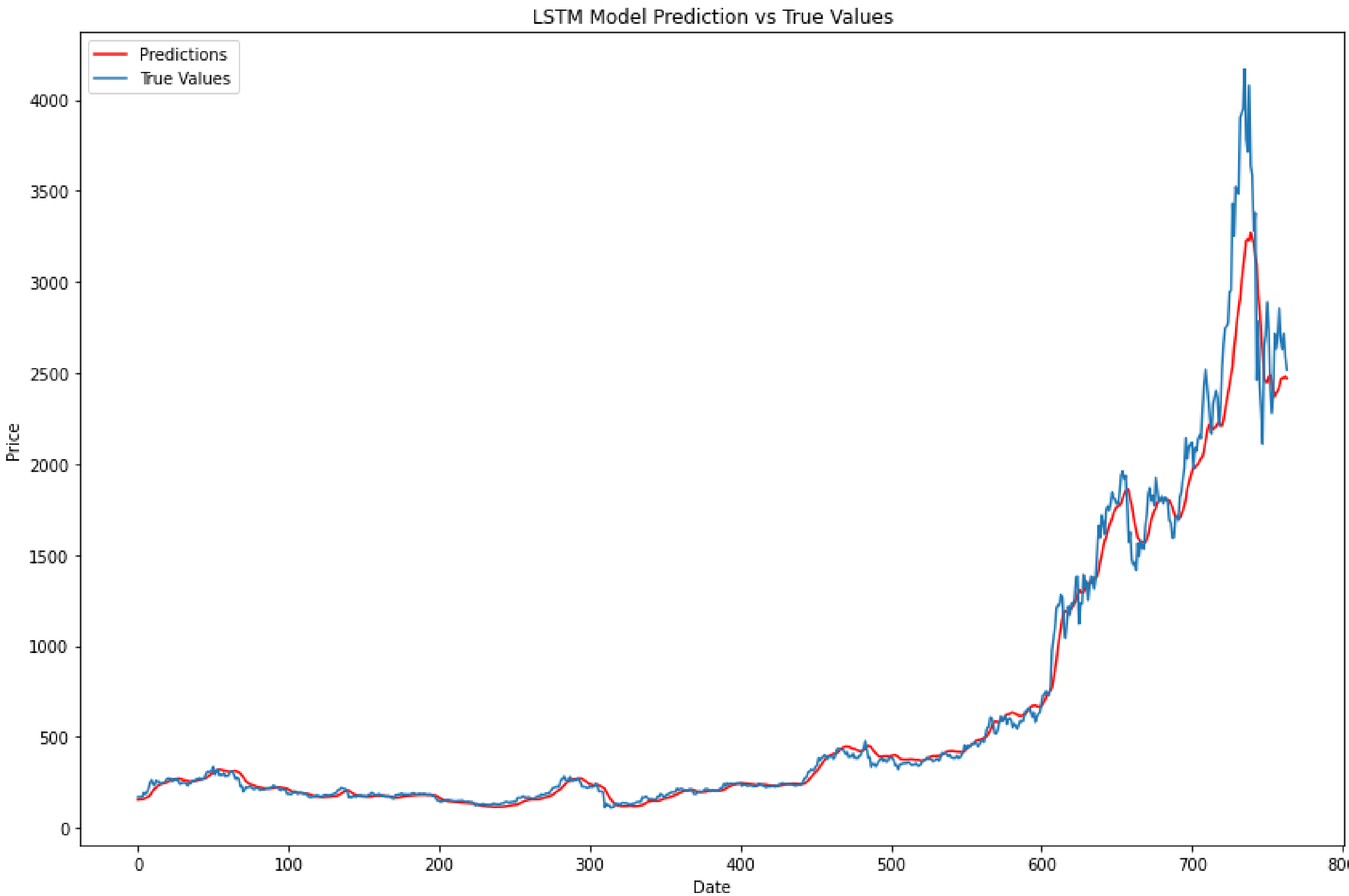



```
(1189, 1)
(764, 1)
```

	Close	Pred
Date		
2019-05-07	169.80	155.897034
2019-05-08	170.95	157.136978
2019-05-09	170.29	158.405106
2019-05-10	173.14	159.395905
2019-05-11	194.30	160.662506
...	...	...

	Close	Pred
Date		
2021-06-04	2688.19	2463.614014
2021-06-05	2630.58	2473.620117
2021-06-06	2715.09	2472.622803
2021-06-07	2590.26	2482.221436
2021-06-08	2517.44	2471.073975

```
RMSE = 135.5502955813682
```



	The second model will also have a single LSTM layer and 256 units, however a discrete dropout layer will also be added. 100 Epochs

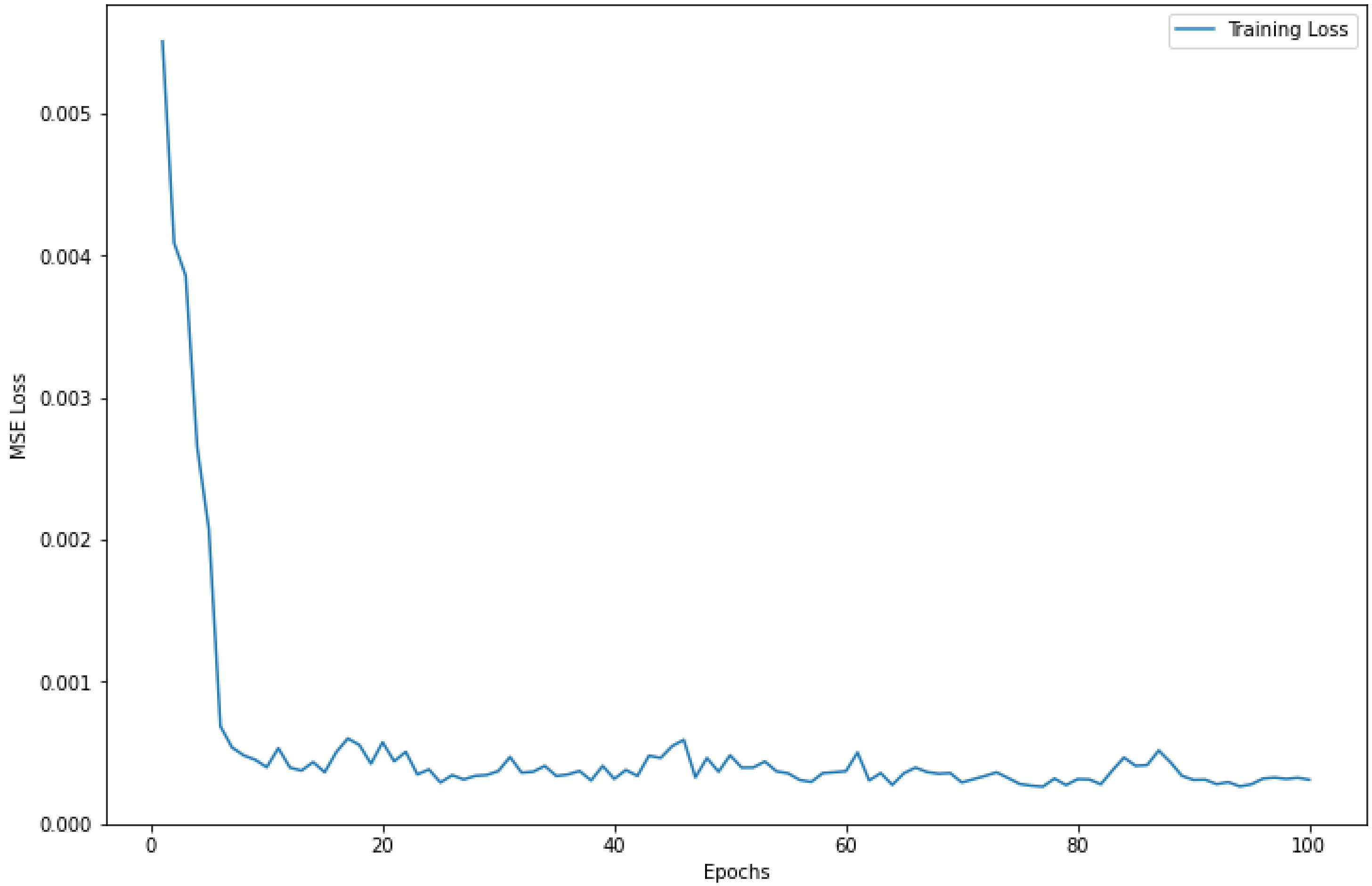
In [ ]:

```
# Model 2

model2 = Sequential()
model2.add(LSTM(256, return_sequences=False,
                 input_shape=(10,2), dropout=0.2))
model2.add(Dropout(0.2))
model2.add(Dense(units=1))

# Compile the model
model2.compile(optimizer='adam', loss='mean_squared_error', metrics=['MeanSquaredError'])

# Summarize the model
model2.summary()
history = model2.fit_generator(train_data, epochs=100, verbose=0)

# Plot loss by epoch
loss = history.history['loss']
epochs = range(1, 101)
plt.figure(figsize=(12,8))
plt.plot(epochs, loss)
plt.legend(['Training Loss'])
plt.xlabel('Epochs')
plt.ylabel('MSE Loss')
plt.show();

# Predict
train_pred = model2.predict_generator(train_data)
test_pred = model2.predict_generator(test_data)

# Inverse the transformation we did earlier so we have the true values of the predictions
train_pred = scaler.inverse_transform(train_pred)
test_pred = scaler.inverse_transform(test_pred)
```

```python
# Helper function
def get_y_from_generator(gen):
    '''
    Get all targets y from a TimeseriesGenerator instance.
    '''
    y = None
    for i in range(len(gen)):
        batch_y = gen[i][1]
        if y is None:
            y = batch_y
        else:
            y = np.append(y, batch_y)
    y = y.reshape((-1,1))
    print(y.shape)
    return y

# Get the y values
train_output = get_y_from_generator(train_data)
test_output = get_y_from_generator(test_data)

# Reverse transform those
train_output = scaler.inverse_transform(train_output)
test_output = scaler.inverse_transform(test_output)


# Plot
fig, ax = plt.subplots(figsize=(12, 8))
ax.plot(test_pred, label='Predictions', color='red')
ax.plot(test_output, label="True Values")
ax.set_xlabel('Date')
ax.set_ylabel('Price')
plt.legend()
ax.set_title('LSTM Model Prediction vs True Values')
plt.tight_layout()
```

```python
# plt.savefig('lstm')

# Show predictions and RMSE
rmse_df2 = pd.DataFrame(df['Close'], index=df.index[1369:])
rmse_df2['Pred'] = test_pred
display(rmse_df2)
rmse = math.sqrt(mean_squared_error(rmse_df2['Close'], rmse_df2['Pred']))
print(f'RMSE = {rmse}')
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_2 (LSTM)                (None, 256)               265216
_________________________________________________________________
dropout (Dropout)            (None, 256)               0
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 257
=================================================================
Total params: 265,473
Trainable params: 265,473
Non-trainable params: 0
_________________________________________________________________
```

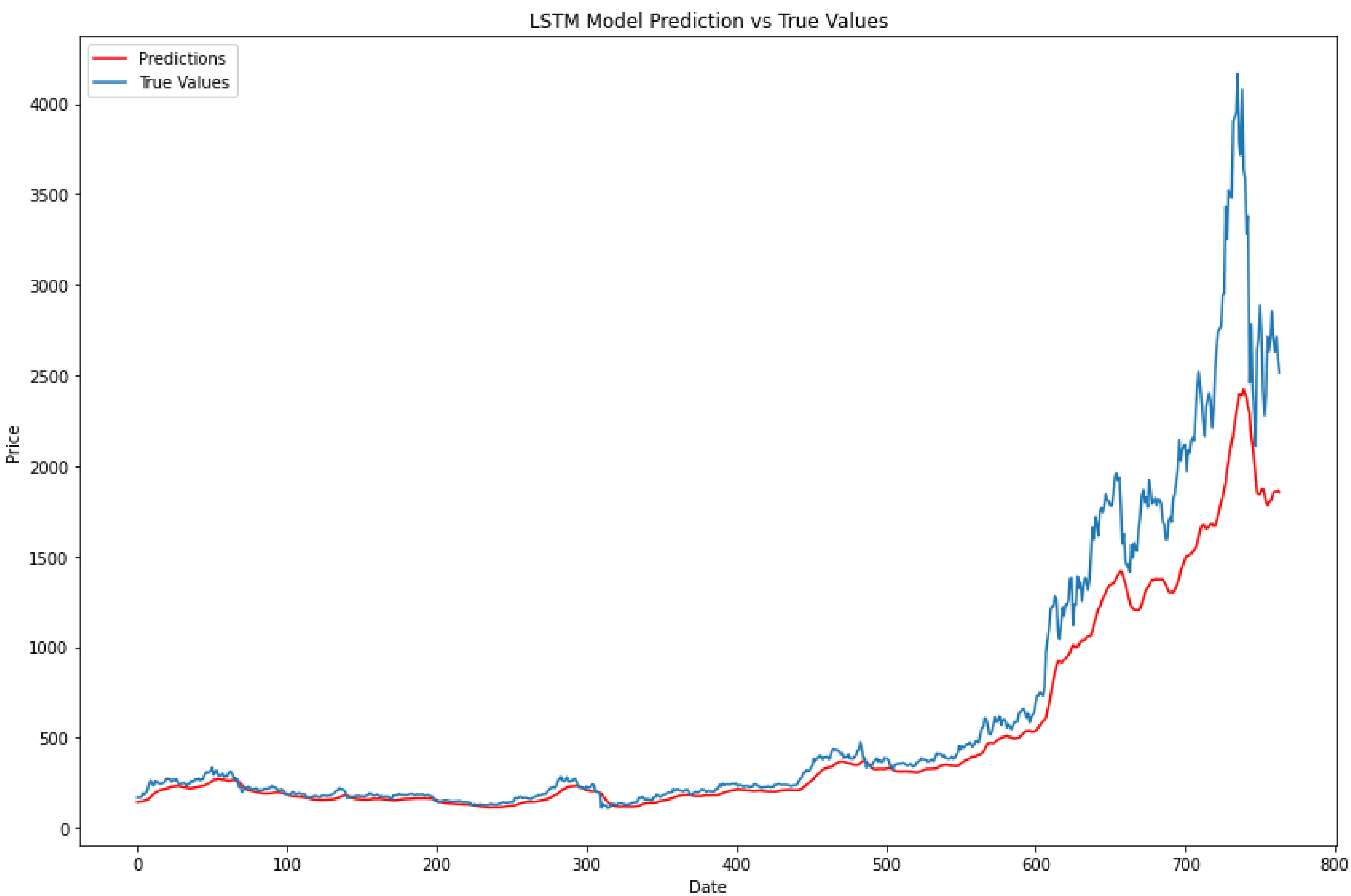



```
(1189, 1)
(764, 1)
```

	Close	Pred
Date		
2019-05-07	169.80	145.502274
2019-05-08	170.95	146.396439
2019-05-09	170.29	147.344574
2019-05-10	173.14	148.073669
2019-05-11	194.30	149.057648
...	...	...

	Close	Pred
Date		
2021-06-04	2688.19	1854.424805
2021-06-05	2630.58	1858.958130
2021-06-06	2715.09	1856.833984
2021-06-07	2590.26	1864.461670
2021-06-08	2517.44	1855.171875

```
RMSE = 320.34766611276393
```



	The third model will be more complex than the previous two. The model will have three LSTM layers rather than just one, with each layer having 256 units. 30 Epochs

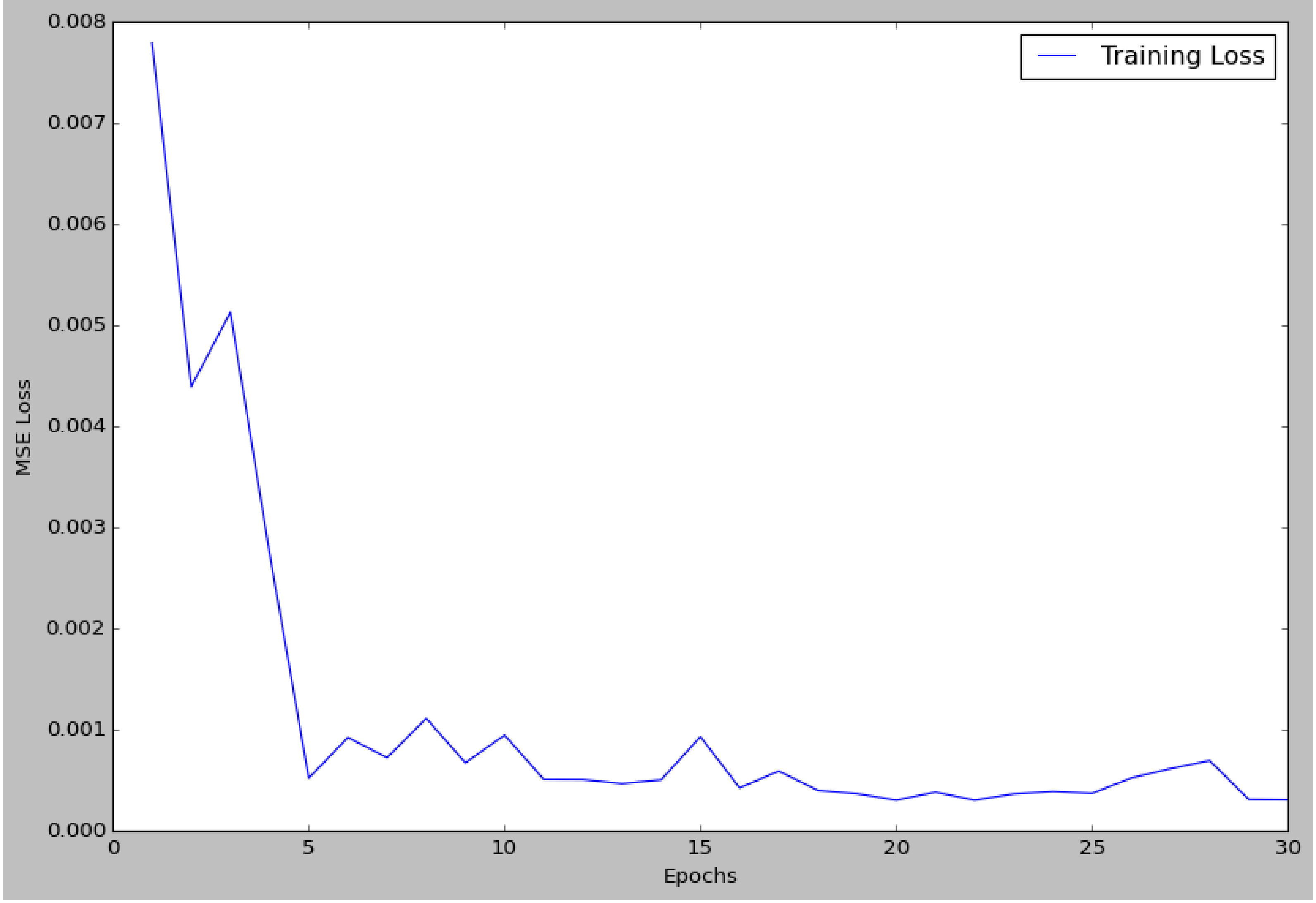
In [ ]:

```
# Model 3 (Greater complexity, dropout is specified inside the LSTM model parameters)
# Read this https://stackoverflow.com/questions/50720670/using-dropout-with-keras-and-lstm-gru-cell to under
## between a dropout LAYER and the dropout PARAMETER in the LSTM function

# Create the model!
model3 = Sequential()
model3.add(LSTM(units=256, return_sequences=True,
                input_shape=(10,2), dropout=0.2))
model3.add(LSTM(units=256, return_sequences=True,
                dropout=0.2))
model3.add(LSTM(units=256, dropout=0.2))
model3.add(Dense(units=1))

# Compile the model
model3.compile(optimizer='adam', loss='mean_squared_error', metrics=['MeanSquaredError'])

# Summarize the model
model3.summary()

# Run the model
history = model3.fit_generator(train_data, epochs=30, verbose=0)

# Predict the data using the model!
train_pred = model3.predict_generator(train_data)
test_pred = model3.predict_generator(test_data)

# Inverse the transformation we did earlier so we have the true values of the predictions
train_pred = scaler.inverse_transform(train_pred)
test_pred = scaler.inverse_transform(test_pred)

# Plot loss per epoch
loss = history.history['loss']
epochs = range(1, 31)
```

```python
plt.figure(figsize=(12,8))
plt.plot(epochs, loss)
plt.legend(['Training Loss'])
plt.xlabel('Epochs')
plt.ylabel('MSE Loss')
plt.show();

# Helper function
def get_y_from_generator(gen):
    '''
    Get all targets y from a TimeseriesGenerator instance.
    '''
    y = None
    for i in range(len(gen)):
        batch_y = gen[i][1]
        if y is None:
            y = batch_y
        else:
            y = np.append(y, batch_y)
    y = y.reshape((-1,1))
    print(y.shape)
    return y

# Get the y values
train_output = get_y_from_generator(train_data)
test_output = get_y_from_generator(test_data)

# Reverse transform those
train_output = scaler.inverse_transform(train_output)
test_output = scaler.inverse_transform(test_output)


# Plot
fig, ax = plt.subplots(figsize=(12, 8))
```

```python
ax.plot(test_pred, label='Predictions', color='red')
ax.plot(test_output, label="True Values")
ax.set_xlabel('Date')
ax.set_ylabel('Price')
plt.legend()
ax.set_title('LSTM Model Prediction vs True Values')
plt.tight_layout()
plt.savefig('lstm')

# Show predictions and RMSE
rmse_df3 = pd.DataFrame(df['Close'], index=df.index[1369:])
rmse_df3['Pred'] = test_pred
display(rmse_df3)
rmse = math.sqrt(mean_squared_error(rmse_df3['Close'], rmse_df3['Pred']))
print(f'RMSE = {rmse}')
```

```
Model: "sequential_8"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_18 (LSTM)               (None, 10, 256)           265216
_________________________________________________________________
lstm_19 (LSTM)               (None, 10, 256)           525312
_________________________________________________________________
lstm_20 (LSTM)               (None, 256)               525312
_________________________________________________________________
dense_8 (Dense)              (None, 1)                 257
=================================================================
Total params: 1,316,097
Trainable params: 1,316,097
Non-trainable params: 0
_________________________________________________________________
```



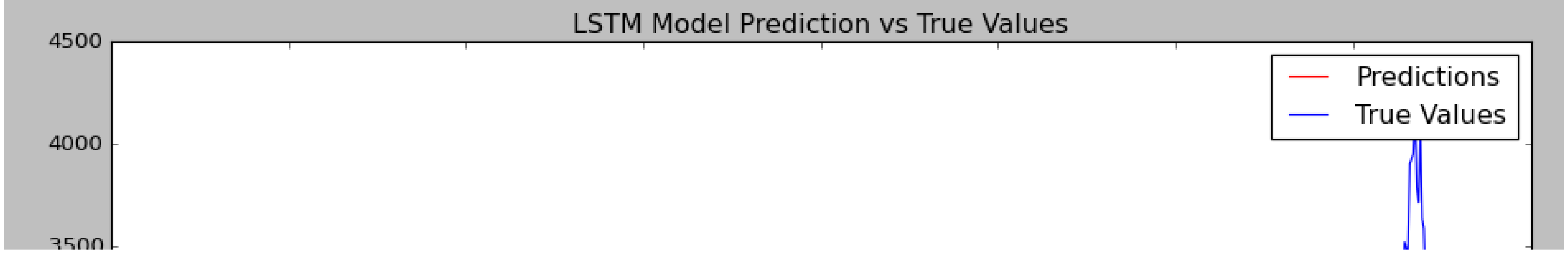

```
(1189, 1)
(764, 1)
```

	Close	Pred
dt		
2019-05-07	169.80	173.351135
2019-05-08	170.95	174.282211
2019-05-09	170.29	175.338318
2019-05-10	173.14	176.389633

	Close	Pred
dt		
2019-05-11	194.30	177.476547
...	...	...
2021-06-04	2688.19	2232.976807
2021-06-05	2630.58	2248.329834
2021-06-06	2715.09	2259.835938
2021-06-07	2590.26	2269.604248
2021-06-08	2517.44	2273.897461

764 rows × 2 columns

```
RMSE = 201.18370469167448
```



	Originally, 30 epochs were used for the model. The "Loss vs Epoch" graph suggested that the loss could further be reduced, as it still had a clear downward trend rather than evening out in order to show the values of the loss converged. The fourth mode will be identical to the third, however the amount of epochs will be increased to 100

In [ ]:

```python
# Model 4 (same model, more epochs)

# Create the model!
model4 = Sequential()
model4.add(LSTM(units=256, return_sequences=True,
                input_shape=(10,2), dropout=0.2))
model4.add(LSTM(units=256, return_sequences=True,
                dropout=0.2))
model4.add(LSTM(units=256, dropout=0.2))
model4.add(Dense(units=1))

# Compile the model
model4.compile(optimizer='adam', loss='mean_squared_error', metrics=['MeanSquaredError'])

# Summarize the model
model4.summary()

# Fit the model
history = model4.fit_generator(train_data, epochs=200, verbose=0)

# Predict the data using the model!
train_pred = model4.predict_generator(train_data)
test_pred = model4.predict_generator(test_data)

# Inverse the transformation we did earlier so we have the true values of the predictions
train_pred = scaler.inverse_transform(train_pred)
test_pred = scaler.inverse_transform(test_pred)

# Plot loss per epoch
loss = history.history['loss']
epochs = range(1, 201)
plt.figure(figsize=(12,8))
plt.plot(epochs, loss)
```

```
plt.legend(['Training Loss'])
plt.xlabel('Epochs')
plt.ylabel('MSE Loss')
plt.show();

# Helper function
def get_y_from_generator(gen):
    '''
    Get all targets y from a TimeseriesGenerator instance.
    '''
    y = None
    for i in range(len(gen)):
        batch_y = gen[i][1]
        if y is None:
            y = batch_y
        else:
            y = np.append(y, batch_y)
    y = y.reshape((-1,1))
    print(y.shape)
    return y

# Get the y values
train_output = get_y_from_generator(train_data)
test_output = get_y_from_generator(test_data)

# Reverse transform those
train_output = scaler.inverse_transform(train_output)
test_output = scaler.inverse_transform(test_output)


# Plot
fig, ax = plt.subplots(figsize=(12, 8))
ax.plot(test_pred, label='Predictions', color='red')
ax.plot(test_output, label="True Values")
```

```python
ax.set_xlabel('Date')
ax.set_ylabel('Price')
plt.legend()
ax.set_title('LSTM Model Prediction vs True Values')
plt.tight_layout()
plt.savefig('lstm')

# Show predictions and RMSE
rmse_df4 = pd.DataFrame(df['Close'], index=df.index[1369:])
rmse_df4['Pred'] = test_pred
display(rmse_df4)
rmse = math.sqrt(mean_squared_error(rmse_df4['Close'], rmse_df4['Pred']))
print(f'RMSE = {rmse}')# Predict the data using the model!
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_3 (LSTM)                (None, 10, 256)           265216
_________________________________________________________________
lstm_4 (LSTM)                (None, 10, 256)           525312
_________________________________________________________________
lstm_5 (LSTM)                (None, 256)               525312
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 257
=================================================================
Total params: 1,316,097
Trainable params: 1,316,097
Non-trainable params: 0
_________________________________________________________________
```

	The fifth and final model will be identical to the fourth model, however the number of units per layer will be increased to 2048.

In [ ]:

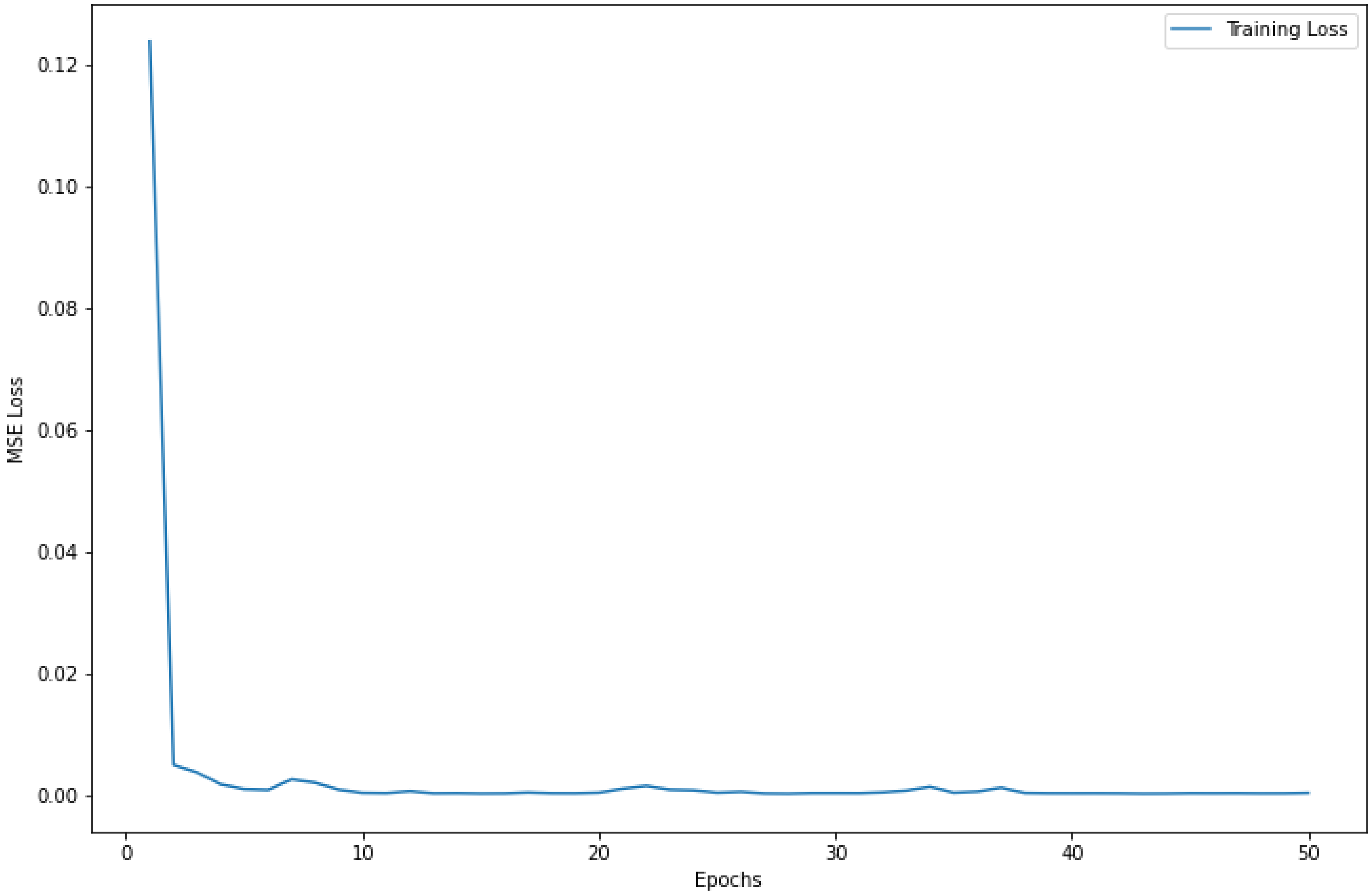
```python
# Model 5


# Create the model!
from keras.layers import Dropout
model5 = Sequential()
model5.add(LSTM(2048, return_sequences=True,
                  input_shape=(10,2), dropout=0.2))
model5.add(Dropout(0.2))
model5.add(LSTM(2048, return_sequences=True, dropout=0.2))
model5.add(Dropout(0.2))
model5.add(LSTM(2048, return_sequences=False, dropout=0.2))
model5.add(Dropout(0.2))
model5.add(Dense(units=1))

# Compile the model
model5.compile(optimizer='adam', loss='mean_squared_error')

# Summarize the model
model5.summary()

# Fit the model
history = model5.fit_generator(train_data, epochs=50, verbose=0)

# Plot loss by epoch
loss = history.history['loss']
epochs = range(1, len(history.history['loss'])+1)
plt.figure(figsize=(12,8))
plt.plot(epochs, loss)
plt.legend(['Training Loss'])
plt.xlabel('Epochs')
plt.ylabel('MSE Loss')
plt.show();
```

```python
# Predict
train_pred = model5.predict_generator(train_data)
test_pred = model5.predict_generator(test_data)

# Inverse the transformation we did earlier so we have the true values of the predictions
train_pred = scaler.inverse_transform(train_pred)
test_pred = scaler.inverse_transform(test_pred)

# Helper function
def get_y_from_generator(gen):
    '''
    Get all targets y from a TimeseriesGenerator instance.
    '''
    y = None
    for i in range(len(gen)):
        batch_y = gen[i][1]
        if y is None:
            y = batch_y
        else:
            y = np.append(y, batch_y)
    y = y.reshape((-1,1))
    print(y.shape)
    return y

# Get the y values
train_output = get_y_from_generator(train_data)
test_output = get_y_from_generator(test_data)

# Reverse transform those
train_output = scaler.inverse_transform(train_output)
test_output = scaler.inverse_transform(test_output)
```

```python
# Plot
fig, ax = plt.subplots(figsize=(12, 8))
ax.plot(test_pred, label='Predictions', color='red')
ax.plot(test_output, label="True Values")
ax.set_xlabel('Date')
ax.set_ylabel('Price')
plt.legend()
ax.set_title('LSTM Model Prediction vs True Values')
plt.tight_layout()
plt.savefig('lstm')

# Show predictions and RMSE
rmse_df5 = pd.DataFrame(df['Close'], index=df.index[1369:])
rmse_df5['Pred'] = test_pred
display(rmse_df5)
rmse = math.sqrt(mean_squared_error(rmse_df5['Close'], rmse_df5['Pred']))
print(f'RMSE = {rmse}')
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_6 (LSTM)                (None, 10, 2048)          16801792
_________________________________________________________________
dropout (Dropout)            (None, 10, 2048)          0
_________________________________________________________________
lstm_7 (LSTM)                (None, 10, 2048)          33562624
_________________________________________________________________
dropout_1 (Dropout)          (None, 10, 2048)          0
_________________________________________________________________
lstm_8 (LSTM)                (None, 2048)              33562624
_________________________________________________________________
dropout_2 (Dropout)          (None, 2048)              0
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 2049
=================================================================
Total params: 83,929,089
```

```
Trainable params: 83,929,089
Non-trainable params: 0
_________________________________________________________________
```



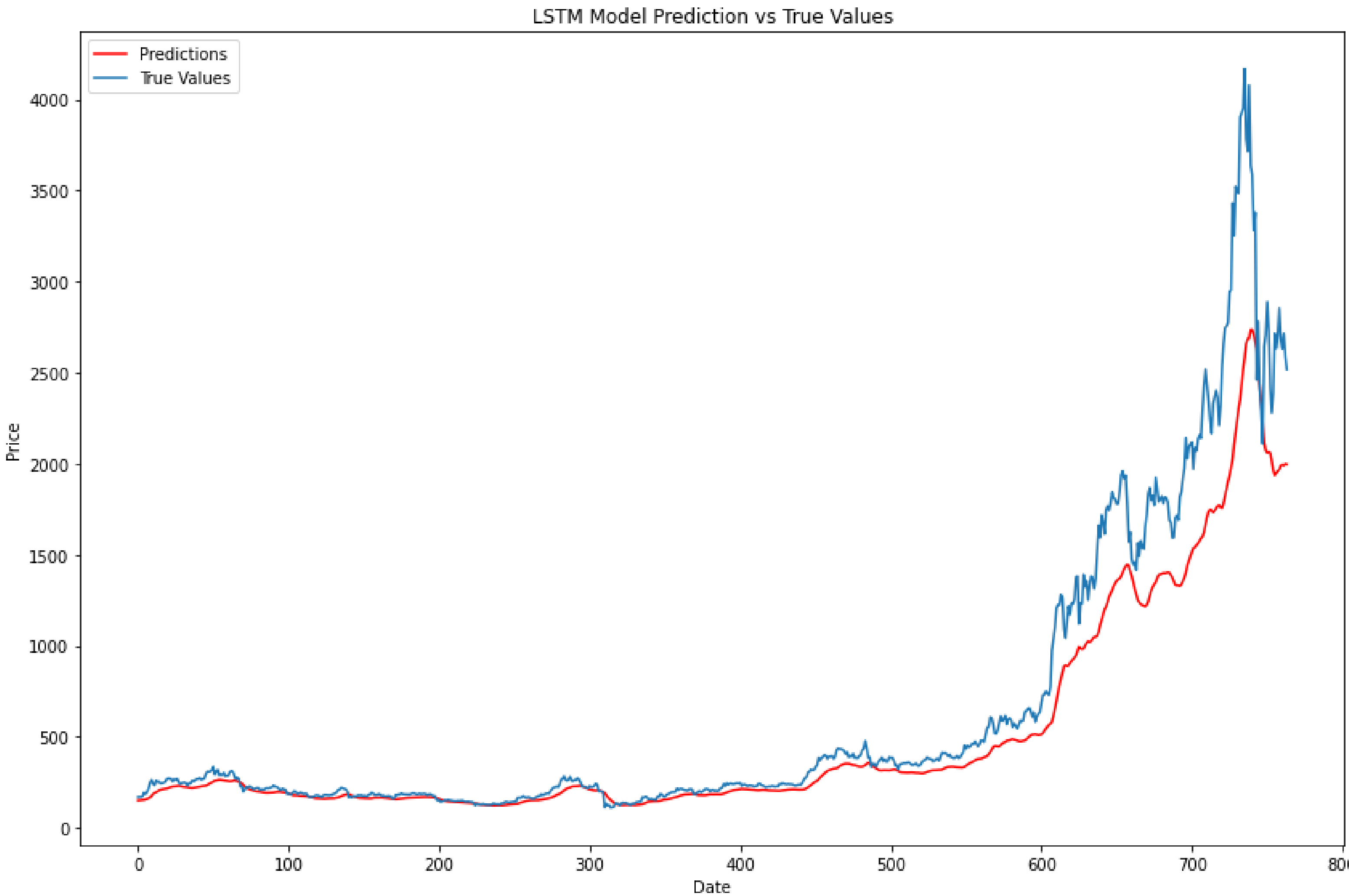

```
(1189, 1)
(764, 1)
```

	Close	Pred
Date		
2019-05-07	169.80	151.342651
2019-05-08	170.95	152.354904
2019-05-09	170.29	153.072327

	Close	Pred
Date		
2019-05-10	173.14	153.775528
2019-05-11	194.30	154.552979
...	...	...
2021-06-04	2688.19	1988.932739
2021-06-05	2630.58	1995.205078
2021-06-06	2715.09	1990.319580
2021-06-07	2590.26	2000.098511
2021-06-08	2517.44	1997.131226

764 rows × 2 columns

```
RMSE = 284.6646972825068
```



6.5.1.1 Overall Results

The best performing model was the model with:

- 1 LSTM layer
- 256 units per layer
- Dropout specified within the LSTM layer rather than being a discrete layer itself

The model predicted higher than actual prices for roughly the first 550 timesteps, and then predicted lower than actual prices for the remaining timesteps.

Overall, the model predictions followed the trend of the actual prices quite closely, correctly timing (although very roughly) the sharp rises and falls in the price of Ethereum. Volatility is what makes trading Ethereum so difficult, and a model that can even roughly predict the highly volatile time periods of the asset can be very useful.

6.6 Summary of Results

Model	RMSE
Random Walk	493.49
Auto-ARIMA	1053.25
Prophet(No Exo)	506.81
Prophet(Exo)	277.92
LSTM (No Exo)	135.55

6.7 Profit/Revenue Calculations

Now that the models have been constructed, let's calculate the net profit made from three different trading strategies:

1. LSTM strategy
2. Simple Moving Average Strategy
3. Buy-and-Hold Strategy

(For the SMA strategy, we will be using the fastquant package. It's details can be found here: https://pypi.org/project/fastquant/#description (https://pypi.org/project/fastquant/#description))

6.7.1 LSTM

In [ ]:
```
investments = 100000
Buy = 0
Sell = 0
for index, pred in enumerate(rmse_df1['Pred']):
  if index==763:
    break
  elif rmse_df1['Pred'][int(index+1)] > pred:
    investments = investments + rmse_df1['Close'][index]
    # print('Buy')
    Buy += 1
  elif rmse_df1['Pred'][index+1] < pred:
    investments = investments - rmse_df1['Close'][index]
    # print('Sell')
    Sell += 1
print(investments)
print(f'Total Buy Orders: {Buy}')
print(f'Total Sell Orders: {Sell}')
```

```
273357.7999999999
Total Buy Orders: 453
Total Sell Orders: 310
```

6.7.1.1 Strategy

The LSTM Trading Strategy is described as such:

- When the model predicts a rise in value for the following day, one unit of Ethereum is bought
- When the model predicts a decline in value for the following day, one unit of Ethereum is sold

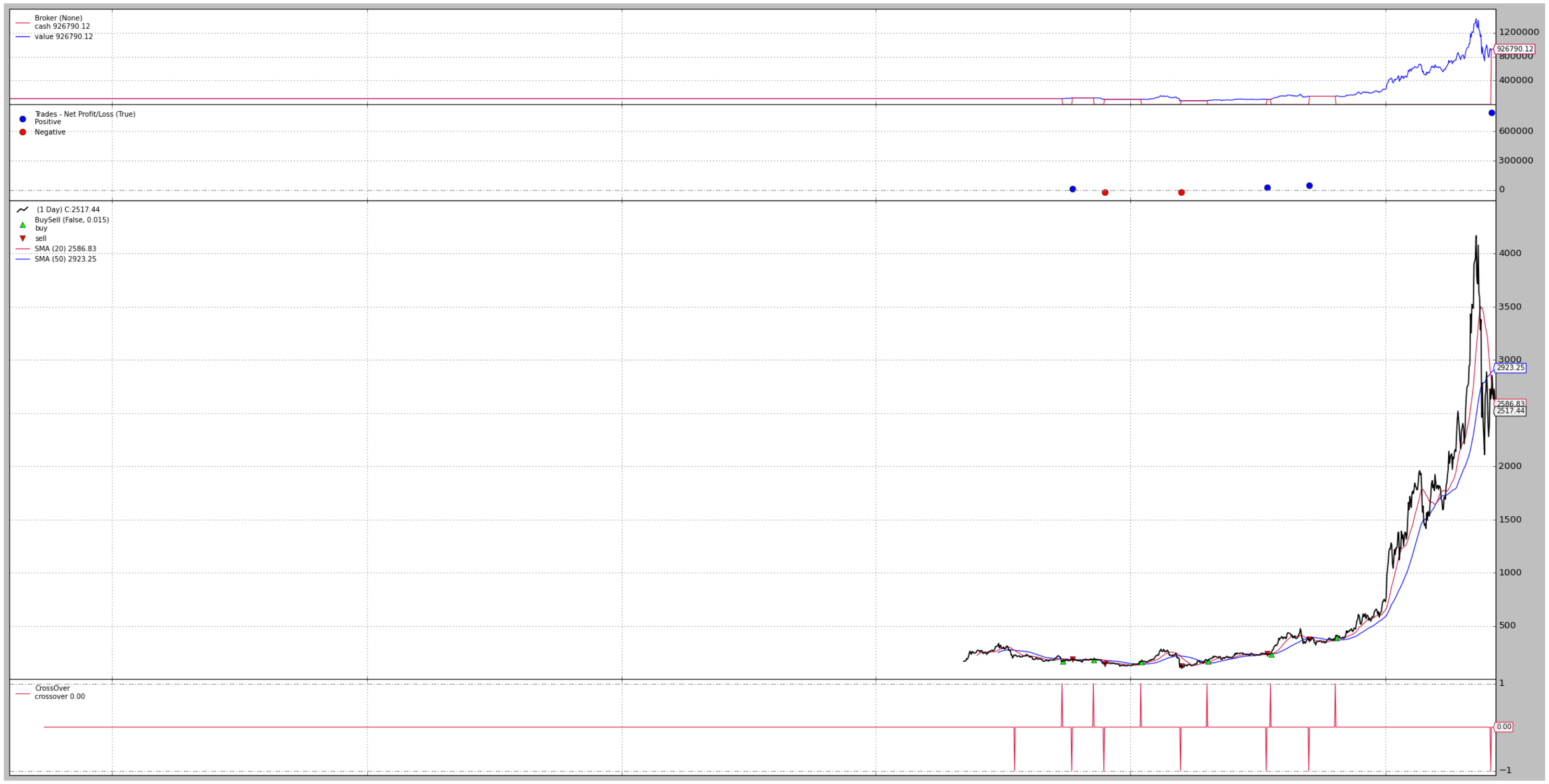
6.7.1.2 Overall Performance

```
* The final portfolio value of  $273,357.79
    * This is a total profit of $173,357.79
* Increased original investment by 2.733x
```

6.7.2 Exponential Moving Average Strategy

In [ ]:

```python
from fastquant import backtest
eth = pd.DataFrame(df['Close'][1369:], index=df.index)
backtest(strategy='smac', data=eth, fast_period=20, slow_period=50, verbose=0)
# plt.savefig('SMA')
```




```
<Figure size 2400x1200 with 0 Axes>
```

6.7.2.1 Strategy

The SMA Trading Strategy follows this logic

- When the moving average intersections indicate a buy opportunity, then one unit of Ethereum will be bought.
- When the moving average intersections indicate a sell opportunity, the one unit of Ethereum is sold.

6.7.2.2 Overall performance

> * Final portfolio value of $926,790.12
>   * Total profit margin of $828,790.12
> * Multiplied initial investment by 9.268x

6.7.3 Buy-and-Hold Strategy

6.7.3.1 Strategy

The Buy-and-Hold strategy follows this logic:

- Make an initial investment of $100,000 and never sell nor buy more.

6.7.3.2 Overall Performance

> * Final Portfolio value of $953,250.79
>   * Total profit margin of $853,250.79
> * Multiplied original investment by 9.533x