Time Series Forecasting - Stock Prices

In [11]:
```
#!pip3 install tiingo[pandas]
```

In [12]:
```
import datetime
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import pickle
import scipy.stats as stats
from statsmodels.graphics.tsaplots import plot_acf
import keras
from tiingo import TiingoClient
```

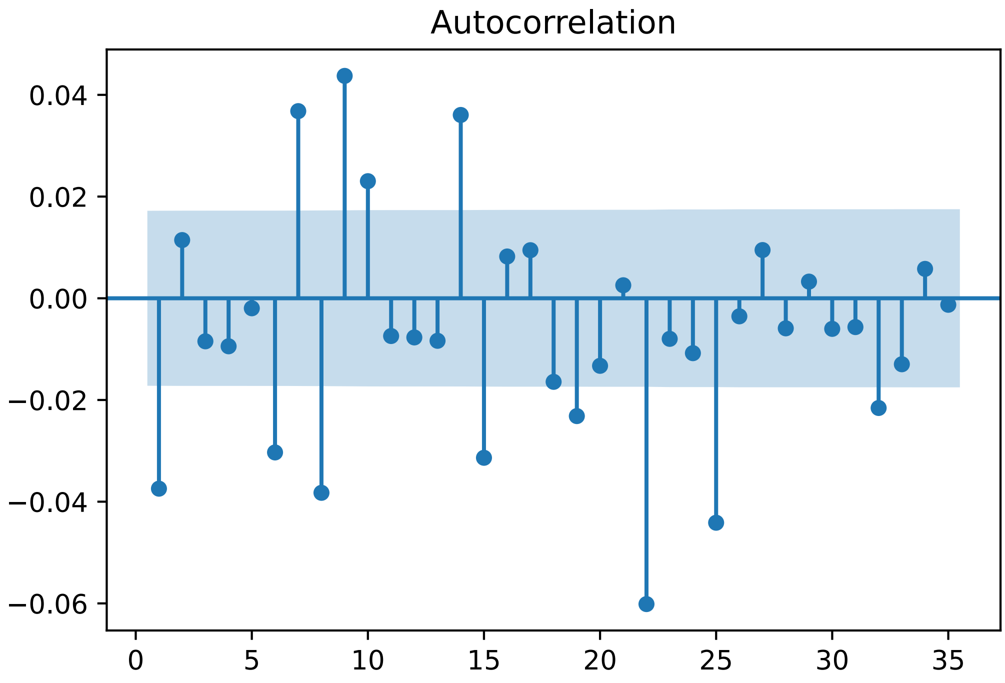
In [13]:
```
# Stream stock price data from Tiingo's API
client = TiingoClient({"session":True, "api_key":"3b31c3a06438982185ad2b3ff8ebd80550

ticker = "IBM"

dt_end = datetime.datetime.now()
dt_start = datetime.datetime.fromtimestamp(0)
tiingo_df = client.get_dataframe(ticker, frequency='daily', startDate=dt_start, endD
df = tiingo_df[tiingo_df.columns[5:5+4]]
df.columns = ['close', 'high', 'low', 'open']
df
```

Out[13]:

	close	high	low	open
date				
1970-01-02 00:00:00+00:00	8.150767	8.173114	8.134008	8.145181
1970-01-05 00:00:00+00:00	8.228979	8.228979	8.178700	8.178700
1970-01-06 00:00:00+00:00	8.234566	8.245739	8.184287	8.228979
1970-01-07 00:00:00+00:00	8.240152	8.240152	8.184287	8.234566
1970-01-08 00:00:00+00:00	8.256912	8.256912	8.212219	8.240152
...	...	...	...	...
2021-06-07 00:00:00+00:00	148.020000	148.740000	147.170000	147.550000
2021-06-08 00:00:00+00:00	149.070000	150.200000	148.120000	148.120000
2021-06-09 00:00:00+00:00	150.670000	151.070000	148.820000	149.030000
2021-06-10 00:00:00+00:00	150.540000	152.840000	149.760000	151.470000
2021-06-11 00:00:00+00:00	151.280000	151.845000	150.370000	150.430000

12975 rows × 4 columns

In [14]:
```
arr = pd.Series(df['close'].diff())
plot_acf(arr[1:], lags = 35, zero=False)
plt.show()
```



In [15]:

```
def create_dataset(df, time_steps):
    samples = []
    date = []
    for counter in range(0,df.shape[0]-time_steps):
        samples.append((df.iloc[counter:counter+time_steps]/df.iloc[counter+time_ste
        date.append(df.index[counter+time_steps])
    return samples, date
```

In [16]:

```
def create_lstm(seq_shape, layer_size_array):
    encoder_layers = []

    decoder_layers = []

    repeat_vector = [keras.layers.RepeatVector(n=seq_shape[0])]

    time_distributed = [keras.layers.TimeDistributed(keras.layers.Dense(units=seq_sh

    for layer_size, counter in zip(layer_size_array, range(len(layer_size_array))):
        if(counter==0 and counter==(len(layer_size_array)-1)):
            encoder_layers.append(keras.layers.LSTM(units=layer_size, input_shape=se
        elif(counter==0):
            encoder_layers.append(keras.layers.LSTM(units=layer_size, input_shape=se
        elif(counter!=(len(layer_size_array)-1)):
            encoder_layers.append(keras.layers.LSTM(units=layer_size, return_sequenc
        else:
            encoder_layers.append(keras.layers.LSTM(units=layer_size, return_sequenc
        decoder_layers.append(keras.layers.LSTM(units=layer_size, return_sequences=T
    layers = encoder_layers + repeat_vector + list(reversed(decoder_layers)) + time_

    model = keras.Sequential(layers)

    model.compile(loss='mean_absolute_error', optimizer='adam')

    return model
```

In [17]:

```
train_df = df[:-df.shape[0]//3]
test_df = df[-df.shape[0]//3:]
```

```
display(train_df)
display(test_df)
```

date	close	high	low	open
1970-01-02 00:00:00+00:00	8.150767	8.173114	8.134008	8.145181
1970-01-05 00:00:00+00:00	8.228979	8.228979	8.178700	8.178700
1970-01-06 00:00:00+00:00	8.234566	8.245739	8.184287	8.228979
1970-01-07 00:00:00+00:00	8.240152	8.240152	8.184287	8.234566
1970-01-08 00:00:00+00:00	8.256912	8.256912	8.212219	8.240152
...	...	...	...	...
2004-03-31 00:00:00+00:00	58.563259	58.818326	58.352830	58.709923
2004-04-01 00:00:00+00:00	58.901222	59.098899	58.422973	58.454856
2004-04-02 00:00:00+00:00	60.068152	60.291335	59.513382	59.653669
2004-04-05 00:00:00+00:00	60.055398	60.176555	59.628162	59.908735
2004-04-06 00:00:00+00:00	59.749318	59.806708	59.315705	59.685552

8650 rows × 4 columns

date	close	high	low	open
2004-04-07 00:00:00+00:00	59.353965	59.672799	58.990496	59.538889
2004-04-08 00:00:00+00:00	59.379472	60.189308	59.016002	59.940618
2004-04-12 00:00:00+00:00	59.774825	60.170178	59.558019	59.621785
2004-04-13 00:00:00+00:00	59.328459	59.966125	58.984119	59.806708
2004-04-14 00:00:00+00:00	59.749318	59.851345	58.729053	58.729053
...	...	...	...	...
2021-06-07 00:00:00+00:00	148.020000	148.740000	147.170000	147.550000
2021-06-08 00:00:00+00:00	149.070000	150.200000	148.120000	148.120000
2021-06-09 00:00:00+00:00	150.670000	151.070000	148.820000	149.030000
2021-06-10 00:00:00+00:00	150.540000	152.840000	149.760000	151.470000
2021-06-11 00:00:00+00:00	151.280000	151.845000	150.370000	150.430000

4325 rows × 4 columns

In [18]:
```
seq_shape = (30, 4)
layer_size = [int(0.1*seq_shape[0]*seq_shape[1])]

train = create_dataset(train_df, seq_shape[0])
test = create_dataset(test_df, seq_shape[0])
```

In [19]:
```
train_mode = True
```

```python
if(train_mode):
    lstm_auto = create_lstm(seq_shape, layer_size)
    lstm_auto.fit(np.array(train[0]) - 1, np.array(train[0]) - 1, epochs=60, batch_s
```

```
Epoch 1/60
87/87 [==============================] - 5s 13ms/step - loss: 0.0427
Epoch 2/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0297
Epoch 3/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0238
Epoch 4/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0188
Epoch 5/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0180
Epoch 6/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0176
Epoch 7/60
87/87 [==============================] - 1s 15ms/step - loss: 0.0170
Epoch 8/60
87/87 [==============================] - 1s 17ms/step - loss: 0.0163
Epoch 9/60
87/87 [==============================] - 1s 15ms/step - loss: 0.0155
Epoch 10/60
87/87 [==============================] - 1s 16ms/step - loss: 0.0151
Epoch 11/60
87/87 [==============================] - 2s 17ms/step - loss: 0.0150
Epoch 12/60
87/87 [==============================] - 1s 16ms/step - loss: 0.0147
Epoch 13/60
87/87 [==============================] - 2s 18ms/step - loss: 0.0146
Epoch 14/60
87/87 [==============================] - 2s 18ms/step - loss: 0.0147
Epoch 15/60
87/87 [==============================] - 1s 15ms/step - loss: 0.0145
Epoch 16/60
87/87 [==============================] - 1s 15ms/step - loss: 0.0144
Epoch 17/60
87/87 [==============================] - 1s 17ms/step - loss: 0.0143
Epoch 18/60
87/87 [==============================] - 1s 17ms/step - loss: 0.0144
Epoch 19/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0143
Epoch 20/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0142
Epoch 21/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0143
Epoch 22/60
87/87 [==============================] - 1s 13ms/step - loss: 0.0141
Epoch 23/60
87/87 [==============================] - 1s 13ms/step - loss: 0.0141
Epoch 24/60
87/87 [==============================] - 1s 13ms/step - loss: 0.0141
Epoch 25/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0139
Epoch 26/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0140
Epoch 27/60
87/87 [==============================] - 1s 15ms/step - loss: 0.0137
Epoch 28/60
87/87 [==============================] - 1s 15ms/step - loss: 0.0139
Epoch 29/60
87/87 [==============================] - 1s 16ms/step - loss: 0.0138
Epoch 30/60
87/87 [==============================] - 1s 16ms/step - loss: 0.0137
Epoch 31/60
87/87 [==============================] - 1s 15ms/step - loss: 0.0138
Epoch 32/60
87/87 [==============================] - 2s 17ms/step - loss: 0.0138
Epoch 33/60
```

```
87/87 [==============================] - 1s 16ms/step - loss: 0.0138
Epoch 34/60
87/87 [==============================] - 1s 13ms/step - loss: 0.0135
Epoch 35/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0136
Epoch 36/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0135
Epoch 37/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0135
Epoch 38/60
87/87 [==============================] - 1s 13ms/step - loss: 0.0135
Epoch 39/60
87/87 [==============================] - 1s 13ms/step - loss: 0.0134
Epoch 40/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0134
Epoch 41/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0133
Epoch 42/60
87/87 [==============================] - 1s 16ms/step - loss: 0.0134
Epoch 43/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0134
Epoch 44/60
87/87 [==============================] - 1s 17ms/step - loss: 0.0133
Epoch 45/60
87/87 [==============================] - 1s 15ms/step - loss: 0.0132
Epoch 46/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0131
Epoch 47/60
87/87 [==============================] - 2s 18ms/step - loss: 0.0132
Epoch 48/60
87/87 [==============================] - 1s 17ms/step - loss: 0.0131
Epoch 49/60
87/87 [==============================] - 1s 13ms/step - loss: 0.0129
Epoch 50/60
87/87 [==============================] - 1s 13ms/step - loss: 0.0130
Epoch 51/60
87/87 [==============================] - 1s 13ms/step - loss: 0.0129
Epoch 52/60
87/87 [==============================] - 1s 13ms/step - loss: 0.0130
Epoch 53/60
87/87 [==============================] - 1s 13ms/step - loss: 0.0128
Epoch 54/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0129
Epoch 55/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0128
Epoch 56/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0126
Epoch 57/60
87/87 [==============================] - 1s 13ms/step - loss: 0.0128
Epoch 58/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0127
Epoch 59/60
87/87 [==============================] - 1s 13ms/step - loss: 0.0126
Epoch 60/60
87/87 [==============================] - 1s 14ms/step - loss: 0.0125
```

In [20]:

```
error = np.abs(lstm_auto.predict(np.array(test[0]) - 1) - (np.array(test[0]) - 1))
error = error.reshape(error.shape[0], error.shape[1]*error.shape[2])
err_ser = pd.Series(error.mean(axis=1))
err_ser.index = test[1]
err_ser
```

Out[20]:

```
2004-05-20 00:00:00+00:00    0.006538
2004-05-21 00:00:00+00:00    0.006840
2004-05-24 00:00:00+00:00    0.006839
2004-05-25 00:00:00+00:00    0.007543
2004-05-26 00:00:00+00:00    0.006592
                               ...
```

```
2021-06-07 00:00:00+00:00    0.005852
2021-06-08 00:00:00+00:00    0.006067
2021-06-09 00:00:00+00:00    0.006353
2021-06-10 00:00:00+00:00    0.006468
2021-06-11 00:00:00+00:00    0.005570
Length: 4295, dtype: float64
```

In [21]:

```
mean =  err_ser.rolling(250).mean().dropna()
std =  err_ser.rolling(250).std().dropna()
err_ser_sub =  err_ser.loc[std.index[0]:]
err_ser_sub
```

Out[21]:

```
2005-05-17 00:00:00+00:00    0.021902
2005-05-18 00:00:00+00:00    0.023832
2005-05-19 00:00:00+00:00    0.027592
2005-05-20 00:00:00+00:00    0.030131
2005-05-23 00:00:00+00:00    0.028962
                               ...
2021-06-07 00:00:00+00:00    0.005852
2021-06-08 00:00:00+00:00    0.006067
2021-06-09 00:00:00+00:00    0.006353
2021-06-10 00:00:00+00:00    0.006468
2021-06-11 00:00:00+00:00    0.005570
Length: 4046, dtype: float64
```

In [22]:

```
vol_time_series = (df['close'].rolling(30).std()/df['close']).loc[err_ser_sub.index[
price_time_series = df['close'].loc[err_ser_sub.index[0]:]
```

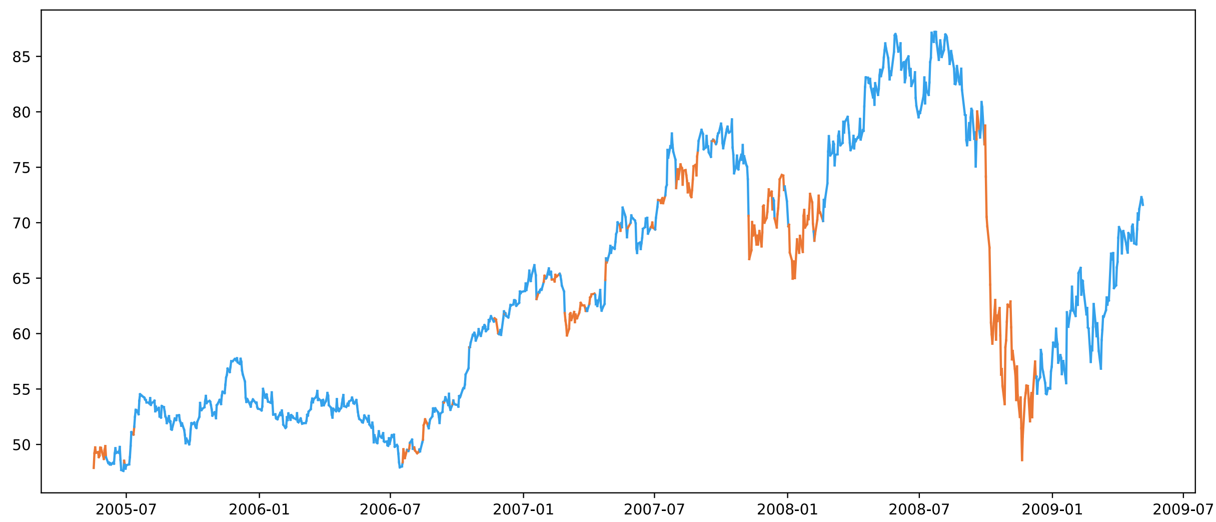
In [23]:

```
def multi_color_line_plotter(x ,y , condition):
    plt.figure(figsize=(14,6))

    for x1, x2, y1,y2, cond in zip(x, x[1:], y, y[1:], condition):
        if cond:
            plt.plot([y1, y2], [x1, x2], '#eb7734')
        else:
            plt.plot([y1, y2], [x1, x2], '#34a1eb')

    plt.show()
```

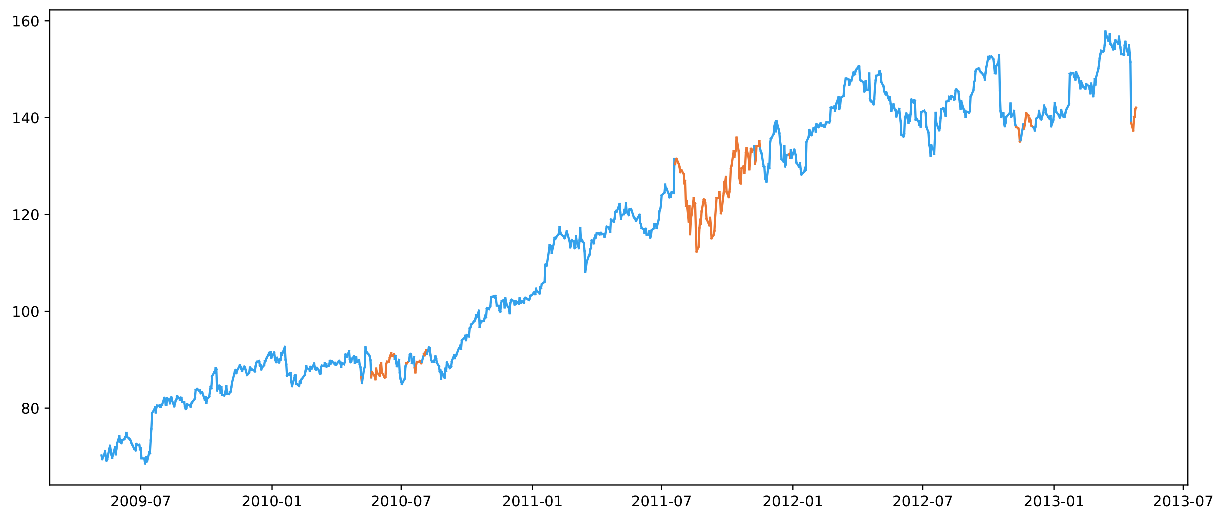
In [24]:

```
condition = (err_ser_sub>(mean+(1*std)))

print("PRICE SERIES DATA")
for counter in range(0,5000,1000):
    multi_color_line_plotter(price_time_series.iloc[counter:counter+1000],
                             price_time_series.iloc[counter:counter+1000].index,
                             condition.iloc[counter:counter+1000])

print("VOLUME SERIES DATA")

multi_color_line_plotter(vol_time_series,
                         vol_time_series.index,
                         condition)
```

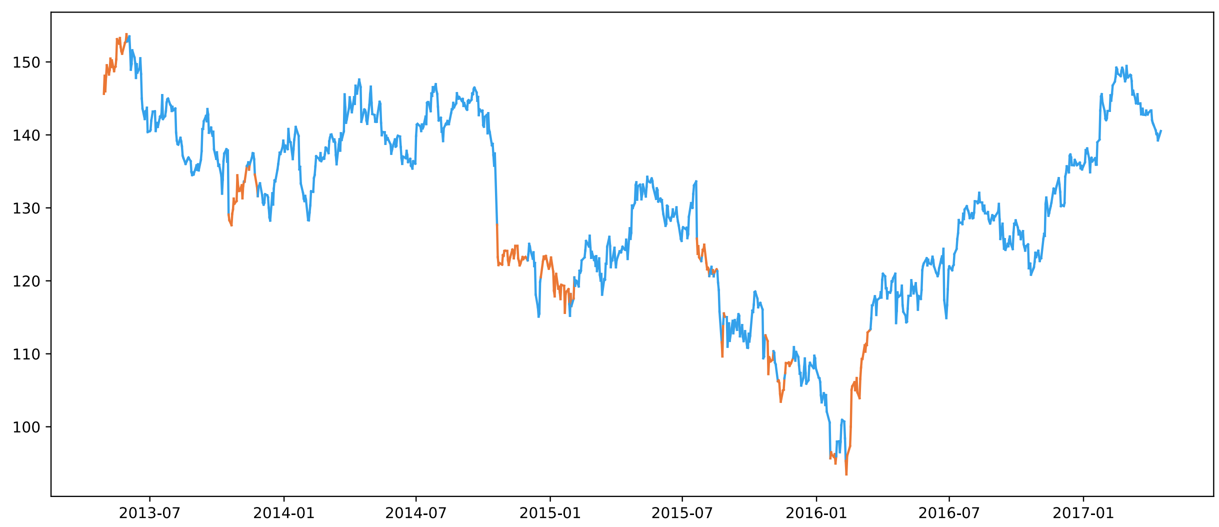
```
PRICE SERIES DATA
```



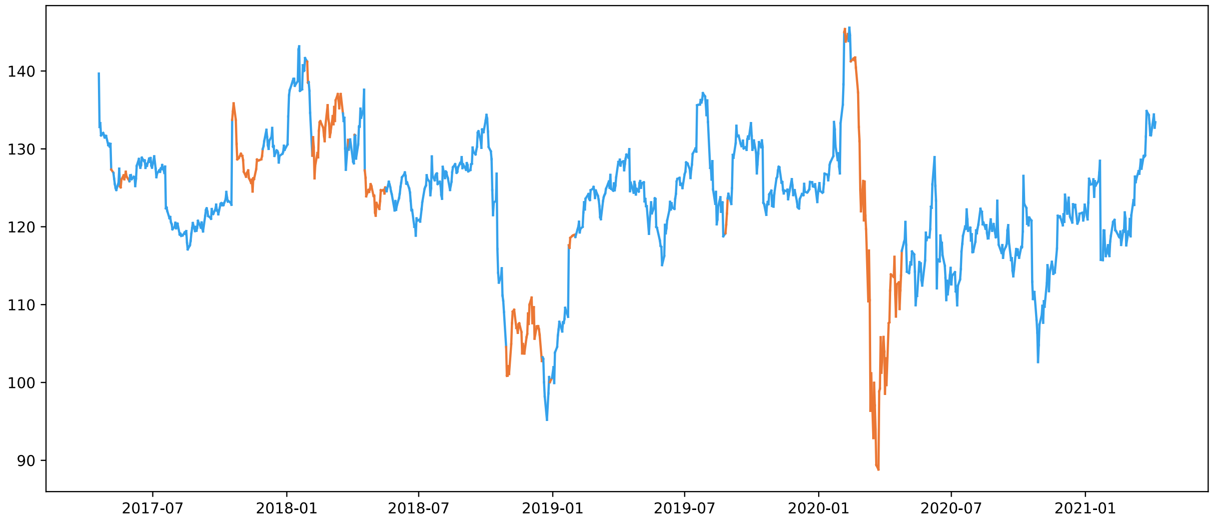
85
80
75
70
65
60
55
50
2005-07
2006-01
2006-07
2007-01
2007-07
2008-01
2008-07
2009-01
2009-07

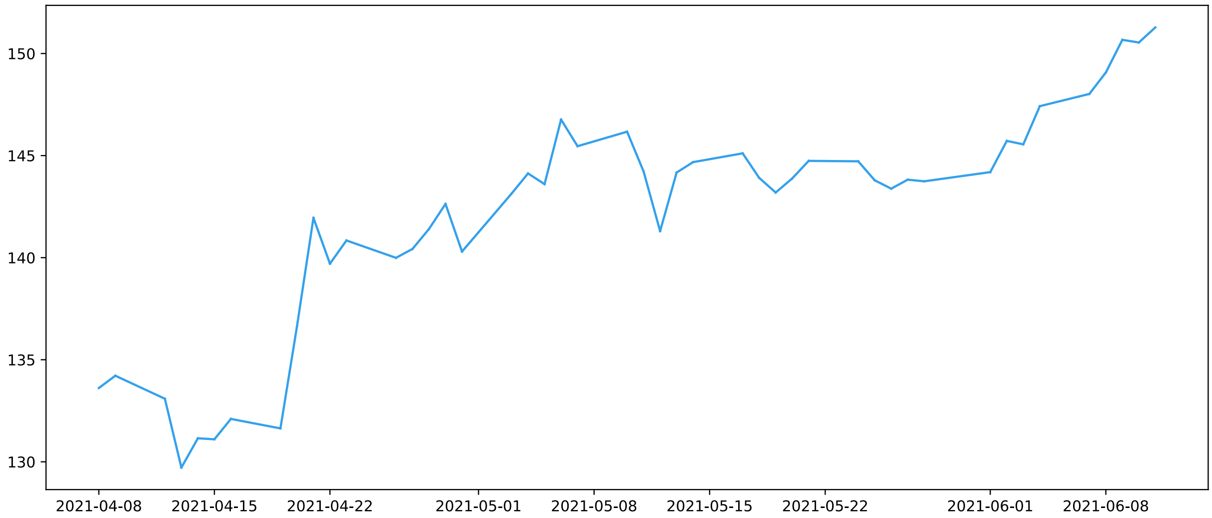


160
140
120
100
80
2009-07
2010-01
2010-07
2011-01
2011-07
2012-01
2012-07
2013-01
2013-07

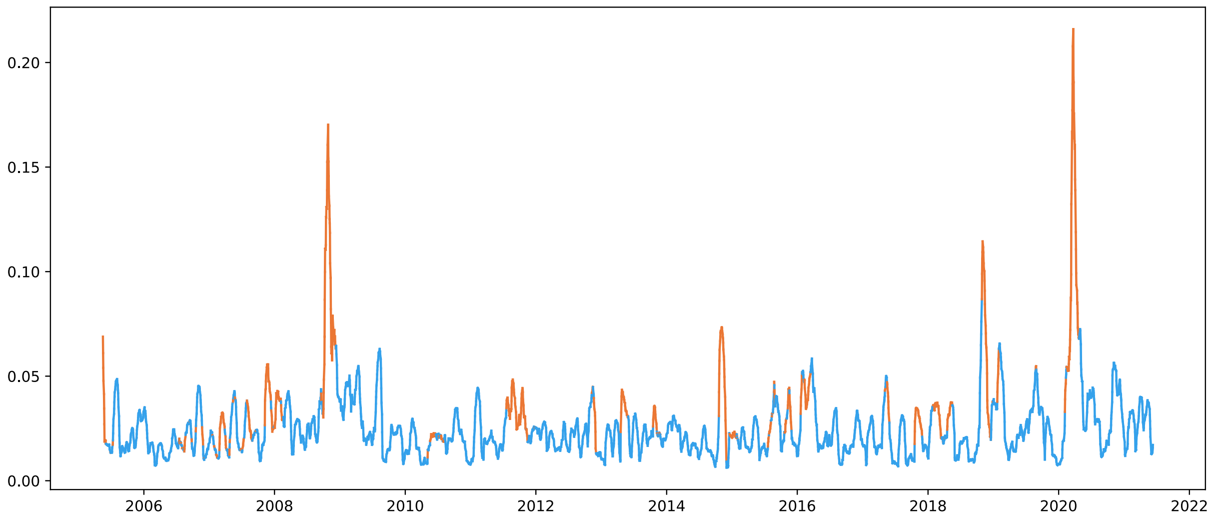


150
140
130
120
110
100
2013-07
2014-01
2014-07
2015-01
2015-07
2016-01
2016-07
2017-01





VOLUME SERIES DATA



In [25]:
```
stats.ttest_ind(vol_time_series[condition], vol_time_series[condition.apply(lambda x
```

Out[25]:
```
3.346401346125253e-178
```