ReadMe

This exercise is about Bitcoin. The data records all trades at Coinbase in March 2020. Unluckily, we only see market price and quantity traded. But the data gives the indicator of “BUY” or “SELL” on the taker side. This indicator is not available for most of equity trades dataset.

Questions:

- Calculate Kyle’s lambda (market impact) for all the data in March
- Calculate Kyle’s lambda (market impact), volume, signed volume, volume-weighted price by day and hour
- Plot constructed variables in the previous bullet point
- What patterns do you see? Make some comments
- Is there momentum in Bitcoin returns?
- Can you figure out good predictor variables for returns?
- Construct a trading strategy based on your analysis
- Plot the performance of the trading strategy

Import the relevant modules

In [27]:
```
import pandas as pd
pd.options.mode.chained_assignment = None  # default='warn'
import numpy as np
import yfinance as yf
import requests
from math import sqrt
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import datatable as dt
from datatable import dt, f, by, g, join, sort, update, ifelse
import os
import math
import gzip
from datetime import datetime
from regpyhdfe import Regpyhdfe
import warnings
```

In [52]:
```
# Read in all files in the folder (note that some files have difference size
base_dir = '/Users/a.kanstantsinau/Downloads/BTC_coinbase_trades'

# Empty list to store df
dataframes_list = []

# Credit to ChatGPT for helping with .csv.gz
# Iterate over each folder in the base directory
for folder_name in os.listdir(base_dir):
    folder_path = os.path.join(base_dir, folder_name)
```

```
    # Check if it's a directory
    if os.path.isdir(folder_path):
        # Iterate over each file in the folder
        for file_name in os.listdir(folder_path):
            file_path = os.path.join(folder_path, file_name)

            # Check if the file is a .csv.gz
            if file_path.endswith('.csv.gz'):
                # Read the compressed CSV into a DataFrame
                with gzip.open(file_path, 'rt') as f:
                    df = pd.read_csv(f)

                # Append the DataFrame to the list
                dataframes_list.append(df)

# Concatenate all DataFrames in the list into a single DataFrame
bitcoin_df = pd.concat(dataframes_list, ignore_index=True)
```

In [53]:

```
# First we need to split bitcoin df columns
column_names = bitcoin_df.columns[0].split(';')
bitcoin_df = bitcoin_df[bitcoin_df.columns[0]].str.split(';', expand=True)

# Assign the columns
bitcoin_df.columns = column_names
```

In [54]:

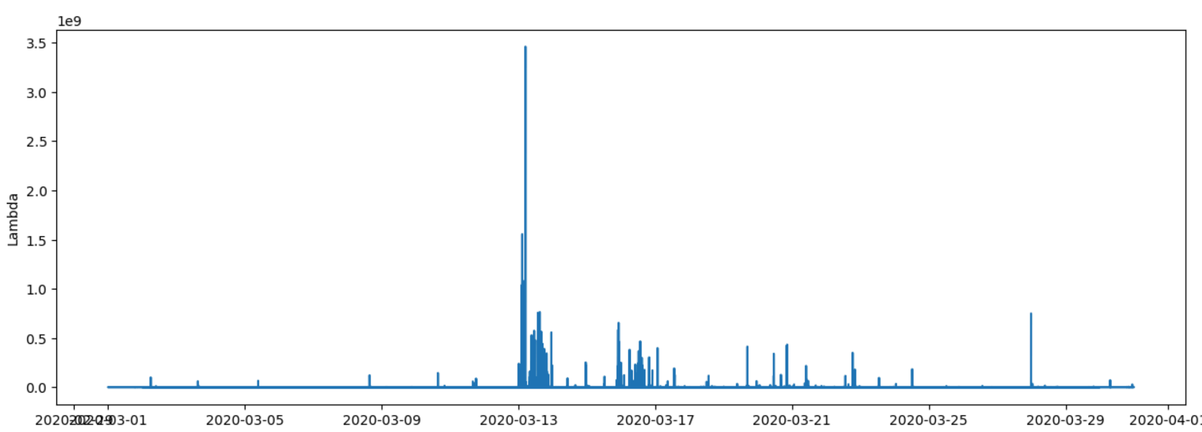
```
# Make price and base amount columns numbers
bitcoin_df['price'] = bitcoin_df['price'].str.replace('[^0-9.]', '', regex=T
bitcoin_df['base_amount'] = bitcoin_df['base_amount'].str.replace('[^0-9.]',

# Create lambda column
bitcoin_df['lambda'] = abs(bitcoin_df['price'].shift(1) - bitcoin_df['price'
bitcoin_df.head(5)
```

Out[54]:

	time_exchange	time_coinapi	guid	price	base_amount
0	2020-03-07T00:00:00.4122620	2020-03-07T00:00:00.4748686	6131eff3-d0c4-46c6-9ce0-dee7f12eb56e	9158.51	0.017000
1	2020-03-07T00:00:00.4263060	2020-03-07T00:00:00.4903598	1b95b626-9a8c-4e37-ab7f-a759caee1706	9158.51	0.020000
2	2020-03-07T00:00:02.1293840	2020-03-07T00:00:02.1912774	706b9548-901a-492d-85e8-0ca748d87f93	9158.51	0.031866
3	2020-03-07T00:00:02.7543310	2020-03-07T00:00:02.8193264	b0dbad26-7915-481c-b536-6d70b7f6f246	9158.51	0.004999
4	2020-03-07T00:00:04.4254900	2020-03-07T00:00:04.5051976	596ee51a-8907-4494-9560-50442f9e2e0c	9158.51	0.001468

In [55]:

```python
# Convert date columns to date
bitcoin_df['time_exchange'] = pd.to_datetime(bitcoin_df['time_exchange'])
bitcoin_df['time_coinapi'] = pd.to_datetime(bitcoin_df['time_coinapi'])

# Set index
bitcoin_df.set_index('time_exchange', inplace=True)

# Plot March lambda
plt.figure(figsize=(15,5))
plt.plot(bitcoin_df.index, bitcoin_df['lambda'], label='Lambda')
plt.xlabel('Date')
plt.ylabel('Lambda')
plt.show()
```



In [56]:
```
# Get price impact
bitcoin_df['Price Impact'] = (bitcoin_df['price'].shift(1) - bitcoin_df['pri
```

In [57]:
```
# Calculate the return
bitcoin_df['Return'] = bitcoin_df['price'].pct_change()
```

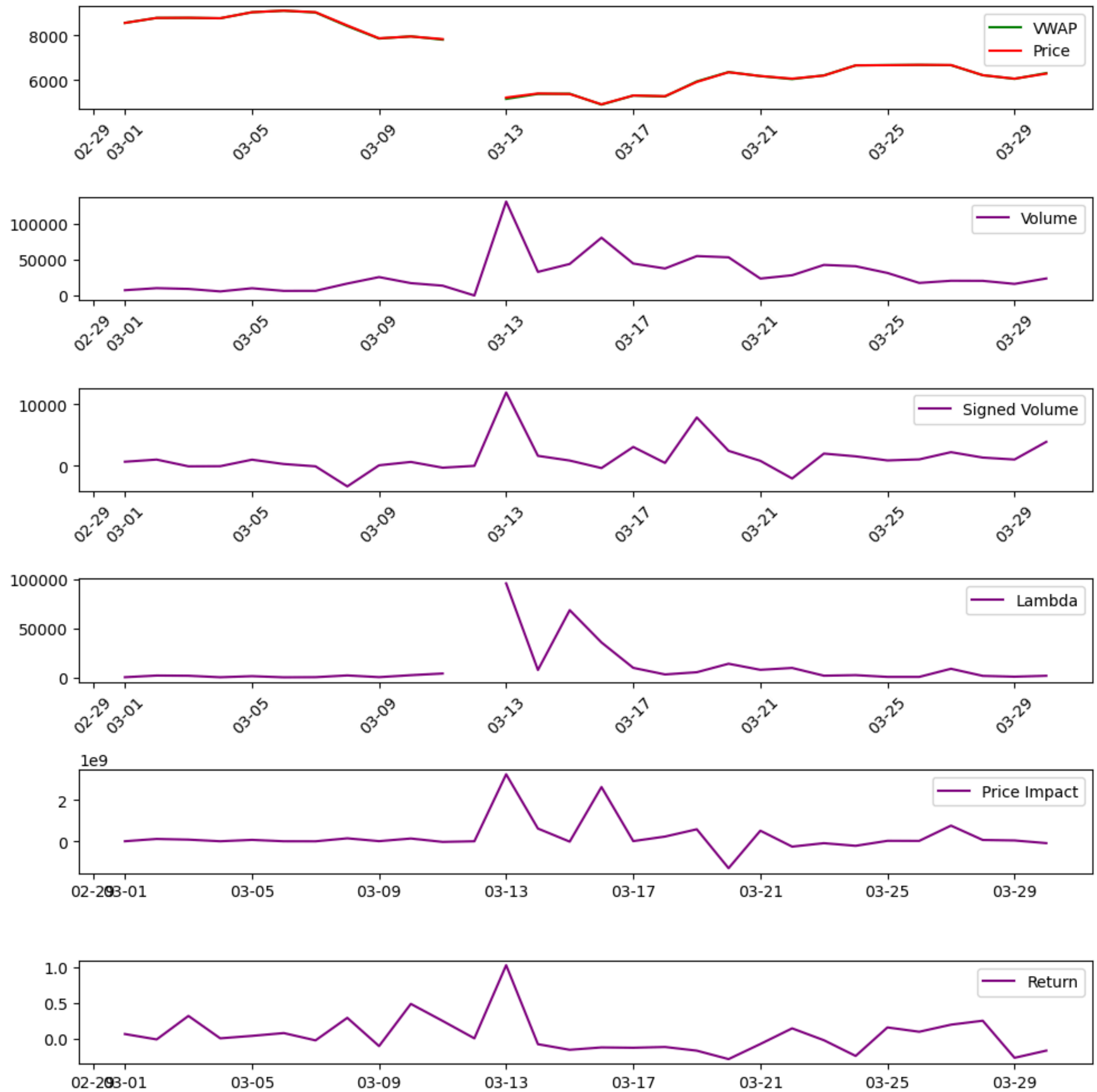
In [59]:
```
# Supress warnings for future use
warnings.simplefilter(action='ignore', category=FutureWarning)
warnings.filterwarnings('ignore', category=RuntimeWarning)

# Get signed volume
bitcoin_df['numeric_taker_side'] = bitcoin_df['taker_side'].apply(lambda x:
bitcoin_df['signed_volume'] = bitcoin_df['base_amount'] * bitcoin_df['numeri

# Create new list for daily and hourly values
daily_bitcoin_df = pd.DataFrame()
hourly_bitcoin_df = pd.DataFrame()

# Calculate values on a daily basis
for name, group in bitcoin_df.groupby(pd.Grouper(freq='D')):
    volume = group['base_amount'].sum()
    signed_volume = group['signed_volume'].sum()
    vwap = (group['price'] * group['base_amount']).sum() / group['base_amour
    price = group['price'].mean()
    kyles_lambda = group['lambda'].mean()
    price_impact = group['Price Impact'].sum()
    my_return = group['Return'].sum()

    # Add values to the dataframe
    daily_bitcoin_df = daily_bitcoin_df.append({
        'Date': name,
        'Volume': volume,
        'Signed Volume': signed_volume,
        'VWAP': vwap,
        'Price': price,
        'Lambda': kyles_lambda,
        'Price Impact': price_impact,
        'Return': my_return
    }, ignore_index = True)

daily_bitcoin_df.head(5)
```

Out[59]:

	Date	Volume	Signed Volume	VWAP	Price	Lambda	Pric
0	2020-03-01	7353.139605	670.057258	8549.464432	8549.104019	167.744675	1.078
1	2020-03-02	10216.692545	1017.293502	8772.556464	8771.874792	1864.348493	1.124
2	2020-03-03	9152.706926	-72.819076	8774.882854	8778.829091	1656.394232	7.821
3	2020-03-04	5688.585097	-53.073086	8755.681862	8758.051194	121.277132	5.542
4	2020-03-05	10073.314212	1003.244877	9025.289703	9025.864126	1226.571195	6.645

In [61]:

```
# Create plots for each column against date
fig, axs = plt.subplots(6, 1, figsize=(10,10))
axs[0].plot(daily_bitcoin_df['Date'], daily_bitcoin_df['VWAP'], label='VWAP'
axs[0].plot(daily_bitcoin_df['Date'], daily_bitcoin_df['Price'], label='Pric

axs[1].plot(daily_bitcoin_df['Date'], daily_bitcoin_df['Volume'], label='Vol

axs[2].plot(daily_bitcoin_df['Date'], daily_bitcoin_df['Signed Volume'], lab

axs[3].plot(daily_bitcoin_df['Date'], daily_bitcoin_df['Lambda'], label='Lam

axs[4].plot(daily_bitcoin_df['Date'], daily_bitcoin_df['Price Impact'], labe

axs[5].plot(daily_bitcoin_df['Date'], daily_bitcoin_df['Return'], label='Ret

# Code Credit ChatGPT
date_form = mdates.DateFormatter("%m-%d")
for ax in axs.flat:
    ax.xaxis.set_major_formatter(date_form)
    ax.legend()

# Rotate date labels for clarity
plt.setp(axs[0].xaxis.get_majorticklabels(), rotation=45)
plt.setp(axs[1].xaxis.get_majorticklabels(), rotation=45)
plt.setp(axs[2].xaxis.get_majorticklabels(), rotation=45)
plt.setp(axs[3].xaxis.get_majorticklabels(), rotation=45)

plt.tight_layout()
plt.show()
```



In [63]:
```python
# Repeat the same process for daily values
for name, group in bitcoin_df.groupby(pd.Grouper(freq='H')):
    volume = group['base_amount'].sum()
    signed_volume = group['signed_volume'].sum()
    vwap = (group['price'] * group['base_amount']).sum() / group['base_amour
    price = group['price'].mean()
    kyles_lambda = group['lambda'].mean()
    price_impact = group['Price Impact'].sum()
    my_return = group['Return'].sum()

    hourly_bitcoin_df = hourly_bitcoin_df.append({
        'Date': name,
        'Volume': volume,
        'Signed Volume': signed_volume,
        'VWAP': vwap,
        'Price': price,
        'Lambda': kyles_lambda,
        'Price Impact': price_impact,
        'Return': my_return
```

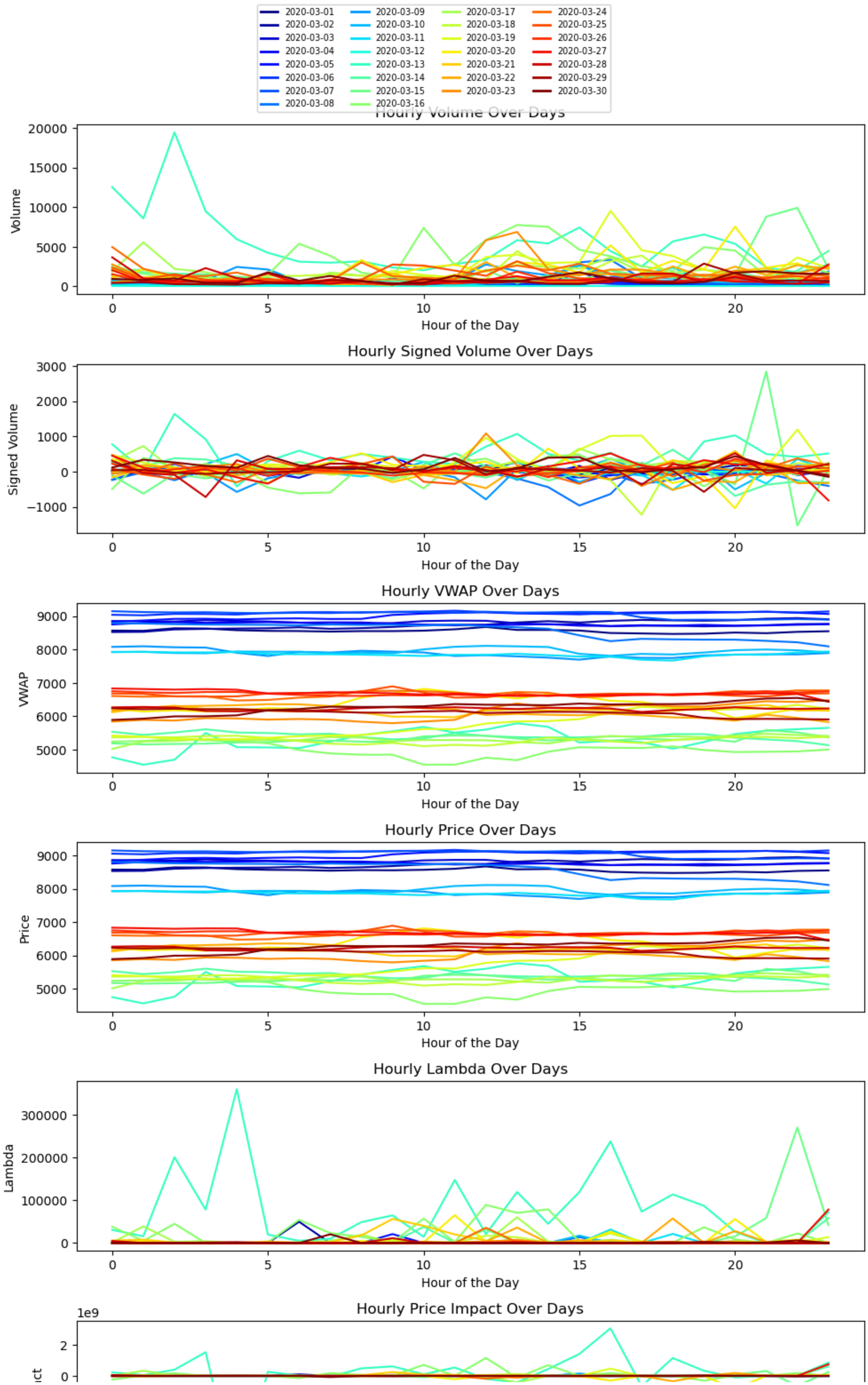
```
    }, ignore_index=True)

hourly_bitcoin_df.head(5)
```

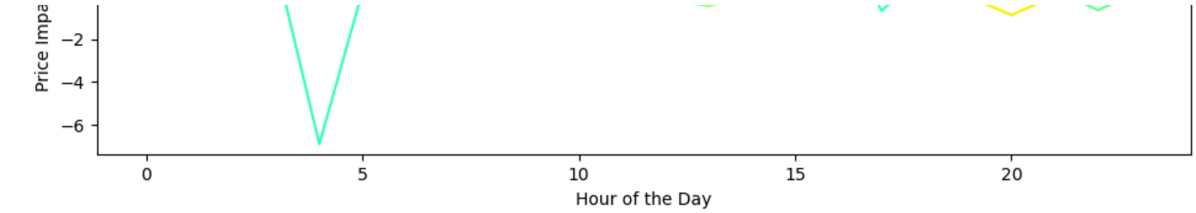
Out[63]:

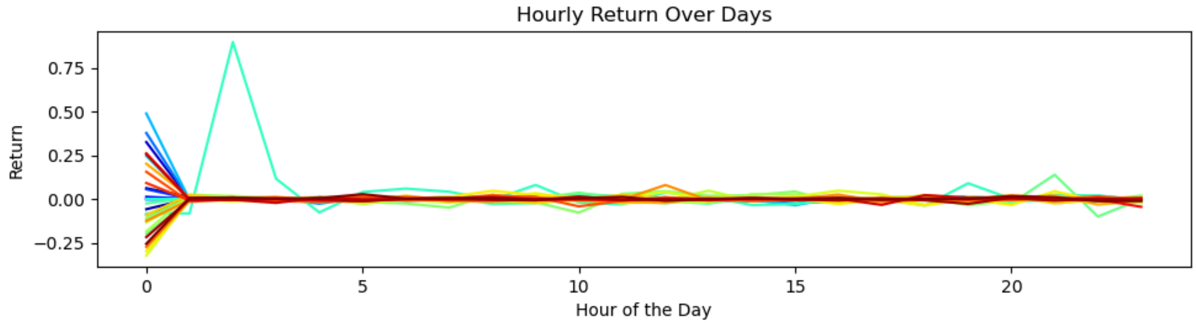
	Date	Volume	Signed Volume	VWAP	Price	Lambda	Price
0	2020-03-01 00:00:00	514.619429	45.744323	8567.692894	8571.759153	141.768492	-68810.
1	2020-03-01 01:00:00	391.800589	-9.060931	8560.983080	8566.824289	175.472037	-329177.
2	2020-03-01 02:00:00	248.169058	2.646862	8637.702911	8637.605797	89.949865	-23732.4
3	2020-03-01 03:00:00	266.848771	-13.897015	8629.865826	8635.287055	61.380060	-29966.9
4	2020-03-01 04:00:00	305.307608	-8.713283	8580.148682	8585.868744	52.843142	10128.

In [71]:

```
# Set new index
#hourly_bitcoin_df.set_index('Date', inplace=True)

# Plate hourly values, day on day
dates = hourly_bitcoin_df.index.normalize().unique()
colors = plt.cm.jet(np.linspace(0, 1, len(dates)))

# Create plots
fig, axs = plt.subplots(7, 1, figsize=(10, 20))  # One subplot for each valu

for i, col in enumerate(['Volume', 'Signed Volume', 'VWAP', 'Price', 'Lambda
    # Plot each day with a unique color
    for date, color in zip(dates, colors):
        daily_data = hourly_bitcoin_df[hourly_bitcoin_df.index.date == date.
        axs[i].plot(daily_data.index.hour, daily_data[col], label=date.strft

    axs[i].set_title(f'Hourly {col} Over Days')
    axs[i].set_xlabel('Hour of the Day')
    axs[i].set_ylabel(col)

handles = [plt.Line2D([0], [0], color=color, lw=2) for color in colors]
labels = [date.strftime('%Y-%m-%d') for date in dates]
fig.legend(handles, labels, loc='upper center', ncol=4, fontsize='x-small')

plt.tight_layout(rect=[0, 0, 1, 0.95])  # Adjust the rect to fit the custom
plt.show()
```


2020-03-01
2020-03-02
2020-03-03
2020-03-04
2020-03-05
2020-03-06
2020-03-07
2020-03-08
2020-03-09
2020-03-10
2020-03-11
2020-03-12
2020-03-13
2020-03-14
2020-03-15
2020-03-16
2020-03-17
2020-03-18
2020-03-19
2020-03-20
2020-03-21
2020-03-22
2020-03-23
2020-03-24
2020-03-25
2020-03-26
2020-03-27
2020-03-28
2020-03-29
2020-03-30
Hourly Volume Over Days
Volume
Hour of the Day
Hourly Signed Volume Over Days
Signed Volume
Hour of the Day
Hourly VWAP Over Days
VWAP
Hour of the Day
Hourly Price Over Days
Price
Hour of the Day
Hourly Lambda Over Days
Lambda
Hour of the Day
Hourly Price Impact Over Days
1e9





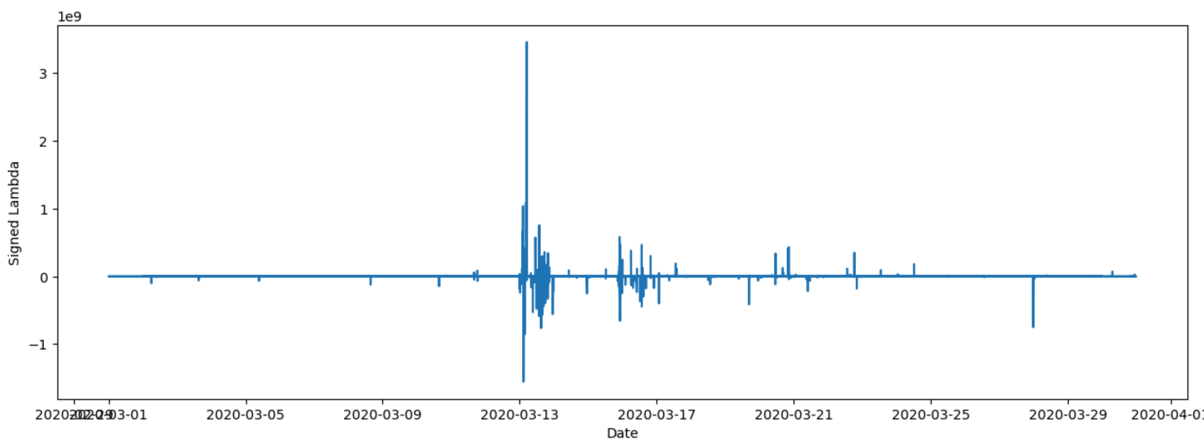
Based on the graphs, we can say that the huge price changes (price drop around 3/13) reflect in more variance. We can see how blue (beginning of the month) and red (end of the month) graphs don't have much variance and tend to stay around the same level in every metric, which the green yellow are more volatile and also have much higher lambda.

In [72]:
```
# Get signed lambda
bitcoin_df['Signed Lambda'] = bitcoin_df['lambda'] * bitcoin_df['numeric_tak
bitcoin_df.head(5)
```

Out[72]:

	time_coinapi	guid	price	base_amount	taker_si
time_exchange					
2020-03-07 00:00:00.412262	2020-03-07 00:00:00.474868600	6131eff3-d0c4-46c6-9ce0-dee7f12eb56e	9158.51	0.017000	B
2020-03-07 00:00:00.426306	2020-03-07 00:00:00.490359800	1b95b626-9a8c-4e37-ab7f-a759caee1706	9158.51	0.020000	B
2020-03-07 00:00:02.129384	2020-03-07 00:00:02.191277400	706b9548-901a-492d-85e8-0ca748d87f93	9158.51	0.031866	B
2020-03-07 00:00:02.754331	2020-03-07 00:00:02.819326400	b0dbad26-7915-481c-b536-6d70b7f6f246	9158.51	0.004999	B
2020-03-07 00:00:04.425490	2020-03-07 00:00:04.505197600	596ee51a-8907-4494-9560-50442f9e2e0c	9158.51	0.001468	B

In [74]:
```
plt.figure(figsize=(15, 5))
plt.plot(bitcoin_df.index, bitcoin_df['Signed Lambda'], label='Signed Lambda
plt.xlabel('Date')
plt.ylabel('Signed Lambda')
plt.show()
```



In [2]:
```
# Assign trading side

# Calculate trading signed trading volume (buy - sell)

# Calcuate return
```

Calculate price impact

Note that price impact means price movement due to 1 dollar of trade of 1 share of trade. Question, why is it better to define price impact using Δp of trader than Δp share of trade?

Overall price impact

Price impact by hour

This requires to first aggregate data to data/hour level

Forecasting Power of lambda

Try signed lambda

Trading Strategy based on Signed lambda

According to the information it seems like it makes sense to go with the market, meaning we buy when lambda is positive and sell when the lambda is negative.