Alpaca API Trading

Selected 4 assets to construct a portfolio, namely, Apple stocks and 3 other ETF securities, SPDR S&P 500 ETF Trust, Vanguard 500 Index Fund ETF and Vanguard Total Bond Market Index Fund ETF.

In [70]:
```
#imported libraries
import requests
import json
import pandas_datareader as web
import pandas as pd
import numpy as np
import datetime
import yfinance as yf
import scipy
from scipy.optimize import minimize
import matplotlib.pyplot as plt
import mplfinance as fplt
```

In [71]:
```
#called data for Adjusted Closing price of assets.
def get_data(tickers):
    df = yf.download(tickers)["Adj Close"]
    df.columns = tickers
    df.ffill().dropna(inplace = True)
    return(df)
```

In [72]:
```
#called Alpaca Broker API
API_KEY = "PKAFXSUMNDHG6RKLUCAF"
SECRET_KEY = "ZSMYUTPibqRt8aBkx9bI785e5x4ryRcNLMafD4Fi"
BASE_URL = "https://paper-api.alpaca.markets"
ACCOUNT_URL = BASE_URL + "/v2/account"
ORDERS_URL =  BASE_URL + "/v2/orders"

def stocks(symbol, quantity, side, type_, time_in_force):
    stocks_data = {
            "symbol": symbol,
            "qty": quantity,
            "side": side,
            "type": type_,
            "time_in_force": time_in_force
            }


    response = requests.post(ORDERS_URL, data=json.dumps(stocks_data), headers= {"ALPCA-API-KEY-ID": API_KEY,
        'APCA-API-SECRET-KEY': SECRET_KEY})
    return json.loads(response.content)
```

In [73]:
```
tickers = ["SPY", "BND", "VOO", "AAPL"]
```

In [74]:
```
#created a function with equal weights for all securities.
def equal_weight(tickers):
    optimal = [1/len(tickers) for i in range(len(tickers))]
    return optimal
```

In [75]:
```
#calculated returns
df_stocks = get_data(tickers)
returns = np.log(df_stocks / df_stocks.shift(1))
returns
```

```
[*********************100%%**********************]  4 of 4 completed
```

Out[75]:

Date	SPY	BND	VOO	AAPL
1980-12-12	NaN	NaN	NaN	NaN
1980-12-15	-0.053581	NaN	NaN	NaN
1980-12-16	-0.076231	NaN	NaN	NaN
1980-12-17	0.024450	NaN	NaN	NaN
1980-12-18	0.028580	NaN	NaN	NaN
...	...	...	...	...
2024-01-08	0.023887	0.004389	0.014175	0.014202
2024-01-09	-0.002266	-0.000137	-0.001518	-0.002433
2024-01-10	0.005655	-0.001781	0.005639	0.006575
2024-01-11	-0.003228	0.005197	-0.000441	-0.000343
2024-01-12	0.001777	0.002044	0.000692	0.000457

10862 rows × 4 columns

In [76]:

```
df_stocks
```

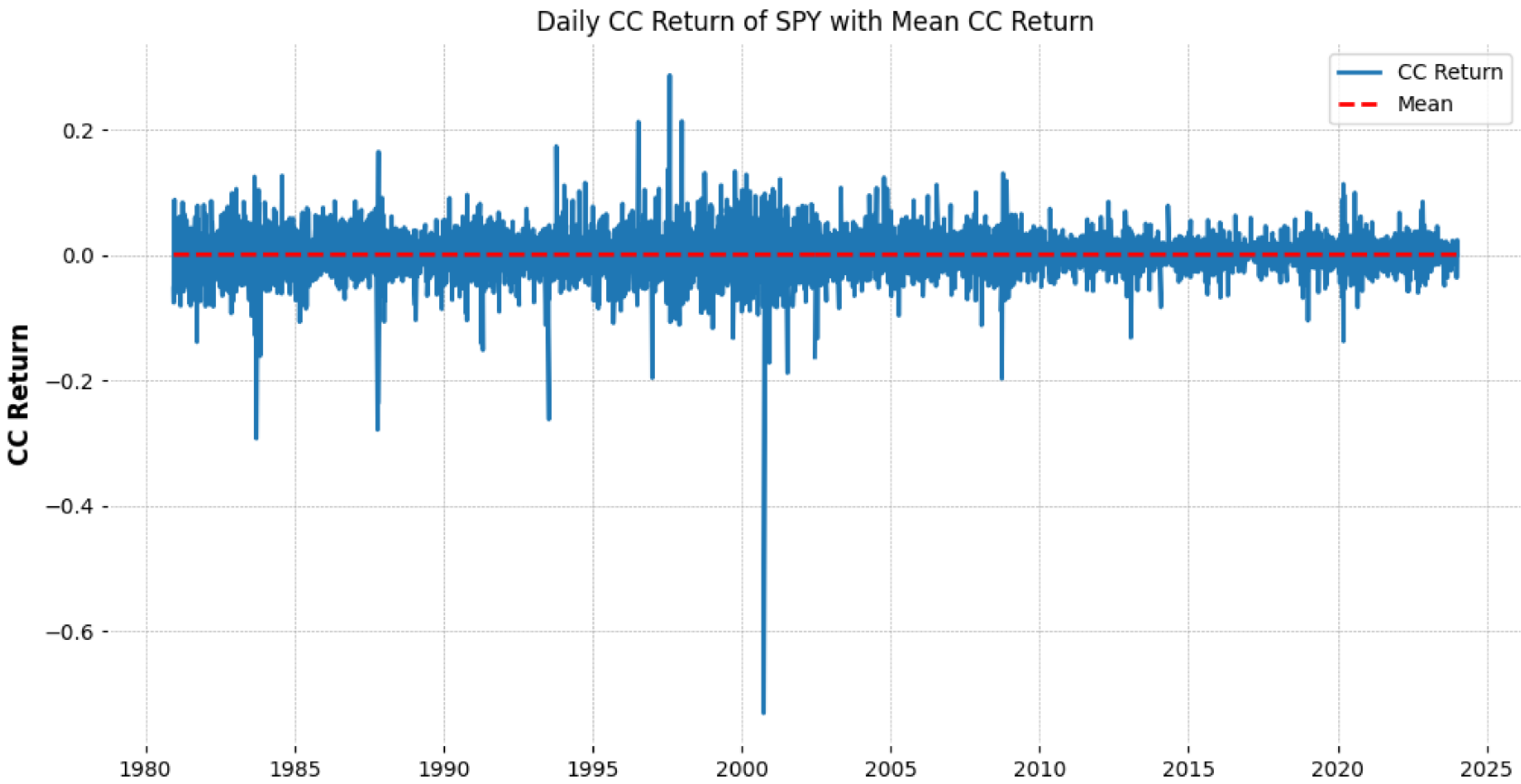
Out[76]:

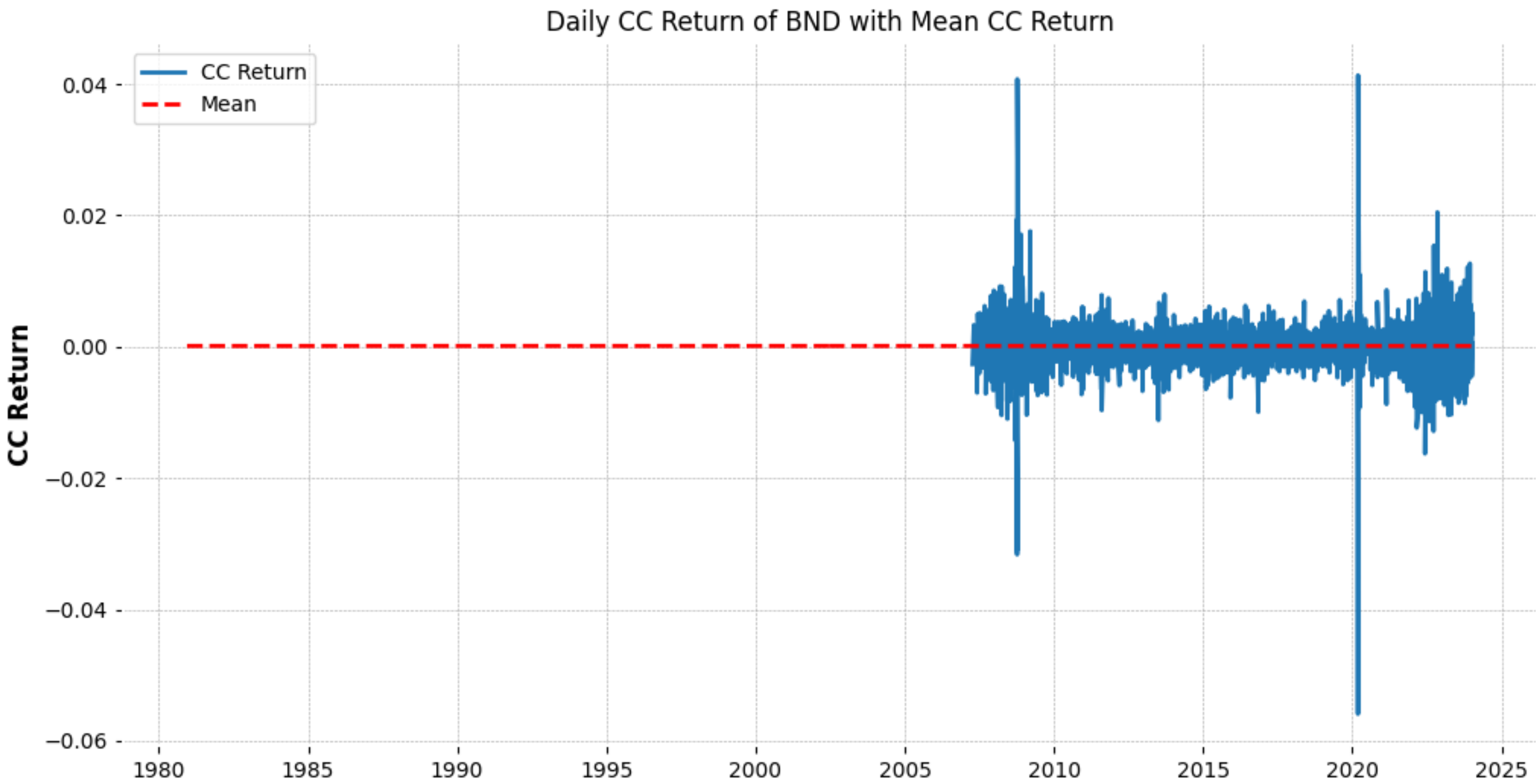
Date	SPY	BND	VOO	AAPL
1980-12-12	0.099319	NaN	NaN	NaN
1980-12-15	0.094137	NaN	NaN	NaN
1980-12-16	0.087228	NaN	NaN	NaN
1980-12-17	0.089387	NaN	NaN	NaN
1980-12-18	0.091978	NaN	NaN	NaN
...	...	...	...	...
2024-01-08	185.559998	73.070000	474.600006	436.130005
2024-01-09	185.139999	73.059998	473.880005	435.070007
2024-01-10	186.190002	72.930000	476.559998	437.940002
2024-01-11	185.589996	73.309998	476.350006	437.790009
2024-01-12	185.919998	73.459999	476.679993	437.989990

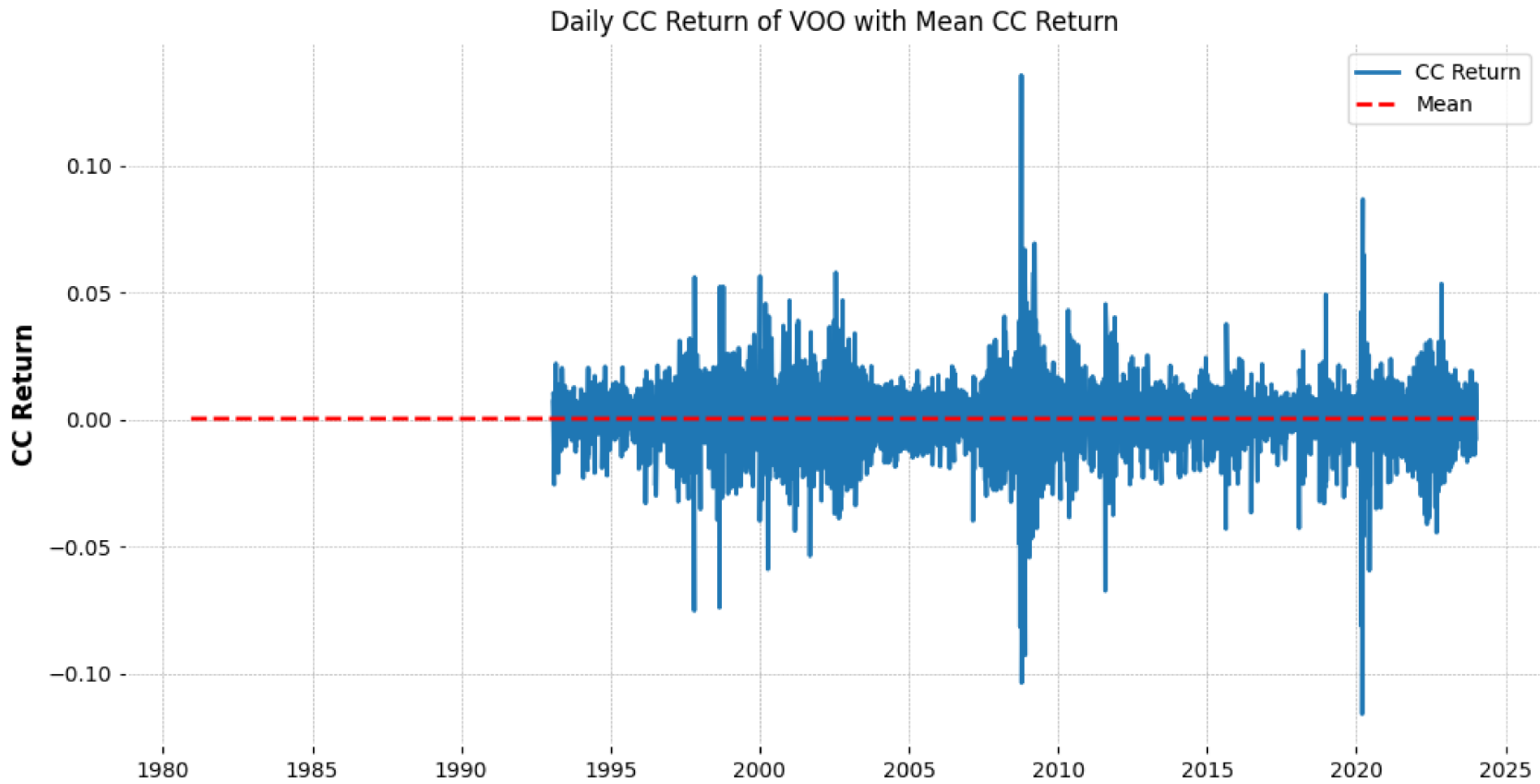
10862 rows × 4 columns

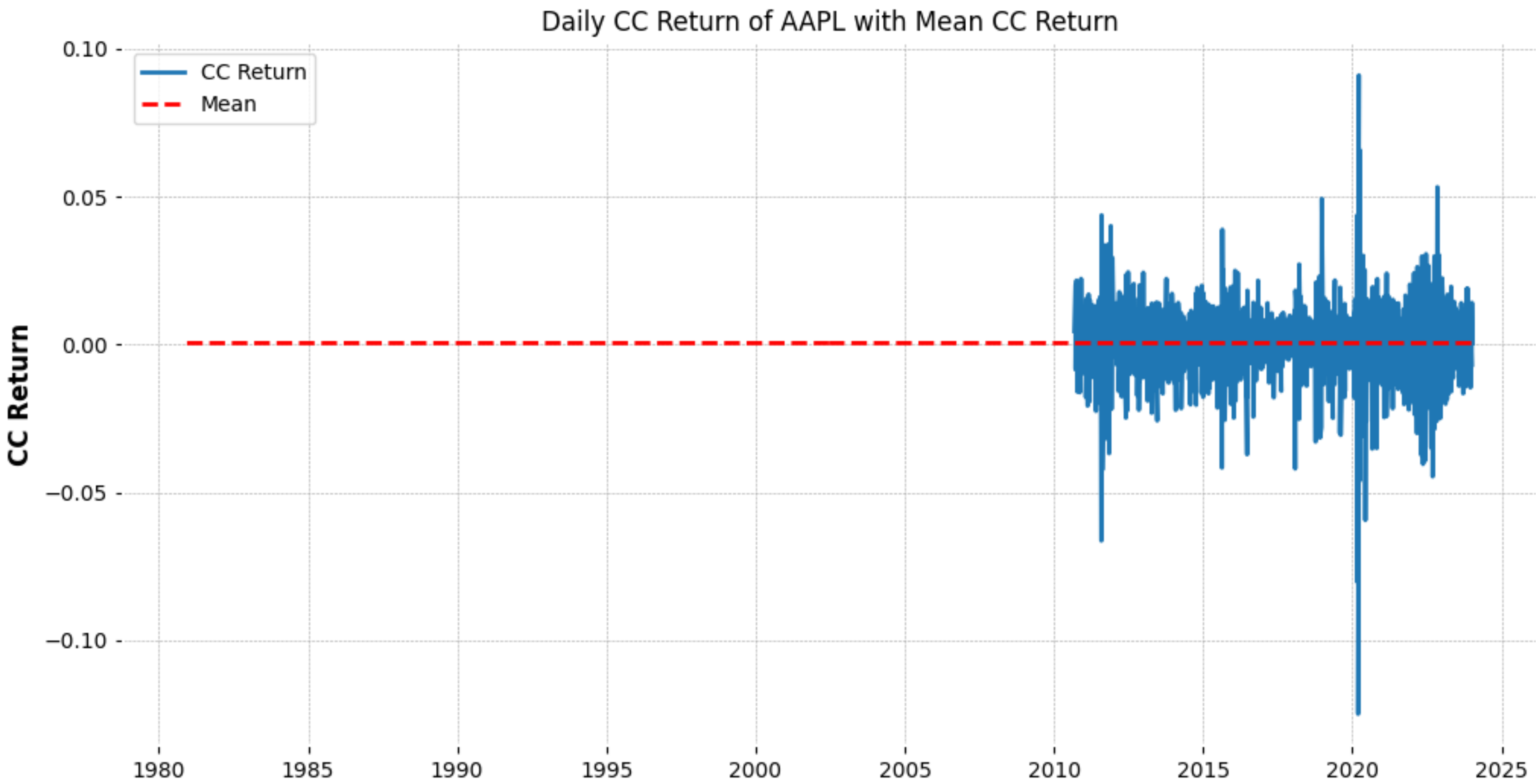
In [77]:
```
#Mean Continuously Compounding returns
for ticker in tickers:
    df_stocks[f'{ticker}_CC_returns'] = np.log(np.array(df_stocks[ticker][1:])/df_stocks[ticker][:-1])
    df_stocks[f'{ticker}_mean_CC_return'] = np.mean(df_stocks[f'{ticker}_CC_returns'][:-1])

    plt.figure(figsize=(12,6))
    plt.plot(f'{ticker}_CC_returns', data=df_stocks[:-1])
    plt.plot(f'{ticker}_mean_CC_return', 'r--', data=df_stocks[:-1])
    plt.ylabel('CC Return')
    plt.legend(('CC Return', 'Mean'))
    plt.title(f'Daily CC Return of {ticker} with Mean CC Return')
    plt.show()
```


Daily CC Return of SPY with Mean CC Return
CC Return
Mean
CC Return
0.2
0.0
−0.2
−0.4
−0.6
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025


Daily CC Return of BND with Mean CC Return
CC Return
Mean
CC Return
0.04
0.02
0.00
−0.02
−0.04
−0.06
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025


Daily CC Return of VOO with Mean CC Return
CC Return
Mean
0.10
0.05
0.00
−0.05
−0.10
CC Return
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025


Daily CC Return of AAPL with Mean CC Return
CC Return
Mean
CC Return
0.10
0.05
0.00
−0.05
−0.10
1980
1985
1990
1995
2000
2005
2010
2015
2020
2025

In [78]:
```
#Calling data for tickers for candle Stick graph
def data(tickers):
    dt = yf.download(tickers, start='2014-01-01',
                     end='2023-12-29',
                     interval='1d',
                     progress=False)
    dt.ffill().dropna(inplace = True)
    return(dt)
tickers = ["SPY", "BND", "VOO", "AAPL"]
assets = data(tickers)
assets.head()
```

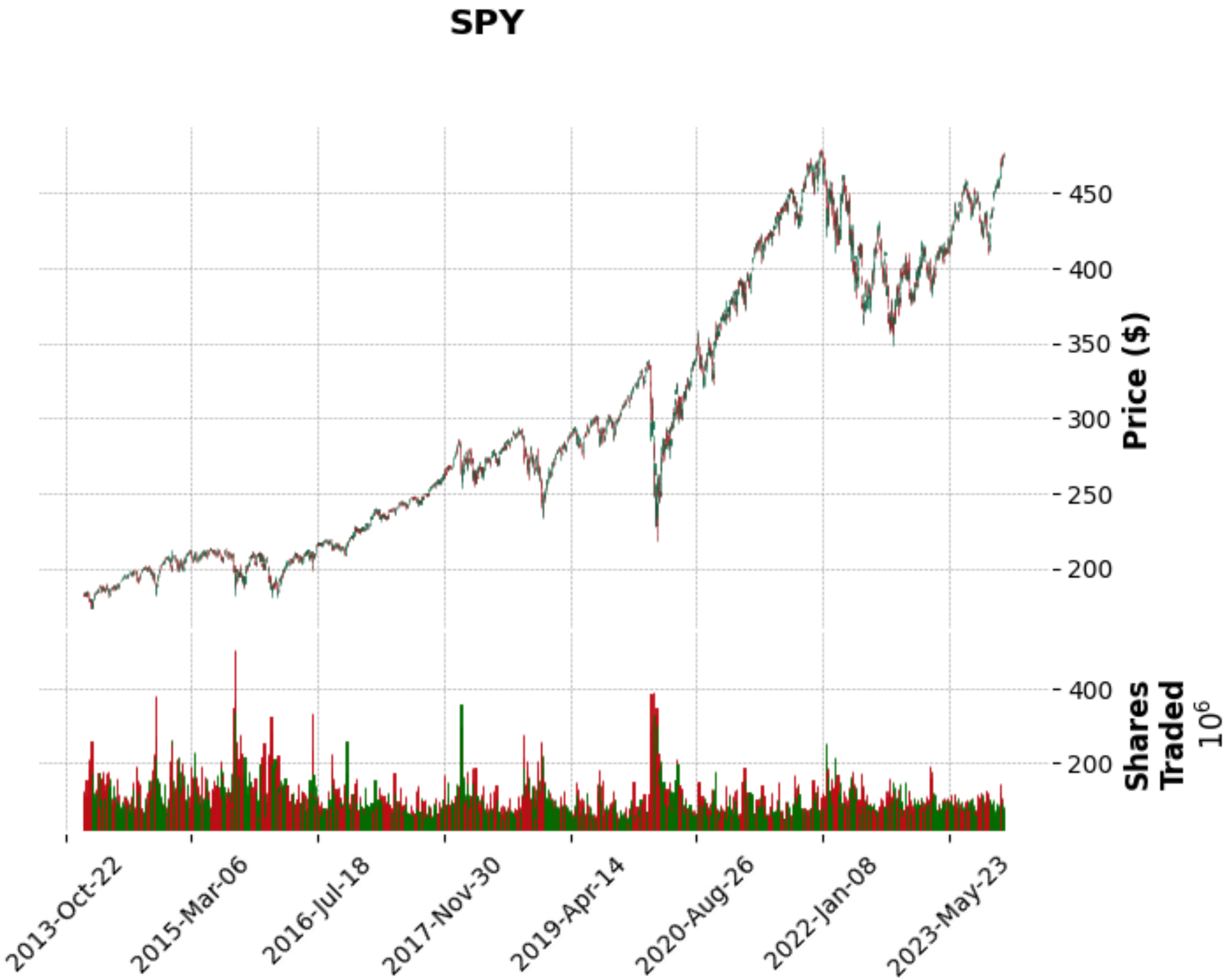
Out[78]:

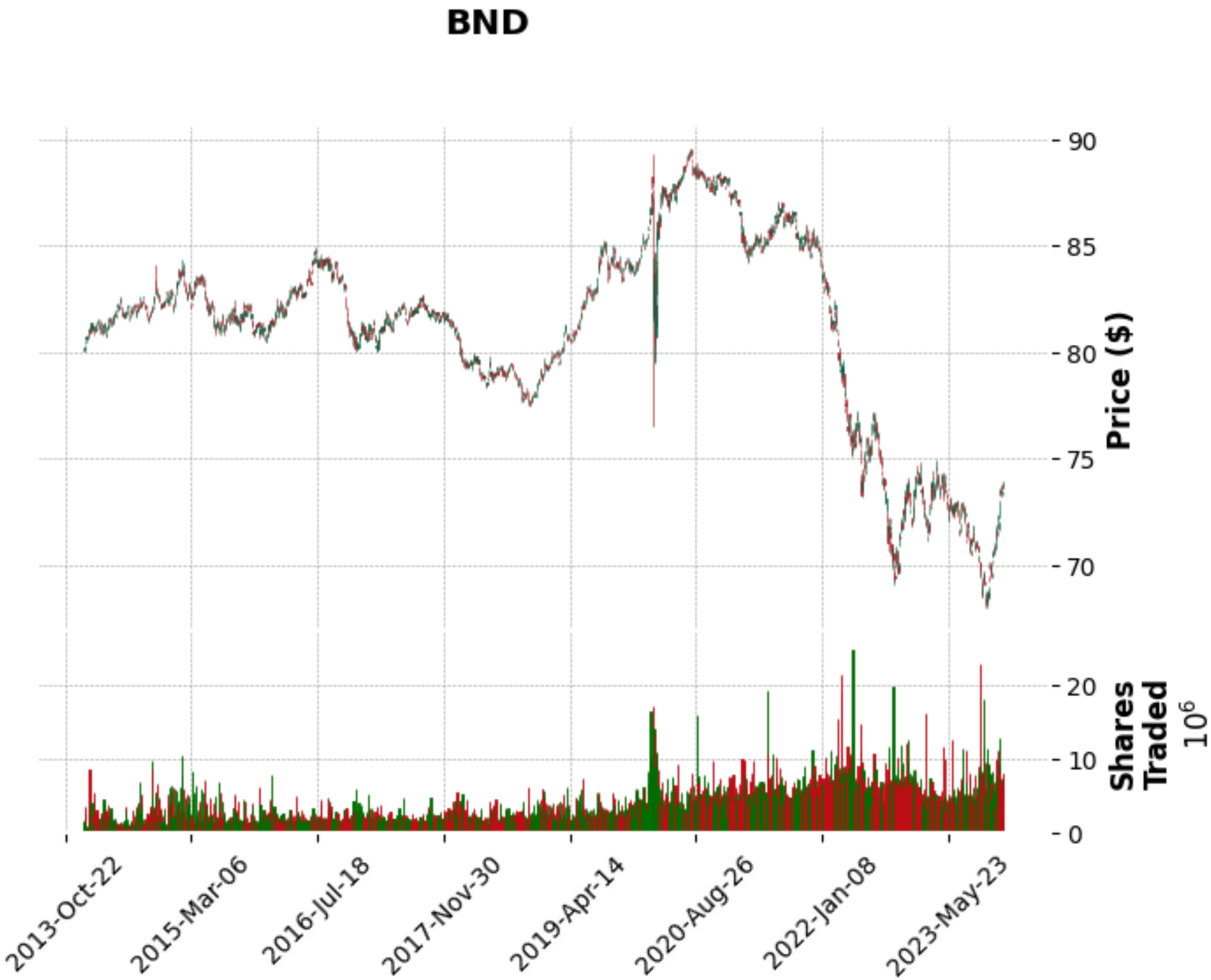
	Adj Close				Close				High		...	
	AAPL	BND	SPY	VOO	AAPL	BND	SPY	VOO	AAPL	BND	...	
Date												
2014-01-02	17.318729	61.362770	152.669144	140.151871	19.754642	80.120003	182.919998	167.630005	19.893929	80.180000	...	182.47
2014-01-03	16.938303	61.370464	152.644104	140.026443	19.320715	80.129997	182.889999	167.479996	19.775000	80.209999	...	182.63
2014-01-06	17.030672	61.424118	152.201782	139.675293	19.426071	80.199997	182.360001	167.059998	19.528570	80.260002	...	182.08
2014-01-07	16.908875	61.500637	153.136520	140.544861	19.287144	80.300003	183.479996	168.100006	19.498571	80.300003	...	182.94
2014-01-08	17.015959	61.301517	153.169937	140.603333	19.409286	80.040001	183.520004	168.169998	19.484285	80.160004	...	182.88

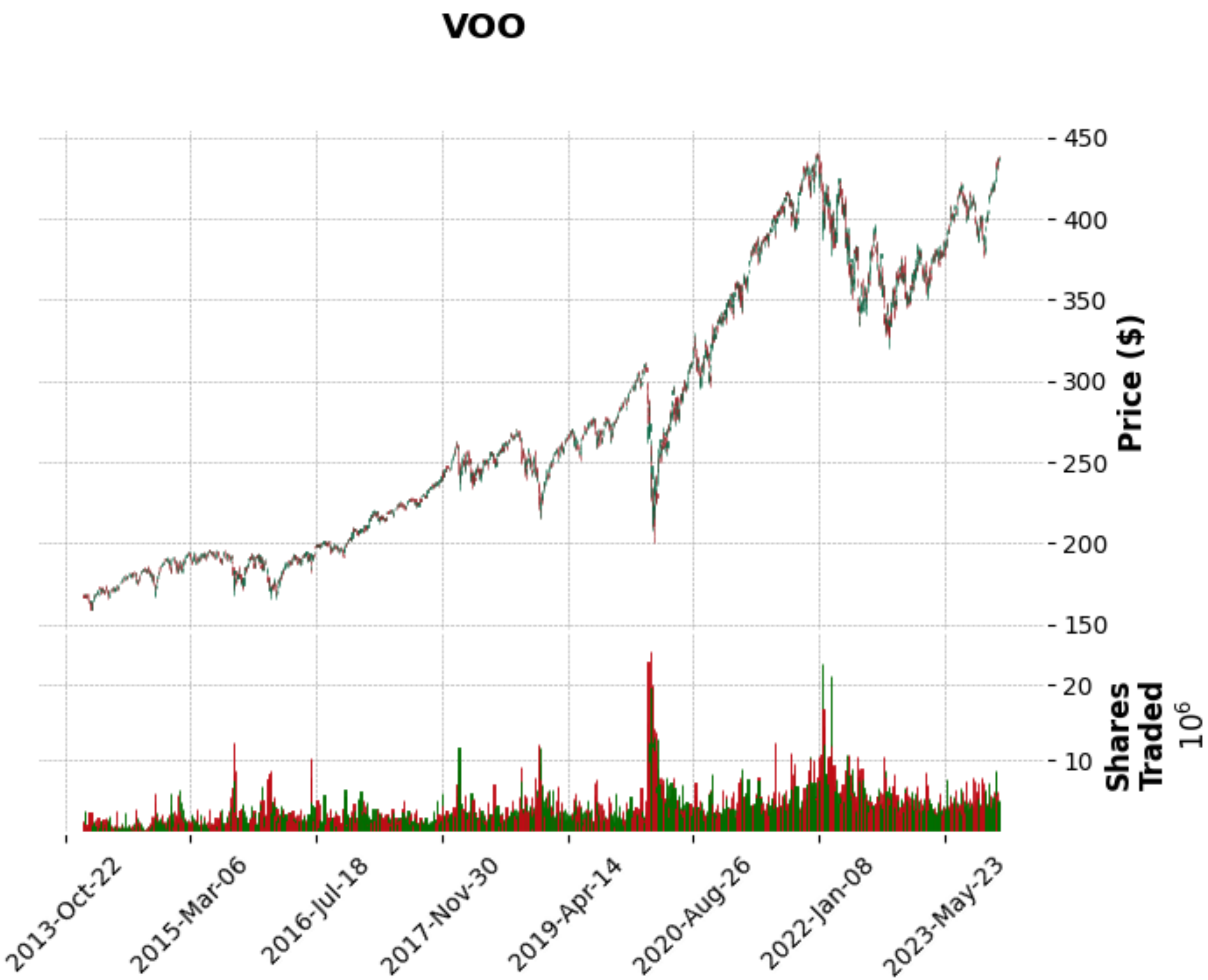
5 rows × 24 columns

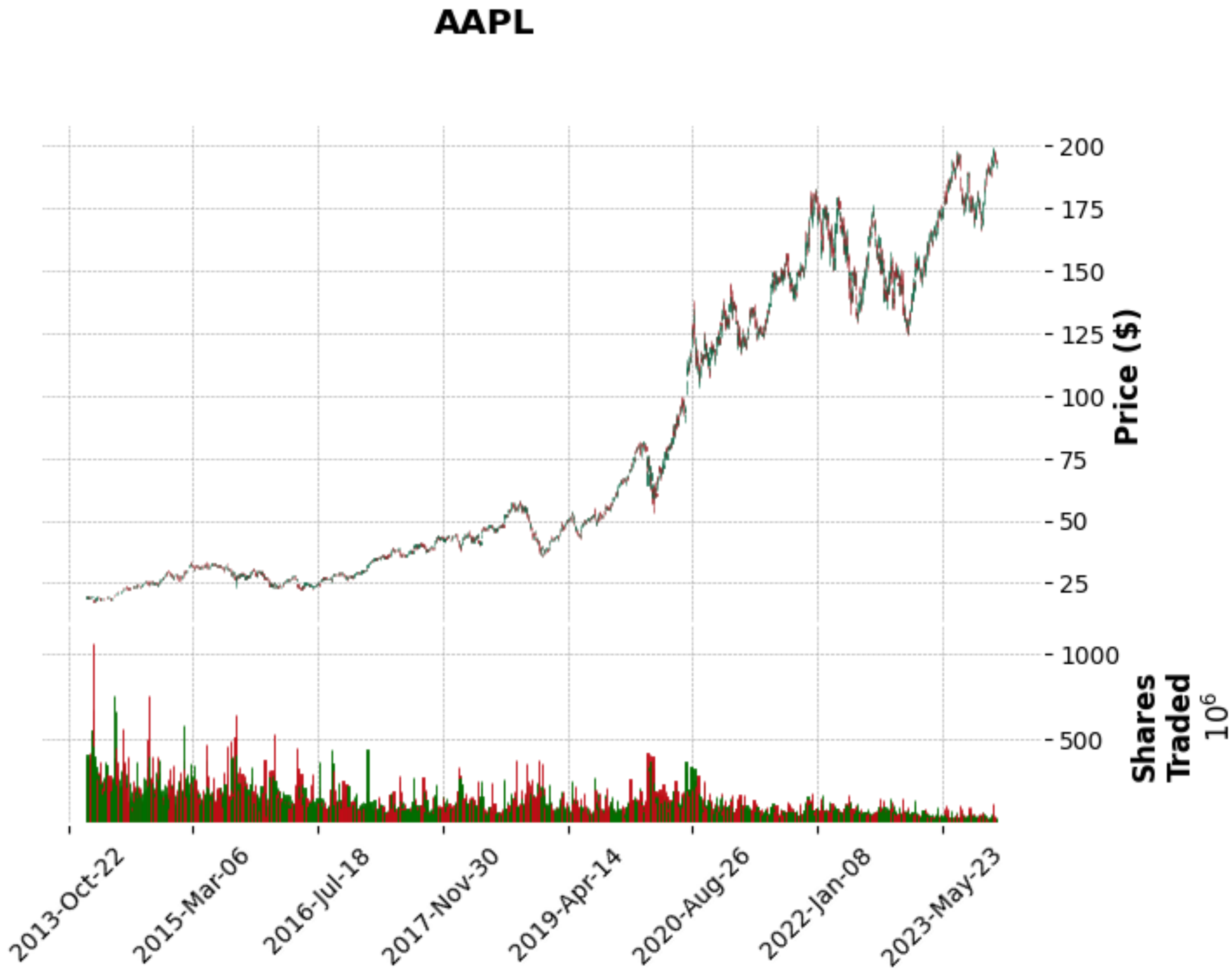
In [79]:
```
# Candle Stick Plot to analyse the trend in securities' prices.
for ticker in tickers:
    df_ticker = pd.DataFrame({
        'Open': assets['Open', ticker],
        'Close': assets['Close', ticker],
        'High': assets['High', ticker],
        'Low': assets['Low', ticker],
        'Volume': assets['Volume', ticker],
    })

    fplt.plot(
        df_ticker,
        type='candle',
        title=f'{ticker}',
        style='charles',
        ylabel='Price ($)',
        volume=True,
        ylabel_lower='Shares\nTraded',
        show_nontrading=True,
         warn_too_much_data=len(df_ticker),
    )
```


SPY
450
400
350
300
250
200
Price ($)
400
200
Shares Traded
10^6
2013-Oct-22
2015-Mar-06
2016-Jul-18
2017-Nov-30
2019-Apr-14
2020-Aug-26
2022-Jan-08
2023-May-23


BND
90
85
80
75
70
Price ($)
20
10
0
Shares Traded
10^6
2013-Oct-22
2015-Mar-06
2016-Jul-18
2017-Nov-30
2019-Apr-14
2020-Aug-26
2022-Jan-08
2023-May-23


VOO
450
400
350
300
250
200
150
Price ($)
20
10
Shares Traded
10^6
2013-Oct-22
2015-Mar-06
2016-Jul-18
2017-Nov-30
2019-Apr-14
2020-Aug-26
2022-Jan-08
2023-May-23


AAPL
200
175
150
125
100
75
50
25
Price ($)
1000
500
Shares Traded 10^6
2013-Oct-22
2015-Mar-06
2016-Jul-18
2017-Nov-30
2019-Apr-14
2020-Aug-26
2022-Jan-08
2023-May-23

In [80]:
```
#calculated minimum variance portfolio with the 4 securities.
def minimum_variance(returns):
    def find_port_variance(weights):
        # this is actually std
        cov = returns.cov()
        port_var = np.sqrt(np.dot(weights.T, np.dot(cov, weights)) * 250)
        return port_var

    def weight_cons(weights):
        return np.sum(weights) - 1


    bounds_lim = [(0, 1) for x in range(len(returns.columns))] # change to (-1, 1) if you want to short
    init = [1/len(returns.columns) for i in range(len(returns.columns))]
    constraint = {'type': 'eq', 'fun': weight_cons}

    optimal = minimize(fun=find_port_variance,
                       x0=init,
                       bounds=bounds_lim,
                       constraints=constraint,
                       method='SLSQP'
                       )

    return list(optimal['x'])
```

In [81]:
```
equal_w=equal_weight(tickers)
equal_w
```

Out[81]:
```
[0.25, 0.25, 0.25, 0.25]
```

In [82]:
```
min_var_w=minimum_variance(returns)
min_var_w
```

Out[82]:
```
[0.00018777827990091746,
 0.9188034851392441,
 0.06292607821418948,
 0.018082658366665522]
```

minVarWeights = get_minimum_variance_weights(tickers) minVarWeights

In [83]:
```
#created a function to purchase the correct amount of assets based on the minimum variance portfolio with Broker
tickers = ["SPY", "BND", "VOO", "AAPL"]
df_stocks = get_data(tickers)
minVarWeights = min_var_w

r = requests.get(ACCOUNT_URL, headers = {'APCA-API-KEY-ID': API_KEY,
                                         'APCA-API-SECRET-KEY':  SECRET_KEY})

info = json.loads(r.content)
accountval = float(info["cash"])

shares = []
for i, symbol in enumerate(tickers):
    weight = minVarWeights[i]
    price = df_stocks[symbol][-1]
    qty = (weight*accountval)/price
    qty = qty//1
    shares.append(qty)
#purchase
for i, symbol in enumerate(tickers):
    qty = shares[i]

    stocks(symbol, qty, "buy", "market", "gtc")
```

```
[*********************100%%**********************]  4 of 4 completed
```

In [84]:
```
#number of shares to be purchased based on the above assessment for minimum variance portfolio
shares
```

Out[84]:
```
[0.0, 23.0, 0.0, 0.0]
```

As per our analysis we need to purchase, 0 SPY, 1252 BND, 13 VOO and 4 AAPL, number of securities for minimum variance portfolio.