Data lab 4 - Portfolio Performance Attribution and Factor Model

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Note 1: Review what you have learned in Data labs, DataCamp assignments, and in-class sample code.

Note 2: Chapter "Performance Attribution" of DataCamp course "Introduction to Portfolio Analysis in Python" is a useful reference.

Note 3: This note serves as a guide. You are free to tinker with it!

1. Revisit the all-weather portfolio you crafted. Create the maximum Sharpe portfolio's daily return dataframe and then merge it with Fama French's five return factors.

If you have attempted the optional bonus, why not include the portfolios with L2 regularization and Black-Litterman model too.

In [ ]:
```
# Import the necessary packages
import yfinance as yf
import datetime as dt
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [ ]:
```
# Pick a list of stocks that form your all-weather portfolio
symbols_list = ["AAPL", "PG", "NEE", "UNH", "UNP", "INFY", "COST", "MDT", "A
# Draw data for the past five years
start = dt.datetime(2017,9,1)
end = dt.datetime(2022,9,1)
data = yf.download(symbols_list, start=start, end=end)
#Illustrative, change into yours!
data.head(5)
```

```
[*********************100%***********************]  10 of 10 completed
```

Out[ ]:

Date	AAPL	AMT	COST	INFY	MDT	NEE	PG	
2017-08-31	38.911678	133.133514	146.150085	6.548218	71.802498	33.610596	80.494652	18
2017-09-01	38.923550	131.083252	147.548721	6.478371	71.294838	33.532448	80.721458	18
2017-09-05	38.456127	132.135376	148.387924	6.395426	71.089989	33.554783	80.887215	18
2017-09-06	38.415798	131.352997	148.126831	6.382329	71.134521	33.105930	80.887215	18
2017-09-07	38.261570	132.180283	148.518494	6.364868	71.205765	33.382832	81.105316	18

5 rows × 60 columns

In [ ]:

```
# Keep only the adjusted close in the dataframe
# Note that the date is in the index
price = data["Adj Close"]
```

In [ ]:

```
# Calculate return using method pct_change
# Find out more about .pct_change with help!
daily_return = price.pct_change()
daily_return.head(5)
```

Out[ ]:

Date	AAPL	AMT	COST	INFY	MDT	NEE	PG	U
2017-08-31	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
2017-09-01	0.000305	-0.015400	0.009570	-0.010667	-0.007070	-0.002325	0.002818	0.004
2017-09-05	-0.012009	0.008026	0.005688	-0.012803	-0.002873	0.000666	0.002053	-0.002
2017-09-06	-0.001049	-0.005921	-0.001760	-0.002048	0.000626	-0.013377	0.000000	-0.004
2017-09-07	-0.004015	0.006298	0.002644	-0.002736	0.001002	0.008364	0.002696	0.002

In [ ]:

```
# function that takes portfolio weights and creates a time-series of daily p
def portfolio_return_series(daily_returns, weights):

    '''
    INPUTS
    daily returns: dataframe of daily returns. Each ticker column contains t
```

```
    weights: numpy array of the portfolio weight on each ticker (sorted in a

    OUTPUTS
    portfolio_daily_returns: the portfolio return series given the weights

    '''

    # Create portfolio daily returns
    portfolio_daily_returns = daily_returns.dot(weights)
    return portfolio_daily_returns
```

In [ ]:

```
## Install PyPortfolioOpt package
# !pip install PyPortfolioOpt

# Import the packages
from pypfopt.expected_returns import mean_historical_return
from pypfopt.risk_models import CovarianceShrinkage
from pypfopt.efficient_frontier import EfficientFrontier
from pypfopt import risk_models
from pypfopt import expected_returns
```

The Maximum Sharpe Portfolio

In [ ]:

```
# Calculate expected returns mu
# Calculate expected returns mu
mu = expected_returns.mean_historical_return(price)

# Calculate the covariance matrix S
cov_matrix_d = daily_return.cov()

# Obtain the efficient frontier
ef = EfficientFrontier(mu, cov_matrix_d)

# Calculate weights for the maximum Sharpe ratio portfolio
raw_weight_maxsharpe = ef.max_sharpe()
clean_weight_maxsharpe = ef.clean_weights()
# Inspect the calculated weights
print("Raw weight: ", raw_weight_maxsharpe)
print("Cleaned weight: ", clean_weight_maxsharpe)
```

```
Raw weight:  OrderedDict([('AAPL', 0.1739143426119843), ('AMT', 0.0), ('COS
T', 0.5956967361123512), ('INFY', 0.1138867273976108), ('MDT', 0.0), ('NEE',
0.0974206294319005), ('PG', 0.0), ('UNH', 0.0190815644461531), ('UNP', 0.0),
('V', 0.0)])
Cleaned weight:  OrderedDict([('AAPL', 0.17391), ('AMT', 0.0), ('COST', 0.59
57), ('INFY', 0.11389), ('MDT', 0.0), ('NEE', 0.09742), ('PG', 0.0), ('UNH',
0.01908), ('UNP', 0.0), ('V', 0.0)])
```

The minimum volatility portfolio

In [ ]:

```
# Obtain the efficient frontier
mu = expected_returns.mean_historical_return(price)
sigma = risk_models.sample_cov(price)
ef = EfficientFrontier(mu, sigma)
# Calculate weights for the minimum volatility portfolio
raw_weight_minvol = ef.min_volatility()
clean_weight_minvol = ef.clean_weights()
print("Raw weight: ", raw_weight_minvol)
print("Cleaned weight: ", clean_weight_minvol)
```

```
Raw weight:  OrderedDict([('AAPL', 0.0), ('AMT', 0.0095738604123881), ('COS
T', 0.2400398134362626), ('INFY', 0.1156782240463269), ('MDT', 0.16097299224
3892), ('NEE', 0.073952174523665), ('PG', 0.3411636783501854), ('UNH', 0.0),
('UNP', 0.05861925698728), ('V', 0.0)])
Cleaned weight:  OrderedDict([('AAPL', 0.0), ('AMT', 0.00957), ('COST', 0.24
004), ('INFY', 0.11568), ('MDT', 0.16097), ('NEE', 0.07395), ('PG', 0.3411
6), ('UNH', 0.0), ('UNP', 0.05862), ('V', 0.0)])
```

In [ ]:

```python
# 1. Daily portfolio returns for the equally-weighted portfolio
equal_weight = np.repeat(0.1, 10)
equal_weight_return = portfolio_return_series(daily_return, equal_weight)
# Extract the first element from the function output for daily returns
equal_weight_first_element = equal_weight_return.iloc[1]

# 2. Daily portfolio returns for the maximum Sharpe portfolio
# Extract the first element from the function output for daily returns
clean_weight_maxsharpe_list = list(clean_weight_maxsharpe.values())
clean_weight_maxsharpe_array = np.array(clean_weight_maxsharpe_list)
max_sharpe_daily_return = portfolio_return_series(daily_return, clean_weight
max_sharpe_first_element = max_sharpe_daily_return.iloc[1]

# 3. Daily portfolio returns for the minimum volatility portfolio
# Extract the first element from the function output for daily returns
clean_weight_minvol_list = list(clean_weight_minvol.values())
clean_weight_minvol_array = np.array(clean_weight_minvol_list)
minvol_daily_return = portfolio_return_series(daily_return, clean_weight_min
minvol_first_element = minvol_daily_return.iloc[1]



# Merge the three series side-by-side into a dataframe
# Note the index is date
portfolio_returns = pd.concat([equal_weight_return, max_sharpe_daily_return,
# Rename column names
portfolio_returns = portfolio_returns.rename(columns = {0: 'portfolio_ew', 1
print(portfolio_returns)
```

```
            portfolio_ew  portfolio_maxsharpe  portfolio_minvol
Date
2017-08-31           NaN                  NaN               NaN
2017-09-01     -0.001321             0.004394          0.000662
2017-09-05     -0.003501            -0.000136         -0.000513
2017-09-06     -0.001780            -0.002856         -0.001092
2017-09-07      0.003493             0.001432          0.002346
...                  ...                  ...               ...
2022-08-25      0.010632             0.011389          0.008686
2022-08-26     -0.028264            -0.032142         -0.027499
2022-08-29     -0.004806            -0.005425         -0.004553
2022-08-30     -0.013817            -0.011904         -0.012361
2022-08-31     -0.005800            -0.005827         -0.006683

[1259 rows x 3 columns]
```

In [ ]:

```python
# Inspect the last five observations of the portfolio_returns dataframe
portfolio_returns.tail(5)
```

Out[ ]:

Date	portfolio_ew	portfolio_maxsharpe	portfolio_minvol
2022-08-25	0.010632	0.011389	0.008686
2022-08-26	-0.028264	-0.032142	-0.027499
2022-08-29	-0.004806	-0.005425	-0.004553
2022-08-30	-0.013817	-0.011904	-0.012361
2022-08-31	-0.005800	-0.005827	-0.006683

In [ ]:

```python
# Read the csv file with factor returns with pd.read_csv()
# Note: place the file where your Jupyter notebook is
factor_returns = pd.read_csv("F-F_Research_Data_5_Factors_2x3_daily.csv")

# Divide all factor returns by 100
# Consistent with how we calculate portfolio returns
factor_returns.iloc[:, 1:] = (factor_returns.iloc[:, 1:]).div(100)

print(factor_returns)
```

```
           Date  Mkt-RF     SMB     HML     RMW     CMA       RF
0      19630701 -0.0067  0.0002 -0.0035  0.0003  0.0013  0.00012
1      19630702  0.0079 -0.0028  0.0028 -0.0008 -0.0021  0.00012
2      19630703  0.0063 -0.0018 -0.0010  0.0013 -0.0025  0.00012
3      19630705  0.0040  0.0009 -0.0028  0.0007 -0.0030  0.00012
4      19630708 -0.0063  0.0007 -0.0020 -0.0027  0.0006  0.00012
...         ...     ...     ...     ...     ...     ...      ...
14890  20220825  0.0145  0.0014 -0.0001  0.0012 -0.0041  0.00008
14891  20220826 -0.0338 -0.0028  0.0169  0.0024  0.0087  0.00008
14892  20220829 -0.0072 -0.0038  0.0042  0.0023  0.0042  0.00008
14893  20220830 -0.0111 -0.0038 -0.0024 -0.0024  0.0012  0.00008
14894  20220831 -0.0074  0.0022 -0.0044 -0.0063 -0.0012  0.00008

[14895 rows x 7 columns]
```

This file is from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research and is created by CMPT_ME_BEME_OP_INV_RETS_DAILY using the 202208 CRSP database. The 1-month TBill return is from Ibbotson and Associates. For more details on the factor returns, please read http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5_factors_2x3.html

In [ ]:

```python
# Inspect the dataframe with info()
factor_returns.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14895 entries, 0 to 14894
Data columns (total 7 columns):
 #   Column   Non-Null Count   Dtype
---  ------   --------------   -----
 0   Date     14895 non-null   int64
 1   Mkt-RF   14895 non-null   float64
 2   SMB      14895 non-null   float64
 3   HML      14895 non-null   float64
 4   RMW      14895 non-null   float64
 5   CMA      14895 non-null   float64
 6   RF       14895 non-null   float64
dtypes: float64(6), int64(1)
memory usage: 814.7 KB
```

In [ ]:

```
# Inspect the last five observations

factor_returns.tail(5)
factor_returns['Date'] = pd.to_datetime(factor_returns['Date'].astype(str),
factor_returns = factor_returns.set_index('Date')

factor_returns.index = factor_returns.index.date
portfolio_returns.index = pd.to_datetime(portfolio_returns.index, format = "
portfolio_returns.index = portfolio_returns.index.date
```

In [ ]:

```
# Merge portfolio daily returns with factor returns
port_factor_return = pd.concat([portfolio_returns, factor_returns[dt.date(20
```

In [ ]:

```
# Inspect the last five observations
port_factor_return.tail(5)
```

Out[ ]:

	portfolio_ew	portfolio_maxsharpe	portfolio_minvol	Mkt-RF	SMB	HML	RI
2022-08-25	0.010632	0.011389	0.008686	0.0145	0.0014	-0.0001	0.0
2022-08-26	-0.028264	-0.032142	-0.027499	-0.0338	-0.0028	0.0169	0.0
2022-08-29	-0.004806	-0.005425	-0.004553	-0.0072	-0.0038	0.0042	0.0
2022-08-30	-0.013817	-0.011904	-0.012361	-0.0111	-0.0038	-0.0024	-0.0
2022-08-31	-0.005800	-0.005827	-0.006683	-0.0074	0.0022	-0.0044	-0.0

In [ ]:

```
factors = ['Mkt-RF', 'SMB', 'HML', 'RMW', 'CMA']
portfolio_return = ['portfolio_ew', 'portfolio_maxsharpe', 'portfolio_minvol

# Print correlation table. Hint use .corr()
port_factor_return.corr()
```

Out[ ]:

	portfolio_ew	portfolio_maxsharpe	portfolio_minvol	Mkt-RF	S
portfolio_ew	1.000000	0.854123	0.936758	0.913960	0.0014
portfolio_maxsharpe	0.854123	1.000000	0.868340	0.805127	-0.0750
portfolio_minvol	0.936758	0.868340	1.000000	0.820802	-0.0500
Mkt-RF	0.913960	0.805127	0.820802	1.000000	0.1705
SMB	0.001464	-0.075042	-0.050095	0.170599	1.0000
HML	-0.030055	-0.211225	-0.020380	-0.037520	0.3087
RMW	0.023702	0.005965	0.083346	-0.122989	-0.1882
CMA	-0.185516	-0.239465	-0.122856	-0.280367	0.0330
RF	-0.015121	-0.020674	-0.009502	-0.030524	-0.0429

2. Examine visually the correlation between portfolio and factor returns

Hint: Write functions for repetitive lines of codes

In [ ]:

```
# function that takes portfolio and factor returns and creates 20-day rollin
def portfolio_factor_correlation(portfolio_type, df):

    '''
    INPUTS
    portfolio type: portfolio_ew, portfolio_maxsharpe, portfolio_minvol
    df: dataframe containing portfolio and factor returns

    OUTPUTS
    plot the 20-day rolling correlation between a portfolio and a factor ret

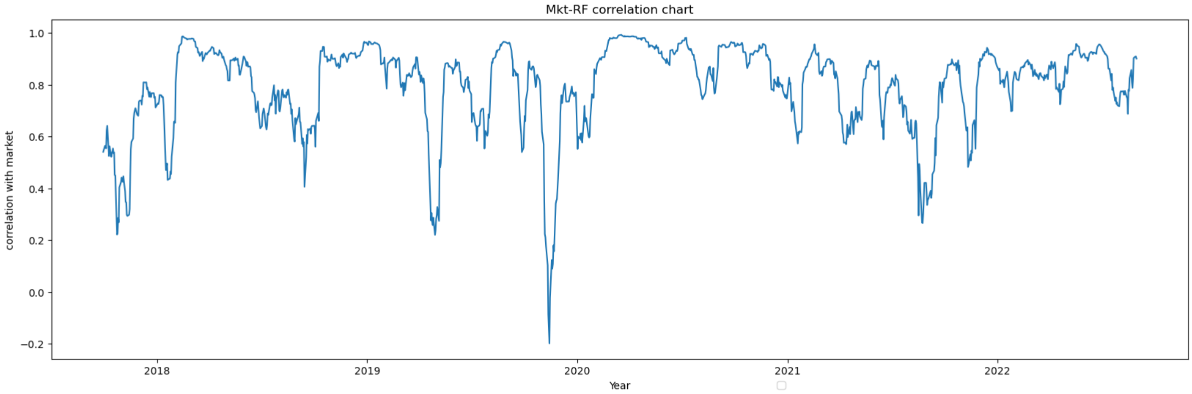
    '''
    plt.figure(figsize=(40,10))
    for factor in factors:
        column_name = factor + "_corr"
        # Calculate 20-day rolling correlation with the market
        df[column_name] = df[portfolio_type].rolling(20).corr(df[factor])

        # Plot the correlation between a portfolio and factor returns
        plt.figure(figsize=(20, 6))
        plt.title(factor + " correlation chart")
        plt.xlabel('Year')
        plt.ylabel("correlation with market")
        sns.lineplot(data=df[column_name])
        plt.legend(bbox_to_anchor =(0.65, -0.05))
        plt.show()
    return
```

In [ ]:

```
# Call the function portfolio_factor_correlation for the equally weighted po
portfolio_factor_correlation(portfolio_return[0], port_factor_return)
```

```
No artists with labels found to put in legend.  Note that artists whose labe
l start with an underscore are ignored when legend() is called with no argum
ent.
<Figure size 4000x1000 with 0 Axes>
```



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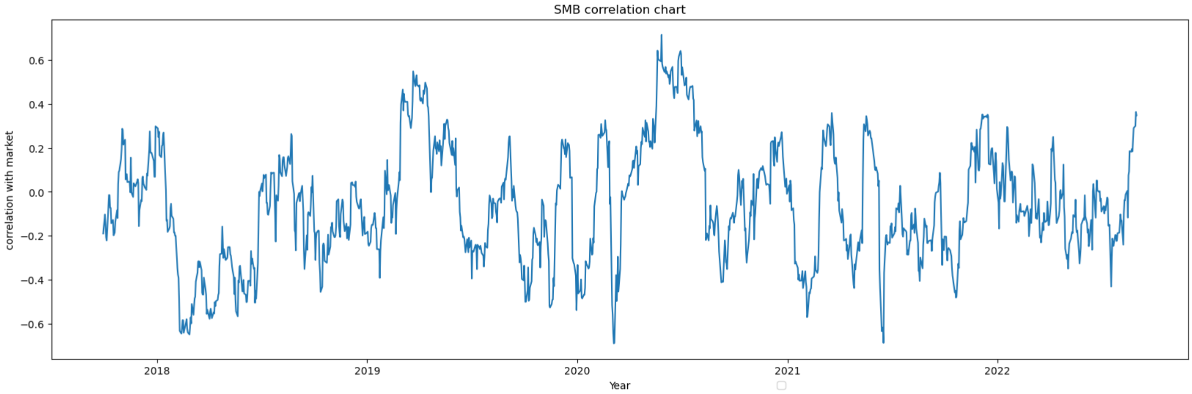

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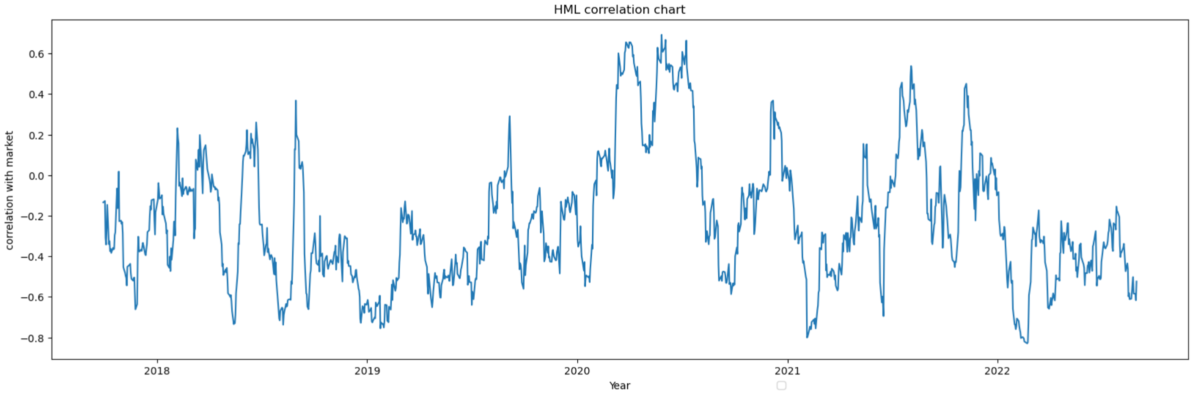

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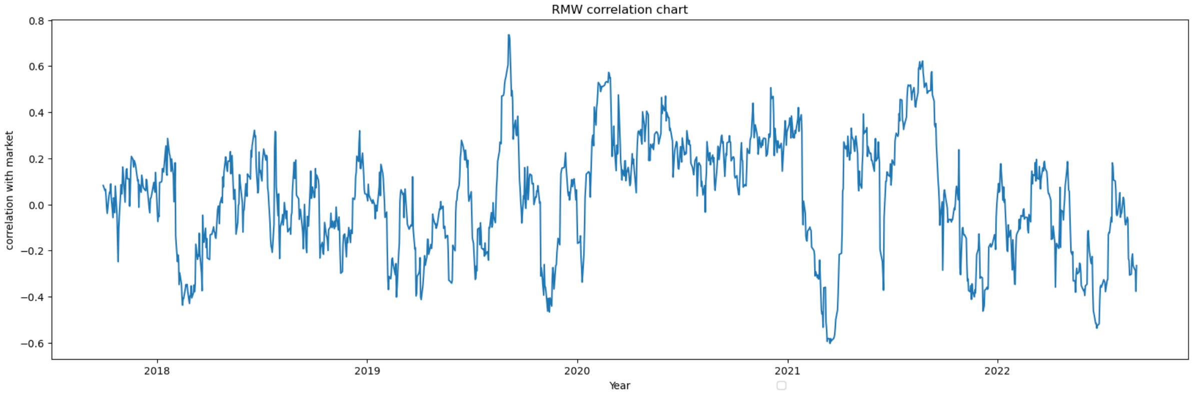

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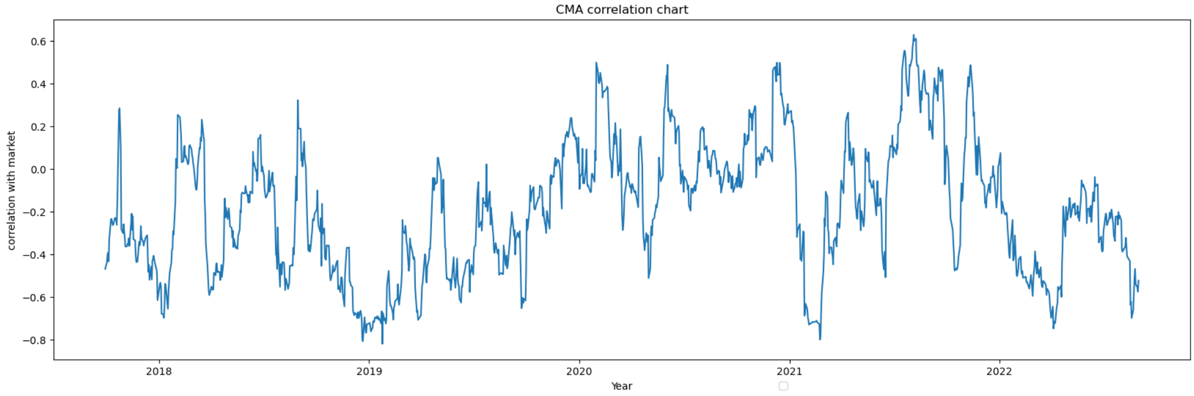

In [ ]:
```
# Call the function portfolio_factor_correlation for the maximum Sharpe port
portfolio_factor_correlation(portfolio_return[1], port_factor_return)
```

```
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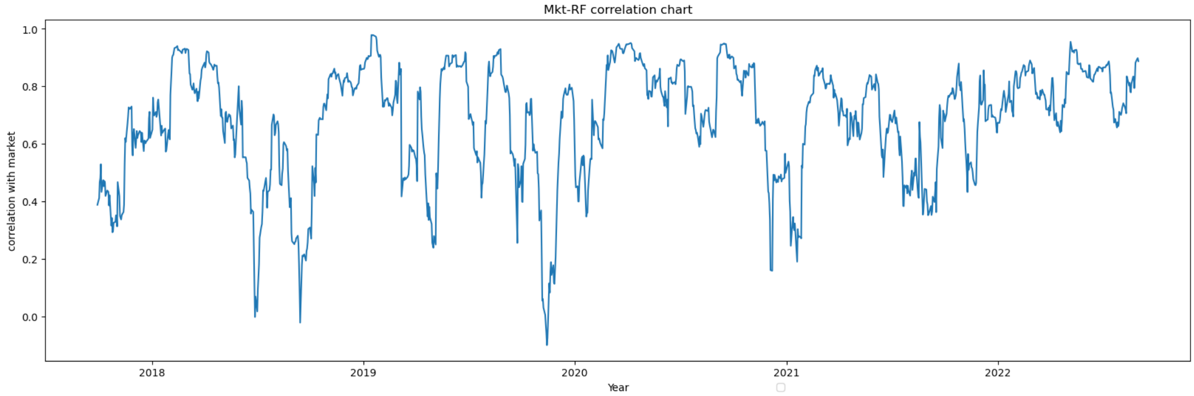
l start with an underscore are ignored when legend() is called with no argum
ent.
```

```
<Figure size 4000x1000 with 0 Axes>
```

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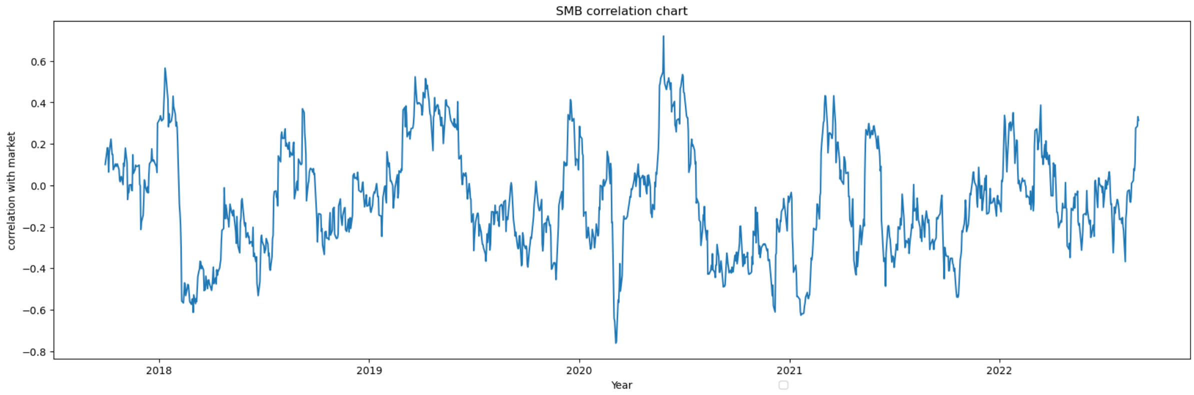


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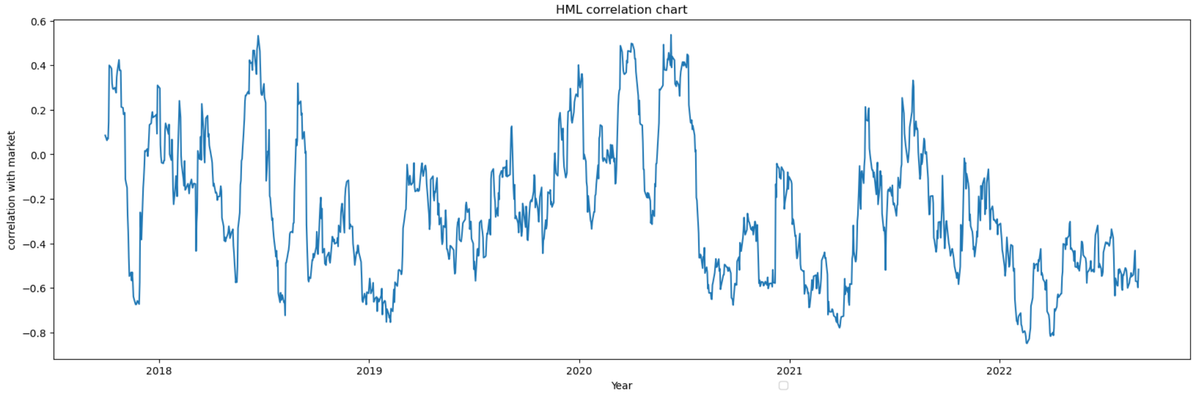


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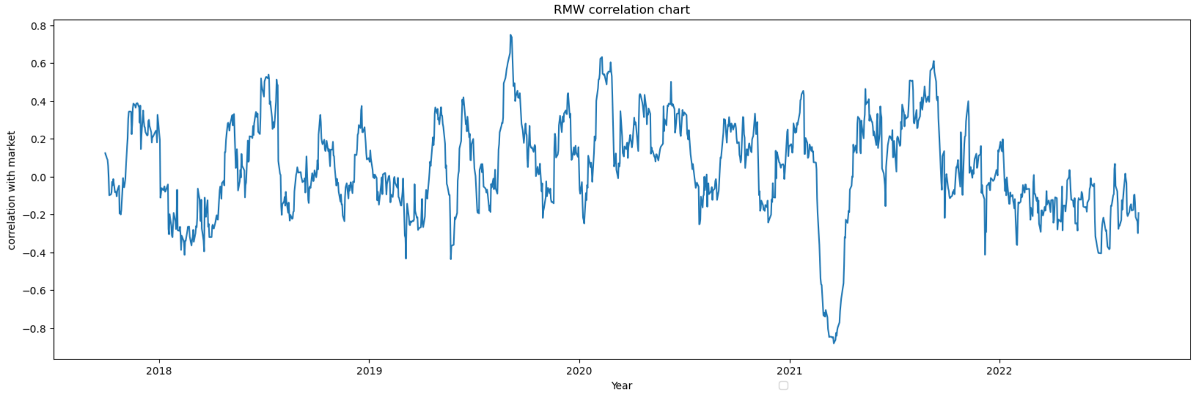


```
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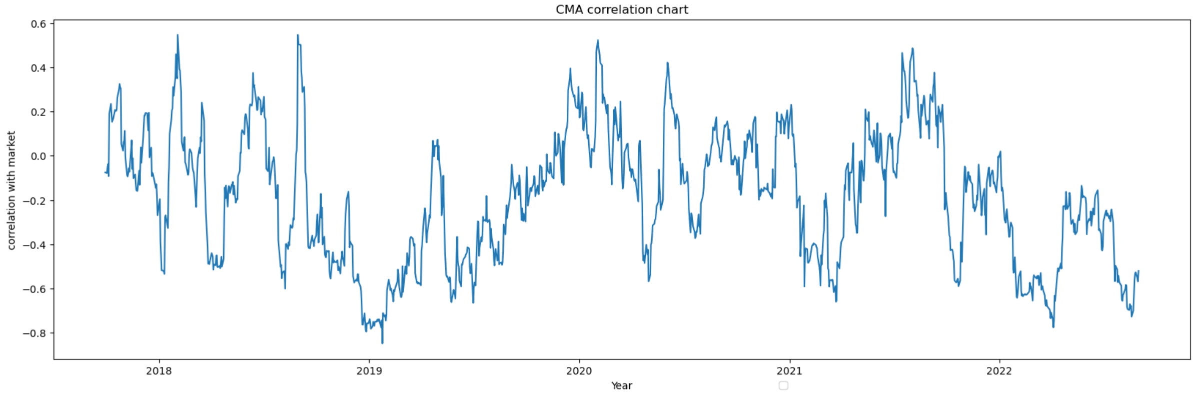
ent.
```



In [ ]:
```
# Call the function portfolio_factor_correlation for the minimum volatility
portfolio_factor_correlation(portfolio_return[2], port_factor_return)
```

```
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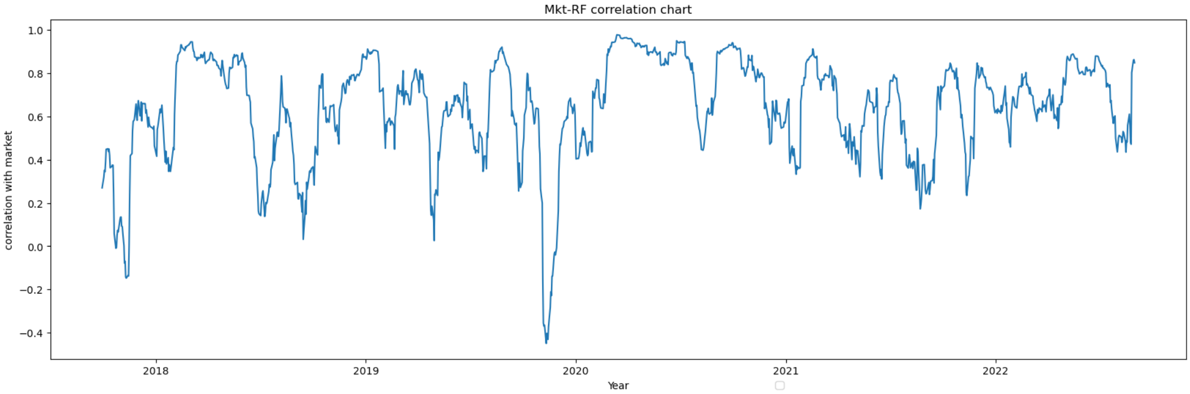
l start with an underscore are ignored when legend() is called with no argum
ent.
<Figure size 4000x1000 with 0 Axes>
```

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l start with an underscore are ignored when legend() is called with no argum
ent.
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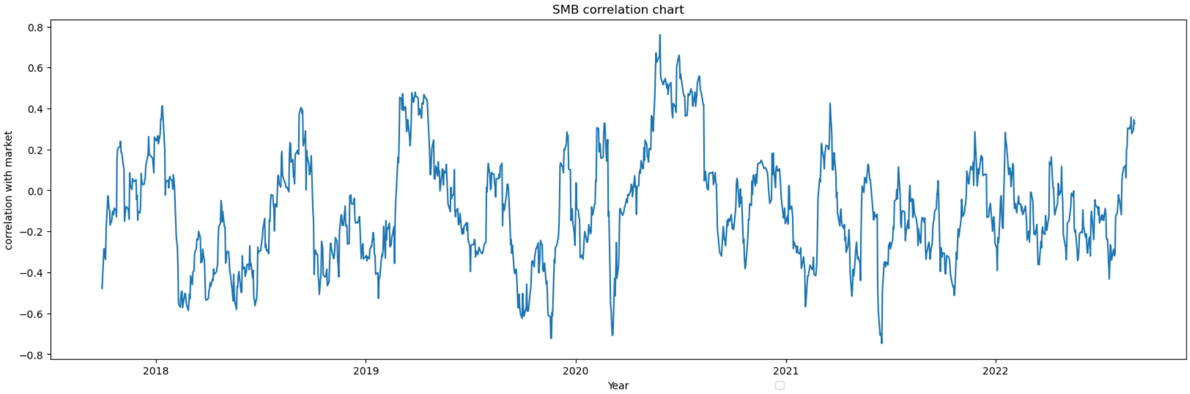


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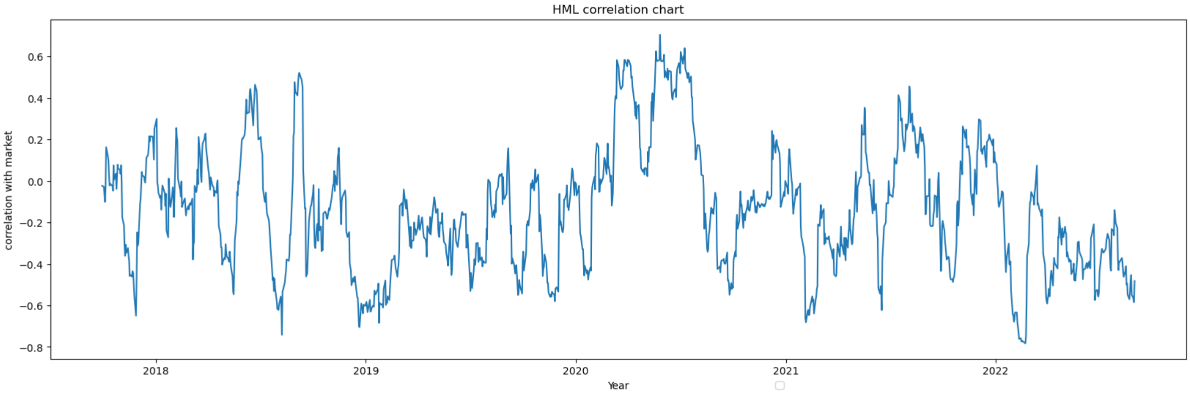
ent.
```

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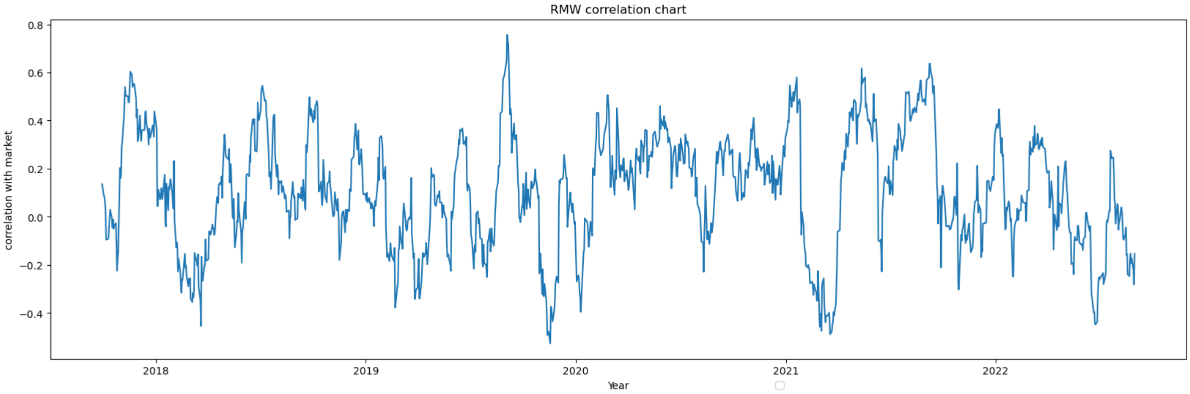
```

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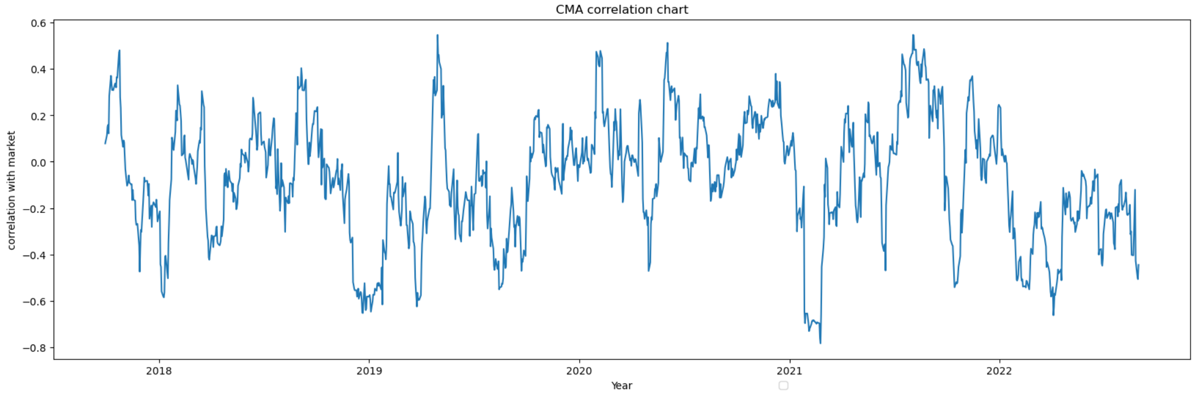
```



3. Regress the portfolio return on each factor and assess the portfolio's sensitivity to each factor.

For the curious, optional challenge, how do you test whether the intercept (i.e., alpha) is significantly different from the risk-free rate for a single-factor regression?

Hint: Write functions for repetitive lines of codes

In [ ]:
```
port_factor_return = port_factor_return.iloc[1:]
```

In [ ]:
```
# Import the ols function
import statsmodels.api as sm
import scipy.stats
# function that takes portfolio and factor returns and run a regression of p
# it reports the portfolio sensitivity to a return factor
def portfolio_factor_sensitivity(portfolio_type, df):

    '''
    INPUTS
    portfolio type: portfolio_ew, portfolio_maxsharpe, portfolio_minvol
    df: dataframe containing portfolio and factor returns

    OUTPUTS
    regression result of a portfolio on a return factor

    '''
    for factor in factors:

        # Create the regression model object
        model = sm.OLS(df[factor], df[portfolio_type]).fit()
        # Fit the model
        prediction = model.predict(df[factor])
        # Print the parameters of the fitted model
        b1 = model.params
        print("Parameters of the fitted model: \nb1: %f" % (b1))
        # Optional challenge: testing the hypothesis that the intercept is s
        # Hint: F-test
        f = np.var(df[portfolio_type], ddof=1)/np.var(df['RF'], ddof=1)
        nun = df[portfolio_type].size-1
        dun = df['RF'].size-1
        p_value = 1-scipy.stats.f.cdf(f, nun, dun)
        #print("p-value: ", p_value)
        #print(model.summary())
    return
```

In [ ]:
```
# Call the function portfolio_factor_sensitivity for the equally weighted po
portfolio_factor_sensitivity(portfolio_return[0], port_factor_return)
```

```
Parameters of the fitted model:
b1: 0.997673
Parameters of the fitted model:
b1: 0.000820
Parameters of the fitted model:
b1: -0.026844
Parameters of the fitted model:
b1: 0.012198
Parameters of the fitted model:
b1: -0.075223
```

In [ ]:

```
# Call the function portfolio_factor_sensitivity for the maximum Sharpe port
portfolio_factor_sensitivity(portfolio_return[1], port_factor_return)
```

```
Parameters of the fitted model:
b1: 0.816061
Parameters of the fitted model:
b1: -0.041706
Parameters of the fitted model:
b1: -0.172684
Parameters of the fitted model:
b1: 0.003781
Parameters of the fitted model:
b1: -0.090083
```

In [ ]:

```
# Call the function portfolio_factor_sensitivity for minimum volatility port
portfolio_factor_sensitivity(portfolio_return[2], port_factor_return)
```

```
Parameters of the fitted model:
b1: 0.982848
Parameters of the fitted model:
b1: -0.032929
Parameters of the fitted model:
b1: -0.020096
Parameters of the fitted model:
b1: 0.044207
Parameters of the fitted model:
b1: -0.054461
```

4. Regress the portfolio return on all factors and assess the portfolio's sensitivity to factors.

For the curious, optional challenge, how do you test whether the intercept (i.e., alpha) is significantly different from the risk-free rate for a multi-factor regression?

Hint: Write functions for repetitive lines of codes

In [ ]:

```
# Import the ols function
import statsmodels.api as sm

# function that takes portfolio and factor returns and run a regression of p
# it reports the portfolio sensitivity to a return factor
def portfolio_all_factor_sensitivity(portfolio_type, df):

    '''
    INPUTS
    portfolio type: portfolio_ew, portfolio_maxsharpe, portfolio_minvol
    df: dataframe containing portfolio and factor returns

    OUTPUTS
    regression result of a portfolio on a return factor
```

```
    '''

    # Create the model object
    model = sm.OLS(df[portfolio_type], df[factors]).fit()
    # Fit the model
    prediction = model.predict(df[factors])
    # Print the parameters of the fitted model
    b1, b2, b3, b4, b5 = model.params
    print("Parameters of the fitted model: \nb1: %f\nb2: %f\nb3: %f\nb4: %f\
    # Optional challenge: testing the hypothesis that the intercept is signi
    # Hint: F-test
    f = np.var(df[portfolio_type], ddof=1)/np.var(df['RF'], ddof=1)
    nun = df[portfolio_type].size-1
    dun = df['RF'].size-1
    p_value = 1-scipy.stats.f.cdf(f, nun, dun)
    print("p-value: ", p_value)

    return
```

In [ ]:

```
# Call the function portfolio_all_factor_sensitivity for the equally weighte
portfolio_all_factor_sensitivity(portfolio_return[0], port_factor_return)
```

```
Parameters of the fitted model:
b1: 0.890260
b2: -0.215038
b3: -0.062412
b4: 0.237891
b5: 0.216651
p-value:  1.1102230246251565e-16
```

In [ ]:

```
# Call the function portfolio_all_factor_sensitivity for the maximum Sharpe
portfolio_all_factor_sensitivity(portfolio_return[1], port_factor_return)
```

```
Parameters of the fitted model:
b1: 0.858899
b2: -0.181376
b3: -0.373036
b4: 0.394095
b5: 0.370812
p-value:  1.1102230246251565e-16
```

In [ ]:

```
# Call the function portfolio_all_factor_sensitivity for the minimum volatil
portfolio_all_factor_sensitivity(portfolio_return[2], port_factor_return)
```

```
Parameters of the fitted model:
b1: 0.752627
b2: -0.228914
b3: -0.094102
b4: 0.302692
b5: 0.310557
p-value:  1.1102230246251565e-16
```

5. Optional Bonus. Construct a multi-factor pricing model for assets based on Arbitrage Pricing Theory.

The Arbitrage Pricing Theory (APT) is a theory of asset pricing that holds that an asset's returns can be forecasted with the linear relationship of an asset's expected returns and the macroeconomic (e.g., GDP, changes in inflation, yield curve changes, changes in interest rates, market sentiments, exchange rates) or firm-specific statistical factors that affect the asset's risk. Hint: You can draw these variables straight into your Jupyter notebook via Refinitiv API.

The APT is a substitute for the Capital Asset Pricing Model (CAPM) in that both assert a linear relation between assets' expected returns and their covariance with other random variables. (In the CAPM, the covariance is with the market portfolio's return.) The covariance is interpreted as a measure of risk that investors cannot avoid by diversification. The slope coefficient in the linear relation between the expected returns and the covariance is interpreted as a risk premium ~ "Arbitrage Pricing Theory (Guberman and Wang 2005).

In [ ]:
```
import refinitiv.data as rd
import refinitiv.dataplatform.eikon as ek

start='2017-09-01'
end='2022-08-31'

US_10y_bond_yield = pd.read_excel("US_10y_bond_yield.xlsx")
US_interest_rate = pd.read_excel("US_interest_rate.xlsx")
Exchange_rate = pd.read_excel("Exchange_Rate_Data.xlsx")
```

In [ ]:
```
US_10y_bond_yield = US_10y_bond_yield.iloc[::-1]
US_interest_rate = US_interest_rate.iloc[::-1]
Exchange_rate = Exchange_rate.iloc[::-1]
US_interest_rate = US_interest_rate.iloc[:-2]
```

In [ ]:
```
US_10y_bond_yield['Date'] = pd.to_datetime(US_10y_bond_yield['Date'].astype(
US_10y_bond_yield = US_10y_bond_yield.set_index('Date')
US_interest_rate['Date'] = pd.to_datetime(US_interest_rate['Date'].astype(st
US_interest_rate = US_interest_rate.set_index('Date')

Exchange_rate = Exchange_rate.rename(columns = {"Exchange Date": 'Date'})
Exchange_rate['Date'] = pd.to_datetime(Exchange_rate['Date'].astype(str), fo
Exchange_rate = Exchange_rate.set_index('Date')
```

In [ ]:
```
market_data = pd.concat([US_10y_bond_yield, US_interest_rate, Exchange_rate]
```

In [ ]:
```
market_data = market_data.fillna(method='ffill')
market_data = market_data.rename(columns = {"US10YT=RR": "US_10y_bond_yield"
```

In [ ]:
```
market_data.index = market_data.index.date
```

In [ ]:
```
market_port_factor_return = pd.concat([market_data, port_factor_return], axi
market_port_factor_return = market_port_factor_return.fillna(method='ffill')
market_port_factor_return
```

Out[ ]:

	US_10y_bond_yield	US_interest_rate	USD_CNY_FOREX	portfolio_ew	portfolio_max
2017-09-01	2.157	1.23056	6.5552	-0.001321	0.0
2017-09-04	2.157	1.23167	6.5269	-0.001321	0.0
2017-09-05	2.070	1.23111	6.5345	-0.003501	-0.(
2017-09-06	2.106	1.23222	6.5221	-0.001780	-0.0
2017-09-07	2.061	1.23500	6.4830	0.003493	0.(
...	...	...	...	...	
2022-08-25	3.024	2.49343	6.8477	0.010632	0.(
2022-08-26	3.035	2.52386	6.8715	-0.028264	-0.(
2022-08-29	3.110	2.52386	6.9067	-0.004806	-0.0
2022-08-30	3.110	2.56400	6.9100	-0.013817	-0.(
2022-08-31	3.132	2.55343	6.8890	-0.005800	-0.0

1305 rows × 17 columns

In [ ]:

```
# Import the ols function
import statsmodels.api as sm

market_factors = ["US_10y_bond_yield", "US_interest_rate", "USD_CNY_FOREX"]
# function that takes portfolio and factor returns and run a regression of p
# it reports the portfolio sensitivity to a return factor
def portfolio_market_factor_sensitivity(portfolio_type, df):

    '''
    INPUTS
    portfolio type: portfolio_ew, portfolio_maxsharpe, portfolio_minvol
    df: dataframe containing portfolio and factor returns

    OUTPUTS
    regression result of a portfolio on a return factor

    '''

    # Create the model object
    model = sm.OLS(df[portfolio_type], df[market_factors]).fit()
    # Fit the model
    prediction = model.predict(df[market_factors])
    # Print the parameters of the fitted model
```

```python
    b1, b2, b3 = model.params
    print("Parameters of the fitted model: \nb1: %f\nb2: %f\nb3: %f" % (b1,

    return
```

In [ ]:
```python
portfolio_market_factor_sensitivity(portfolio_return[0], market_port_factor_
```

```
Parameters of the fitted model:
b1: -0.000744
b2: 0.000406
b3: 0.000278
```

In [ ]:
```python
portfolio_market_factor_sensitivity(portfolio_return[1], market_port_factor_
```

```
Parameters of the fitted model:
b1: -0.000913
b2: 0.000445
b3: 0.000355
```

In [ ]:
```python
portfolio_market_factor_sensitivity(portfolio_return[2], market_port_factor_
```

```
Parameters of the fitted model:
b1: -0.000796
b2: 0.000485
b3: 0.000260
```

Acknowledgement: This notebook is inspired by DataCamp course "Introduction to Portfolio Analysis in Python" by Charlotte Werger.