

Code (Vomit) | : P

1. Collection (of Data)

```
In [ ]: import yfinance as yf
import pandas as pd

# List of ETF tickers
tickers = ['FXE', 'EWJ', 'GLD', 'QQQ', 'SPY', 'SHV', 'DBA', 'USO', 'XBI', 'ILF', 'E

# Download historical data for each ETF
start_date = '2007-03-01'
end_date = '2024-03-31'
data = yf.download(tickers, start=start_date, end=end_date)

# Only keep the adjusted close prices
adj_close = data['Adj Close']

# Save data to CSV
adj_close.to_csv('etf_prices.csv')
```

[*****100%*****] 12 of 12 completed

2. Construction (of) \mathcal{THE} Factor Model

```
In [ ]: import pandas as pd

# Load the Fama-French factors CSV
file_path = './F-F_Research_Data_Factors_daily.CSV'

# Read the CSV with specified delimiter and skip initial rows if necessary
try:
    # Check if there are any header rows to skip
    with open(file_path, 'r') as file:
        lines = file.readlines()
        for i, line in enumerate(lines[:10]): # Inspect the first 10 lines
            print(f"Line {i + 1}: {line}")

    # Adjust the skiprows parameter based on the output
    ff_data = pd.read_csv(file_path, skiprows=4, index_col=0)
    ff_data.index = pd.to_datetime(ff_data.index, format='%Y%m%d')
    ff_data = ff_data.loc['2007-03-01':'2024-03-31']

    print(ff_data.head()) # Display the first few rows to verify
except Exception as e:
    print(f"Error reading the CSV file: {e}")
```

Line 1: This file was created by CMPT_ME_BEME_RETS_DAILY using the 202403 CRSP database.

Line 2: The Tbill return is the simple daily rate that, over the number of trading days

Line 3: in the month, compounds to 1-month TBill rate from Ibbotson and Associates Inc.

Line 4:

Line 5: ,Mkt-RF,SMB,HML,RF

Line 6: 19260701, 0.10, -0.25, -0.27, 0.009

Line 7: 19260702, 0.45, -0.33, -0.06, 0.009

Line 8: 19260706, 0.17, 0.30, -0.39, 0.009

Line 9: 19260707, 0.09, -0.58, 0.02, 0.009

Line 10: 19260708, 0.21, -0.38, 0.19, 0.009

Error reading the CSV file: time data "Copyright 2024 Kenneth R. French" doesn't match format "%Y%m%d", at position 25710. You might want to try:

- passing `format` if your strings have a consistent format;
- passing `format='ISO8601'` if your strings are all ISO8601 but not necessarily in exactly the same format;
- passing `format='mixed'`, and the format will be inferred for each element individually. You might want to use `dayfirst` alongside this.

```
In [ ]: import pandas as pd
import statsmodels.api as sm

# Function to Load and process Fama-French factors
def fama_french_factors(start_date, end_date, file_path):
    try:
        # Load the Fama-French factors data, skipping the first 4 metadata lines
        ff_data = pd.read_csv(file_path, skiprows=3, index_col=0)
        ff_data.index = pd.to_datetime(ff_data.index, format='%Y%m%d', errors='coerce')

        # Drop rows with invalid dates
        ff_data = ff_data.dropna()

        # Sort the index to ensure it is in chronological order
        ff_data = ff_data.sort_index()

        # Slice the data for the specified date range
        ff_data = ff_data.loc[start_date:end_date]
        return ff_data
    except Exception as e:
        print(f"Error processing the Fama-French data: {e}")
        return None

# Usage example
start_date = '2007-03-01'
```

```

end_date = '2024-03-31'
file_path = './F-F_Research_Data_Factors_daily.CSV'

ff_factors = fama_french_factors(start_date, end_date, file_path)

# Proceed with the analysis
if ff_factors is not None:
    etf_data = pd.read_csv('etf_prices.csv', index_col=0, parse_dates=True)
    etf_returns = etf_data.pct_change().dropna()

    # Merge ETF returns with Fama-French factors
    merged_data = etf_returns.join(ff_factors, how='inner')

    # Estimate factor loadings for each ETF
    factor_loadings = {}
    for ticker in etf_data.columns:
        model = sm.OLS(merged_data[ticker], sm.add_constant(merged_data[['Mkt-RF',
        results = model.fit()
        factor_loadings[ticker] = results.params

    # Convert factor loadings to a DataFrame
    factor_loadings_df = pd.DataFrame(factor_loadings).T
    factor_loadings_df.columns = ['Alpha', 'Mkt-RF', 'SMB', 'HML']
    factor_loadings_df.to_csv('factor_loadings.csv')

    print(factor_loadings_df.head())

```

	Alpha	Mkt-RF	SMB	HML
DBA	-0.000032	0.002360	-0.000186	0.000630
EPP	-0.000142	0.010475	-0.000677	0.001387
EWJ	-0.000139	0.007755	-0.000921	0.000244
FEZ	-0.000184	0.011116	-0.000657	0.001652
FXE	-0.000074	0.001090	0.000042	0.000097

3. Optim(ization)

3.05 misc

```

In [ ]: import numpy as np

def is_symmetric(matrix, tol=1e-8):
    """Check if a matrix is symmetric/Hermitian within a tolerance."""
    return np.allclose(matrix, matrix.T, atol=tol)

```

3.1 Strat \mathcal{I}

```

In [ ]: import cvxpy as cp
import numpy as np

def optimize_strategy_I(expected_returns, cov_matrix, factor_loadings, beta_constraint):
    n = len(expected_returns)
    w = cp.Variable(n)
    portfolio_return = expected_returns @ w

```

```

# Ensure the covariance matrix is symmetric
cov_matrix = (cov_matrix + cov_matrix.T) / 2

# Check if the covariance matrix is symmetric/Hermitian
if not is_symmetric(cov_matrix):
    raise ValueError("Covariance matrix is not symmetric/Hermitian.")

portfolio_risk = cp.quad_form(w, cov_matrix)

# Calculate the portfolio beta using factor loadings
portfolio_beta = factor_loadings['Mkt-RF'].values @ w

constraints = [
    cp.sum(w) == 1,
    portfolio_beta >= beta_constraints[0],
    portfolio_beta <= beta_constraints[1],
    w >= -2,
    w <= 2
]

# Objective function: maximizing return minus risk-adjusted return
objective = cp.Maximize(portfolio_return - lambd * cp.norm(portfolio_risk, 2))
prob = cp.Problem(objective, constraints)
prob.solve()

return w.value

# Example usage
beta_constraints = [-0.5, 0.5]
lambd = 0.1
expected_returns = factor_loadings_df['Alpha'].values
cov_matrix = etf_returns.cov().values

optimal_weights_I = optimize_strategy_I(expected_returns, cov_matrix, factor_loadings)
print("Optimal weights for Strategy I:", optimal_weights_I)

```

```

Optimal weights for Strategy I: [ 1.57452502 -1.99997055 -1.99999286 -1.99999298 -1.
99999269  1.9999992
-0.57456848  1.99999897  1.99999577  1.99999792 -1.99999753  1.99999822]

```

```

In [ ]: import cvxpy as cp
import numpy as np

def optimize_strategy_I(expected_returns, cov_matrix, factor_loadings, beta_constraints):
    n = len(expected_returns)
    w = cp.Variable(n)
    portfolio_return = expected_returns @ w

    # Ensure the covariance matrix is symmetric
    cov_matrix = (cov_matrix + cov_matrix.T) / 2

    portfolio_risk = cp.quad_form(w, cov_matrix)

    # Calculate the portfolio beta using factor loadings
    portfolio_beta = factor_loadings['Mkt-RF'].values @ w

```

```

constraints = [
    cp.sum(w) == 1,
    portfolio_beta >= beta_constraints[0],
    portfolio_beta <= beta_constraints[1],
    w >= -2,
    w <= 2
]

# Objective function: maximizing return minus risk-adjusted return
objective = cp.Maximize(portfolio_return - lambda * cp.norm(portfolio_risk, 2))
prob = cp.Problem(objective, constraints)
prob.solve()

return w.value

# Example usage
beta_constraints = [-0.5, 0.5]
lambda = 0.1
expected_returns = factor_loadings_df['Alpha'].values
cov_matrix = etf_returns.cov().values

optimal_weights_I = optimize_strategy_I(expected_returns, cov_matrix, factor_loadings)
print("Optimal weights for Strategy I:", optimal_weights_I)

```

Optimal weights for Strategy I: [1.57452502 -1.99997055 -1.99999286 -1.99999298 -1.99999269 1.9999992
-0.57456848 1.99999897 1.99999577 1.99999792 -1.99999753 1.99999822]

3.2 Strat II

```

In [ ]: from scipy.optimize import minimize

def tracking_error_volatility(weights, returns_data, benchmark_returns):
    # Calculate portfolio returns
    portfolio_returns = returns_data @ weights
    # Calculate tracking error volatility
    return np.sqrt(np.var(portfolio_returns - benchmark_returns))

def optimize_strategy_II(expected_returns, returns_data, factor_loadings, beta_constraints):
    n = len(expected_returns)

    def objective(weights):
        portfolio_return = expected_returns @ weights
        te_vol = tracking_error_volatility(weights, returns_data, benchmark_returns)
        return -(portfolio_return - lambda * te_vol)

    constraints = [
        {'type': 'eq', 'fun': lambda w: np.sum(w) - 1},
        {'type': 'ineq', 'fun': lambda w: beta_constraints[1] - np.sum(w * factor_loadings[:, 1])},
        {'type': 'ineq', 'fun': lambda w: np.sum(w * factor_loadings[:, 0]) - beta_constraints[0]},
        {'type': 'ineq', 'fun': lambda w: 2 - w},
        {'type': 'ineq', 'fun': lambda w: w + 2}
    ]

    bounds = [(-2, 2) for _ in range(n)]
    result = minimize(objective, np.ones(n) / n, bounds=bounds, constraints=constraints)

```

```

    return result.x

# Example usage
beta_constraints = [-2, 2]
lambda = 0.1
benchmark_returns = etf_returns['SPY'].values
returns_data = etf_returns.values # Adjusted to use returns data directly

optimal_weights_II = optimize_strategy_II(expected_returns, returns_data, factor_lo
print("Optimal weights for Strategy II:", optimal_weights_II)

```

```

Optimal weights for Strategy II: [ 0.02058621  0.1072614   0.09340881  0.10845794
 0.02415552  0.03810605
 0.08879167  0.19751428  0.05704948  0.17376242 -0.05986655  0.15077276]

```

4. The Test (of b A c K)

```

In [ ]: import pandas as pd
import matplotlib.pyplot as plt

# Define the combined backtesting function
def backtest_combined(strategies, start_date, end_date, rebalance_period='7D', **kw
    results = {}
    dates = pd.date_range(start=start_date, end=end_date, freq=rebalance_period)

    for name, strategy_func in strategies.items():
        backtest_data = etf_returns[(etf_returns.index >= start_date) & (etf_return
        portfolio_values = [100] # Starting portfolio value

        for i in range(len(dates) - 1):
            current_data = backtest_data.loc[:dates[i]]
            cov_matrix = current_data.cov().values
            # Ensure the covariance matrix is symmetric
            cov_matrix = (cov_matrix + cov_matrix.T) / 2
            if not is_symmetric(cov_matrix):
                raise ValueError("Covariance matrix is not symmetric/Hermitian.")
            expected_returns = current_data.mean().values
            optimal_weights = strategy_func(expected_returns, cov_matrix, **kwargs)

            # Calculate portfolio returns for the next period
            period_returns = (backtest_data.loc[dates[i]:dates[i+1]] @ optimal_weig
            portfolio_values.append(portfolio_values[-1] * (1 + period_returns).pro

        results[name] = (portfolio_values, dates)

    return results

# Strategy functions
strategy_func_I = lambda exp_returns, cov_mat, **kwargs: optimize_strategy_I(
    exp_returns, cov_mat, factor_loadings_df, beta_constraints=[-0.5, 0.5], lambda=0
)

strategy_func_II = lambda exp_returns, cov_mat, **kwargs: optimize_strategy_II(
    exp_returns, etf_returns.loc[:dates[0]].values, factor_loadings_df, beta_constr
    lambda=0.1, benchmark_returns=etf_returns['SPY'].loc[:dates[0]].values

```

```
)

strategies = {
    'Strategy I': strategy_func_I,
    'Strategy II': strategy_func_II
}

# Perform backtesting
results = backtest_combined(strategies, start_date='2007-03-01', end_date='2024-03-

# Plot results
plt.figure(figsize=(12, 6))
for name, (portfolio_values, dates) in results.items():
    plt.plot(dates, portfolio_values, label=name)
plt.xlabel('Date')
plt.ylabel('Portfolio Value')
plt.title('Backtesting Results for Strategy I and Strategy II')
plt.legend()
plt.show()
```