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MULTI FACTOR INVESTING

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The Team

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I'm a second year Master's in Financial Engineering candidate at Lehigh with a background in Math and industry experience in a hedge fund. My projects have been focused on Multi-Factor investing, Index development, NLP in CDS and other financial instruments, and machine learning optimization.

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MFE'25

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MFE'26

Vincent Batten

MFE 4+`1

Overview

Introduction

Factors:

- Characteristics that explain the return of equities and influence variations in portfolios
- For this project, we are focusing on the Fama-French factors such as size, value, and market risk

Multi-factor investing :

- An investment strategy that combines multiple factors to achieve specific investment goals, like higher returns or lower risk
- It enhances diversification and seeks to optimize portfolio performance

Objectives

- To create a systematic framework for multifactor investing in equities
- To systematically identify, measure, and integrate factor exposure that historically drive returns.
- To provide a structured approach for building diversified portfolios that are tailored to capture these factors while maximizing risk-adjusted returns.
- Identify optimal rebalancing and holding period for various factor exposures

Goals:

- Using Monte Carlo simulations, learn about the expectation and variance of the portfolio for specific target exposures and compare its performance with the SP 500
- Implement strategies such as hedging to note its impact on factor decay as well as on rebalancing of the portfolio
- Discover new target exposures using reinforcement learning that relies on back tested information which offer better downside protection
- Understand the optimal holding period for factor combinations
- Compare the effect of tax-loss harvesting, alpha signal from alternative data on performance

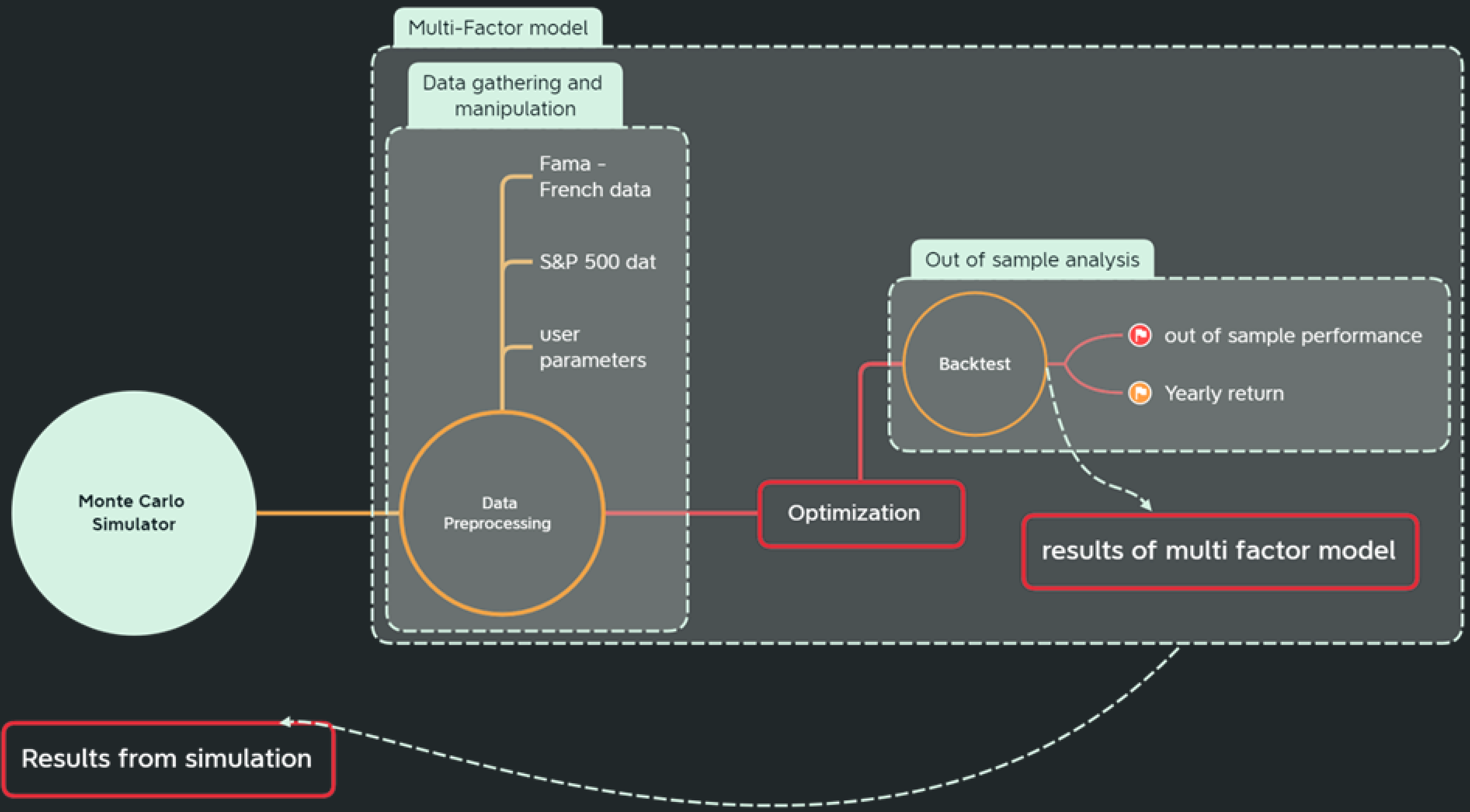
Project

Optimization

- Minimizes the error term in portfolio returns
- Ensures the portfolio's factor exposure aligns with the desired factor exposures
- Optimizes the number of shares to be bought/sold
- Minimizes transaction costs

Constraints:

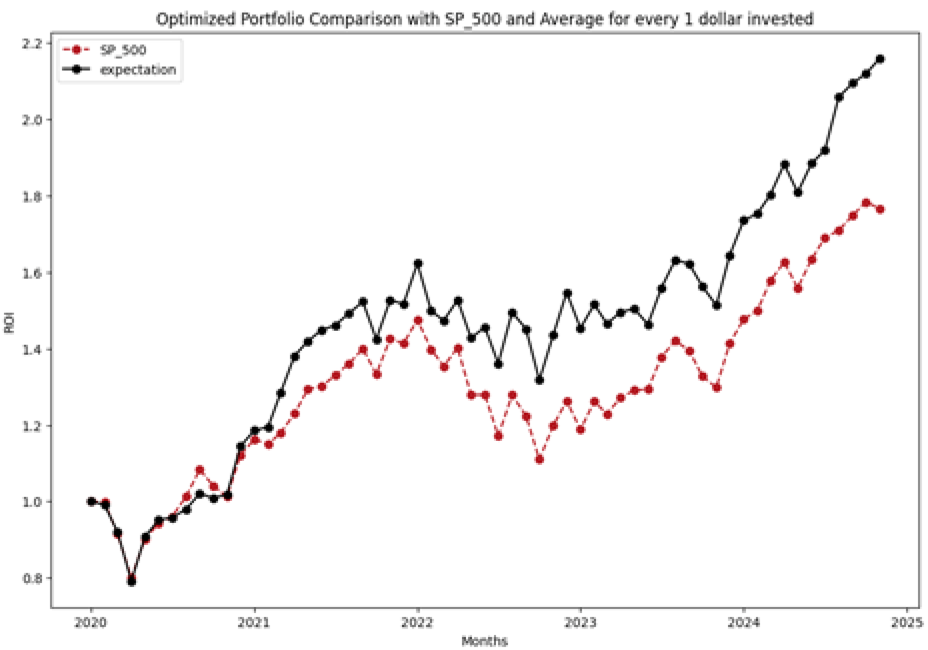
- Weight constraints
- Error constraints
- Transaction costs constraint
- Number of stocks constraint


Multi-Factor model
Data gathering and manipulation
Fama - French data
S&P 500 dat
user parameters
Monte Carlo Simulator
Data Preprocessing
Optimization
Out of sample analysis
Backtest
out of sample performance
Yearly return
results of multi factor model
Results from simulation

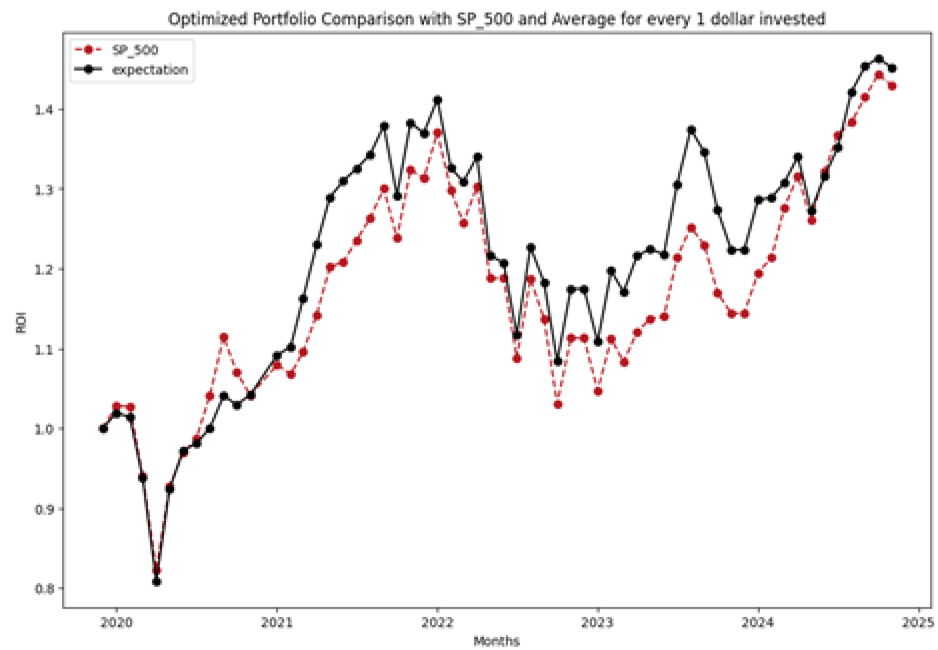
Findings from Monte Carlo Simulations

Base case (Pure market strategy)

Non-Rebalancing

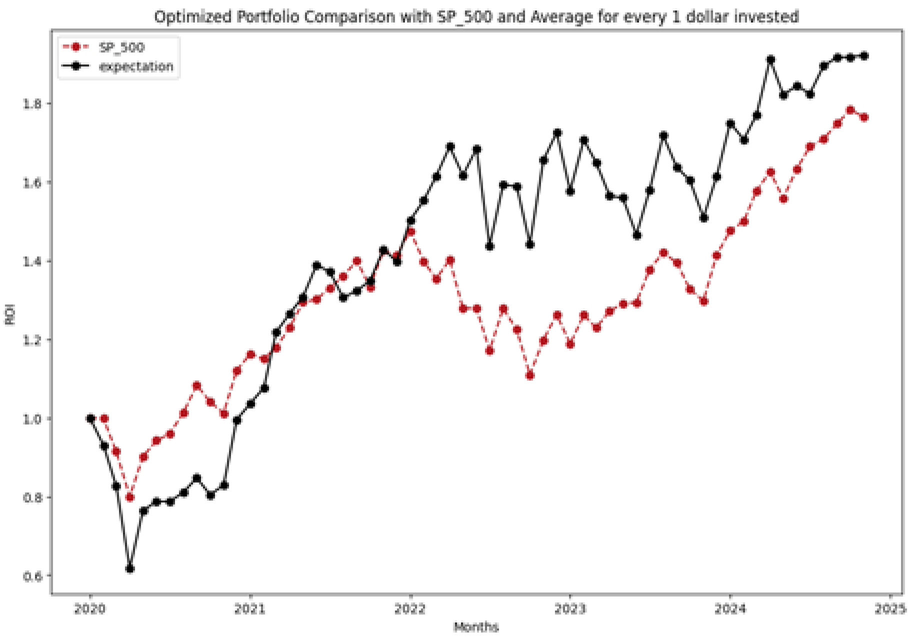


Rebalancing

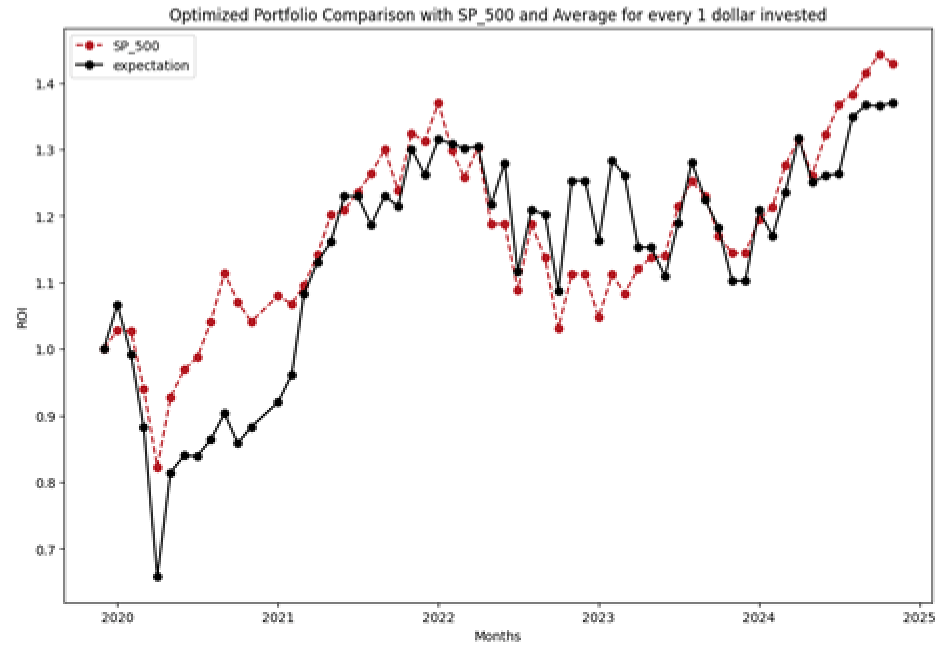


Reinforcement case (1,0.7,0.7 strategy)

Non-Rebalancing

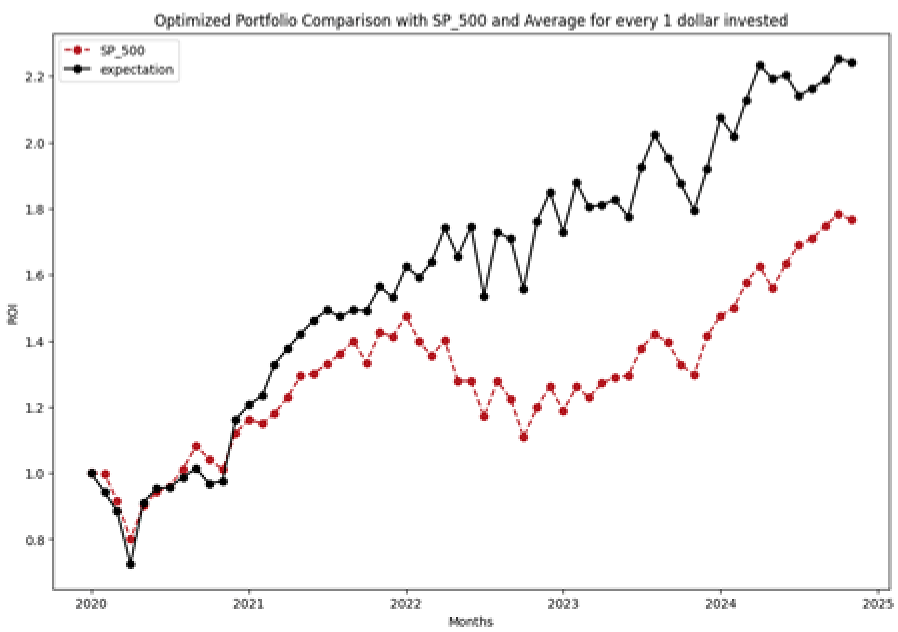


Rebalancing

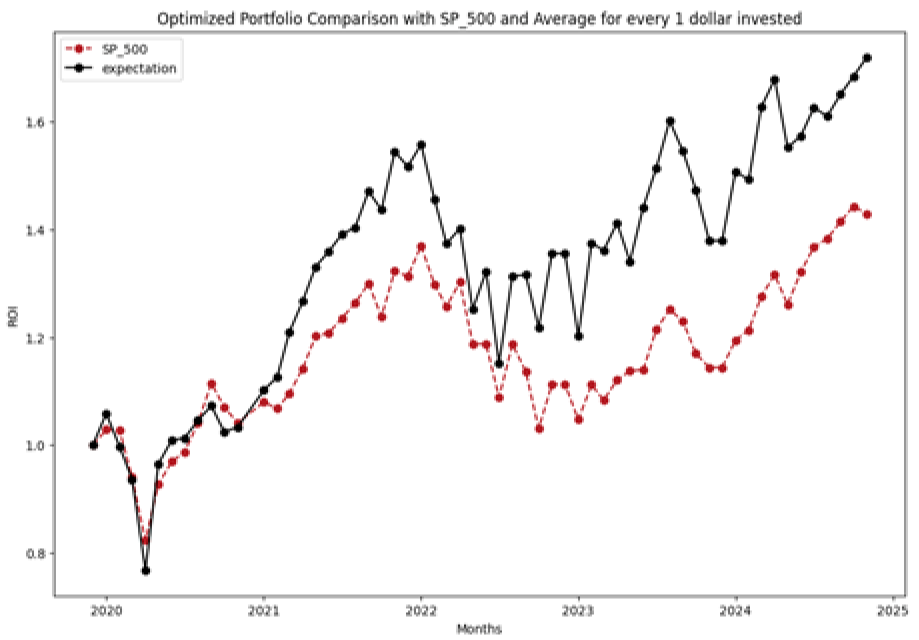


New best case (1,1,0 strategy)

Non-Rebalancing

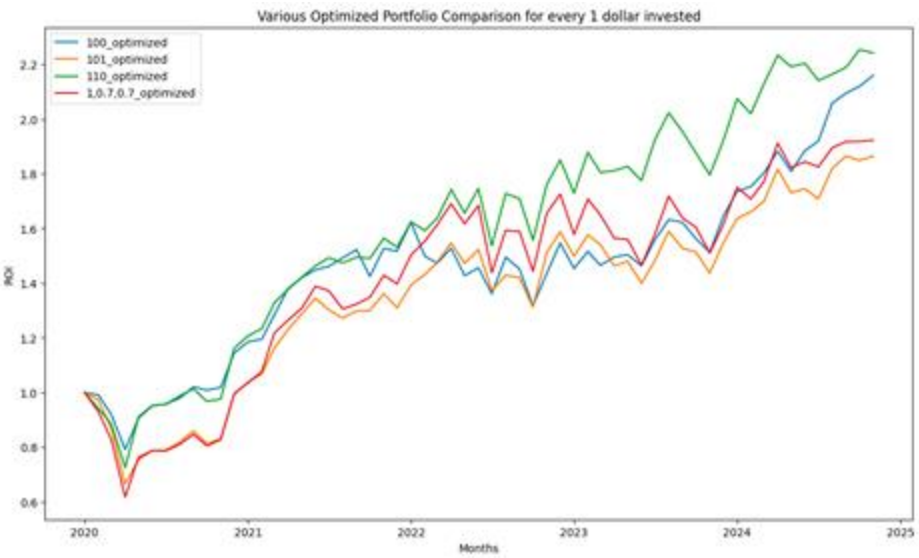


Rebalancing

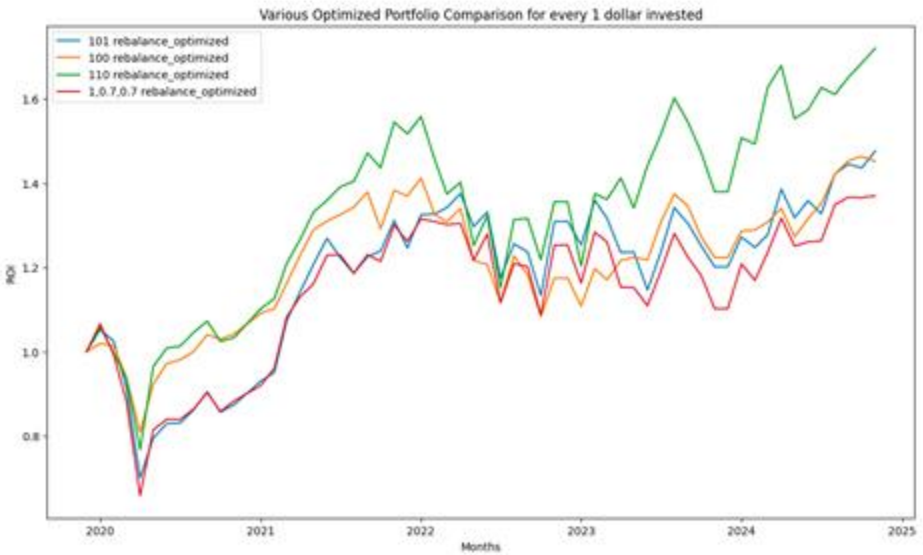


Non Rebalancing vs Rebalancing

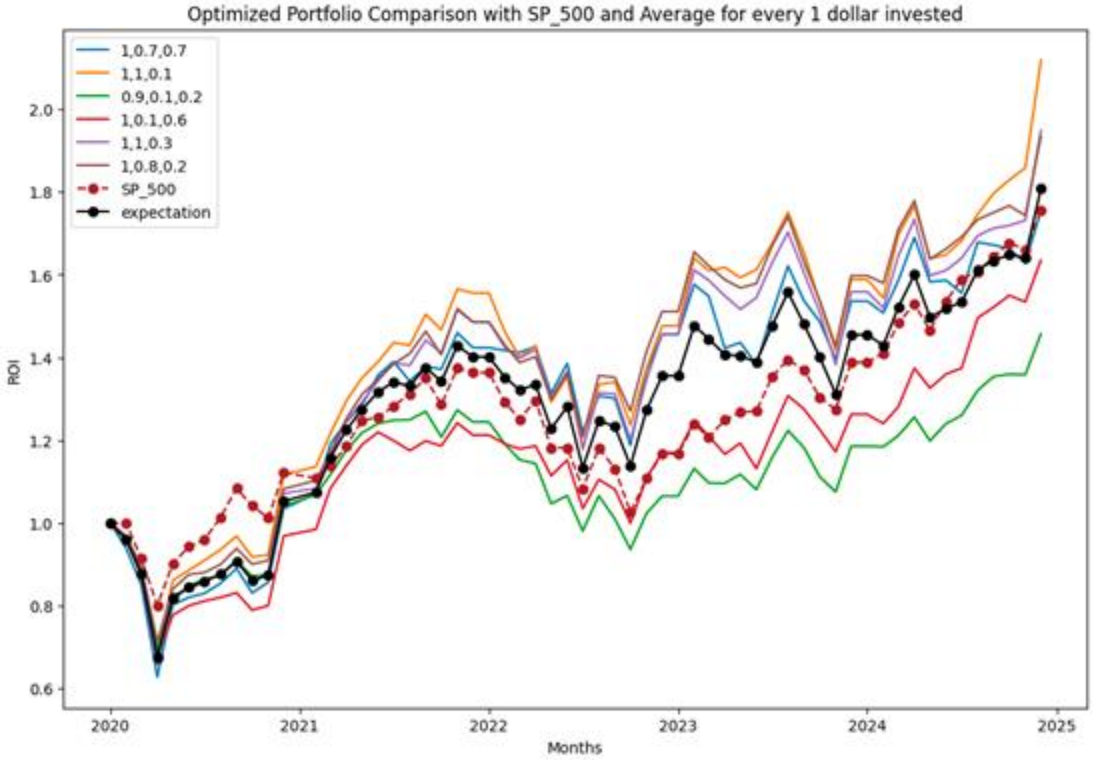
Non-Rebalancing



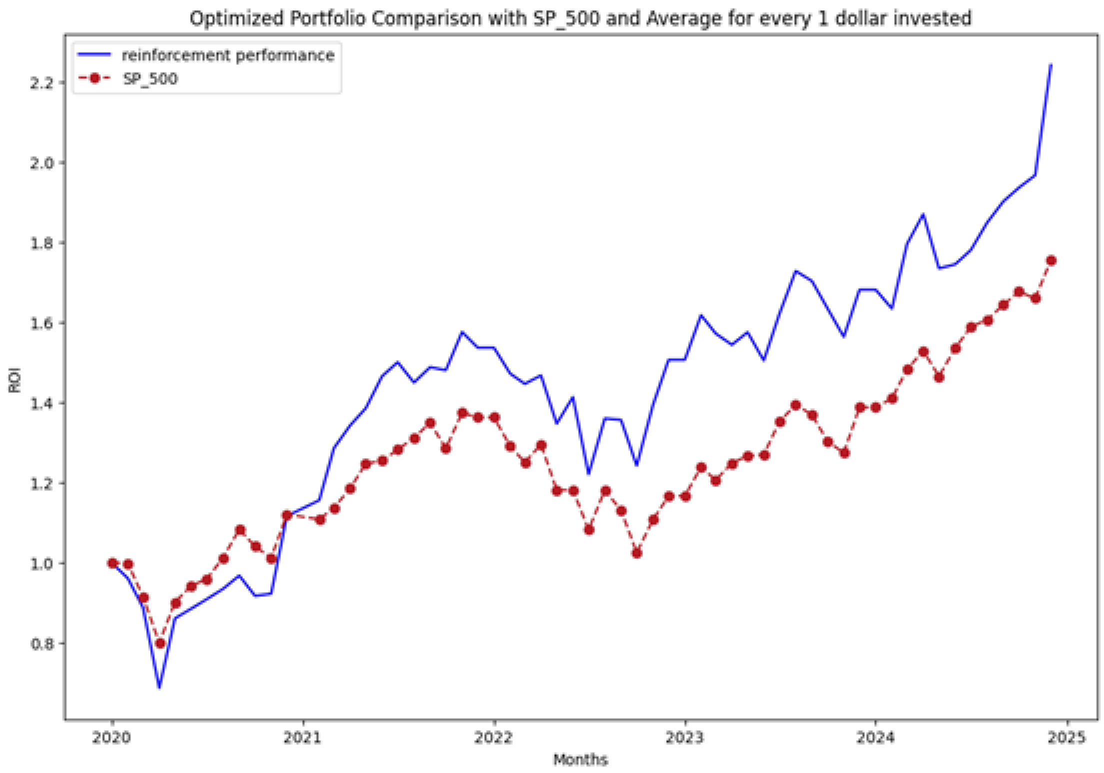
Rebalancing



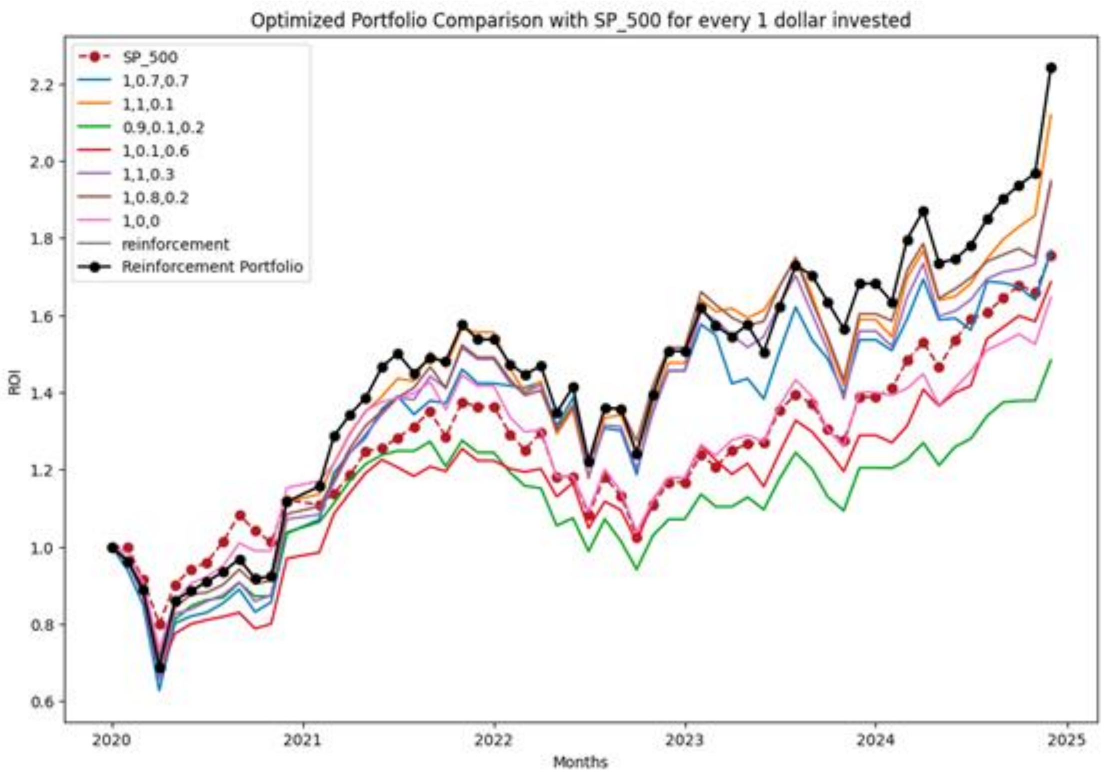
Performance of different strategies

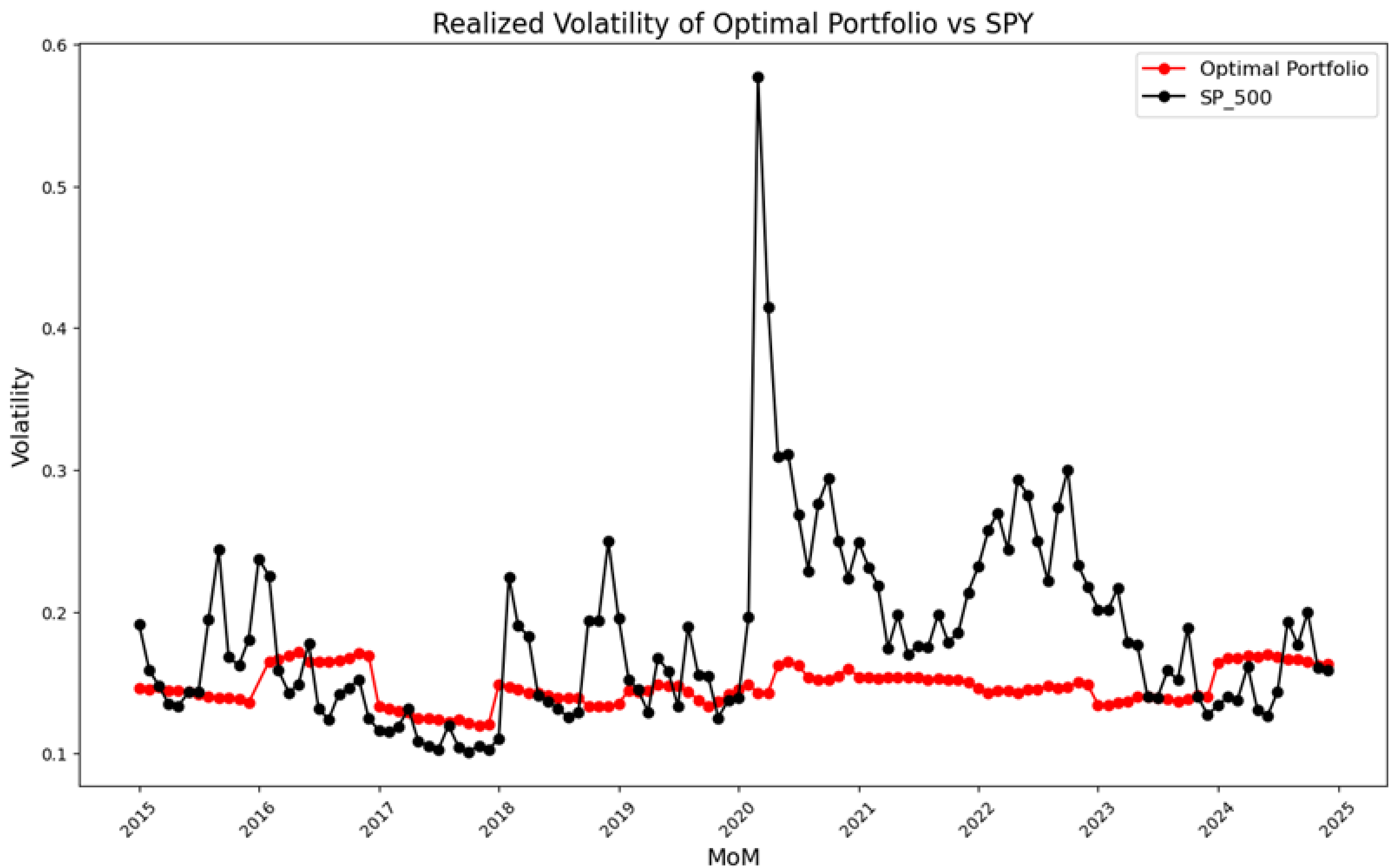


Reinforcement performance

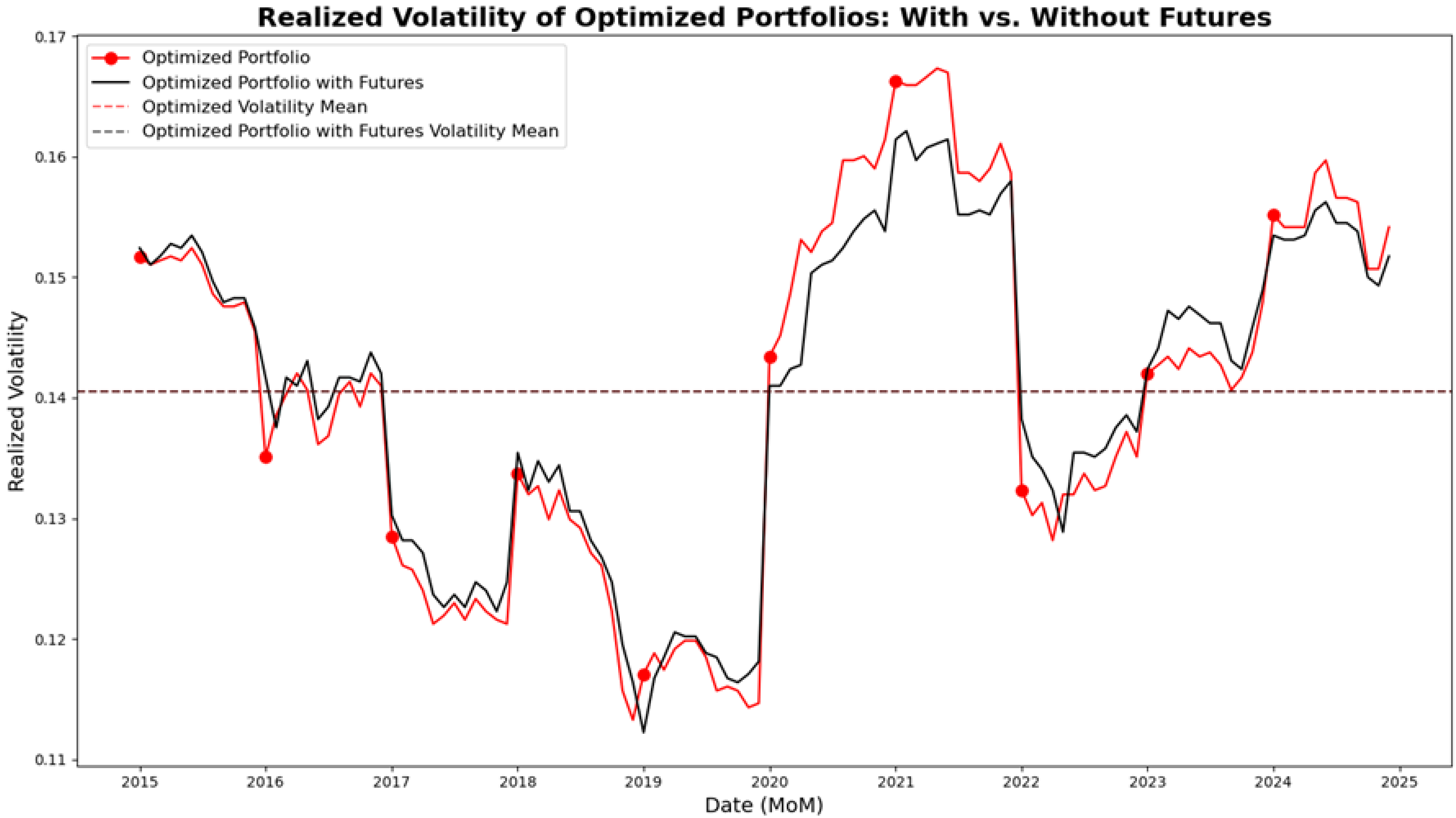


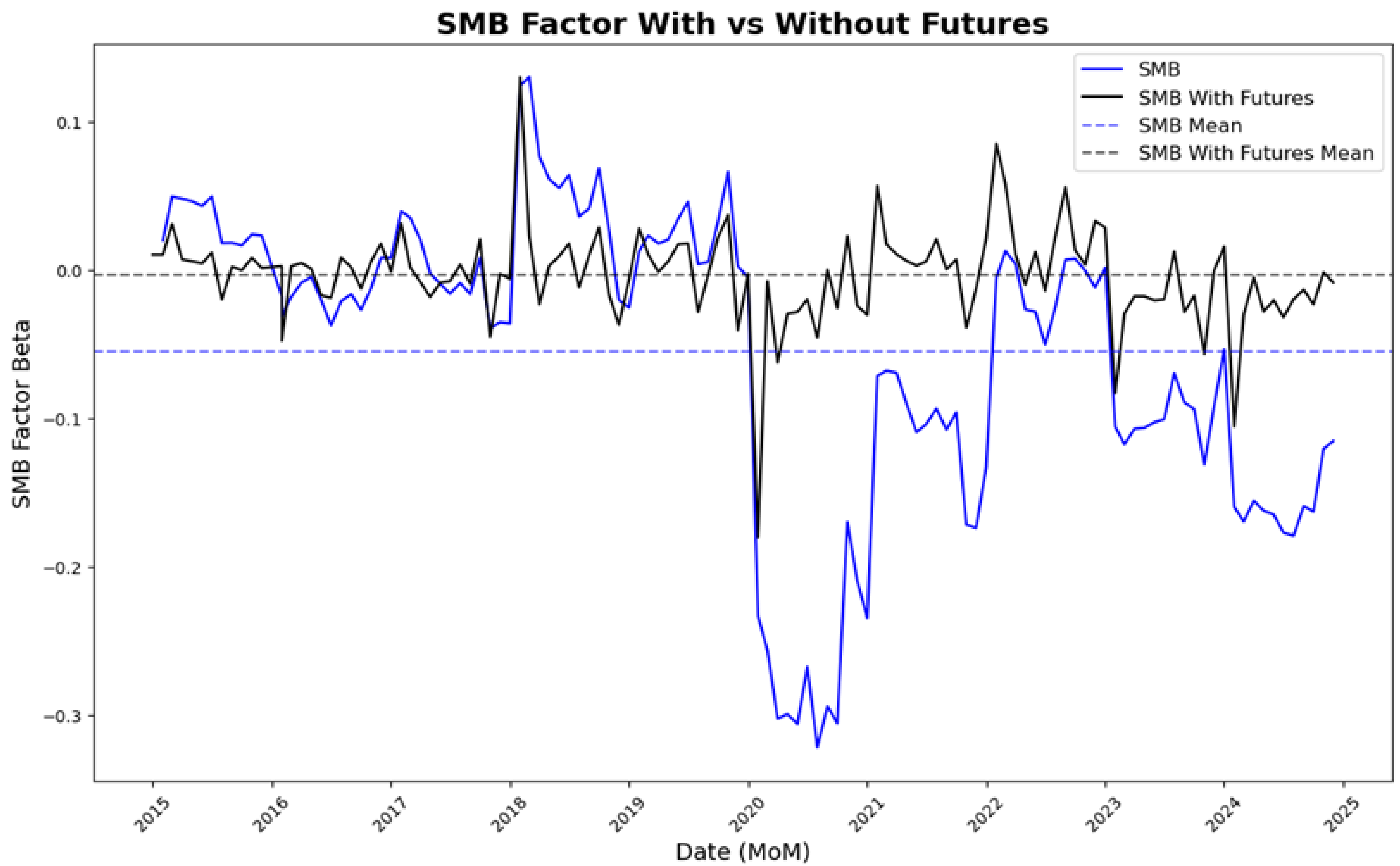
Reinforcement performance

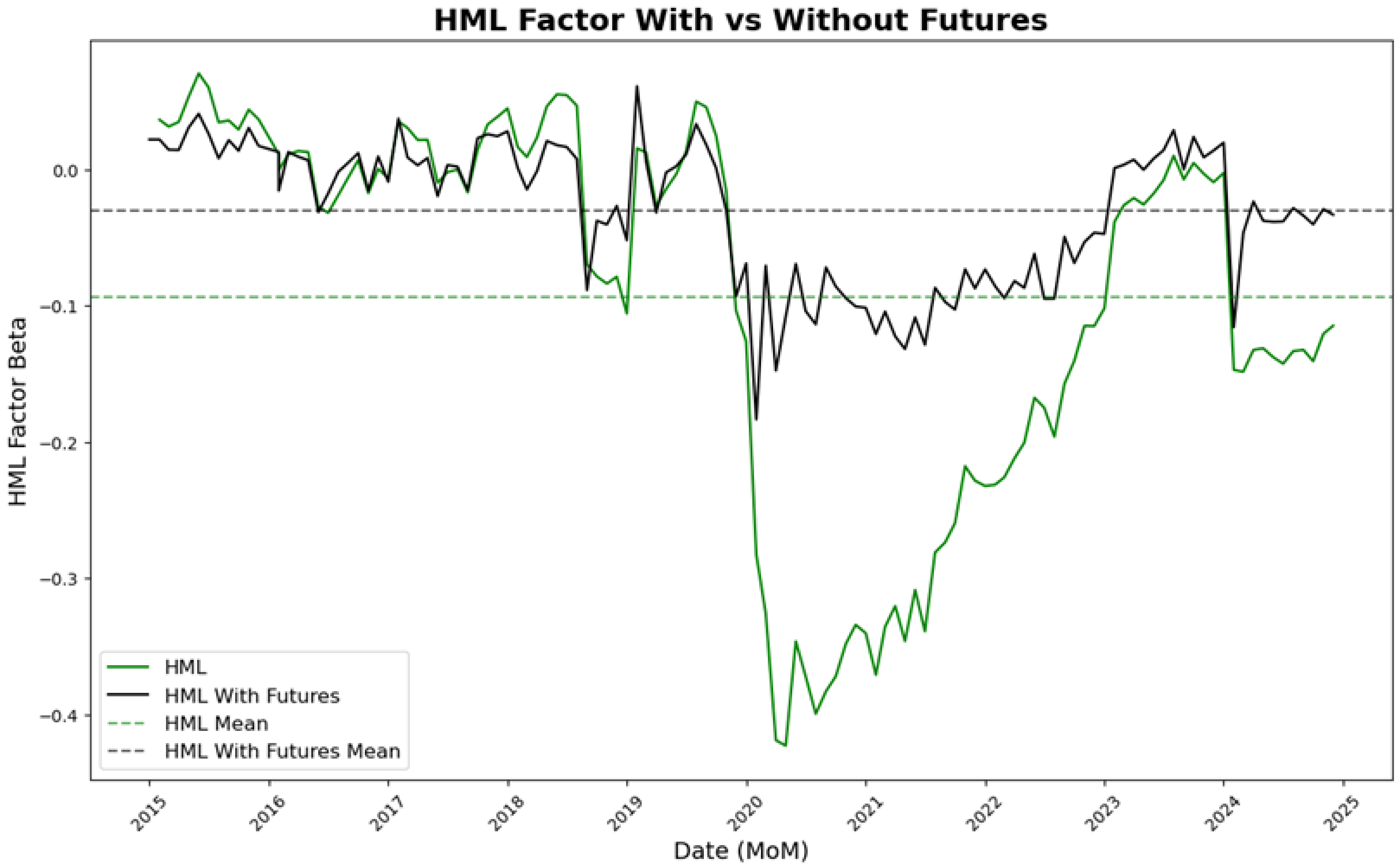




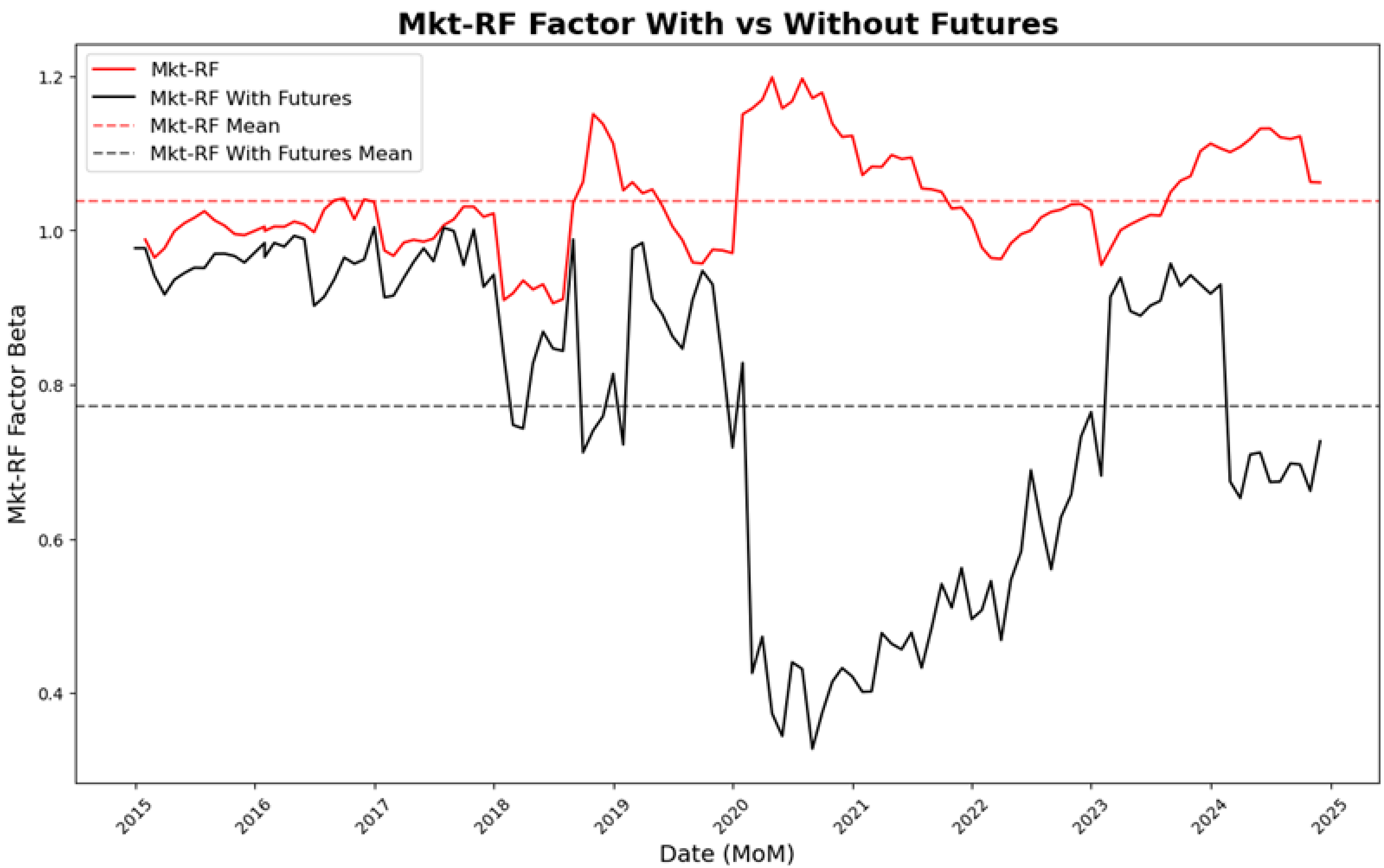
Realized Volatility of Optimal Portfolio vs SPY
Optimal Portfolio
SP_500
Volatility
MoM
0.1
0.2
0.3
0.4
0.5
0.6
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
2025


Realized Volatility of Optimized Portfolios: With vs. Without Futures
Optimized Portfolio
Optimized Portfolio with Futures
Optimized Volatility Mean
Optimized Portfolio with Futures Volatility Mean
Realized Volatility
Date (MoM)
0.17
0.16
0.15
0.14
0.13
0.12
0.11
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
2025


SMB Factor With vs Without Futures
SMB
SMB With Futures
SMB Mean
SMB With Futures Mean
SMB Factor Beta
0.1
0.0
−0.1
−0.2
−0.3
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
2025
Date (MoM)



HML Factor With vs Without Futures
HML Factor Beta
0.0
−0.1
−0.2
−0.3
−0.4
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
2025
Date (MoM)
HML
HML With Futures
HML Mean
HML With Futures Mean


Mkt-RF Factor With vs Without Futures
Mkt-RF
Mkt-RF With Futures
Mkt-RF Mean
Mkt-RF With Futures Mean
Mkt-RF Factor Beta
1.2
1.0
0.8
0.6
0.4
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
2025
Date (MoM)

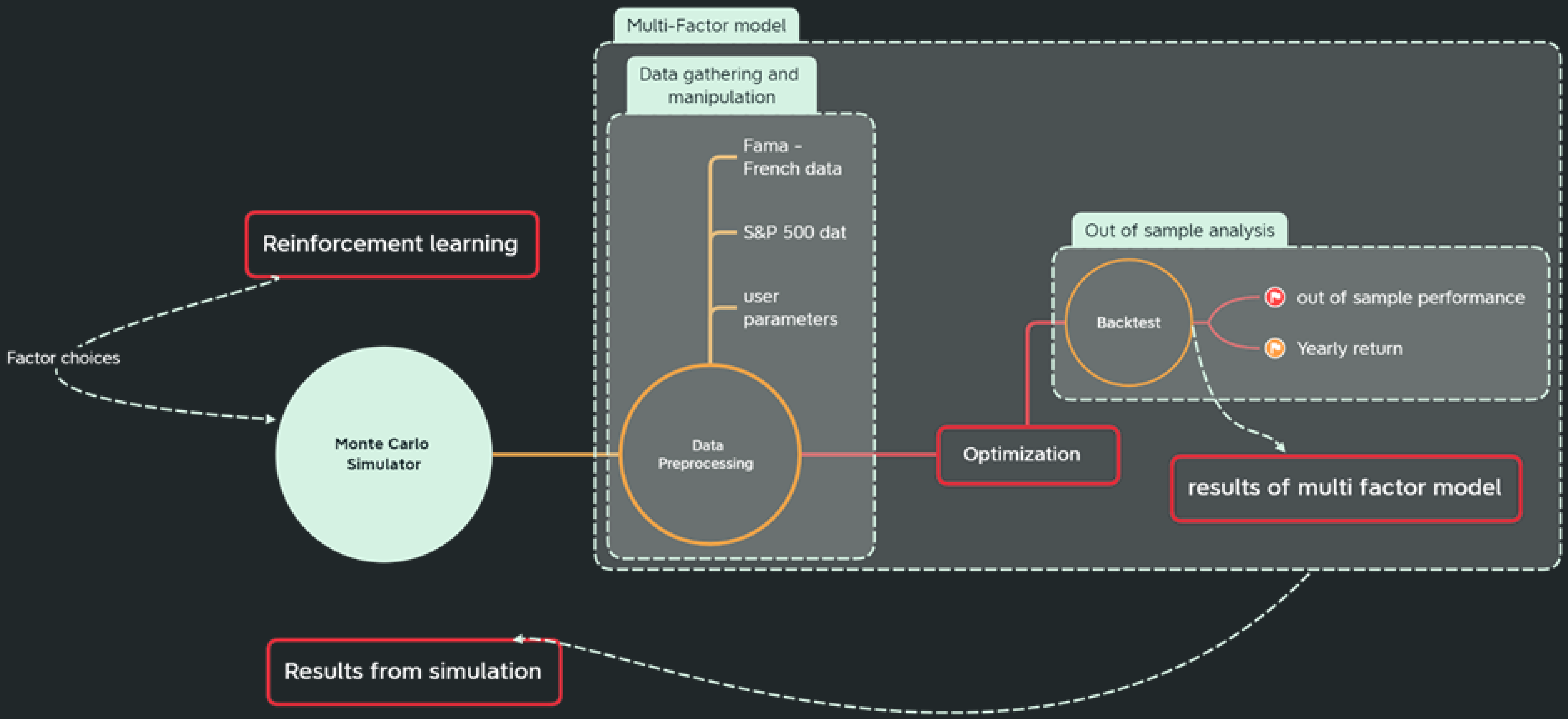
Alpha Signal Framework

- Developed an alpha signal framework based on a dataset of news headlines
- Utilized an LLM model to extract sentiment labels and their associated probabilities
- Engineered features using statistical measures such as standard deviation, skewness, kurtosis, and various aggregations of existing features to create a weekly data point

Reinforcement Learning

Bandit algorithm

- To find new combinations of factors that provide better downside protection compared with the benchmark
- Enhanced with Monte Carlo simulations to explore new combinations and avoid previously tested options.
- Prioritizes changes in factor combinations that could yield improved downside protection.
- Uses ϵ-equalizing algorithm to have higher exploration & lower exploitation
- Avoids redundancy and concentrates computational efforts on discovering new, promising strategies.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Results from simulation

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Results from Reinforcement Learning

Market Beta	Size beta	Value beta	Year 1	Sharpe Ratio
SP500	SP500	SP500	13.0%	0.66
1	0.5	0.5	-15.6%	0.64
1	1	1	-5.3%	0.65
1	0	1	-4.1%	0.57
1	0	0	3.9%	0.61
1.1	0	0	4.2%	0.63
0.8	1	0.3	7.8%	0.88
1	1	0	13.3%	0.84
0.8	1	0	20.0%	1.00
0.8	1.1	0	23.1%	1.08

Strategies

For Enhanced Returns and Risk Management

- Futures Hedging
- Tax loss harvesting
- Alpha signals from alternative data

Futures Hedging

- Using futures on indices with the highest hedge ratios to maintain exposure to individual factors
- To prevent factor decay by maintaining consistent factor weights without the need for frequent rebalancing
- To protect against short-term market movements
- Uses a ML algorithm to pick the optimal future from a basket of index futures

TLH Optimizer (Tax Loss Harvesting)

Tax-loss harvesting is a way to convert investment losses into tax savings.

Modified the Optimization Model by adding more constraints:

Identify losing positions → Find assets with **unrealized losses**.

Sell the losing asset → Realize a **capital loss**.

Offset taxable gains → Reduce capital gains or deduct against income.

Avoid the wash sale rule → Wait 30+ days before rebuying the same asset.

Alpha signal generator

- The overall goal of this is to try to find a relationship between the sentiment analysis and our factors
- If we find meaningful relationships, then we could factor this into our rebalancing strategy
- It can additionally be used as a constraint as to what to sell/buy when rebalancing
- Using unstructured data, we are able to identify equities that are to be avoided in our portfolio construction

SVRG Optimization

Objective: Minimize the error between portfolio returns and expected returns subject to constraints like:

- Non-negative weights
- Weight sum equals 1
- Transaction cost constraints
- Maximum number of assets with non-zero weights

How SVRG Enhances Optimization:

Efficient Convergence:

SVRG handles large datasets by reducing the variance in gradient estimates, leading to faster convergence compared to traditional optimization methods.

Constraints Handling:

SVRG efficiently integrates constraints such as transaction costs and weight limits, reducing the optimization complexity by using variance-reduced gradients to avoid large changes in weights.

Task completed the last 2 weeks

- New system is up and running
- Tax loss harvesting optimizer is designed and implemented
- New project set up and outlook has been implemented
- Gathered the insights requested for identifying the performance difference between different strategies
- Future simulator was tested and integrated into the main functionalities

Current goals

- To determine the optimal rebalancing interval, balancing risk and return across various factors.
- To identify and develop new beta strategies that offer sustainable long-term performance and less volatility
- Compare the effectiveness of rebalancing strategies like future-based hedging versus tax loss harvesting
- To understand the effect of alpha signal from alternative data on betas

Thank you for your time

To answer any further questions, please contact:

Johanan Pranesh
johananantonoutlook.com

Future hedging results

Betas at 7/1/17

Mkt-RF	0.718374
SMB	0.159458
HML	-0.510511

ETF Name	Position	Number of Contracts	Cost of Contracts ($)	EOM Value ($)	P/L ($)	P/L (%)
ES=F	NO ACTION	0.0	0.000	0.000	0.00	0.00
IWM	NO ACTION	0.0	0.000	0.000	0.00	0.00
IWB	LONG	9.0	16290.421	16420.808	130.39	0.11
IWD	LONG	2.0	58762.751	59388.438	625.69	0.53
IWF	SHORT	2.0	43454.827	43743.888	-289.06	-0.24

Risk Factor

Value Factor

Size Factor

Period	Contracts	Action	Hedge Profit
3	0.0	no action	$0.00
6	0.0	no action	$0.00
9	1.0	SHORT	$-524.75

Period	Contracts	Action	Hedge Profit
3	1.0	SHORT	$-247.70
6	1.0	SHORT	$-333.00
9	1.0	SHORT	$-226.00

Period	Contracts	Action	Hedge Profit
3	3.0	LONG	$743.10
6	2.0	SHORT	$-666.00
9	1.0	SHORT	$-320.50