ERASMUS UNIVERSITEIT ROTTERDAM × ROBECO

Seminar Group C

Presentation Overview

Introduction

Improving the Prediction of Cross-Sectional Government Bond Returns through ML

Methodology

01 Models

Which models are we using?

OLS (All), OLS (4 factor), Elastic Net, GLM

RF, XGB, SVM, NN

02 Variable Selection

How did we select variables?

Which variables were selected?

03 Feature Importance

How are we planning to measure feature importance?

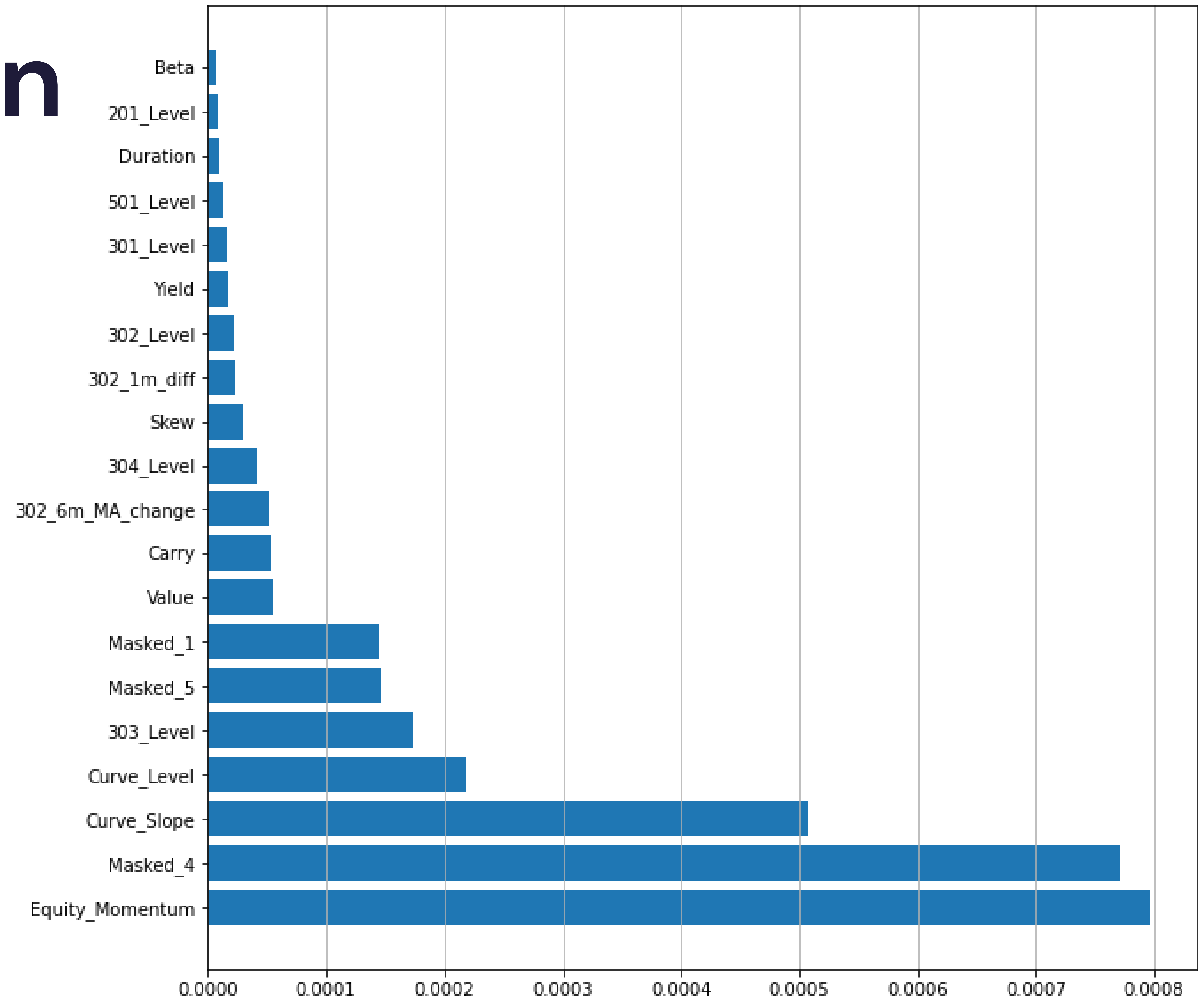
-> Dive more in the section Results

04 Training methods

Which 5 ways of training and predicting?

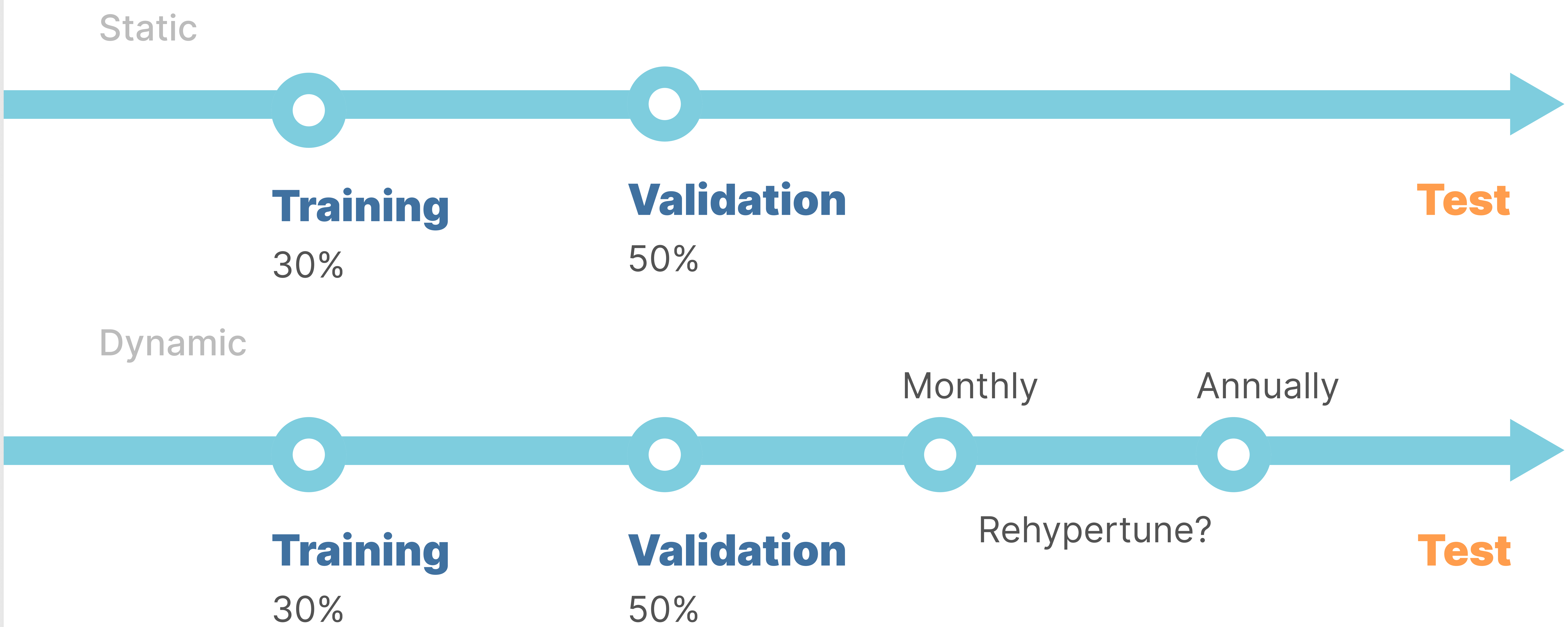
Variable selection

The most important predictors according to elastic net regularization (lambda parameter)



- Top 20 features
- 3 Masked variables

Training methods



Results

We discuss results in 3 sections

R2

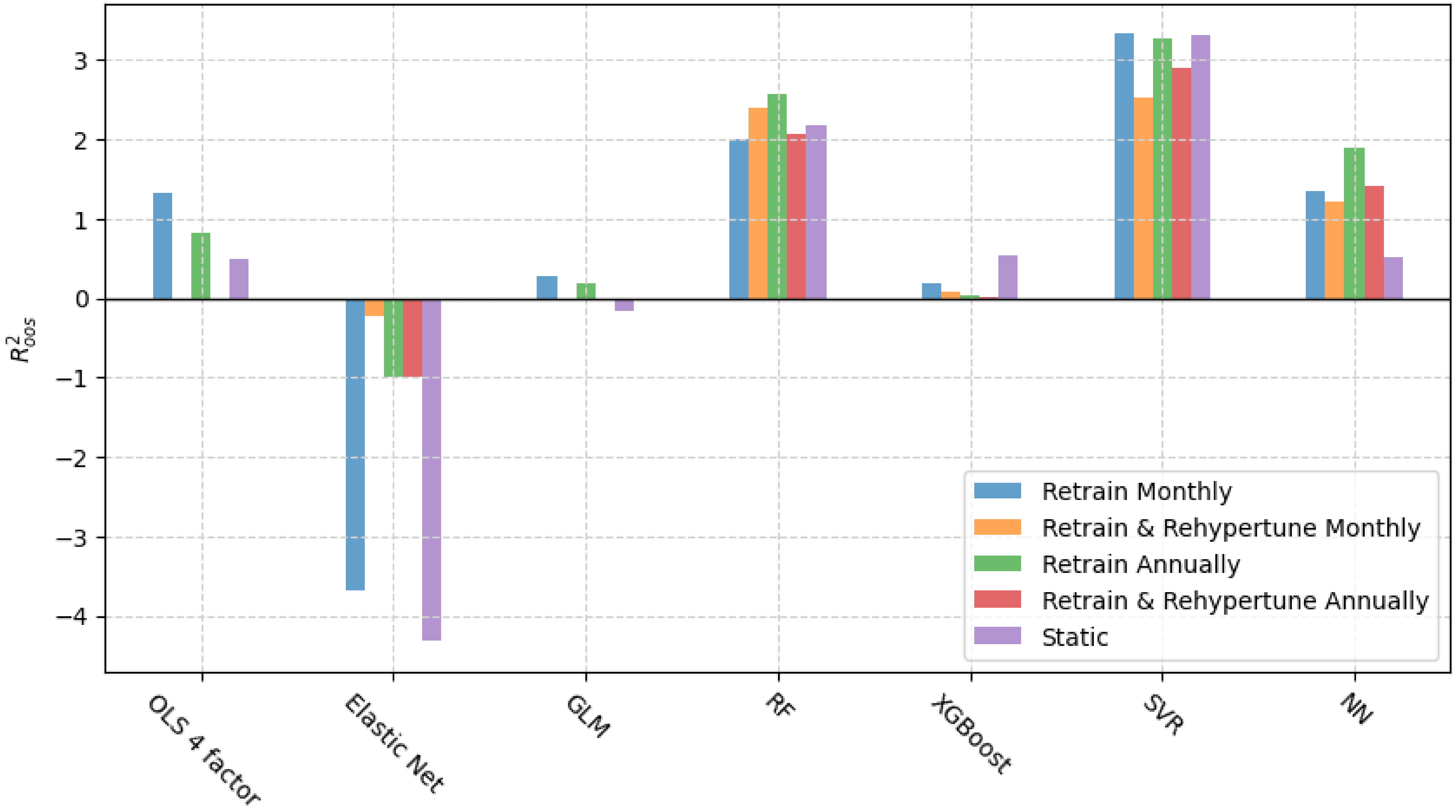
Model evaluation

VIM

Feature Importance

Profit?

Portfolio formation



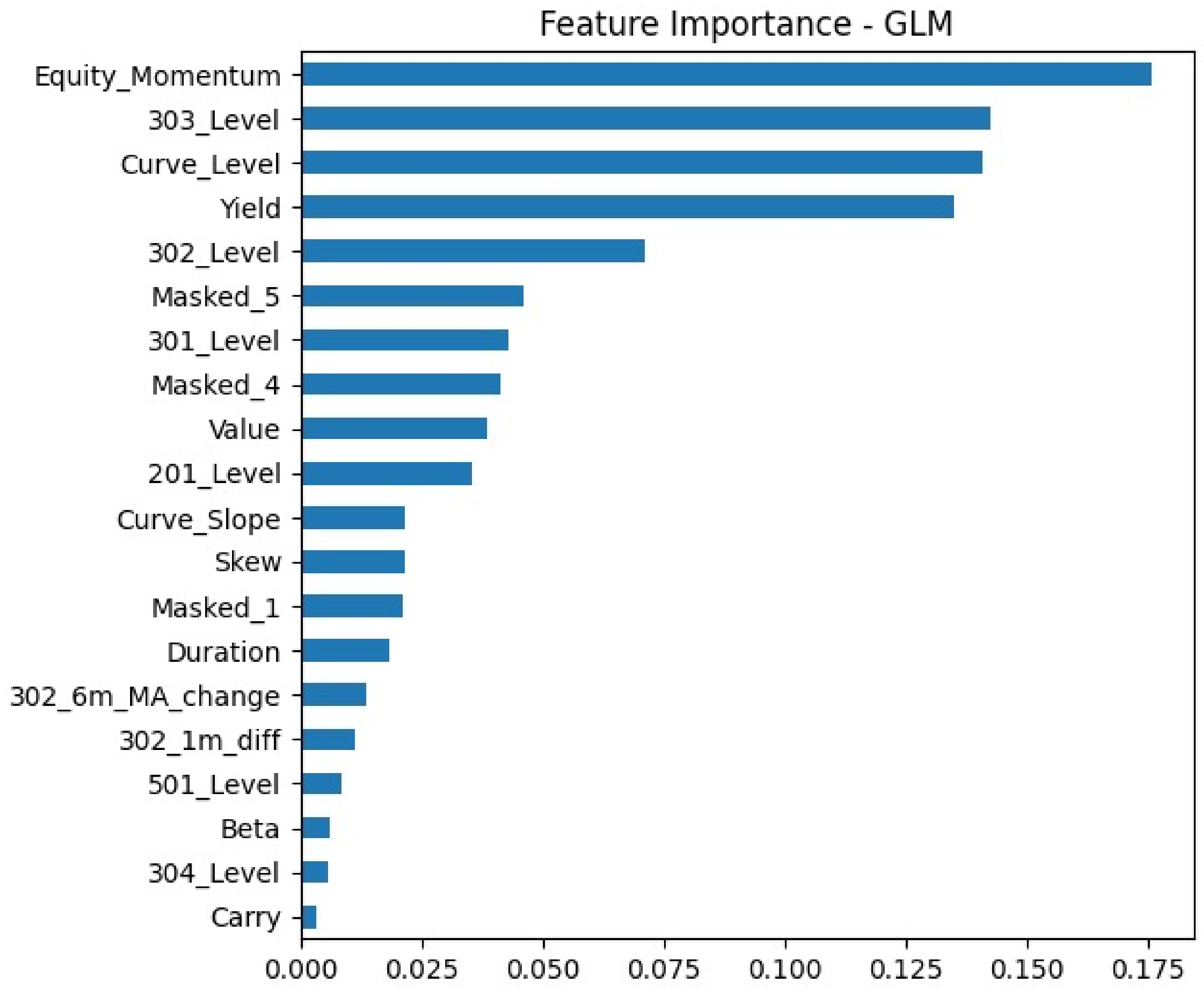
Model Evaluation

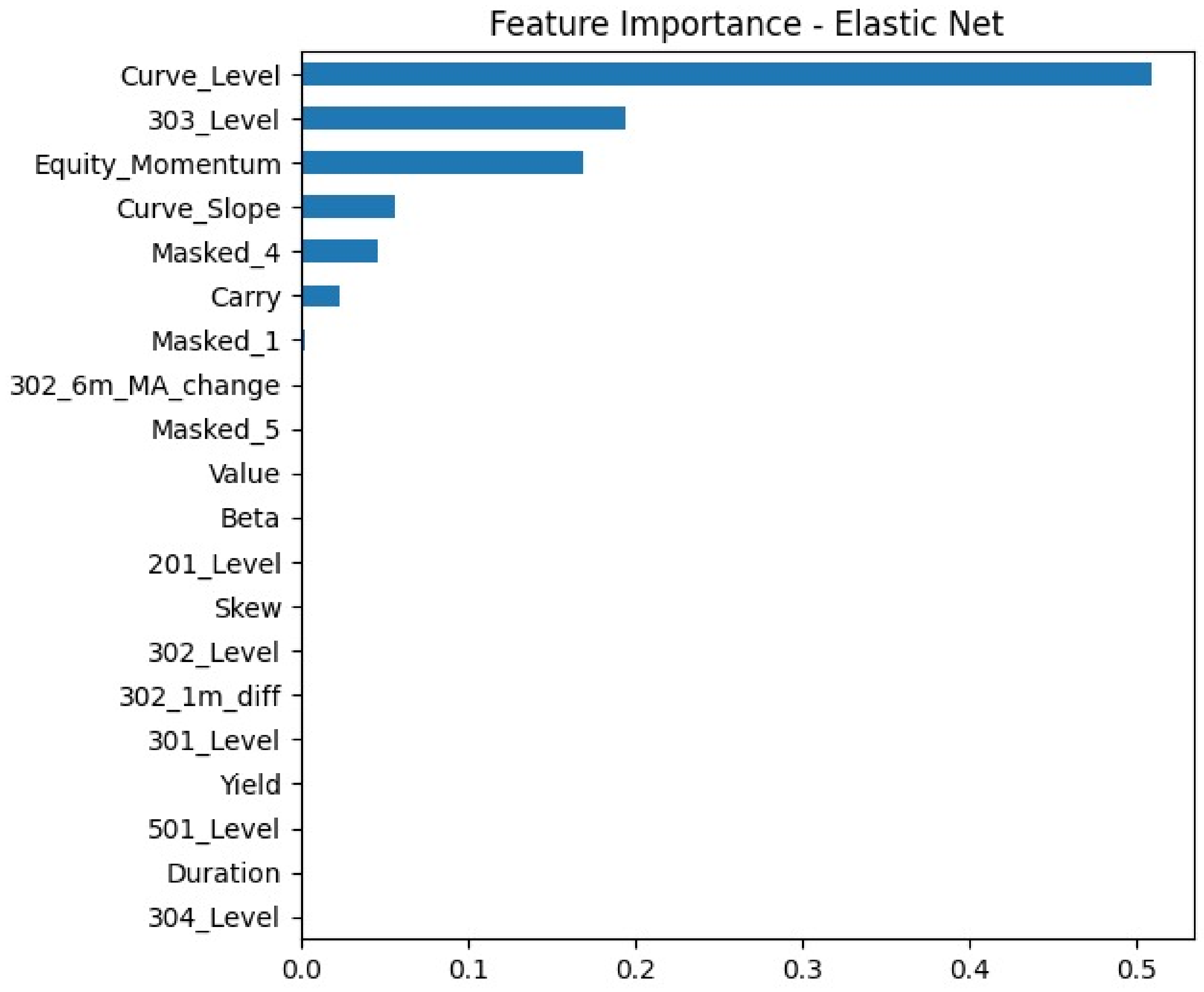
Evaluated all ML-models using R-squared

Feature Importance

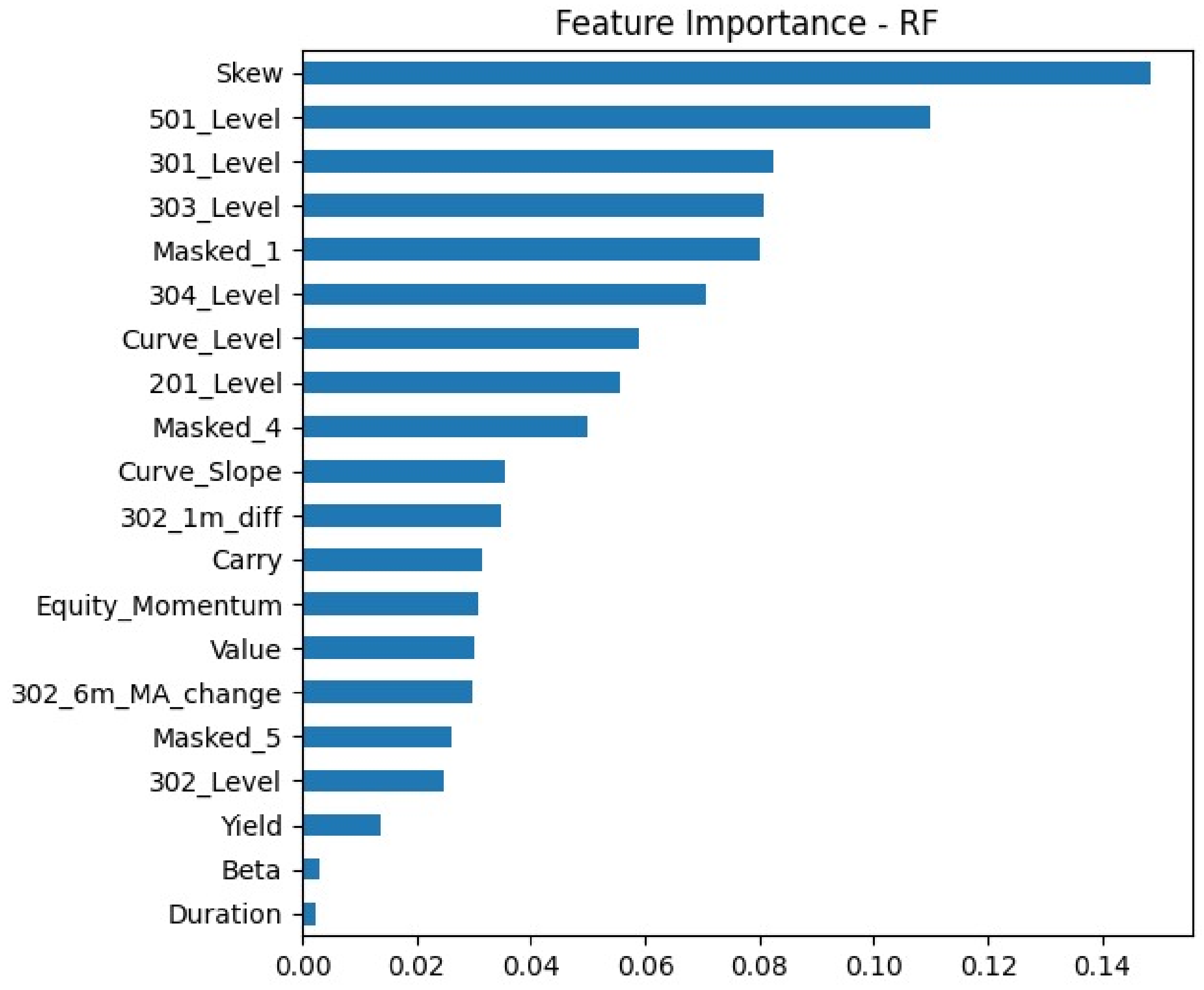
Method

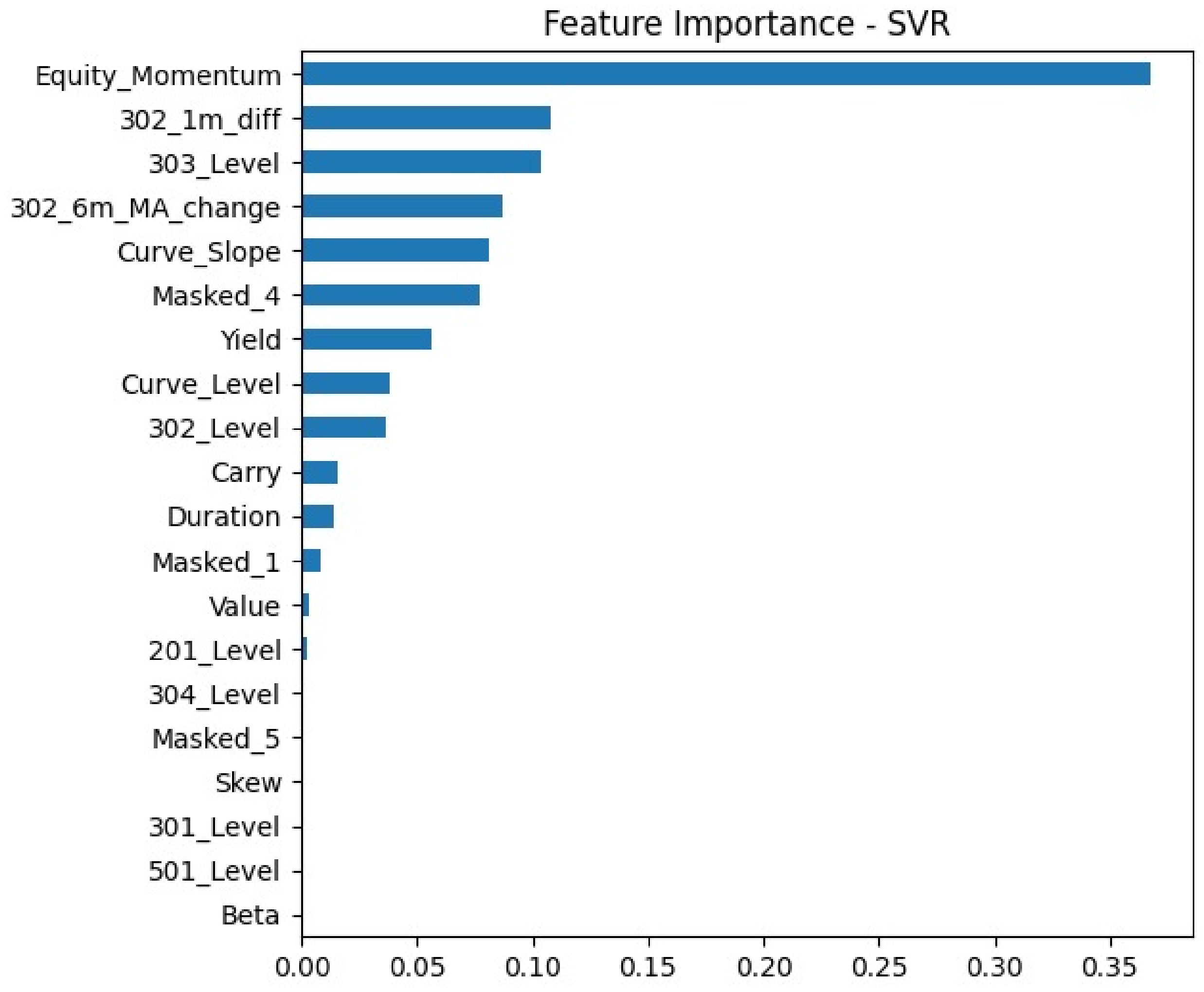
1. After fitting a model, the respective in-sample R2 is computed
2. For each feature, the same metric is computed after setting the respective feature equal to its mean.

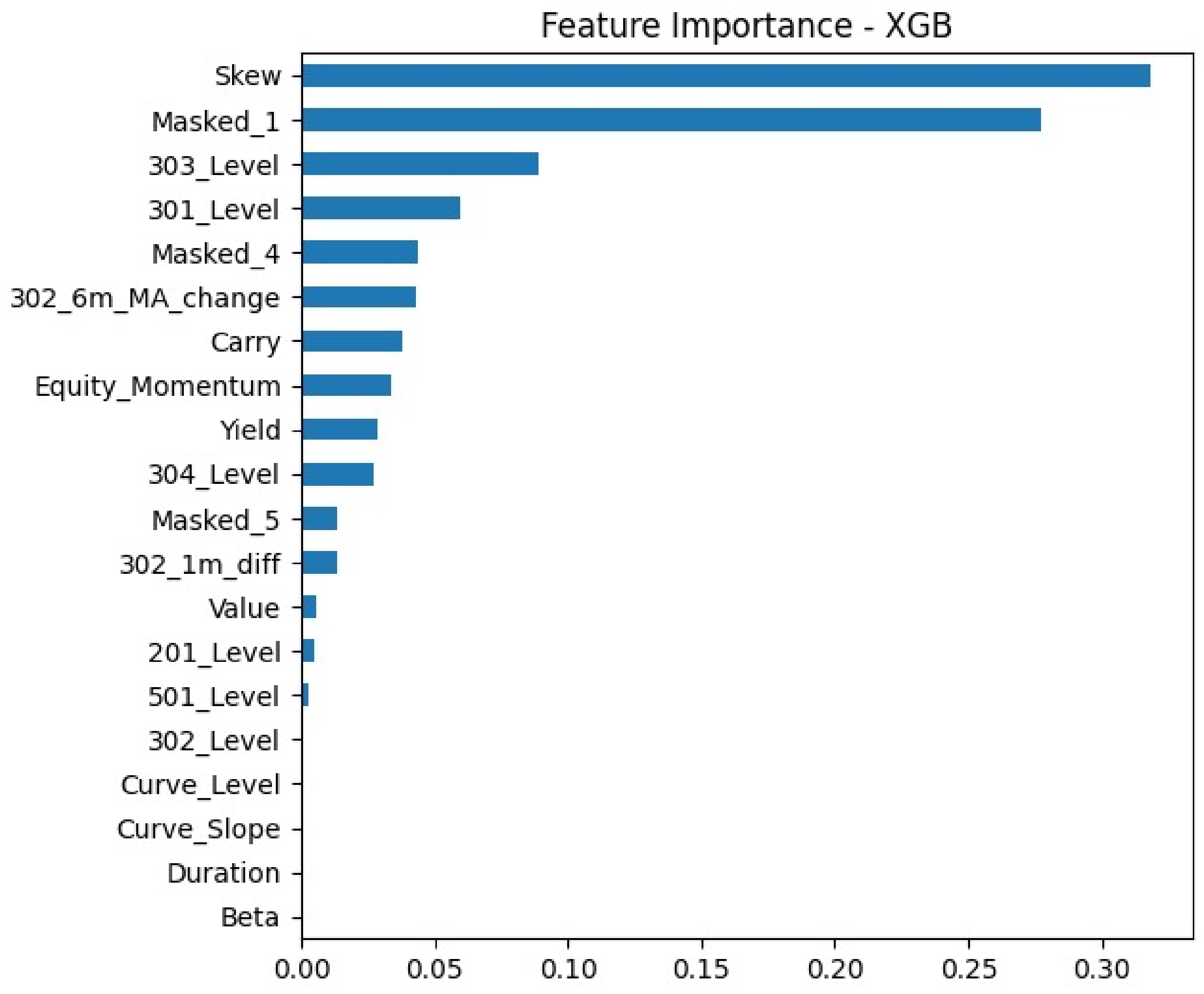


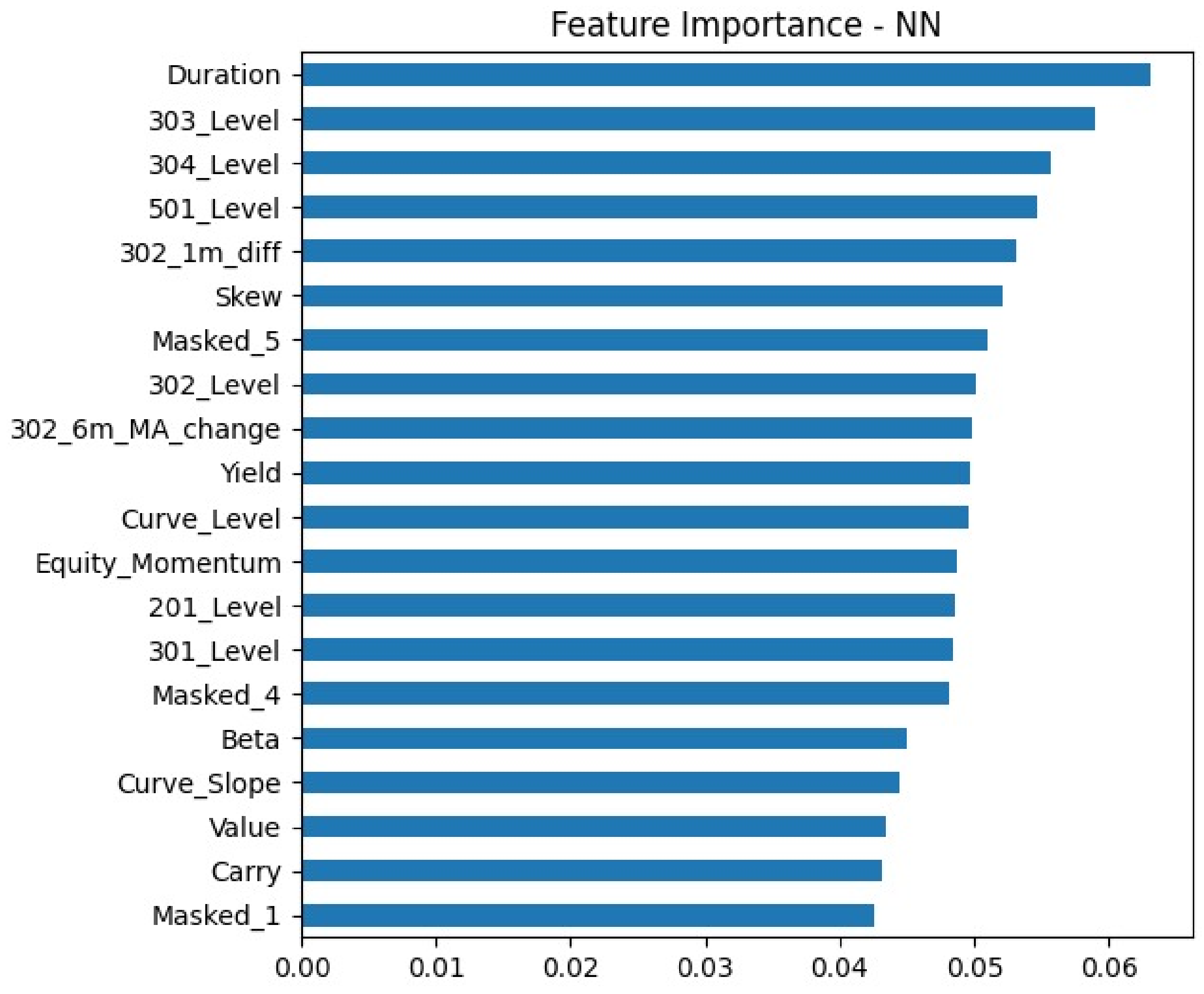


Feature Importance









Portfolio

- OOS forecasting period: May 2006 – May 2022 (17 years)
- Equal weight portfolio
  - strong empirical properties
  - monthly rebalance
- 30-40-30 split; total 35 bonds cross-sectionally
- Long-short portfolio (H-L); net zero investment
- Performance mis-alignment (individual vs portfolio)
- Portfolio performance influenced by cross-correlations: Gu et. al. (2020)
- 73% of OOS correlations > 0.5
- Top tier credit rated nations (AAA, AA+ etc.)
- Typical government bond characteristics observed

Table 2: Performance of Machine Learning Portfolios

	OLS-MF				OLS-All			
	Pred	Avg	Std	SR	Pred	Avg	Std	SR
Low 30% (L)	0.01	0.03	0.13	0.69	-0.11	0.03	0.16	0.56
Mid 40%	0.02	0.03	0.16	0.62	0.02	0.03	0.15	0.62
High 30% (H)	0.03	0.03	0.19	0.59	0.14	0.04	0.19	0.67
H - L	0.03	0.01	0.12	0.17	0.25	0.01	0.12	0.30
	ENet				GLM			
	Pred	Avg	Std	SR	Pred	Avg	Std	SR
Low 30% (L)	-0.05	0.02	0.11	0.51	0.04	0.02	0.13	0.45
Mid 40%	-0.03	0.03	0.17	0.67	0.05	0.03	0.17	0.66
High 30% (H)	-0.01	0.04	0.20	0.62	0.05	0.04	0.19	0.69
H - L	-0.03	0.03	0.17	0.67	0.01	0.02	0.12	0.56
	RF				XGBoost			
	Pred	Avg	Std	SR	Pred	Avg	Std	SR
Low 30% (L)	0.04	0.02	0.16	0.54	0.04	0.03	0.16	0.60
Mid 40%	0.05	0.03	0.16	0.64	0.06	0.03	0.16	0.64
High 30% (H)	0.07	0.03	0.17	0.70	0.08	0.03	0.16	0.64
H - L	0.03	0.01	0.10	0.29	0.05	0.00	0.11	0.04
	SVR				NN			
	Pred	Avg	Std	SR	Pred	Avg	Std	SR
Low 30% (L)	0.03	0.03	0.16	0.56	0.00	0.03	0.14	0.65
Mid 40%	0.04	0.03	0.16	0.70	0.04	0.03	0.16	0.63
High 30% (H)	0.05	0.03	0.16	0.61	0.07	0.03	0.17	0.62
H - L	0.02	0.00	0.10	0.10	0.07	0.01	0.10	0.17

Separate long-short

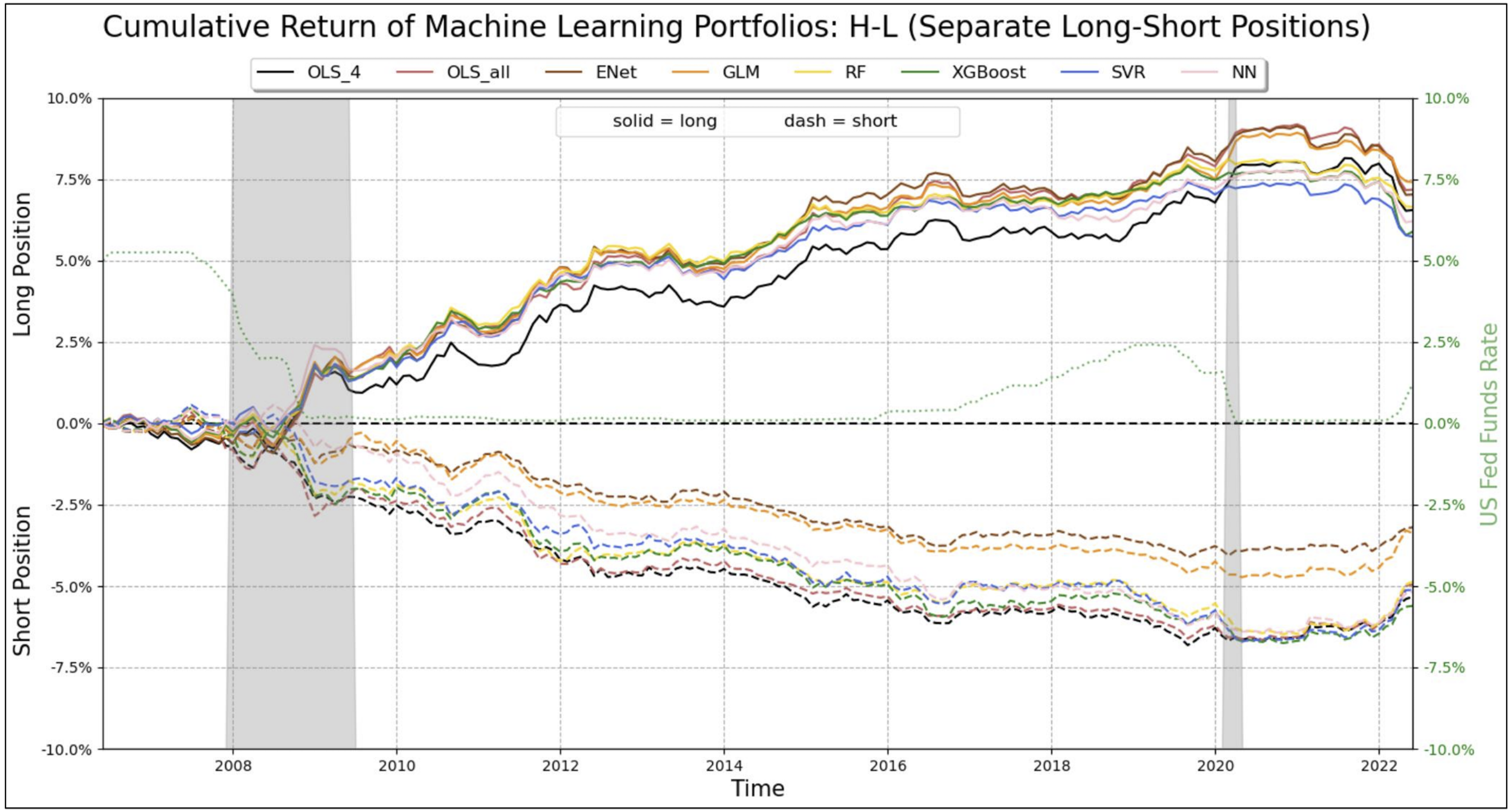
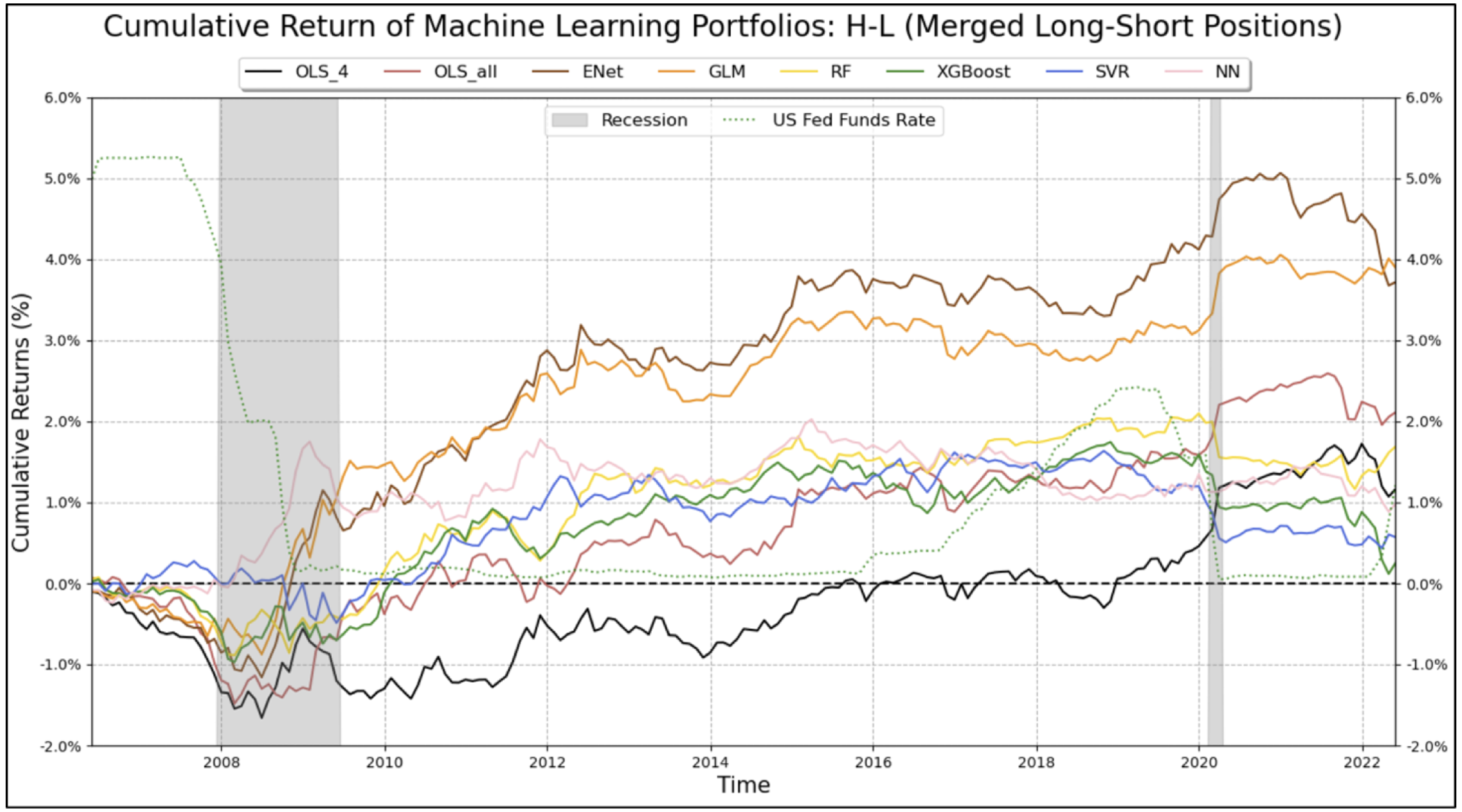
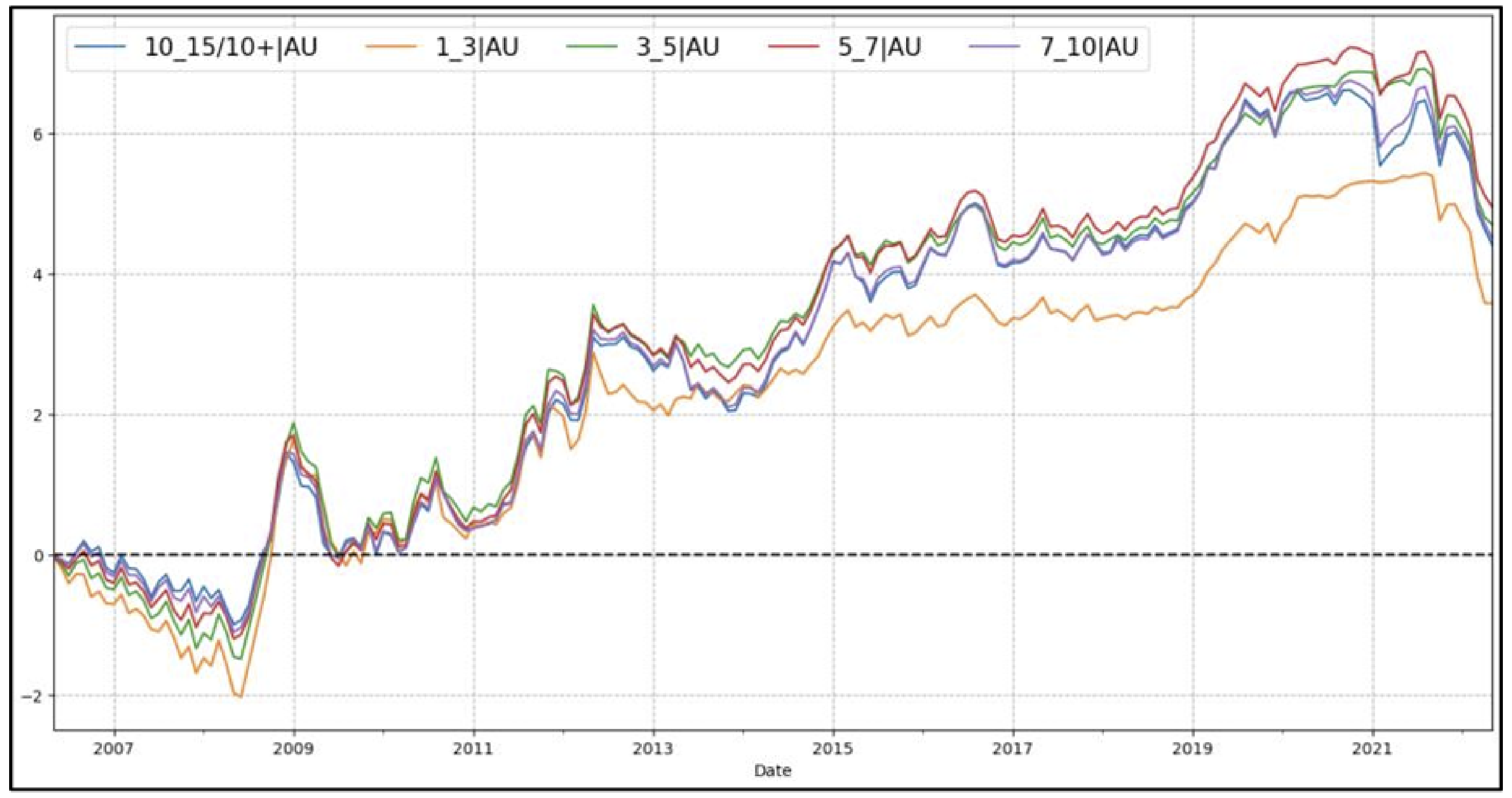


Table 3: Key Performance Metrics of Long-Short Machine Learning (Bond) Portfolios (Equal Weighted)

	OLS-MF	OLS-All	ENet	GLM	RF	XGBoost	SVR	NN
Max DD (%)	1.56	1.56	1.39	0.78	0.96	1.62	1.20	1.14
Max 1M Loss (%)	0.33	0.37	0.41	0.35	0.43	0.40	0.42	0.35
Turnover (%)	41.9	111.5	59.3	71.3	139.3	138.8	118.1	100.1
R^2_{oos}	-0.05	-9.92	0.01	-0.01	-0.11	-0.21	-0.01	-0.40
Information Ratio	0.17	0.30	0.48	0.56	0.29	0.04	0.10	0.17
Appraisal Ratio	-0.69	0.55	0.30	1.08	0.92	0.28	0.31	-0.25



Actual return evolution OOS (AUS)



Actual return evolution OOS (US)


SKILLS
ERASMUS UNIVERSITEIT ROTTERDAM
×
ROBECO
Thank you! Questions?