Alpha Go Everywhere: Machine Learning and International Stock Returns

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Working Paper

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2020-04-15

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1. Introduction

Background & Motivation

- Machine learning is widely adopted in recent empirical asset pricing literatures. This is partly motivated by the long list of characteristics that seem to predict returns.
- Machine learning can improve the explanatory power over traditional linear models, but complex algorithms are difficult to interpret economically and prone to overfitting.
- Most studies conduct their analyses on only one market—the U.S, in this paper, we apply machine learning methods to predict international stock returns.

1. Introduction

Question: Whether machine learning can capture market-specific return-characteristic relationships internationally?

- Overall, the evidence is mixed.
- While neural network (NN) models work well internationally, regression trees (RTs) show signs of overfitting in some occasions.

1. Introduction

Research contents

- Predicting U.S. stock returns with 12 predictors
- Predicting international stock returns with the U.S.-estimated models.
- Predicting international stock returns with market-specific models.
- Pooling all stocks to illustrate models' predictability.
- Robustness tests & Discussion

1. Introduction

Input: U.S. data
Output: U.S. stock return

Purpose is to compare the performance of our models with those in GKX, who input more than 900 features.

Input: U.S. data
Output: international stock return

Applying the U.S.-estimated model to each of the 33 markets individually.

Input: market-specific data
Output: international stock return

1. Results
2. In-Sample and Out-of-Sample R2
3. Return-Characteristics Relationships

Input: whole market data
Output: international stock return

Use three different international asset pricing models to examine whether the machine learning models capture something beyond the commonly known factors

Robustness tests & Discussion

1.Introduction

Related researches

- Gu, Shihao, Bryan T Kelly, and Dacheng Xiu, 2020, Empirical asset pricing via machine learning, Review of Financial Studies.
- Freyberger, Neuhierl, and Weber (2020) propose an adaptive group LASSO procedure to select characteristics.
- Feng, Giglio, and Xiu (2020) develop a regularized two-pass cross-sectional regression approach and show that only a small number of factors remain significant over time.
- Bianchi, Büchner, and Tamoni (2020) show that NN and RTs improve the predictions of U.S. Treasury bond returns over linear techniques.
- Karolyi and Stulz (2003) and Lewis (2011) show that International stocks can be priced locally or globally.

1.Introduction

Contribution

- Our paper belongs to the burgeoning literature that predicts asset returns with machine learning.
- Although machine learning is powerful, our paper argues that overfitting can be a problem and we should exercise caution when applying it to different markets
- While using local factors and characteristics is important, our results suggest that the relationships between returns and characteristics seem to vary across countries.
- Our NN models provide a way to price stock returns locally with more characteristics and in a larger set of markets.

2. Method & Data

1) Linear Models

In this paper, we use these linear models: OLS-3, OLS-3 with Huber loss, OLS, OLS with Huber loss, LASSO, RIDGE, and ENET.

- “-3” means: size, momentum, and book-to-market ratio.
- Penalty function: $\|\boldsymbol{\theta}\|_p = \left(\sum_{i=1}^{n} |\theta_i|^p\right)^{1/p}.$
- Huber loss:

$$\text{Huber Loss} = \begin{cases} v_{i,t}^2, & \text{if } |v_{i,t}| \le \xi \\ 2\xi|v_{i,t}| - \xi^2, & \text{if } |v_{i,t}| > \xi \end{cases}$$

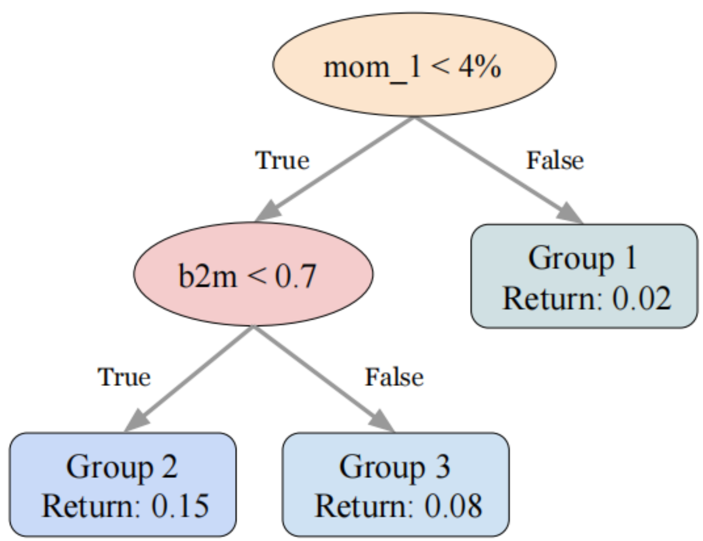
	Loss Function	Penalty Function
OLS	MSE	None
OLS+H	Huber Loss	None
LASSO	MSE	$\lambda_1 * \|\boldsymbol{\theta}\|_1$
RIDGE	MSE	$\lambda_2 * \|\boldsymbol{\theta}\|_2$
ENET	MSE	$\lambda_1 * \|\boldsymbol{\theta}\|_1 + \lambda_2 * \|\boldsymbol{\theta}\|_2$
RF	MSE	None
GBRT+H	Huber Loss	None
NN1–NN5	MSE	$\lambda_1 * \|\boldsymbol{\theta}\|_1$

2. Method & Data

2) Regression Trees and Ensemble Learning

- For example, this regression tree, with a depth of two, the function can be formally written as:

$$f = 0.15 \times \mathbf{1}_{\{mom\_1<4\%\}}\mathbf{1}_{\{b2m<0.7\}} + 0.08 \times \mathbf{1}_{\{mom\_1<4\%\}}\mathbf{1}_{\{b2m\geq0.7\}} + 0.02 \times \mathbf{1}_{\{mom\_1\geq4\%\}}.$$

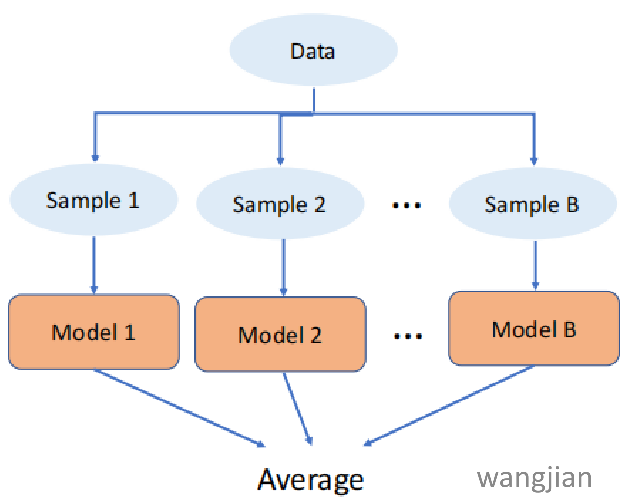


2. Method & Data

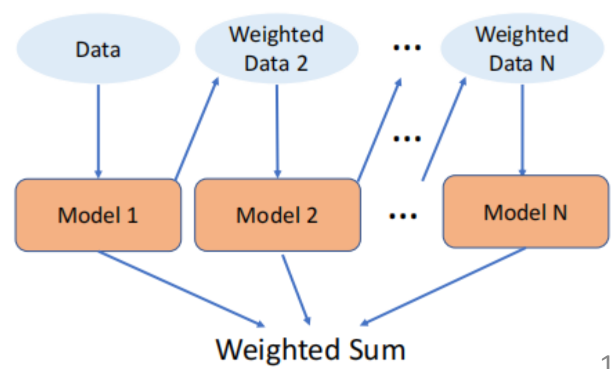
2) Regression Trees and Ensemble Learning

- A tree model is prone to overfit because it gives much freedom to fit the data compared with linear models.
- Therefore, the estimation process needs to be heavily regularized, and in our paper, we use two "ensemble" learning methods to address:

Bagging



Boosting

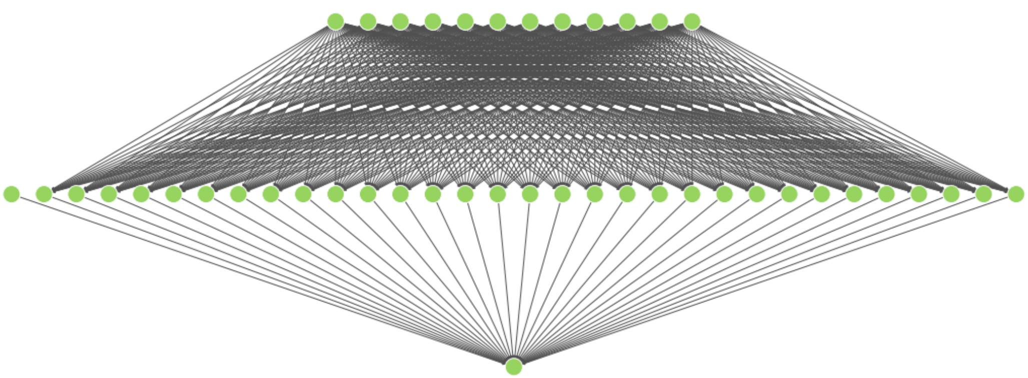


2. Method & Data

3) Neural Network (NN)

- In this paper, we mainly explore the most widely used “vanilla” neural network.
- Figure provides a schematic of a one-layer neural network (NN1) used in our paper, where green circles denote the input features, hidden units, and output variables, from top to bottom.
- Activation function:

$$ReLU(x) = \begin{cases} 0, & \text{if } x < 0 \\ x, & \text{otherwise} \end{cases}$$



2. Method & Data

Data sources

- DataStream: Stock returns, trading volume, market capitalization, and industry information.
- Factset: Accounting ratios (book-to-market and sales-to price)
- For the U.S. and China, we use the data with CRSP and CSMAR respectively

Detail:

- We winsorize raw returns at the top and bottom 2.5% in each exchange.
- We download data for as many countries as possible and require each market to have at least 100 stocks with valid observations of return and the 12 characteristics for at least 3 years.

2. Method & Data

Acronym	Definition	in the 10 predictors
mom_1	1-month reversal	Yes
logsize	Log market capitalization	Yes
mom_12	12-month momentum	Yes
mom_6	6-month momentum	Yes
chmom_6	Change in mom_6	Yes
maxret	Maximum daily return	Yes
indmom_a_12	Industry 12-month equal-weighted momentum	Yes
retvol	Return volatility (standard deviation) of daily return	Yes
logdolvol	Log Dollar trading volume	No
sp	Sales to price	Yes
turn	Share turnover	No
b2m	Book to market	Yes

3. Empirical results

I. Post-estimation Evaluation

1) Out-of-sample R2

$$R^2_{oos} = 1 - \frac{\sum_{(i,t)\in \text{Test}} (r_{i,t} - \hat{r}_{i,t})^2}{\sum_{(i,t)\in \text{Test}} r^2_{i,t}}$$

- Since the distribution of portfolio returns is sensitive to the dependence among stock returns, a good stock-level prediction model does not necessarily produce accurate portfolio-level forecasts.
- Portfolio R2oos: 1) sort stocks into deciles based on the prediction of models; 2) Within each decile, consider both equal weight and value weight by stocks' market capitalization, and rebalance the portfolio every month.

3. Empirical results

I. Post-estimation Evaluation

2) Sharpe Ratio

- We calculate the Sharpe ratio of long-short portfolio returns.
- The key difference between R2 and Sharpe ratios is that the calculation of the former involves predicted returns while the latter only uses the rank of predicted returns.

3) Relative Importance of Predictors.

- Sum of the Squares of the partial Derivatives(SSD)
- For the contribution of the j^{th} input variable, where x_k means the k^{th} observation. And than we normalize all variables' SSD to sum of one.

$$\mathrm{SSD}_j = \sum_k \left(\left. \frac{\partial \hat{f}}{\partial x_j} \right|_{x=x^k} \right)^2$$

3. Empirical results

II. Predicting U.S. Stock Returns with 12 Predictors

		OLS-3	OLS-3+H	OLS	OLS+H	LASSO	RIDGE	ENET	RF	GBRT+H	NN1	NN2	NN3	NN4	NN5
R^2_{oos}	GKX		0.16		-3.46			0.11	0.33	0.34	0.33	0.39	0.40	0.39	0.36
	CJZ	0.29	0.25	0.42	0.25	0.45	0.42	0.45	0.83	0.64	0.75	0.81	0.79	0.73	0.71
Sharpe Ratio (EW)	GKX		0.83					1.33	1.48	1.73	2.13	2.33	2.36	2.45	2.15
	CJZ	0.81	0.68	1.55	1.57	1.44	1.55	1.53	2.29	2.20	2.56	2.69	2.60	2.44	2.59
Sharpe Ratio (VW)	GKX		0.61					0.39	0.98	0.81	1.17	1.16	1.20	1.35	1.15
	CJZ	0.40	0.44	0.33	0.54	0.30	0.33	0.39	1.03	0.49	0.94	1.07	1.06	1.00	1.39

- Overall, with the 12 stock characteristics, our machine learning models appear to have similar return predictability to models in GKX using more than 900 inputs.
- To examine the extent to which noisy signals can harm the performance of machine learning models, we run a simulation exercise.

No. of simulated features	0			10			100			500			900		
	OLS	NN1	NN5	OLS	NN1	NN5	OLS	NN1	NN5	OLS	NN1	NN5	OLS	NN1	NN5
R^2_{oos}	0.42	0.75	0.71	0.42	0.77	0.64	0.41	0.69	0.67	0.37	0.67	0.55	0.32	0.59	0.51
Sharpe Ratio (EW)	1.55	2.56	2.59	1.56	2.61	2.33	1.55	2.40	2.05	1.53	2.02	1.87	1.42	1.91	1.81
Sharpe Ratio (VW)	0.33	0.94	1.39	0.30	0.85	1.06	0.36	0.61	1.01	0.25	0.59	0.77	0.26	0.63	0.61
Portfolio R^2_{oos} (EW)	3.41	4.85	4.55	3.40	4.64	4.10	3.35	4.10	4.33	3.00	4.15	3.88	2.56	3.70	3.55
Portfolio R^2_{oos} (VW)	0.97	3.03	2.95	0.88	3.00	2.79	0.83	2.57	2.99	0.10	2.88	2.63	-0.74	2.14	2.50

3. Empirical results

III. Predicting International Stock Returns with the U.S.-Estimated Models

- First, in most of the markets, machine learning-based models outperform traditional models (i.e., OLS-3 and OLS) or the passive market portfolio.
- Second, models taking into account nonlinear and complex interaction effects (i.e., RTs and NN models) outperform linear machine learning models (LASSO and RIDGE)

	Sharpe Ratio (EW)			Sharpe Ratio (VW)			R^2_{oos}		
	Tree−Linear	NN−Linear	NN−Tree	Tree−Linear	NN−Linear	NN−Tree	Tree−Linear	NN−Linear	NN−Tree
difference	0.47	0.69	0.22	0.22	0.52	0.29	-0.08	0.16	0.24
# of +	30	29	25	26	31	27	16	20	26
fraction of +	0.91	0.88	0.76	0.79	0.94	0.82	0.48	0.61	0.79

	Equal-Weighted												Value-Weighted											
	Market	OLS-3	OLS	LASSO	RIDGE	RF	GBRT+H	NN1	NN2	NN3	NN4	NN5	Market	OLS-3	OLS	LASSO	RIDGE	RF	GBRT+H	NN1	NN2	NN3	NN4	NN5
USA	0.58	0.81	1.55	1.44	1.55	2.29	2.20	2.56	2.69	2.60	2.44	2.59	0.53	0.40	0.33	0.30	0.33	1.03	0.49	0.94	1.07	1.06	1.00	1.39
Japan	0.85	0.42	0.60	0.54	0.60	1.19	1.18	1.76	1.77	1.62	1.38	1.60	0.46	0.06	0.24	0.31	0.24	0.49	0.79	0.61	0.65	0.33	0.50	0.67
China	0.51	1.43	1.06	1.30	1.06	1.90	1.74	1.80	1.96	1.76	1.88	2.18	0.37	0.90	0.61	0.89	0.61	1.12	1.20	1.12	1.23	1.23	1.28	1.44
India	0.70	0.87	0.68	0.45	0.68	1.93	1.45	1.89	1.91	1.94	1.84	1.99	0.54	0.48	-0.12	-0.30	-0.12	0.12	0.40	-0.24	0.16	0.40	0.13	0.53
Korea	0.59	1.11	1.16	1.05	1.16	1.77	1.57	2.45	2.48	2.13	1.88	1.91	0.32	0.13	0.34	0.40	0.34	1.01	0.79	1.07	1.04	0.92	0.70	0.68
Hong_Kong	0.42	0.67	0.63	0.54	0.63	1.94	1.43	2.00	1.94	2.24	1.98	1.97	0.32	0.11	0.04	-0.06	0.03	0.41	0.05	1.01	0.60	0.80	0.57	0.73
France	0.74	1.06	1.77	2.03	1.78	2.61	2.22	2.57	2.81	2.78	2.61	2.71	0.47	0.77	0.48	0.47	0.48	0.47	0.54	0.82	1.22	0.83	0.76	1.20
Taiwan	0.44	0.31	-0.12	-0.19	-0.12	0.42	0.50	1.39	1.45	1.41	1.32	1.48	0.40	-0.17	-0.45	-0.48	-0.45	-0.13	-0.03	0.48	0.57	0.33	0.44	0.60
Australia	0.65	1.04	2.43	2.02	2.43	4.19	3.83	4.10	4.22	4.45	4.36	4.24	0.53	0.66	0.31	-0.44	0.30	0.72	0.60	1.50	1.67	1.56	1.75	2.01
United_Kingdom	0.42	0.37	0.43	0.15	0.42	1.36	1.25	1.32	1.46	1.24	1.29	1.19	0.54	0.46	0.11	-0.34	0.12	0.71	0.30	0.35	0.77	0.52	0.77	0.30
Thailand	0.74	0.73	0.36	0.09	0.37	0.96	0.63	1.07	1.32	1.26	1.39	1.23	0.41	0.51	-0.22	-0.51	-0.22	0.18	0.08	0.45	0.58	0.54	0.72	0.64
Singapore	0.23	0.68	2.16	2.33	2.17	2.53	2.75	3.36	3.32	3.25	3.00	3.48	0.27	0.06	0.21	0.22	0.22	0.79	0.75	1.48	1.64	1.38	1.56	2.01
South_Africa	1.10	1.53	1.72	1.58	1.72	1.79	1.39	1.41	1.56	1.57	1.56	1.49	0.67	0.53	0.72	0.33	0.72	0.90	0.62	0.61	0.93	0.86	0.84	0.90
Sweden	0.54	0.69	1.12	1.12	1.08	1.71	1.49	1.72	1.81	1.74	1.96	1.81	0.37	0.55	0.09	0.32	0.07	0.97	0.70	0.48	0.65	0.58	0.84	0.65
Poland	0.29	0.88	0.63	0.60	0.63	1.67	1.47	1.97	1.95	1.97	1.84	1.68	0.33	0.33	-0.16	-0.13	-0.16	0.79	0.57	0.33	0.94	0.86	0.91	0.64
Turkey	0.82	0.16	0.06	-0.06	0.07	0.51	0.36	0.79	0.75	0.63	0.59	0.52	0.67	-0.10	-0.03	-0.01	-0.03	0.18	0.12	0.43	0.59	0.45	0.38	0.58
Italy	0.04	0.38	0.10	0.10	0.10	0.98	0.90	0.85	0.79	0.77	0.63	0.64	0.08	0.37	0.02	0.06	0.04	0.70	0.40	0.58	0.65	0.57	0.41	0.47
Vietnam	0.74	0.85	1.54	1.51	1.54	2.33	2.15	3.01	2.62	2.45	2.71	2.63	0.59	0.09	0.25	-0.13	0.25	0.66	0.27	1.09	1.17	1.03	1.07	0.99
Switzerland	0.53	0.75	0.53	0.31	0.53	0.90	0.76	0.80	0.82	1.07	0.89	1.04	0.28	0.79	0.35	0.25	0.34	0.68	0.60	0.42	0.38	0.65	0.63	0.77
Israel	0.49	1.00	0.95	0.92	0.95	1.03	0.93	1.07	1.21	1.12	1.09	1.14	0.00	0.92	0.30	0.04	0.30	0.75	0.50	0.90	1.14	0.91	1.03	1.21
Indonesia	0.98	0.67	0.08	-0.23	0.09	0.49	0.09	0.32	0.25	0.26	0.28	0.15	0.93	0.54	0.29	0.13	0.32	0.75	0.43	0.73	0.54	0.65	0.52	0.44
Greece	0.34	0.46	2.00	2.08	2.00	2.48	2.59	2.79	2.76	2.73	2.77	2.60	-0.02	-0.15	0.19	0.59	0.19	0.71	0.68	1.18	0.81	0.85	0.49	1.12
Philippines	1.12	0.75	1.20	1.26	1.20	1.64	1.39	1.50	1.40	1.55	1.52	1.64	0.88	0.07	0.41	0.30	0.40	0.57	0.46	0.81	0.95	1.08	0.74	1.14
Denmark	0.54	0.33	0.84	0.87	0.84	1.44	1.45	1.42	1.60	1.70	1.39	1.38	0.76	0.51	0.04	0.08	0.04	0.77	0.41	0.47	0.68	0.97	0.63	0.81
Finland	0.52	0.84	0.81	0.56	0.81	1.08	1.15	0.74	0.84	0.95	0.86	1.14	0.12	0.40	0.02	0.08	0.02	0.46	0.18	0.24	0.29	0.69	0.36	0.65
Sri_Lanka	0.96	0.27	1.28	2.14	1.29	2.16	2.29	1.88	1.78	1.65	1.78	2.03	1.04	-0.14	0.54	0.70	0.54	1.46	1.43	1.33	0.97	1.12	0.74	1.67
Norway	0.05	0.41	0.37	0.28	0.38	0.96	0.72	1.12	1.06	1.12	1.10	1.21	0.25	0.32	-0.13	-0.09	-0.12	0.54	0.50	0.54	0.37	0.70	0.72	0.31
Saudi_Arabia	0.26	0.25	-0.05	0.26	-0.07	1.20	0.72	0.68	0.81	0.64	0.61	0.41	0.36	0.06	0.08	0.24	0.06	0.70	0.46	0.48	0.26	0.20	0.27	0.10
Jordan	0.38	0.37	-0.10	-0.22	-0.10	0.97	0.57	1.41	1.26	1.32	1.09	1.18	-0.04	-0.33	-0.24	0.00	-0.24	0.77	0.29	0.55	0.65	1.02	0.41	0.63
Chile	0.85	0.86	0.21	-0.25	0.23	0.46	0.30	0.04	0.29	0.23	0.40	0.30	0.65	0.52	0.21	-0.06	0.21	0.38	0.15	0.24	0.36	0.33	0.62	0.39
Belgium	0.59	0.46	0.07	-0.07	0.07	0.67	0.75	0.70	0.64	0.78	0.59	0.55	0.41	0.54	-0.29	-0.50	-0.29	0.13	-0.12	0.30	0.11	0.51	0.02	0.24
Kuwait	0.29	0.50	0.70	0.74	0.71	1.15	1.19	1.58	1.62	1.53	1.71	1.48	0.21	0.41	0.37	0.07	0.37	0.73	0.93	0.95	1.04	1.10	1.31	0.97
Spain	0.33	0.48	0.24	-0.32	0.25	0.43	0.36	0.07	0.43	0.40	0.54	0.43	0.37	0.44	0.29	-0.15	0.30	0.47	0.75	0.07	0.74	0.61	0.68	0.31
Russia	1.22	0.28	0.77	0.74	0.76	0.73	0.79	0.78	0.67	0.72	0.94	0.74	0.90	0.23	0.26	0.38	0.26	0.66	0.57	0.56	0.70	0.54	0.65	0.47

3. Empirical results

IV. Predicting International Stock Returns with Market-Specific Models

1)results

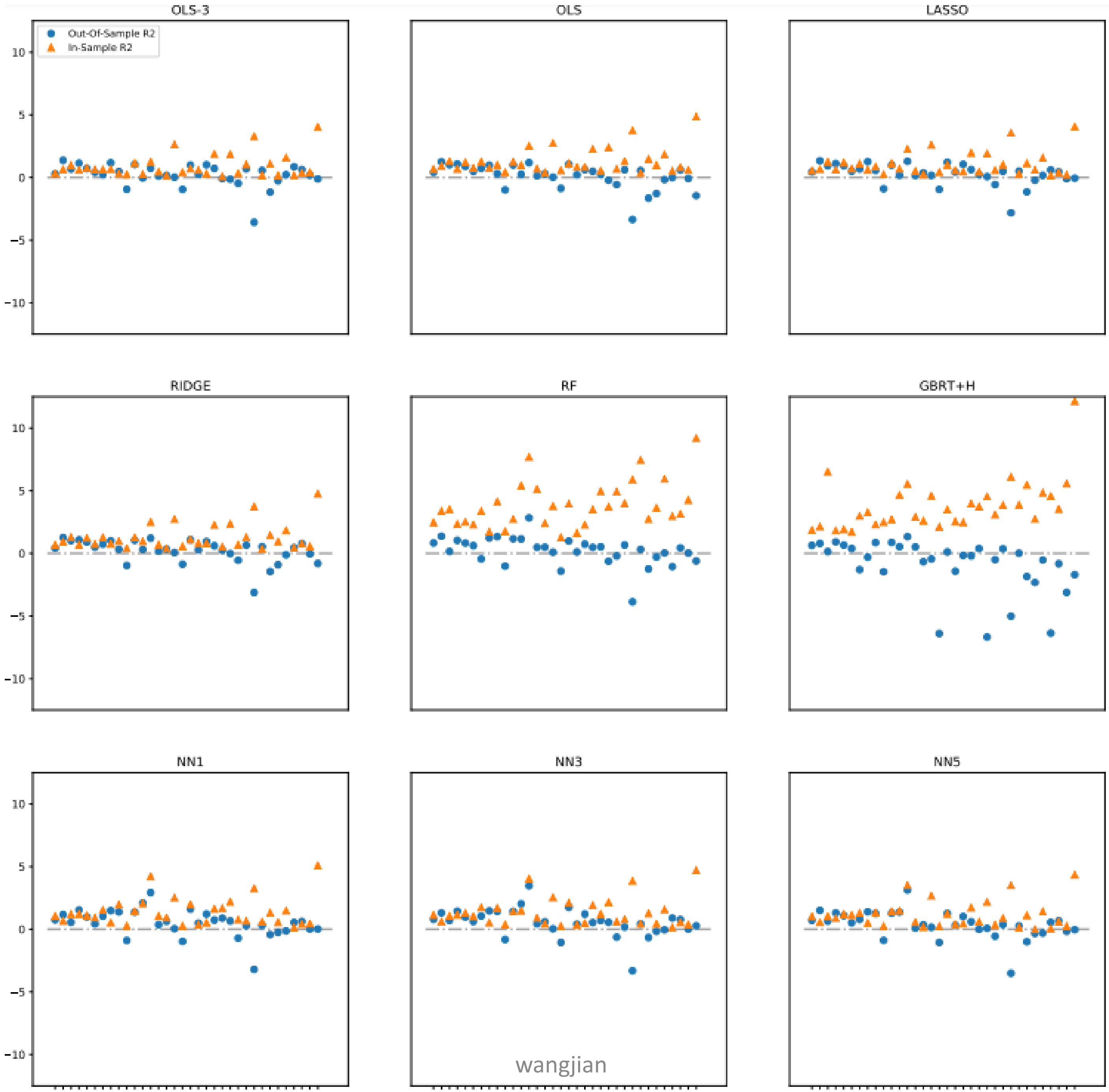
- The result is similar to what we find with U.S.-estimated models, NN models exhibit the strongest return predictability in most of the markets.
- However, different from the U.S.-estimated models, market-specific tree models seem to underperform linear models.

		Sharpe Ratio (EW)			Sharpe Ratio (VW)			R^2_{oos}		
		Tree−Linear	NN−Linear	NN−Tree	Tree−Linear	NN−Linear	NN−Tree	Tree−Linear	NN−Linear	NN−Tree
All markets	*difference*	-0.14	0.59	0.73	-0.26	0.38	0.63	-0.16	0.33	0.48
	# of +	12	27	31	8	27	29	9	25	29
	fraction of +	0.36	0.82	0.94	0.24	0.82	0.88	0.27	0.76	0.88
Top half	*difference*	0.04	0.81	0.78	-0.18	0.45	0.62	0.05	0.46	0.41
	# of +	10	14	14	4	13	15	7	13	15
	fraction of +	0.62	0.88	0.88	0.25	0.81	0.94	0.44	0.81	0.94
Bottom half	*difference*	-0.3	0.38	0.68	-0.33	0.31	0.64	-0.35	0.2	0.54
	# of +	2	13	17	4	14	14	2	12	14
	fraction of +	0.12	0.76	1	0.24	0.82	0.82	0.12	0.71	0.82

2) In-Sample and Out-of-Sample R2

Based on the results of 33 markets, it is true that tree models can achieve a high in-sample $R2$ in almost all markets, but the high $R2$ does not survive out of the sample.

	OLS-3	OLS	LASSO	RIDGE	RF	GBRT+H	NN1	NN2	NN3	NN4	NN5
USA	0.29	0.42	0.45	0.42	0.83	0.64	0.75	0.81	0.79	0.73	0.71
	(0.32)	(0.67)	(0.56)	(0.67)	(2.47)	(1.85)	(1.05)	(1.02)	(1.14)	(1.15)	(1.03)
Japan	1.38	1.25	1.34	1.25	1.37	0.79	1.17	1.31	1.30	1.26	1.51
	(0.64)	(0.92)	(0.67)	(0.92)	(3.38)	(2.14)	(0.66)	(0.63)	(0.62)	(0.60)	(0.57)
China	0.67	1.02	0.95	1.02	0.16	0.15	0.56	0.65	0.70	0.78	0.65
	(0.99)	(1.30)	(1.25)	(1.30)	(3.52)	(6.51)	(1.21)	(1.11)	(1.06)	(1.03)	(1.03)
India	1.14	1.08	1.11	1.08	1.04	0.92	1.54	1.60	1.44	1.44	1.30
	(0.61)	(0.68)	(0.64)	(0.68)	(2.34)	(1.83)	(1.21)	(1.31)	(1.15)	(1.07)	(0.89)
Korea	0.71	0.89	0.94	0.90	0.82	0.66	0.98	0.94	0.97	1.08	1.09
	(0.76)	(1.23)	(1.18)	(1.23)	(2.53)	(1.91)	(1.09)	(1.10)	(1.31)	(1.28)	(1.19)
Hong_Kong	0.42	0.50	0.51	0.50	0.62	0.39	0.43	0.63	0.62	0.86	0.52
	(0.64)	(0.75)	(0.70)	(0.75)	(2.29)	(1.71)	(0.93)	(0.90)	(1.03)	(1.13)	(1.13)
France	0.24	0.72	0.68	0.73	-0.44	-1.29	1.05	0.91	1.06	1.13	0.78
	(0.63)	(1.26)	(1.12)	(1.26)	(3.37)	(3.00)	(1.53)	(1.61)	(1.74)	(1.63)	(1.31)
Taiwan	1.17	0.98	1.26	1.01	1.22	-0.30	1.49	1.33	1.47	1.50	1.39
	(0.67)	(0.77)	(0.61)	(0.76)	(1.73)	(3.26)	(0.53)	(0.51)	(0.53)	(0.52)	(0.50)
Australia	0.48	0.30	0.57	0.32	1.33	0.86	1.38	1.40	1.43	1.35	1.26
	(0.33)	(1.00)	(0.85)	(0.99)	(4.13)	(2.30)	(1.98)	(1.59)	(1.68)	(1.81)	(1.32)
United_Kingdom	-0.93	-0.98	-0.89	-0.96	-1.02	-1.46	-0.89	-1.00	-0.81	-0.66	-0.88
	(0.24)	(0.42)	(0.26)	(0.40)	(1.75)	(2.50)	(0.27)	(0.23)	(0.37)	(0.32)	(0.26)
Thailand	1.05	1.00	1.00	1.05	1.16	0.87	1.36	1.23	1.42	1.41	1.28
	(1.15)	(1.26)	(1.12)	(1.25)	(2.74)	(2.70)	(1.43)	(1.20)	(1.41)	(1.49)	(1.42)
Singapore	-0.03	0.25	0.19	0.31	1.15	0.54	2.09	1.94	2.03	2.09	1.36
	(0.26)	(0.98)	(0.70)	(0.97)	(5.40)	(4.66)	(2.07)	(1.55)	(1.47)	(1.88)	(1.48)
South_Africa	0.73	1.18	1.29	1.21	2.84	1.33	2.93	3.11	3.47	3.56	3.13
	(1.25)	(2.52)	(2.27)	(2.50)	(7.69)	(5.54)	(4.22)	(3.67)	(4.04)	(4.10)	(3.52)
Sweden	0.12	0.15	0.17	0.18	0.49	0.52	0.36	0.36	0.43	0.36	0.10
	(0.46)	(0.70)	(0.52)	(0.69)	(5.13)	(2.90)	(1.05)	(1.14)	(0.90)	(0.87)	(0.57)
Poland	0.16	0.30	0.38	0.33	0.50	-0.67	0.64	0.59	0.60	0.35	0.35
	(0.14)	(0.40)	(0.24)	(0.39)	(2.41)	(2.60)	(0.92)	(0.63)	(0.44)	(0.23)	(0.18)
Turkey	0.03	0.03	0.17	0.07	0.10	-0.44	0.05	0.16	0.04	0.07	0.16
	(2.64)	(2.74)	(2.60)	(2.74)	(3.78)	(4.59)	(2.53)	(2.56)	(2.54)	(2.65)	(2.67)
Italy	-0.94	-0.86	-0.94	-0.86	-1.41	-6.39	-0.97	-1.11	-1.06	-1.04	-1.06
	(0.42)	(0.57)	(0.43)	(0.56)	(1.27)	(2.11)	(0.26)	(0.16)	(0.24)	(0.24)	(0.24)



OLS-3
OLS
LASSO
Out-Of-Sample R2
In-Sample R2
RIDGE
RF
GBRT+H
NN1
NN3
NN5
10
5
0
−5
−10

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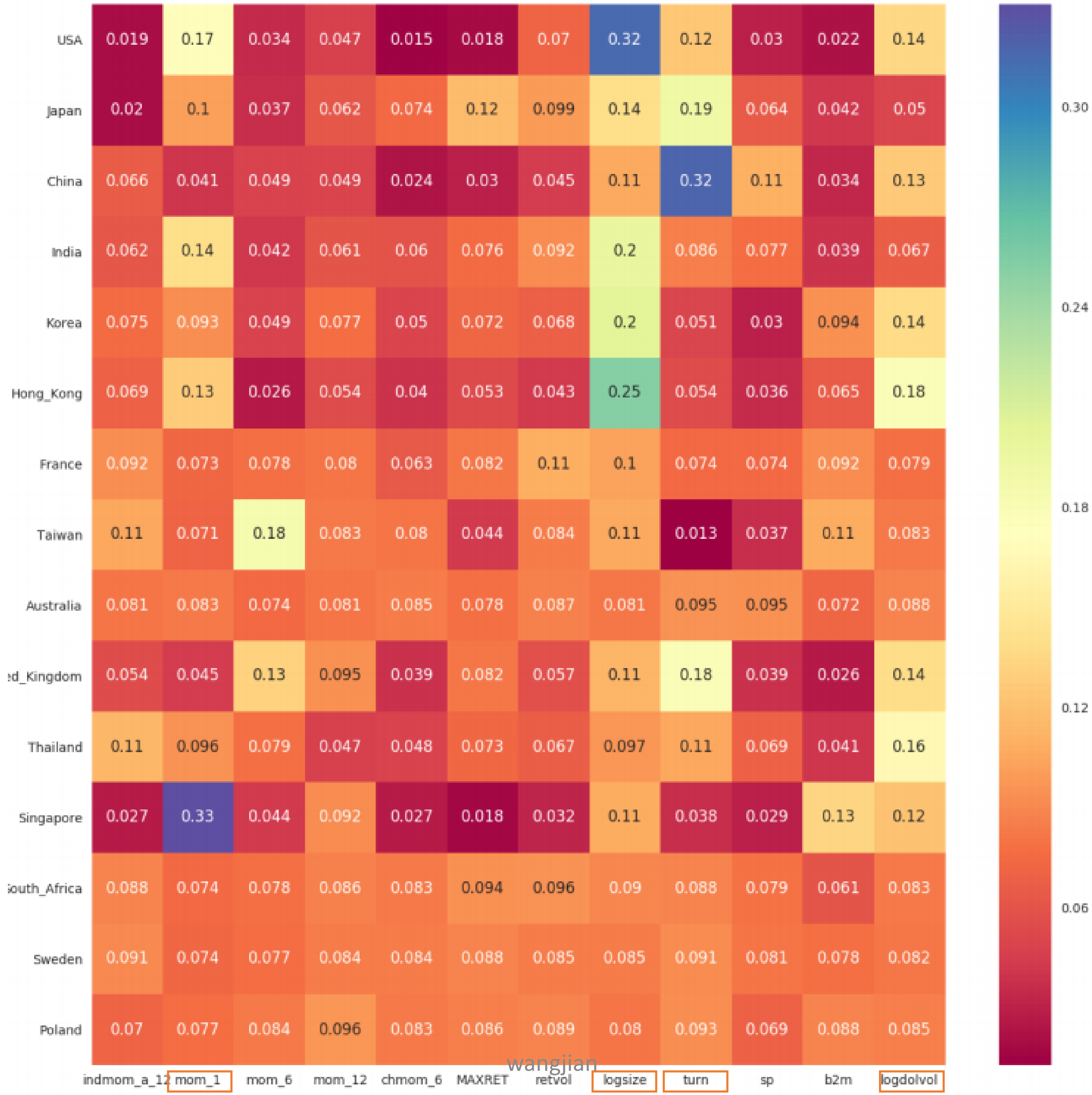
3. Empirical results

IV. Predicting International Stock Returns with Market-Specific Models

3)Return-Characteristics Relationships: Common or Market-Specific?

- On the one hand, there are common similarities in the return-characteristic relationship across international equity markets.
  - size (logsize); turnover rate (turn); volume (logdolvol)
- On the other hand, some market-specific features show up.
  - (mom_1)


USA 0.019 0.17 0.034 0.047 0.015 0.018 0.07 0.32 0.12 0.03 0.022 0.14
Japan 0.02 0.1 0.037 0.062 0.074 0.12 0.099 0.14 0.19 0.064 0.042 0.05
China 0.066 0.041 0.049 0.049 0.024 0.03 0.045 0.11 0.32 0.11 0.034 0.13
India 0.062 0.14 0.042 0.061 0.06 0.076 0.092 0.2 0.086 0.077 0.039 0.067
Korea 0.075 0.093 0.049 0.077 0.05 0.072 0.068 0.2 0.051 0.03 0.094 0.14
Hong_Kong 0.069 0.13 0.026 0.054 0.04 0.053 0.043 0.25 0.054 0.036 0.065 0.18
France 0.092 0.073 0.078 0.08 0.063 0.082 0.11 0.1 0.074 0.074 0.092 0.079
Taiwan 0.11 0.071 0.18 0.083 0.08 0.044 0.084 0.11 0.013 0.037 0.11 0.083
Australia 0.081 0.083 0.074 0.081 0.085 0.078 0.087 0.081 0.095 0.095 0.072 0.088
ed_Kingdom 0.054 0.045 0.13 0.095 0.039 0.082 0.057 0.11 0.18 0.039 0.026 0.14
Thailand 0.11 0.096 0.079 0.047 0.048 0.073 0.067 0.097 0.11 0.069 0.041 0.16
Singapore 0.027 0.33 0.044 0.092 0.027 0.018 0.032 0.11 0.038 0.029 0.13 0.12
South_Africa 0.088 0.074 0.078 0.086 0.083 0.094 0.096 0.09 0.088 0.079 0.061 0.083
Sweden 0.091 0.074 0.077 0.084 0.084 0.088 0.085 0.085 0.091 0.081 0.078 0.082
Poland 0.07 0.077 0.084 0.096 0.083 0.086 0.089 0.08 0.093 0.069 0.088 0.085
indmom_a_12 mom_1 mom_6 mom_12 chmom_6 MAXRET retvol logsize turn sp b2m logdolvol
0.30
0.24
0.18
0.12
0.06

3. Empirical results

IV. Predicting International Stock Returns with Market-Specific Models

3)Return-Characteristics Relationships: Common or Market-Specific?

- On the one hand, there are common similarities in the return-characteristic relationship across international equity markets. On the other hand, some market-specific features show up.
- Whether market-specific models perform better than their U.S.-estimated counterparts

		OLS-3	OLS	LASSO	RIDGE	RF	GBRT+H	NN1	NN2	NN3	NN4	NN5
	difference	0.399	0.733	0.710	0.731	0.328	0.247	0.899	0.928	0.968	0.725	0.777
Sharpe Ratio (EW)	# of +	25	29	30	27	22	22	26	27	26	25	27
	fraction of +	0.758	0.879	0.909	0.818	0.667	0.667	0.788	0.818	0.788	0.758	0.818
	difference	0.185	0.368	0.389	0.423	0.357	0.151	0.354	0.497	0.505	0.455	0.506
Sharpe Ratio (VW)	# of +	18	22	25	22	24	17	24	25	25	26	26
	fraction of +	0.545	0.667	0.758	0.667	0.727	0.515	0.727	0.758	0.758	0.788	0.788
	difference	0.093	0.592	0.080	0.578	1.391	3.277	0.345	0.334	0.385	0.454	0.638
R^2_{oos}	# of +	15	20	18	21	24	19	20	19	19	19	17
	fraction of +	0.455	0.606	0.545	0.636	0.727	0.576	0.606	0.576	0.576	0.576	0.515

3. Empirical results

IV. Pooling All Stocks

- In the top panel, it shows that NN models perform the best.
- Given the larger pool of stocks and the important role of price trend predictors in machine learning models, it is not surprising that the outperformance is achieved with relatively higher portfolio turnover rate.

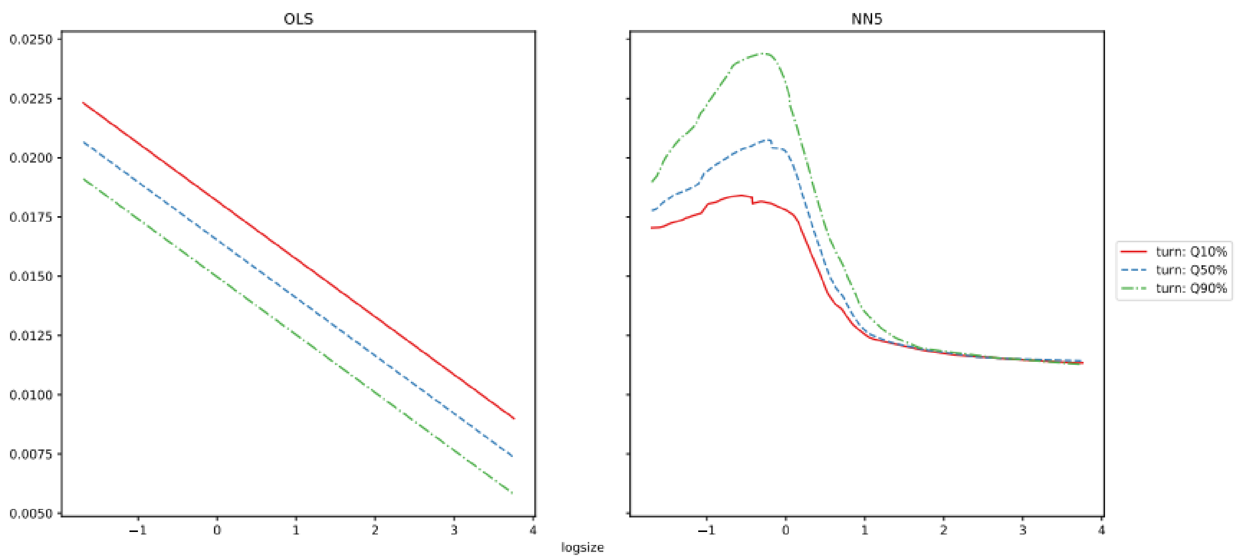
	Market	OLS-3	OLS	LASSO	RIDGE	RF	GBRT+H	NN1	NN2	NN3	NN4	NN5
Sharpe Ratio (EW)	0.71	1.23	2.06	2.00	2.06	3.21	3.05	3.39	3.36	3.43	3.31	3.51
Sharpe Ratio (VW)	0.51	0.54	0.53	0.40	0.52	1.21	0.62	1.08	1.22	1.39	1.57	1.32
R^2_{oos}		0.47	0.46	0.53	0.47	0.52	0.66	0.84	0.74	0.78	0.77	0.72
Portfolio R^2_{oos} (EW)		4.50	5.04	5.11	5.04	6.34	5.75	6.83	6.60	6.73	6.62	6.05
Portfolio R^2_{oos} (VW)		3.27	1.06	1.32	1.05	3.09	0.12	3.12	2.66	3.62	3.38	2.88
	Drawdowns and Turnover (Equally Weighted)											
Max DD (%)	51.68	28.23	16.80	21.47	16.80	26.33	21.53	13.12	7.07	13.47	11.17	10.61
Max 1M Loss (%)	29.02	17.55	14.45	15.14	14.45	16.70	16.18	13.12	7.07	13.47	11.17	10.61
Turnover (%)		49.53	156.83	172.35	156.91	155.41	159.66	149.03	147.37	146.99	148.48	147.31
	Drawdowns and Turnover (Value Weighted)											
Max DD (%)	52.29	40.47	45.79	45.25	45.37	32.49	34.07	42.05	31.79	33.89	25.02	31.55
Max 1M Loss (%)	22.84	21.57	14.57	20.37	14.57	19.99	18.31	18.42	19.50	17.97	14.38	16.70
Turnover (%)		46.60	140.12	169.97	140.30	174.59	172.90	150.71	157.71	158.16	161.18	161.28

	Market	OLS-3	OLS	LASSO	RIDGE	RF	GBRT+H	NN1	NN2	NN3	NN4	NN5
	Risk-adjusted Performance using FF5 + Mom model, 1992-2017 (Equally Weighted)											
Mean Return		1.58	2.56	2.51	2.56	3.52	3.44	4.00	3.89	3.99	3.82	3.85
α		1.45	2.67	2.67	2.67	3.25	3.27	3.91	3.86	3.91	3.82	3.81
$t(\alpha)$		5.03	8.49	8.36	8.50	12.24	12.27	13.96	13.87	13.90	13.62	13.87
R^2		10.73	7.47	7.99	7.51	9.37	9.06	9.82	7.97	9.00	9.18	7.62
Information Ratio		0.35	0.60	0.59	0.60	0.86	0.86	0.98	0.97	0.98	0.96	0.97
	Risk-adjusted Performance using HKK model, 1981-2010 (Equally Weighted)											
Mean Return		1.70	3.25	3.21	3.26	4.08	3.96	4.51	4.55	4.60	4.44	4.44
α		1.42	3.34	3.32	3.34	4.08	3.94	4.50	4.53	4.58	4.45	4.46
$t(\alpha)$		4.66	10.35	10.22	10.31	15.22	14.34	16.04	16.12	16.22	15.85	16.82
R^2		4.03	1.91	2.07	1.85	2.75	1.85	3.48	2.45	3.03	2.57	2.16
Information Ratio		0.29	0.65	0.64	0.65	0.95	0.90	1.01	1.01	1.02	0.99	1.06
	Risk-adjusted Performance using KW model, 1990-2010 (Equally Weighted)											
Mean Return		1.82	3.2	3.18	3.21	4.16	4.06	4.62	4.68	4.68	4.52	4.48
α		1.71	3.47	3.47	3.48	4.22	4.17	4.74	4.82	4.78	4.65	4.62
$t(\alpha)$		4.89	9.27	9.19	9.26	13.32	12.91	14.58	14.72	14.47	14.19	14.86
R^2		7.20	6.72	6.41	6.79	3.51	4.50	6.77	5.15	5.10	5.28	4.20
Information Ratio		0.34	0.65	0.64	0.65	0.93	0.90	1.02	1.03	1.01	0.99	1.04

The *R*2 of the factor models is low, typically below 10%, particularly for NN, suggesting that the factors can only explain a small fraction of the returns of the NN-based strategies.

3. Empirical results

V. Discussion

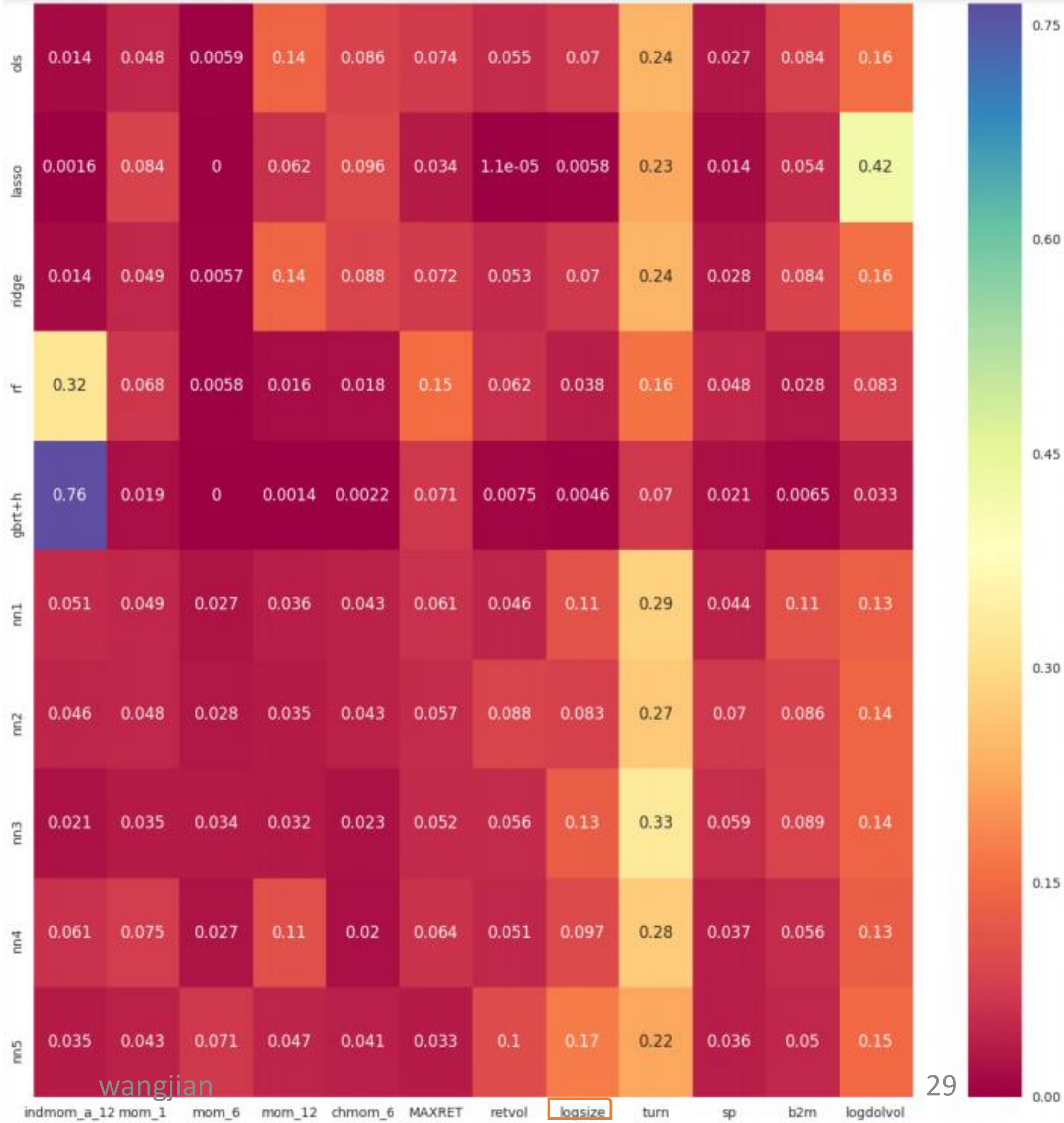


- Liu, Stambaugh, and Yuan (2019) drop the smallest 30% of firms in constructing the size factor in China, pointing out that the value of these firms incorporates the possibility of reverse mergers. (in which small public firms will be acquired by private firms to circumvent IPO constraints and go public)

3. Empirical results

V. Discussion

- We also see that the variable importance of size in Figure is higher for NN5 than OLS, suggesting that NN5 can make better use of the size information to rank the returns of small stocks.



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4. Conclusion

- In the U.S. market, even with only 12 characteristics, the predictive power and profitability of complex machine learning models are comparable to those documented in previous studies using hundreds of variables.
- Training our models using U.S. data and applying them on international stocks concludes that neural network (NN) outperforms linear models, possibly because of the nonlinear and complex interactions among the predictors.
- There are signs that regression trees overfit the in-sample data and underperform linear models, especially in countries where there are few observations.
- We take the first step to study the size effect in China, which is different from the U.S. and the rest of the world.