Alpha Go Everywhere: Machine Learning and International Stock Returns

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International Stock Returns

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    - Fama & French (1998, 2012, 2017), Hou, Karolyi, Kho (2011), Rouwenhorst (1998)
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- Not fully integrated: The predictive power of different firm characteristics varies across markets
- Not fully segmented: Information obtained from the firm characteristics in a foreign market may be relevant for local stocks

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  - Capable of detecting non-monotonic relationships and complex interactions between returns and many characteristics even without local knowledge
    - Say, the price limit rules in China and the investor clientele in India)
  - Able to explore various foreign variables and their interactions with local variables, which may not be ideal in a linear setting

Our Paper

- We use stock characteristics to predict international stock returns in 31 markets
  - Gu, Kelly, Xiu (GKX 2020) examine the U.S. market with 94 stock characteristics, 8 macroeconomic variables, and 74 sector dummies (920 predictors $= 94 \times (8 + 1) + 74$)
  - We use GKX's methods and set of potential hyperparameter values
  - Data availability is lower internationally. We use 36 features
  - (Our U.S. results are similar to those in GKX)
- Following GKX, we compare
  - Linear (OLS, OLS with Huber loss, LASSO, RIDGE, ENET)
  - Tree models (RF and GBRT+H)
  - Neural network (NN) models with 1–5 hidden layers (NN1–NN5)

Main Findings

- We train and validate our models using U.S. data and apply them on each of the 31 markets ("U.S.-trained models")
  - A stringent out-of-sample test: hyperparameters and parameters estimated from the U.S.
  - NNs and tree models outperform linear models in forming profitable portfolios and predicting return rankings (but not in terms of R^2; Kelly, Malamud, Zhou, 2021)

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  - NNs and tree models outperform linear models in forming profitable portfolios and predicting return rankings (but not in terms of R^2; Kelly, Malamud, Zhou, 2021)
- We construct market-specific models and compare them with the U.S.-trained models
  - We train and validate our models separately for each country
  - NNs achieve even stronger results
  - Trees underperform linear models, especially in markets where the number of observations is low

Main Findings

- Local NN models outperform U.S.-Trained NN models
  - Bigger improvements in profitability when
    - The local NN is less similar to the U.S.-trained NN, measured by the central kernel alignment (CKA) similarity index (Kornblith et al., 2019)
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    - The NN has more hidden layers
- We examine cross-market integration
  - U.S. market returns predict other markets' returns (Rapach, Strauss, Zhou, 2013)
  - Local NNs can be further improved by adding U.S.-based variables
    - U.S. characteristic gaps: $95^{th} - 5^{th}$ of a stock characteristic (Cohen, Polk, Vuolteenaho, 2003; Huang, 2021)
  - The variable importance of the U.S. characteristic gaps increases with the market integration metrics constructed by Bekaert et al. (2011) and Akbari, Ng, Solnik (2020)

Data and Methodology

- 36 variables include past returns, market cap, volume, past returns of the industry, and accounting information: DataStream
- US data from CRSP and China data from CSMAR
- We require at least 100 stocks for at least 3 years: 31 markets + U.S.

- We divide the sample period into 3 parts
  1. Train: Estimate the model subject to a particular set of hyperparameter values
  2. Validate: Construct forecasts and calculate objective functions based on the estimated model from the training sample. Iteratively search for hyperparameters that optimize the objective functions
  3. Test: Not used for estimation or tuning. "Out-of-sample"

Data and Methodology

- Standardize all predictors in each month in each market to zero mean and unit standard deviation
- Outcome variable: Excess return in USD in the next month (denominated in USD, in excess of the corresponding market return)
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- We evaluate the models using
  - Annualized Sharpe Ratio of the long–short portfolio (long top decile, short bottom decile of predicted returns)
  - Out-of-sample R^2: $1 - \frac{\sum_{(i,t)\in \text{Test}} (r_{i,t} - \hat{r}_{i,t})^2}{\sum_{(i,t)\in \text{Test}} r_{i,t}^2}$
  - Rank Correlation: Spearman rank correlation between predicted and realized returns
  - Decile Score Distance: Distance between the long portfolio's actual return deciles and the short portfolio's
  - Sum of the Squares of the partial Derivatives (SSD): Measuring variable importance

U.S.-Trained Models: Summary

	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	0.41	0.65	0.25	-0.05	0.37	0.42	-1.17	0.01	1.18
# of +	26	30	25	15	27	29	8	17	30
fraction of +	0.84	0.97	0.81	0.48	0.87	0.94	0.26	0.55	0.97

	Rank Correlation			Decile Score Distance		
	Tree−Linear	NN−Linear	NN−Tree	Tree−Linear	NN−Linear	NN−Tree
difference	1.69	1.75	0.06	0.15	0.22	0.07
# of +	26	29	15	26	28	22
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Machine learning models, NNs in particular, outperform linear models in forming profitable portfolios and predicting return rankings (but not in terms of R^2, probably because of extreme values)

Market-Specific Models: Summary

		Sharpe Ratio (EW)			Sharpe Ratio (VW)		
		Tree−Linear	NN−Linear	NN−Tree	Tree−Linear	NN−Linear	NN−Tree
All markets	*difference*	0.17	0.60	0.44	-0.21	0.41	0.61
	# of +	19	26	25	12	25	28
	fraction of +	0.59	0.81	0.78	0.38	0.78	0.88

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All markets	*difference*	-0.04	1.08	1.12	0.02	0.20	0.19
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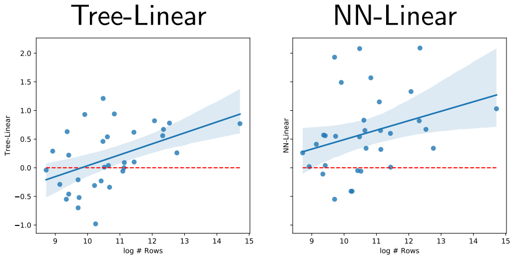
NNs continue to outperform

Trees show signs of overfitting, especially in markets where the number of observations is low

Market-Specific Models: Performance vs Log # Obs



Sharpe Ratio (EW)

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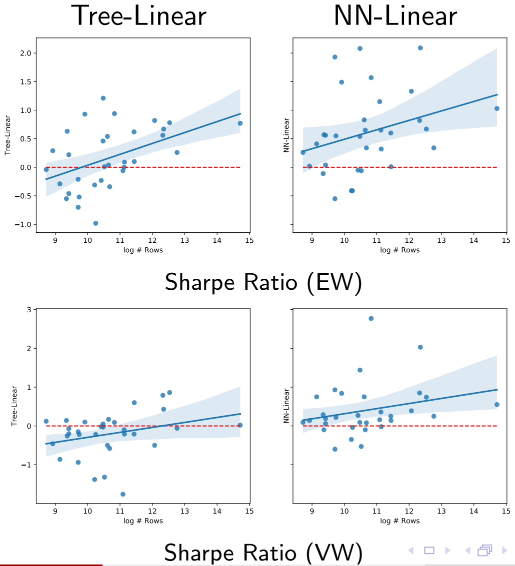

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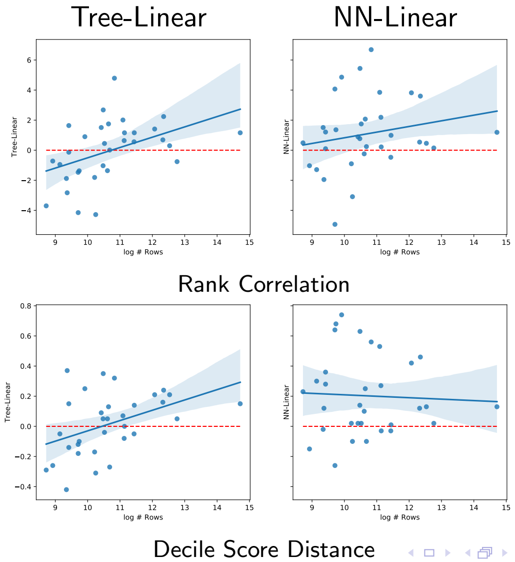

Market-Specific Models vs U.S.-Trained Models

		NN1	NN2	NN3	NN4	NN5
Sharpe Ratio (EW)	difference	0.74	0.77	0.75	0.69	0.74
	# of +	26	26	26	24	27
	fraction of +	0.84	0.84	0.84	0.77	0.87
Sharpe Ratio (VW)	difference	0.52	0.46	0.40	0.42	0.52
	# of +	24	23	24	23	23
	fraction of +	0.77	0.74	0.77	0.74	0.74

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Sharpe Ratio (EW)	difference	0.74	0.77	0.75	0.69	0.74
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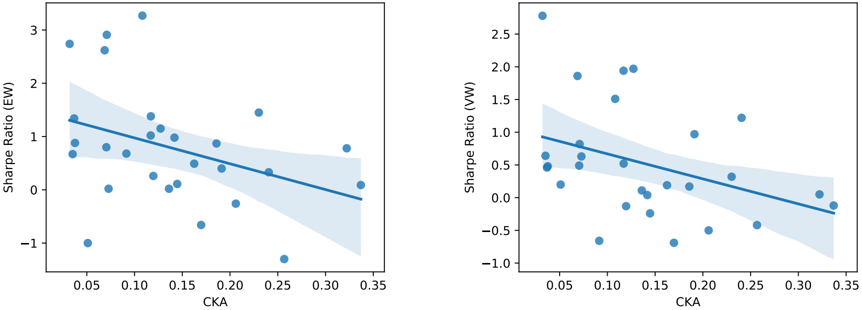
Sharpe Ratio (VW)	difference	0.52	0.46	0.40	0.42	0.52
	# of +	24	23	24	23	23
	fraction of +	0.77	0.74	0.77	0.74	0.74

Local NN models outperform U.S.-Trained NN models

Market-Specific vs U.S.-Trained Models: CKA Similarity

Centered Kernel Alignment (CKA, Kornblith et al., 2019) Similarity in the last hidden layer

Market-specific NN5 – U.S.-trained NN5



Sharpe Ratio (EW) Sharpe Ratio (VW)

Cross-Market Integration

In each market-specific NN, we add top 10 U.S. characteristic gaps plus their interaction terms with the corresponding local characteristic

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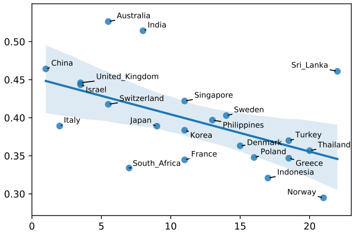
Augmented model - Original model (Top 25 markets)

		NN1	NN2	NN3	NN4	NN5	Best NN
Sharpe Ratio (EW)	difference	0.10	0.07	0.12	0.16	0.04	0.12
	# of +	13	12	16	16	13	18
	fraction of +	0.52	0.48	0.64	0.64	0.52	0.72
Sharpe Ratio (VW)	difference	0.07	0.17	0.33	0.31	0.42	0.29
	# of +	15	16	17	21	19	22
	fraction of +	0.60	0.64	0.68	0.84	0.76	0.88

Cross-Market Integration: U.S. Variable Importance



Segmentation (Bekaert et al. (2011))

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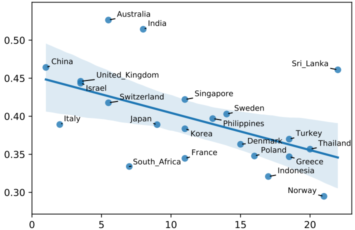

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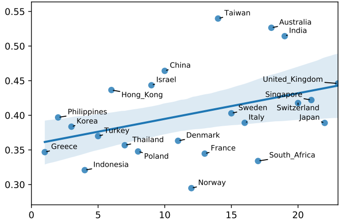
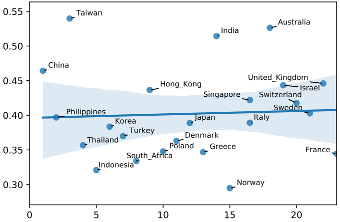


Economic Integration
(Akbari, Ng, and Solnik (2020))



Financial Integration
(Akbari, Ng, and Solnik (2020))

Conclusion

- In the U.S. and most of the 31 international markets, we obtain high Sharpe Ratios
    - Train and validate models using U.S. data, or separately for each country
    - Neural network models are powerful, suggesting that non-linearity and complex interactions are important
    - Tree models can overfit and underperform linear models, especially when the number of observations is low
- Market-specific models outperform U.S.-trained models
    - Market-specific details are important
- Local NNs can be further improved by adding U.S.-based variables
    - Markets are (partially) integrated