What Can Analysts Learn from Artificial Intelligence about Fundamental Analysis?

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Accounting Based Equity Valuation

$$V_0^E = \text{CSE}_0 + \sum_{t=1}^{\infty} (\boxed{\text{ROCE}_t} - \rho_w + 1) \times \text{CSE}_{t-1} \times \rho_w^{-t}$$

Core issue: How to forecast profitability?

- How to use accounting information?
- Which accounting information should be used?
- How long should the forecast horizon be?
- Which valuation framework should be used?

Nissim & Penman (2001)

ROCE

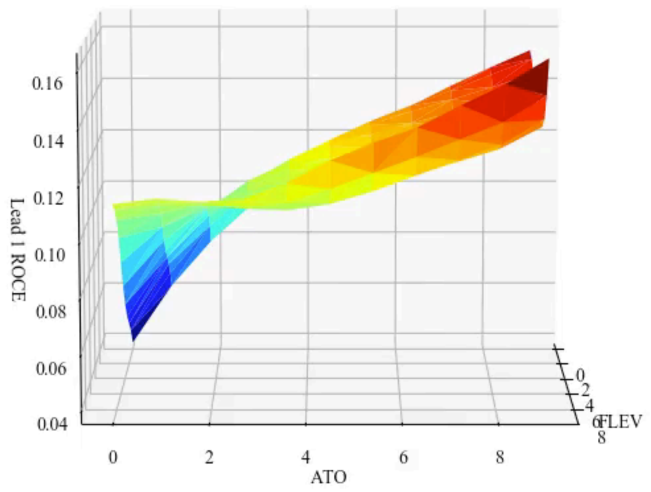
Level 0

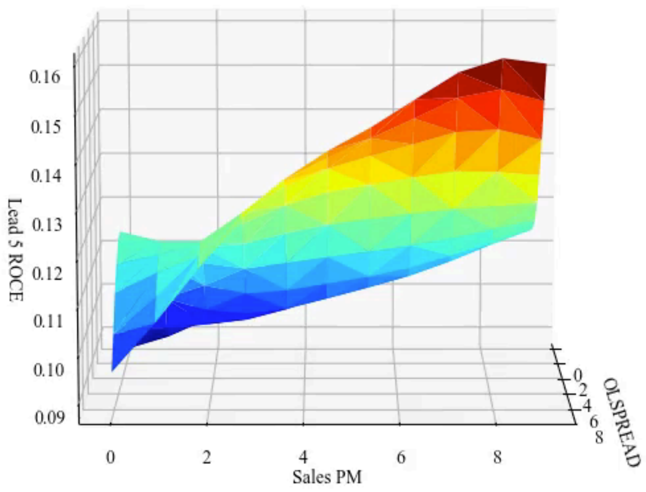
Problem: Non-Linearities

“[W]e began the empirical analysis by attempting to estimate multivariate models to forecast residual operating income, RNOA, and growth in NOA from the pooled cross-section and time-series data [...] the models performed poorly in prediction out of sample [...] the relationship between current and future drivers is non-linear, so pooled, linear models are not likely to work well.”

Nissim & Penman (2001) p. 128

Problem: Non-Linearities



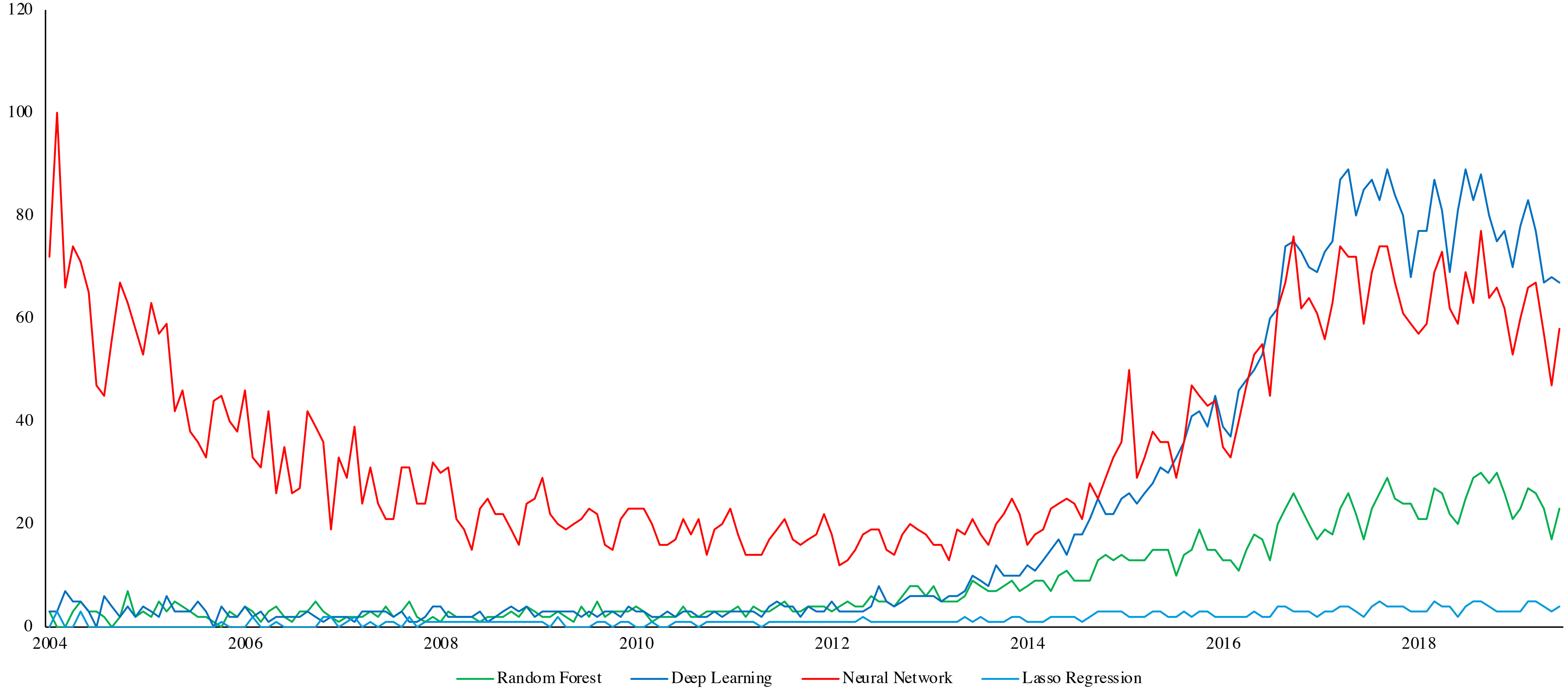


OLS can not solve the issue:

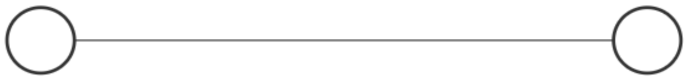
- Example: Model with 1 dependent variable and 10 independent variables
- Simple linear regression: 1 + 10 = 11 parameters
- Add squares and cubes: 1 + 10 + 10 + 10 = 31 parameters
- Add interactions: 1 + 10 + 10 + 10 + 29! = 8.84 × e^{30} parameters

Solution: Deep Learning

Deep Learning

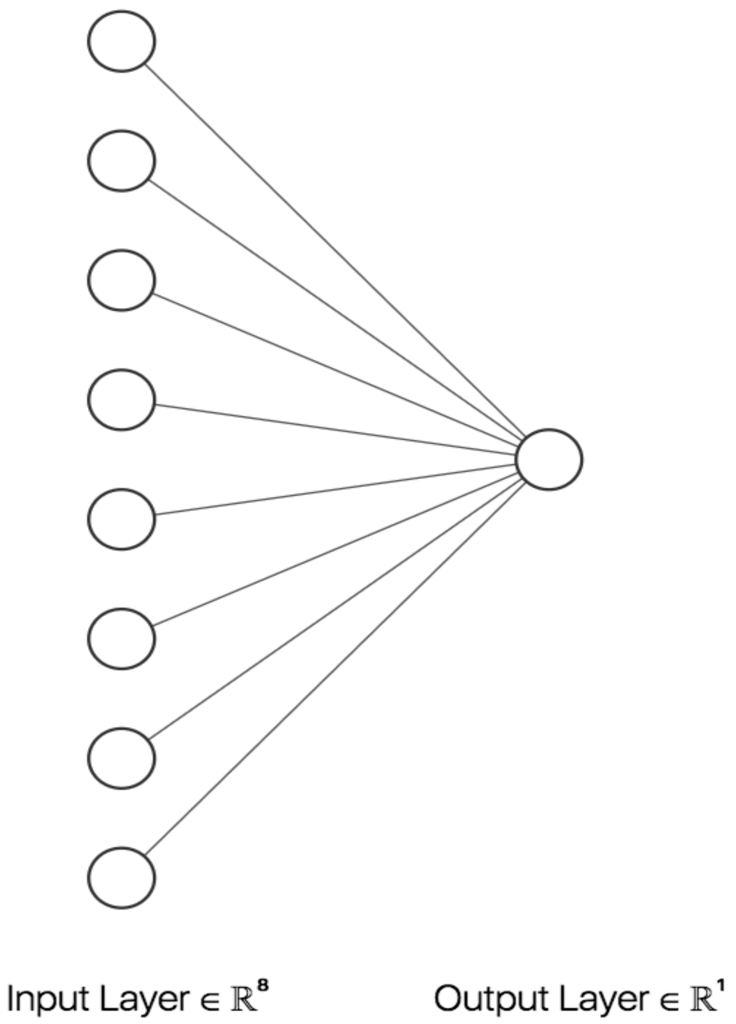


Random Walk (Watts & Leftwich 1977)

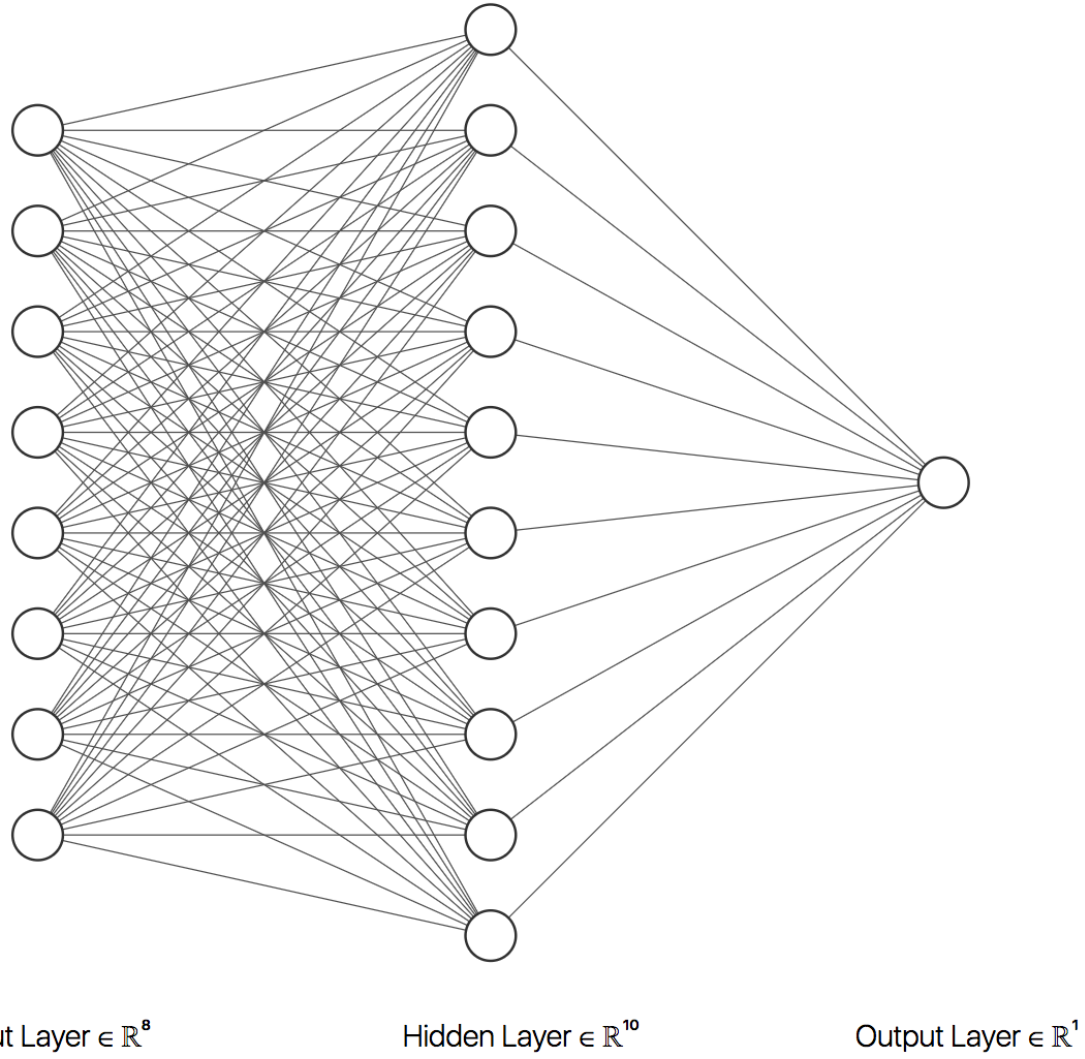


Input Layer $\in \mathbb{R}^1$ Output Layer $\in \mathbb{R}^1$

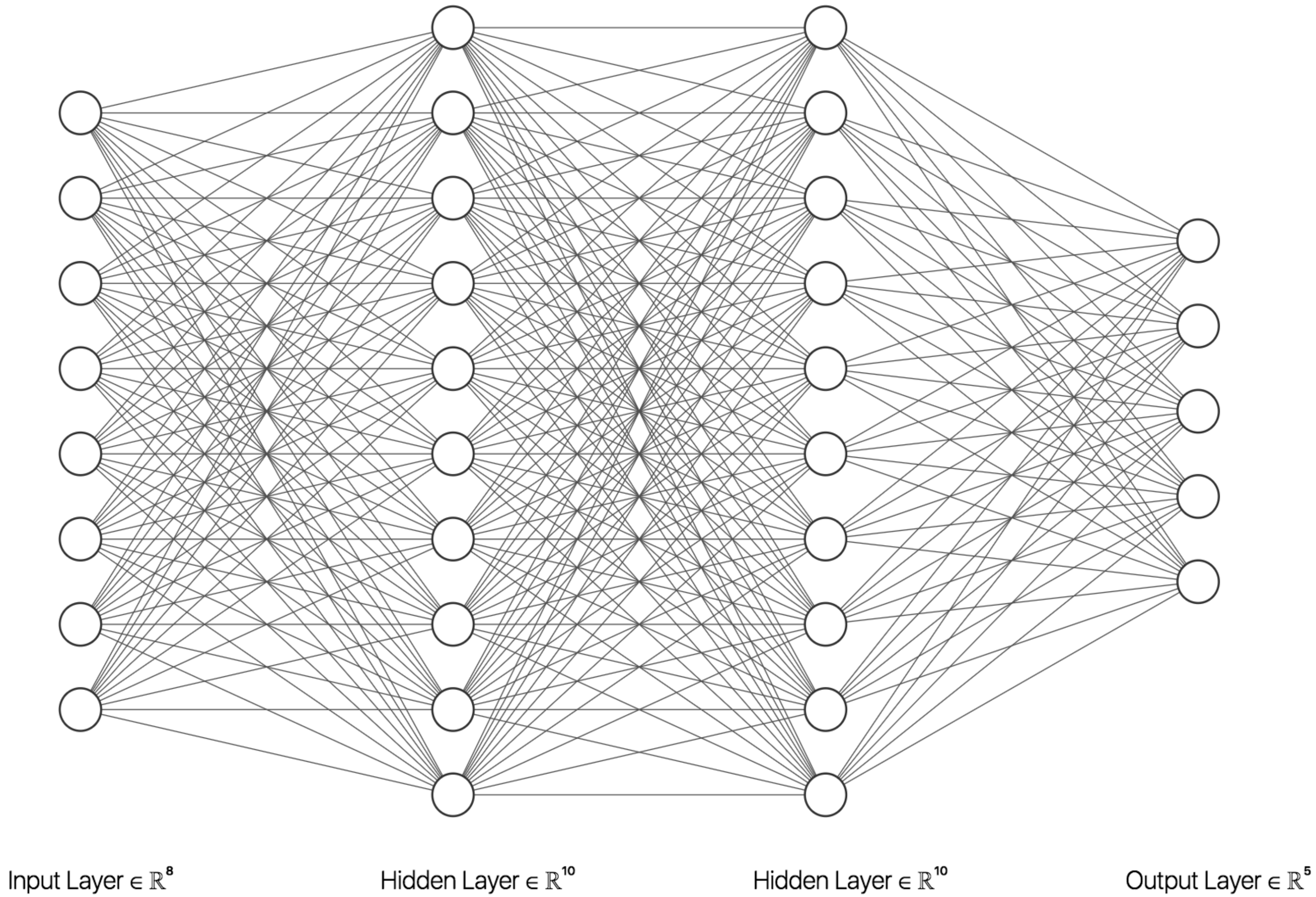
Linear Model (Hou et al. 2012)

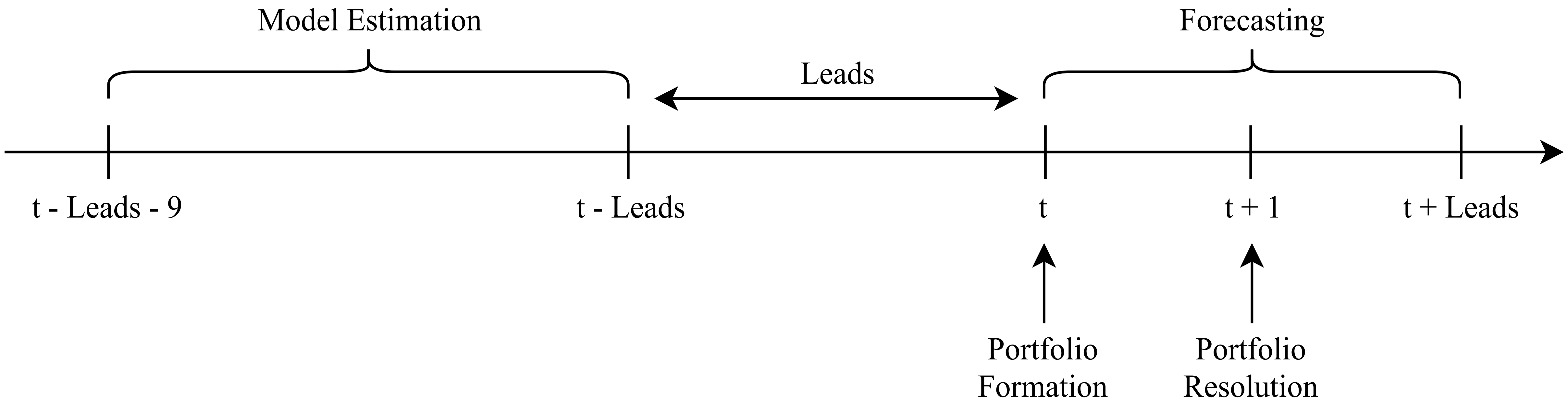


Shallow Neural Network



Deep Neural Network



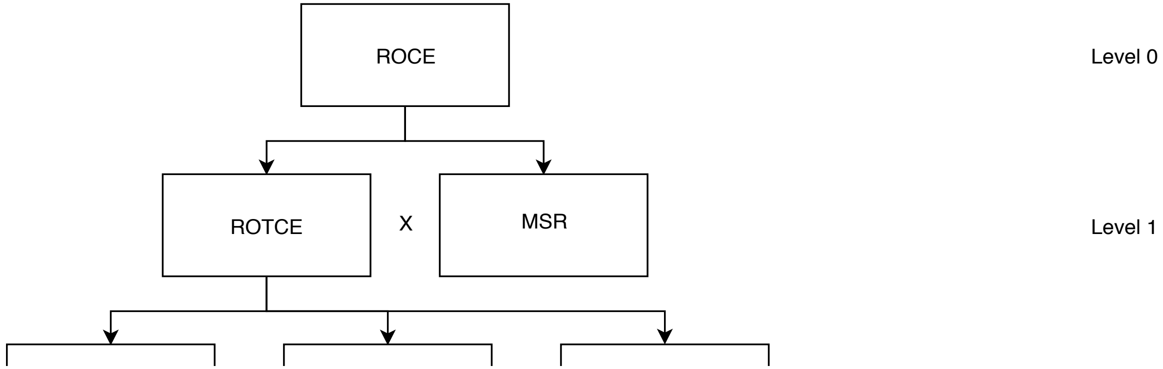


1. Forecast profitability (ROCE/RNOA)
2. Use valuation model to derive value estimate
3. Form hedge portfolios based on VP ratios
4. Calculate Carhart (1997) 4 Factor Model Alphas
5. Regress model Alphas on FSA design choices

Hypotheses

How do FSA design choices affect performance?

1. Higher level of forecast disaggregation
2. Focus o
3. Focus o
4. I



$$V_0^E = \mathrm{CSE}_0 + \sum_{t=1}^{T} \frac{(\mathrm{ROCE}_t - \rho_w + 1) \times \mathrm{CSE}_{t-1}}{\rho_w^{-t}} + \frac{(\mathrm{ROCE}_{T+1} - \rho_w + 1) \times \mathrm{CSE}_T}{\rho_w^T \times (\rho_w - g)}$$

$$V_0^E = \mathrm{NOA}_0 - \mathrm{NFO}_0 + \sum_{t=1}^{T} \frac{(\mathrm{RNOA}_t - \rho_W + 1) \times \mathrm{NOA}_{t-1}}{\rho_W^{-t}} + \frac{(\mathrm{RNOA}_{T+1} - \rho_W + 1) \times \mathrm{NOA}_T}{\rho_W^T \times (\rho_W - g)}$$

Profit Forecasting Results

Mean ROCE Forecasting AFE

	Core 0, Level 1	Core 0, Level 2	Core 0, Level 3	Core 0, Level 4	Core 1, Level 1	Core 1, Level 2	Core 1, Level 3	Core 1, Level 4
Leads 1, Lags 0	0.1095†	0.1105†	0.1118†	0.1125†	0.1095†	0.1046†	0.1084†	0.1068†
Leads 1, Lags 1	0.1089†	0.1105†	0.1132†	0.1130†	0.1086†	0.1053†	0.1104†	0.1104†
Leads 1, Lags 3	0.1084†	0.1128†	0.1157†	0.1152†	0.1085†	0.1079†	0.1128†	0.1116†
Leads 1, Lags 5	0.1093†	0.1156†	0.1190	0.1179†	0.1093†	0.1102†	0.1165†	0.1150†
Leads 5, Lags 0	0.1100†	0.1114†	0.1132†	0.1143†	0.1100†	0.1059†	0.1087†	0.1082†
Leads 5, Lags 1	0.1088†	0.1113†	0.1134†	0.1135†	0.1088†	0.1066†	0.1086†	0.1089†
Leads 5, Lags 3	0.1088†	0.1125†	0.1152†	0.1145†	0.1088†	0.1069†	0.1115†	0.1118†
Leads 5, Lags 5	0.1100†	0.1149†	0.1185	0.1185	0.1100†	0.1090†	0.1150†	0.1151†
Leads 10, Lags 0	0.1108†	0.1117†	0.1147†	0.1153†	0.1108†	0.1071†	0.1100†	0.1089†
Leads 10, Lags 1	0.1097†	0.1113†	0.1147†	0.1148†	0.1098†	0.1068†	0.1106†	0.1110†
Leads 10, Lags 3	0.1087†	0.1116†	0.1161†	0.1163†	0.1086†	0.1075†	0.1134†	0.1138†
Leads 10, Lags 5	0.1095†	0.1146†	0.1191	0.1201	0.1096†	0.1094†	0.1164†	0.1161†

Mean RNOA Forecasting AFE

	Core 0, Level 1	Core 0, Level 2	Core 0, Level 3	Core 0, Level 4	Core 1, Level 1	Core 1, Level 2	Core 1, Level 3	Core 1, Level 4
Leads 1, Lags 0	0.0915	0.0789†	0.0793†	0.0801†	0.0915	0.0751†	0.0783†	0.0772†
Leads 1, Lags 1	0.0909	0.0788†	0.0797†	0.0798†	0.1201	0.0786†	0.0835†	0.0784†
Leads 1, Lags 3	0.0905	0.0803†	0.0823†	0.0819†	0.1095†	0.0758†	0.0785†	0.0801†
Leads 1, Lags 5	0.0909	0.0823†	0.0848	0.0846†	0.1086†	0.0763†	0.0783†	0.0821†
Leads 5, Lags 0	0.0915	0.0797†	0.0810†	0.0820†	0.1085†	0.0767†	0.0799†	0.0788†
Leads 5, Lags 1	0.0912	0.0792†	0.0805†	0.0809†	0.1093†	0.0784†	0.0830†	0.0788†
Leads 5, Lags 3	0.0910	0.0804†	0.0815†	0.0813†	0.1100†	0.0763†	0.0786†	0.0796†
Leads 5, Lags 5	0.0913	0.0815†	0.0847	0.0840†	0.1088†	0.0763†	0.0791†	0.0818†
Leads 10, Lags 0	0.0921	0.0794†	0.0817†	0.0817†	0.1088†	0.0771†	0.0808†	0.0783†
Leads 10, Lags 1	0.0914	0.0791†	0.0815†	0.0815†	0.1100†	0.0779†	0.0834†	0.0790†
Leads 10, Lags 3	0.0911	0.0794†	0.0825†	0.0825†	0.1108†	0.0783†	0.0772†	0.0807†
Leads 10, Lags 5	0.0915	0.0810†	0.0843†	0.0855	0.1098†	0.0787†	0.0784†	0.0833†

Hedge Portfolio Results

ROCE-based Alphas

	Core 0, Level 1	Core 0, Level 2	Core 0, Level 3	Core 0, Level 4	Core 1, Level 1	Core 1, Level 2	Core 1, Level 3	Core 1, Level 4
Leads 1, Lags 0	-0.0048	0.0085	-0.0031	-0.0088	-0.0043	0.0066	-0.0001	0.0090
Leads 1, Lags 1	0.0009	0.0172	0.0026	0.0041	0.0007	0.0026	-0.0016	0.0021
Leads 1, Lags 3	0.0026	0.0039	-0.0011	0.0059	0.0031	0.0113	0.0119	0.0153
Leads 1, Lags 5	0.0022	0.0041	0.0099	0.0042	0.0021	0.0138	0.0150	0.0053
Leads 5, Lags 0	-0.0316*	-0.0010	0.0386	-0.0218	-0.0317*	0.0154	0.0151	0.0436
Leads 5, Lags 1	-0.0155	-0.0027	0.0025	0.0514**	-0.0144	0.0336	0.0240	0.0190
Leads 5, Lags 3	-0.0067	-0.0323	-0.0085	0.0170	-0.0086	-0.0259	-0.0053	0.0389
Leads 5, Lags 5	-0.0013	-0.0255	-0.0071	0.0378	-0.0004	0.0433	0.0139	0.0119
Leads 10, Lags 0	-0.0113	0.0156	0.0041	0.0347	-0.0159	0.0380	0.0299	0.0431**
Leads 10, Lags 1	0.0246	0.0529**	0.0351	0.0477*	0.0132	0.0233	0.0340	0.0416**
Leads 10, Lags 3	0.0323	-0.0068	-0.0028	-0.0109	0.0346	0.0210	0.0170	0.0464*
Leads 10, Lags 5	0.0347	0.0095	0.0092	0.0228	0.0338	0.0028	-0.0097	-0.0055

RNOA-based Alphas

	Core 0, Level 1	Core 0, Level 2	Core 0, Level 3	Core 0, Level 4	Core 1, Level 1	Core 1, Level 2	Core 1, Level 3	Core 1, Level 4
Leads 1, Lags 0	-0.0844***	-0.0879***	-0.0844***	-0.0942***	-0.0846***	-0.0924***	-0.0896***	-0.0961***
Leads 1, Lags 1	-0.0843***	-0.0864***	-0.0872***	-0.0934***	-0.0844***	-0.0944***	-0.0919***	-0.0924***
Leads 1, Lags 3	-0.0867***	-0.0817***	-0.0844***	-0.0926***	-0.0862***	-0.0902***	-0.0936***	-0.0924***
Leads 1, Lags 5	-0.0923***	-0.0919***	-0.0870***	-0.0904***	-0.0924***	-0.0867***	-0.0839***	-0.0872***
Leads 5, Lags 0	-0.0237*	0.0559***	0.0946***	0.0535**	-0.0236*	0.0425**	0.0353**	0.0405*
Leads 5, Lags 1	-0.0132	0.0314	0.0389**	0.0588***	-0.0131	0.0595***	0.0443**	0.0455***
Leads 5, Lags 3	-0.0138	0.0048	0.0167	0.0196	-0.0151	0.0420*	0.0056	0.0500**
Leads 5, Lags 5	-0.0304	0.0165	0.0587*	0.0433	-0.0229	0.0508	0.0239	0.0526*
Leads 10, Lags 0	-0.0172	0.0392	0.0609***	0.0790***	-0.0180	0.0495**	0.0641***	0.0484*
Leads 10, Lags 1	0.0026	0.0765***	0.0589***	0.0291	-0.0037	0.0638***	0.0768***	0.0834***
Leads 10, Lags 3	0.0105	0.0755***	0.0509***	0.0678***	0.0061	0.0700***	0.0587***	0.0605***
Leads 10, Lags 5	0.0047	0.0532**	0.0512***	0.0545**	0.0065	0.0384*	0.0733***	0.0410**

Hypothesis 1: Ratio Disaggregation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Quantile	Mean	P5	P10	P25	P50	P75	P90	P95
Level 2	0.023***	0.036***	0.030***	0.030***	0.017**	0.010***	0.010***	0.010***
	(5.475)	(5.893)	(6.041)	(10.873)	(2.053)	(2.605)	(4.222)	(10.620)
Level 3	0.024***	0.037***	0.032***	0.030***	0.019**	0.007**	0.007**	0.012***
	(5.730)	(6.485)	(6.746)	(10.637)	(2.346)	(2.170)	(2.581)	(3.980)
Level 4	0.028***	0.038***	0.029***	0.032***	0.020**	0.012***	0.012***	0.012***
	(6.620)	(6.255)	(6.102)	(9.101)	(2.348)	(3.872)	(7.113)	(14.933)
Other FSA Ind.	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	192	192	192	192	192	192	192	192
R^2	0.851	0.686	0.700	0.678	0.596	0.596	0.610	0.618

Hypothesis 2: Core Items

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Quantile	Mean	P5	P10	P25	P50	P75	P90	P95
Core	0.003	0.001	-0.001	0.001	0.006**	0.001	0.001	-0.000
	(1.046)	(0.280)	(-0.632)	(0.449)	(2.018)	(0.713)	(0.391)	(-0.185)
Other FSA Ind.	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	192	192	192	192	192	192	192	192
R^2	0.851	0.686	0.700	0.678	0.596	0.596	0.610	0.618

Hypothesis 3: Operating Activities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Quantile	Mean	P5	P10	P25	P50	P75	P90	P95
ROCE	0.093***	0.092***	0.092***	0.095***	0.099***	0.093***	0.090***	0.089***
	(29.019)	(12.895)	(26.669)	(48.586)	(32.622)	(65.565)	(38.793)	(109.408)
ROCE × Leads 5	-0.114***	-0.124***	-0.119***	-0.114***	-0.125***	-0.120***	-0.104***	-0.104***
	(-17.869)	(-12.654)	(-14.297)	(-17.601)	(-15.643)	(-13.596)	(-21.920)	(-5.307)
ROCE × Leads 10	-0.118***	-0.121***	-0.126***	-0.122***	-0.131***	-0.120***	-0.121***	-0.120***
	(-18.927)	(-13.240)	(-25.334)	(-16.472)	(-16.020)	(-18.221)	(-36.093)	(-41.570)
Other FSA Ind.	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	192	192	192	192	192	192	192	192
R^2	0.851	0.686	0.700	0.678	0.596	0.596	0.610	0.618

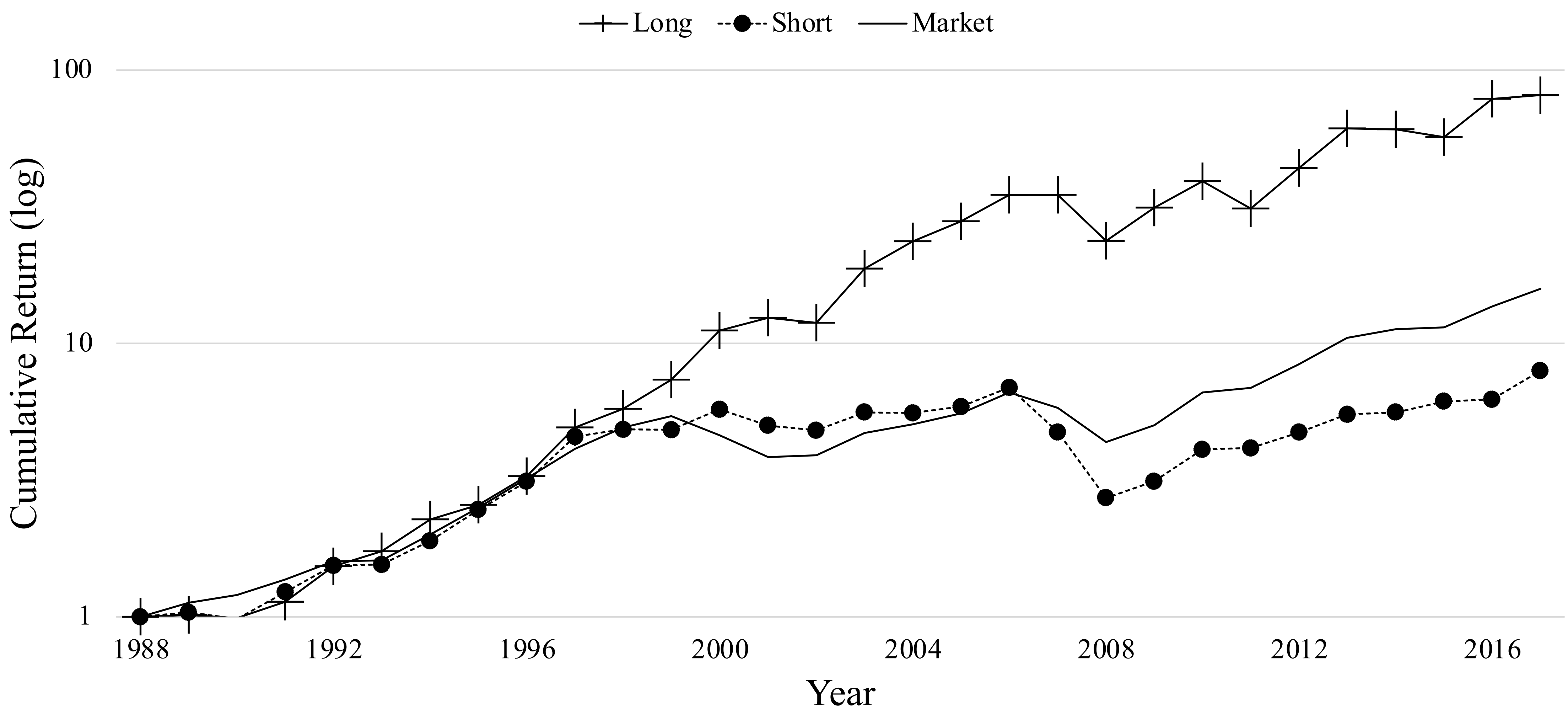
Hypothesis 4: Forecast Horizon

Quantile	(1) Mean	(2) P5	(3) P10	(4) P25	(5) P50	(6) P75	(7) P90	(8) P95
Leads 5	0.115*** (23.851)	0.111*** (12.860)	0.100*** (23.679)	0.108*** (23.442)	0.124*** (18.419)	0.128*** (28.487)	0.131*** (47.010)	0.133*** (6.866)
Leads 10	0.133*** (29.692)	0.123*** (21.804)	0.123*** (40.377)	0.129*** (25.580)	0.144*** (23.010)	0.148*** (25.928)	0.152*** (74.005)	0.151*** (61.394)
Other FSA Ind.	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	192	192	192	192	192	192	192	192
R^2	0.851	0.686	0.700	0.678	0.596	0.596	0.610	0.618

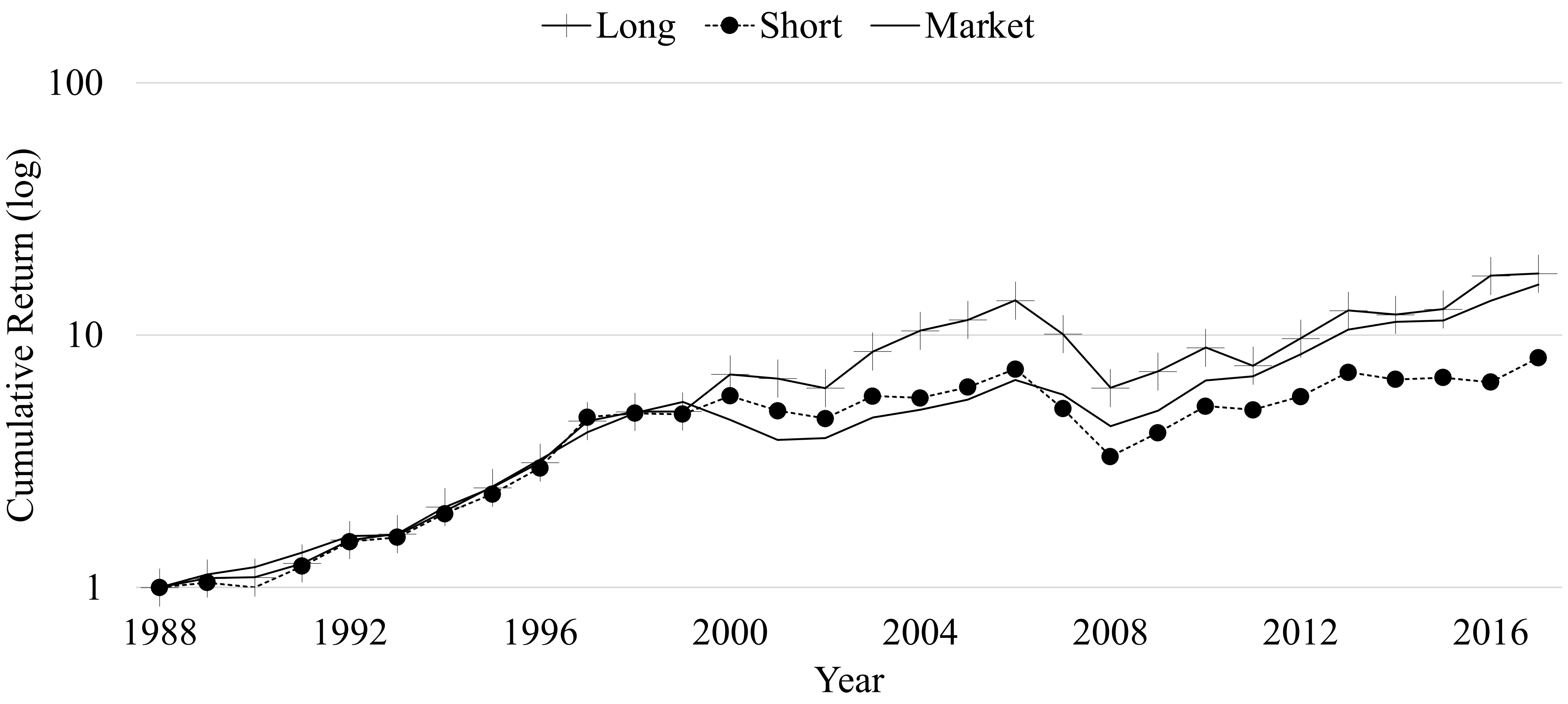
Hypothesis 5: Historical Information

Quantile	(1) Mean	(2) P5	(3) P10	(4) P25	(5) P50	(6) P75	(7) P90	(8) P95
Lags 1	0.006	0.008	0.001	-0.000	0.009**	0.009**	0.002	0.005**
	(1.536)	(1.275)	(0.393)	(-0.104)	(2.477)	(2.547)	(0.957)	(2.209)
Lags 3	-0.002	-0.004	-0.001	-0.002	0.001	0.003	-0.002	-0.002
	(-0.408)	(-0.547)	(-0.213)	(-0.888)	(0.284)	(0.956)	(-0.692)	(-1.604)
Lags 5	-0.000	-0.002	0.002	-0.000	0.004	0.003	-0.001	-0.002
	(-0.022)	(-0.254)	(0.396)	(-0.103)	(1.150)	(1.001)	(-0.609)	(-1.323)
Other FSA Ind.	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	192	192	192	192	192	192	192	192
R^2	0.851	0.686	0.700	0.678	0.596	0.596	0.610	0.618

Deep Learning Performance



OLS Performance



Estimator Comparison

Model	(1) NN VW	(2) NN EW	(3) OLS VW	(4) OLS EW	(5) LAD VW	(6) LAD EW
Mkt-Rf	-0.164	0.174	0.013	-0.303	-0.041	-0.124
	(-0.689)	(0.706)	(0.117)	(-1.242)	(-0.154)	(-0.552)
HML	0.534***	0.524**	0.209*	0.085	0.301*	0.125
	(4.624)	(2.615)	(1.969)	(0.582)	(1.901)	(0.812)
SMB	0.170	1.330*	0.278	0.655	0.927***	1.021
	(0.416)	(1.959)	(1.288)	(1.015)	(2.933)	(1.277)
UMD	-0.153	-0.085	-0.114	0.080	-0.007	0.019
	(-0.617)	(-0.392)	(-0.715)	(0.424)	(-0.043)	(0.092)
Alpha	0.095***	0.076**	0.000	0.056	0.049	0.062
	(4.108)	(2.564)	(0.010)	(1.142)	(1.704)	(1.688)
Observations	29	29	29	29	29	29
NW SEs	3 lags	3 lags	3 lags	3 lags	3 lags	3 lags

Cross-Sectional Variation

Model	(1) Ret_{t+1}	(2) Ret_{t+1}	(3) Ret_{t+1}	(4) Ret_{t+1}
VP Rank	0.021***	0.003**	0.009***	0.004**
	(3.19)	(2.23)	(3.62)	(2.37)
VP Rank × Size	-0.002***			
	(-2.83)			
VP Rank × Loss		0.006*		
		(1.85)		
VP Rank × Distress			-0.084**	
			(-2.07)	
VP Rank × Tech				0.015**
				(2.18)
Controls	YES	YES	YES	YES
Observations	30,129	30,129	29,606	30,129
Adj. R^2	0.154	0.154	0.155	0.154
Fixed Effects	Firm & Year	Firm & Year	Firm & Year	Firm & Year

Conclusion

- Prior literature struggles to estimate non-linearities in structural valuation models
- Advances in computing power & machine learning enable powerful tool: Deep Leaning
- We use Deep Learning to estimate dynamics in Nissim & Penman (2001)
- Yields more accurate out-of-sample ROCE and RNOA predictions
- Yields excess returns
- Performance derives from greater disaggregation and long-horizon forecasts of operating activities (but not from focus on historical info and core items)

Thank you!