Timing the Factor Zoo via Visualization: Evidence from Deep Learning

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Motivation

- Question on factor risk premia predictability.
  - **Diverse sources of factors** come from both risk characteristics and human behavior.
  - Hard to generate **one-size-fits-all** characteristic to derive robust factor predictability.
- Complexity of factor time series make difficult to find meaningful patterns.
  - Discovering dynamics embedded in time series needs to **encode a range of features** (degree, duration, locus, overall trajectory).
  - Representing factor in **single visualization** retains sufficient information of full history.
  - Employing CNN can recognize complex and non-linear pattern in images.

Research questions

- Whether CNN return forecast is robust predictors of equity factors?
- Each factor **visualized** to be standardized price and volatility charts and **learned by CNN** to determine timing weights.
- Performance of all groups of factors significantly improved using CNN-based timing weights.

Contribution

- Contribute to literature regarding predictability of equity factors.
  - Prior literature: **past cumulative return** predict future performance (Arnott et al., 2023; Ehsani, 2022); **return volatility** (Barroso, 2015; Moreira, 2017); **valuation ratios** of factors (Baba et al., 2021; Haddad et al., 2020).
  - Contradiction: significant disappearance of factor momentum (Fan et al., 2022); improve via volatility manage disappear if limit to arbitrage (Barroso, 2021); valuation ratio cannot get robust timing in C&Z factors (Neuhierl et al., 2023).
  - Extend: equity factor premia highly predictable based on image representation of factor, serving as **upper bound** for factor premia predictability.

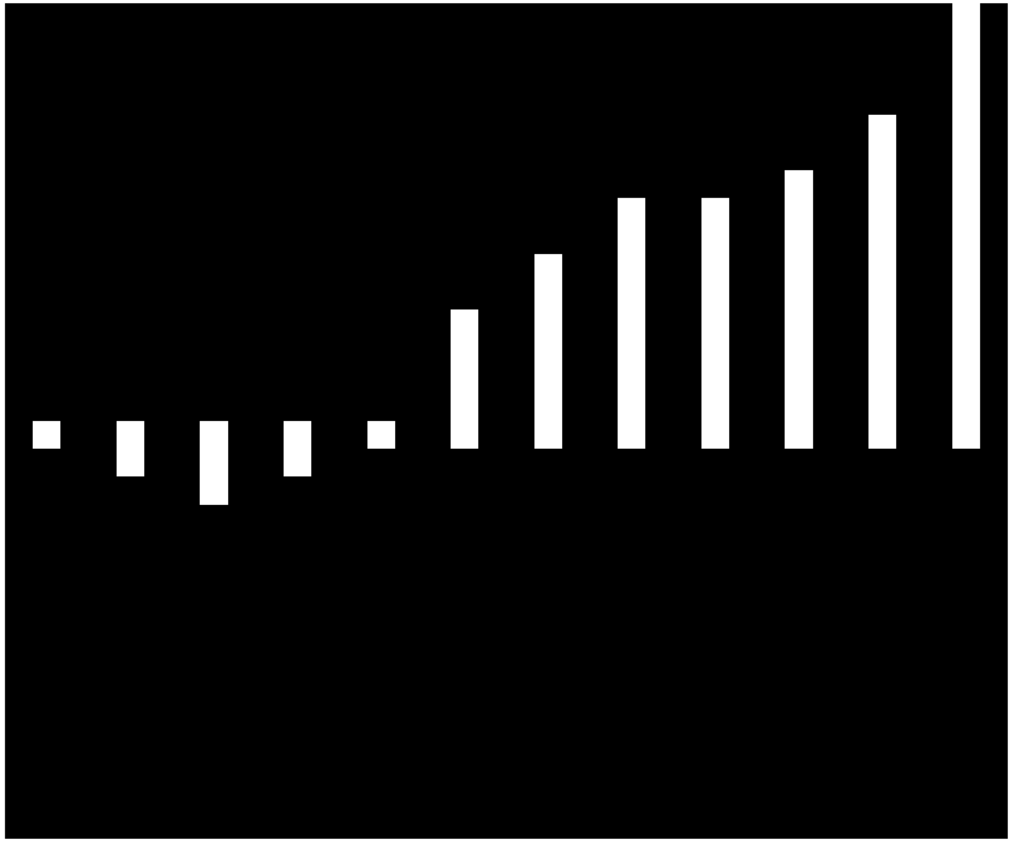
Contribution

- Contribute to literature on asset pricing implications of financial data image.
  - Prior literature: cumulative return expectations (Murray et al., 2024); stock candlestick charts (Jiang, 2023); firm fundamentals (Christensen et al., 2024).
  - Extend: prior focus on firm-level price, volume, or earnings bar data, this study generates images from **equity factors**, exhibiting different dynamics.

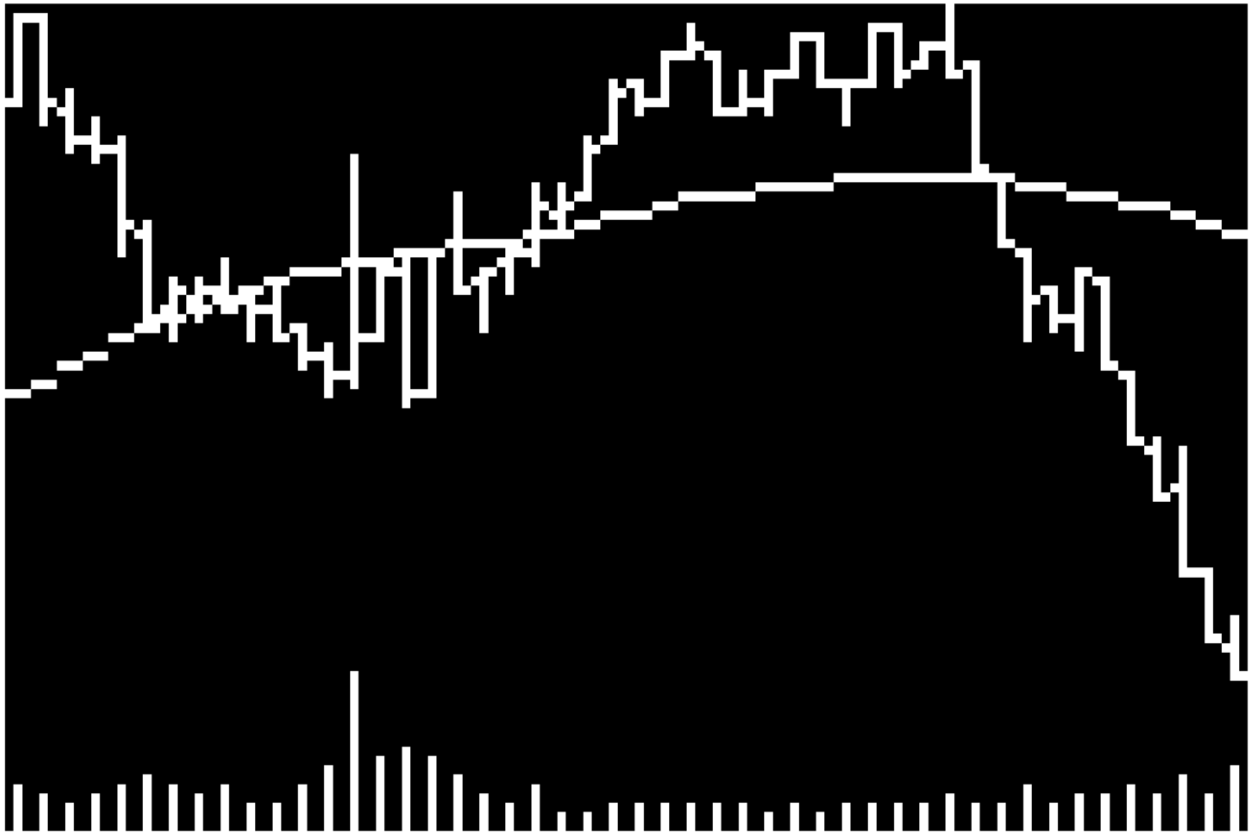
Image-representation of equity factors

- C&Z data set
  - Include **212 factors with daily returns** constructed from long-short portfolios based on firm characteristics documented in top academic journals.
- Combine two approaches with equal weights
  - MMX: Murray, Xia, and Xiao (2024) visualize **cumulative past returns**, capturing factor momentum or reversals.
  - JKX: Jiang, Kelly, and Xiu (2023) visualize **candle charts,** capturing factor returns, volumes, price jumps, and crashes.

Image-representation of equity factors



MXX-Based Factor Images



JKX-Based Factor Images

CNN model training

- CNN architecture: standard CNN, CNN-LSTM
- Loss function: MSE, MAE
- Factor return transformation : z-score ($f_{j,t}^{\sigma}$), normal-distribution ($f_{j,t}^{Norm}$), uniform-distribution ($f_{j,t}^{Pcl}$)
- Sample split: Training & Validation: 1927–1973; Test: 1974–2018
- Weight allocation: EW, EWPM
- Cross-validation: fit each of 64 models in different subsets of training sample.

Factor timing ability

- Average IC (ω_{CNN})
  - Average correlation between model forecasts in month t and realized factor return in month $t+1$ across all factors.
  - Weight 64 model forecasts based on in-sample IC to generate out-of-sample forecast.

	Mean	ΔIC_{CNN}^{MOM}	Std	5%	25%	50%	75%	95%
t+1	0.087	0.017	0.076	-0.035	0.038	0.083	0.138	0.223
t+2	0.084	0.005	0.092	-0.069	0.020	0.086	0.144	0.238
t+3	0.081	0.003	0.100	-0.073	0.008	0.076	0.148	0.246
t+6	0.084	0.003	0.118	-0.083	0.001	0.073	0.157	0.275
t+12	0.064	0.000	0.144	-0.142	-0.036	0.057	0.157	0.310
t+24	0.015	0.018	0.190	-0.264	-0.120	0.008	0.115	0.332
t+36	0.026	0.025	0.193	-0.255	-0.115	0.008	0.140	0.361

Factor timing via time-series tests

- Timing signal to scale original factor returns.
  - $f_{j,t+1}^{CNN} = \omega_{j,t}^{CNN} \times f_{j,t+1}$
- Regress timed factor returns $f_{j,t+1}^{CNN}$ on untimed counterpart.
  - $f_{j,t+1}^{CNN} = \alpha_j + \beta_j f_{j,t+1} + \epsilon_{j,t+1}$
- Difference in Sharpe ratios between timed and untimed factor.
  - $\Delta SR_j = SR\left(f_j^{CNN}\right) - SR(f_j)$

Panel A: 12 Month-Window								
	α		$\alpha \geq 0$		$\alpha \leq 0$		ΔSR	
FullSample	0.59	(9.86)	183	[107]	29	[3]	0.04	(5.87)
Intangibles	0.53	(7.77)	36	[23]	5	[1]	0.06	(5.13)
Investment	0.37	(6.53)	29	[21]	5	[0]	0.01	(0.29)
Momentum	1.03	(11.49)	19	[14]	2	[0]	0.05	(3.38)
Other	0.73	(4.35)	37	[19]	7	[2]	0.03	(2.02)
Profitability	0.45	(6.37)	13	[6]	1	[0]	0.06	(3.32)
Trading frictions	0.40	(8.01)	24	[11]	8	[0]	0.03	(2.07)
Value vs. growth	0.67	(6.11)	25	[13]	1	[0]	0.05	(3.07)

Panel B: 24 Month-Window								
	α		$\alpha \geq 0$		$\alpha \leq 0$		ΔSR	
FullSample	0.41	(7.94)	184	[88]	28	[1]	0.03	(3.96)
Intangibles	0.28	(9.29)	34	[16]	7	[0]	0.04	(3.17)
Investment	0.30	(7.86)	32	[18]	2	[0]	0.05	(3.71)
Momentum	0.67	(7.32)	19	[8]	2	[0]	0.02	(1.41)
Other	0.67	(3.76)	37	[14]	7	[0]	0.00	(-0.01)
Profitability	0.33	(6.04)	11	[6]	3	[0]	0.04	(2.34)
Trading frictions	0.23	(6.11)	25	[8]	7	[1]	0.01	(0.38)
Value vs. growth	0.40	(10.42)	26	[18]	0	[0]	0.07	(5.59)

Factor timing via cross-sectional tests

- Sort universe of 212 equity factors into quintile portfolios based on $\omega_{j,t}^{CNN}$
  - Each of extreme portfolios (highest and lowest quintiles) contains 46 factors.
  - Three middle quintiles contain 40 factors
- Post publication bias
  - Performance of wide range of factors deteriorates after their publications.
  - At every point in time, use only factors underlying papers already published on factor sorting.

	Low	2	3	4	High	HML
			(I). Performance			
Ret	0.016	0.255	0.498	0.680	1.220	1.204
STD	2.007	1.091	0.989	1.397	2.550	4.120
SR	0.028	0.810	1.745	1.687	1.657	1.012
			(II). Regressions			
CAPM α	0.126	0.362***	0.596***	0.772***	1.306***	1.180***
	(1.26)	(7.83)	(11.30)	(12.62)	(11.35)	(6.50)
MKTRF	-0.121***	-0.116***	-0.107***	-0.101***	-0.095**	0.026
	(-3.35)	(-6.76)	(-7.68)	(-4.80)	(-2.23)	(0.37)
FF-5 α	-0.106	0.210***	0.483***	0.687***	1.224***	1.330***
	(-1.05)	(4.92)	(10.01)	(8.06)	(7.99)	(5.45)
MKTRF	-0.037	-0.065***	-0.078***	-0.080***	-0.077**	-0.039
	(-1.35)	(-6.51)	(-7.38)	(-3.67)	(-2.00)	(-0.62)
SMB	-0.038	-0.002	0.057***	0.055	0.067	0.105
	(-0.73)	(-0.08)	(2.88)	(1.41)	(0.81)	(0.79)
HML	0.189***	0.112***	0.032	0.009	-0.116	-0.305
	(2.61)	(4.98)	(1.13)	(0.15)	(-0.86)	(-1.51)
RMW	0.288**	0.131***	0.030	-0.015	-0.025	-0.313
	(2.56)	(4.95)	(0.64)	(-0.18)	(-0.17)	(-1.23)
CMA	0.059	0.095***	0.175***	0.178***	0.306**	0.247
	(0.73)	(3.01)	(4.91)	(3.06)	(2.07)	(1.14)

New ideas

- Use LLM to recognize images.
- Integrate multiple factor information to study interaction effects between factors.

假期工作计划

- 基于注意力机制的中国上市公司财报文本分析
  - GPT和Deepseek都做一下
  - 表格数据的处理（目前直接删除了表格内容，后续考虑融合文本和数据）
  - 财报与股价相联系，研究市场对披露的反应
  - 扩充其他公司披露文件