THE OHIO STATE UNIVERSITY
FISHER COLLEGE OF BUSINESS

The Factor Model Failure Puzzle

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Outline

This Paper in a Nutshell

- Factor Models: $\mathbb{E}[r] = \beta \cdot \mathbb{E}[r^*]$, with $r^* =$ max SR portfolio
- First factor model was the CAPM ($r^* = r_m$)
- Then we started to add other factors:
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  - Finding: no r^* prices well the r^* from other models OOS
  - Explanation: large T but also many $\mathbb{E}[r]$ predictors

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Models for r^* Estimation

Table 1. Zoo of Asset Pricing Models

Initialism	Factor Method $f(Z_t)$	MVE Collapse Method b
BPZ_F	Bryzgalova et al. (2020) forest	Bryzgalova et al. (2020)
BPZ_L	linear characteristic-weighted portfolios	Bryzgalova et al. (2020)
BSV	linear characteristic-weighted portfolios	Brandt et al. (2009)
DGU	linear characteristic-weighted portfolios	DeMiguel et al. (2007)
DMRS	Daniel, Mota, Rottke, and Santos (2020)	Bryzgalova et al. (2020)
D_F	Davis (2021) random forest	$b = 1$
D_{NN}	Davis (2021) neural network	$b = 1$
FF3	Fama and French (1993)	Bryzgalova et al. (2020)
FF6	Fama and French (2015) with Carhart (1997) momentum	Bryzgalova et al. (2020)
GKX	Gu et al. (2021)	Bryzgalova et al. (2020)
HXZ	Hou et al. (2014)	Bryzgalova et al. (2020)
KNS	linear characteristic-weighted portfolios	Kozak et al. (2020)
KPS	Kelly et al. (2019)	Bryzgalova et al. (2020)
SL	Sharpe (1964b) and Lintner (1965) CAPM	$b = 1$
SY	Stambaugh and Yuan (2016)	Bryzgalova et al. (2020)

Correlations Between r^* from Different Models

Table 3. Dimson Adjusted Factor-MVE Portfolio Correlations

	(1) SL	(2) FF_3	(3) GKX	(4) BPZ_F	(5) DGU	(6) FF_6	(7) D_F	(8) SY	(9) DMRS	(10) HXZ	(11) D_{NN}	(12) BPZ_L	(13) KNS	(14) KPS	(15) BSV
SL	1.														
FF3	0.764	1.													
GKX	0.758	0.71	1.												
BPZ_F	0.219	0.222	0.163	1.											
DGU	0.439	0.734	0.446	0.593	1.										
FF6	-0.023	0.492	0.153	-0.02	-0.052	1.									
D_F	1.069	0.932	0.657	0.391	0.346	0.017	1.								
SY	-0.018	0.34	0.165	-0.021	-0.041	0.635	0.021	1.							
DMRS	0.186	0.438	0.21	0.054	0.043	0.553	0.21	0.293	1.						
HXZ	-0.042	0.227	0.115	-0.089	-0.126	0.648	-0.05	0.745	0.38	1.					
D_{NN}	0.457	0.741	0.463	0.67	0.968	0.011	0.951	-0.127	0.241	-0.153	1.				
BPZ_L	0.515	0.861	0.483	0.552	0.896	0.126	0.871	0.098	0.226	-0.007	0.814	1.			
KNS	0.51	0.847	0.481	0.53	0.857	0.144	0.852	0.118	0.243	0.017	0.798	0.978	1.		
KPS	0.468	0.426	0.338	0.425	0.435	-0.042	0.618	-0.103	0.083	-0.054	0.561	0.551	0.572	1.	
BSV	0.403	0.589	0.365	0.39	0.564	0.159	0.624	0.232	0.219	0.154	0.613	0.749	0.796	0.626	1.

Alpha from $r^*_{Row} = \alpha + \beta \cdot r^*_{Column} + \epsilon$

Table 5. Out-of-Sample Unconditional Dimson Alphas

	α^*_{ij}														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Pricing Portfolio j														
	SL	FF_3	GKX	BPZ_F	DGU	FF_6	D_F	SY	DMRS	HXZ	D_{NN}	BPZ_L	KNS	KPS	BSV
Test Asset i															
SL		0.009	0.011	0.028**	0.043***	0.028**	-0.010	0.022*	0.024*	0.018	0.055***	0.042***	0.040***	0.013	0.020
FF_3	0.017*		0.017	0.034**	0.036***	0.009	-0.008	0.009	0.018	0.010	0.033**	0.006	0.001	0.021	-0.009
GKX	0.027*	0.022		0.042**	0.045***	0.034*	-0.001	0.022	0.033*	0.023	0.037**	0.020	0.013	0.010	-0.007
BPZ_F	0.056***	0.054***	0.055***		0.047***	0.065***	0.037***	0.065***	0.065***	0.068***	0.025***	0.023***	0.021**	0.011	0.018*
DGU	0.052***	0.036**	0.043**	0.029		0.079***	-0.009	0.081***	0.064***	0.098***	-0.070***	-0.089***	-0.100***	-0.082***	-0.112***
FF_6	0.088***	0.067***	0.080***	0.089***	0.091***		0.086***	0.017	0.027**	-0.007	0.082***	0.063***	0.060***	0.111***	0.057***
D_F	0.053***	0.048***	0.053***	0.062***	0.064***	0.085***		0.079***	0.074***	0.085***	0.031**	0.017	0.009	-0.018	-0.016
SY	0.102***	0.087***	0.093***	0.102***	0.104***	0.045***	0.099***		0.067***	0.006	0.106***	0.083***	0.080***	0.130***	0.068***
DMRS	0.105***	0.093***	0.100***	0.107***	0.108***	0.062***	0.092***	0.081***		0.061***	0.086***	0.078***	0.073***	0.091***	0.064***
HXZ	0.134***	0.124***	0.127***	0.139***	0.141***	0.076***	0.137***	0.058***	0.091***		0.145***	0.129***	0.127***	0.161***	0.116***
D_{NN}	0.162***	0.146***	0.153***	0.135***	0.113***	0.176***	0.094***	0.190***	0.150***	0.197***		0.001	-0.016*	-0.038**	-0.057***
BPZ_L	0.159***	0.139***	0.150***	0.140***	0.116***	0.164***	0.099***	0.165***	0.150***	0.176***	0.031***		-0.016***	0.004	-0.055***
KNS	0.173***	0.154***	0.164***	0.155***	0.132***	0.176***	0.115***	0.177***	0.162***	0.187***	0.048***	0.017***		0.018	-0.046***
KPS	0.218***	0.215***	0.215***	0.205***	0.203***	0.236***	0.178***	0.243***	0.223***	0.239***	0.133***	0.136***	0.124***		0.079***
BSV	0.236***	0.224***	0.230***	0.224***	0.211***	0.234***	0.194***	0.225***	0.224***	0.228***	0.140***	0.117***	0.098***	0.103***	
Span	0	2	2	1	0	1	4	3	1	5	0	4	3	7	4

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8) *Pricing Portfolio j*	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	SL	FF_3	GKX	BPZ_F	DGU	FF_6	D_F	SY	DMRS	HXZ	D_{NN}	BPZ_L	KNS	KPS	BSV
Test Asset i															
SL		0.009	0.011	0.028**	0.043***	0.028**	-0.010	0.022*	0.024*	0.018	0.055***	0.042***	0.040***	0.013	0.020
FF_3	0.017*		0.017	0.034**	0.036***	0.009	-0.008	0.009	0.018	0.010	0.033**	0.006	0.001	0.021	-0.009
GKX	0.027*	0.022		0.042**	0.045***	0.034*	-0.001	0.022	0.033*	0.023	0.037**	0.020	0.013	0.010	-0.007
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Table 8. Out-of-Sample Unconditional Dimson Alphas for Meta Portfolios

	(1) meta_{BSV}	(2) meta_{DGU}	(3) meta_{BPZ}
SL	0.004	-0.004	0.035**
FF_3	0.036**	-0.039***	0.037**
GKX	0.032*	-0.020	0.046**
BPZ_F	0.061***	0.020**	0.041***
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D_NN	0.178***	-0.016	0.028
BPZ_L	0.181***	-0.014	0.052**
KNS	0.192***	-0.003	0.059**
KPS	0.185***	0.080***	0.030*
BSV	0.242***	0.072***	0.108***
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Theory: Empirical Results Follow if Large $P = N_{Predictors}$

- Traditional World: $T \to \infty$ and P fixed
- "Big Data World": $T \to \infty$ and $P \to \infty$ (with $c = P/T$)

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  - Observable r^* parameters but noisy predictors:

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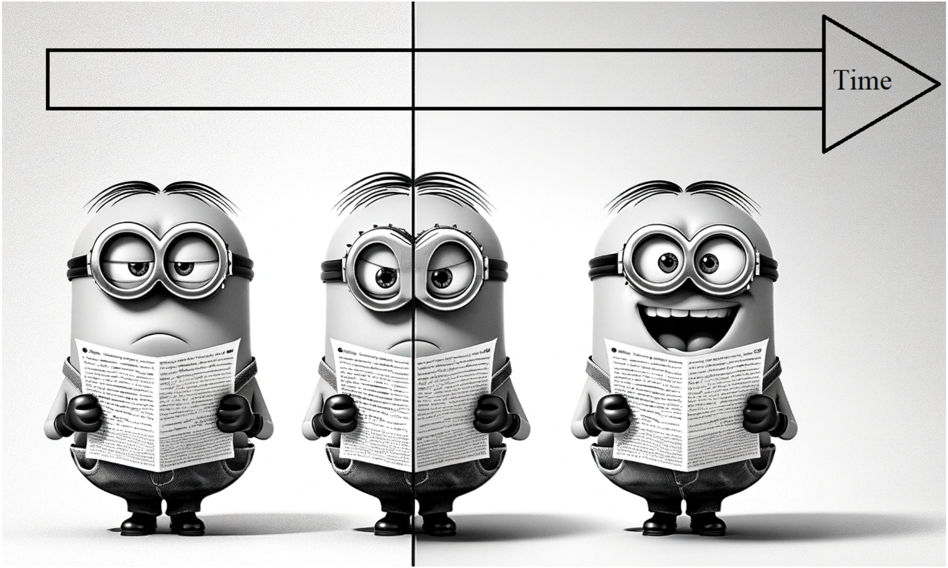

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- Two purposes for building a factor model:

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Some Minor Comments

1) Section 2 has to be shorter (mostly notation + section 2.4)

2) Some alphas are very large (e.g., $\alpha > 20\%$)

3) Given (2), you should consider trading costs
(Jensen, Kelly, Malamud, Pedersen (2022))

4) If machine learning fails due to the multi-step process of converging predictors into weights, then Reinforcement Learning could help (Cong, Tang, Wang, Zhang (2022))

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