Discussion of

"What do the portfolios of individual investors reveal about the cross section of equity returns?"

by Betermier, Calvet, Knüpfer and Kvaerner

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Overview of the page

"Modern asset pricing models are built on asset demand [...]. However, the common practice is to ignore institutional or household holdings data in estimating these models, even though these data are direct observations of asset demand."

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"[...] explanations for household portfolio heterogeneity requires a more general characterization of the structure of heterogeneity – a parsimonious summary of who owns what."

Balasubramaniam, Campbell, Ramadorai & Ranish (2023)

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This paper sides with those who think that *both* asset demand and investors' heterogeneity matter in equilibrium.

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$$\Downarrow$$

Investors' characteristics as "risk factors"!

Overview of the paper

Factor structure
in holdings

$$\underbrace{\boldsymbol{\omega}^i}_{\substack{\text{investor's}\\ \text{portfolio}}} = \underbrace{\tau}_{\substack{\text{tangency}\\ \text{portfolio}}} + \sum_{k=1}^{K} \eta_k^i \underbrace{\boldsymbol{d}_k}_{\substack{\text{systematic}\\ \text{tilts}}} + \underbrace{\boldsymbol{u}^i}_{\substack{\text{idiosyncratic}\\ \text{tilts}}}$$

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$$\Downarrow \text{ market clearing}$$

Factor structure in returns

$$f_0 = \boldsymbol{m}'\boldsymbol{R}^e, \qquad f_k = \boldsymbol{d}_k'\boldsymbol{R}^e \quad \xRightarrow{\text{N.B.}} \quad f_0 \not\perp f_k$$

Overview of the paper

Candidates for $\boldsymbol{d}_k$

- $\hookrightarrow$ Socioeconomic factors.
- $\hookrightarrow$ These correlate with sentiment/risk aversion.
  - $\hookrightarrow$ Intertemporal CAPM.

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  - Intertemporal CAPM.

Main results:

- Age and wealth help to explain:
  - Commonalities in portfolio holdings.
  - Cross-sectional variation of stock returns.
- Pricing information which is not subsumed by risk factors á-la Fama and French (e.g., value, size, etc).

Comment #1

Factor structure of investors' portfolios (j stock, g group),

$$\omega^{g}_{j,t} = \underbrace{\tau_{j,t} + \sum_{k=1}^{K} \eta^{g}_{k,t} d_{k,j,t}}_{\text{theory}}$$

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Empirical test:

$$\widehat{f}_{k,j,t} = a^k + \lambda^k_{Mkt} \cdot m_{j,t} + \lambda^k_{Age} \cdot g_{Age,j,t} + \lambda^k_{Wealth} \cdot g_{Wealth,j,t} + \epsilon^k_{j,t},$$

- $g_{Age,j,t}$ stock j in a LS portfolio on age.
- $g_{Wealth,j,t}$ stock j in a LS portfolio on wealth.
- $m_{j,t}$ stock j in the market portfolio.

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- $\hookrightarrow$ $g_{Age,j,t}$ stock j ~~in a LS portfolio on~~ by group age.
- $\hookrightarrow$ $g_{Wealth,j,t}$ stock j ~~in a LS portfolio on~~ by group wealth.
- $\hookrightarrow$ $m_{j,t}$ stock j in the ~~market~~ characteristic-managed portfolio.

Comment #2

Matching socioeconomic factors with stock returns:

$$\text{Age}_{j,t} = \underbrace{\frac{\sum_{i=1}^{I} N_{j,t}^{i} A_{t}^{i}}{\sum_{i=1}^{I} N_{j,t}^{i}}}_{\substack{\text{Age factor} \\ \text{for stock } j}}, \qquad \text{Wealth}_{j,t} = \underbrace{\frac{\sum_{i=1}^{I} N_{j,t}^{i} WB_{t}^{i}}{\sum_{i=1}^{I} N_{j,t}^{i}}}_{\substack{\text{Wealth factor} \\ \text{for stock } j}}$$

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Panel B: Monthly CAPM Alphas								
	Alpha				t(Alpha)			
	L	M	H	H-L	L	M	H	H-L
Age	-0.82	0.02	0.26	1.08	-2.36	0.14	2.27	2.65
Wealth	-0.85	0.19	0.17	1.01	-2.83	1.93	0.75	2.91
Panel C: Monthly CAPM Betas								
	Beta				t(Beta)			
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Age	1.13	1.07	0.94	-0.19	19.41	36.69	49.50	-2.81
Wealth	1.17	1.01	0.99	-0.18	23.20	59.77	26.74	-3.12

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Expanding to more standard risk factors?

- ↪ Spanning regressions (Table IV) combine Age/Wealth factors.
- ↪ Betas w.r.t to FF factors.

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Comparison vs Fama-French factors based on a bootstrap aggregating ("bagging") approach (Breiman 1996).

$\hookrightarrow$ Ensemble learning method that is commonly used to reduce variance within a noisy dataset.

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Digression: Bagging works for "uncorrelated" models (i.i.d.).

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$$Var(\bar{z}) = \frac{\sigma^2}{n} + \frac{n-1}{n}\rho\sigma^2$$

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$\hookrightarrow$ Logic: The "wisdom of the crowd" requires diverse and independent members of the crowd.

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In this paper bagging as a pure bootstrapping tool.

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3. In-sample max-SR portfolios for each draw m.

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$\hookrightarrow$ In-sample max-SR (average) portfolio for each draw m'

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$\hookrightarrow$ Project (average) estimates out of sample for each m'.

Comment #3b

	Optimized Weights		Fixed Weights
	OS Sharpe Ratio	OS-IS Ratio	OS Sharpe Ratio
	(1)	(2)	(3)
MKT, AGE	0.51	0.74	0.58
MKT, WEALTH	0.54	0.75	0.57
MKT, SMB	0.13	0.48	0.32
MKT, HML	0.17	0.44	0.34
MKT, MOM	0.44	0.69	0.55
MKT, CMA	0.34	0.61	0.15
MKT, RMW	0.49	0.72	0.56
MKT, AGE, WEALTH	0.66	0.73	0.61
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MKT, SMB, RMW	0.48	0.63	0.45
MKT, HML, MOM	0.38	0.55	0.48
MKT, HML, CMA	0.26	0.42	0.25
MKT, HML, RMW	0.43	0.59	0.48
MKT, CMA, RMW	0.52	0.65	0.36
MKT, CMA, MOM	0.48	0.62	0.37
MKT, RMW, MOM	0.55	0.68	0.59
Firm-4	0.34	0.48	0.44
Firm-5	0.44	0.50	0.36
Firm-6	0.50	0.52	0.41
Firm-6, AGE, WEALTH	0.65	0.58	0.48

- $\hookrightarrow$ Average performance across draws $\Longrightarrow$ Confidence intervals?
- $\hookrightarrow$ Nested models $\Longrightarrow$ Spreads in SRs? (Fama and French 2018).

Conclusion

Executive summary:

- $\hookrightarrow$ Really cool paper! I learnt a lot.
- $\hookrightarrow$ Will go in the reading list of my PhD course.