Discussion of

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

by Betermier, Calvet, Knüpfer and Kvaerner

Daniele Bianchi Queen Mary, University of London

"Workshop on Household Finance and Housing" 2023 Bank of England/Imperial College Business School

"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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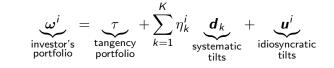
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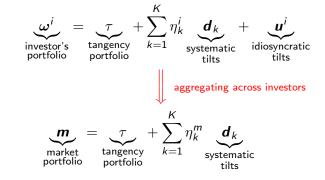
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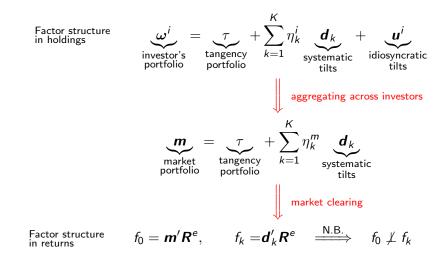
↓ Investors' characteristics as "risk factors"!

Factor structure in holdings



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Candidates for \boldsymbol{d}_k

- \hookrightarrow Socioeconomic factors.
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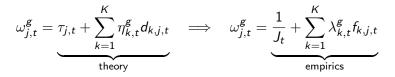
Main results:

- \hookrightarrow Age and wealth help to explain:
 - \hookrightarrow Commonalities in portfolio holdings.
 - \hookrightarrow 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).

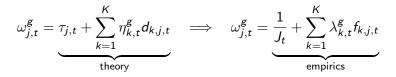
Factor structure of investors' portfolios (j stock, g group),

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

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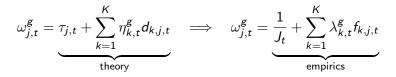


Empirical test:

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

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

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Matching socioeconomic factors with stock returns:

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

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	Panel	l B: M	onthly (CA	PM Al	phas		
Alpha				t(Alpha)				
L	Μ	Н	H-L		L	М	Η	H-L
-0.82	0.02	0.26	1.08		-2.36	0.14	2.27	2.65
-0.85	0.19	0.17	1.01		-2.83	1.93	0.75	2.91
Panel C: Monthly CAPM Betas								
Beta				t(Beta)				
L	Μ	Н	H-L		L	М	Η	H-L
1.13	1.07	0.94	-0.19		19.41	36.69	49.50	-2.81
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	-0.82 -0.85 L 1.13	Alp L Alp -0.82 0.02 -0.85 0.19 -0.85 Ba -0.94	Alpha L M H -0.82 0.02 0.26 -0.85 0.19 0.17 Panel C: M B H L M H 1.13 1.07 0.94	Alpha L M H -0.82 0.02 0.26 1.08 -0.85 0.19 0.17 1.01 Panel C -Weight -Weight -Weight L M H -Weight L M H -Weight 1.13 1.07 0.94 -0.19	Alpha L M H H-L -0.82 0.02 0.26 1.08 -0.85 0.19 0.17 1.01 Panel C: Worthly CA L M H H 1.13 1.07 0.94 -0.19	Alpha H-L L L M H H-L L -0.82 0.02 0.26 1.08 -2.36 -0.85 0.19 0.17 1.01 -2.83 Panel C: Monthly CAPM B E Image: Comparison of the second s	L M H-L L M -0.82 0.02 0.26 1.08 -2.36 0.14 -0.85 0.19 0.17 1.01 -2.83 1.93 Panel C: Monthly CAPM Betas 1.01 -2.84 1.93 Betas .101 .101 .101 .101 L M H .101 .101 .101 .101 L1.13 1.07 0.94 -0.19 19.41 36.69	$ \begin{array}{c c c c c c c c c c c c c c c c c c c $

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Expanding to more standard risk factors?

- → Spanning regressions (Table IV) combine Age/Wealth factors.
- $\begin{array}{rl} \hookrightarrow & \mbox{Betas w.r.t to} \\ & \mbox{FF factors.} \end{array}$

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

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

 \hookrightarrow For uncorrelated samples, z_i , with variance σ^2 , the variance of their average $Var(\overline{z})$ is lower,

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→ Logic: The "wisdom of the crowd" requires diverse and independent members of the crowd.

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

$$\widehat{\Sigma}_{f}^{(m)} = \Sigma_{f}^{(m)} + \gamma \mathbf{I} \qquad \Longrightarrow \qquad \widehat{\tau}^{(m)} = \widehat{\Sigma}_{f}^{-1(m)} \mu_{f}^{(m)}$$

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

$$\widehat{\Sigma}_{f}^{(m')} = \frac{1}{M} \sum_{m=1}^{M} \left(\Sigma_{f}^{(m)} + \gamma \mathbf{I} \right) \implies \widehat{\tau}^{(m')} = \widehat{\Sigma}_{f}^{-1(m')} \mu_{f}^{(m')}$$

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

Comment #3b

	Optimized V	Fixed Weights	
	OS Sharpe Ratio (1)	OS-IS Ratio (2)	OS Sharpe Ratio (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
MKT, SMB, HML	0.08	0.24	0.35
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MKT, SMB, CMA	0.29	0.49	0.24
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.