What Do the Portfolios of Individual Investors Reveal About the Cross-Section of Equity Returns?

Sebastien Betermier
McGill

Laurent E. Calvet
SKEMA

Samuli Knüpfer
Aalto

Jens Kvaerner
Tilburg

Bank of England

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Challenge: Consumption data are noisy and measured at a relatively low frequency.

Information in portfolio holdings

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- End-of-line owners of capital
- Portfolio weights are related to asset prices
- Work in household finance links portfolio choice to investor characteristics

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Documents empirically that a mature-minus-young factor, a high wealth-minus-low wealth factor, and the market factor:

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- **explain common variation in portfolio holdings of individual investors,**
- **price the cross-section of stock returns.**

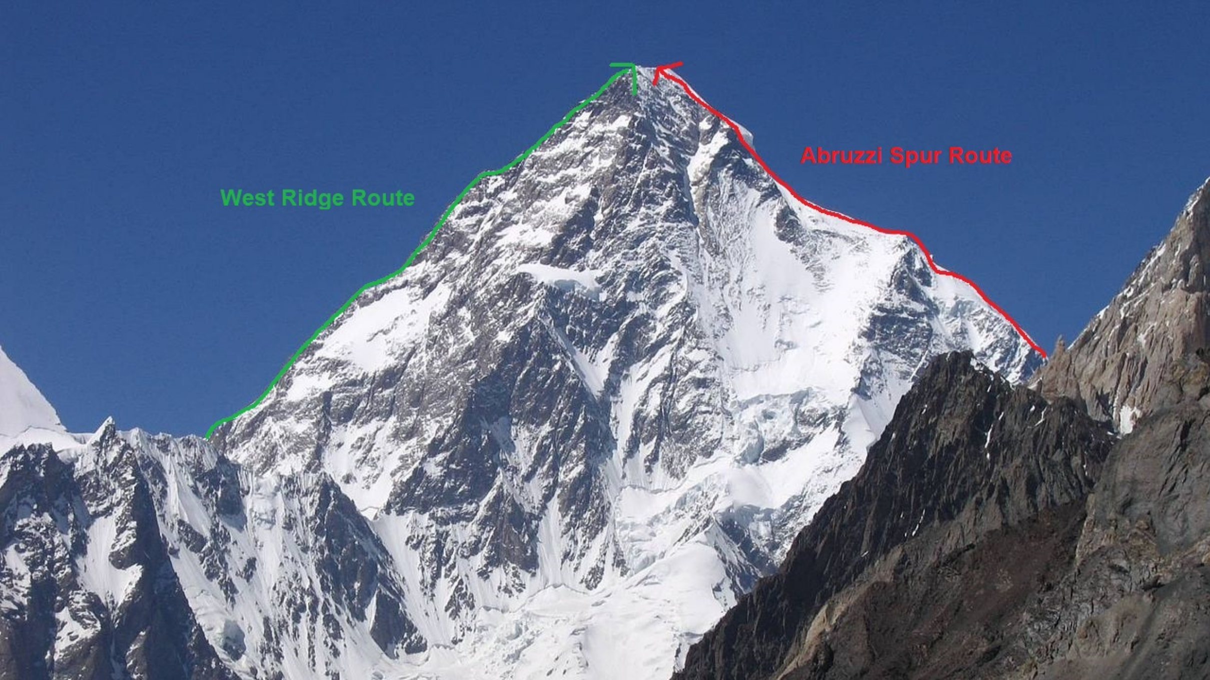
Verifies that measures of investor risk and sophistication explain factor tilts.

Revealed preference

We are not claiming that individual investors drive stock prices.

We are not claiming that investor factors should replace firm factors.


Abruzzi Spur Route


West Ridge Route
Abruzzi Spur Route

Outline

1. **Theoretical motivation**
2. Data
3. Factor structure of investor portfolios
4. Asset pricing tests
5. Factor tilts and investor characteristics

Investor portfolios have a factor structure

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$$\boldsymbol{\omega^i} = \boldsymbol{\tau} + \sum_{k=1}^{K} \eta_k^i \boldsymbol{d_k} + \boldsymbol{u_i} \, .$$

Markowitz portfolio

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$$\boldsymbol{\omega^i} = \underbrace{\boldsymbol{\tau}}_{\text{Markowitz portfolio}} + \sum_{k=1}^{K} \eta_k^i \underbrace{\boldsymbol{d_k}}_{\text{Deviation portfolio (behavioral, hedging...)}} + \boldsymbol{u_i} \, .$$

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Markowitz portfolio

Idiosyncratic deviation

Deviation portfolio (behavioral, hedging...)

Mapping between portfolio factors and pricing factors

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- **The cross-section of returns is priced by $\boldsymbol{m}$ and the deviation portfolios $\boldsymbol{d_k}$.**

Portfolio factors and CAPM deviations

Stocks with low exposures to $\boldsymbol{d_k}$ (that is stocks in low demand) have:

- high CAPM alphas

$$\alpha_j = -\phi \sum_{k=1}^{K} \eta_k^m \sigma_k^2 \left(b_{j,k} - b_{j,m} b_{m,k}\right);$$

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- low CAPM betas

$$b_{j,m} = \frac{\sigma_\tau^2}{\sigma_m^2} b_{j,\tau} + \sum_{k=1}^{K} \eta_k^m \frac{\sigma_k^2}{\sigma_m^2} b_{j,k}.$$

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    - Use theory to find characteristics correlated to η_k^i.
    - Sort investors by these characteristics.

Theory 1: I-CAPM (Merton, 1973)

- Investor i:
  - Has CRRA utility, age $A_t^i \in \{0, \dots, T\}$, and financial wealth W_t^i.
  - Earns the stochastic labor income L_t^i.
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- **Age and wealth control the dimensions of heterogeneity useful for pricing.**

Theory 2: Sentiment

Age is associated with higher efficiency.

- Young investors are prone to fads and bubbles (Greenwood and Nagel, 2009).
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Wealth is also associated with more efficient behavior.

- Investors with more accurate expectations tend to accumulate wealth faster (Sandroni 2000; Fedyk, Heyerdahl-Larsen, and Walden 2013) .
- Evidence that wealthier individuals invest more efficiently (Vissing-Jorgensen, 2003) and have higher Sharpe ratios (Calvet, Campbell, and Sodini 2007) .

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Data challenge

- **Linking portfolio decisions of investors to pricing factors requires:**
  - a diverse pool of investors,
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  - Accounting and stock price data for all stocks on OSE (400+).

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Factor structure of investor portfolios

- **We consider $G = 93$ groups of individual investors and construct the $J_t \times G$ matrix $\boldsymbol{\Omega_t}$ containing the demeaned weights of the groups' portfolios.**

- Each group consists of $10,000+$ similar investors sorted by:
  - permanent income;
  - wealth
    defined as financial wealth + real estate + vehicles + business assets - debt;
  - age, gender, district of residence;
  - occupation, education level, field of study.

Principal component analysis

- We apply a PCA to the portfolio weight matrix $\boldsymbol{\Omega_t}$:

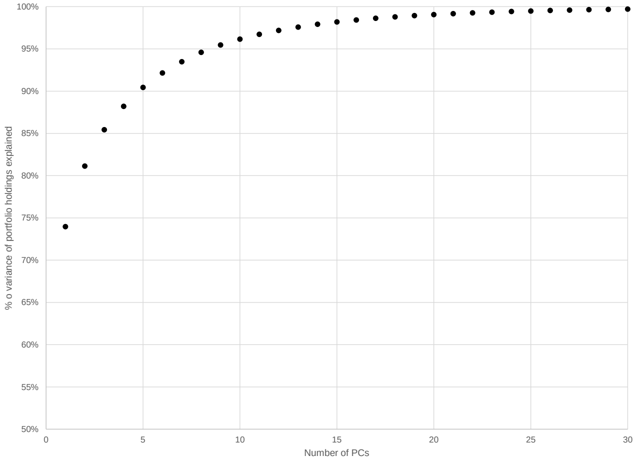
$$\boldsymbol{\Omega_t} = \boldsymbol{F_t}\,\boldsymbol{\Lambda_t},$$

orthogonal factors
$(J_t \times G)$

factor loadings
$(G \times G)$

- Obtained by diagonalizing the $G \times G$ matrix $\Omega_t'\,\Omega_t$, which contains the covariance of the portfolio weights held by each pair of investor groups.

Portfolios have a strong factor structure



Explaining the principal components

- **We regress PC portfolios on market weights, age, and wealth portfolios**

$$f_{k,j,t} = a^k + \lambda^k_{\text{mkt}}\, m_{j,t} + \lambda^k_{\text{age}}\, g_{\text{age},j,t} + \lambda^k_{\text{wealth}}\, g_{\text{wealth},j,t} + \epsilon^k_{j,t},$$

  where

  - $f_{k,j,t}$: weight of stock j in PC portfolio k at t,
  - **age portfolio:** long portfolio of investors $60+$ years, short investors < 30 years,
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$\rightarrow$ **Age and wealth explain most of the common variation in portfolio tilts.**

Outline

Investor pricing portfolios

Method 1: Use the age and wealth portfolios defined above.

- Strong asset pricing performance.

Method 2: Form long-short portfolios of stocks sorted by the characteristics of their stockholders.

- Comparable to firm factors (HML, RMW, ...).

Example: Age characteristic

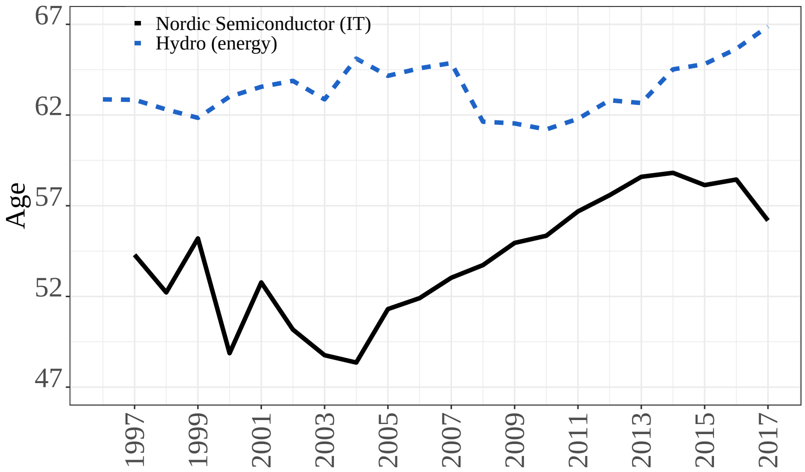
Age$_{j,t}$ of stock j at the end of year t is the weighted average age of the individual investors who own it:

$$\textbf{Age}_{j,t} = \frac{\sum_{i=1}^{I} N^{i}_{j,t} A^{i}_{t}}{\sum_{i=1}^{I} N^{i}_{j,t}}$$

where:

- $N^{i}_{j,t}$: number of shares of stock j held by investor i at t,
- A^{i}_{t}: age of investor i at t.

Example: Age characteristic (cont.)



Investor factors: Age and wealth

Sort stocks by **Age**$_{j,t}$ and **Wealth**$_{j,t}$

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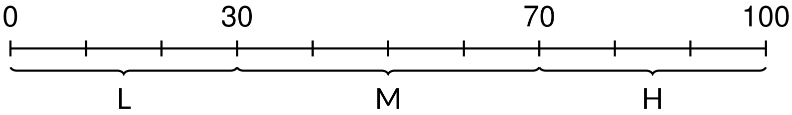
Construct value-weighted long-short portfolios:



Age:	Young	Mature
Wealth:	Low Wealth	High Wealth

Investor factors: Average returns

Monthly Returns								
	Average Return				t(Average Return)			
	L	M	H	H-L	L	M	H	H-L
Age	0.09	0.91	1.07	**0.98**	0.17	2.12	2.96	**2.37**
Wealth	0.08	1.04	1.00	**0.92**	0.17	2.73	2.38	**2.59**

Investor factors: CAPM alphas

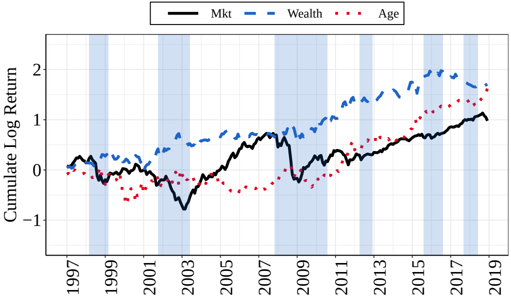
Monthly CAPM Alphas								
	Alpha				t(Alpha)			
	L	M	H	H-L	L	M	H	H-L
Age	-0.82	0.02	0.26	1.09	-2.36	0.14	2.27	2.65
Wealth	-0.85	0.19	0.17	1.01	-2.83	1.93	0.75	2.91

Investor factors: CAPM betas

Monthly CAPM Betas								
	Beta				t(Beta)			
	L	M	H	H-L	L	M	H	H-L
Age	1.12	1.09	0.94	**-0.18**	18.94	37.62	49.63	**-2.54**
Wealth	1.15	1.01	0.99	**-0.17**	22.72	59.88	26.88	**-2.82**

Investor factors: Dynamics

Age, Wealth, and Market Factors



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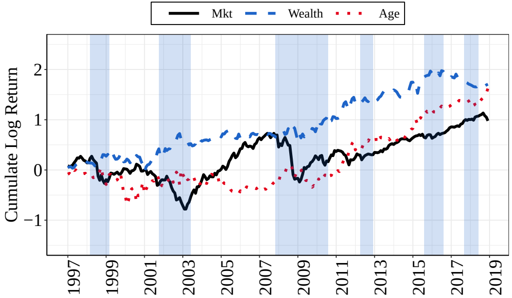
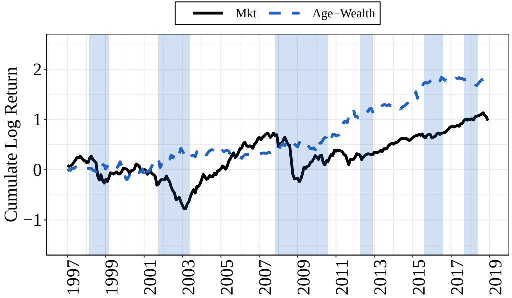


Combined Age-Wealth Factor



Spanning tests

Panel A: Regressions of Combined Age-Wealth Factor on Firm Factors					
	Dependent Variable: Combined Age-Wealth Factor				
	(1)	(2)	(3)	(4)	(5)
Constant	**1.047*****	**1.066*****	**0.852*****	**0.759*****	**0.661*****
	(0.288)	**(0.257)**	**(0.243)**	**(0.245)**	**(0.237)**
MKT	-0.187^{***}	-0.305^{***}	-0.255^{***}	-0.199^{***}	-0.183^{***}
	(0.048)	(0.045)	(0.043)	(0.046)	(0.044)
SMB		-0.479^{***}	-0.452^{***}	-0.311^{***}	-0.327^{***}
		(0.066)	(0.062)	(0.068)	(0.065)
HML		-0.186^{***}	-0.159^{***}	-0.164^{***}	-0.149^{***}
		(0.051)	(0.048)	(0.048)	(0.046)
MOM			0.200^{***}		0.151^{***}
			(0.033)		(0.033)
RMW				0.278^{***}	0.217^{***}
				(0.047)	(0.047)
CMA				0.061	0.053
				(0.046)	(0.044)
Observations	264	264	264	264	264
Adjusted R^2	0.050	0.248	0.339	0.346	0.393

Spanning tests

Panel B: Regressions of Firm Factors on Combined Age-Wealth Factor					
	Dependent Variable:				
	SMB	HML	MOM	RMW	CMA
	(1)	(2)	(3)	(4)	(5)
Constant	**0.343**	**0.424**	**0.456**	**0.341**	**0.528**
	(0.225)	**(0.313)**	**(0.435)**	**(0.320)**	**(0.333)**
MKT	−0.267***	−0.164***	−0.103	−0.093*	−0.194***
	(0.038)	(0.053)	(0.073)	(0.054)	(0.056)
Age-Wealth	−0.348***	−0.252***	0.570***	0.591***	0.123*
	(0.047)	(0.065)	(0.091)	(0.067)	(0.070)
Observations	264	264	264	264	264
Adjusted R^2	0.239	0.064	0.149	0.257	0.061

Other investor factors

	Regressions of Additional Factor on Age-Wealth Factor AW_t				
	α	t(α)	b	t(b)	R^2
Additional Factor Defined by Socioeconomic Characteristic:					
Male dummy	0.05	0.15	-0.67	-8.90	0.23
Education level	-0.04	-0.11	0.16	2.26	0.02
Labor-to-wealth	-0.49	-1.49	-0.18	2.69	0.03
Permanent income	-0.51	-1.44	0.19	2.56	0.02
Retirement dummy	0.06	0.22	0.89	15.01	0.46
Additional Factor Defined by Occupational Sector:					
Resource industries	0.20	0.53	0.09	1.22	0.01
Petroleum	0.06	0.17	-0.11	-1.54	0.01
Consumer manufacturing	0.12	0.33	-0.03	-0.37	0.00
Material manufacturing	-0.25	-0.74	0.08	1.11	0.00
Technological manufacturing	0.02	0.05	-0.33	-4.52	0.08
Public administration	0.15	0.51	0.16	2.82	0.03
Construction	0.24	0.73	-0.48	-7.11	0.17
....					

Out-of-sample Sharpe ratio: MKT + 1 factor

We build on the bootstrap evaluation approach of Fama and French (2018).

- Randomly select "in-sample" and "out-of-sample" months.
- Construct tangency portfolios based on factors in sample.
- Estimate Sharpe ratios of these portfolios out of sample.
- Report average out-of-sample Sharpe ratio.

	Optimized Weights		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

Out-of-sample Sharpe ratio: MKT + 2-6 factors

	Optimized Weights		Fixed Weights
	OS Sharpe Ratio (1)	OS-IS Ratio (2)	OS Sharpe Ratio (3)
MKT, AGE, WEALTH	0.66	0.73	0.61
MKT, SMB, HML	0.08	0.24	0.35
MKT, SMB, MOM	0.39	0.59	0.46
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

Outline

1. Theoretical motivation
2. Data
3. Factor structure of investor portfolios
4. Asset pricing tests
5. **Factor tilts and investor characteristics**

Measuring factor tilts

We partition investors into two groups:

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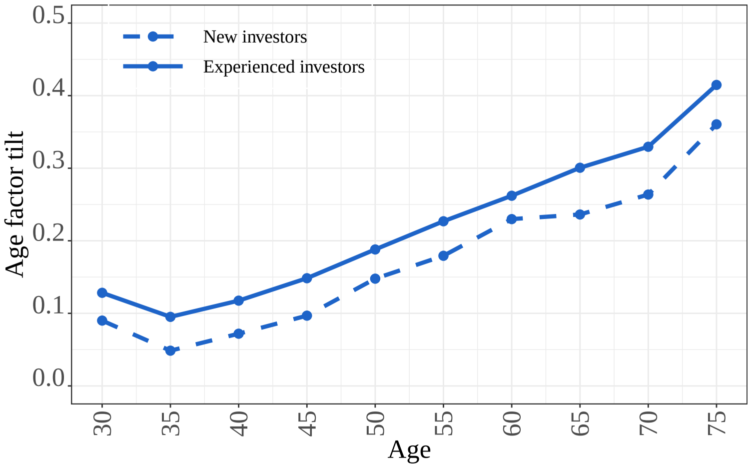
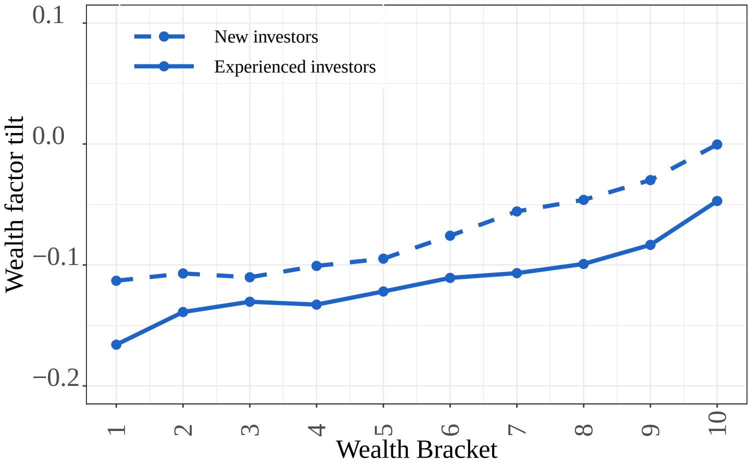
Proportion of the stock portfolio in the **long** leg of the factor.

Proportion of the stock portfolio in the **short** leg of the factor.

Large variation of age factor tilt over the life-cycle



Large variation of wealth factor tilt across wealth brackets



We regress factor tilts on investor characteristics

- **Risk exposures:**
  - debt-to-income ratio,
  - systematic labor income risk (Guvenen and Yogo, 2017).

We regress factor tilts on investor characteristics

- **Risk exposures:**
  - debt-to-income ratio,
  - systematic labor income risk (Guvenen and Yogo, 2017).
- **Investor sophistication:**
  - stock market experience,
  - graduate and business education,
  - working in finance.

Regressions of age factor tilt on characteristics

	Dependent Variable: Age Factor Tilt				
	(1)	(2)	(3)	(4)	(5)
Risk Exposures:					
Income beta	-0.093***	-0.089***	-0.064***	-0.122***	-0.088***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Debt-to-income ratio			-0.010***		-0.010***
			(0.003)		(0.002)
Experience, Education, and Gender:					
Stock market experience	0.014***	0.014***	0.015***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Male dummy			-0.135***		-0.134***
			(0.007)		(0.006)
Master's degree dummy				0.021**	0.027***
				(0.009)	(0.009)
Business education dummy				0.024***	0.028***
				(0.007)	(0.007)
Finance occupation dummy				0.116**	0.088
				(0.055)	(0.054)

Regressions of wealth factor tilt on characteristics

	Dependent Variable: Wealth Factor Tilt				
	(1)	(2)	(3)	(4)	(5)
Risk Exposures:					
Income beta	-0.047***	-0.044***	-0.036***	-0.070***	-0.059***
	(0.008)	(0.009)	(0.008)	(0.010)	(0.011)
Debt-to-income ratio		0.001		0.001	
		(0.002)		(0.002)	
Experience, Education, and Gender:					
Stock market experience	0.007***	0.007***	0.007***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Male dummy			-0.046***		-0.043***
			(0.012)		(0.014)
Master's degree dummy				-0.002	0.0003
				(0.010)	(0.011)
Finance education dummy				0.032***	0.033***
				(0.007)	(0.008)
Finance occupation dummy				0.077**	0.067*
				(0.031)	(0.033)

Regression takeaways

- **Both measures of risk exposure are negatively correlated to the tilts.**
- **Graduate education, business education, finance sector occupation, and stock market experience are all associated with higher tilts.**
- **Women have stronger tilts toward the high wealth and mature portfolios.**
- **Hedging motives and sentiment jointly drive factor tilts.**
  - There might be interdependencies between the two channels Kozak, Nagel, and Santosh (2018).

Mapping factor tilts to stock characteristics

Stocks held by mature and wealthy investors have high profitability, size, and book-to-market ratio, and low beta, volatility, investment growth, and turnover.

	Age-Sorted Portfolios				Wealth-Sorted Portfolios			
	L	M	H	H-L	L	M	H	H-L
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Years in sample	8.00	10.00	13.00	5.00	7.00	9.00	16.00	9.00
Institutional ownership share (%)	3.10	6.40	6.40	3.36	5.10	6.40	4.40	-0.67
Turnover (% per month)	7.23	1.65	0.56	-6.67	5.26	2.17	0.38	-4.88
Volatility	0.25	0.13	0.09	-0.16	0.24	0.14	0.08	-0.16
CAPM beta	0.88	0.83	0.67	-0.22	0.94	0.84	0.66	-0.28
Size (million NOK)	384	1342	1485	1102	508	1103	2118	1610
BE/ME	0.72	0.70	0.68	-0.05	0.55	0.65	0.89	0.34
Profitability (%)	0.03	0.07	0.09	0.06	0.05	0.07	0.08	0.03
Investment growth (%)	0.04	0.07	0.09	0.05	0.09	0.07	0.07	-0.02

Conclusion

We show theoretically that portfolios of stocks sorted by the age and wealth of their individual investors should produce powerful pricing factors.

Age and wealth explain both (i) the common variation in the portfolios of individual investors and (ii) the cross-section of stock returns.

Factor tilts are linked to measures of investor risk and experience.

This approach may be useful to price other asset classes.

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