ASSET DEMAND OF U.S. HOUSEHOLDS

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  - How investors allocate between cash and risky assets.
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- Develop a new methodology to estimate demand curves across asset classes.

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   - Disaggregated to security level.

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- The most wealthy are counter cyclical and the least wealthy are pro cyclical.
  - The representative household end up being counter cyclical.
- Disagreement increases during downturns.
- Ultra high net households are insensitive to stock returns.

RELATED LITERATURE

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- Then, researchers moved to account data from large financial institutions. An example is Barber and Odean (2000) who studied the trading behavior of retail investors from 1991 to 1996 using data from a large discount broker.

RELATED LITERATURE

- Detailed data on households portfolios are available in Sweden and India. Recently, Balasubramaniam et al. (2021) propose a cross-sectional factor model of direct stock holdings in the Indian stock market.

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  - The difference from our model is that we focus on flows across multiple asset classes and allow for time-variation in the factors.

DATA CHARACTERISTICS

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- Monthly observations from January 2016 to August 2021.

DATA CHARACTERISTICS

Broad asset classes	Narrow asset classes
Cash & Cash Equivalents	Cash, Cash Equivalents
Fixed Income	U.S. Municipals/Tax Exempt, U.S. Treasuries and Agencies, U.S. TIPS, U.S. Investment Grade, U.S. High Yield, U.S. Bank Loans, International Developed Markets, Emerging Markets, Opportunistic, Other Fixed Income, Unknown Fixed Income
Equities	U.S. Equities, Concentrated Equity Positions, Global Equities, Developed Markets - Americas, Developed Markets - EMEA, Developed Markets - Asia Pacific, Emerging & Frontier Markets, Other Equities, Unknown Equities
Mixed Allocation	Asset Allocation Vehicle, Held Away Accounts
Alternatives	Hedge Funds, Private Equity & Venture, Real Estate Funds, Concentrated Alts. Positions, Unknown Alts., Other Alts, Direct Private Companies, Direct Real Estate, Direct Loans
Non-Financial Assets	Collectibles and Other
Liability	Liability

Fig 1: Asset class definitions.

SUMMARY STATISTICS

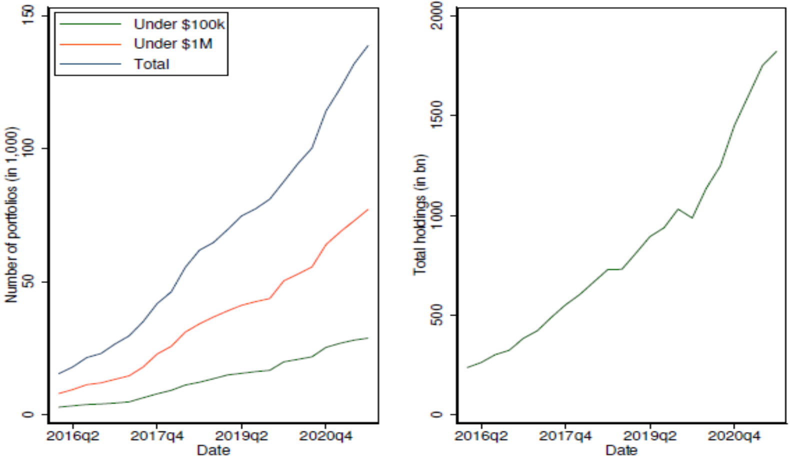

Fig 2: Number of Portfolios and Total Assets.

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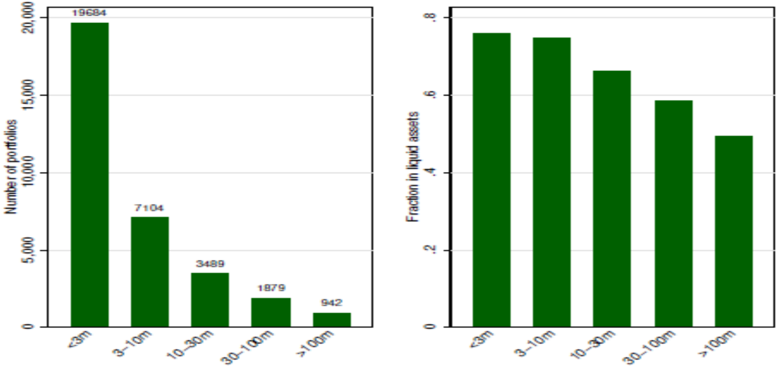


Fig 3: Number of Portfolios and the Fraction Invested in liquid Assets.

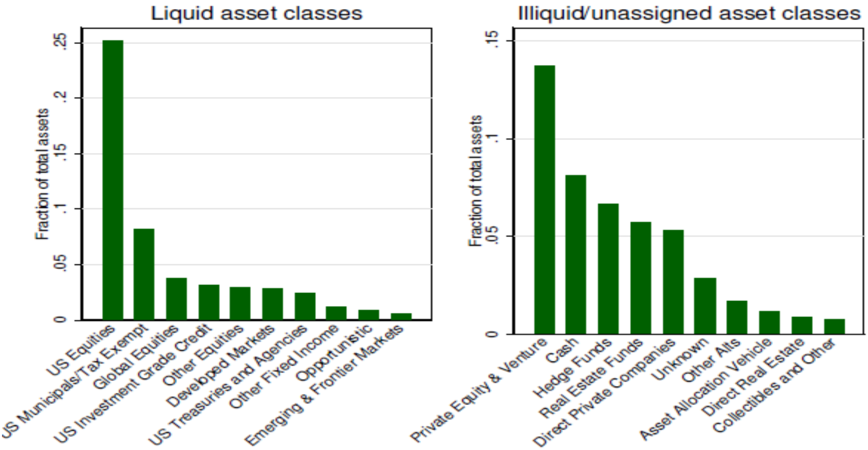


Fig 4: Fraction Invested in Narrow Asset Classes.

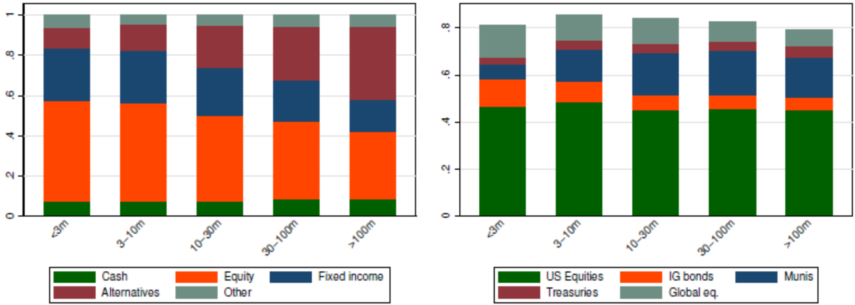


Fig 5: Fractions invested in broad and narrow asset classes by wealth group.

WEALTH AND PORTFOLIOS

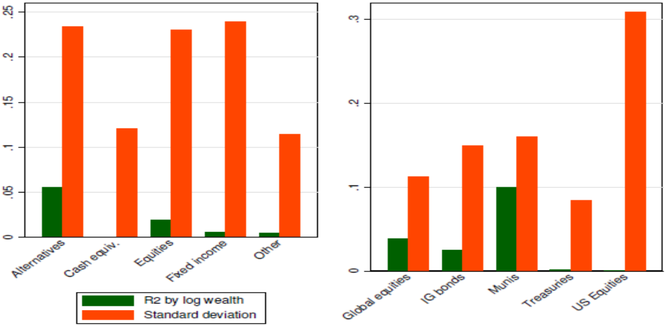
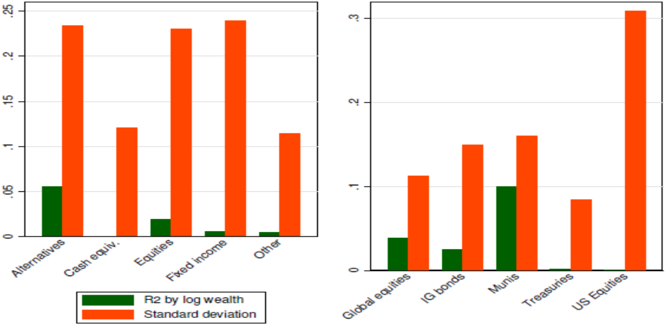


Fig 6: R-squared of a regression of portfolio weights on log wealth.

WEALTH AND PORTFOLIOS

- Wealth by itself does not explain portfolio composition.



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FLOW ANALYSIS

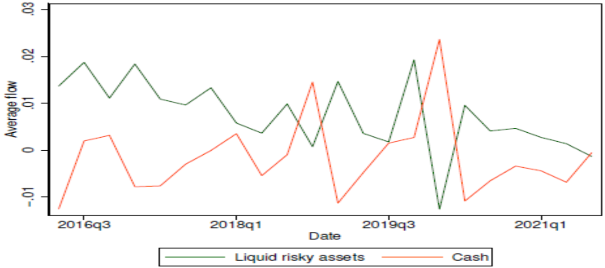
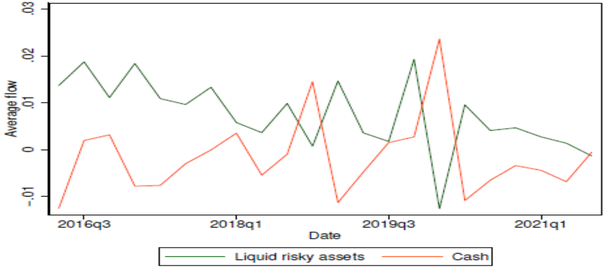


Fig 7: Dynamics of flow to cash and liquid risky assets.

FLOW ANALYSIS

- Time series correlation between flows of cash and risky assets is -51.5%.



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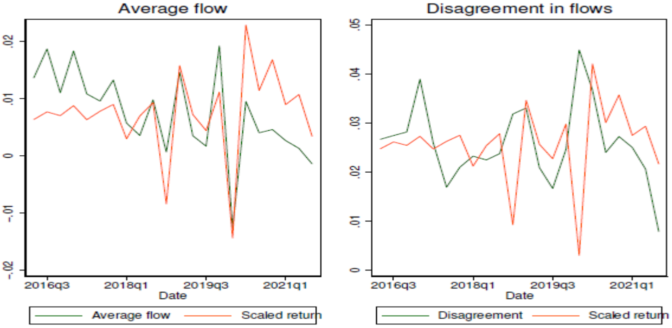
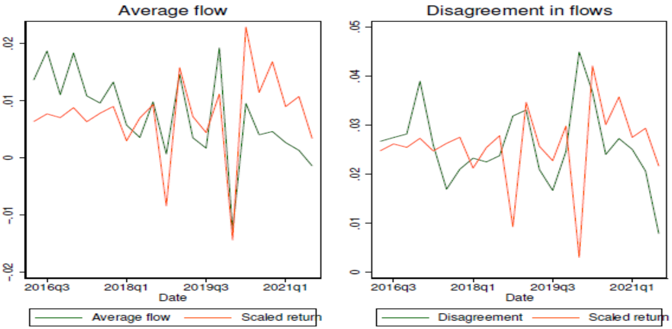


Fig 8: Flows to liquid risky assets, returns, and disagreement.

FLOW ANALYSIS

- Time series correlation on the left: 57%.



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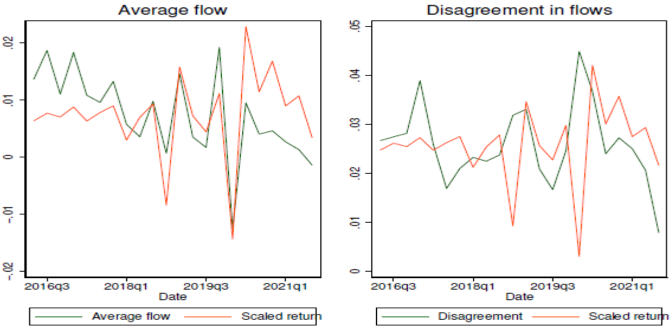
FLOW ANALYSIS

- Time series correlation on the left: 57%.
- Time series correlation on the right: -14.3%.



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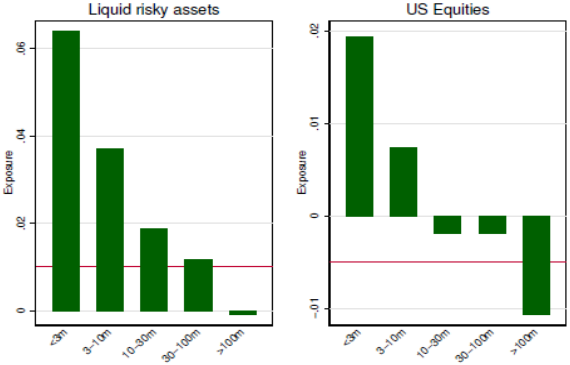
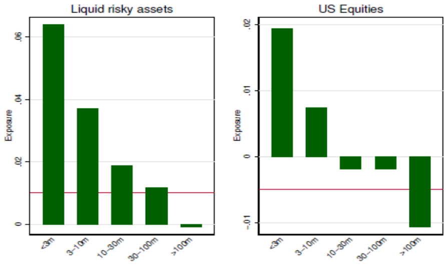


Fig 9: Regression coefficients of flows on returns by wealth group.

FLOW ANALYSIS

- Households flows sensitivity to returns decline monotonically in wealth.



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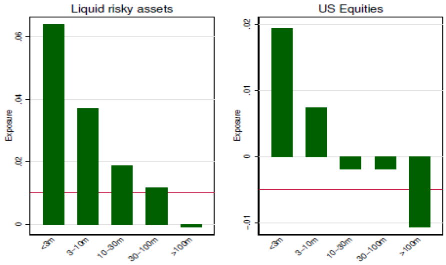
- Households flows sensitivity to returns decline monotonically in wealth.
- Wealthy households flows are counter cyclical.



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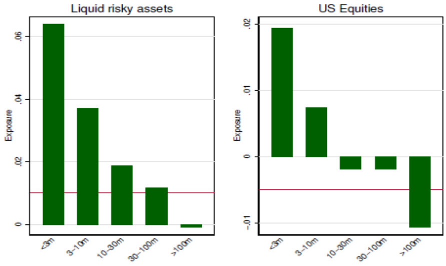

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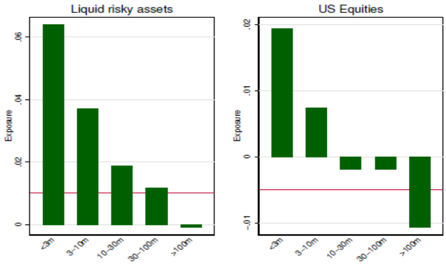
FLOW ANALYSIS

- However, the magnitudes are modest.
- A 10% decline in the stock market leads to a 0.1% inflow into equities for UHN and -0.2% inflow for the relatively poorer.



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DECOMPOSING FLOWS

- We develop a framework to measure how investors reallocate capital between asset classes.

$$f_{int} = \alpha_n + \beta_n f_{it}^{Liq} + \gamma_n f_{it}^{Cash} + f_{int}^{*} \tag{1}$$

- Given that $f_{it}^{Liq} = \sum_{n \in L} f_{int}$.

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$$f_{int} = \alpha_n + \beta_n f_{it}^{Liq} + \gamma_n f_{it}^{Cash} + f_{int}^{*} \tag{2}$$

- Given that $f_{it}^{Liq} = \sum_{n \in L} f_{int}$.
- f_{int}^{*} are the flows that are independent from keeping portfolio's shares, so it captures the rebalancing across asset classes.

THE FACTOR MODEL

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- Where k indexes the number of factors.
- The loadings, $\lambda^{(k)}_{it}$ capture the exposure of investor i in quarter t to factor k.

THE FACTOR MODEL

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  3. Combination of rebalances from U.S. Treasuries and corporate bonds to U.S. municipal bonds and from global equities to U.S. equities.

THE FACTOR MODEL

- There is a strong factor structure in rebalancing flows. This fact, combined with the takeaways from the flow analysis, provide valuable inputs for future macro-finance models with heterogeneity.

ASSET DEMAND ESTIMATION

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- The idea is that changes in the volatility of valuations, holdings, and the covariance of holding can be used to estimate demand. Solves the problem of not knowing all holdings of households.

ASSET DEMAND ESTIMATION

- The model departs from a logit where θ_{int} is the allocation to asset n within the portfolio of liquid risky assets; m is log market cap and δ is the portfolio weight relative to cash.

$$\theta_{int} = \frac{\exp(\delta_{int})}{\sum_m \exp(\delta_{imt})},$$

where

$$\delta_{int} = \beta_{in} m_{int} + \nu_{int}$$

and the elasticity is given by $1 - \beta_{in}$.

AN EXTERNAL VALIDITY TEST

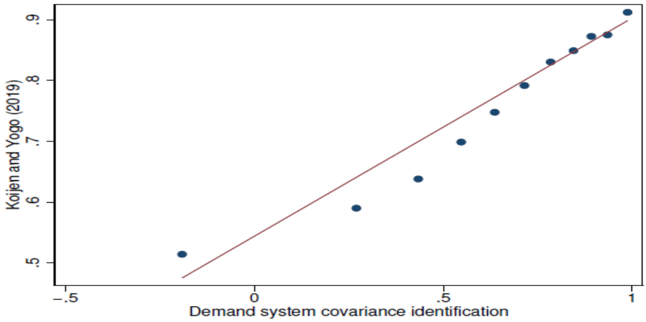


Fig 10: Comparison of estimates.

EMPIRICAL RESULTS

- Results are generally small, in line with the literature on asset demand estimation.

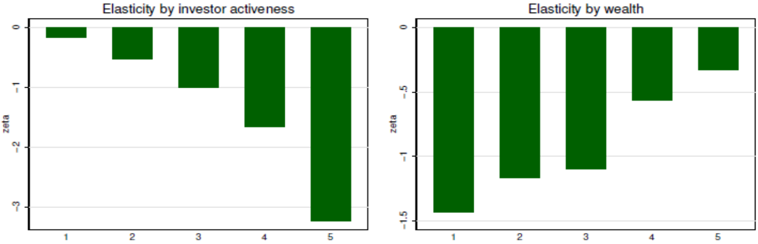
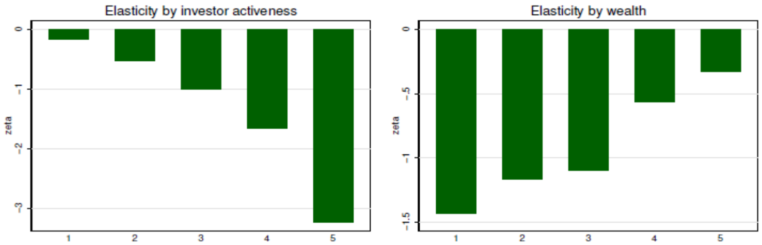


Fig 11: Elasticity estimates for the allocation between cash and risky assets.

EMPIRICAL RESULTS

- Significant heterogeneity across investors.



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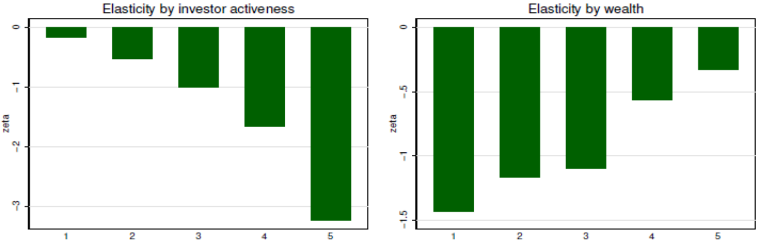
EMPIRICAL RESULTS

- Estimates are negative, consistent with positive feedback trading.



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EMPIRICAL RESULTS

- For Global equities, U.S. equities and Treasuries, demand is more elastic for more active investors.
- Demand for municipal bonds is inelastic across groups (tax exemption).

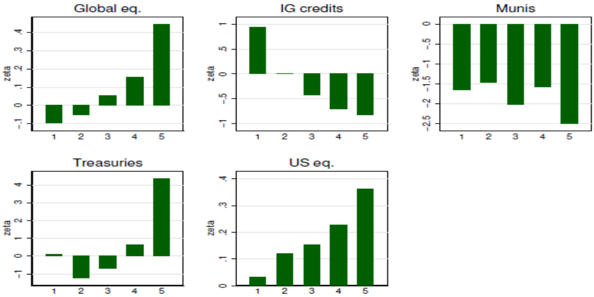

Fig 12: Elasticity estimates for the allocation across liquid risky assets by activeness.

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- Demand elasticities are smaller than implied by CAPM, vary significantly across wealth and are negative, pointing to positive feedback trading.

THANKS

- Pedro Borges, Master’s student at University of São Paulo. (pedro.borges10@usp.br)
- Open to work on Household Finance!