# Asset Demand of U.S. Households

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# MOTIVATION

- Demand system asset pricing: Jointly understand asset prices, macro variables, characteristics, portfolio holdings, and flows.
- Modeling the asset demand system is key to obtain credible quantitative answers to questions involving demand shifts.
  - QE & QT, global savings glut, savings glut of the rich, ESG investing, transition from active to passive.

# Motivation

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- Modeling the asset demand system is key to obtain credible quantitative answers to questions involving demand shifts.
  - QE & QT, global savings glut, savings glut of the rich, ESG investing, transition from active to passive.
- Key finding: Demand is inelastic relative to standard models.
- What is the evidence?
  - The impact of demand shocks on prices.
  - Direct estimates from holdings data.

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- This paper:
  - New data on portfolio holdings and flows of U.S. households to understand asset demand across asset classes.
    - Sample period: 2016 - 2021.
    - Direct and indirect holdings.
    - Public and private markets.
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    - Sample period: 2016 - 2021.
    - Direct and indirect holdings.
    - Public and private markets.
    - Ultra-rich households, which are typically not well represented in surveys.
  - Decompose flows into a price response and demand shocks.
    - Exploit time-variation in the covariance matrix of returns and portfolio rebalancing.
    - We refer to this as demand system covariance identification.

# Data

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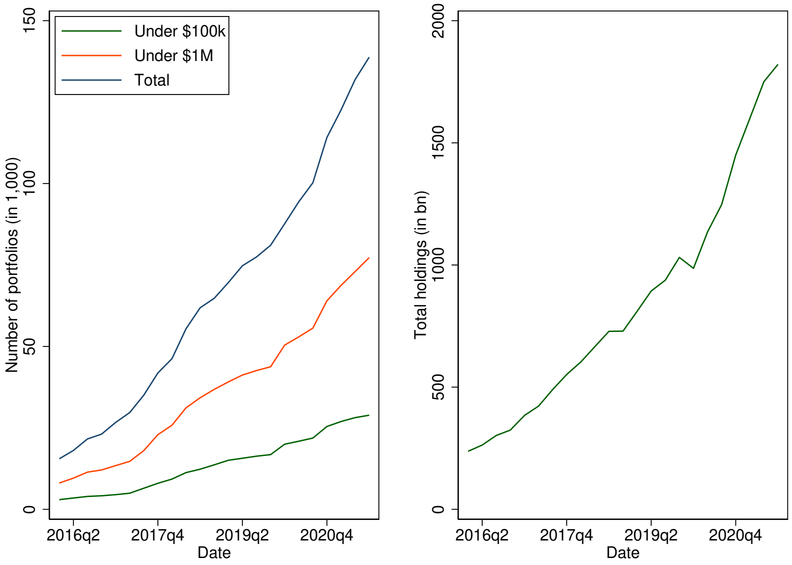
- Data structure and sample selection:
  - Security-level holdings, flows, and returns for all asset classes.
  - 125 households hold a position exceeding $1 bn in a single company. Those positions are removed for confidentiality.

# Asset classes

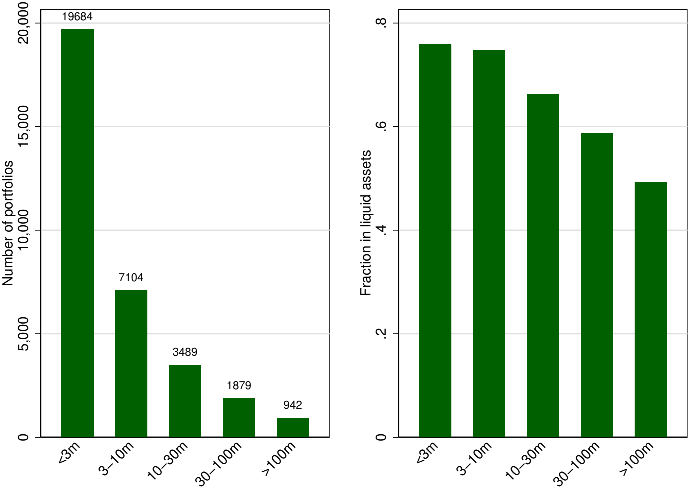
| Broad Asset Class | Narrow Asset Classes |
|---|---|
| Cash | Cash, Cash Equivalents |
| Fixed Income | US Municipals/Tax Exempt, US Treasuries and Agencies, US TIPS, US Investment Grade, US High Yield, US Bank Loans, International Developed Markets, Emerging Markets, Opportunistic, Other Fixed Income, Unknown Fixed Income |
| Equities | US 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-fin. Assets | Collectibles and Other |
| Liability | Liability |

- Asset classes marked blue are grouped into a category liquid.
- Asset classes marked red are grouped into a category cash.

# THE NUMBER OF PORTFOLIOS AND TOTAL HOLDINGS

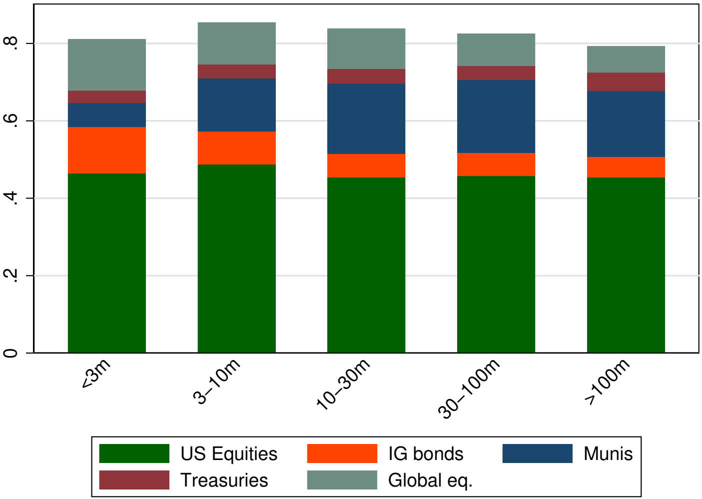


# Portfolio counts and the liquid asset share




- Balloch and Richers (2021) present additional and related results on portfolio holdings.

# Portfolios shares in liquid asset classes




- Takeaway: Within liquid assets, munis increase and IG bonds decline with wealth.

# Defining flows

- We define flows as
$$f_{int} = \frac{F_{int}}{A^{DH}_{i,t-1}},$$
where $A^{DH}_{it} = A_{i,t-1} + \frac{1}{2}F_{it}$.
- Flow to liquid risky assets: $f^{\text{Liq}}_{it} = \sum_{n\in\mathcal{L}} f_{int}$ and $\mathcal{L}$ the set of liquid risky asset classes.
- Flow to cash: $f^{\text{Cash}}_{it}$.

# A factor model of liquid flows

- We develop a factor model to understand the key rebalancing patterns in the data.
- We model the flow of investor $i$ into liquid asset class $n$ in quarter $t$ as

$$f_{int} = \alpha_n + \beta_n f_{it}^{\text{Liq}} + \gamma_n f_{it}^{\text{Cash}} + f_{int}^{\perp}.$$

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- The definition $f_{it}^{\text{Liq}} = \sum_{n \in \mathcal{L}} f_{int}$ implies

$$\sum_{n \in \mathcal{L}} \alpha_n = \sum_{n \in \mathcal{L}} \gamma_n = \sum_{n \in \mathcal{L}} f_{int}^{\perp} = 0,$$
$$\sum_{n \in \mathcal{L}} \beta_n = 1.$$

- If investors allocate capital in proportion to current holdings, then $\beta_n \simeq \mathbb{E}[\theta_{int}]$.

# A factor model of liquid flows

- We model the rebalancing flows, $f_{int}^{\perp}$, using a factor model

$$f_{int}^{\perp} = \sum_k \lambda_{it}^{(k)} \eta_n^{(k)} + u_{int}.$$

- Economic interpretation
  - $\lambda_{it}^{(k)}$: Propensity of investor $i$ to trade factor $k$.
  - $\eta_n^{(k)}$: Rebalancing strategy of factor $k$, $\sum_{n \in \mathcal{L}} \eta_n^{(k)} = 0$.

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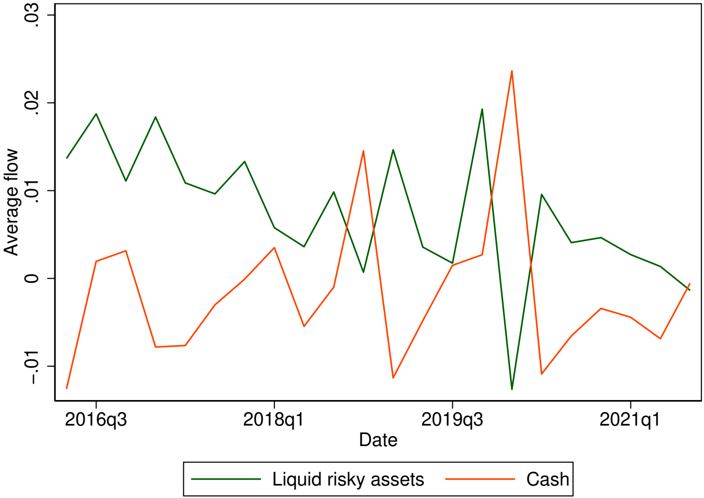
- Putting the model together

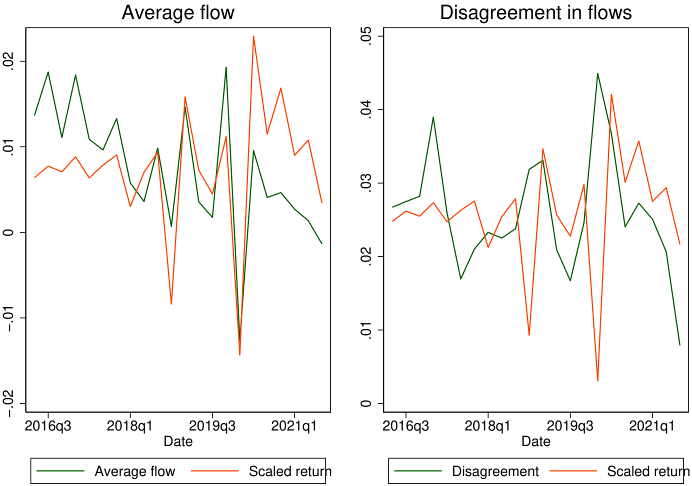
$$f_{int} = \alpha_n + \beta_n f_{it}^{\text{Liq}} + \gamma_n f_{it}^{\text{Cash}} + \sum_{k} \lambda_{it}^{(k)} \eta_{n}^{(k)} + u_{int}.$$

# FLOWS TO LIQUID ASSETS AND CASH, $f_{it}^{\text{LIQ}}$ AND $f_{it}^{\text{CASH}}$



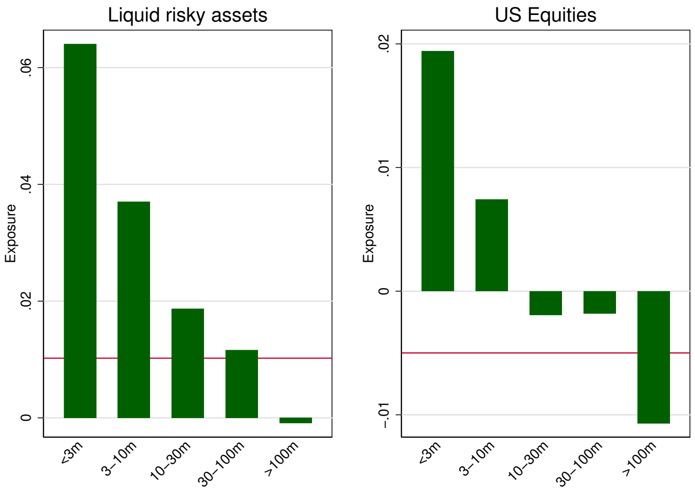

- Takeaway: During market turmoil, households on average sell risky assets and tilt to cash.

# Flows, disagreement, and equity returns




- Takeaway: Average flows are pro-cyclical, while disagreement is counter-cyclical.

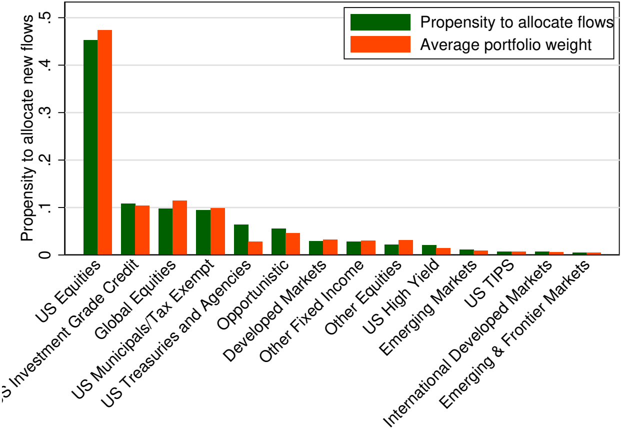
# Flows, returns, and the wealth distribution




- Takeaway: Less rich households act pro-cyclically, while the ultra-rich stabilize equity markets.

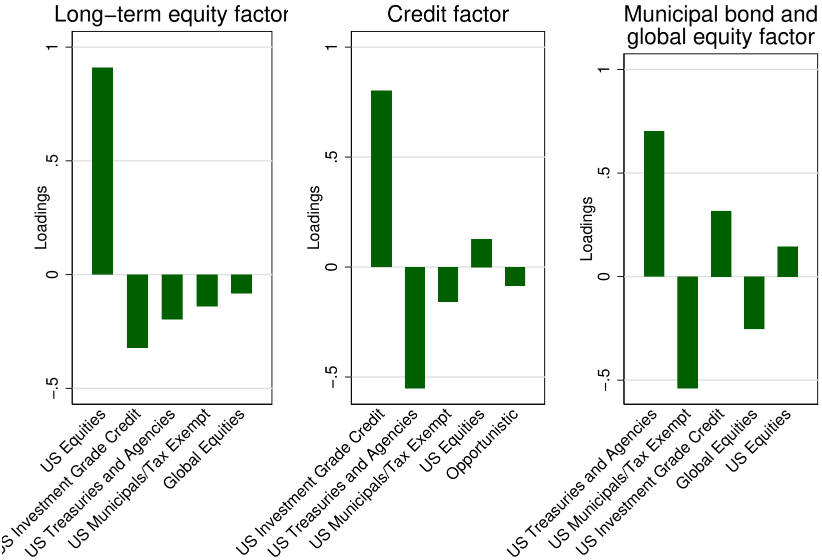
# Propensity to allocate new flows

- Estimate $f_{int} = \alpha_n + \beta_n f_{it}^{\text{Liq}} + \gamma_n f_{it}^{\text{Cash}} + f_{int}^{\perp}$.




- Takeaway: Households, on average, rebalance proportional to prior holdings ($\beta_n \simeq \mathbb{E}[\theta_{int}]$).

# KEY REBALANCING DIMENSIONS



# From flows to demand curves

- The previous descriptive analysis summarizes how investors rebalance across asset classes.
- Investor flows can be due to
  - Movements along the demand curve (i.e., (in)elasticity).
  - Shifts in the demand curve.
- We propose a new methodology to separate those forces.

# Logit model of asset demand

- Assets are split into inside assets, indexed by $a = 1, \dots, A$, and an outside asset, indexed by $a = 0$.
- For inside assets, the fraction invested in stock $a$ is given by

$$\theta_a = \frac{\exp(\delta_a)}{1 + \sum_b \exp(\delta_b)},$$

where

$$\delta_a = c + \beta m_a + \beta_1' x_a + \nu_a.$$

with $m_a$ denoting log market cap, $x_a$ firm characteristics, and $\nu_a$ the demand shifter.

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with $m_a$ denoting log market cap, $x_a$ firm characteristics, and $\nu_a$ the demand shifter.

- The goal is to estimate $\beta$, which cannot be done via OLS as $\mathbb{E}[m_a \nu_a]$ may not be zero.
- We directly observe $\delta_a$ as $\delta_a = \ln \frac{\theta_a}{\theta_0}$.

# Demand system covariance identification (DCIS)

- We model

$$m_a = \sigma_{ma}\tilde{m}_a,$$
$$\nu_a = \sigma_{\nu a}\tilde{\nu}_a,$$

  where $\sigma_{\tilde{m}} = \sigma_{\tilde{\nu}} = 1$.
- The heteroskedasticity is captured by $\sigma_{ma}$ and $\sigma_{\nu a}$.

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- The heteroskedasticity is captured by $\sigma_{ma}$ and $\sigma_{\nu a}$.
- Standardized demand shifters and log valuations are correlated

$$\tilde{\nu}_a = \rho\tilde{m}_a + \tilde{\nu}_a^{\perp},$$

where $\mathbb{E}[\tilde{m}_a\tilde{\nu}_a^{\perp}] = 0$ and $\sigma_{\tilde{\nu}^{\perp}} = \sqrt{1-\rho^2}$.

# DCIS: Simple example

- Assume that there are two groups of stocks that differ in their volatility of valuations, $j = L, H$.

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- Assume that there are two groups of stocks that differ in their volatility of valuations, $j = L, H$.
- The model then implies

$$\delta_a = c + \psi^j m_a + \beta_1' x_a + \nu_a^\perp,$$

for $j = L, H$ and where

$$\psi^j = \psi(\sigma^j_{\nu^\perp/m}) = \beta + g(\rho)\sigma^j_{\nu^\perp/m},$$

where $\sigma^j_{\nu^\perp/m} = \frac{\sigma^j_{\nu^\perp}}{\sigma^j_m}$.

- With just two volatility regimes, we can identify $\beta$.

# DCIS: Economic intuition

- Traditionally, demand estimation uses instruments that covary with valuations (relevance) but not with investor $i'$s demand shifters (exclusion).
- Those instruments, via market clearing, capture demand shifters of other investors that are uncorrelated with investor $i$.
- When regressing $\delta_a$ on $m_a$, the slope, $\psi(\sigma^j_{\nu^\perp/m})$, is a biased estimate of $\beta$

$$\psi(\sigma^j_{\nu/m}) = \beta + g(\rho)\sigma^j_{\nu^\perp/m}.$$

  - The bias, $g(\rho)\sigma^j_{\nu^\perp/m}$, shrinks to zero when $\sigma^j_{\nu^\perp/m} \to 0$.
  - $\sigma^j_{\nu^\perp/m} = 0$ implies that demand shocks of investor $i$ are zero, as is the case for IV estimators.

# DCIS: General case

- There are $J$ volatility regimes, $j = 1, \ldots, J$.
- We then model the slope as a more flexible function of $\sigma^j_{\nu^\perp/m}$,

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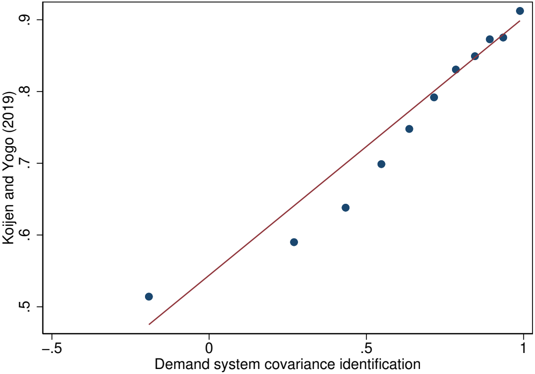
- Main identifying assumption

$$\lim_{\sigma^j_{\nu^\perp/m} \to 0} f(\sigma^j_{\nu^\perp/m}) = 0,$$

implying that $\lim_{\sigma^j_{\nu^\perp/m} \to 0} \psi^j = \beta$.
- The paper contains formal conditions and results for convergence, and an extension to inertia.

# Comparison with KY19 methodology

- Data from 1980.Q1 to 2017.Q4.
  - Average (standard deviation) estimate using KY19 instrument is 0.83 (0.26). DSCI gives 0.79 (0.32).
  - The correlation between estimates is 44.4%.



# Demand elasticities across asset classes

- The demand for a given asset class as the product of two portfolio shares

$$\theta_{int} = (1 - \theta_{ict})\tilde{\theta}_{int},$$

where

$$\tilde{\theta}_{int} = \frac{\exp\left(\delta_{int}\right)}{\sum_m \exp\left(\delta_{imt}\right)},$$

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

- The model implies, with $\zeta_{in} = 1 - \beta_{in}$ the elasticity of demand,

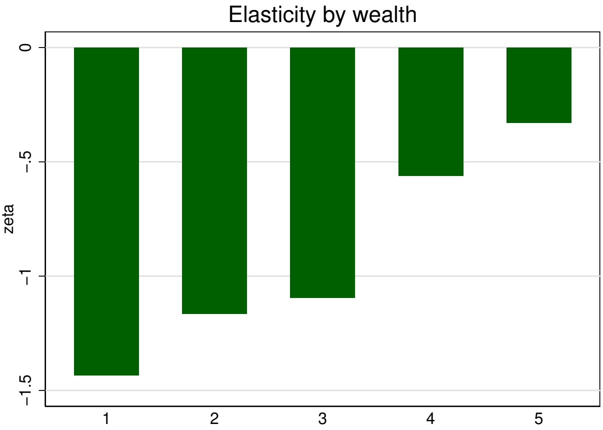
$$f_{inmt} = -\zeta_{in} r_{int} + \zeta_{im} r_{imt} + \Delta\nu_{inmt},$$

where $f_{inmt} \equiv \frac{F_{int}}{A_{in,t-1}} - \frac{F_{imt}}{A_{im,t-1}}$.

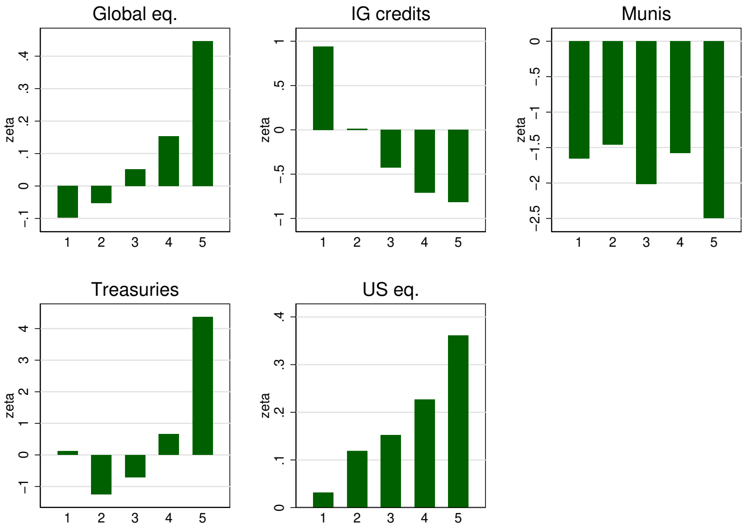
- We follow a similar model for the allocation between cash and risky assets.

# Elasticity estimates risky asset versus cash

- We estimate the model across two volatility regimes for five groups of households, grouped by wealth.



# Elasticity estimates across risky asset classes



# Conclusions

- We study the asset allocation decision of U.S. households using:
  - A descriptive factor model.
  - A model of asset demand.
- We develop a new methodology to estimate demand elasticities that can be used in the absence of instruments.
- In progress:
  - Dynamic extension, including inertia.
  - Theory explaining:
    - Why elasticities are low.
    - Why elasticities differ across asset classes.