ASSET DEMAND OF U.S. HOUSEHOLDS

Xavier Gabaix
Ralph S.J. Koijen
Federico Mainardi
Sangmin S. Oh
Motohiro Yogo

Harvard, Chicago³, Princeton

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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.
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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.
NEW DATA AND METHODOLOGY

Holdings data are from institutions due to data limitations.

- The household sector is modeled as the complement.
- Yet, households are at the core of macro-finance models.

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.
- 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.
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DATA

▶ Data source: Addepar.

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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

<table>
<thead>
<tr>
<th>Broad Asset Class</th>
<th>Narrow Asset Classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cash</td>
<td>Cash, Cash Equivalents</td>
</tr>
<tr>
<td>Equities</td>
<td>US Equities, Concentrated Equity Positions, Global Equities, Developed Markets - Americas, Developed Markets - EMEA, Developed Markets - Asia Pacific, Emerging &amp; Frontier Markets, Other Equities, Unknown Equities</td>
</tr>
<tr>
<td>Mixed Allocation</td>
<td>Asset Allocation Vehicle, Held Away Accounts</td>
</tr>
<tr>
<td>Alternatives</td>
<td>Hedge Funds, Private Equity &amp; Venture, Real Estate Funds, Concentrated Alts. Positions, Unknown Alts., Other Alts, Direct Private Companies, Direct Real Estate, Direct Loans</td>
</tr>
<tr>
<td>Non-fin. Assets</td>
<td>Collectibles and Other</td>
</tr>
<tr>
<td>Liability</td>
<td>Liability</td>
</tr>
</tbody>
</table>

- 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

Graph showing the number of portfolios (in 1,000) and total holdings (in bn) over different dates.
Baloch 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.
We define flows as
\[ f_{int} = \frac{F_{int}}{A_{i,t}^{DH}}, \]
where \( A_{it}^{DH} = A_{i,t-1} + \frac{1}{2} F_{it}. \)

Flow to liquid risky assets: \( f_{it}^{\text{Liq}} = \sum_{n \in \mathcal{L}} f_{int} \) and \( \mathcal{L} \) the set of liquid risky asset classes.

Flow to cash: \( f_{it}^{\text{Cash}}. \)
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

$$f_{int} = \alpha_n + \beta_n f_{it}^{\text{Liq}} + \gamma_n f_{it}^{\text{Cash}} + f_{int}.$$
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- The definition $f_{it}^{\text{Liq}} = \sum_{n \in L} f_{int}$ implies

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

$$\sum_{n \in L} \beta_n = 1.$$

- If investors allocate capital in proportion to current holdings, then $\beta_n \sim \mathbb{E}[\theta_{int}]$. 
We model the rebalancing flows, $f_{\text{int}}$, using a factor model

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

Economic interpretation

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

$$f_{int} = \alpha_n + \beta_n f_{it}^{\text{Liq}} + \gamma_n f_{it}^{\text{Cash}} + \sum_k \lambda^{(k)}_{it} \eta^{(k)}_n + u_{int}. $$
**Flows to liquid assets and cash, $f_{it}^{\text{LIQ}}$ and $f_{it}^{\text{CASH}}$**

<table>
<thead>
<tr>
<th>Date</th>
<th>Liquid risky assets</th>
<th>Cash</th>
</tr>
</thead>
<tbody>
<tr>
<td>2016q3</td>
<td>-0.1</td>
<td>0</td>
</tr>
<tr>
<td>2018q1</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>2019q3</td>
<td>0.03</td>
<td>-0.01</td>
</tr>
<tr>
<td>2021q1</td>
<td>0.01</td>
<td>0.02</td>
</tr>
</tbody>
</table>

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.
**Takeaway:** Less rich households act pro-cyclically, while the ultra-rich stabilize equity markets.
**PROPENSITY TO ALLOCATE NEW FLOWS**

- Estimate \( f_{int} = \alpha n + \beta n f_{it}^{\text{Liq}} + \gamma n f_{it}^{\text{Cash}} + f_{int}^{-} \).

**Takeaway:** Households, on average, rebalance proportional to prior holdings \((\beta_n \approx \mathbb{E}[\theta_{int}]\)).
**Key Rebalancing Dimensions**

**Long-term Equity Factor**
- Loadings: Long-term equity factor

**Credit Factor**

**Municipal Bond and Global Equity Factor**

First three factors explain approximately 65% of all rebalancing.
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 $a = 1, \ldots, A$, 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 $\delta_a = \ln \frac{\theta_a}{\theta_0}$. 
We model

\[ m_a = \sigma_{ma} \tilde{m}_a, \]
\[ \nu_a = \sigma_{va} \tilde{\nu}_a, \]

where \( \sigma_{\tilde{m}} = \sigma_{\tilde{\nu}} = 1. \)

The heteroskedasticity is captured by \( \sigma_{ma} \) and \( \sigma_{va} \).
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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 \( \sigma_{\tilde{\nu}^\perp} = \sqrt{1 - \rho^2}. \)
Assume that there are two groups of stocks that differ in their volatility of valuations, $j = L, H$. 
DCIS: Simple example

- 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

$$\psi^j = \psi(\sigma_{v^\perp/m}^j) = \beta + g(\rho)\sigma_{v^\perp/m}^j,$$

where $\sigma_{v^\perp/m}^j = \frac{\sigma_{v^\perp}^j}{\sigma_m^j}$.

- 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, $\psi(\sigma^j_{v^\perp/m})$, is a biased estimate of $\beta$

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

► The bias, $g(\rho)\sigma^j_{v^\perp/m}$, shrinks to zero when $\sigma^j_{v^\perp/m} \to 0$.

► $\sigma^j_{v^\perp/m} = 0$ 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 $\sigma_{v^\perp}^j / m$,

$$
\psi^j = \beta + f(\sigma_{v^\perp}^j / m).
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There are $J$ volatility regimes, $j = 1, \ldots, J$.

We then model the slope as a more flexible function of $\sigma^j_{v^\perp/m}$,

$$\psi^j = \beta + f(\sigma^j_{v^\perp/m}).$$

Main identifying assumption

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

implying that $\lim_{\sigma^j_{v^\perp/m} \to 0} \psi^j = \beta$.

The paper contains formal conditions and results for convergence, and an extension to inertia.
Comparing with KY19 methodology

  - 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 system covariance identification](chart.png)
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

\[ \tilde{\theta}_{int} = \frac{\exp(\delta_{int})}{\sum_m \exp(\delta_{imt})}, \]

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.
We estimate the model across two volatility regimes for five groups of households, grouped by wealth.
Elasticity estimates across risky asset classes

Global eq.

IG credits

Munis

Treasuries

US eq.
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.