Asset Demand of U.S. Households

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Abstract

We use new monthly security-level data on portfolio holdings, flows, and returns of U.S. households to understand asset demand across multiple asset classes. Our data cover a wide range of households across the wealth distribution – including ultra-high-net-worth (UHNW) households – and holdings in many asset classes, including public and private assets. We first develop a descriptive model to summarize households' rebalancing behavior. We find that less wealthy households rebalance from liquid risky assets to cash during market downturns, while UHNW households tend to purchase risky assets during those periods and thus stabilize market fluctuations. This pattern is particularly pronounced for U.S. equities. Across risky asset classes, three factors explain most of the variation in portfolio rebalancing and those factors target the long-term equity premium, the credit premium, and the premium on municipal bonds. Next, we develop a new framework to estimate demand curves across asset classes. While nesting traditional models as a special case, our framework allows for a muted response of asset demand to fluctuations in asset prices and easily extends to account for inertia. Our new estimator of asset demand curves exploits variation in second moments of returns and portfolio rebalancing, and can even be used when only a fraction of all holdings in a market can be observed. Our preliminary results indicate that asset demand elasticities are smaller than those implied by standard theories, vary significantly across the wealth distribution, and are negative for various groups, pointing to positive feedback trading. In sum, we think that our framework and data paint a coherent picture of U.S. households that captures, quite uniquely, their rebalancing behavior across the wealth distribution and across broad asset classes.

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1 Introduction

We study the asset demand of U.S. households, including ultra-high-net-worth (UHNW) households, across a wide range of asset classes. Households play a central role in modern asset pricing models, either by investing directly in financial markets or by allocating capital to intermediaries. Yet, the data available in the U.S. are still quite limited (we discuss the related literature in detail below).

We use new monthly security-level data from Addepar, a wealth management platform for investment advisors, to fill this gap. Addepar provides wealth managers with real-time portfolio information to guide investment decisions. The Addepar data contain security-level information on holdings, flows, and returns that aggregate to narrow asset classes (e.g., U.S. equities or U.S. investment-grade corporate bonds) and broad asset classes (e.g., equities, fixed income, and alternatives). We observe the data at a monthly frequency from January 2016 to August 2021.[1] The platform has been growing rapidly during our sample period, and the total assets (number of portfolios) in our data increase from \$237 billion (15,515) to \$1.82 trillion (138,795).

Our data have two important advantages compared with existing data sets for U.S. households. First, we have data on UHNW individuals, with close to a thousand households who own more than \$100 million in assets. This group of households, which may be particularly relevant for asset prices, is typically under-represented in other data sources. The broad coverage across the wealth distribution also allows us to extrapolate our estimates to construct demand curves for the "representative U.S. household." Second, we have broad coverage across asset classes and at high frequencies. The asset classes covered in the data include public and private assets and are all disaggregated to security-level positions. Such broad and detailed coverage is not even available for most U.S. institutions.

After documenting basic facts about investors' portfolios across the wealth distribution, we turn our focus to understanding flows and portfolio rebalancing. We define the flow to liquid risky assets as aggregate flows across 14 asset classes of which U.S. equities is the largest. This analysis reveals three main sets of findings.

First, the average flows to liquid risky assets and cash are strongly negatively correlated. In addition, while the average flow to risky assets is strongly positively correlated with aggregate equity returns, the dispersion in flows across investors is negatively correlated with returns. This implies that, on average, investors sell during economic downturns and disagreement increases during those turbulent times.

Second, we estimate how the flow to liquid risky assets responds to aggregate stock returns across the wealth distribution. Quite strikingly, we find that the sensitivity declines sharply in wealth. In fact, the flows of households with assets over \$100 million are essentially insensitive to stock returns. This low sensitivity could be consistent with wealthy households being inert or it

[1] We receive updates of the data with a 6-month delay.

can reflect rebalancing within liquid risky assets from Treasuries to U.S. equities, for instance. To separate these hypotheses, we estimate the sensitivity of flows to U.S. equities to aggregate stock returns. We find that while less wealthy households act pro-cyclically, UHNW households buy equities during downturns and thus stabilize markets by providing elasticity. Given the skewness in the wealth distribution, the value-weighted correlation between US equity flows and returns is negative, implying that the representative household in our data stabilizes equity markets during market downturns.

Third, we introduce a simple decomposition to estimate the main rebalancing directions across risky assets using principal components analysis (PCA). We find that the first three principal components explain approximately 65% of all rebalancing variation across the 14 asset classes. In addition, we show that the factor loadings form a long-short portfolio across asset classes and summarize the key rebalancing directions of households (although they may disagree on the direction and magnitude of the trade). The three factors carry intuitive economic interpretations. The first factor rebalances from U.S. equities to long-duration fixed income such as U.S. Treasuries and agencies, municipal and tax exempt bonds, and U.S. investment-grade corporate bonds. This factor therefore bets on the long-term equity risk premium. The second factor rebalances from U.S. investment-grade bonds to U.S. Treasuries, and thus represents a bet on the credit premium. The third factor combines two trades. The first trade rebalances from U.S. Treasuries and U.S. investment-grade corporate bonds to municipal and tax exempt bonds, while the second rebalances from global equities to U.S. equities. The third factor thus bets on the premium for municipal bonds as well as global equities versus U.S. equities. Taken together, these results summarize key dimensions of rebalancing in terms of cash, the aggregate flow to liquid risky assets, and rebalancing flows across liquid risky assets that are informative for the design of macro-finance models with rich heterogeneity.

This first part of the paper is mostly descriptive. Next, we develop a more structural model of demand across asset classes to examine whether the correlation between flows and returns is due to movements along the demand curve (due to elastic demand or positive feedback trading) or correlated demand shocks. This analysis extends the recent literature on demand system asset pricing. The goal of this literature is to develop equilibrium asset pricing models that are consistent with observed asset prices, portfolio holdings, and potentially firm characteristics and macro variables. In this literature, it is common practice to construct the holdings of the aggregate household sector as the difference between shares outstanding and the aggregate holdings of institutions. While this is the best practice when only institutional data are available, we are able to to estimate households' demand curves directly using disaggregated data.

We develop a new estimator to estimate asset-class level demand elasticities. The traditional approach to estimate asset demand elasticities is to use an idiosyncratic demand shock to one group of investors, which – via market clearing – impacts the price, and can then be used to estimate the demand elasticity of other investors (Koijen and Yogo, 2019; Gabaix and Koijen, 2021). As we only observe portfolio holdings for a subset of households, and we do not observe the holdings of institutions at the same high frequency and across many asset classes, these methods cannot be applied in this setting without additional data.

To overcome this problem, we propose a new method to identify asset demand from variation in the demand system covariance matrix (i.e., the covariance matrix of changes in asset demand and returns). Our new approach, which we call "demand system covariance identification," extends identification through heteroskedasticity (Rigobon, 2003) to asset pricing applications with incomplete holdings data and lack of exogenous demand shocks (e.g., index additions or deletions). While nesting the traditional mean-variance portfolio-choice model, our framework allows for a muted response to prices and expected returns, consistent with the recent evidence on inelastic financial markets. We show that the economic intuition behind our estimator can be viewed as a limit in which the impact of confounding demand shocks, which lead to a bias in elasticity estimates, converges to zero.

The procedure can be applied across securities for a given investor, as in Koijen and Yogo (2019), or across time periods and asset classes, as in this paper. As a warm-up, we apply the new methodology to estimate the micro-elasticity of the demand for stocks, and compare our results with those of Koijen and Yogo (2019). We find that, despite relying on very different methodologies, the estimates are quite strongly correlated across the two methods. This gives a validation to our new methodology.

We then proceed to our novel structural goal – estimate the elasticities between cash and risky asset classes and, separately, the elasticities across risky asset classes. We allow for different elasticities across asset classes. We group investors either by wealth or a measure of activeness as captured by the volatility of investors' flows. Our preliminary results indicate that asset demand elasticities are smaller than those implied by standard theories, vary significantly across the wealth distribution, and are negative for various groups, pointing to positive feedback trading.

In ongoing work, we are exploring dynamic extensions of the model to account for inertia[2] and reaching-for-yield. This may provide a new perspective on the strong response of asset prices to monetary policy shocks (Bernanke and Kuttner, 2005).

The paper proceeds as follows. In Section 2, we introduce the data, sample selection, and we provide summary statistics. We then study the allocation and flows across narrow asset classes in Section 3. In Section 4 we develop on new methodology to estimate demand curves across assets and asset classes. We apply it in Section 5 to estimate demand curves across narrow asset classes. We conclude in Section 6.

[2]See Calvet et al. (2009) and Andersen et al. (2020) for recent models of gradual rebalancing and inertia in the context of portfolio rebalancing and mortgage refinancing decisions.

Related literature

Our first contribution is to the literature that analyzes the asset demand of households, including high-net-worth households. This literature uses various data sources and methodologies to understand how investors trade and allocate capital, both across assets and asset classes as well as over the life cycle. We summarize this literature in Table A1 of Appendix A and provide additional details below.

The earlier literature uses publicly available data such as the Survey of Consumer Finances (SCF) to examine cross-sectional differences in portfolio composition (e.g. Friend and Blume, 1975; Heaton and Lucas, 2000).[3] While the SCF has detailed information on households' balance sheets, it is self-reported and is therefore subject to measurement error. Subsequently, researchers have used actual account data, mainly sourced from large financial institutions and brokerage firms. Early examples include Barber and Odean (2000), who study the trading behavior of retail investors from 1991 to 1996 using data from a large discount broker, and Ameriks and Zeldes (2004) who analyze the equity share over the life cycle using data from the SCF and TIAA-CREF.

The increased availability of such granular data from proprietary sources has shed new light on the behavior of individual investors in recent years. First, one strand of this literature combines surveys with data on portfolio holdings to study the beliefs and actions of investors jointly. Giglio et al. (2021a) use survey data of a sample of U.S.-based clients of Vanguard matched to administrative data on portfolio allocation to estimate the pass-through from beliefs to actions. Bender et al. (2022) use data from a survey administered through UBS to a sample of 2,484 affluent U.S. investors to connect their beliefs to their investments in equities. Second, much progress has been made to study the heterogeneity in asset allocations across investors and its determinants. For example, Egan et al. (2021) use data from BrightScope Beacon on portfolio allocations for a large sample of 401(k) plans and link the cross-sectional variation in asset allocations across plans to heterogeneous expectations of investors. Third, account-level data that track investors over time have yielded insights on how investors invest and save over the life cycle. For instance, using individual investors' account-level data from a large U.S. financial institution, Cole et al. (2022) study asset allocation decisions over the life cycle, highlighting the significant impact that target date funds have had in recent years. Finally, such new data has been used to study the role of retail demand during turbulent times. Among others, Hoopes et al. (2016) use administrative data from the IRS at a daily frequency between 2008 and 2009 to analyze the behavior of individual investors during the market turmoil at the beginning of the Great Financial Crisis.

The Addepar data that we use in this paper offer broad coverage across the wealth distribution and contain security-level holdings, flows, and returns across multiple asset classes (both public and private markets) for mostly U.S. investors. Balloch and Richers (2021) is the first paper to use

[3] Curcuru et al. (2010) provides a comprehensive review of the literature on related empirical and theoretical developments.

asset-class level data from Addepar to study how asset class allocations and investment returns vary across the wealth distribution during the period from 2016 to 2019. The new version of the Addepar data that we use contains security-level information. Our primary focus is on understanding how investors rebalance across asset classes, which we examine using descriptive factor models and by estimating models of demand using a new methodology.

Detailed data available on household portfolio holdings are also available in several Scandinavian countries and in India. In Norway, the government's wealth tax requires taxpayers to report their asset holdings in their tax filings, and these data are available on an annual basis since 1993. Using these data, Fagereng et al. (2020) study the heterogeneity in returns across the wealth distribution both within and across asset classes, and Betermier et al. (2022) construct factors by sorting stocks based on characteristics of investors that own them. These factors then explain both variation in portfolio holdings and cross-sectional variation in stock returns.

The government in Sweden also collects detailed information on the finances of every household in the country. These data have been used to study the participation and diversification of households in financial markets (Calvet et al., 2007) and to estimate the cross-sectional distribution of structural preference parameters in a rich life-cycle model of saving and portfolio choice (Calvet et al., 2021).[4] Calvet et al. (2009) is of particular relevance to our paper as they study the portfolio rebalancing of Swedish investors. After documenting passive and active changes in the risky share of each household over time, they propose a simple model to capture the relation between active and passive rebalancing while allowing for heterogeneity across households. Our paper complements their findings by proposing a factor model of rebalancing across multiple risky asset classes for U.S. investors. In addition, we estimate the demand curve of investors to separate portfolio flows that respond to prices (that is, changes along the demand curve) from actual shifts in the demand curve.

Both the Norwegian and the Swedish data are available at the annual frequency, which makes it difficult to evaluate higher-frequency phenomena. Naturally, researchers have utilized datasets from other countries that offer monthly or daily observations, albeit for a subset of the asset classes. For example, Grinblatt and Keloharju (2000) use daily stockholdings of Finnish investors from 1994 to 1996 to relate past returns and flows. Using the same data source extended to 2002, Grinblatt et al. (2011) examine the role of IQ in driving investors' decisions.

Monthly data on the trading and holdings of almost all Indian equity investors has been recently used to study topics such as the effects of experience on investor behavior (Anagol et al., 2015, Campbell et al., 2014) and the role of return heterogeneity in driving wealth inequality (Campbell et al., 2019). Most notably, Balasubramaniam et al. (2021) propose a cross-sectional factor model of direct stock holdings in the Indian stock market, which shares similarities with our factor model

[4]Massa and Simonov (2006) also study the behavior of Swedish investors using granular data, but they do not make use of the government records as in the aforementioned papers. Instead, they use the Longitudinal Individual Data for Sweden (LINDA) which provides detailed information on income, real estate, and wealth for a representative sample of the Swedish population.

for investor flows. The main difference is that our factor model focuses on flows across multiple asset classes and allows for time-variation in the factors. Also, as discussed before, we also estimate the demand curve to separate movements in the demand curve from those along the demand curve.

Second, our paper contributes to the recent literature on demand system asset pricing (Koijen and Yogo, 2019; Gabaix and Koijen, 2021; Haddad et al., 2022; Bretscher et al., 2022). The goal in this literature is to jointly understand data on prices, portfolio holdings, flows, and firm characteristics or macro variables. A key finding that has emerged from this literature is that asset demand is much more inelastic than those implied by standard theories. As only institutional holdings data are publicly available in the U.S., it is common practice to impute the aggregate holdings of households as the difference between the supply and the aggregate holdings of institutions. In addition, holdings data across asset classes is not available for all institutions. By using the Addepar data, we can study the household sector in detail, both within and across asset classes.

2 Data and summary statistics

2.1 Definitions and notation

We denote time by t and investors by i, $i = 1, ..., I$. We index security-level asset holdings by a (e.g., Apple versus Google stock), which can be aggregated to narrow asset classes that we index by n (e.g., U.S. equities or U.S. Treasuries) or broad asset classes that we index by c (e.g., equities or fixed income). We provide the precise definitions of asset classes in Section 2.3. To define the notation, we use narrow asset classes to index variables, and this notation extends to individual securities and broad asset classes.

We denote assets by A_{int}, dollar flows by F_{int}, and dollar returns by $R^{\$}_{int}$. We also observe time-weighted returns in our data, which we denote by r_{int}.[5] The inter-period budget constraint is then given by

$$A_{int} = A_{in,t-1} + R^{\$}_{int} + F_{int}. \tag{1}$$

We denote aggregate assets by $A_{it} \coloneqq \sum_n A_{int}$, aggregate flows by $F_{it} \coloneqq \sum_n F_{int}$, and aggregate dollar return by $R^{\$}_{it} \coloneqq \sum_n R^{\$}_{int}$. We define portfolio weights as $\theta_{int} = \frac{A_{int}}{A_{it}}$.

We denote flows, expressed as a fraction of total assets, by $f_{int} = \frac{F_{int}}{A^{DH}_{i,t-1}}$, where $A^{DH}_{i,t-1} \coloneqq \frac{1}{2}(A_{it} - R^{\$}_{it} + A_{i,t-1}) = A_{i,t-1} + \frac{1}{2}F_{it}$. In this definition, $A_{it} - R^{\$}_{it}$ corresponds to end-of-period wealth in the absence of price effects. Our definition of flows follows Davis and Haltiwanger (1992), and leads to

[5] We winsorize the security-level monthly time-weighted return at -300% and 300% for each security before aggregating the returns at the level of narrow asset classes using value weights.

a more robust definition of flows when $A_{i,t-1}$ is close to zero. We then also define

$$f_{it} = \frac{F_{it}}{A^{DH}_{i,t-1}} = \sum_n \frac{F_{int}}{A^{DH}_{i,t-1}} = \sum_n f_{int}, \tag{2}$$

which satisfies $f_{it} \in [-2, 2]$.

2.2 Data sources

Addepar Our primary data source is Addepar. Addepar is a wealth management platform that specializes in data aggregation, analytics, and reporting for complex investment portfolios that include public and private assets. It provides asset owners and advisors an overview of their financial positions. When possible, Addepar directly receives data on holdings and flows from custodians. It then combines these data with information on returns from various data sources.

Addepar works with over 400 financial advisors, family offices, and large financial institutions that manage data for over $3 trillion of assets on the company's platform, ranging from the affluent to the ultra-high-net-worth investor segments.

Our sample contains security-level, monthly data from January 2016 to August 2021. We receive monthly updates with a delay of six months to preserve the confidentiality of the data. Given our main focus on flows, we aggregate the data to quarterly observations, as it may take some time for households to rebalance their portfolios in response to new information. We have data on public and private assets. The holdings include both direct and indirect holdings (such as ETFs, hedge funds, and mutual funds). Portfolios are the unit of observation in Addepar. The same household or family can have multiple portfolios. We cannot identify which portfolios are connected and we will refer to portfolios as households.[6]

Addepar imposes two additional screens to preserve the confidentiality of the data. First, given that households receive investment advice from financial advisors, advisors that make up more than 10% of all portfolios in a given month are removed. If a portfolio is once removed via this process, it will not appear in subsequent months. Second, Addepar removes concentrated positions that exceed $1 billion in equities or companies that can be traced back to reveal a household's identity. We do observe which accounts are affected by this screen, and there are 125 such accounts in our sample.

ThomsonReuters, CRSP, and Compustat To benchmark our new methodology to estimate demand elasticities to those estimated in Koijen and Yogo (2019), we use their data. These data combine institutional investors' holdings from the Security and Exchange Commission (SEC) Form

[6]For some observations, the holdings in multiple asset classes are identical, suggesting that those are multiple portfolios belonging to the same household or family.

13F,[7] CRSP, and Compustat. We refer to Koijen and Yogo (2019) for details on the data construction.

2.3 Asset class definitions and summary statistics

Our sample of Addepar data includes information on 159,198 distinct client portfolios from 2016.Q1 to 2021.Q3. Table 1 provides the definition of asset classes in the Addepar data. In Online Appendix A, we describe each of the asset classes in more detail.

Table 1: Asset class definitions
This table reports the asset class taxonomy. We categorize the narrow asset classes, which are indexed by n, into seven broad asset classes. The narrow asset classes are obtained from Addepar's internal classification.

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

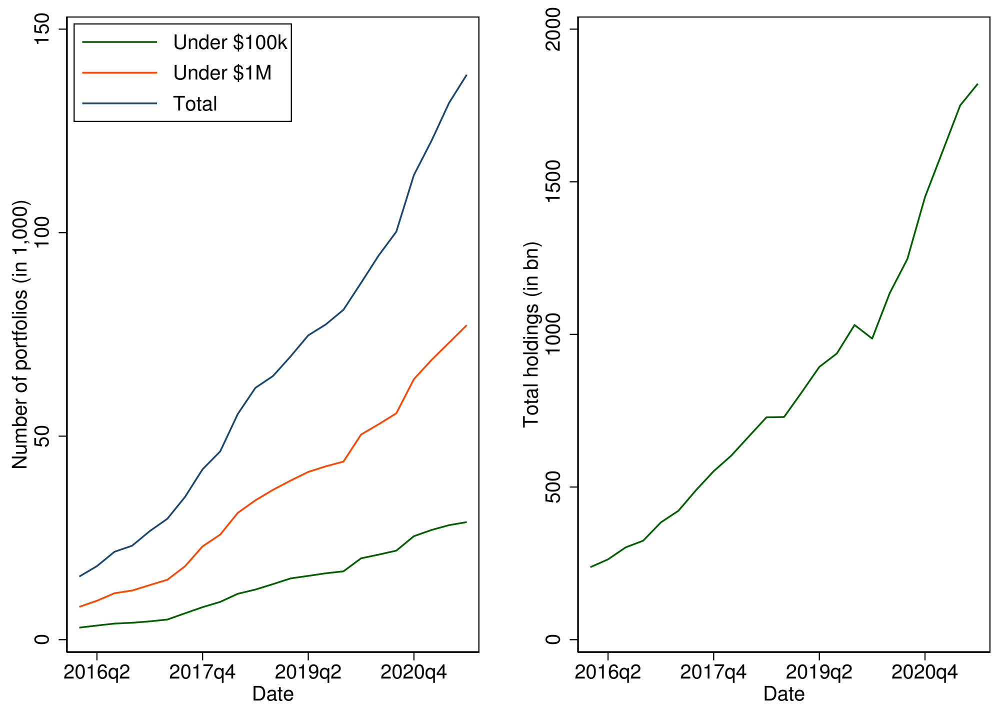
We make several adjustments to the classification of asset classes. First, when holdings are classified as Unknown Equities and the investment sub type[8] is either a mutual fund or ETF, we relabel the asset class to U.S. Equities when the Morningstar classification is U.S. Equity or to Global Equities when the Morningstar Classification is International Equity.

Second, we merge Unknown Equities into Other Equities and we do the same for fixed income. Third, we combine all narrow asset classes in Developed Markets (Americas, Asia Pacific, and EMEA) into a single equity category Development Markets. Lastly, we combine Cash and Cash Equivalents into a single narrow asset class Cash.

[7]All institutional investment managers that exercise investment discretion on accounts holding Section 13(f) securities, exceeding $100 million in total market value, must file the form.

[8]Investment type and subtype provide additional detail on the nature of the asset class.

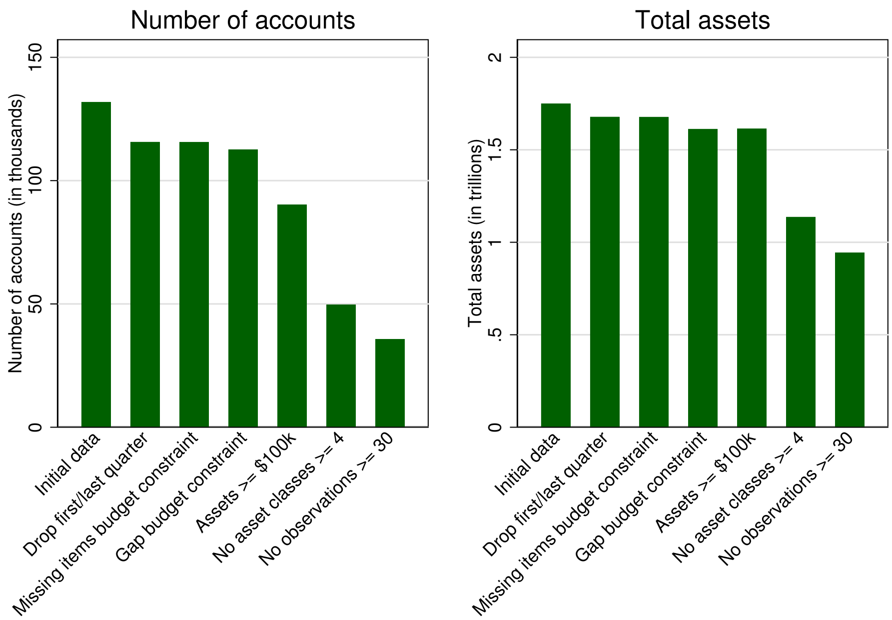
Figure 1: Number of portfolios and total assets
In the left panel, we plot the total number of portfolios, the number of portfolios that are smaller than $1 million, and the number of portfolios that are smaller than $100k. In the right panel, we plot the total value of assets in our sample. The sample period is from January 2016 to August 2021.



We define liquid and illiquid asset classes in our analysis below. Using the definitions in Table 1, the liquid asset classes include Developed Markets, Emerging & Frontier Markets, Emerging Markets, Global Equities, International Developed Markets, Opportunistic, U.S. Equities, U.S. High Yield, U.S. Investment Grade Credit, U.S. Municipals/Tax Exempt, U.S. TIPS, U.S. Treasuries and Agencies, Other Equities, Other Fixed Income. We analyze cash separately for reasons we discuss below. All other narrow asset classes in Table 1 excluding cash are classified as illiquid.

In Figure 1, we summarize the number of portfolios in the left panel and households' total assets on the platform in the right panel before imposing any screens. The number of portfolios grows from 15,515 in 2016.Q1 to 138,795 in 2021.Q3. The sharp increase in the number of portfolios reflects the growth of the Addepar platform during our sample period. Households' total assets grow from $237 billion to $1.82 trillion during the same period.

Figure 2: The impact of sample selection screens on the number of portfolios and total assets
This figure summarizes the impact of the sample selection screens discussed in Section 2.4. In the left panel, we show the impact on the number of accounts. In the right panel, we show the impact on the total assets covered in our sample. The results are presented for 2021.Q2, the last complete quarter of our sample.



2.4 Sample selection

We impose a series of sample selection screens in constructing our final sample. These screens ensure that we focus on households who are active in multiple asset classes so that we have broad coverage for the empirical analysis. Also, by imposing restrictions on the number of asset classes, it is less likely that only part of a households' assets are covered on the Addepar platform. The screens also remove infrequent data errors. We will discuss each of the screens and then summarize the impact on the size of our sample.

We start by removing the quarter in which a household is onboarded onto the platform as flows tend to be more volatile during this period (for instance, as the beginning-of-period assets are unknown for some or all of the asset classes). We remove the last quarter that we observe a given household for the same reason.[9]

Second, we remove household-quarter observations when an item from the budget constraint is missing – that is, the starting value, $A_{in,t-1}$, the ending value, A_{int}, the flow, F_{int}, or the dollar return, $R^{\$}_{int}$. Third, we remove household-quarter observations if the budget constraint does not hold

[9]It is uncommon for households to leave the platform during our sample period.

for at least one of the liquid narrow asset classes.[10] Fourth, for a small fraction of observations, the starting value and ending value coincide. While this can happen for cash accounts, this is unlikely to be correct for risky assets. Therefore, we set returns and flows to zero for such observations in liquid narrow asset classes that are not cash. This leads to an adjustment in 1.93% of all narrow asset class-quarter observations.[11]

Fifth, we drop household-quarter observations with fewer than \$100k in assets (across liquid and illiquid asset classes as well as cash). This screen also mitigates the concern that we capture only part of a household's assets. Sixth, we restrict to households with positive assets in the beginning or at the end of the period in at least four liquid asset classes. As we are interested in measuring rebalancing across asset classes, we focus on households who are active across multiple liquid asset classes. Lastly, we include a household only when there are more than 30 observations across all liquid asset classes and quarters. This screen ensures that we can estimate household-level factor loadings.

We summarize the impact of each of the screens in Figure 2 for the second quarter of 2021, which is the last complete quarter of our sample. In the left panel we report the total number of accounts and in the right panel we report the total assets covered.

The sample selection screens that have a noticeable impact on the size of the sample are: first, to remove the onboarding quarter; second, to impose a size constraint; third, to require positive positions in at least four asset classes; and finally to require at least 30 observations across quarters and liquid asset classes. As wealthier households are more likely to satisfy these screens, the impact is larger in terms of the number of portfolios compared with total assets.

We assign households to one one of five groups based on total wealth in a given quarter: A_{it} <\$3m, A_{it} ∈[\$3m, \$10m), A_{it} ∈[\$10m, \$30m), A_{it} ∈[\$30m, \$100m), and A_{it} ≥\$100m. We conclude our sample construction by winsorizing the flows, f_{int}, at the 2.5% and 97.5% percentiles by narrow asset class and quarter, and balancing the panel in terms of holdings (across liquid and illiquid asset classes as well as cash) and flows (across liquid asset classes as well as cash).

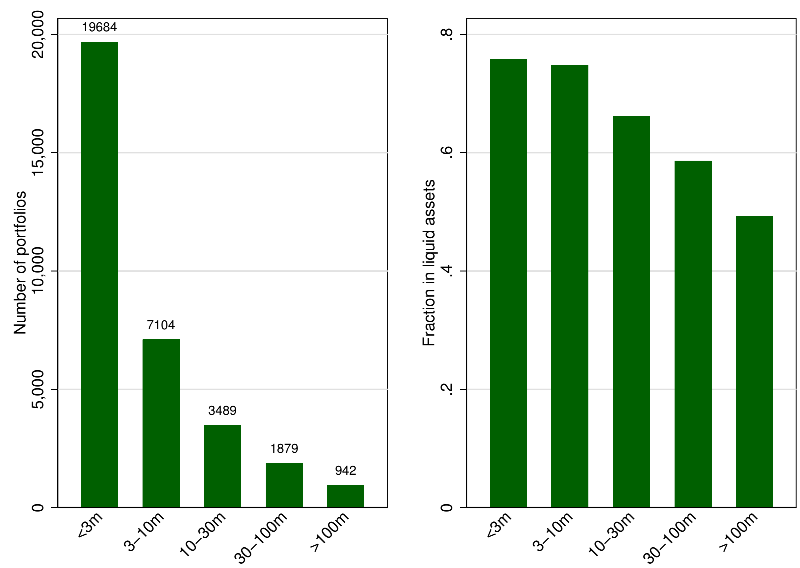
3 Asset demand across asset classes

We lead off our analysis by studying households' asset demand across asset classes. We proceed in three steps. First, we report a series of summary statistics regarding households' portfolio holdings

[10] We allow for a small margin of error of \$1,000 or 0.5% of the average (absolute value) of the ending and starting value.

[11] In those cases, we often observe that the flow is the negative of the dollar returns. The reason is that the system has additional information about either the return or the flow, and completes the missing items in those instances to ensure that the budget constraint holds. Alternatively, we can drop those observations. However, as we balance the panel below, this alternative data construction step would be equivalent to setting those flows to zero and mis-measuring the level of assets.

Figure 3: Number of portfolios and the fraction invested in liquid assets by wealth group
In the left panel, we plot the number of portfolios in each of the five wealth groups. In the right panel, we plot the average fraction invested in liquid risky assets. The results are presented for 2019.Q4.



in Section 3.1. These results complement the findings in Balloch and Richers (2021). We also report basic statistics on flows across broad asset classes. Second, we study the flow to liquid risky assets and cash in Section 3.2. Third, we estimate a factor model to analyze portfolio rebalancing across risky liquid asset classes and implement it in Section 3.3.

3.1 Summary statistics on portfolio holdings and flows

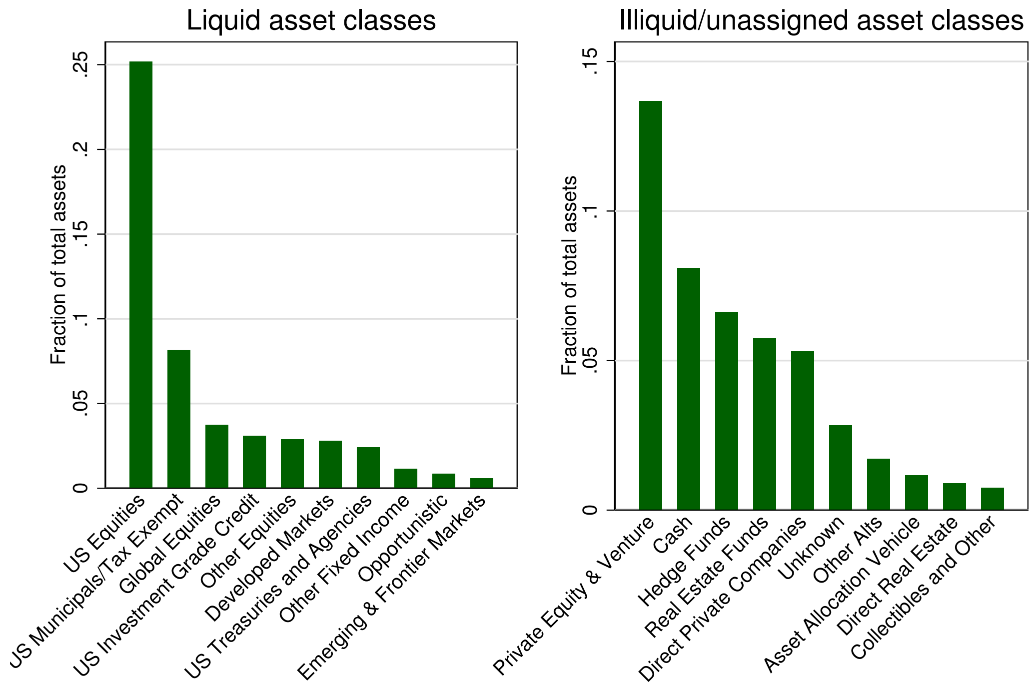
We first provide basic summary statistics on portfolio holdings across broad and narrow asset classes. We select a quarter in the middle of the sample, 2019.Q4, to present the results.

We plot the total number of portfolios in each of the wealth groups in the left panel of Figure 3. While the number of portfolios naturally declines in wealth, there are still 942 portfolios in our sample with more than $100 million in assets. We plot the fraction of total assets invested in liquid risky asset classes in 2019.Q4 in the right panel. As expected, wealthier households allocate a larger fraction to illiquid asset classes such as hedge funds, private equity, and other alternatives. We explore this pattern in more detail below.

In Figure 4, we plot the average portfolio shares across investors in 2019.Q4 for the 10 largest liquid risky asset classes (left panel) and the 10 largest illiquid asset classes (right panel).[12] Among

[12]We treat cash separately (that is, we do not classify it as part of the liquid risky assets and illiquid assets) for reasons that we discuss in Section 3.2. In Figure 4, we report the average share in cash in the right panel, having noted that we do not treat it as an illiquid asset class.

Figure 4: Fraction invested in narrow asset classes
In the left panel, we plot the average portfolio shares in the largest 10 liquid risky asset classes. In the right panel, we plot the portfolio shares for the illiquid asset classes as well as cash. The results are presented for 2019.Q4.



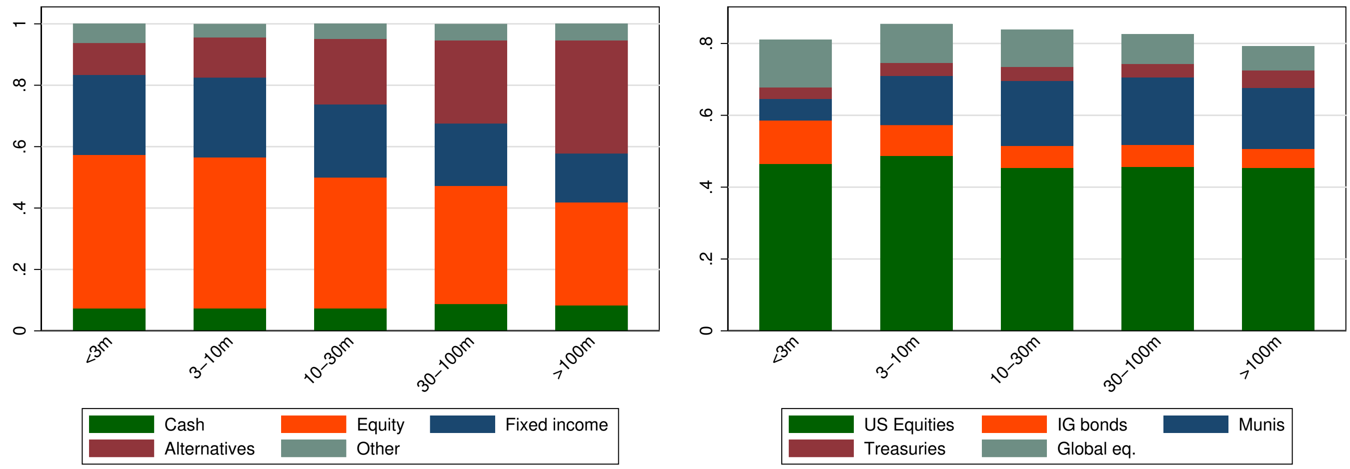
liquid asset classes, U.S. equities is the dominant asset class, followed by municipal bonds, global equities, and U.S. investment grade bonds. Among illiquid asset classes, the dominant asset class is private equity and venture capital, followed by hedge funds, and real estate funds.

We summarize the fraction invested in broad asset classes by wealth group in 2019.Q4 in the left panel of Figure 5. In line with the right panel of Figure 3, wealthier households allocate a larger fraction to alternatives, while reducing their portfolio shares in public equities and fixed income. The fractions invested in cash and other assets is stable across the wealth distribution.

We plot the portfolio shares invested in five large liquid risky asset classes across the wealth distribution in the right panel of Figure 5: U.S. equities, municipal and tax-exempt bonds, Treasuries, U.S. investment-grade bonds, and global equities. These five asset classes account for approximately 80% of all assets invested in liquid risky assets. While the shares are fairly stable, the fraction invested in municipal bonds increases with wealth, at the expense of U.S. investment grade bonds and global equities. This pattern may be driven by the tax benefits provided by municipal bonds.

These figures point to meaningful differences in households' asset allocations across the wealth distribution. That said, wealth cannot explain all (or even most) of the heterogeneity in portfolio

Figure 5: Fractions invested in broad and narrow asset classes by wealth group
In the left panel, we plot the average fractions invested in broad asset classes (Cash, Equity, Fixed income, Alternatives, Other). In the right panel, we plot the average fractions invested in the five largest liquid risky asset classes (U.S. Equities, U.S. Investment-grade bonds, Municipal and tax-exempt bonds, Treasuries, and Global equities). The results are presented for 2019.Q4.



holdings. To illustrate this, we estimate the following simple regression:

$$\theta_{int} = a_{0n} + a_{1n} \ln A_{it} + e_{int}, \tag{3}$$

at the level of broad and narrow asset classes and we record the R^2 value in Figure 6. We also report the standard deviation of θ_{int} to summarize the heterogeneity in portfolio holdings in a simple way.

We focus on broad asset classes in the left panel and on the five large liquid risky asset classes in the right panel. Across the board, we find that the R^2 values are low, as is commonly observed in the household finance literature. The fraction invested in municipal bonds is best explained by wealth with an R^2 value close to 10%. This implies that other determinants of households' portfolios such as differences in beliefs, perceptions of risk, risk preferences, et cetera are more important in explaining heterogeneity in portfolio shares.

For most of the paper, we will focus on flows and demand across liquid risky asset classes, as households cannot easily move capital across illiquid asset classes such as hedge funds and private equity. We conclude this section by documenting the cumulative flows across broad asset classes in Figure 7. During this 5-year period, the cumulative flows have been positive for fixed income and equities, and negative for cash (which includes money market funds). One potential interpretation is that households reallocated capital to riskier, higher-yielding assets during the low-rate environment. We also note the flow to cash during the fourth quarter of 2018 and the first quarter of 2020 when the aggregate U.S. stock market declined. We will revisit this pattern in Section 3.2. Overall, the average cumulative flows are quite modest and amount to 5-10% of assets over this 5-year period.

Figure 6: Heterogeneity in portfolio shares that cannot be explained by wealth
The orange bars correspond to the standard deviation of portfolio shares in broad asset classes (left panel) and the largest five narrow asset classes (right panel). The green bars correspond to the R-squared of a regression of portfolio weights on log wealth (see (3)). The results are presented for 2019.Q4.

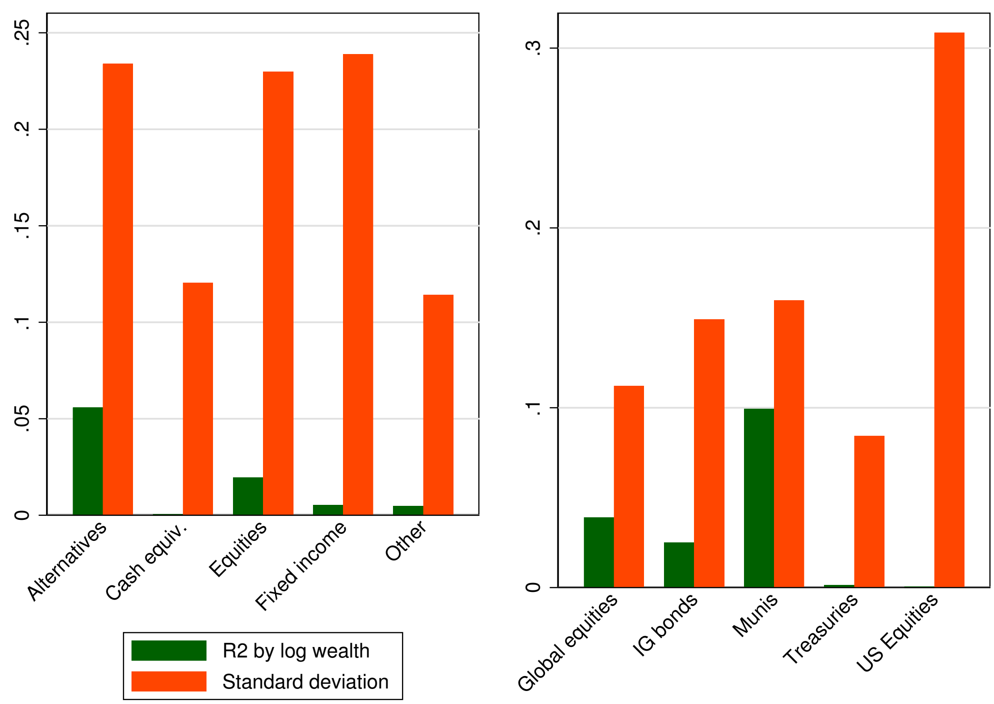
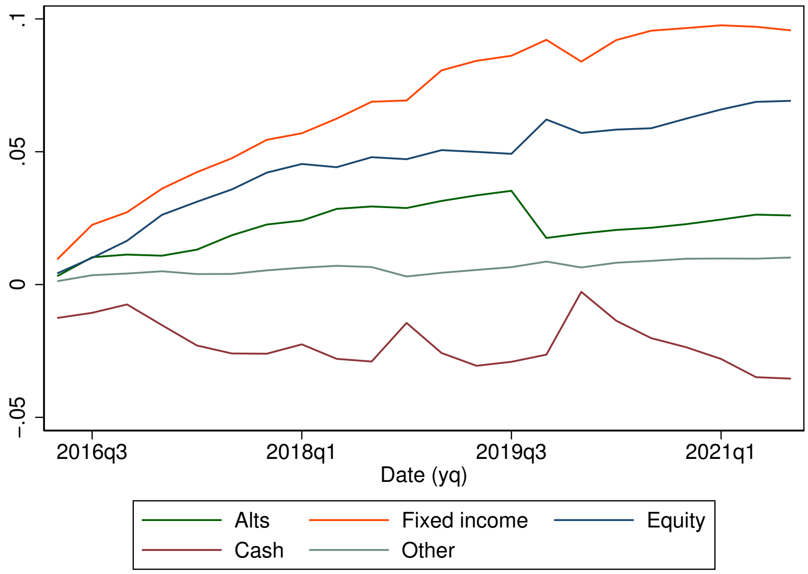


Figure 7: Flows to broad asset classes
We plot the flow into broad asset classes during our sample period from 2016.Q1 to 2021.Q3. Flows are scaled by total assets.



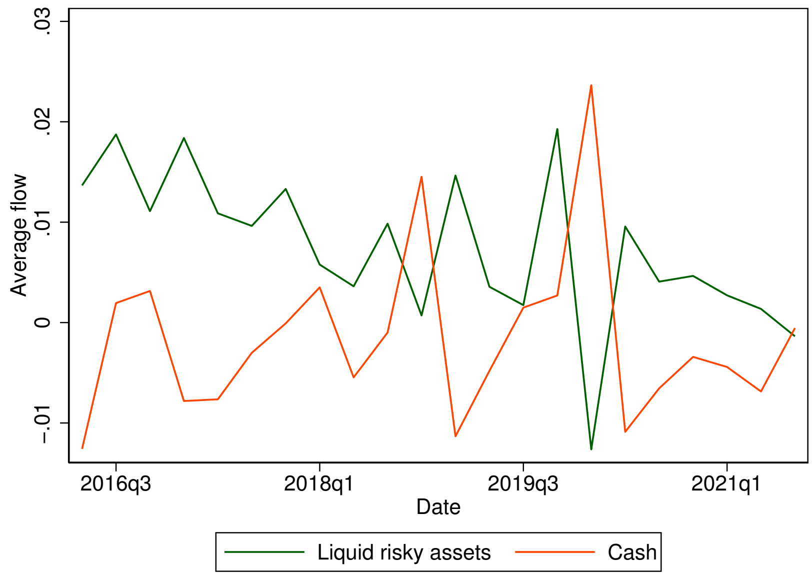
3.2 Aggregate flows to liquid risky assets and cash

Our main focus is on the allocation and reallocation of capital to liquid risky asset classes and cash. We first explore two aggregate flow measures for each investor in a given quarter. The first measures the flow to cash, where cash includes bank accounts and money market mutual funds. We denote this flow by f_{it}^{Cash}. The second measures the aggregate flow to liquid risky asset classes. We denote this flow by $f_{it}^{\text{Liq}} := \sum_{n \in \mathcal{L}} f_{int}$, where $\mathcal{L}$ is the set of liquid risky asset classes as defined in Section 2.3.

In Figure 8, we plot the equal-weighted average of f_{it}^{Cash} and f_{it}^{Liq} across investors in a given quarter. Three observations stand out from these series. First, the flows to cash and liquid risky assets are strongly negatively correlated: the time-series correlation is -51.5%. This implies that cash is an important substitute for liquid risky assets. Second, the flow to liquid risky assets falls during times of financial market turmoil, such as the last the quarter of 2018 and the first quarter of 2020, while the flow to cash is positive during those same periods. This highlights the role that cash plays as a safe asset in investors' portfolios.

Third, the flow to cash is about as volatile as the flow to all liquid risky assets. Both series have a quarterly volatility of 0.8%. Yet, the average cash share is only 7.6% versus 73.0% for the fraction invested in liquid risky assets. This comparison implies that cash is disproportionally volatile. As another way to illustrate the volatility of flows to cash, we plot the average share invested in a particular asset class on the horizontal axis and the (quarterly) standard deviation of flows on the

Figure 8: Dynamics of the flow to cash and liquid risky assets
We plot the average flow to liquid risky assets, $\frac{1}{I}\sum_i f_{it}^{\text{Liq}}$, in green and the average flow to cash, $\frac{1}{I}\sum_i f_{it}^{\text{Cash}}$, in orange. The sample period is from 2016.Q1 to 2021.Q3.



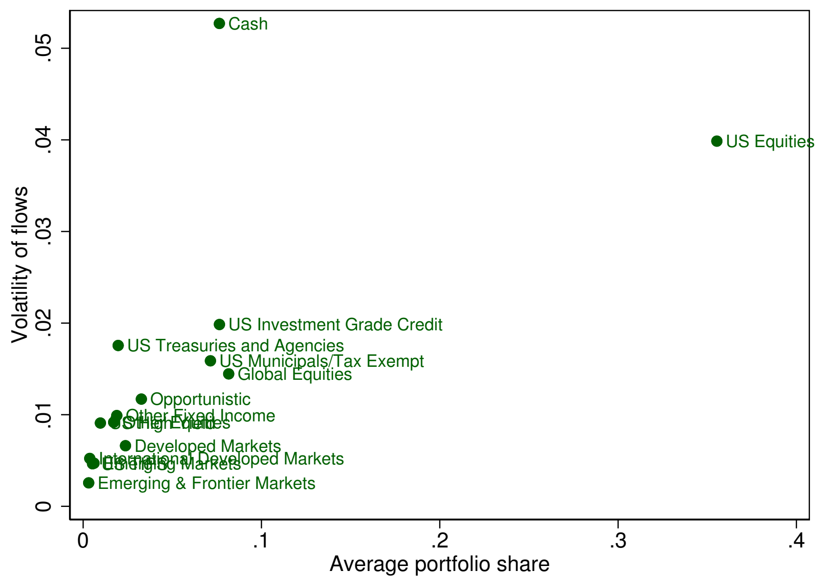
vertical axis in Figure 9. We measure both moments across all investors and quarters. For all asset classes except cash, the volatility of flows aligns closely with the average fraction invested in that asset class; the quarterly volatility of flows is about 10% of the average fraction invested in the asset class. Using this simple metric, we would expect the flow to cash to be less than 1% per quarter, but we find it to be close to 5%.

Economically, the reason is that cash serves two purposes. First, as we discussed before, cash serves as a safe asset: the flows are strongly negatively correlated with the flows to liquid risky assets and increase during times of stress while the opposite is true for the flow to liquid risky assets. This unique aspect of cash can make it excessively volatile due to risk aversion or sentiment shocks.

In addition to being a safe asset, cash holdings are used to buffer liquidity shocks. Those volatile liquidity shocks affect the flow to cash but they do not affect the flow to liquid risky assets. This separate determinant of flows to cash adds volatility, yet those cash holdings are less likely to be used for investment purposes. Given this dual role that flows to cash play, we analyze these flows separately from f_{it}^{Liq}.

Next, we explore the link between market conditions and the flow to liquid risky assets in more detail. We first plot the time series of f_{it}^{Liq}, again averaged across investors in a given quarter, alongside the return on the aggregate U.S. stock market from CRSP in the left panel of Figure 10. We adjust the mean and standard deviation of the return series to match those of the flow series. The two series are strongly positively correlated; the time-series correlation between the average

Figure 9: Portfolio shares and the volatility of flows
We plot the average portfolio share allocated to liquid risky asset classes and cash on the horizontal axis and the volatility of flows to the same asset classes on the vertical axis. The sample period is from 2016.Q1 to 2021.Q3.



flow and U.S. stock market returns is 57%.

In the right panel of Figure 10, we plot the disagreement across investors as measured by the inter-quartile range of f_{it}^{Liq} across investors in a given quarter. We also plot this series alongside the return on the U.S. stock market, adjusting the mean and standard deviation of the return series to match those of the disagreement series as before. In this case, we find that the correlation is -14.3%, implying that disagreement goes up during market downturns. This pattern is particularly salient on the downside during the two most extreme quarters in our sample, that is, the last quarter of 2018 and the first quarter of 2020.

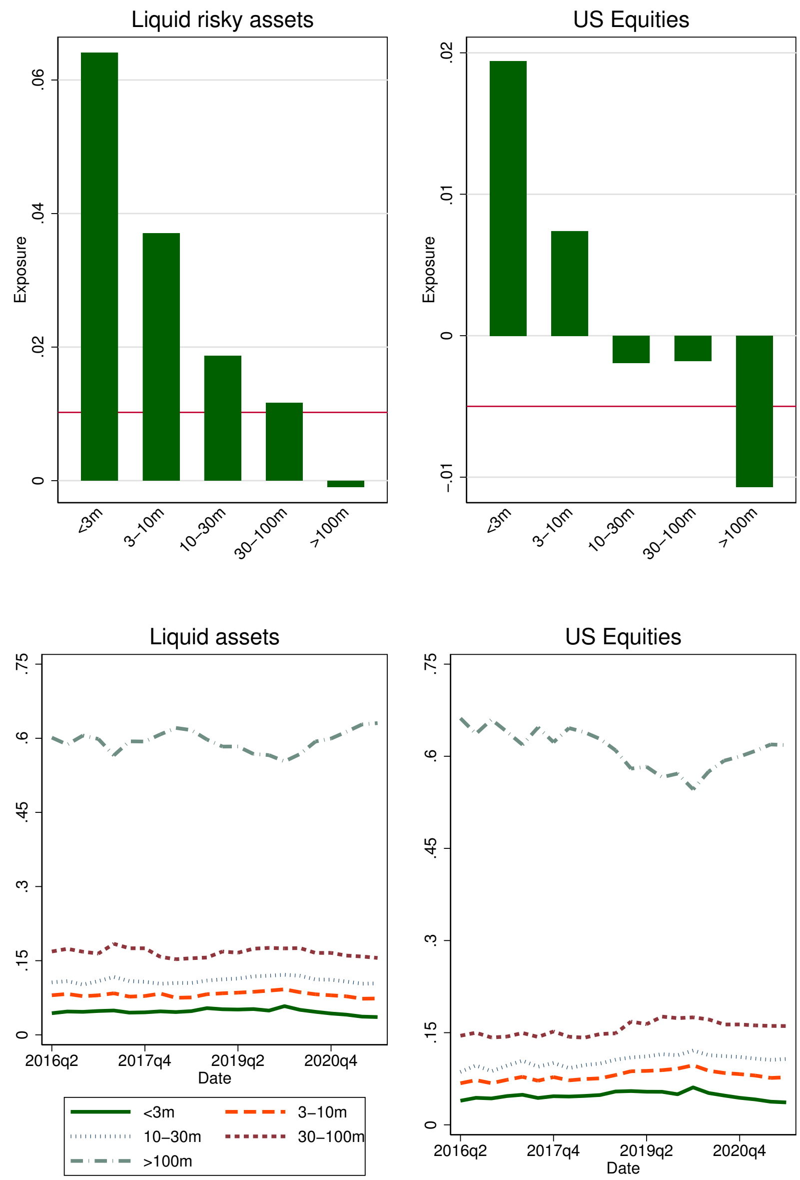
Motivated by the correlations between the average flow, disagreement in flows, and the return on the U.S. stock market, we conclude this section by analyzing how the sensitivity of flows to stock returns varies across the wealth distribution. To this end, we first average f_{it}^{Liq} across investors in a given wealth group and quarter. We then regress the average flow for this wealth group on the U.S. stock market return in the time series.

In the left panel of Figure 11, we plot the estimated slope coefficient for each of the wealth groups. Quite remarkably, we find that the slopes monotonically decline in wealth. In fact, for the households with more than \$100 million in assets, the slope turns slightly negative. Yet, for most households, the slope is positive, implying that households (other than the UHNW households) sell liquid risky assets during market downturns and thus act pro-cyclically. This behavior amplifies price fluctuations of risky assets.

Figure 10: Flows to liquid risky assets, returns, and disagreement
In the left panel, we plot the time series of f_{it}^{Liq}, averaged across investors in a given quarter, alongside the return on the U.S. stock market from CRSP. We adjust the mean and standard deviation of the return series to match those of the flow series. In the right panel, we plot the disagreement in flows to liquid risky asset classes, as measured by the inter-quartile range of f_{it}^{Liq} across investors in a given quarter, alongside the return on the U.S. stock market. As before, we adjust the mean and standard deviation of the return series to match those of the disagreement series. The sample period is from 2016.Q1 to 2021.Q3.

Figure 11: Exposure of flows to aggregate returns by wealth group

In the top left panel, we plot the slope coefficients of a regression of flows to liquid risky assets on the aggregate return on the U.S. stock market by wealth group. In the top right panel, we plot the slope coefficients of a regression of flows to U.S. equities on the aggregate return on the U.S. stock market by wealth group. The red horizontal line in each figure is the wealth-weighted average of the sensitivities. In the left panel, we use liquid risky asset shares as weights, while in the right panel we use U.S. equity shares. We plot these shares in the bottom panels. The sample period is from 2016.Q1 to 2021.Q3.



We cannot assess from these results whether households act pro-cyclically because their demand curves slope up (that is, chase returns) or because their demand shocks are correlated with those of other investors. That is, we cannot tell from these correlations whether the co-movement is due to shifts along the demand curve or shifts in the demand curve itself. In Section 4 and 5, we make progress on this question.

In the bottom panels of Figure 11, we plot the wealth shares represented by each of the groups. Even though we have about 20 times as many households in the first versus the fifth wealth group, the shares in liquid wealth (left panel) and U.S. equity holdings (right panel) of the fifth wealth group are more than 10 times higher than the wealth shares of the first wealth group. As a result, the wealthy households receive more weight if we construct the representative household. The wealth-weighted average (using liquid wealth shares to aggregate the groups) sensitivity is summarized by the red horizontal line.

For wealthy households, there are two interpretations of their muted response to market returns. One potential interpretation is that wealthy households are more inert and hardly respond to turmoil in financial markets. Such inelastic behavior would indirectly contribute to amplifying demand shocks of other investors by lowering the elasticity of the overall market (Gabaix and Koijen, 2022). However, another interpretation is that wealthy investors instead provide elasticity to the stock market and reallocate capital from fixed income asset classes to equities, thereby leaving the overall flow to liquid risky asset classes largely insensitive to market returns.

To separate these hypotheses, we zoom in on U.S. equities, which is the largest liquid risky asset class and the asset class that best captures how investors respond to fluctuations in the U.S. stock market. We therefore repeat the same analysis as before, but now regressing f_{int} for U.S. equities (rather than f_{it}^{Liq}) on U.S. stock returns for each of the wealth groups.

In the right panel of Figure 11, we plot the estimated slope coefficients for each of the wealth groups. As in the left panel, the less wealthy households (those with assets below \$10 million) act pro-cyclically. However, the new insight that emerges from this figure is that (ultra) high net worth households provide elasticity to the market by buying equities during economic downturns. This pattern rejects the idea that wealthy households are fully inert and supports the notion that they actively reallocate capital. As in the left panel, we construct a representative household for these data by computing the weighted average sensitivity (using U.S. equity holdings to compute the weights). As wealthy households receive much more weight, the overall sensitivity is negative.

Despite the striking pattern, we note that the empirical magnitude of the effect is quite modest. A 10% decline in the stock market leads to a 0.1% inflow into equities for very rich households (over \$100 million in assets), and a -0.2% inflow (i.e., an outflow) for relatively poorer (less than \$3 million in assets). So while the main qualitative takeaway is that wealthy households provide elasticity to the market, the main quantitative takeaway is that the magnitudes are small.

We summarize the results in Table 2 for the flow to liquid risky assets and Table 3 for the flow

Table 2: Sensitivity of liquid risky asset flows to U.S. equity returns
The table reports the results of regression of liquid risky asset flows on the returns on aggregate U.S. stock market for the the five wealth groups in the first five columns. The final column uses the difference in flows between the fifth and the first wealth group. We report the t-statistics (computed using heteroskedasticity-robust standard errors) in parentheses. The sample period is from 2016.Q1 to 2021.Q3.

	<3m	3-10m	10-30m	30-100m	>100m	Difference
US equity return	0.064	0.037	0.019	0.012	-0.001	-0.065
	(4.07)	(1.94)	(0.92)	(0.82)	(-0.06)	(-5.97)
Constant	0.005	0.006	0.008	0.006	0.006	0.001
	(2.92)	(4.27)	(4.77)	(5.44)	(4.73)	(1.06)
Observations	22	22	22	22	22	22
R^2	0.406	0.221	0.054	0.035	0.000	0.495

to U.S. equities. The first five columns in each table correspond to the five wealth groups, and the sixth column uses the difference in flows between wealth group 5 (wealth above \$100m) and group 1 (wealth below \$3m).

We find that the flows in the extreme wealth groups are statistically different from each other, despite the short sample. An advantage of our sample is that there are large swings in returns, mostly during the last quarter of 2018 and the first quarter of 2020 (during the COVID-19 pandemic). That said, our sample is short and it will be interesting to update these estimates as more data become available and to understand whether these covariances remain stable over time or differ depending on certain economic conditions.

3.3 Decomposing flows

The analysis in the previous section focused largely on the flow to cash and all liquid risky assets. In this section, we extend the analysis by studying how households allocate capital across liquid risky asset classes.

We develop a simple framework that allows us to use principal components analysis (PCA) to measure how investors reallocate capital from one asset class to another. We first remove the factors that we analyzed in the previous section via the following panel regression

$$f_{int} = \alpha_n + \beta_n f_{it}^{\text{Liq}} + \gamma_n f_{it}^{\text{Cash}} + f_{int}^{\perp}. \tag{4}$$

Given that $f_{it}^{\text{Liq}} = \sum_{n \in \mathcal{L}} f_{int}$, it follows that $\sum_{n \in \mathcal{L}} \beta_n = 1$ and $\sum_{n \in \mathcal{L}} \alpha_n = \sum_{n \in \mathcal{L}} \gamma_n = \sum_{n \in \mathcal{L}} f_{int}^{\perp} = 0$.

In this regression, we are primarily interested in the residuals, $f_{int}^{\perp}$. The property that $f_{int}^{\perp}$ sum

Table 3: Sensitivity of U.S. equity flows to U.S. equity returns
The table reports the results of regression of liquid risky asset flows on the returns on aggregate U.S. stock market for the the five wealth groups in the first five columns. The final column uses the difference in flows between the fifth and the first wealth group. We report the t-statistics (computed using heteroskedasticity-robust standard errors) in parentheses. The sample period is from 2016.Q1 to 2021.Q3.

	<3m	3-10m	10-30m	30-100m	>100m	Difference
US equity return	0.019	0.007	-0.002	-0.002	-0.011	-0.030
	(4.20)	(2.51)	(-0.62)	(-0.47)	(-1.83)	(-3.26)
Constant	0.000	0.001	0.003	0.002	0.001	0.001
	(0.62)	(3.38)	(5.81)	(4.84)	(2.83)	(1.05)
Observations	22	22	22	22	22	22
R^2	0.237	0.083	0.006	0.007	0.163	0.343

to zero across all liquid risky asset classes makes $f_{int}^{\perp}$ an appealing measure of rebalancing flows. Indeed, if $f_{it}^{\text{Liq}} = f_{it}^{\text{Cash}} = 0$, then all rebalancing across asset classes is captured by $f_{int}^{\perp}$.

The regression coefficients in (4) also have a natural interpretation. The slope on f_{it}^{Liq}, β_n, measures how new flows to liquid risky assets are allocated across asset classes. If households maintain fairly stable portfolio shares over time, we expect $\beta_n \simeq \mathbb{E}[\theta_{int}]$, that is, capital is allocated in proportion to existing portfolio shares. The slope on f_{it}^{Cash}, γ_n, measures how flows to cash may be correlated to flows to a particular asset class. The intercept, α_n, measures broad reallocation trends during our sample period. Empirically, both α_n and γ_n are economically small and we will not explore them in further detail in the remainder of this section.

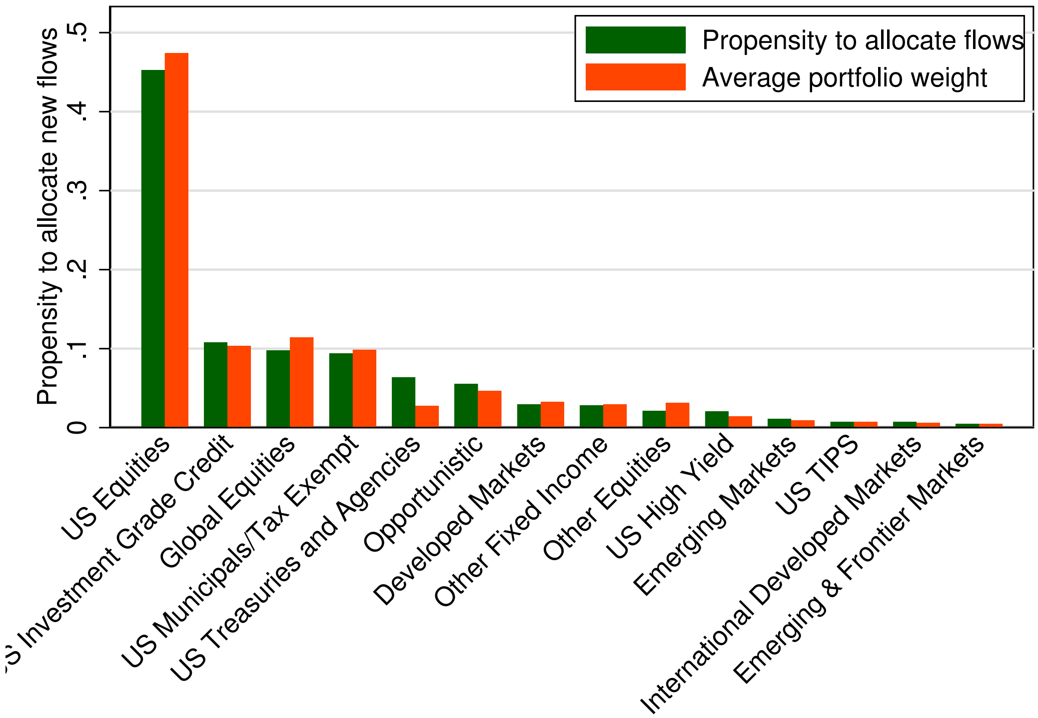
In the second step of the analysis, we model the rebalancing flows, $f_{int}^{\perp}$, using a factor model

$$f_{int}^{\perp} = \sum_k \lambda_{it}^{(k)} \eta_n^{(k)} + u_{int}, \tag{5}$$

where $k = 1, ..., K$ indexes the number of factors. We estimate the factor model using PCA. Economically, as $\sum_{n \in \mathcal{L}} \eta_n^{(k)} = 0$, these coefficients represent a long-short trading strategy – for instance, purchasing U.S. equities and selling Treasuries. We are therefore particularly interested in measuring $\eta_n^{(k)}$ as they summarize the key rebalancing dimensions in the data. The loadings, $\lambda_{it}^{(k)}$, capture the exposure of investor i in quarter t to factor k. The residual, u_{int}, capture the idiosyncratic rebalancing decisions of an investor due to idiosyncratic views about a particular asset class.

We report the estimates of β_n in (4) alongside the average portfolio shares in Figure 12 for each of the liquid risky asset classes. As discussed before, if investors maintain fairly constant shares, we

Figure 12: Allocation of new flows
We plot the estimates of β_n in equation (4) for all the liquid risky asset classes. We compare the estimates to the average portfolio shares, $\mathbb{E}[\theta_{int}]$. If investors maintain stable shares invested in the different asset classes, then we expect $\beta_n \simeq \mathbb{E}[\theta_{int}]$. The sample period is from 2016.Q1 to 2021.Q2.



expect $\beta_n \simeq \mathbb{E}[\theta_{int}]$. The figure shows that the estimates of β_n align closely with $\mathbb{E}[\theta_{int}]$, implying that, at least on average, constant portfolio shares is a reasonable way to model demand. We will use this feature in the asset demand model in the next sections.

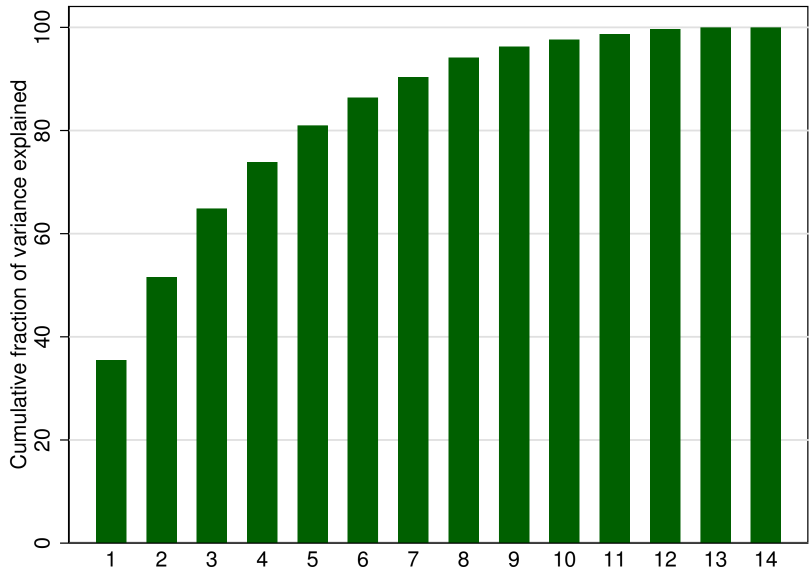
In the next step, we estimate the factor model based on the rebalancing flows, $f_{int}^{\perp}$. In Figure 13, we summarize the fraction of the variance in $f_{int}^{\perp}$ explained by the factors. As the figure makes clear, there are important common components and the first three factors explain about 65% of the variation in portfolio rebalancing.

We now explore the properties of those rebalancing factors. In Figure 14, we report the estimates of $\eta_n^{(k)}$ for the first three factors, which explain about 65% of the variation in $f_{int}^{\perp}$. As we discussed before, these loadings have the convenient property that $\sum_{n\in\mathcal{L}} \eta_n^{(k)} = 0$, which means that they can be interpreted as long-short (or dollar-neutral) trades.

The factors have a clear economic interpretation. The first factor rebalances from U.S. equities to long-duration fixed income, such as U.S. investment-grade corporate bonds, Treasuries and agencies, and municipal bonds. This factor therefore captures the long-term equity risk premium.

The second factor rebalances from U.S. investment grade bonds to U.S. Treasuries and agencies. This factor therefore captures the credit spread. The third factor is a combination of two

Figure 13: Factor structure in portfolio rebalancing
We plot the share of variance of $f_{int}^{\perp}$ explained by the principal components, see equation (5). The sample period is from 2016.Q1 to 2021.Q2.

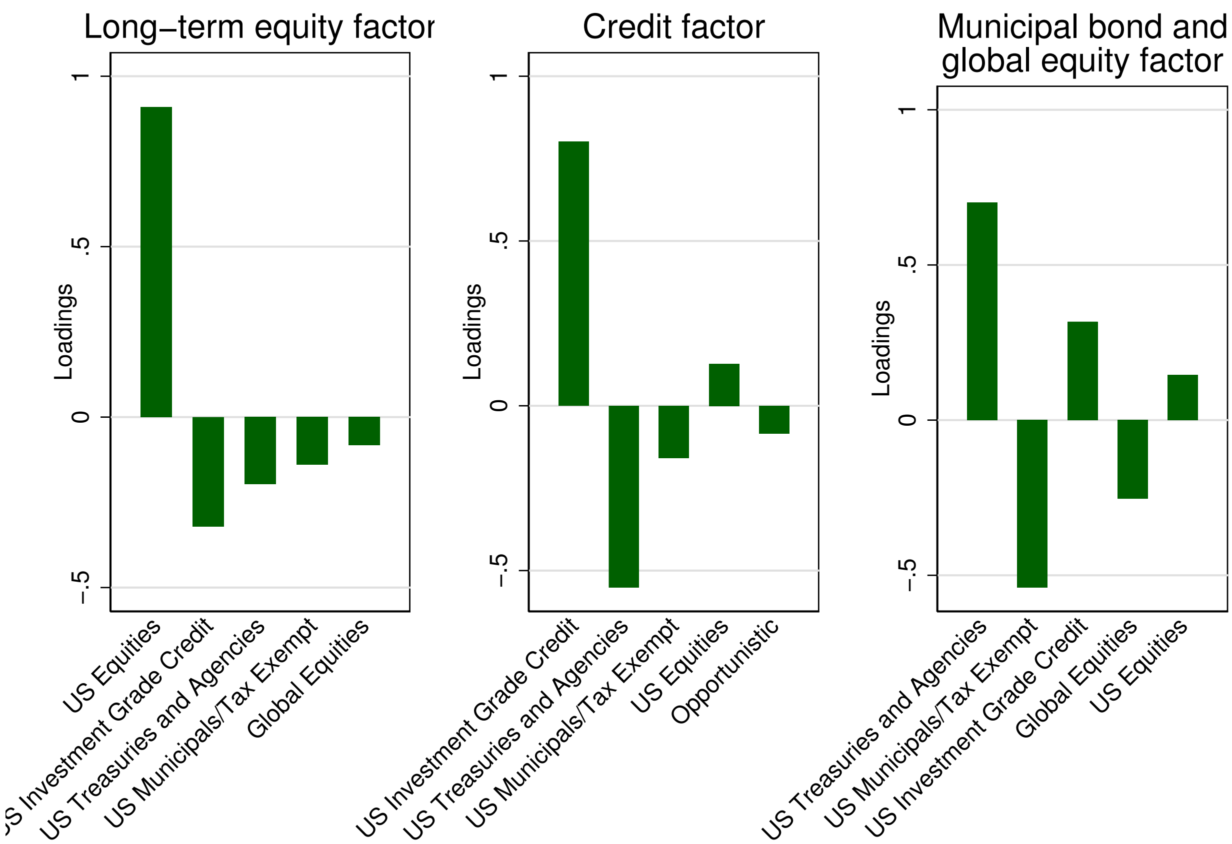


economically interpretable trades. The first rebalances from U.S. Treasuries and agencies and U.S. investment-grade corporate bonds to U.S. municipal and tax exempt bonds. We have seen before that municipal bonds play a nontrivial role in households' portfolios, in particular for wealthier investors. The second leg of this factor rebalances from global equities to U.S. equities. Hence, the third factor captures a combination of the risk premium in municipal debt markets relative to other safe fixed income markets and the risk premium on global equities relative to U.S. equities.

Taken together, this section provides three main insights. First, the flow to liquid risky assets (cash) is on average strongly positively (negatively) correlated with the return on the aggregate stock market. However, there is significant disagreement among households, and particularly during market downturns. Second, the sensitivity of liquid risky asset flows, and in particular the flow to liquid risky assets, declines with wealth. The wealth-weighted sensitivity is therefore closer to zero than the equal-weighted sensitivity. Third, there is a strong factor structure in rebalancing flows. The three main factors take bets on the long-term equity risk premium, the credit premium, and the premium associated with municipal bonds and global versus U.S. equities. These facts combined provide valuable important inputs into the design of macro-finance models with rich heterogeneity as well as for models with a representative household sector.

Figure 14: Rebalancing exposures across asset classes

We report the estimates of $\eta_n^{(k)}$, for $k = 1, 2, 3$, in equation (5). The coefficients capture the main rebalancing directions based on $f_{int}^{\perp}$. The sample period is from 2016.Q1 to 2021.Q2.



4 Asset demand estimation: Methodology

Section 3 provided descriptive evidence on the dynamics of flows across asset classes. Flows either reflect a response to prices (that is, changes along the demand curve) or shifts in the demand curve due to, for instance, changes in perceived risk or risk aversion. Our next goal is to separate those two effects. This is a nontrivial task as returns and demand shocks are plausibly correlated.

In this section, we provide a new way to estimate demand elasticities that can be applied at the level of individual securities, narrow asset classes, and broad asset classes. In Section 4.1, we provide a simple example to explain the methodology and then discuss the general methodology in Section 4.2 as well as potential applications in Section 4.3. We then extend the model in Section 4.4 to account for inertia in rebalancing. We emphasize that this part of the paper is more preliminary, and future versions of this paper will contain additional extensions and refinements.

4.1 An illustrative example

We start with a simple example to explain the main idea using the logit model of demand of Koijen and Yogo (2019).[13] In terms of data, we use a single quarter of portfolio holdings of a single investor, and we therefore omit subscripts i and t to simplify the exposition. Also, σ_x denotes the standard deviation of a random variable x, σ_{xy} denotes the covariance between random variables x and y, and $\sigma_{x/y}$ denotes the ratio of volatilities, $\sigma_{x/y} = \frac{\sigma_x}{\sigma_y}$.

The assets are split into inside assets, indexed by $a = 1, \ldots, A$, and an outside asset, indexed by $a = 0$.[14] For inside assets, demand is modeled as

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

where

$$\delta_a = c + \beta_0 m_a + \nu_a, \tag{6}$$

with m_a denoting log market cap and ν_a the demand shifter.[15] The model implies that we can directly observe δ_a as $\delta_a = \ln \frac{\theta_a}{\theta_0}$.

Our goal is to estimate β_0, which determines the price elasticity of demand,[16] but this parameter is not identified without further structure. After all,[17] based on information in second moments, we have three moments ($\sigma_{m\delta}$, σ_δ, and σ_m) but four parameters (β_0, σ_m, σ_ν, and $\sigma_{m\nu}$). The typical

[13]We refer to Koijen and Yogo (2019) for a micro-foundation of this demand curve.

[14]To fix ideas, one can think of the outside asset as cash.

[15]Koijen and Yogo (2019) model ν_a as a function of observable asset characteristics, $\nu_a = \beta_1' x_a + \epsilon_a$, where x_a are stock characteristics and ϵ_a latent demand. We discuss how to incorporate characteristics below.

[16]In the logit model of demand, the demand elasticity is approximately equal to $1 - \beta_0$, see Koijen and Yogo (2019) for further details.

[17]We ignore the constant c, which is identified and not of interest to us.

approach to asset demand estimation is to use instrumental variables that correlate with m_a but not with ν_a. By market clearing, variation in m_a that is unrelated to ν_a corresponds to demand shifters of other investors that are uncorrelated to ν_a.[18] The traditional approach to identify asset demand elasticities leverages this intuition by considering the inclusion of stocks into a broadly equity index (Harris and Gurel, 1986a; Shleifer, 1986). Then, the demand of index investors is used as an exogenous demand shifter that affects prices, and this can in turn be used to estimate the demand elasticity of investors unconstrained by the benchmark.

The demand shifter needs to affect a large group of investors to meaningfully move prices (instrument relevance). This is a challenge in our setting as we do not observe holdings of most investors for all the asset classes that we consider. This is a broader challenge in estimating asset demand, and we propose a methodology to estimate demand in those settings.

Our approach builds on the ideas in Rigobon (2003) to identify elasticities based on heteroskedasticity. Suppose we are interested in estimating the demand curve of investor i. Then changes in the volatility of valuations, holdings, and the covariance of holdings and valuations can be used to estimate demand. Intuitively, an instrument for price can be viewed as the limiting case where the volatility of other investors' demand shifters is nonzero, while the demand shifter of investor i has no volatility. We show that fluctuations in second moments can be used for this purpose as well when we do not have an instrument.

As a starting point, we assume that valuations and demand shifters are heteroskedastic,

$$\begin{aligned} m_a &= \sigma_{ma}\tilde{m}_a, \\ \nu_a &= \sigma_{\nu a}\tilde{\nu}_a, \end{aligned}$$

where $\sigma_{\tilde{m}} = \sigma_{\tilde{\nu}} = 1$. The heteroskedasticity is captured by σ_{ma} and $\sigma_{\nu a}$. We then project the (standardized) demand shocks on (standardized) valuations,

$$\tilde{\nu}_a = \rho\tilde{m}_a + \tilde{\nu}_a^{\perp}, \tag{7}$$

where $\mathbb{E}[\tilde{m}_a\tilde{\nu}_a^{\perp}] = 0$ and $\sigma_{\tilde{\nu}^{\perp}} = \sqrt{1-\rho^2}$. We discuss below how the linear dependence in (7) can be relaxed considerably in Section 4.2.

This structure suffices to estimate demand elasticities. To explain the simplest case, we first consider two groups of stocks that differ in their volatility of valuations, and generalize this below. We index the groups by $j = L, H$, corresponding to low and high volatility. We then have six moments ($\sigma^j_{m\delta}$, σ^j_{δ}, and σ^j_m for $j = L, H$) and six parameters (β_0, ρ, σ^j_m, and σ^j_{ν} for $j = L, H$), and the model is identified. Rather than simply matching moments and parameters, we derive

[18] The market clearing equation is given by $\sum_i A_i\theta_{ia} = M_a$, which implies that instruments generally require a shift in demand of a group of investors other than i to identify the demand elasticity of investor i.

the solution for β_0, which illustrates the economic intuition behind the estimator and also guides generalizations in the next section.

We substitute (7) in (6)

$$\delta_a = c + \psi^j m_a + \nu_a^{\perp}, \tag{8}$$

where $\nu_a^{\perp} = \sigma_\nu^j \tilde{\nu}_a^{\perp}$, implying $\sigma_{\nu^{\perp}}^j = \sigma_\nu^j \sqrt{1-\rho^2}$, and

$$\psi^j = \psi(\sigma_{\nu^{\perp}/m}^j) = \beta_0 + g(\rho)\sigma_{\nu^{\perp}/m}^j, \tag{9}$$

where $g(\rho) = \frac{\rho}{\sqrt{1-\rho^2}}$. Equation (8) is a regression model that allows us to estimate ψ^j and $\sigma_{\nu^{\perp}}^j$ for each group. We can also estimate σ_m^j for each group, implying that we can estimate $\sigma_{\nu^{\perp}/m}^j$. Equation (9) then provides two equations (one for each group j) in two unknowns, β_0 and $g(\rho)$, where $\psi(0) = \beta_0$.

The solution for β_0 clarifies the economic intuition behind the estimator. When regressing δ_a on m_a, the slope coefficient is a biased estimate of β_0 as valuations and demand shifters may be correlated. The second term in (9), $g(\rho)\sigma_{\nu/m}^j$, captures the bias and it would be zero if valuations and demand shifters are uncorrelated ($\rho = 0$). As it may be the case that $\rho \neq 0$, we can use the fact that the bias goes to zero also when $\sigma_{\nu/m} = \frac{\sigma_\nu}{\sigma_m} \to 0$. In the limit, when $\sigma_{\nu/m} = 0$, the volatility of demand shifters is zero while there is variation in valuations, which, by market clearing, is due to demand shifters of other investors. As can estimate ψ^j and $\sigma_{\nu/m}^j$, we can estimate their dependence and compute the limit $\lim_{\sigma_{\nu/m}\to 0} \psi(\sigma_{\nu/m})$ to estimate β_0.

Modeling demand in changes Before generalizing this, we note that all results in this section go through when estimating the model in changes instead of levels. Indeed, we can replace δ_{at} by $\Delta\delta_{at} = \delta_{at} - \delta_{a,t-1}$, m_{at} by r_{at},the return on stock a, and ν_{at} by $\Delta\nu_{at} = \nu_{at} - \nu_{a,t-1}$, and model the heteroskedasticity of returns and demand shocks instead of valuations and demand shifters.

Multiple groups We conclude this section by discussing how we can use multiple regimes, $j = 1, \ldots, J$. In this case, (8) remains the same and we estimate it for every group. With multiple groups, however, we can generalize (9) to

$$\psi^j = \beta_0 + f(\sigma_{\nu^{\perp}/m}^j),$$

by allowing a more flexible relation between demand shocks and valuations in (7), which is the main economic restriction. It is an assumption about the dependence of investors' demand shocks and returns. The main identifying assumption is that

$$f(\sigma_{\nu^{\perp}/m}) \to 0,$$

when $\sigma_{\nu^\perp/m} \to 0$. Intuitively, the assumption is that when the residual latent demand goes to zero, the volatility of investors' demand shocks goes to zero as well, and there is no endogeneity bias. Instead of having a perfect instrument, we can use variation in $\sigma_{\nu^\perp/m}$ to estimate how the bias varies as the volatility ratio changes, and extrapolate from those estimates to the case where $\sigma_{\nu^\perp/m} \to 0$.

Weak instruments When using instrumental variables to estimate demand elasticities, a common concern is that the instruments are sufficiently strong. While we do not use instruments, we briefly discuss what it takes for the estimates to be precise. As the earlier discussion makes clear, we are interested in estimating $\psi(\sigma_{\nu^\perp/m}) = \beta_0 + f(\sigma_{\nu^\perp/m})$ and, given those estimates, $\lim_{\sigma_{\nu^\perp/m} \to 0} \psi(\sigma_{\nu^\perp/m}) = \beta_0$. If we consider the basic linear case, this is a regression of ψ on $\sigma_{\nu^\perp/m}$ across groups, which can be estimated precisely when $\sigma_{\nu^\perp/m}$ has sufficient variation. This logic extends to the general case.

4.2 The general case with characteristics

So far, we have formed J groups of stocks, for instance, ten deciles of stocks sorted by a certain characteristic. We now extend the basic idea to avoid grouping stocks based on a single characteristic, and use all characteristics instead. This is the procedure we implement in Section 5.1 to compare this new methodology to the IV estimator in Koijen and Yogo (2019).

We denote a stock's characteristics by x_a. We then model the dependence of log market cap on characteristics as $m_a = \beta_m' x_a + m_a^x$. We model the demand as

$$\delta_a = c + \beta_0 m_a + \beta_1' x_a + \nu_a. \tag{10}$$

We also define the OLS regression coefficient ψ_a and the residuals $\nu_a^\perp$ obtained by regressing δ_a on (m_a, x_a) in (10). The generalized model of second moments is then

$$\sigma_{ma} = \exp(\gamma_m' x_a),$$
$$\sigma_{\nu^\perp a} = \exp(\gamma_\epsilon' x_a).$$

The main assumption is then that in

$$\psi_a = \beta_0 + f(\sigma_{\nu^\perp ma}),$$

it holds that $f(\sigma_{\nu^\perp ma}) \to 0$ as $\sigma_{\nu^\perp ma} \to 0$. In the simplest case, f is linear. The core insight remains, however, that as the volatility of demand shocks goes to zero, the demand elasticity can be identified from the intercept of a regression of ψ_a on $\sigma_{\nu^\perp ma}$, where the regression can be nonlinear and potentially puts more weight on observations for which $\sigma_{\nu^\perp ma}$ is small.

Concretely, we implement the following procedure:

1. Regress δ_a on log market capitalization, m_a, characteristics, x_a, and the interaction of m_a and x_a. We collect the residuals, $e_{\nu^\perp a}$.

2. Regress m_a on characteristics and collect the residuals, e_{ma}.

3. Estimate the volatility models

$$\ln\left((e_{\nu^\perp a})^2\right) = \gamma_{\nu^\perp 0} + \gamma'_{\nu^\perp} x_a + u_{\nu^\perp a},$$
$$\ln\left(e_{ma}^2\right) = \gamma_{m0} + \gamma'_m x_a + u_{ma}.$$

4. We form the estimate proportional to the volatility ratio, $\sigma^2_{\nu^\perp ma} = \exp(\gamma_{\epsilon 0} - \gamma_{m0} + (\gamma_\epsilon - \gamma_m)' x_a)$.

5. In the simplest linear case, we regress

$$\delta_a = c + (\beta_0 + \lambda \sigma_{\nu^\perp ma}) m_a + \beta'_1 x_a + \epsilon_a.$$

We provide a formal analysis of the sufficient conditions for this procedure to recover β_0 in Appendix B.

4.3 Potential applications

We briefly summarize three potential applications of our new estimator of demand elasticities. In each case, we specify the way we form the J groups and the assumption we make about elasticities. These are just examples to illustrate the flexibility of this approach, and the list is by no means exhaustive.

Stock-level elasticities that are constant across stocks A first example is (as discussed throughout this section so far) to form J groups based on a stock characteristic (such as a stock's CAPM beta). For instance, we form deciles based on this characteristic and estimate σ^j_m, ψ^j, and $\sigma^j_{\nu^*}$ for each of the groups, $j = 1, \ldots, 10$. This provides an alternative approach to estimating the model in Koijen and Yogo (2019). We directly compare the sets of estimates in Section 5.1.

Stock-level elasticities that are constant across time The elasticity estimates in the literature are fairly stable over time. However, the results in Haddad et al. (2022) suggest that elasticities may vary across stocks and they show, for instance, that demand elasticities may decline in stocks' market capitalization. In this case, β_0 varies across stocks, β_{0a}. We can estimate this dependence by forming J groups across time periods. For instance, we can estimate σ^j_m, ψ^j, and $\sigma^j_{\nu^*}$ for small-cap stocks in J consecutive quarters and use the variation across quarters to estimate the elasticity for small-cap stocks. We can then repeat this exercise for mid- and large-cap stocks.

Asset-class level elasticities In the third example, we consider the case in which we estimate the model in changes at the level of asset classes. In this case, we can take advantage of the fact that asset-class returns are heterogeneous across investors as they are under-diversified and do not form strict value-weighted portfolios. In this case, we have r_{int} for investor i, asset class n, and period t. We then form J groups across quarters for a given asset class. The central assumption is that elasticities are constant for investors with the same characteristics, such as wealth or the degree of diversification. In this case, we estimate σ_m^j, ψ^j, and $\sigma_{\nu^*}^j$ across investors for a given asset class and quarter using variation in returns and rebalancing across investors in that asset class and quarter. The second step is then the same as before. We implement this procedure in Section 5.2.

4.4 Extension to inertia

We conclude this section by discussing how the model can be extended to account for inertia. We refer to δ_{at}^v as the "virtual demand" of a non-inertial fund and model it as in (6),

$$\delta_{at}^v = c_t + \beta_0 m_{at} + \nu_{at}.$$

If investors do not rebalance, the passive change in demand is given by $\delta_{at}^p = \delta_{a,t-1} + r_{at} - r_{pt}$, where $r_{pt} = \sum_a \theta_{a,t-1} r_{at}$.

We then model actual demand as

$$\delta_{at} = (1-\phi)\,\delta_{at}^p + \phi\delta_{at}^\nu,$$

where ϕ is the speed of mean-reversion to the virtual demand. The model implies

$$\delta_{at} = \hat{c}_t + (1-\phi)\,(\delta_{a,t-1} + r_{at}) + \phi(\beta_0 m_{at} + \nu_{at}),$$

where $\hat{c}_t = \phi c_t - (1-\phi)\,r_{pt}$. In changes, we have

$$\Delta\delta_{at} = \Delta\hat{c}_t + (1-\phi)\,(\Delta\delta_{a,t-1} - r_{a,t-1}) + (\phi\beta_0 + 1 - \phi) r_{at} + \phi\Delta\nu_{at}.$$

If we assume $\Delta\nu_{at}$ is i.i.d. over time, we can regress $\Delta\delta_{at}$ on $\Delta\delta_{a,t-1} - r_{a,t-1}$ and r_{at} for J groups, assuming the same structure as before for $\Delta\nu_{at}$. This allows to estimate $1-\phi$ and $\phi\beta_0+1-\phi$, hence ϕ and β_0. The short-run elasticity is approximately equal to $\phi(1-\beta_0)$ and the long-run elasticity is approximately equal to $1-\beta_0$.

5 Asset demand estimation: Empirical results

We are now ready to estimate the demand system across asset classes. First, as a warm up and validity check, in Section 5.1 we use our new methodology to estimate the elasticity of demand for individual stocks. We compare it to the estimates in Koijen and Yogo (2019), who use a very different methodology that relies on an instrument variables approach. Despite the large methodological differences, we find that the estimates are strongly positively correlated. This analysis gives an external validation of the new methodology we introduce in this paper.

Given this, we proceed in Section 5.2 to our main goal, we estimate asset-class level demand elasticities using the Addepar data.

5.1 The asset demand of large institutions across U.S. equities

We start from the definition

$$\delta_{iat} = \ln \frac{\theta_{iat}}{\theta_{i0t}} = c_{it} + \beta_{0it} m_{at} + \beta_{1it}' x_{at} + \nu_{iat}.$$

We focus on the large asset managers that are not pooled in KY19. The characteristics are market beta, profitability, log book equity, dividends-to-assets, and asset growth. For each manager in a given quarter, we implement the procedure outlined in Section 4.2.

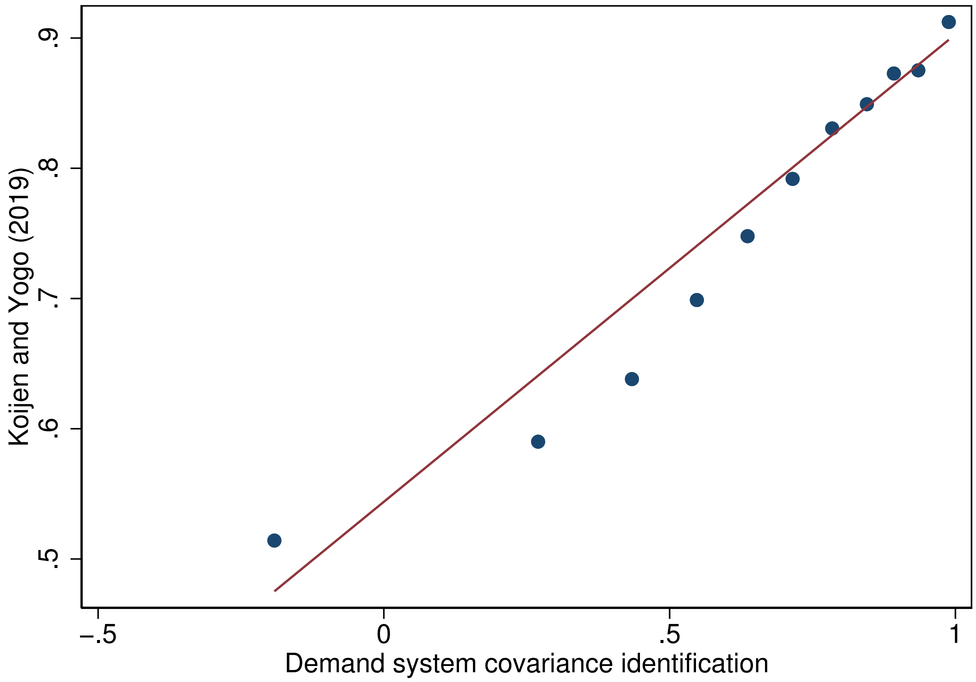
This results in an estimate of β_{0it}. In the logit model of demand, the elasticity is then (approximately) given by $1 - \beta_{0it}$.[19] We implement the procedure for every quarter from 1980.Q1-2017.Q4. The average (standard deviation) of the estimates across managers and quarters in KY19 is 0.83 (0.26). If we use our new approach, we find an average (standard deviation) of the estimates of 0.79 (0.32). The correlation between the estimates (across all investors and quarters) is 44.4%. In Figure 15, we plot the bin-scatter, which illustrates that the estimates from both procedures are quite correlated.

5.2 The asset demand of households across asset classes

We now return to the Addepar data and model the demand across five major asset classes (U.S. Equities, Global Equities, U.S. Treasuries and Agencies, Municipal and Tax-exempt Bonds, and U.S. Investment Grade Bonds) as well as cash. We discuss the model, the estimation strategy, sample selection, and empirical results.

[19]We impose $\beta_{0it}^c = \min(\beta_{0it}, 1)$ to avoid that individual demand curves slope up, which is also imposed in Koijen and Yogo (2019).

Figure 15: Comparison of estimates



5.2.1 Asset demand model

We model the demand for a given asset class as the product of two portfolio shares

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

where θ_{ict} is the fraction invested in cash relative to cash plus liquid risky assets (based on the five asset classes) and $\tilde{\theta}_{int}$ is the allocation to asset class n within the portfolio of liquid risky assets, with $\sum_{n=1}^{5} \tilde{\theta}_{int} = 1$. We split the allocation decision in two parts to allow for a different elasticity of substitution between the risky assets and cash, and between the five risky asset classes. As discussed in Section 3.1 (and in particular in Figures 8 and 11), cash and risky liquid assets are strongly negatively correlated.

We discuss the model for liquid risky assets, and the model of cash versus risky assets works analogously. We model

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

where

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

We write the model in changes to be consistent with Section 3.1, which implies that for any two risky asset classes n and m

$$\begin{aligned}\Delta \ln \frac{\tilde{\theta}_{int}}{\tilde{\theta}_{imt}} &= \Delta\delta_{int} - \Delta\delta_{imt} \\ &= \beta_{0in} r_{int} - \beta_{0im} r_{imt} + \Delta\nu_{int} - \Delta\nu_{imt}.\end{aligned}$$

We note that $\frac{A_{int}}{A_{in,t-1}} = 1 + r_{int} + \frac{F_{int}}{A_{in,t-1}}$ and $\Delta\delta_{int} - \Delta\delta_{imt} = \ln\frac{A_{int}}{A_{in,t-1}} - \ln\frac{A_{imt}}{A_{im,t-1}} \simeq \frac{F_{int}}{A_{in,t-1}} - \frac{F_{imt}}{A_{im,t-1}} + r_{int} - r_{imt}$. We define $\zeta_{0in} = 1 - \beta_{0in}$, which is the key input to computing the demand elasticity. Demand curves slope down when $\zeta_{0in} > 0$. Combining these results implies

$$f_{inmt} = -\zeta_{0in} r_{int} + \zeta_{0im} r_{imt} + \Delta\nu_{inmt},$$

where $f_{inmt} \equiv \frac{F_{int}}{A_{in,t-1}} - \frac{F_{imt}}{A_{im,t-1}}$ is the relative flow and $\Delta\nu_{inmt} \equiv \Delta\nu_{int} - \Delta\nu_{imt}$ the relative demand shock.

A similar logic leads to the following model that describes allocation between liquid risky assets and cash

$$f_{ilt} - f_{ict} = -\zeta_{0il} r_{ilt} + \Delta\nu_{ilct}, \tag{11}$$

where f_{ilt} is the flow to risky assets (relative to the holdings of liquid risky assets), f_{ict} is the flow to cash (relative to cash holdings in the previous period), r_{ilt} is the (value-weighted) portfolio return on liquid risky assets, and $\Delta\nu_{ilct}$ is the relative demand shock. We do not include the return on cash as it would capture a (slow-moving) reaching-for-yield effect, which is hard to identify in our short sample. This may change, however, if the rapid increase in interest rates continues.

5.2.2 Estimation strategy

We start from the model of demand for risky assets. To allow for heterogeneity in elasticities across households, we estimate the model separately for five different groups of households. To assign households to groups, we compute, for each investor i, the percentile rank of $|f_{int}|$ per quarter and asset class, and subsequently average these ranks across all quarters and asset classes for a given investor. Using the resulting measure of investor activeness, we form five groups and we run the estimation separately on each of them.

We estimate the parameters using heteroskedasticity across time periods. As in Figure 10, investor disagreement varies with equity returns. We therefore use dispersion in equity returns across investors in a given quarter to classify quarters into two regimes. For each regime and group of investors, we then estimate

$$f_{inmt} = -\psi_{nt} r_{int} + \psi_{mt} r_{imt} + \sigma_{\nu nmt} \Delta\tilde{\nu}^{\perp}_{inmt},$$

where

$$\psi_{nt} = -\zeta_n + \lambda_n \sigma_{\nu^{\perp}_{nm}/r_n t},$$
$$\psi_{mt} = -\zeta_m + \lambda_m \sigma_{\nu^{\perp}_{nm}/r_m t},$$

and where we omitted the dependence of estimated parameters on the specific group of investors to simplify notation. We index the regimes by 0 and 1, and we estimate $(\psi_{nj}, \psi_{mj}, \sigma_{r_n j}, \sigma_{r_m j}, \sigma_{\nu^{\perp}_{nm} j})$, for $j = 0, 1$. For each group of investors, the solution for the elasticities is then given by

$$\zeta_n = \psi_{n0} - \frac{\psi_{n1} - \psi_{n0}}{\sigma_{\nu^{\perp}_{nm}/r_n 1} - \sigma_{\nu^{\perp}_{nm}/r_n 0}} \sigma_{\nu^{\perp}_{nm}/r_n 0},$$
$$\zeta_m = \psi_{m0} - \frac{\psi_{m1} - \psi_{m0}}{\sigma_{\nu^{\perp}_{nm}/r_m 1} - \sigma_{\nu^{\perp}_{nm}/r_m 0}} \sigma_{\nu^{\perp}_{nm}/r_m 0}.$$

In future versions, we extend this approach to multiple volatility regimes. We follow the same procedure for estimating the allocation between cash and liquid risky assets, except that we only estimate a single elasticity, see (11).

5.2.3 Empirical results

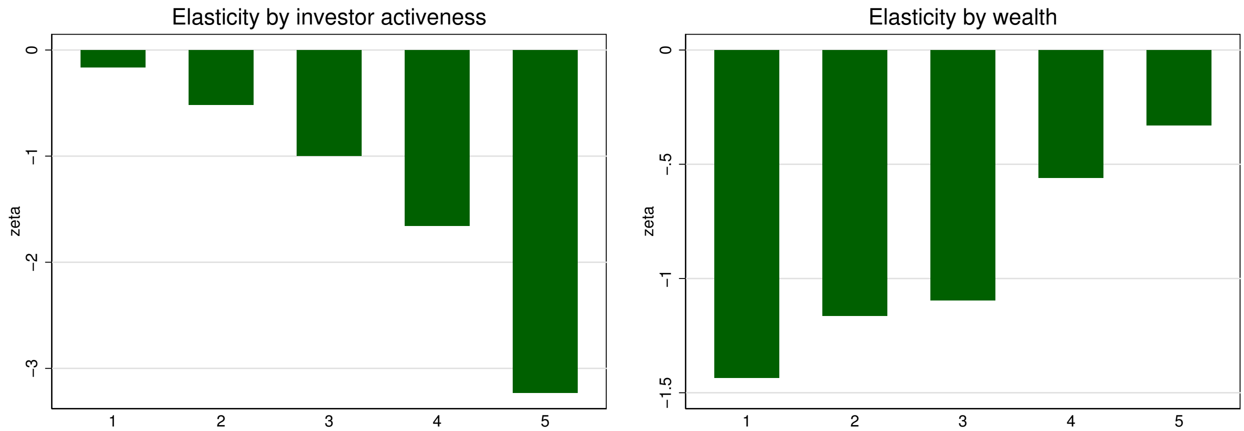
We present our preliminary results in this section. We emphasize that these estimates may change as we extend and refine the methodology.[20]

Allocation between cash and risky assets In Figure 16, we plot the estimates of ζ_{il} for five groups based on rebalancing activity (left panel) and by wealth group (right panel). The estimates reveal three insights. First, the elasticity estimates are generally small, in line with the literature on asset demand estimation. Second, there is significant heterogeneity across investors, which is well captured by typically rebalancing activity (left panel) and even by wealth group (right panel). Third, the estimates are not just small but also slightly negative, consistent with positive feedback trading. This clarifies how to interpret the results in Figure 11, which could be consistent with $\zeta_{il} < 0$ or correlated demand shocks. The estimates in Figure 16 are consistent with the former interpretation.

Allocation across liquid risky asset classes In Figure 17, we plot the elasticities across asset classes for investor groups formed by activeness. As in Figure 16, we find that the elasticity estimates are generally low, and there is substantial heterogeneity across groups of households (except for municipal bonds). For global equities, U.S. equities, and Treasuries, demand is more elastic for

[20] In estimating the models in this section, we impose that there are at least 3 years of data for a given asset class and investor and that the investor is active in at least two asset classes of which one is US equities.

Figure 16: Elasticity estimates for the allocation between cash and liquid risky assets



more active investors. The opposite is true for investment-grade corporate bonds–or rather, it is more negative for more active investors. The demand for municipal bonds is inelastic for all groups, perhaps reflecting the fact that those bonds offer other advantages to investors given their tax-exempt status (Babina et al., 2021).

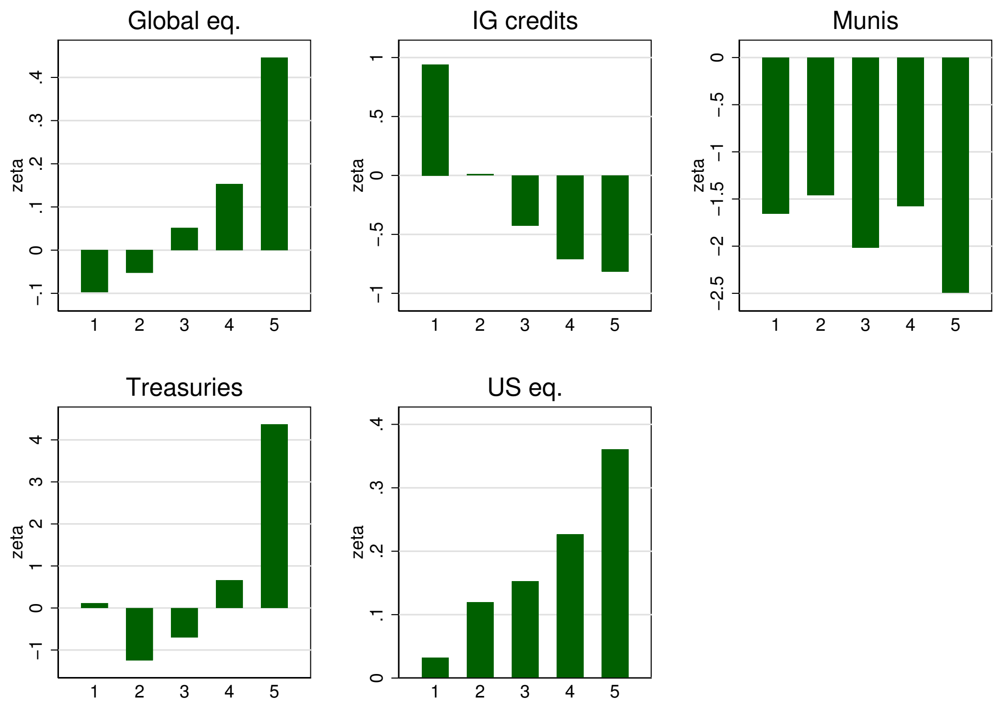
6 Conclusion

We use new monthly security-level data on portfolio holdings, flows, and returns of U.S. households to estimate asset demand across asset classes and individual assets. Our data feature broad coverage across the wealth distribution – including ultra-high-net-worth (UHNW) households – and spans multiple asset classes, covering both public and private assets.

Our data have two important advantages. First, we have data on UHNW individuals, with well over a thousand households who own more than $100 million in assets. This group of households that may be relevant for asset prices is typically under-represented in other data sources. The broad coverage across the wealth distribution also allows us to extrapolate our estimates to construct demand curves for the "representative U.S. household." Second, we have broad coverage across asset classes and at high frequencies. The assets classes covered in the data include public and private assets and are all disaggregated to security-level data. Such a broad perspective is not even available for most U.S. institutions.

We provide four main contributions. First, we provide two methodological contributions to analyze flows and asset demand across broad asset classes. In the first, we develop a descriptive factor model for flows to measure (i) how investors allocate capital to cash and to all risky asset classes combined and (ii) how investors reallocate capital across risky asset classes. In the second, we develop a new methodology to identify and estimate demand curves across asset classes. This approach relies on restrictions on the time variation in the covariance matrix of flows and returns,

Figure 17: Elasticity estimates for the allocation across liquid risky assets



and can be applied in many settings where broad coverage of holdings is unavailable.

Second, our empirical results show that the flow to risky assets (and particularly equities) is pro-cyclical for less wealthy households (assets below \$3 million) and counter-cyclical for wealthy households (assets above \$10 million and in particular above \$100 million). Wealthy households therefore stabilize fluctuations in risky asset markets, while less wealthy households contribute to markets' excess volatility. Due to the skewness in the wealth distribution, the value-weighted average correlation between flows and returns for U.S. equities is negative for the representative household in our sample.

Third, the factor model identifies three key rebalancing factors that are economically meaningful. These factors present bets on the long-term equity premium, the credit premium, the municipal bond premium, and the premium on U.S. equities versus global equities.

Fourth, our preliminary results indicate that asset demand elasticities are smaller than those implied by standard theories, vary significantly across the wealth distribution, and are negative for various groups of investors, pointing to positive feedback trading.

In future iterations of this paper, we plan to extend the demand model to account for inertia, and hence have a more complete dynamic description of the asset demand of U.S. households.

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Appendix

A Literature review

In Table A1, we summarize related literature on portfolio choice decisions by households.

Table A1: **Summary of Literature on Household Portfolio Choice**

Source	Data Source	Coverage	Asset Classes	Key Questions
Heaton and Lucas (2000)	Survey of Consumer Finances	U.S. (1989-1995)	Various	Determinants of household portfolio choice with a particular focus on the role of entrepreneurial income risk
Barber and Odean (2000)	Brokerage firm	U.S. (1991-1996)	Equity	Trading frequency and portfolio tilts of households
Giglio et al. (2021)	Survey to Vanguard Clients	U.S. (2017-2020)	Equity	Relationship between investor beliefs and portfolios, focusing on the pass-through of beliefs and their formation
Bender et al. (2022)	Survey through UBS	U.S. (March 2018)	Various	Determinants of investment decisions of high net-worth individuals
Cole et al. (2022)	Financial Institution	U.S. (2015-2017)	Various	Portfolio choice and retirement contributions over the investor life cycle
Hoopes et al. (2016)	IRS	U.S. (2008-2009)	Equity	Trading behavior during market distress
Balloch and Richers (2021)	Addepar	U.S. (2016-2020)	Various	Heterogeneity in asset allocation and returns by wealth
Egan et al. (2021)	BrightScope Beacon	U.S. (2009-2019)	Various	Determinants of 401(k) allocations, focusing on risk aversion and beliefs
Fagereng et al. (2020)	Norwegian administrative data	Norway (2004-2015)	Various	Return heterogeneity by wealth
Betermier et al. (2022)	Norwegian administrative data	Norway (1996-2017)	Equity	Relation between individual portfolios and cross-sectional equity returns
Calvet et al. (2007)	Swedish Wealth and Income Registry	Sweden (1999-2002)	Various	Efficiency of household investment decisions focusing on under-diversification and non-participation
Calvet et al. (2009)	Swedish Wealth and Income Registry	Sweden (1999-2002)	Various	Determinants of portfolio rebalancing and participation in risky financial markets
Calvet et al. (2021)	Swedish Wealth and Income Registry	Sweden (1999-2007)	Various	Distribution of preference parameters across households
Massa and Simonov (2006)	Longitudinal Individual Data for Sweden	Sweden (1995-2000)	Various	Portfolio allocation to hedge non-financial income
Grinblatt and Keloharju (2000)	Finnish Central Securities Depository	Finland (1994-1996)	Equity	Role of past returns in driving investor behavior
Grinblatt et al. (2021)	Finnish Central Securities Depository	Finland (1995-2002)	Equity	Determinants of stock market participation
Anagol et al. (2015)	Indian National Securities Depository	India (2007-2012)	Equity	Effect of investment experiences on future investment behavior
Campbell et al. (2014)	Indian National Securities Depository	India (2004-2012)	Equity	Effect of investment experiences on future investment behavior
Campbell et al. (2019)	Indian National Securities Depository	India (2002-2011)	Equity	Relationship between return heterogeneity and equity wealth inequality
Balasubramaniam et al. (2021)	Indian National Securities Depository	India (2011)	Equity	Determinants of direct stock holdings

This table summarizes the literature on household portfolio choice that is relevant for our work. For each source, we report the data source, the coverage (sample, location, and timeline), the main asset classes of interest, and key research questions addressed in the work.

B Identification of demand elasticities via heterogeneous demand volatilities: A formal result

Suppose that the true model is

$$\delta_{ia} = \beta_{0ia} m_a + \nu_{ia} \tag{12}$$

with potentially ν_{ia} correlated with m_a. In practice, we add control x_a, so that m_a should be understood as the book to market ratio of a stock, or (in a dynamic settings) its return. But for simplicity of exposition, and concentrate on the key identification issue, we omit here the controls x_a.

By orthogonalization, we define

$$\psi_{ia} = \beta_{0ia} + \frac{cov\left(\nu_{ia}, m_a\right)}{var\left(m_a\right)} \tag{13}$$

where $\frac{cov(\nu_{ia},m_a)}{var(m_a)}$ is a nuisance term. We have $\delta_a = \psi_{ia} m_a + \nu_{ia}^{\perp}$, with

$$\psi_{ia} = \bar{\psi}\left(x_{ia}\right) + \varepsilon_{ia}^{\psi} \tag{14}$$

where $\mathbb{E}\left[\varepsilon_{ia}^{\psi}\right] = 0$.

We assume that:

$$\left|\frac{cov\left(\nu_{ia}, m_a\right)}{var\left(m_a\right)}\right| \leq M \sigma_{\nu_{ia}^{\perp}} \tag{15}$$

for some finite constant M: when the idiosyncratic demand shocks are small, then true demand shocks are small. This is a very weak condition. One sufficient condition for that is that $corr\left(\nu_{ia}, m_a\right)^2 \leq \rho^2$ with some $\rho^2 < 1$.

We also assume:

$$\mathbb{E}\left[\left(\varepsilon_{ia}^{\psi} m_a\right)^2\right] \leq K \sigma_{\nu_{ia}^{\perp}}^2 \tag{16}$$

for some finite constant K. So, when the idiosyncratic demand shock is small, then the error is small.

Those two conditions hold in a number of micro-founded models. However, condition (16) would not hold if a class of investor could be randomly "sleepy", in the sense that for some classes of investors or stocks, $\sigma_{\nu_{ia}}^2$ could be low and the elasticity of demand ζ_{ia} would go to 0. The condition assume that even when idiosyncratic demand is low, investor still provides elasticity to the system (in practice, perhaps with a lag, something we can explore in the extension to inertial investors).

Then, we can estimate the system in two steps

1. We run

$$\delta_{ia} = \psi^{e}\left(x_{ia}, \gamma^{\psi}\right) m_a + \nu_{ia}^{\perp e} \tag{17}$$

where $\psi^e\left(x_{ia}, \gamma^\psi\right)$ is some parametrization of the inclusive elasticity, e.g. $\psi^e\left(x_{ia}\right) = \gamma^{\psi\prime} x_{ia}$.

2. We estimate σ_{m_a} and $\sigma_{\nu_{ia}^{\perp e}}$, for instance as:

$$\sigma_{m_a}^2 = e^{\gamma^r x_a}, \qquad \sigma_{\nu_{ia}^{\perp e}}^2 = e^{\gamma_i^{\nu e} x_a} \tag{18}$$

3. Then, we run (perhaps restricting ourselves to the subsample with small values of $\frac{\sigma_{\nu_{ia}^{\perp}}}{\sigma_{m_a}}$)

$$\delta_{ia} = \left(\beta_0\left(x_{ia}, \gamma^\zeta\right) + b\frac{\sigma_{\nu_{ia}^{\perp e}}}{\sigma_{m_a}}\right) m_a + \varepsilon_{ia} \tag{19}$$

where again γ^ζ is some parameterization, e.g. $\zeta^e\left(x_{ia}, \gamma^\zeta\right) = \gamma^{\zeta\prime} x_{ia}$, and b is a regression coefficient.[21]

The next proposition states that then $\zeta^e\left(x_{ia}, \gamma^\zeta\right)$ is a consistent estimate of the elasticity of demand. The average elasticity is the average one over the values of x_{ia}.[22]

Proposition 1. *Suppose that we have the number of assets, or investors, going to infinity. As we condition to smaller values of* $\frac{\sigma_{\nu_{ia}^{\perp}}}{\sigma_{m_a}}$*, the above procedure yields a consistent estimate of the elasticity* $\bar{\beta}_0\left(x_{ia}\right)$.

Proof. For a very large cross-section (in a or i), Step 1 yields the average $\bar{\psi}\left(x_{ia}\right)$

$$\psi^e\left(x_{ia}, \gamma^\psi\right) = \bar{\psi}\left(x_{ia}\right)$$

so the residual of the regression is not quite the ideal value $\nu_{ia}^{\perp}$, but it is a bit polluted by the unmeasured ε_{ia}^{ψ} from (14):

$$\nu_{ia}^{\perp e} = \nu_{ia}^{\perp} + \varepsilon_{ia}^{\psi} m_a \tag{22}$$

But this discrepancy is small: indeed, we have

$$var\left(\nu_{ia}^{\perp e}\right) = var\left(\nu_{ia}^{\perp}\right)\left(1 + k_{ia}\right)$$

[21] It could be interact with x_{ia},if one wishes to, but this is not necessary for identification.

[22] One could also run

$$q_{ia} = -\left(\bar{\zeta}^e + b\frac{\sigma_{\nu_{ia}^{\perp e}}}{\sigma_{m_a}}\right) m_a + \varepsilon_{ia} \tag{20}$$

but this is less efficient. Indeed, suppose a model

$$y_{ia} = \alpha + m x_{ia} + b\frac{\sigma_{\nu_{ia}^{\perp e}}}{\sigma_{m_a}} + \varepsilon_{ia} \tag{21}$$

and we wish to estimate $\mathbb{E}\left[\alpha + m x_{ia}\right]$. Then, it's more efficient to control for x_{ia} in the regression.

with, by (16),

$$0 \leq k_{ia} \leq K \tag{23}$$

Hence, a small value of the variance of the measured residual $\nu_{ia}^{\perp e}$ implies a small value of the true residual, $\nu_{ia}^{\perp}$. So, conditioning on $var\left(\nu_{ia}^{\perp e}\right) \to 0$ implies conditioning on $var\left(\nu_{ia}^{\perp}\right) \to 0$. Now, when $var\left(\nu_{ia}^{\perp}\right) \to 0$,then the bias (13) goes to 0, because of (15).

Let us analyze (19), in the regime $var\left(\nu_{ia}^{\perp e}\right) \to 0$, which implies $var\left(\nu_{ia}^{\perp}\right) \to 0$. Even if we ran

$$\delta_{ia} = \beta_0^e\left(x_{ia}, \gamma^{\zeta}\right) m_a + \varepsilon_{ia} \tag{24}$$

(with no term $b\frac{\sigma_{\nu_{ia}^{\perp e}}}{\sigma_{r_a}}$) we could get a consistent estimate $\beta_0^e\left(x_{ia}, \gamma^{\zeta}\right) = \mathbb{E}\left[\beta_{0ia}^e | x_{ia}\right]$. The fact that we control for $\frac{\sigma_{\nu_{ia}^{\perp e}}}{\sigma_{m_a}}$ in (19) simply adds some precision.

□

Online Appendix

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A Additional Details on Addepar Data

A.1 Data Structure

We have monthly data at security level on positions held and returns gained by individual investor accounts.

A.1.1 Variables

There are five classes of variables: (i) portfolio and security identifiers, (ii) firm identifiers, (iii) asset class and investment identifiers, (iv) holdings, flows and returns, and (v) variables related to other data sources. We next describe each in detail.

Portfolio and Security Identifiers We observe a unique identifier *portfolio_entity_id* for each account held by investors in our dataset. For securities held by investors, we observe four main identifiers. The first identifier *position_entity_id* is internally generated by Addepar and uniquely identifies a security. While *position_entity_id* is available for any security in the dataset, it is also complemented by CU.S.IP, ISIN and Sedol for securities for which these additional identifiers are available.

Firm Identifiers While we do not observe a unique identifier for firms/advisors, we observe a detail classification of firms based on the nature of their activities. From *firm_vertical*, any firm is first classified as Advisor, Broker Dealer, Consolidators, Family Office, Institutional, Other. Each broad classification in *firm_vertical* is further broken down into *firm_sub_vertical,* the details of which are summarized in Table A2.

Asset Class and Investment Identifiers The dataset spans a variety of asset classes. For each security, we observe the asset class entered by custodians/advisors in *input_asset_class*. Depending on the position, this input can be entered either manually or chosen from a precompiled list. *input_asset_class* is then processed internally by Addepar and rearranged into two additional classifications. The first one is *output_asset_class* which classifies any security in a broad asset class (e.g. Equities, Fixed Income). The second one is *sub_asset_class* that, for each broad asset class (e.g.

Table A2: **Firm Classification**

Category	Type
Advisor	Hybrid Registered Investment Advisor (Hybrid RIA), Independent Registered Investment Advisor (Independent RIA)
Broker Dealer	B/D Advisor, Bank Trust, National and Regional B/D, Private Bank, Wirehouse
Consolidators	Strategic Acquirer, Other
Family Office	Multi-Family Office, Single Family Office
Institutional	Foundation, Hedge Fund, Outsourced Chief Investment Officer (OCIO), Pension
Other	Fund Administrator, Software/Service Provider

Equities), classifies any security within a narrower asset class (e.g. U.S. Equities, Global Equities). Separately from asset classes, we observe the type of investment associated to each position held by each investor. A broad classification is reported in investment_type. Within each broad classification in *investment_type*, we observe a narrower classification in *investment_sub_type*. Importantly, neither investment_type nor *investment_sub_type* are subsets of *sub_asset_class*. Indeed, two positions may have different sub_asset_class but same *investment_sub_type*.

Holdings, Flows, and Returns We also observe monthly holdings, flows, and returns for each position held by each investor. For each position, we observe dollar holdings at the beginning of the month in *starting_valu*e while dollar holdings at month-end are reported in *ending_value*. We observe a synthetic measure of monthly dollar flows in *net_cashflow* as well as the break down of *net_cashflow* into *buys* and *sells*. For specific asset classes, we separately observe measures of investment commitments made by the investors, contributions and distributions (*total_commitments_since_inception, total_commitments, total_contributions, unfunded_commitments, fund_distributions_and_dividends).* Turning to return measures, for each position held by each investor we observe monthly time-weighted return *twr*, internal rate of return *irr*, and dollar return *total_return*. We further observe the breakdown of gains into realized and unrealized, where unrealized gains refer to unsold positions.

Variables Related to Other Sources The dataset further includes variables from alternative data sources. From Preqin, we observe *preqin_id, vintage*, *strategy* and *substrategy*. All variables are also included in the Preqin manual where *preqin_id* is called *FUND ID*, *vintage* is called *VINTAGE / INCEPTION YEAR*, *strategy* is called *ASSET CLASS* and *sub_strategy* is called *STRATEGY*. Using *preqin_id* we can then merge all information in the Preqin manual into the main dataset. From Morningstar, we observe *morningstar_asset_class*, *morningstar_us_asset_class*, *morningstar_global_asset_class*, *morningstar_business_country_cla*, *morningstar_region_breakdown*, *morningstar_category*, *morningstar_security_type*, *morningstar_industry*. From SIX, we observe *six_instrument_type*, *six_security_type*, *six_domicile2*. From Pitchbook and HFRI, we observe *pitchbook_id* and *hfri_id* respectively. We observe a separate classification for bonds in *sp_bond_type*, *sp_bond_sub_type* and *sp_bond_domicile_of_issuer*. Finally, we observe three additional identifiers internally produced by Addepar, namely *issuer_id*, *security_id* and *model_type*. The latter is mainly used as an input in Addepar Navigator to produce predictions about prices and volumes.

A.2 Asset Class and Investment Type Taxonomy

Each position in the data is associated with an asset class and an investment type. The asset class represents a classification of the position into a more general asset category. The investment type is independent of the asset class and refers to the nature of positions held by investors. For instance, a position in a common stock would have asset class equal to Equities and investment type equal to Common Equity. A position in an equity mutual fund would have asset class equal to Equities but investment type equal to Mutual Funds. In Table A3 and A4, we provide the breakdown of asset classes into sub asset classes as well as of investment types into sub investment types.

1. Cash and Cash Equivalents "Cash" includes cash held for non-investment/hedging purposes for personal liquidity/working capital or savings. Examples include Checking accounts, savings accounts, and FX trading accounts. "Cash Equivalents" includes Commercial Paper, Repos, T-Bills, Variable Rate Demand Notes (VRDNs) and obligations (VRDOs), Auction Rate Securities (ARS), and Money Market Funds (MMFs).

2. Fixed Income "U.S. Municipals/Tax Exempt" includes U.S. Municipal (General Obligation / Revenue) bonds such as Sewer Bonds, School Bonds, GO City/State/Town bonds. "U.S. Treasuries and Agencies" refers to U.S. Government and Agency (Fannie/Freddie/Ginnie) debt such as U.S. 30-year or GNMA 10-year. "U.S. Tips" refers to Treasury Inflation-Protected Securities (TIPS). "U.S. Investment Grade Credit" refers to BBB And above-rated debt and "U.S. High Yield" refers to Below BBB-rated debt. "U.S. Bank Loans" refers to traded bank loans such as term loan bullet and balloons. "International Developed Markets" refers to corporate and government debt securities and pooled vehicles with primary exposure to developed markets, while "Emerging Markets" refers to similar assets with primary exposure to emerging markets. "Opportunistic" refers to unconstrained / total return bond strategies. "Unknown Fixed Income" contains assets that client tagged as "Fixed Income" without more granular information, and "Other Fixed Income" contains all the remaining categories.

3. Equities "U.S. Equities refers to equities issued in the U.S., and "Developed Markets - Americas" refers to those issued by primarily U.S.-domiciled or Canadian companies. "Developed Markets

- EMEA” refers to equities from France, Germany, Switzerland, South Africa, etc., while “Developed Markets - Asia Pacific” refers to equities from Australia, Japan, Hong Kong, Singapore, New Zealand. “Emerging & Frontier Markets” refers to equities from China, Brazil, Russia, Venezuela, Romania, Vietnam, etc. “Global Equities” refers to funds that span multiple markets. “Concentrated Equity Positions” contain positions with >$1B in U.S. companies. “Unknown equities” include assets that are identified as equities, but with no other information available, and “Other Equities” contains all the remaining categories.

4. Alternatives “Hedge Funds” includes pooled NAV vehicle as well as asset management products but not regulated like a mutual fund. The funds encompass a range of strategies and can invest in a wide range of securities and asset types. “Private Equity & Venture” refers to pooled drawdown vehicles investing in a range of underlying assets, including buyout, growth equity companies, credit, infrastructure funds, and venture funds. Only includes pooled vehicles, not direct investments. “Real Estate Funds” refers to pooled vehicles investing in real estate excluding REITs. “Direct Private Companies” refers to equity in private companies, including VC-backed companies or "regular operating companies" like hardware stores, gas stations, etc. “Direct Real Estate” refers to ownership or ownership stake in commercial or residential real estate. “Direct Loans” refers to non-securities debt investments, direct loans (lending). “Concentrated Alts Positions” refers to single positions with > $1B in value. “Unknown Alts” refers to alternatives funds of unknown classes, while “Other Alts” includes physical or derivative exposure to commodities, Traded / untraded crypto positions, and other pooled vehicles including exotic pooled vehicles.

5. Non-Financial Assets “Collectibles and Other” includes all remaining assets that do not fit into any of the narrow asset classes.

6. Liability “Liability” refers to Loans taken out by the client (as opposed to loans made by the client, which are considered assets).

7. Mixed Allocation “Asset Allocation Vehicle” refers to Multi asset class vehicles. “Held Away Accounts” refers to Single line positions where we don’t know what the underlying investments are, generally only the type of account (eg 401k, which is an account structure, but can hold a lot of different asset types).

Table A3: **Asset Class Taxonomy**

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

Table A4: **Investment Type Taxonomy**

Category	Type
Bank/Brokerage Account	Brokerage/FX Cash Account, U.S. Bank Account
Collectibles	Collectibles
Derivative	Listed Option
Equity	American Depository Receipts (ADR), Common Equity, International, Preferred Equity, Restricted Equity, Rights/Warrants, Other
Fixed Income	ABS/MBS, Certificate of Deposit (CD), Corporate Bonds, Muni Bonds, Treasuries, U.S. Agency, Other
Held Away	Employee Benefit Plan, Managed Account, Tax-Advantaged Plan, Other
Insurance	Annuities, Other
Limited Partnership	Drawdown LP, NAV LP, Unknown
Loans	Mortgage, Security-Based Loan (SBL) / Margin Loan, Unsecured, Other
Other	Crypto, Other
Private Company	Operating Company, Private Option, Venture Backed Company
Public Fund	Closed End Fund, ETF, Master Limited Partnership (MLP), Money Market Fund (MMF), Mutual Fund, REIT, Other
Real Estate	Commercial Real Estate, Residential Real Estate, Unknown