Asset Demand of U.S. Households

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Abstract

We use novel monthly security-level data on U.S. household portfolio holdings, flows, and returns to analyze asset demand across an extensive range of asset classes, including both public and private assets. Our dataset covers a diverse spectrum of households across the wealth distribution, notably including 372 portfolios exceeding $1 billion in assets. This ensures representation of ultra-high-net-worth (UHNW) households that are typically not well covered in survey data. With these unique data, we study the portfolio rebalancing behavior of households and ask whether (and, if so, which) households play an important stabilizing role in financial markets. Our findings reveal a stark contrast: less affluent households sell U.S. equities amid market downturns, while UHNW households take the opposite side. This behavior is more pronounced among households who rebalance their portfolios more frequently. However, the sensitivity of flows to returns is generally quite small and as the trades of different wealth groups partly offset each other, the aggregate household sector plays a limited role to absorb financial fluctuations. To understand the contrasting trading behavior across households, we show that flows to U.S. equities are negatively correlated with "active returns" (the difference between an investor's return and the market return) for all wealth groups. However, the flows to U.S. equities of less affluent households are also positively correlated with broad market returns – perhaps due to shifts in risk aversion, sentiment, or perceived macroeconomic risk – leading this group of households to act pro-cyclically. Across all asset classes, three factors with intuitive economic interpretations explain 75% of all variation in portfolio rebalancing. Those factors bet on the long-term equity premium, the credit premium, and the premium on municipal bonds. In sum, our framework and data paint a coherent picture of U.S. households' rebalancing behavior across the wealth distribution and across broad asset classes.

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1 Introduction

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 to study their investment behavior. In this paper, we fill this gap using novel monthly security-level data on U.S. household portfolio holdings, flows, and returns to analyze asset demand across an extensive range of asset classes, encompassing both public and private assets.

The trading behavior of households, both across and within asset classes, is of particular interest in the context of the recent literature on demand based asset pricing. A key finding in this literature is that estimates of demand elasticities are well below those implied by standard asset pricing models, both at the level of individual assets, factors, and the market (see Gabaix and Koijen (2021) for a review). This conclusion is based on the price impact of (uninformed) shifts in demand and by direct estimates of demand elasticities. However, due to data limitations, the evidence on demand elasticities is typically based on institutional holdings and trading data, and it is an open question whether households, and in particular the very wealthy ones, play an important role in stabilizing fluctuations in financial markets.[1]

We use new data from Addepar, a wealth management platform for investment advisors, to make progress on this important question. Addepar provides wealth managers with real-time portfolio information to guide investment decisions. Whenever possible, Addepar sources data on a daily frequency from custodians. The daily data on holdings and flows are used to compute daily dollar returns. In this paper, we use flows and returns aggregated to a monthly frequency, alongside monthly snapshots of portfolio holdings. We have access to security-level data with mappings to narrow asset classes (e.g., U.S. equities, private equity, put options) and broad asset classes (e.g., equities, fixed income). We observe data from January 2016 to June 2022, and our data are updated with a 6-month lag. The platform has been growing rapidly during our sample period and the total assets (number of portfolios) in our data have increased from \$188 billion (15,640) to \$1.92 trillion (188,300).

Compared to traditional data sources for U.S. households, our data has two important advantages. First, we have data on ultra-high-net-worth (UHNW) individuals, with more than a thousand portfolios with assets in excess of \$100 million and 372 portfolios with assets exceeding \$1 billion at some point in our sample. This group of households, which is particularly relevant for asset prices, is typically under-represented in other data sources. This broad coverage across the wealth distribution then allows us to extrapolate our estimates to construct the "representative U.S. household." Second, we have broad coverage across asset classes and at high frequencies. The asset classes covered include public and private assets (including, for instance, derivatives) and are

[1] It is common practice in the literature to construct a household sector as the residual from the market clearing condition. However, any mismeasurement in institutional holdings then impacts the holdings of the household sector. In addition, we cannot measure the heterogeneity across households.

all disaggregated to security-level positions. We also observe both direct and indirect holdings such as mutual funds, exchange-traded funds, and hedge funds. Such broad and detailed coverage is not available for most U.S. institutions.

After documenting basic facts about investors' portfolios across the wealth distribution, we focus on understanding flows and portfolio rebalancing decisions to answer our central question, namely whether households can play an important stabilizing role in financial markets. We define the flow to liquid risky assets as aggregate flows across 12 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 risky assets 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 either suggest that wealthy households exhibit a degree of inertia in their investment behavior, or it might reflect rebalancing within the pool of liquid risky assets, such as from Treasuries to U.S. equities.

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 concentration of wealth at the very top of the wealth distribution, the size-weighted sensitivity of U.S. equity flows to broad market returns is negative, implying that the representative household in our data stabilizes equity markets during market downturns. We find that these effects are all amplified when focusing on households who rebalance their portfolios more frequently within U.S. equities.

However, quantitatively, the overall volatility of flows and the sensitivity of flows to returns are quite small. Even during the market turmoil caused by the COVID-19 pandemic, which is in the middle of our sample, the volatility of flows and the sensitivity of flows to returns remain small. Combined with the fact that part of the flows cancel within the household sector, our results imply that households are unlikely to be an important stabilizing force to absorb market fluctuations (Gabaix and Koijen, 2021).

Third, we explore in more detail why households with different levels of wealth respond differently to market returns. We take advantage of the fact that households hold rather heterogeneous portfolios, implying that there are often significant differences between the return on a household's portfolio in U.S. equities and the broad market return. Across the wealth distribution, we find that the R-squared value of regressing an investor's return on the aggregate stock market return declines in wealth, while the CAPM beta is stable at around one. Motivated by this finding, we regress the flow to U.S. equities on the "active return," defined as the investor's return in U.S. equities in excess of the market return, and the market return itself.

We find that the slope on the active return is negative and stable across the wealth distribution, consistent with downward-sloping demand curves and households providing some elasticity to financial markets. However, the slope coefficient on the broad market return is positive for less affluent households, while it is close to zero for UHNW households. Less affluent households therefore appear to respond more strongly to broad market movements, which can affect their risk aversion, sentiment or perception of macroeconomic risks. Taken together, these results imply that less affluent households act pro-cyclically, while the UHNW take the other side. These effects are particularly salient during the COVID-19 pandemic, which is naturally an important observation in our sample. That said, a recurring theme is that flows and the sensitivity of flows to returns are quite small.

The focus in the first part of the paper is on the flow to liquid risky asset classes and the flow to U.S. equities (which is the largest and most salient liquid asset class). In the last part of the paper, we then broaden the analysis and explore how investors rebalance their portfolios across all liquid asset classes in Section 4. To this end, we develop a simple framework using principal components analysis (PCA) to identify the key rebalancing directions. We show that the factor loadings form a zero-cost long-short portfolio, e.g., buy U.S. equities and sell municipal bonds. Households can disagree on how to trade these factors in any given quarter (i.e., these are the factor realizations).

We find that the first three principal components explain approximately 75% of all rebalancing variation across the 12 asset classes. 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 bonds funds (which allocate a majority of their assets to corporate bonds) to U.S. Treasuries. This factor bets on the credit premium. The third factor combines two trades. The first trade rebalances from U.S. Treasuries to municipal and tax exempt bonds, while the second rebalances from global equities to U.S. equities. The third factor thus bets on the municipal bond premium and the global equity premium. These rebalancing directions or factors can be used to design macro-finance models with rich household heterogeneity and multiple risk factors.

The paper proceeds as follows. In Section 2, we introduce the data, discuss how we construct our sample, and we provide summary statistics. We then study the allocation and dynamics of flows in response to returns in Section 3. In Section 4, we estimate the factor model of portfolio rebalancing across asset classes. We conclude in Section 5.

Related literature

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 in this literature to impute the aggregate holdings of the household sector as the difference between the supply and the aggregate holdings of institutions. In addition, holdings data across asset classes are not available for all institutions. By using the Addepar data, we can study the household sector in detail, both within and across asset classes. Our primary focus in this paper is to ask whether households, and in particular the very wealthy ones, can act as an important stabilizing force in financial markets.

Our paper also makes an important contribution to the literature that analyzes the asset demand of households, including UHNW 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).[2] 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

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

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 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.

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; Catherine et al., 2022) 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).[3] 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.

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

[3]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.

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 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.

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 or 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. We use narrow asset classes to index variables when defining the notation, 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}. 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, adjusted for price effects. Our definition of flows follows Davis and Haltiwanger (1992) and leads to 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 at a daily frequency, and recovers the dollar returns by imposing the budget constraint.

As of May 2023, Addepar works with over 850 financial advisors, family offices, and large financial institutions that manage more than $4 trillion of assets on the company's platform, ranging from the affluent to the ultra-high-net-worth investor segments.

Our sample contains monthly security-level data from January 2016 to June 2022. We receive monthly updates with a delay of six months. 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.[4] 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.[5]

Addepar imposes two additional screens for data confidentiality. First, 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 the portfolio identifiers (although not the month) that are affected by this screen. There are 125 such accounts in our sample.

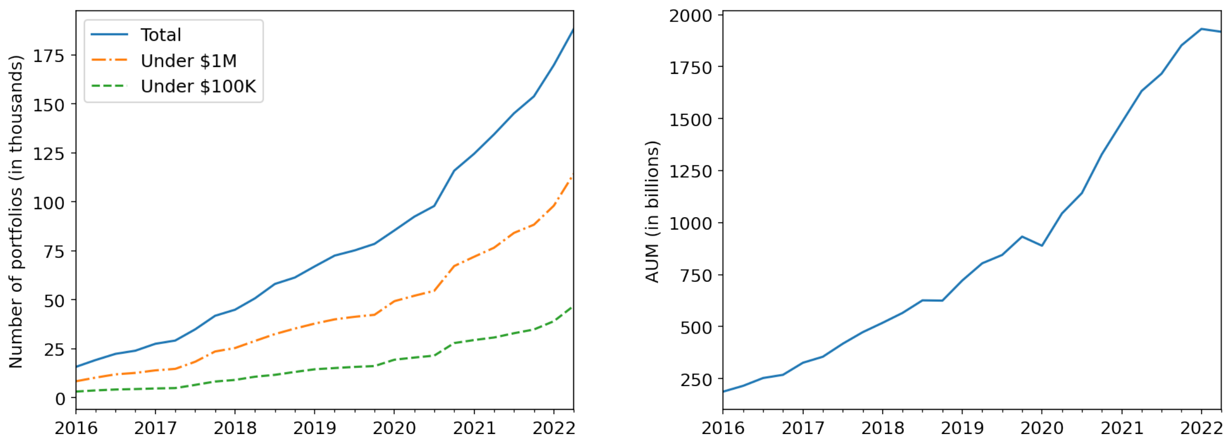
Our sample of Addepar data includes information on 214,961 distinct client portfolios from 2016.Q1 to 2022.Q2. In Figure 1, we summarize the number of portfolios in the left panel and households' total assets on the platform in the right panel before imposing any screens. The number of portfolios grows from 15,640 in 2016.Q1 to 188,300 in 2022.Q2. The sharp increase in the number of portfolios reflects the growth of the Addepar platform during our sample period. Households' total assets grow from $188 billion to $1.92 trillion during the same period.

There are 372 portfolios that exceed $1 billion in assets at some point in our sample. As a point of reference, Forbes reports 735 billionaires in the U.S. in 2023. While these numbers cannot be compared directly, as (i) we observe portfolios and not households, (ii) the masked positions only contain a portfolio identifier and not a date, so we can only compute the statistic over the entire

[4]We provide details on minor cleaning steps performed before aggregating the monthly data at a quarterly frequency in Online Appendix B.

[5]Occasionally, we observe that two portfolios have identical positions, presumably because they belong to the same family. However, we cannot connect those portfolios with the data that we have.

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 June 2022.



sample, (iii) there may be some foreign investors, this comparison does indicate that we have an unusually good coverage of the right tail of the wealth distribution.

2.3 Asset class definitions

Table 1 outlines the asset classes that we use in our analysis. These definitions refine the asset class assignments as defined by Addepar. The details of the asset class assignment are provided in Online Appendix A.

We define liquid and illiquid asset classes in our analysis below. Using the definitions in Table 1, the liquid narrow asset classes include all asset classes in Equity and Fixed Income, except for Other Equity and Other Fixed Income. Also, we analyze cash separately for reasons that we discuss below. The remaining asset classes in Table 1 (excluding cash) are classified as illiquid.

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. Also, by imposing restrictions on the number of asset classes, it is less likely that only a fraction of a household's assets are covered on the Addepar platform. The screens also remove infrequent data errors. We 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

Table 1: Asset class definitions
This table reports the asset class taxonomy. Narrow asset classes, which we index by n, are categorized into five broad asset classes. The broad and narrow asset classes are obtained after imposing corrections to Addepar's internal classification.

Broad asset classes	Narrow asset classes
Cash	Money Market Fund, Certificate of Deposit, Commercial Paper, CAD, CHF, EUR, USD, Other Currency
Fixed Income	Municipal Bonds, U.S. Government/Agency Bonds, Corporate Bonds, Bond Funds, ABS/MBS, Structured Debt, International Government/Agency Bonds, Other Government/Agency Bonds, Other Debt
Equities	U.S. Equity, Global Equity, Developed Market Equity, Emerging Market Equity, Other Equity
Alternatives	Private Equity & Venture, Hedge Funds, Direct Real Estate, Direct Private Companies, Fund of Funds, Real Estate Funds, REITs, Other Funds, Unknown Alts.
Other	Collectibles, Crypto, Derivatives, Liabilities, Other, Other Non-Financial Assets

household for the same reason.[6]

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 for at least one of the liquid narrow asset classes.[7] 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 0.46% of all narrow asset class-quarter observations.[8]

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. Lastly, we restrict to households with positive assets in the beginning or at the end of the period in at least three 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.[9]

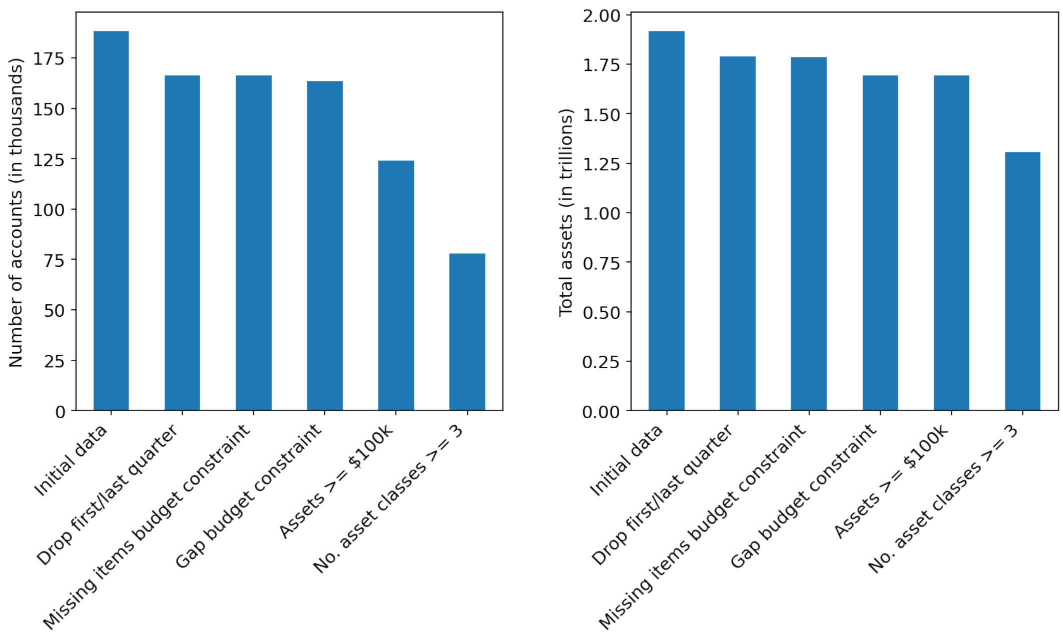
[6]It is uncommon for households to leave the platform during our sample period.

[7]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.

[8]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.

[9]Our results are robust to relaxing this screen to households having only positions in two asset classes of which

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 2022.Q2.



We summarize the impact of each of the screens in Figure 2 for the second quarter of 2022.Q2, which is the last complete quarter of our sample. We report the total number of accounts in the left panel and we report the total assets covered in the right panel. The sample selection screens that have a noticeable impact on the size of the sample are to remove the onboarding quarter, to impose a size constraint, and to require positive positions in at least three asset classes. As wealthier households are more likely to satisfy these screens, the impact is larger in terms of the number of portfolios compared to total assets.

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).

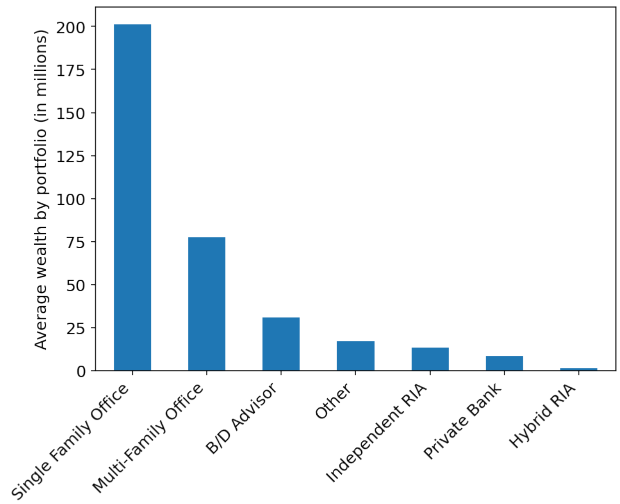
2.5 Investor characteristics

We construct four investor characteristics: total wealth group, advisor type, and measures of turnover and inertia.

Total wealth groups We assign households to one of five groups based on total wealth in a given quarter: A_{it} <\$3m, $A_{it} \in$[\$3m, \$10m), $A_{it} \in$[\$10m, \$30m), $A_{it} \in$[\$30m, \$100m), and $A_{it} \geq$\$100m.

one of the asset classes may be cash.

Figure 3: Average portfolio size by advisor type
This figure reports the average wealth A_{it} across portfolios for six advisor types: Single Family Office, Multi-Family Office, B/D Advisor, Independent RIA, Hybrid RIA, and Private Bank. The remaining advisors are grouped in a single category Other. The results are presented for 2019.Q4.



Advisor type We assign households to one of six groups based on the type of advisor that manages the portfolio: Single Family Office, Multi-Family Office, B/D Advisor, Independent RIA, Hybrid RIA, and Private Bank. These six advisors together advise 94.1% of the total number of portfolios and manage 94.0% of the total assets under management recorded on the platform in 2019Q4. We group portfolios managed by any other advisor into a single category Other. In Online Appendix A, we provide additional details on the types of advisors that we observe in the dataset.

Different types of advisors provide services to investors with very different levels of wealth, as shown in Figure 3. We report the average assets A_{it} across portfolios and by advisor type in 2019.Q4. There is a clear pattern in how investors match with advisors, where the wealthiest investors work with single family offices.

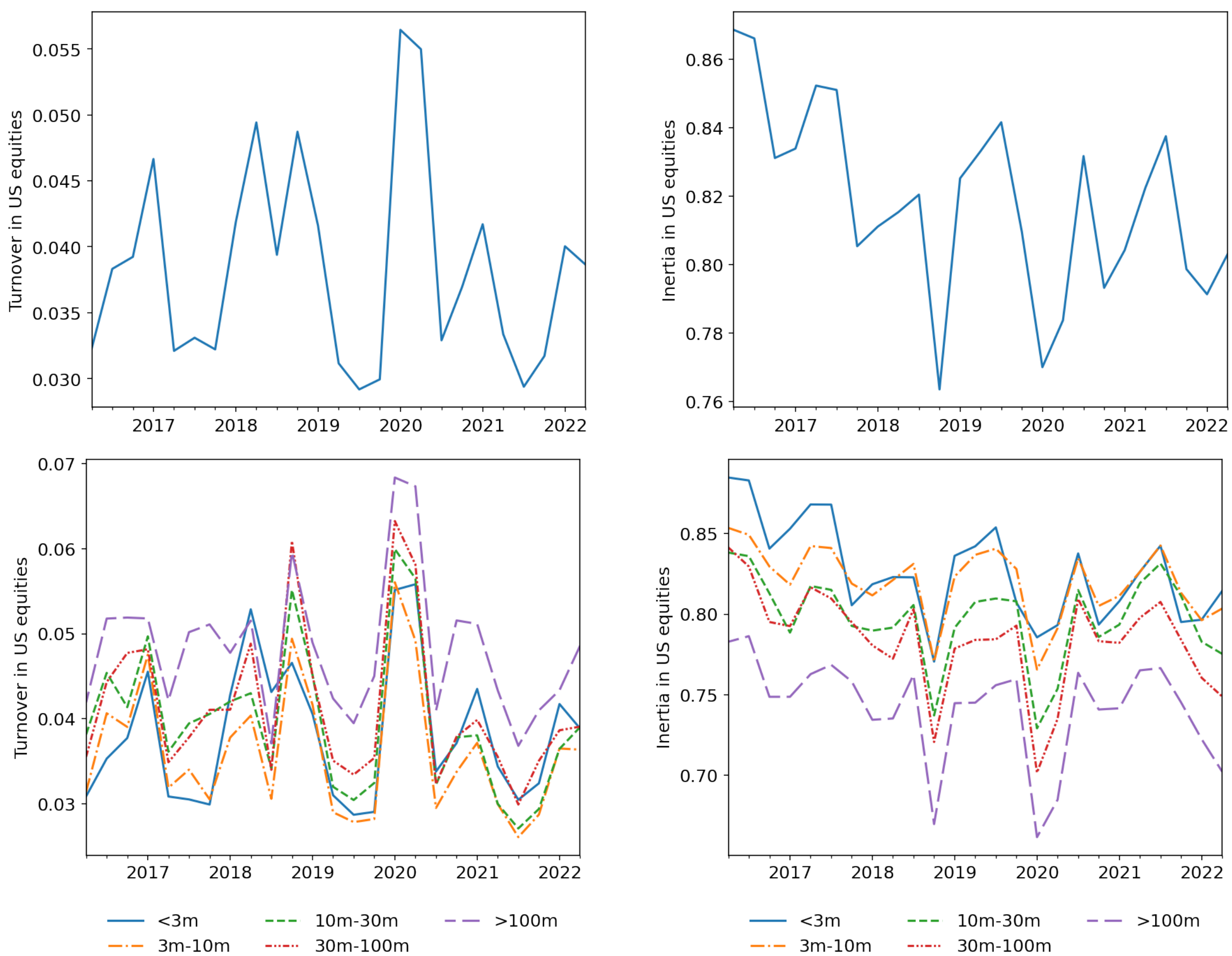
Turnover and inertia within U.S. equities We define two measures to capture how active an investor is using data on U.S. equities, which is the largest liquid asset class. The first measure is turnover, which we compute as

$$T_{it} = \frac{1}{2} \frac{\sum_{a \in \text{U.S. equities}} \mid F_{iat} \mid}{A^{DH}_{i,\text{U.S. equities},t-1}}.$$

We compute the turnover measure each month and then average it per quarter for a given investor.[10] We further winsorize turnover at the 2.5% and 97.5% percentiles by quarter.

[10]The results that follow are robust to construct the turnover measure using all positions in the broad asset class Equities as opposed to positions in U.S. equities only. They are also robust to using the median rather than the mean to convert our measure to a quarterly frequency.

Figure 4: Time-series of turnover and inertia
In the top left panel, we plot the time-series of T_{it}, averaged across all investors in each quarter. In the top right panel, we plot the time-series of I_{it}, averaged across all investors in each quarter. In the bottom left panel, we plot the time-series of average T_{it} by wealth group. In the bottom right panel, we plot the time-series of average I_{it} by wealth group. Both T_{it} and I_{it} are constructed for each month and investor using securities in U.S. equities and subsequently averaged across months. The sample period is from 2016.Q1 to 2022.Q2.



We also construct a measure of inertia based on the cross-section of U.S. equities,

$$I_{it} = \frac{\sum_{a \in \text{U.S. equities}} \mathbb{I}\{F_{iat} = 0\}}{N_{i,\text{U.S. equities},t}},$$

where $\mathbb{I}\{F_{iat} = 0\}$ is an indicator function equal to one if $F_{iat} = 0$ and $N_{i,\text{U.S. equities},t}$ denote the number of securities in U.S. equities held by investor i at time t. We average the monthly values of I_{it} within a quarter to obtain our final measure.

We plot in the top left panel of Figure 4 the time-series of average turnover and the time-series of average inertia in the top right panel. While average turnover is in general quite low, it increases substantially in periods of market turmoil; its peak is in 2020.Q1. By the same logic, investors are less inert during times of market stress. The time-series correlation between inertia and turnover is -57.9%.

The bottom left panel of Figure 4 reports turnover and the bottom right panel plots investors' inertia by wealth group. Quite strikingly, UHNW households rebalance their portfolios more frequently and are less inert than less wealthy households. This more active behavior may in part be due to the presence of different advisor structures, such as single family offices.

3 Asset demand across asset classes

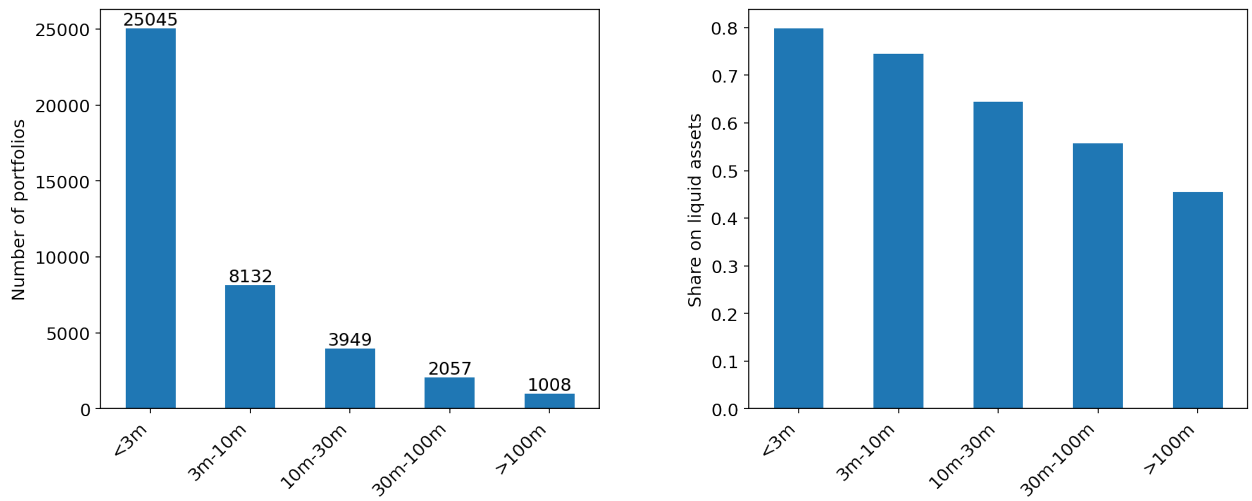
We lead off our analysis by studying households' asset demand across asset classes. We proceed in four steps. First, we document key properties of households' portfolio holdings in Section 3.1. These results complement the results in Balloch and Richers (2021). Second, we study the flow to liquid and illiquid asset classes as well as cash in Section 3.2. In Section 3.3, we then analyze the flow to the largest liquid asset class, U.S. equities, in more detail. While we mostly group households by wealth in this section, we explore other forms of investor heterogeneity in Section 3.4. Lastly, in Section 3.5, we explore how investors respond to own returns relative to broad market returns.

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 5. While the number of portfolios naturally declines in wealth, there are still 1,008 portfolios in our sample with more than $100 million in assets. In the right panel, we plot the fraction of total assets invested in liquid asset classes. Unsurprisingly, wealthier households allocate a larger fraction of their portfolio to illiquid asset classes such as hedge funds, private equity, and other alternatives. We explore this pattern in more detail below.

Figure 5: 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 Figure 6, we plot the average portfolio shares across investors in 2019.Q4 for the 10 largest liquid asset classes (left panel) and the 10 largest illiquid asset classes (right panel).[11] Among liquid asset classes, U.S. equities is the largest asset class, followed by municipal bonds, global equities, and U.S. government bonds. Among illiquid asset classes, the largest asset class is private equity and venture capital, followed by hedge funds and real estate.

We summarize the fraction invested in broad asset classes by wealth group in 2019.Q4 in the left panel of Figure 7. In line with the right panel of Figure 5, wealthier households allocate a larger fraction to alternatives, while reducing their portfolio shares in public equities and fixed income. The fractions invested in other assets are stable across the wealth distribution. Quite surprisingly, the fraction invested in cash is also stable across the wealth distribution.

We plot the portfolio shares invested in five large liquid asset classes across the wealth distribution in the right panel of Figure 7: U.S. equities, municipal and tax-exempt bonds, U.S. government bonds, corporate bonds, and global equities. These five asset classes account for approximately 80% of all assets invested in liquid assets. While the shares are fairly stable, the fraction invested in municipal bonds increases with wealth, at the expense of corporate bonds and global equities. This pattern can be explained by the tax benefits that municipal bonds offer. The smaller allocation to global equities implies that wealthier investors are in fact more home biased in their equity allocation.[12]

[11] We treat cash separately for reasons that we discuss in Section 3.2. In Figure 6, we report the average share in cash in the right panel, having noted that we do not treat it as an illiquid asset class.

[12] One potentially offsetting force is the allocation to hedge funds that may allocate capital to global equity markets. This is something we cannot observe in our data, however.

Figure 6: 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.

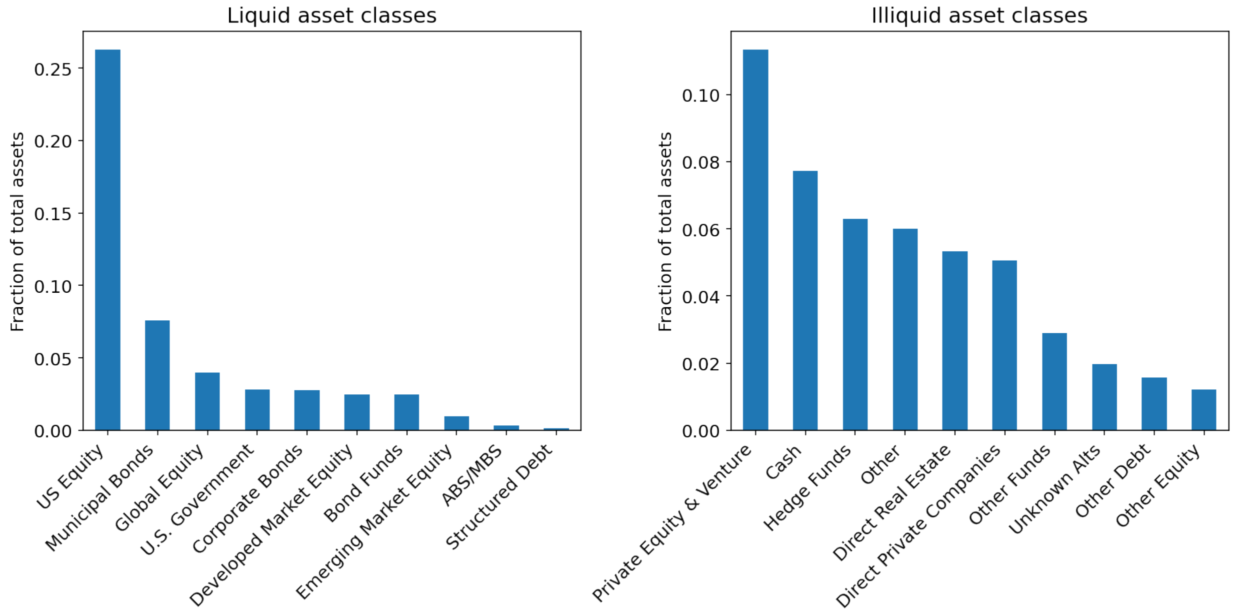


Figure 7: Fractions invested in broad and narrow asset classes by wealth group
In the left panel, we plot the average fractions invested in broad asset classes (Cash, Equity, Fixed income, Alternatives, Other). In the right panel, we plot the average fractions invested in the five largest liquid risky asset classes (U.S. Equities, Corporate bonds, Municipal and tax-exempt bonds, Treasuries, and Global equities). The results are presented for 2019.Q4.

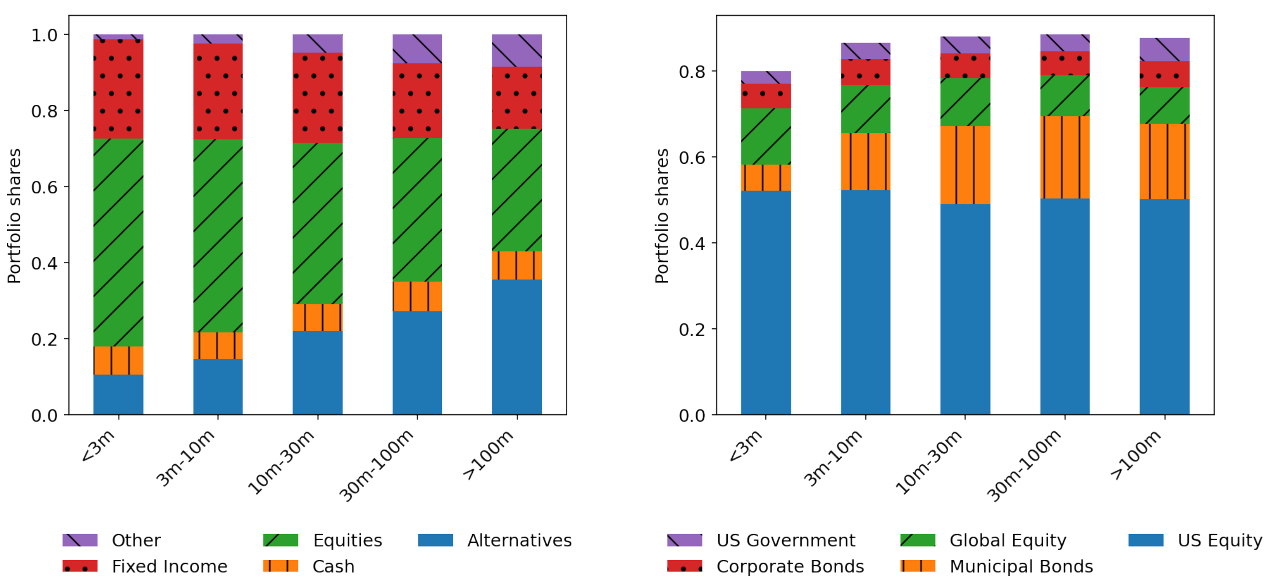
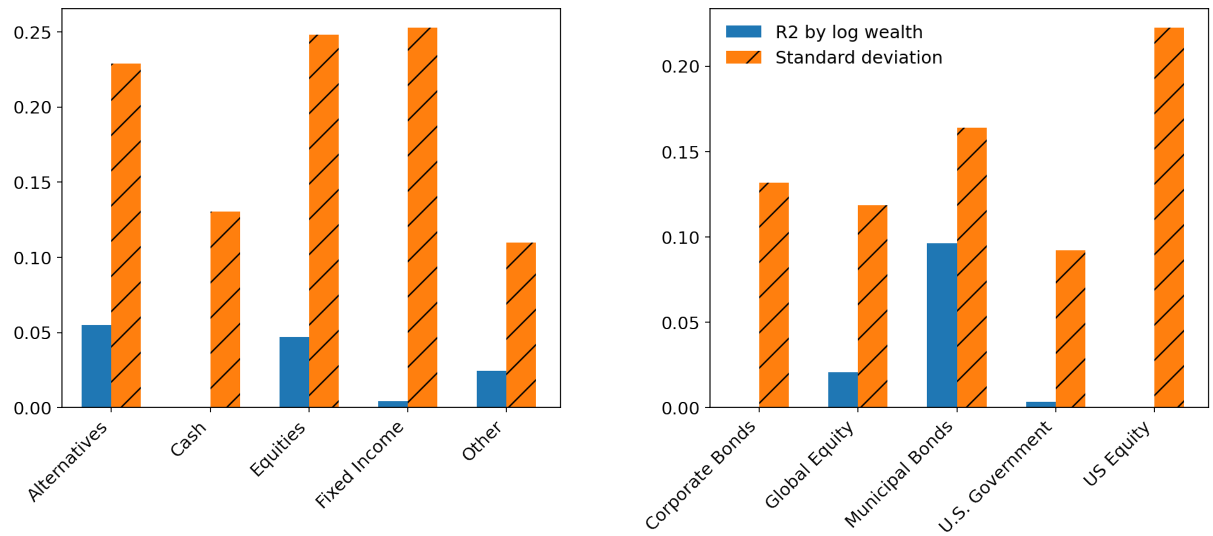


Figure 8: Heterogeneity in portfolio shares that cannot be explained by wealth
The orange bars correspond to the standard deviation of portfolio shares in broad asset classes (left panel) and the largest five narrow asset classes (right panel). The blue bars correspond to the R-squared of a regression of portfolio weights on log wealth (see (3)). The results are presented for 2019.Q4.



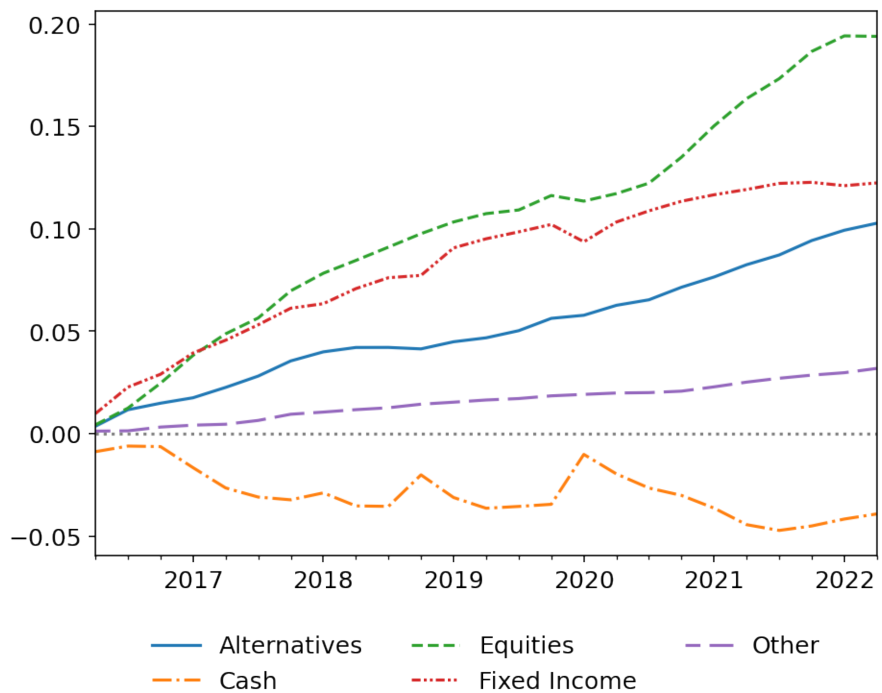
How important are differences in wealth in explaining asset class allocations? The figures presented so far point to meaningful differences in households' asset allocations across the wealth distribution. That said, wealth cannot explain all (or even most) of the heterogeneity in portfolio holdings. To illustrate this point, 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 8. We also report the standard deviation of θ_{int} to summarize the heterogeneity in portfolio holdings across households in a simple way.

We focus on broad asset classes in the left panel and on the five large liquid asset classes in the right panel. In all cases, 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, and risk preferences, are more important in explaining heterogeneity in portfolio shares.

Figure 9: Flows to broad asset classes
We plot the flow into broad asset classes during our sample period from 2016.Q1 to 2022.Q2. Flows are scaled by total assets.



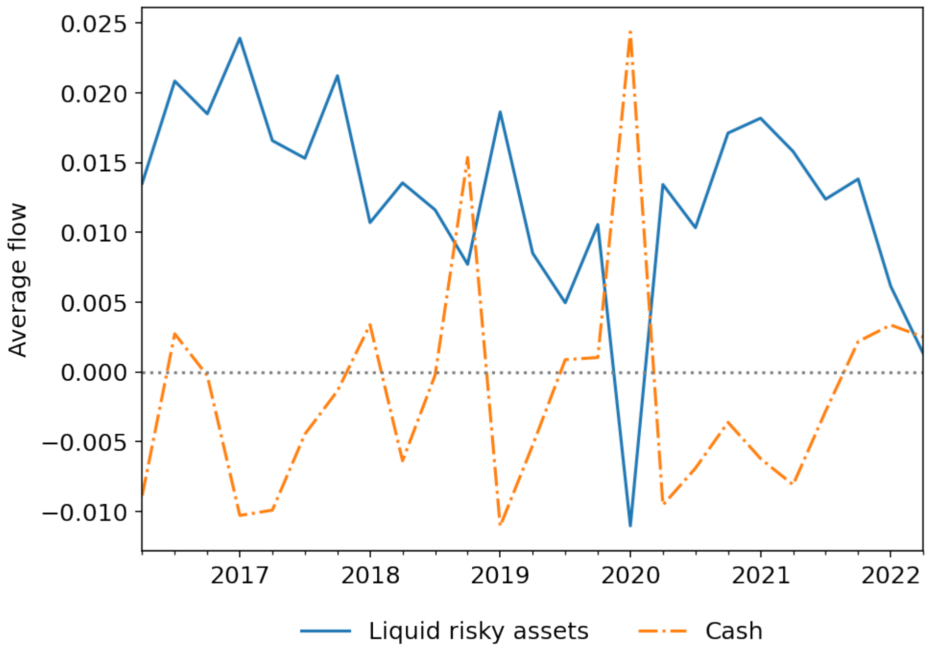
3.2 Flows to broad asset classes

For most of the paper, we will focus on flows and demand across liquid asset classes, as households cannot easily move capital across illiquid asset classes such as hedge funds and private equity. Before zooming in, we plot the cumulative flows across the broad asset classes in Figure 9. During this period, the cumulative flows have been positive for fixed income, equities, and alternatives, 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 indeed see that the flow to cash has turned positive during the last couple of quarters of the sample.

That said, investors allocate more capital to cash during the fourth quarter of 2018 and the first quarter of 2020, which are both quarters during which the aggregate U.S. stock market declined. We will revisit this pattern in subsequent analyses. Overall, the average cumulative flows are quite modest.

Next, we focus on the (re)allocation 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 asset classes. We denote this flow

Figure 10: Dynamics of the flow to cash and liquid risky assets
We plot the average flow to liquid risky assets, $\frac{1}{I}\sum_i f_{it}^{\mathrm{Liq}}$, in blue (solid) and the average flow to cash, $\frac{1}{I}\sum_i f_{it}^{\mathrm{Cash}}$, in orange (dash-dotted). The sample period is from 2016.Q1 to 2022.Q2.



by $f_{it}^{\mathrm{Liq}} := \sum_{n\in\mathcal{L}} f_{int}$, where $\mathcal{L}$ is the set of liquid risky asset classes as defined in Section 2.3.

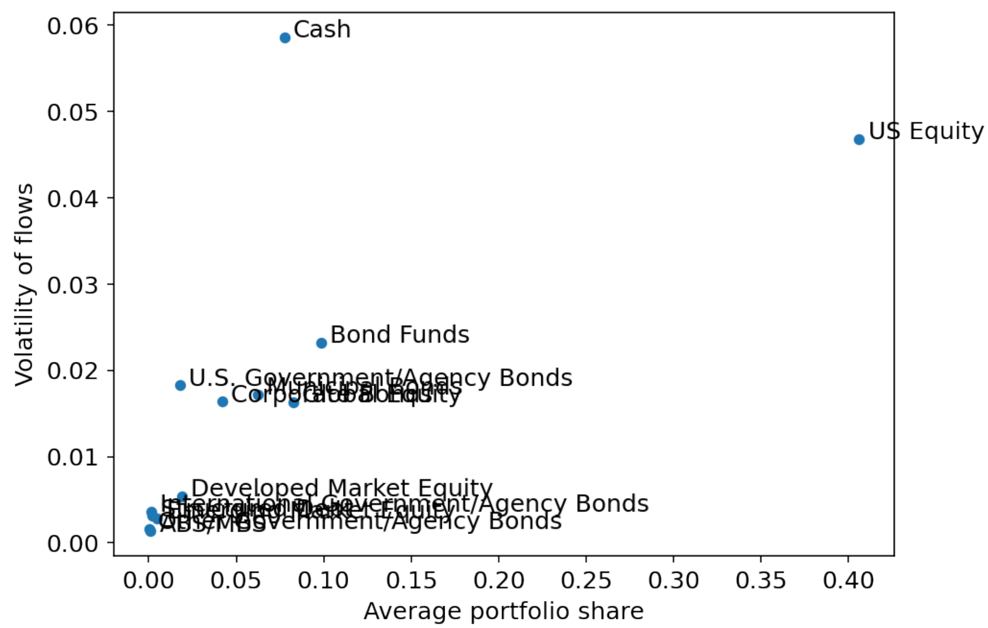
In Figure 10, we plot the equal-weighted average of f_{it}^{Cash} and f_{it}^{Liq} across investors in a given quarter. Three observations stand out from these series. First, the flows to cash and liquid risky assets are strongly negatively correlated: the time-series correlation is -71.0%. This implies that cash is an important substitute for liquid risky assets.[13] 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. Indeed, the quarterly volatility is 0.8% for the former and 0.7% for the latter. Yet, the average cash share is only 7.8% versus 73.8% for the fraction invested in liquid risky assets. This comparison implies that the flow to cash is relatively volatile.

To illustrate the excess volatility of the flow 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 vertical axis in Figure 11. 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

[13] The series are not perfectly negatively correlated as households can allocate capital to illiquid asset classes or adjust their consumption.

Figure 11: 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 2022.Q2.



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%.

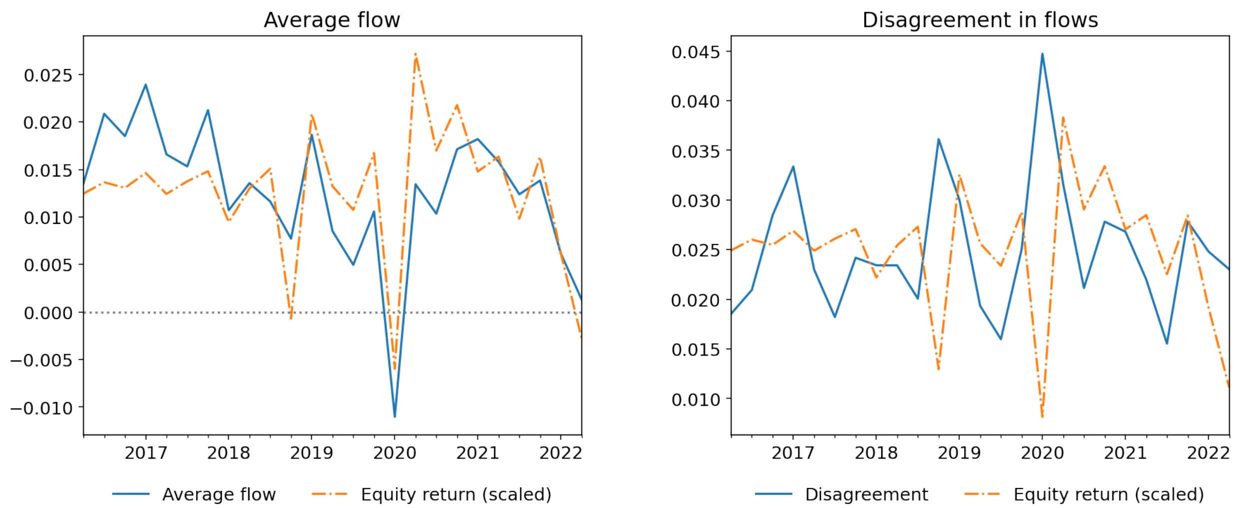
Economically, the reason is that cash serves two purposes. First, as we discussed before, cash serves as a safe asset: the flows are strongly negatively correlated with the flows to liquid assets. This unique aspect of cash can make it excessively volatile due to risk aversion or sentiment shocks.

In addition to acting as 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 other liquid 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 the flow to liquid risky assets.

3.3 Flows and stock market returns

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 12. 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 flow and U.S. stock market returns is 71.1%.

Figure 12: 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 2022.Q2.



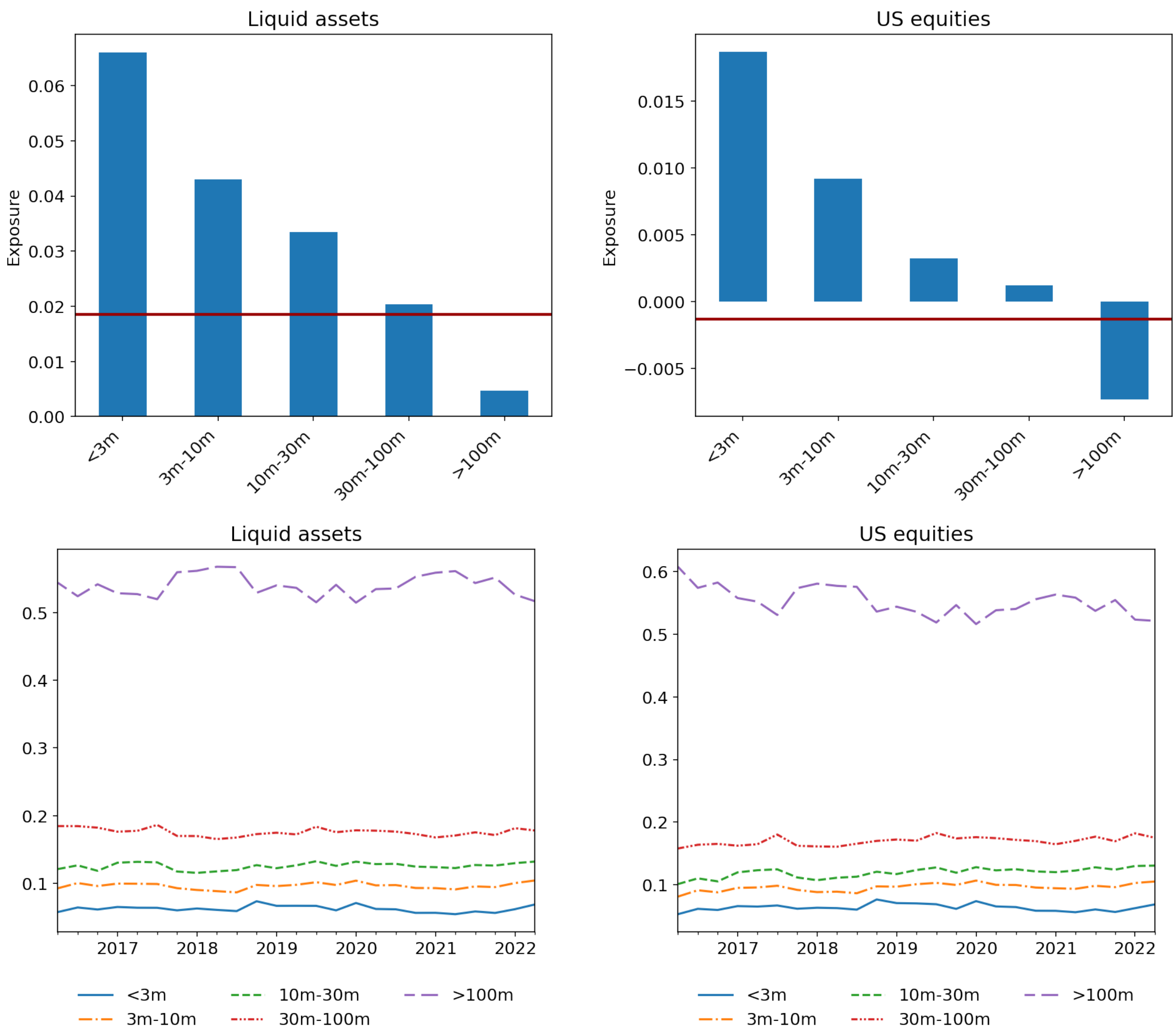
In the right panel of Figure 12, we plot the disagreement across investors as measured by the inter-quartile range of f_{it}^{Liq} across investors in a given quarter. We also plot this series alongside the return on the U.S. stock market, adjusting the mean and standard deviation of the return series to match those of the disagreement series as before. In this case, we find that the correlation is -25.5%, 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: the last quarter of 2018 and the first quarter of 2020.

Motivated by the correlations between flows and the return on the U.S. stock market, we estimate the sensitivity of flows to stock returns across the wealth distribution. We first average f_{it}^{Liq} across investors in a given wealth group and quarter and denote this series by f_{gt}^{Liq} (g indexes wealth groups). We then regress the average flow for each wealth group on the U.S. stock market return,

$$f_{gt}^{\text{Liq}} = \alpha_g + \beta_g r_t^{\text{US, Eq}} + \epsilon_{gt}. \tag{4}$$

In the left panel of Figure 13, we plot the estimated slope coefficient, β_g, for each of the wealth groups. Quite remarkably, we find that the slopes decline monotonically in wealth, and they are all positive. The positive slope estimate for each wealth group implies that households, on average, sell liquid risky assets during market downturns and thus act pro-cyclically. This behavior amplifies

Figure 13: 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 (see (4)). 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 2022.Q2.



price fluctuations of risky assets and acts as a destabilizing force.

In the bottom left panel of Figure 13, we plot the wealth shares for 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. equities (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 a "representative household." The wealth-weighted average (using liquid wealth shares to aggregate the groups) sensitivity is summarized by the horizontal red line in the top left panel.

The muted response of wealthier households can be interpreted in two ways. First, wealthier households may be 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 wealthier 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 interpretations, we zoom in on U.S. equities, which is the largest liquid asset class and the asset class that best captures how investors respond to fluctuations in the U.S. stock market. We repeat the same analysis as before, but now regressing $f_{g,\text{US Eq},t}$ in (4) on U.S. stock returns for each of the wealth groups (instead of f_{gt}^{Liq}).

In the right panel of Figure 13, 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, a new insight from this figure is that UHNW households provide elasticity to the market by buying U.S. equities during economic downturns. As in the left panel, we construct a representative household 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 magnitude of the response is modest and a lot of the response to stock returns averages out within the Addepar population. A 10% decline in the stock market leads to a 0.1% inflow into equities for UHNW households and a -0.2% inflow for households with assets below \$3 million. 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.

To illustrate the variation in the data that drives these coefficient estimates, and differences across wealth groups, we plot the flows to U.S. equities and returns for three wealth groups in Figure 14 for quarterly data and in Figure 15 using monthly data covering the onset of the COVID-19 pandemic from September 2019 to August 2020. Unsurprisingly, these figures highlight the importance of the COVID-19 pandemic during our sample period. As Figure 15 highlights most

Figure 14: Quarterly flows to U.S. equity and returns by wealth group

In the left panel, we plot the time series of quarterly flows to U.S. equities, averaged across investors with assets below \$3 million. In the middle panel, we plot the time series of quarterly flows to U.S. equities, averaged across investors with assets between \$10 million and \$30 million. In the right panel, we plot the time series of quarterly flows to U.S. equities, averaged across investors with assets above \$100 million. In each panel, we also report the aggregate return on the U.S. stock market which we rescale to match the time-series mean and volatility of flows. The sample period is from 2016.Q1 to 2022.Q2.

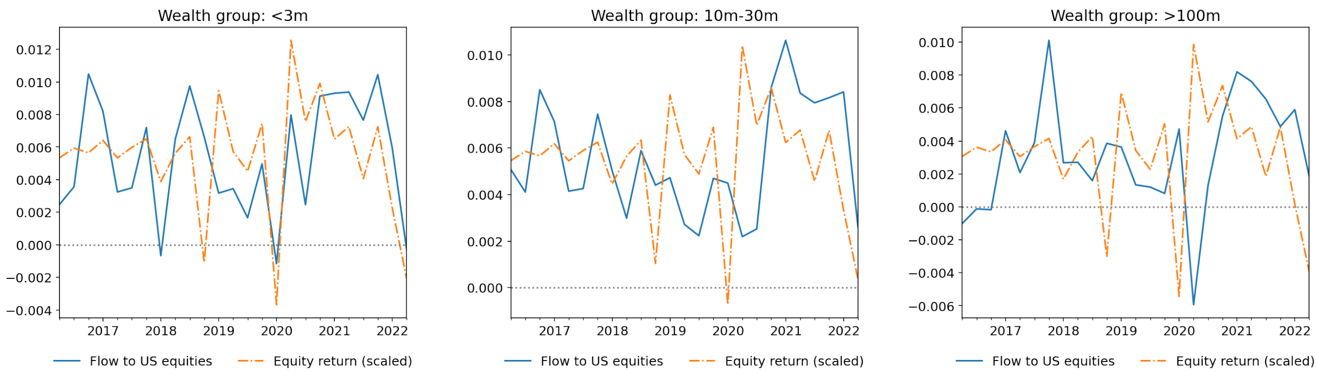


Figure 15: Monthly flows to U.S. equity and returns by wealth group during the COVID-19 pandemic

In the left panel, we plot the time series of monthly flows to U.S. equities, averaged across investors with assets below \$3 million. In the middle panel, we plot the time series of monthly flows to U.S. equities, averaged across investors with assets between \$10 million and \$30 million. In the right panel, we plot the time series of monthly flows to U.S. equities, averaged across investors with assets above \$100 million. In each panel, we also report the aggregate return on the U.S. stock market which we rescale to match the time-series mean and volatility of flows. The sample period is from September 2019 to August 2020.

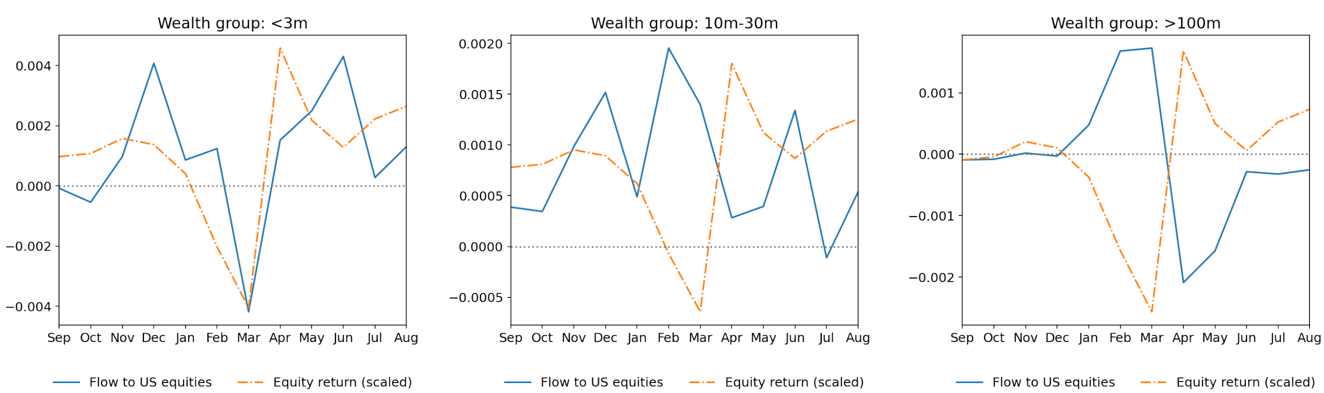
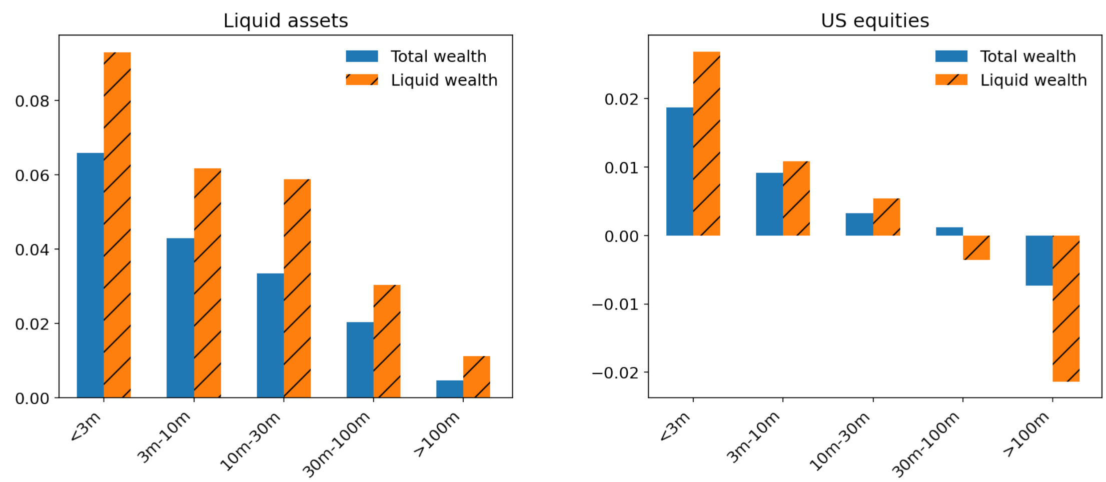


Figure 16: Scaling flows by total wealth or liquid wealth
In the left panel, we plot the slope coefficients of a regression of flows to liquid risky assets on the aggregate return on the U.S. stock market by wealth group (see (4)), where flows are rescaled by liquid wealth rather than total wealth. We compare the slope coefficients with the original estimates obtained by rescaling flows by total wealth. In the right panel, we provide the same comparison for the flows to U.S. equities. The sample period is from 2016.Q1 to 2022.Q2.



clearly, households in the first wealth group trade with the market, while the wealthiest households take the other side: as the market falls, they buy equities and they sell equities when the market bounces back in April and May of 2020. As these households bet against each other, the overall elasticity provided by these households in response to stock market fluctuations is limited.

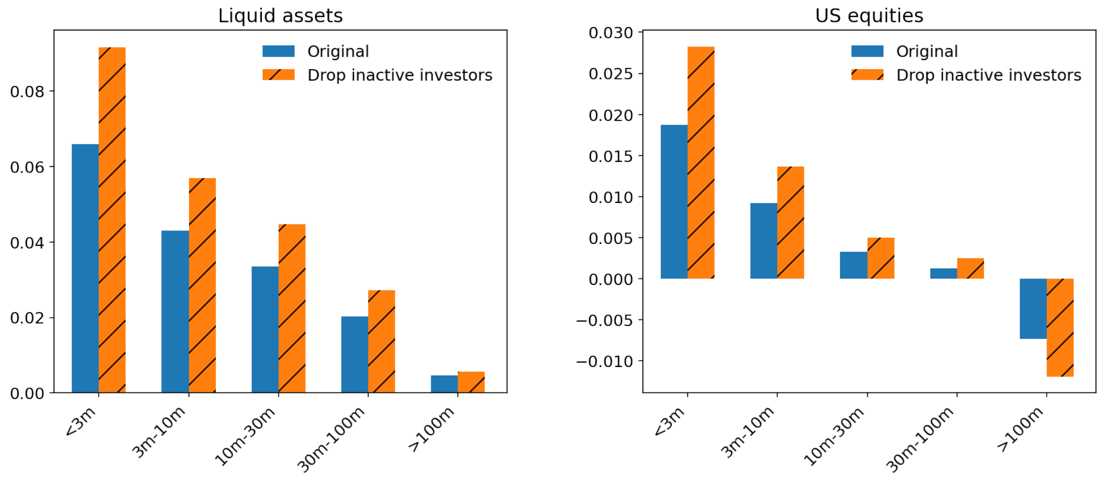
Scaling by liquid wealth instead of total wealth We explore the the robustness of our result from the left panel of Figure 13 to the way in which we compute flows. In computing flows, we have scaled the dollar flows by total wealth. However, Figure 5 shows that the fraction invested in liquid assets declines in wealth, which may lead to a more muted response of flows to liquid assets when we scale dollar flows by total wealth. We therefore repeat the analysis in this section using a measure of flows where we scale by liquid wealth instead of by total wealth.

The results are presented in the left panel of Figure 16. As expected, the estimated slope coefficients increase for each of the wealth groups. However, the main pattern and economic conclusions remain robust. We repeat this exercise also for the flow to U.S. equities in the right panel. Once again, the estimated slope coefficients are amplified but the economic conclusions are unaffected. These key facts are therefore not driven by our choice to scale flows by total wealth.

3.4 Heterogeneity beyond wealth

We conclude this section by exploring how the sensitivity of flows to stock market returns varies across households along dimensions other than wealth.

Figure 17: Investor activeness and the sensitivity of flows to returns
In the 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 (see (4)), after we drop investors in the bottom third of turnover by wealth group and quarter. We compare the slope coefficients with the original estimates obtained by considering all investors. In the right panel, we provide the same comparison for the flows to U.S. equities. The sample period is from 2016.Q1 to 2022.Q2.



In Figure 17, we repeat our analysis of regressing the flow to liquid assets (left panel) or to U.S. equities (right panel) on stock market returns. In addition to our benchmark results, we also compute the average flow after dropping the bottom one third of households in terms of turnover. Importantly, as our measure of turnover is computed within U.S. equities, we explore whether those households are also more active across asset classes. The results in Figure 17 indicate that this is indeed the case as all the sensitivities are amplified when omitting the most inactive investors within U.S. equities.

In Figure 18, we explore how the sensitivity varies by advisor type. Separating the advisor and investor is generally challenging, and this is particularly the case here as advisor type and wealth are strongly correlated (see Figure 3). In Figure 18, we rank the advisors by the average size of the portfolios. We find that the sensitivity of flows to liquid assets (left panel) and to U.S. equities (right panel) broadly follow the same pattern as the splits by wealth that we discussed earlier in this section. There are two noticeable exceptions, namely multi-family offices and hybrid RIA. In ongoing work, we are exploring the advisor types in more detail.

3.5 Which returns matter to investors?

In connecting flows to returns, we have so far used the return on the aggregate U.S. equity market. As investors hold fairly heterogeneous portfolios, we now explore whether they respond differently to their own return relative to the return on the market.

We first connect investors' returns to aggregate stock market returns using the following regres-

Figure 18: Average portfolio size by advisor type
In the 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 advisor type. In the 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 advisor type. We order advisor types based on the average wealth of portfolios that they advised, from lowest to highest. The sample period is from 2016.Q1 to 2022.Q2.

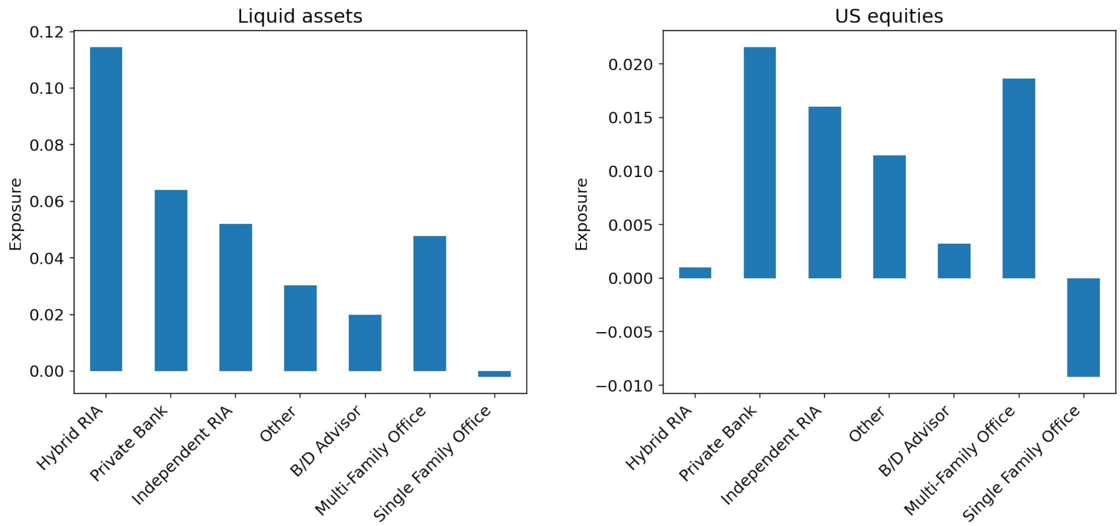
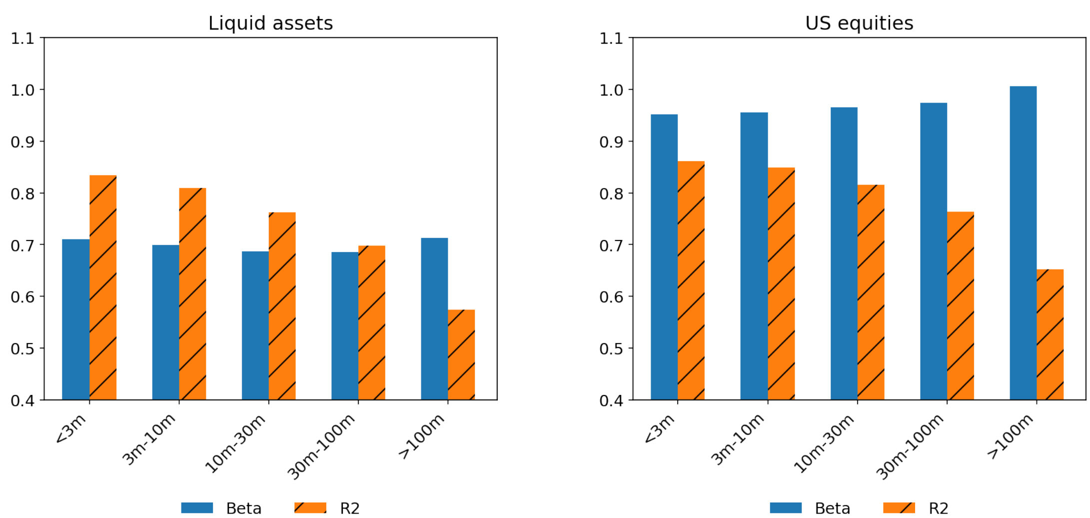


Figure 19: The relation between investor returns and aggregate equity returns
In the left panel, for each wealth group, we report the slope coefficients and R^2 of a panel regression of returns on liquid assets on the aggregate return on the U.S. stock market by wealth group. In the right panel, we report the slope coefficients and R^2 of a panel regression of returns on U.S. equities on the aggregate return on the U.S. stock market by wealth group. The sample period is from 2016.Q1 to 2022.Q2.



sion for each of the wealth groups,

$$r_{i,\text{US equities},t} = \alpha_g + \beta_g r_t^{\text{US, Eq}} + u_{it},$$

and analogously for the return on liquid wealth. We report the betas and R^2 values in Figure 19 for liquid wealth (left panel) and U.S. equities (right panel). In both panels, we find that the betas are fairly stable across wealth groups. The betas are around 0.7 in case of liquid wealth as investors allocate a significant fraction of their wealth to fixed income securities. The beta of US equities is, as expected, close to one. More interestingly, however, is that the R^2 value declines in wealth. This implies that wealthier investors deviate more from simply holding the market portfolio.

As there is significant independent variation in returns, in particular for the wealthiest investors, and as the betas are close to one for U.S. equity returns, we explore how the flow to U.S. equities is related to various measures of returns. We consider three regressions that we estimate by wealth group:

$$f_{i,\text{US Equities},t} = \gamma_{0g} + \gamma_{1g} r_t^{\text{US, Eq}} + u_{it}, \tag{5}$$

$$f_{i,\text{US Equities},t} = \gamma_{0g} + \gamma_{1g} r_{i,\text{US equities},t} + u_{it}, \tag{6}$$

$$f_{i,\text{US Equities},t} = \gamma_{0g} + \gamma_{1g} \left(r_{i,\text{US equities},t} - r_t^{\text{US, Eq}}\right) + \gamma_{2g} r_t^{\text{US, Eq}} + u_{it}. \tag{7}$$

The first regression (5) is analogous to (4). In regression (6), we instead relate flows to U.S. equities to investors' own returns. Lastly, in regression (7), we relate the flows to the return in excess of the aggregate return and the aggregate return itself.

The results are reported in Table 2. The columns correspond to the different wealth groups. The first panel reports the results for regression (5). As before, we find that the coefficient declines in wealth. When using investors' own return instead of the aggregate stock market return in the second panel, we find that the coefficient displays a similar pattern. However, when we split the return in the "active return", $r_{i,\text{US equities},t} - r_t^{\text{US, Eq}}$, and the aggregate return on the market in the third panel, which corresponds to regression (7), we find that investors have a similar response to the active return and the coefficient is negative. This implies that all wealth groups act counter-cyclically to the active return. However, less wealthy households also respond to the broad market return and this coefficient is positive. Combined with the fact that the active return is a smaller fraction of the overall return for less wealthy households (see Figure 19), this pattern explains why we find the positive slope coefficient in the first panel.

Taken together, these results paint a coherent picture of the trading behavior of households across the wealth distribution. All households sell equities if the active return is positive, consistent with downward-sloping demand curves.[14] However, less wealthy households also respond to broader

[14]We cannot interpret the slope coefficients are demand elasticities as we do not instrument the active returns, and

Table 2: Returns and the flow to U.S. equities
In the top panel, we report the slope coefficients of a panel regression of flows to U.S. equities on the aggregate return on the U.S. stock market by wealth group (see (5)). In the middle panel, we report the slope coefficients of a panel regression of flows to U.S. equities on investors' returns on U.S. equities by wealth group (see (6)). In the bottom panel, we report the slope coefficients of a panel regression of flows to U.S. equities on both investors' returns on U.S. equities in excess of the aggregate return and the aggregate return itself by wealth group (see (7)). Standard errors are clustered by year-quarter.

	$< 3m$	$3m - 10m$	$10m - 30m$	$30m - 100m$	$> 100m$
(1) Panel on $r_t^{\text{US, Eq}}$					
· Coefficient on $r_t^{\text{US, Eq}}$	0.0209***	0.0105*	0.0030	0.0015	−0.0066
	(0.0053)	(0.0054)	(0.0059)	(0.0051)	(0.0080)
(2) Panel on $r_{i,\text{US equities},t}$					
· Coefficient on $r_{i,\text{US equities},t}$	0.0156***	0.0069	−0.0013	−0.0017	−0.0116**
	(0.0054)	(0.0053)	(0.0053)	(0.0043)	(0.0052)
(3) Panel on $r_{i,\text{US equities},t} - r_t^{\text{US, Eq}}$ & $r_t^{\text{US, Eq}}$					
· Coefficient on $r_{i,\text{US equities},t} - r_t^{\text{US, Eq}}$	−0.0243***	−0.0159***	−0.0210***	−0.0121***	−0.0210***
	(0.0073)	(0.0052)	(0.0034)	(0.0047)	(0.0043)
· Coefficient on $r_t^{\text{US, Eq}}$	0.0197***	0.0098*	0.0023	0.0012	−0.0065
	(0.0054)	(0.0054)	(0.0059)	(0.0051)	(0.0080)

market conditions and this leads to overall flows for this wealth group that are positively correlated with U.S. equity returns. These households may take cues from broad market movements, and negative market returns may lead to increased risk aversion, weaker investor sentiment, or perceptions of increased macro-economic risk.

4 What are common rebalancing directions?

We explore in this section how investors rebalance their portfolios across asset classes. We develop the framework in Section 4.1 and present the results in Section 4.2. By identifying the common rebalancing directions, this analysis can guide future theoretical work on heterogeneous agent macro-finance models that feature multiple asset classes.

4.1 A factor model for portfolio rebalancing

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

$$f_{int} = \alpha_n + \beta_n f_{it}^{\text{Liq}} + \gamma_n f_{it}^{\text{Cash}} + f_{int}^{\perp}. \tag{8}$$

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 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, β_n and γ_n, in (8) 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,[15] 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

$$f_{int}^{\perp} = \sum_k \lambda_{it}^{(k)} \eta_n^{(k)} + u_{int}, \tag{9}$$

active returns can therefore be correlated with investors' demand shocks. That said, we typically find that demand shocks and returns are positively correlated, which leads to an upward bias in γ_{1g}. This suggests that investors' demand curves slope down for active returns.

[15] Such stable shares are consistent with logit models of asset demand, see Koijen and Yogo (2019).

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. These loadings vary across investors investors and over time. Intuitively, investors may trade a factor that is long U.S. equities and short U.S. Treasuries in one quarter and reverse this trade in the next quarter. Then λ_{it} corresponding to that factor will have the opposite sign, while the trading direction, as captured by η_n, remains constant. Lastly, the residual, u_{int}, capture the idiosyncratic rebalancing decisions of an investor due to idiosyncratic views about a particular asset class.

4.2 Empirical results

We report the estimates of β_n in (8) alongside the average portfolio shares in Figure 20 for each of the liquid risky asset classes. As discussed before, if investors maintain fairly constant shares, we 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.

In the next step, we estimate the factor model based on the rebalancing flows, $f_{int}^{\perp}$. In Figure 21, 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 75% of the variation in portfolio rebalancing.

We now explore the properties of those rebalancing factors. In Figure 22, we report the estimates of $\eta_n^{(k)}$ for the first three factors, which explain about 75% 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 bond funds to U.S. Government bonds. Bond funds invest the majority in corporate bonds, although not everything. The second factor therefore captures the credit spread in fixed income markets. The third factor is a combination of two economically interpretable trades. The first rebalances from municipal bonds to U.S. Government bonds and bond funds. 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.

Figure 20: Allocation of new flows
We plot the estimates of β_n in equation (8) 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 2022.Q2.

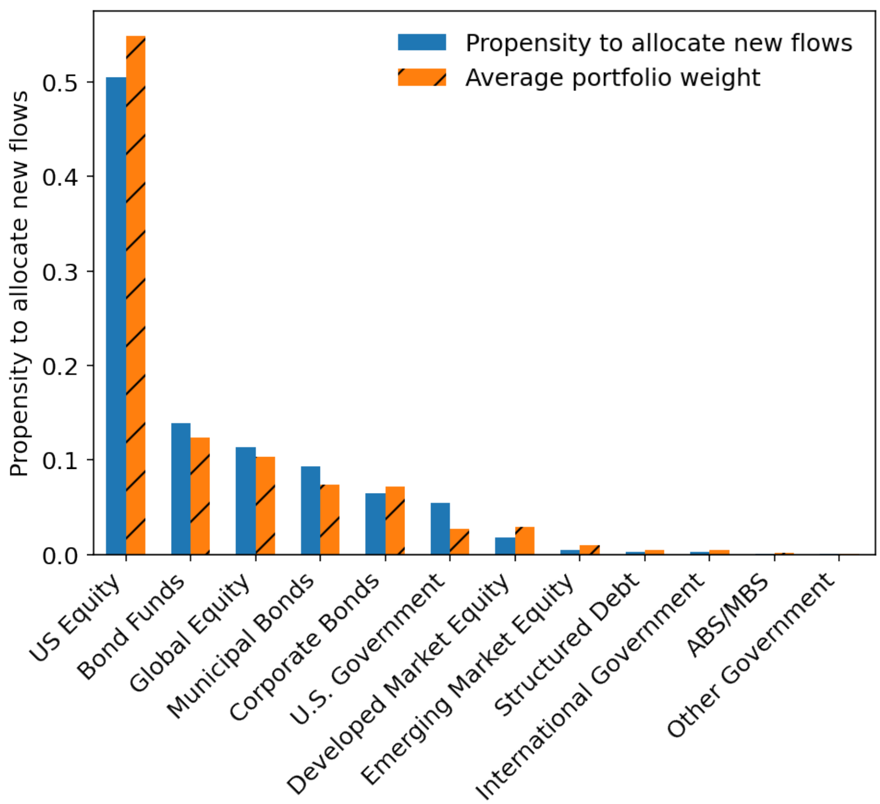


Figure 21: Factor structure in portfolio rebalancing
We plot the share of variance of $f_{int}^{\perp}$ explained by the principal components, see equation (9). The sample period is from 2016.Q1 to 2022.Q2.

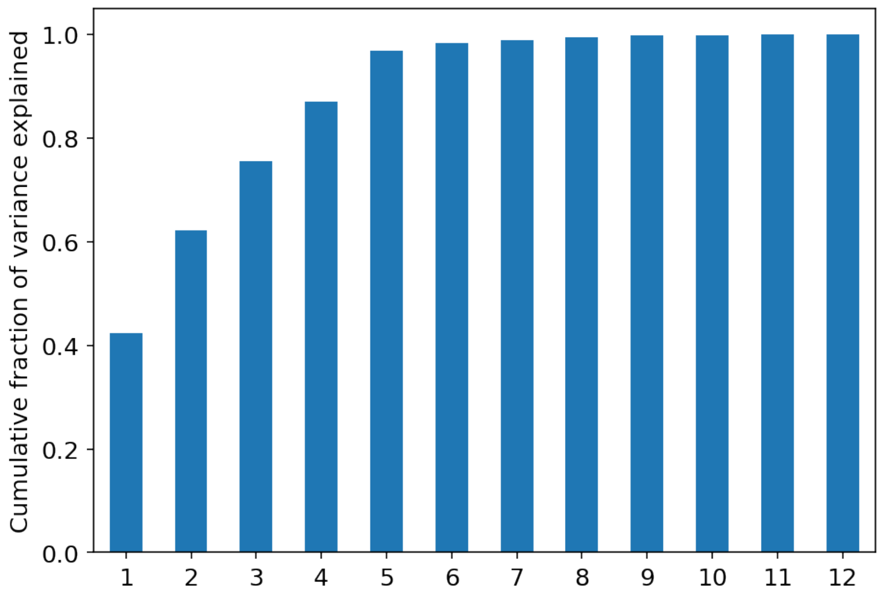
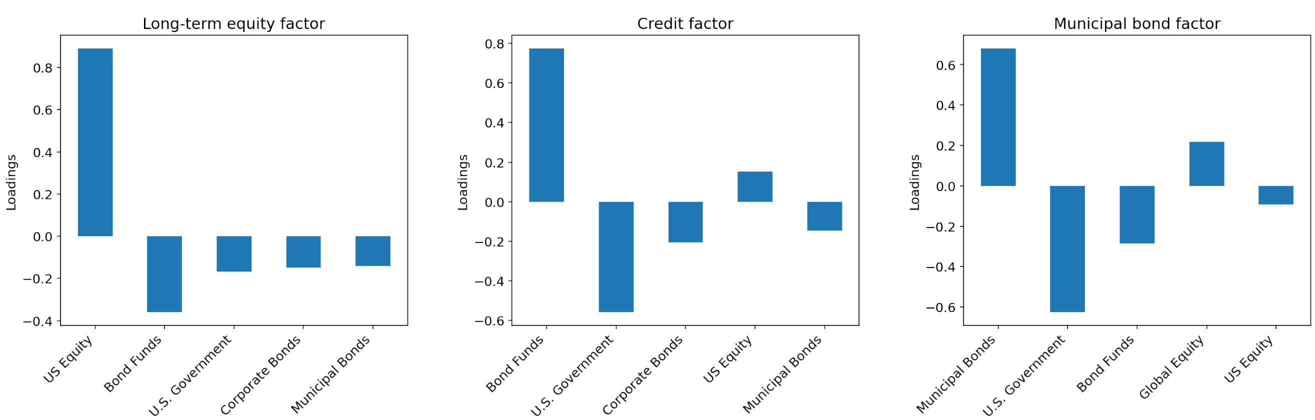


Figure 22: Rebalancing exposures across asset classes
We report the estimates of $\eta_n^{(k)}$, for $k = 1, 2, 3$, in equation (9). The coefficients capture the main rebalancing directions based on $f_{int}^{\perp}$. The sample period is from 2016.Q1 to 2022.Q2.



Taken together we find that 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.

5 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 and 372 portfolios with assets that exceed $1 billion at some point in the sample. This group of households that is 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 explore 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 document four key facts. First, UHNW households buy equity during downturns; less wealthy households take the other side. Second, the effects are amplified for investors who are more active in equity markets (in the cross-section) correlate strongly with advisor types. Third, the flows to U.S. equities are negatively correlated with active returns for all wealth groups, but the flows of less wealthy households are also strongly positively correlated with broad market returns. Fourth, there is a strong factor structure in rebalancing across asset classes along economically meaningful factors that target risk premia associated with U.S. equity markets, credit markets, municipal bond markets, and the global equity premium. These facts combined provide important inputs into the design of macro-finance models with rich heterogeneity across households.

References

Ameriks, John and Stephen P. Zeldes, "How do household portfolio shares vary with age?," Technical Report, National Bureau of Economic Research 2004.

Anagol, Santosh, Vimal Balasubramaniam, and Tarun Ramadorai, "The effects of experience on investor behavior: Evidence from Indiaś IPO lotteries," *Available at SSRN*, 2015, *2568748.*

Balasubramaniam, Vimal, John Y Campbell, Tarun Ramadorai, and Benjamin Ranish, "Who Owns What? A Factor Model for Direct Stock Holding," Technical Report, National Bureau of Economic Research 2021.

Balloch, Cynthia Mei and Julian Richers, "Asset Allocation and Returns in the Portfolios of the Wealthy," 2021.

Barber, Brad M and Terrance Odean, "Trading is hazardous to your wealth: The common stock investment performance of individual investors," *The journal of Finance*, 2000, *55* (2), 773–806.

Bender, Svetlana, James J Choi, Danielle Dyson, and Adriana Z Robertson, "Millionaires speak: What drives their personal investment decisions?," *Journal of Financial Economics*, 2022, *146* (1), 305–330.

Betermier, Sebastien, Laurent E Calvet, Samuli Knüpfer, and Jens Kvaerner, "What Do the Portfolios of Individual Investors Reveal About the Cross-Section of Equity Returns?," *Available at SSRN 3795690*, 2022.

Bretscher, Lorenzo, Lukas Schmid, Ishita Sen, and Varun Sharma, "Institutional Corporate Bond Pricing," Technical Report, Swiss Finance Institute - HEC Lausanne 2022.

Calvet, Laurent E., John Y. Campbell, and Paolo Sodini, "Down or Out: Assessing the Welfare Costs of Household Investment Mistakes," *Journal of Political Economy*, 2007, *115* (5), 707–747.

Calvet, Laurent E., John Y. Campbell, and Paolo Sodini, "Fight Or Flight? Portfolio Rebalancing by Individual Investors," *Quarterly Journal of Economics*, 2009, *124* (1), 301–348.

Calvet, Laurent E, John Y Campbell, Francisco Gomes, and Paolo Sodini, "The cross-section of household preferences," Technical Report, National Bureau of Economic Research 2021.

Campbell, John Y, Tarun Ramadorai, and Benjamin Ranish, "Getting better or feeling better? How equity investors respond to investment experience," Technical Report, National Bureau of Economic Research 2014.

Campbell, John Y, Tarun Ramadorai, and Benjamin Ranish, "Do the rich get richer in the stock market? Evidence from India," *American Economic Review: Insights*, 2019, *1* (2), 225–40.

Catherine, Sylvain, Paolo Sodini, and Yapei Zhang, "Countercyclical income risk and portfolio choices: Evidence from Sweden," *Swedish House of Finance Research Paper*, 2022, (20-20).

Cole, Allison, Jonathan A Parker, Antoinette Schoar, and Duncan Simester, "Household Portfolios and Retirement Saving over the Life Cycle," Technical Report, National Bureau of Economic Research 2022.

Curcuru, Stephanie, John Heaton, Deborah Lucas, and Damien Moore, "Heterogeneity and portfolio choice: Theory and evidence," in "Handbook of financial econometrics: Tools and techniques," Elsevier, 2010, pp. 337–382.

Davis, Steven J. and John Haltiwanger, "Gross Job Creation, Gross Job Destruction, and Employment Reallocation," *The Quarterly Journal of Economics*, 1992, *107* (3), 819–863.

Egan, Mark L, Alexander MacKay, and Hanbin Yang, "What Drives Variation in Investor Portfolios? Evidence from Retirement Plans," Technical Report, National Bureau of Economic Research 2021.

Fagereng, Andreas, Luigi Guiso, Davide Malacrino, and Luigi Pistaferri, "Heterogeneity and persistence in returns to wealth," *Econometrica*, 2020, *88* (1), 115–170.

Friend, Irwin and Marshall E Blume, "The demand for risky assets," *The American Economic Review*, 1975, *65* (5), 900–922.

Gabaix, Xavier and Ralph SJ Koijen, "In search of the origins of financial fluctuations: The inelastic markets hypothesis," Technical Report, National Bureau of Economic Research 2021.

Gabaix, Xavier and Ralph SJ Koijen, "In search of the origins of financial fluctuations: The inelastic markets hypothesis," Technical Report, National Bureau of Economic Research 2022.

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephen Utkus, "Five facts about beliefs and portfolios," *American Economic Review*, 2021, *111* (5), 1481–1522.

Grinblatt, Mark and Matti Keloharju, "The investment behavior and performance of various investor types: a study of Finland's unique data set," *Journal of financial economics*, 2000, *55* (1), 43–67.

Grinblatt, Mark, Matti Keloharju, and Juhani Linnainmaa, "IQ and stock market participation," *The Journal of Finance*, 2011, *66* (6), 2121–2164.

Haddad, Valentin, Paul Huebner, and Erik Loualiche, "How Competitive is the Stock Market? Theory, Evidence from Portfolios, and Implications for the Rise of Passive Investing," Technical Report, National Bureau of Economic Research 2022.

Heaton, John and Deborah Lucas, "Portfolio choice and asset prices: The importance of entrepreneurial risk," *The journal of finance*, 2000, *55* (3), 1163–1198.

Hoopes, Jeffrey, Patrick Langetieg, Stefan Nagel, Daniel Reck, Joel Slemrod, and Bryan Stuart, "Who sold during the crash of 2008-9? evidence from tax-return data on daily sales of stock," Technical Report, National Bureau of Economic Research 2016.

Koijen, Ralph SJ and Motohiro Yogo, "A demand system approach to asset pricing," *Journal of Political Economy*, 2019, *127* (4), 1475–1515.

Massa, Massimo and Andrei Simonov, "Hedging, familiarity and portfolio choice," *The Review of Financial Studies*, 2006, *19* (2), 633–685.

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
Catherine et al. (2022)	Swedish Wealth and Income Registry	Sweden (1999-2007)	Equity	
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.

Online Appendix

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

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. The dataset contains 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 within a firm. While *position_entity_id* is available for any security in the dataset, it is also complemented by CUSIP, 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.

Table A2: Firm Classification
This table provides details on the types of advisors observed for each broader advisor category.

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

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. We further observe two additional asset class classifications which are not entered by custodians but rather internally generated by Addepar. 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. Equities), classifies any security within a narrower asset class (e.g. U.S. Equity, Global Equity). 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_incepti* *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*ss, *morningstar_region_breakdown*, *morningstar_category*, *morningstar_sector*, *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.

Variables used for asset class assignment Addepar employs an internal algorithm to impute the narrow and broad asset classes based on the following input variables: *cfi_code*, a universal six letter code provided by ISO 10962 and attributed to the entity at the time of issue; *instrument_type*, directly derived from *cfi_code*; *fund_asset_class*, which describes the broad type of fund based on *morningstar_us_asset_class*; *fund_category*, which describes the type of fund based on *morningstar_category*; *bond_term*, which assigns a bond as short-term if the time-to-maturity is lower than one year and long-term otherwise; *domcile_country_class*, which maps the country of domicile into United States, Developed or Emerging; *business_country_class*, which maps the country in which the entity has its headquarter into United States, Developed or Emerging; *cur-*

rency, which provides the native currency of the security. In Section A.2, we provide details on how these input variables are combined to construct the asset class assignment.

A.2 Asset class assignment and 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.

A.2.1 Asset classes

For each broad asset class, we start by reporting the criteria used by Addepar for the assignment of narrow asset classes. A summary of broad and narrow asset classes as we observe in the raw data is provided in Table A3 .

Cash Positions in Addepar are assigned narrow asset class equal to: CAD if *instrument_type* is Bank Account and *currency* is CAD; Certificate of Deposit if *instrument_type* is Certificate of Deposit; CHF if *instrument_type* is Bank Account and *currency* is CHF; Commercial Paper if *instrument_type* is Commercial Paper; EUR if *instrument_type* is Bank Account and *currency* is EUR; Money Market Fund if *instrument_type* is Money Market Fund or if *instrument_type* is ETF/Mutual Funds and *fund_category* is Money Market Taxable or Money Market-Tax Free or Prime Money Market or Ultrashort Bond; Other Currency if *instrument_type* is Bank Account; Other Short Term Government Bonds if *instrument_type* is Government/Agency Bonds and *bond_term* is Short; Short Term US Government Bonds if *instrument_type* is Government/Agency Bonds, *bond_term* is Short and either *domicile_country_class* or *business_country_class* is United States; USD if *instrument_type* is Bank Account and *currency* is USD.

Fixed Income Positions in Addepar are assigned narrow asset class equal to: ABS/MBS if *instrument_type* is ABS/MBS; Bond Funds if *instrument_type* is ETF/Mutual Funds and *fund_asset_class* is Taxable Bond or if *instrument_type* is ETF/Mutual Funds and *fund_category* is either Intermediate Core-Plus Bond or Intermediate Core Bond or Short-Term Bond or Multisector Bond; Corporate Bonds if *instrument_type* is either Corporate Bonds or Depository Receipts on Debt; International Government/Agency Bonds if *instrument_type* is Government/Agency Bonds, *bond_term* is either Long or Unknown and *business_country_class* (or *domicile_country_class*) is either Developed or Emerging; Municipal Bonds if *instrument_type* is Municipal Bonds or if *instrument_type* is Mutual Funds/ETF and *fund_asset_class* is Municipal Bond; Other Debt if *instrument_type* is Other Debt; Structured Debt if *instrument_type* is either Structured Debt or Convertible Bonds; U.S. Government/Agency Bonds if *instrument_type* is Government/Agency Bonds, *bond_term* is either Long or Unknown and *business_country_class* (or *domicile_country_class*) is United States; U.S. Government/Agency Bonds if *instrument_type* is Government/Agency Bonds, *bond_term* is Long and both *business_country_class* and *domicile_country_class*) are unavailable;

Equities Positions in Addepar are assigned narrow asset class equal to: Call Option if *instrument_type* is Call Option; Developed Market Equity if *instrument_type* is Depository Receipts on Equities or Common Equity or Preferred Equity or Convertible Equity or Preferred Convertible Equity or Limited Partnership Units or Structured Equity or Other Equity and *business_country_class* (or *domicile_country_class*) is Developed; Emerging Market Equity if *instrument_type* is Depository Receipts on Equities or Common Equity or Preferred Equity or Convertible Equity or Preferred Convertible Equity or Limited Partnership Units or Structured Equity or Other Equity and *business_country_class* (or *domicile_country_class*) is Emerging; Global Equity if *instrument_type* is ETF or Mutual Funds and *fund_asset_class* is International Equity; Other Equity if *instrument_type* is Depository Receipts on Equities or Common Equity or Preferred Equity or Convertible Equity or Preferred Convertible Equity or Limited Partnership Units or Structured Equity or Other Equity or Rights/Warrants or Acquisition Company; Other Funds if *instrument_type* is either Mutual Funds or ETF; Put Option if *instrument_type* is Put Option; REITs if *instrument_type* is REITs; U.S. Equity if *instrument_type* is Depository Receipts on Equities or Common Equity or Preferred Equity or Convertible Equity or Preferred Convertible Equity or Limited Partnership Units or Structured Equity or Other Equity and *business_country_class* (or *domicile_country_class*) is United States; U.S. Equity if *instrument_type* is either ETF or Mutual Funds and *fund_asset_class* is U.S. Equity.

Alternatives Positions in Addepar are assigned narrow asset class equal to: Direct Private Companies if *instrument_type* is Direct Private Companies; Fund of Funds if *instrument_type* is Fund of Funds; Hedge Funds if *instrument_type* is Hedge Funds; Private Equity & Venture if *instrument_type* is Private Equity & Venture; Real Estate Funds if *instrument_type* is Real Estate Funds; Unknown Alts if *instrument_type* is Unknown Alts.

Real Estate Positions in Addepar are assigned narrow asset class equal to Direct Real Estate if *instrument_type* is either Other Direct Real Estate or Direct Residential Real Estate.

Other Positions in Addepar are assigned narrow asset class equal to: Collectibles if *instrument_type* is Collectibles; Crypto if *instrument_type* is Crypto; Liabilities if *instrument_type* is Loans/Liabilities; Other Derivatives if *instrument_type* is either Other Derivative or Forwards/Futures; Other Non-Financial Assets if *instrument_type* is Other Non-Financial Assets.

Adjustments made to the Addepar classification We make several adjustments to the assignment of asset classes imputed by Addepar. First, we reclassify REITs and Direct Real Estate into Alternatives. Second, we merge Short Term U.S. Government Bonds into U.S. Government/Agency Bonds. Similarly, we merge Other Short Term Government Bonds into Unknown Government/Agency Bonds and relabel the narrow asset class as Other Government/Agency Bonds. Third, we merge Call Option, Put Option, and Other Derivatives into a single narrow asset class Derivatives to which we assign broad asset class Other. Fourth, we combine Money Market Fund, Certificate of Deposit, Commercial Paper, CAD, CHF, EUR, USD, Other Currency into a single narrow asset class Cash. Fifth, when holdings are classified as Other Funds and the fund asset class is Sector Equity, we relabel the narrow asset class to U.S. Equity if either the business country class

Table A3: Initial asset class definitions
This table summarizes broad and narrow asset classes that we observe in the dataset, before any correction is made. Narrow asset classes are categorized into six broad asset classes. The broad and narrow asset classes are obtained from Addepar's internal classification.

Broad asset classes	Narrow asset classes
Cash	Money Market Fund, Certificate of Deposit, Commercial Paper, CAD, CHF, EUR, USD, Short Term U.S. Government Bonds, Other Short Term Government Bonds, Other Currency
Fixed Income	Municipal Bonds, U.S. Government/Agency Bonds, Corporate Bonds, Bond Funds, ABS/MBS, Structured Debt, International Government/Agency Bonds, Unknown Government/Agency Bonds, Other Debt
Equities	U.S. Equity, Global Equity, Developed Market Equity, Emerging Market Equity, REITs, Call Option, Put Option, Other Equity, Other Funds
Alternatives	Private Equity & Venture, Hedge Funds, Real Estate Funds, Direct Private Companies, Fund of Funds, Unknown Alts.
Real Estate	Direct Real Estate
Other	Collectibles, Crypto, Liabilities, Other, Other Derivatives, Other Non-Financial Assets

or the domicile country class is United States.[16] For the remaining observations in Other Funds, we change the broad asset class from Equities to Alternatives. Lastly, we perform several adjustments to holdings classified as Bond Funds: if the fund category is either Intermediate Government or Long Government, we modify the narrow asset class to U.S. Government/Agency Bonds if either the business country class or the domicile country class is United States; if the fund category is Corporate Bond or High Yield Bond, we relabel the narrow asset class to Corporate Bonds; if the fund category is Preferred Stock, we reclassify the asset class to the equity category Other Equity; finally, we reclassify positions to Cash when the fund category is Ultrashort Bond.

In Table A4, we report the classification of broad and narrow narrow asset classes used in the paper and obtained by performing the above corrections on Addepar internal classification.

A.2.2 Investment types

Although not directly used in the paper, Table A5 reports for completeness the breakdown of investment types into investment sub types observed in the dataset.

B Additional details on cleaning steps

We provide further details on cleaning steps that are performed before aggregating the dataset at quarterly frequency. These cleaning steps have the objective to correct infrequent data issues or to ensure proper measurement for the variables of interest.

First, for 9,931 portfolios, we observe that the last date of the incubation period is later than the first month in which the portfolio appears in dataset. For these portfolios, we drop any month that predates the last historical date. Similarly, for a minority of portfolios, we observe positions

[16]Fund asset class, business country class, domicile country class, and fund category provide further details on the nature or geography of the positions observed in the dataset.

Table A4: Corrected asset class definitions
This table summarizes broad and narrow asset classes used in the paper. Narrow asset classes are categorized into five broad asset classes. The broad and narrow asset classes are obtained by imposing corrections on Addepar's internal classification.

Broad asset classes	Narrow asset classes
Cash	Money Market Fund, Certificate of Deposit, Commercial Paper, CAD, CHF, EUR, USD, Other Currency
Fixed Income	Municipal Bonds, U.S. Government/Agency Bonds, Corporate Bonds, Bond Funds, ABS/MBS, Structured Debt, International Government/Agency Bonds, Other Government/Agency Bonds, Other Debt
Equities	U.S. Equity, Global Equity, Developed Market Equity, Emerging Market Equity, Other Equity
Alternatives	Private Equity & Venture, Hedge Funds, Direct Real Estate, Direct Private Companies, Fund of Funds, Real Estate Funds, REITs, Other Funds, Unknown Alts.
Other	Collectibles, Crypto, Derivatives, Liabilities, Other, Other Non-Financial Assets

classified as historical segments. To avoid focusing on incubation periods where investors do not trade then, for each investor, we drop all months that predate the last date on which an historical segment was present in the portfolio.

Second, *net_cashflow* in Addepar is measured net of dividends and distributions, which we observe in *fund_distributions_and_dividends*. To ensure that *net_cashflow* properly measure investors' rebalancing, we add *fund_distributions_ and_dividends* back to *net_cashflow* and we subtract it from *total_return*.

Third, in the dataset at monthly frequency and security-level. We observe a minority of observations with extreme time-weighted return which we correct in three steps. We start by replacing missing returns with the median return by narrow asset class-month or by CUSIP-month for all CUSIP-months for which we observe at least three observations with available return. We then construct a robust measure of standard deviation as the interquartile range by narrow asset class-month, divided by 1.35. For any CUSIP-month for which we observe at least three observations with available return, we flag any return that deviates from the median return by CUSIP-month by more than one robust standard deviation and we replace it with the median return by CUSIP-month. For those CUSIP-months for which we observe less than three observations, we flag any return that is higher (lower) than the 99^{th} (1^{st}) percentile of returns by narrow asset class-month and we replace it with the 99^{th} (1^{st}) percentile of returns by narrow asset class-month if the narrow asset class is not Cash. If the narrow asset class is Cash, we replace these extreme returns with the median return by month. To control for rare cases of extreme returns that are not corrected through the procedure, we winsorize returns at -300% and 300% for each security before aggregating the returns at the level of narrow asset classes using value weights.

Finally, we observe a small number of investors in the monthly dataset for which all narrow asset classes other than Other have either zero *starting_value* or zero *ending_value*. To avoid considering historical segments where investors do not trade, we drop any portfolio-month when two conditions are met: (i) in the previous month, the investor had either zero *starting_value* or zero *ending_value* in all narrow asset classes other than Other; (ii) in the current month, the investor had zero *starting_value* in all narrow asset classes other than Other.

Table A5: Investment Type Taxonomy

This table provides the breakdown of investment types and investment sub types observed in the dataset.

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