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LIMITED RISK TRANSFER BETWEEN INVESTORS:
A NEW BENCHMARK FOR MACRO-FINANCE MODELS

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

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Limited Risk Transfer Between Investors: A New Benchmark for Macro-Finance Models
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ABSTRACT

We define risk transfer as the percent change in the market risk exposure for a group of investors over a given period. We estimate risk transfer using novel data on U.S. investors' portfolio holdings, flows, and returns at the security level with comprehensive coverage across asset classes and broad coverage across the wealth distribution (including 400 billionaires). Our key finding is that risk transfer is small with a mean absolute value of 0.65% per quarter. Leading macro-finance models with heterogeneous investors predict risk transfer that exceeds our estimate by a factor greater than ten because investors react too much to the time-varying equity premium. Thus, the small risk transfer is a new moment to evaluate macro-finance models. We develop a model with inelastic demand, calibrated to the standard asset pricing moments on realized and expected stock returns, that explains the observed risk transfer. The model is adaptable to other macro-finance applications with heterogeneous households.

Xavier Gabaix
Department of Economics
Harvard University
Littauer Center
1805 Cambridge St
Cambridge, MA 02138
and NBER
xgabaix@fas.harvard.edu

Ralph S. J. Koijen
University of Chicago
Booth School of Business
5807 S Woodlawn Ave
Chicago, IL 60637
and NBER
Ralph.koijen@chicagobooth.edu

Federico Mainardi
Booth School of Business
University of Chicago
5807 S. Woodlawn Avenue
Chicago, IL 60637
fmainard@chicagobooth.edu

Sangmin Simon Oh
Columbia Business School
665 W 130th St
New York, NY 10027
oh@gsb.columbia.edu

Motohiro Yogo
Department of Economics
Princeton University
Julis Romo Rabinowitz Building
Princeton, NJ 08544
and NBER
myogo@princeton.edu

1 Introduction

We propose risk transfer as a new micro moment to evaluate macro-finance models. We define risk transfer as the percent change in the market risk exposure for a group of investors over a given period. The wealth-weighted sum of risk transfer is zero in the population of investors. However, the absolute risk transfer for a group of investors, averaged in the time series, is highly informative about a core mechanism of macro-finance models with heterogeneous households.

Heterogeneity in risk aversion (Chan and Kogan 2002; Gârleanu and Panageas 2015; Kekre and Lenel 2022) or optimism (Martin and Papadimitriou 2022) is a leading explanation for the observed variation in stock allocation (or market risk exposure) across households. Moreover, these models generate realistic variation in the equity premium over time. In these models, households that have lower risk aversion or are more optimistic have higher stock allocations, and they become relatively wealthier after a positive shock to the stock market. These households want to increase their market risk exposure, resulting in a positive risk transfer. On the opposite side, households that have higher risk aversion or are more pessimistic become relatively poorer after a positive shock to the stock market. These households want to decrease their market risk exposure, resulting in a negative risk transfer. These effects amplify the initial shock and lower the equity premium. Although these models are calibrated to asset prices, they are not tested on the core mechanism of risk transfer.

To estimate risk transfer, we need high quality panel data on household portfolios with comprehensive coverage across asset classes and broad coverage across the wealth distribution. We use novel data on U.S. investors' portfolio holdings, flows, and returns at the security level from Addepar, which is a wealth management platform for investment advisors. The asset pricing theory makes predictions about market risk exposures rather than portfolio shares. Therefore, we map portfolio holdings to market risk exposures, using estimated betas by asset class. We use liquid assets (i.e., equity and fixed income securities) only because illiquid assets (e.g., private equity and direct private companies) are difficult to trade and would mechanically lower our estimate of risk transfer. The key finding is that mean absolute risk transfer is 0.65% per quarter (e.g., market risk exposure changes from 0.5 to 0.50325). We find consistently low estimates for groups of households sorted by market risk exposure.

Leading macro-finance models, calibrated to explain the time-varying equity premium, imply much bigger risk transfer. For example, a traditional model of portfolio choice (i.e., mean-variance asset demand) predicts risk transfer of 270%, which is over two orders of magnitude greater than our estimate of 0.65%. The heterogeneous investor model of Gârleanu and Panageas (2015) predicts risk transfer of 78% for the high risk aversion group and 3.5% for the low risk aversion group, which exceed our estimate by a factor greater than ten. The problem with these macro-finance models is that rational investors react too much to the time-varying equity premium.

We propose an alternative model in which investors have a dampened reaction to the time-varying equity premium, which implies inelastic demand in the long run (Gabaix and Koijen 2023). We also add slow adjustment toward the target stock allocation to be more consistent with observed portfolios. Beyond asset pricing, our modeling techniques may be useful in other macro-finance applications that rely on realistic portfolio choice (Kaplan, Moll, and Violante 2018).

This paper would not be possible without the Addepar data, which we briefly describe. Addepar provides wealth managers with real-time portfolio information to guide investment decisions. Whenever possible, Addepar receives daily data on portfolio holdings and flows from custodians, which they use to compute daily dollar returns. In this paper, we aggregate portfolio flows and returns to a monthly frequency, paired with monthly snapshots of portfolio holdings. Addepar maps security-level data to narrow asset classes (e.g., U.S. equity, private equity, and put options) and broad asset classes (e.g., equity and fixed income). Our sample covers January 2016 to March 2023. The platform has been growing rapidly during our sample period, and the total assets (number of portfolios) have increased from \$180 billion (13,765) to \$2.33 trillion (235,350). Balloch and Richers (2023) is the first paper to use the Addepar data, documenting how asset class allocations and investment returns vary across the wealth distribution. We use the same data but focus on how investors rebalance their market risk exposure to test macro-finance models.

The Addepar data have two important advantages relative to household surveys and other administrative data for U.S. households. First, the data cover ultra-high-net-worth (UHNW) investors with nearly a thousand portfolios with assets exceeding \$100 million and 439 portfolios with assets exceeding \$1 billion at some point in our sample. This group of households, which is particularly relevant for asset prices, is under-represented in household surveys. This broad coverage across the wealth distribution gives us a representative estimate of risk transfer for U.S. households. Second, we have comprehensive coverage across asset classes at the security level. The data cover public and private assets (including derivatives) as well as direct and indirect holdings (e.g., mutual funds, exchange-traded funds, and hedge funds). We cannot get such broad and detailed coverage for most U.S. institutional investors.

Related literature We offer risk transfer as a new statistic to test macro-finance models with heterogeneous households. We follow a long literature that provides descriptive statistics that are informative about heterogeneity in household consumption, income, wealth, and portfolios. The literature on household consumption documents heterogeneous risk exposures across households (Mankiw and Zeldes 1991; Brav, Constantinides, and Geczy 2002; Vissing-Jørgensen 2002). The literature on household income documents heterogeneous exposure to systematic and idiosyncratic risk (Guvenen, Ozkan, and Song 2014; Guvenen et al. 2021) and the dynamics of income inequality (Piketty and Saez 2003). The literature on household wealth documents the dynamics of wealth inequality and its relation to asset prices (Campbell, Ramadorai, and Ranish 2019; Fagereng et al. 2020; Smith, Zidar, and Zwick 2023; Gomez and Gouin-Bonenfant 2024).

The literature on household portfolios studies how household portfolio choice relates to risk preferences (Calvet, Campbell, and Sodini 2007; Egan, MacKay, and Yang 2021), income risk (Heaton and Lucas 2000; Bender et al. 2022; Catherine, Sodini, and Zhang 2022), life-cycle effects (Ameriks and Zeldes 2004; Betermier et al. 2022; Cole et al. 2022; Balasubramaniam et al. 2023), and beliefs (Campbell, Ramadorai, and Ranish 2014; Giglio et al. 2021). This literature also studies the determinants of trading (Barber and Odean 2000; Grinblatt and Keloharju 2000; Calvet, Campbell, and Sodini 2009; Hoopes et al. 2016) and stock market participation (Anagol, Balasubramaniam, and Ramadorai 2015). We provide a more detailed summary of this literature in Appendix B.

This paper also contributes to the literature on demand system asset pricing (Koijen and Yogo 2019; 2020; Gabaix and Koijen 2023). The goal of this literature is to jointly understand asset prices, portfolio holdings and flows, firm characteristics, and macro variables. This literature confirms the earlier evidence that asset demand is much less elastic than predictions of standard asset pricing models (Harris and Gurel 1986; Shleifer 1986; Chang, Hong, and Liskovich 2014). Since only institutional holdings data are publicly available in the United States, this literature imputes the aggregate holdings of the household sector as the difference between the shares outstanding and the aggregate institutional holdings. Moreover, we observe portfolio holdings of both equity and fixed income for only a subset of institutions, namely mutual funds and insurance companies. The Addepar data provide much more detail on the portfolio holdings of the household sector across households and asset classes. These data allow us to estimate risk transfer and to ask whether households, particularly the very wealthy ones, are an important stabilizing force in financial markets.

Outline The paper proceeds as follows. In Section 2, we introduce the data, discuss how we construct our sample, and we provide summary statistics. In Section 3 we define risk transfer, and detail how rational models tend to predict very high value of risk transfer. We then conclude. Proofs are in Section D.1 of the online appendix.

2 Data and summary statistics

2.1 Definitions of assets and flows

We denote time by t and *i*nvestors by i, $i = 1, ..., I$. We index security-level *a*sset holdings by a (e.g., Apple stock), which can be aggregated to *n*arrow asset classes that we index by n (e.g., U.S. equities or U.S. Treasuries) or broad asset *c*lasses 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 dollar 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-temporal 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 $A^{DH}_{i,t-1} \coloneqq \frac{1}{2}(A_{it} - R^{\$}_{it} + A_{i,t-1}) = A_{i,t-1} + \frac{1}{2}F_{it}$. Our definition of flows follows Davis and Haltiwanger (1992) and, when $A_{i,t-1}$ is close to zero, it leads to a definition of flows that is more robust than the more elementary $f_{int} = \frac{F_{int}}{A_{i,t-1}}$. In this definition, $A_{it} - R^{\$}_{it}$ corresponds to end-of-period wealth, adjusted for valuation effects. 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 November 2023, Addepar works with 1,000 financial advisors, family offices, and large financial institutions that manage more than $4.5 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 March 2023. 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.[1] 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.[2]

Addepar imposes two additional screens for data confidentiality. First, advisors that account for more than 10% of all portfolios in a given month are removed. Once a portfolio is 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 that are affected by this screen in each month. There are 140 such accounts in our sample.

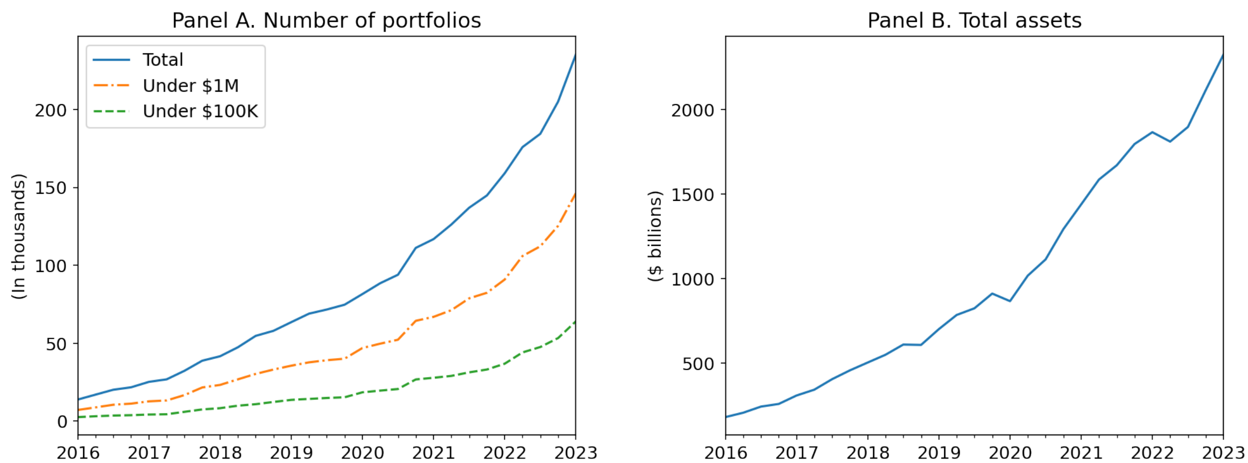
Our sample of Addepar data includes information on 272,247 distinct client portfolios from 2016.Q1 to 2023.Q1. In Figure 1, we summarize the number of portfolios in Panel A and households' total assets on the platform in Panel B before imposing any screens. The number of portfolios grows from 13,765 in 2016.Q1 to 235,350 in 2023.Q1. The sharp increase in the number of portfolios reflects the growth of the Addepar platform during our sample period. Households' total assets grow from $180 billion to $2.33 trillion during the same period.

In Figure 2, we further report the number of billionaires that we observe in each quarter

1. We provide details on minor cleaning steps performed before aggregating the monthly data at a quarterly frequency in Online Appendix C.3.

2. 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 Panel A, 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 Panel B, we plot the total value of assets in our sample. The sample period is from January 2016 to March 2023.



of our sample. In 2023.Q1, the last quarter of our dataset, we observe 304 portfolios with assets in excess of $1 billion. 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) there may be some foreign investors, this comparison does indicate that the coverage of the right tail of the wealth distribution is unusually good in our sample. Overall, there are 439 unique portfolios that exceed $1 billion in assets at some point in our sample.

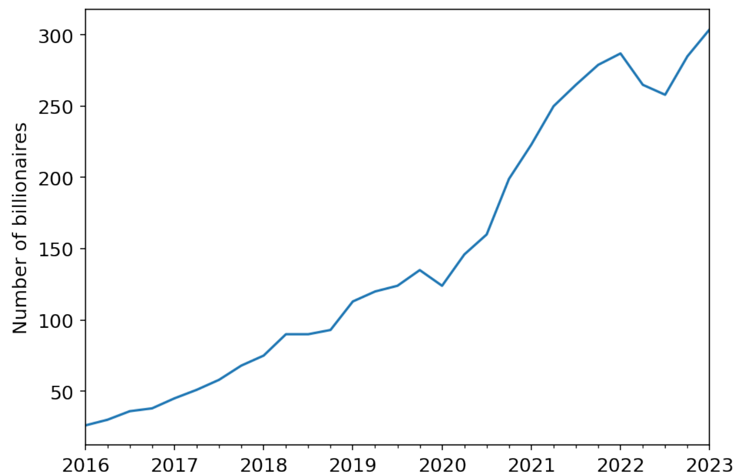
We assign households to one of five groups based on total wealth in a given quarter: A_{it} <\$3m, A_{it} ∈[\$3m, \$10m), A_{it} ∈[\$10m, \$30m), A_{it} ∈[\$30m, \$100m), and A_{it} ≥\$100m.

2.3 Definitions of asset classes

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 C.

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. We treat cash separately as flows to cash are more volatile than other asset classes. The reason is that cash plays a dual role: it is used as a safe asset during times of stress and, second, it absorbs liquidity shocks. In the

Figure 2: Number of billionaires
This figure plots the time-series of the number of portfolios that exceed $1 billion in assets in each quarter of our sample. The sample period is from January 2016 to March 2023.



context of risk transfer, cash does not matter much as its market beta is zero. 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 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 also remove the last quarter that we observe a given household for the same reason.[3]

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.[4] Fourth, for a

3. It is rare for households to leave the platform during our sample period.

4. 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.

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, REITs, Other Equity
Alternatives	Private Equity & Venture, Hedge Funds, Direct Real Estate, Direct Private Companies, Fund of Funds, Real Estate Funds, Other Funds, Unknown Alts.
Other	Collectibles, Crypto, Derivatives, Liabilities, Other, Other Non-Financial Assets

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 0.53% of all narrow asset class-quarter observations.[5]

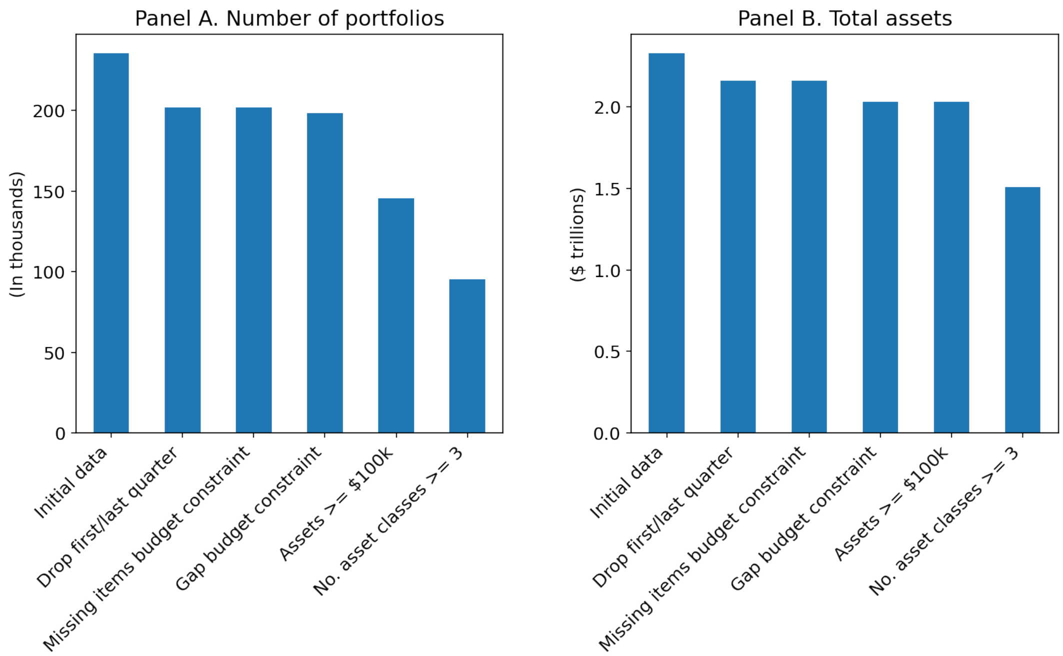
Fifth, we drop household-quarter observations with fewer than $100k in assets (across liquid and illiquid asset classes as well as cash). This screen also mitigates the concern that we capture only part of a household's assets. Lastly, we restrict to households with positive assets in the beginning or at the end of the period in at least three liquid asset classes. As we are interested in measuring rebalancing activity, we focus on households who are active across multiple liquid asset classes.[6]

We summarize the impact of each of the screens in Figure 3 for 2023.Q1, which is the last quarter of our sample. We report the total number of accounts in Panel A and we report the total assets covered in Panel B. 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

5. 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.

6. Our results are robust to relaxing this screen to households having only positions in two asset classes of which one of the asset classes may be cash.

Figure 3: 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 Panel A, we show the impact on the number of accounts. In Panel B, we show the impact on the total assets covered in our sample. The results are presented for 2023.Q1.



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).[7]

2.5 Comparison to the Survey of Consumer Finances

Before proceeding with the core analysis of the paper, we compare our sample of households in the Addepar data with the Survey of Consumer Finances (SCF) to examine the representativeness of our sample relative to the overall U.S. population. We focus on total net worth, liquid asset classes, and cash given the importance of these asset classes in the subsequent analysis. We provide further details and the precise construction of each variable in Appendix C. Balloch and Richers (2023) provide additional details for private asset classes

7. We set flows, returns, and assets to zero for narrow asset classes in which a household does not have a position.

Table 2: Comparison of Addepar and the Survey of Consumer Finances
This table reports median net worth and median wealth in cash, equities, and fixed income for households grouped by net worth. All statistics are in millions of dollars, based on the SCF in Panel A and the Addepar data in Panel B for 2018.Q4.

Panel A. SCF

Group	Sample size	A_{it}	A_{it}^{CEFi}	A_{it}^{Cash}	A_{it}^{Eq}	A_{it}^{Fi}
$A_{it}^{\text{Eq, Dir}} \in [\$0.1m, \$1m)$	328	1.36	1.15	0.07	0.42	0.40
$A_{it}^{\text{Eq, Dir}} \in [\$1m, \$3m)$	164	5.88	5.16	0.29	2.50	1.06
$A_{it}^{\text{Eq, Dir}} \in [\$3m, \$10m)$	142	9.06	7.94	0.31	6.00	1.06
$A_{it}^{\text{Eq, Dir}} \geq \$10m$	133	34.81	29.66	1.67	23.30	3.00
Total	767	2.27	1.91	0.11	0.70	0.55

Panel B. Addepar

Group	Sample size	A_{it}	A_{it}^{CEFi}	A_{it}^{Cash}	A_{it}^{Eq}	A_{it}^{Fi}
$A_{it}^{\text{Eq, Dir}} \in [\$0.1m, \$1m)$	10,400	1.36	1.23	0.08	0.76	0.24
$A_{it}^{\text{Eq, Dir}} \in [\$1m, \$3m)$	3,938	4.53	4.20	0.25	2.76	0.84
$A_{it}^{\text{Eq, Dir}} \in [\$3m, \$10m)$	2,011	15.04	13.03	0.69	8.86	2.15
$A_{it}^{\text{Eq, Dir}} \geq \$10m$	1,154	66.72	56.35	2.81	38.59	5.35
Total	17,503	2.79	2.49	0.15	1.54	0.42

as well as a comparison between Addepar and the sample used in Smith, Zidar, and Zwick (2023).

The SCF is based on a random sample of the census population and tries to provide an unbiased estimate of the population means. However, the survey data are subject to censoring to protect privacy, multiple imputation to fill missing values (when respondents refuse to answer), and other measurement errors. The Addepar data, based on the actual record of asset ownership, do not have these issues. However, we do not know if the sample of households in the Addepar data is representative of the U.S. population, conditional on observed characteristics such as wealth. High net worth households could have multiple accounts in the Addepar data that we are unable to connect. For all of these reasons, a comparison between the Addepar data and the SCF may not be exact.

Three key facts emerge from the comparison. First, the sample size in the Addepar data is an order of magnitude larger than that in the SCF across all wealth levels. For instance, the SCF includes 1,094 households with net worth in excess of $3 million, while the Addepar data includes 12,815 households in this wealth group.

Second, Panel A of Table 2 reports the median of net worth and of the holdings of cash

A_{it}^{Cash}, equities A_{it}^{Eq}, and fixed income A_{it}^{Fi} for the 2019 SCF (that is, as of December 2018). We also report the median of total wealth in these three broad asset classes, denoted by $A_{it}^{\text{CEFi}} = A_{it}^{\text{Cash}} + A_{it}^{\text{Eq}} + A_{it}^{\text{Fi}}$. Panel B does the same for the Addepar data as of December 2018, using concepts of net worth and wealth in the three broad asset classes that most closely mimic the definitions in the SCF. We sort investors in four groups based on total wealth invested in direct equity positions $A_{it}^{\text{Eq, Dir}}$, as this can be measured reliably in both datasets. Despite our caveats discussed before, all statistics match closely for direct equity holdings in the ranges from \$0.1 to \$1 million and from \$1 to \$3 million.

Third, the Addepar data and the SCF diverge at higher levels of direct equity holdings. For households with $A_{it}^{\text{Eq, Dir}}$ greater than \$10 million, the median net worth is \$34.8 million in the SCF and \$66.7 million in the Addepar data. For the same group of households, the median A_{it}^{CEFi} is \$29.7 million in the SCF and \$56.4 million in the Addepar data. This gap can be explained by the fact that the SCF does not accurately capture wealth at the extreme right tail because of survey limitations or the censoring procedure used in the SCF.

2.6 Summary statistics on portfolio holdings

We provide basic summary statistics on portfolio holdings across broad and narrow asset classes. These results complement the results in Balloch and Richers (2023). 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 Panel A of Figure 4. While the number of portfolios naturally declines in wealth, there are still 990 portfolios in our sample with more than \$100 million in assets. We plot the fraction of total assets invested in liquid asset classes in Panel B. 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.

In Figure 5, we plot the average portfolio shares across investors in 2019.Q4 for the 10 largest liquid asset classes (in Panel A) and the 10 largest illiquid asset classes (in Panel B).[8] Among liquid asset classes, U.S. equities is the largest asset class, followed by municipal bonds, global equities, corporate bonds, and U.S. government bonds. Among illiquid asset classes, the largest asset class is private equity and venture capital, followed by hedge funds and direct positions in private companies.

We summarize the fraction invested in broad asset classes by wealth group in 2019.Q4

8. We treat cash separately for reasons that we discuss in Section 2.7. In Figure 5, we report the average share in cash in the right panel, having noted that we do not treat it as an illiquid asset class.

Figure 4: Number of portfolios and the fraction invested in liquid assets by wealth group
In Panel A, we plot the number of portfolios in each of the five wealth groups. In Panel B, we plot the average fraction invested in liquid risky assets. The results are presented for 2019.Q4.

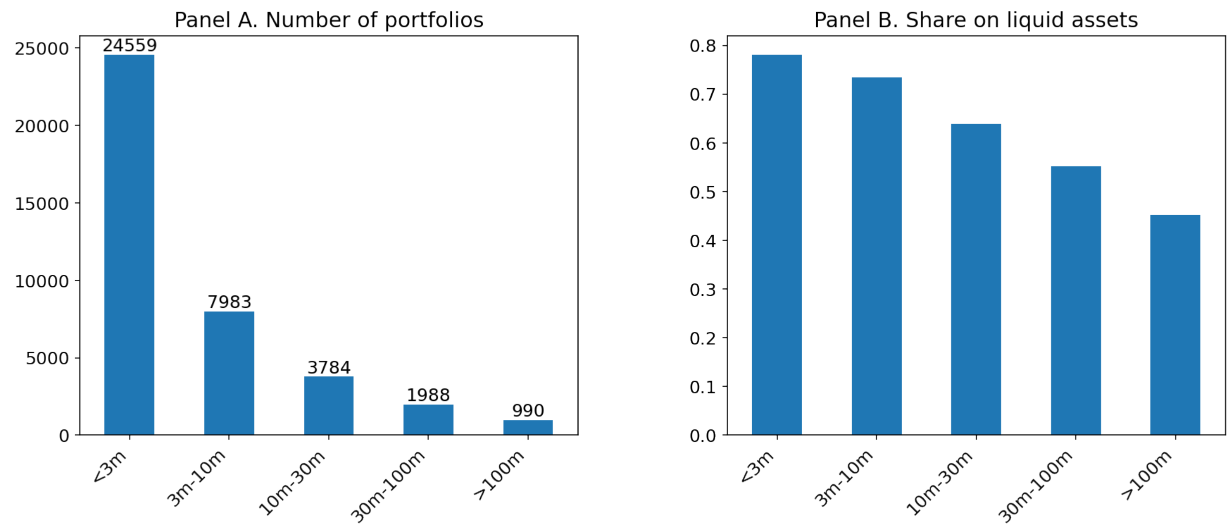


Figure 5: Fraction invested in narrow asset classes
In Panel A, we plot the average portfolio shares in the largest 10 liquid risky asset classes. In Panel B, we plot the portfolio shares for the illiquid asset classes as well as cash. The results are presented for 2019.Q4.

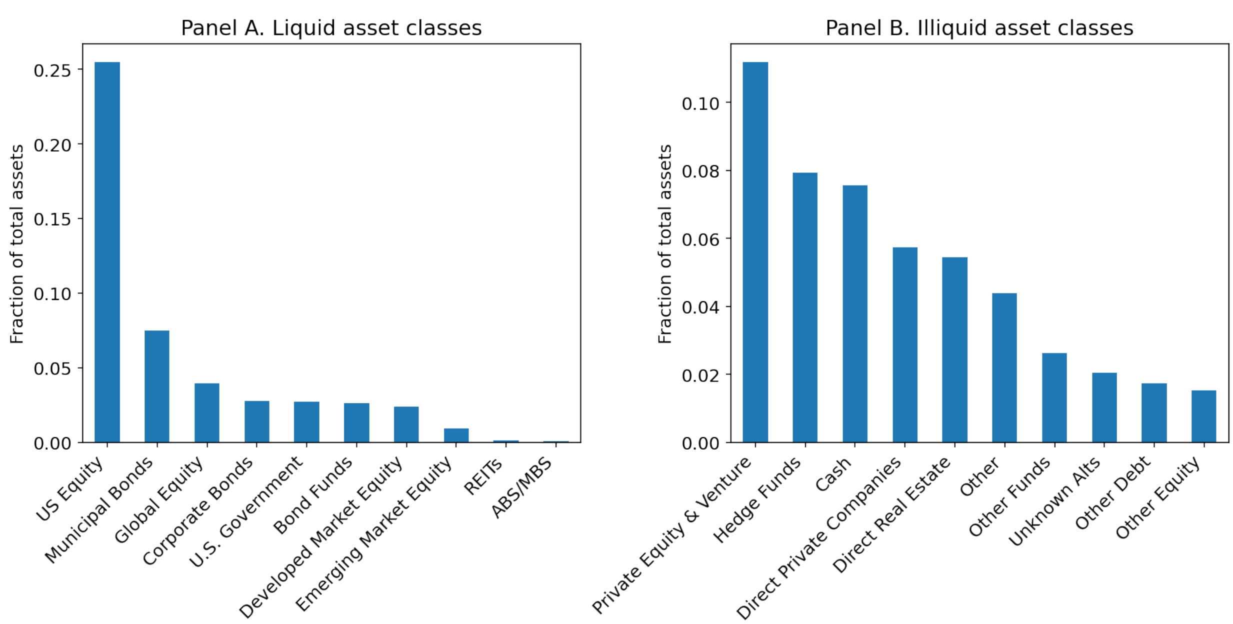
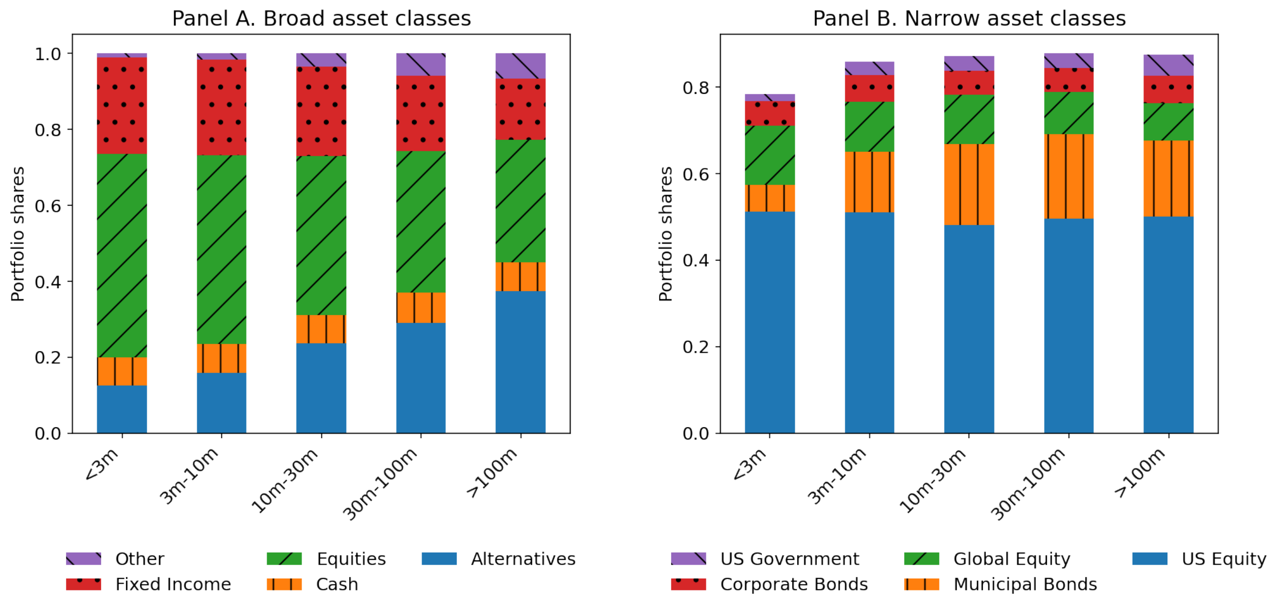


Figure 6: Fractions invested in broad and narrow asset classes by wealth group
In Panel A, we plot the average fractions invested in broad asset classes (Cash, Equity, Fixed income, Alternatives, Other). In Panel B, we plot the average fractions invested in the five largest liquid risky asset classes (U.S. Equities, Corporate bonds, Municipal and tax-exempt bonds, Treasuries, and Global equities). The results are presented for 2019.Q4.



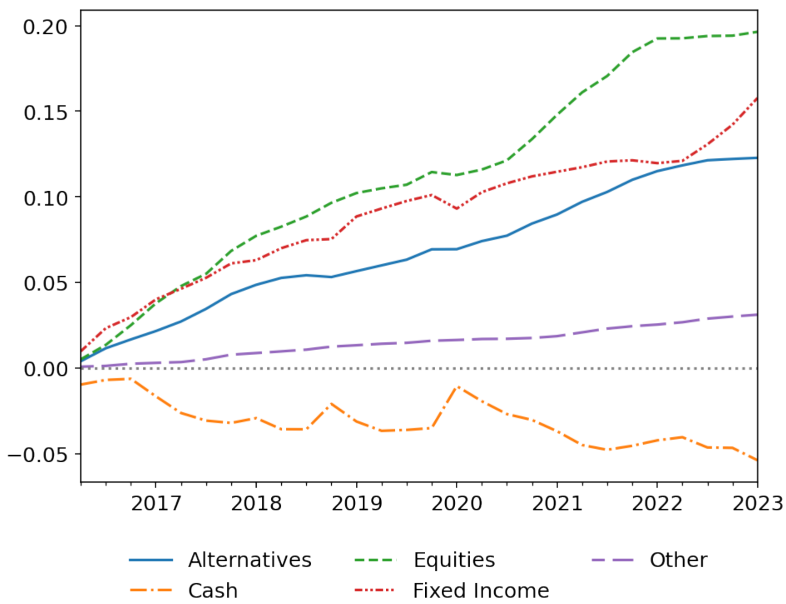
in Panel A of Figure 6. In line with Panel B of Figure 4, wealthier households allocate a larger fraction to alternatives, while reducing their portfolio shares in public equities and fixed income. Quite surprisingly, the fraction invested in cash is stable across the wealth distribution.

We plot the portfolio shares invested in five large liquid asset classes across the wealth distribution in Panel B of Figure 6: 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.[9]

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. We document the heterogeneity in households'

9. One offsetting force may be the allocation to hedge funds that can allocate capital to global equity markets. This is not something we can observe in our data, however.

Figure 7: Flows to broad asset classes
We plot the flow into broad asset classes during our sample period from 2016.Q1 to 2023.Q1. Flows are scaled by total assets.



portfolios beyond wealth in Online Appendix H.

2.7 Flows to broad asset classes

For most of the paper, we focus on flows across liquid asset classes, as households cannot easily move capital across illiquid asset classes such as hedge funds and private equity. Before zooming in and studying risk transfer, we plot the cumulative flows across broad asset classes in Figure 7. 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. During the recent tightening episode of the FED, starting in the Spring of 2022, there have been strong flows to fixed income assets, while the flows to equities and alternatives have stagnated.

Beyond the long-term trends, 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. Overall, the average cumulative flows are quite modest.

3 Risk transfer to evaluate macro-finance models

We propose risk transfer as a new moment to evaluate macro-finance models. New moments are necessary to discriminate existing models that explain (or, more precisely, generate in a calibration) the same old moments and to guide new theories. The first generation of models explained the asset pricing moments: the unconditional and conditional mean and volatility of stock and bond returns (Campbell and Cochrane 1999). The second generation of models added portfolio holdings and flows in stock, bond, and currency markets (Koijen and Yogo 2019; 2020; Gabaix and Koijen 2023). These models explain the earlier evidence that asset demand is much less elastic than predictions of standard asset pricing models (Harris and Gurel 1986; Shleifer 1986; Chang, Hong, and Liskovich 2014). We add risk transfer as a third set of moments and develop a model that explains these moments. The first two sets of moments are already non-trivial targets in representative agent models. Risk transfer, in contrast, is just zero in representative agent models. So, risk transfer is particularly diagnostic for heterogeneous agents models—in finance, but also in macroeconomics (e.g. Kaplan, Moll, and Violante (2018)).

In this section, we first define risk transfer. Then, we see how rational, frictionless macro-finance models tend to considerably overpredict its value: we illustrate this both with a stripped-down Merton model and with a state-of-the art macro-finance model (Gârleanu and Panageas (2015)). We then propose a model that does generate low risk transfer by introducing inelastic demand and slow adjustment. This model and its calibration can serve as a prototype for richer models.

3.1 Definition of risk transfer

We define risk transfer in the simplest setup, with one risky asset ("equities") and the riskless asset. The definition extends naturally to several assets with different risk exposures.[10] We call Q_{it} the share of the equity market owned by individual (or institution) i, and $q_{it} = \ln Q_{it}$ its log. We fix a given horizon, say one period. We form a group g, e.g. investors with above median allocation in equities. We define the risk transfer for group g to be:

$$\mathcal{RT}_{gt} = \Delta q_{gt} \coloneqq \langle \Delta q_{it} \rangle_{i \in g}, \tag{3}$$

10. When there are several classes, conceptually, we convert them into a "exposure to equities" equivalent, using the asset's beta with respect to equities.

where $\langle x_i \rangle_{i \in g}$ denotes the average of x_i over investors i's in group g. It could be equal-weighted, or, in our application, size-weighted, where size is the share of total equities owned by i in the previous period. This is the (log) change in the fraction of total market risk held by investors in group g. If group g buys equities the risk transfer is positive. We average over the agents i in the group, as we want to capture the systematic movement in group g, not idiosyncratic noise. We note that if the group is the universe of investors, the total (size-weighted) risk transfer is 0. Hence, we need strict subgroups of investors: indeed, risk transfer is a key quantity to analyze models with heterogeneous agents. In the baseline, we consider the groups of high vs low initial equity share.

We define the risk transfer ratio to be the risk transfer divided by the average return over the period, taking the absolute value of both quantities:

$$\mathcal{RTR}_g := \frac{\mathbb{E}\left[|\mathcal{RT}_{gt}|\right]}{\mathbb{E}\left[|r_t|\right]}. \tag{4}$$

The risk transfer ratio preferable, as it is independent of the horizon in the idealized limit of a frictionless model with only permanent shocks (though not in a more behavioral model).[11]

One can of course envisage lots of reasonable minor variants, e.g.,

$$\mathcal{RTR}'_g := \sqrt{\frac{\mathbb{E}\left[\mathcal{RT}_{gt}^2\right]}{\mathbb{E}\left[r_t^2\right]}}, \tag{5}$$

which has the same value as $\mathcal{RTR}_g$ in (4) if variables are all Gaussian with mean 0, for instance.[12]

3.2 Empirical values of risk transfer

We operationalize risk transfer in the following manner. We estimate risk transfer as the percent change in the market risk exposure for a group of investors over a quarter. As discussed, we aggregate investors into groups to identify systematic changes in market risk exposure instead of idiosyncratic noise.

11. To see this, call Q_{it} the share of the equity market owned by individual (or institution) i, and $q_{it} = \ln Q_{it}$ its log. The risk transfer ratio is unitless, even in the continuous-time limit. In contrast, in the limit of small intervals Δt, where $\langle dq_{it} \rangle_{i \in g} = \sigma dz_t + \mu dt$, the risk transfer would be $|\mathcal{RT}_{gt}| = \sigma \sqrt{\Delta t}\, |\varepsilon_t|$ for ε_t a standard Gaussian. So $|\mathcal{RT}_{gt}|$ and $|r_t|$ both scales as $\sqrt{\Delta t}$. So$\mathcal{RTR}_g := \frac{\mathbb{E}[|\mathcal{RT}_{gt}|]}{\mathbb{E}[|r_t|]}$ does not depend on Δt (at least, for small time intervals). This stability from "self-normalization" makes the risk transfer ratio preferable.

12. In that case, $\sqrt{\mathbb{E}\left[X^2\right]} \propto \mathbb{E}\,|X|$, with an unimportant proportionality constant which cancels out when taking ratios (indeed, $\sqrt{\mathbb{E}\left[X^2\right]} = \sqrt{\frac{\pi}{2}}\mathbb{E}\left[|X|\right]$).

Table 3: **Estimated Risk Transfer**

This table summarizes the risk exposure $\left(\Theta^{Liq}_{g,t-1}\right)$, risk transfer ($\mathcal{RT}_{gt}$), and risk transfer ratio ($\mathcal{RTR}_g$) computed using the Addepar data. This is all for the liquid part of the portfolios. See Sections 3.1-3.2 for definitions. Each column denotes the group of investors. We first divide investors into two groups: low and high equity share. We also present the analogous results for 10 deciles of equity share. The time horizon for risk transfer is one quarter.

Variable	Groups based risk exposure											
	Low	High	1	2	3	4	5	6	7	8	9	10
$\mathbb{E}\left[\Theta^{Liq}_{g,t-1}\right]$	0.428	0.814	0.208	0.409	0.501	0.569	0.625	0.677	0.732	0.791	0.869	0.915
$\mathbb{E}\left[\lvert\mathcal{RT}_{gt}\rvert\right]$	0.010	0.0031	0.031	0.015	0.0081	0.0070	0.0062	0.0041	0.0050	0.0049	0.0042	0.0055
$\mathcal{RTR}_g$	0.134	0.041	0.410	0.193	0.106	0.091	0.081	0.054	0.066	0.064	0.056	0.072

We focus on liquid assets (Figure 5 lists them). We next map asset holdings into "exposure to equities:" we use the stock market β_n of each asset class n, from Blackrock's capital market assumptions as of May 2024 (see Appendix E). We define market risk exposure for a group of investors g at time $t-1$ as $\Theta^{Liq}_{g,t-1} = \sum_n \beta_n \theta_{gn,t-1}$, where $\theta_{gn,t-1} = \frac{A_{gn,t-1}}{A^{Liq}_{g,t-1}}$ is the portfolio share in asset class n as a share of liquid wealth. We define the change in the market risk exposure for a group of investors g from time $t-1$ to t as $\Phi_{gt} = \sum_n \beta_n f^{Liq}_{gnt}$, where $f^{Liq}_{gnt} = \frac{F_{gnt}}{A^{Liq,DH}_{g,t-1}}$ is the flow into asset class n as a share of liquid wealth. We use liquid assets (defined in Figure 5) only because illiquid assets are difficult to trade and would mechanically lower our estimate of risk transfer. Risk transfer for a group of investors g is $\mathcal{RT}_{gt} = \frac{\Phi_{gt}}{\Theta^{Liq}_{g,t-1}}$.[13]

We create two groups of investors, with above- and below-median equity exposure, and compute risk transfer for each group. More precisely, we sort investors into high and low groups based on their lagged risk exposure, $\Theta^{Liq}_{i,t-1}$. We then aggregate the assets and flows of investors within each group and compute the risk exposures and risk transfer. The time horizon is one quarter.

Table 3 gives the risk transfer in the Addepar data. Consider the first two columns, where we divide the households into low versus high equity share groups (the cutoff being

13. In asset pricing models with a risky asset (with market beta of one) and a riskless asset, the definition of risk transfer simplifies to $\mathcal{RT}_{gt} = \frac{f_{gt}}{\theta_{g,t-1}}$. That is, risk transfer is the percent change in the risky asset share through active rebalancing. As we describe in Appendix D.2, we can use this simpler definition to compute risk transfer in the Gârleanu and Panageas (2015) model.

the median). The average equity shares are respectively 43% and 81%. Their risk transfer is respectively 1.0% and 0.31%. By averaging the two values, we find that the typical risk transfer is $\mathbb{E}\left|\mathcal{RT}_{gt}\right| = \frac{1\%+0.31\%}{2} \simeq 0.65\%$ at the quarterly horizon:

$$\text{Empirical risk transfer: } \mathbb{E}\left|\mathcal{RT}_{gt}\right| = \mathbb{E}\left|\Delta q_{gt}\right| \simeq 0.65\%. \tag{6}$$

This means that a typical group changes the fraction of the equity market it owns by 0.65%. As the typical return in our sample is (in excess of the risk-free rate) $\mathbb{E}\left|r_t\right| = 7.6\%$ in absolute value, we have for the risk transfer ratio: $\mathcal{RTR} = \frac{\mathbb{E}|\Delta q_{gt}|}{\mathbb{E}|r_t|} \simeq \frac{0.65\%}{7.6\%} = 8.7\%$ at the quarterly horizon:

$$\text{Empirical risk transfer ratio: } \mathcal{RTR} = \frac{\mathbb{E}\left|\Delta q_{gt}\right|}{\mathbb{E}\left|r_t\right|} \simeq 8.7\%. \tag{7}$$

The rest of Table 3 refines this, for 10 deciles of equity exposure. The message is similar. Table 11 in the online appendix explores the risk transfer at horizons up to four quarters. As our time sample is short, we have only seven non-overlapping yearly changes, so we recommend taking those values as simply suggestive. Still, the message is broadly similar: a very small risk transfer. In addition, there is a small increase with horizon, consistent with progressive, rather than instantaneous, adjustment.

3.3 Risk transfer in a traditional portfolio choice model

We next consider which models do not and do generate the correct amount of risk transfer. We start with the core model of portfolio choice, which is to demand a quantity of shares equal to

$$Q_{it} = \frac{W_{it}}{P_t} \frac{\pi_t}{\gamma_i \sigma^2}, \tag{8}$$

where P_t is the share price and π_t is the risk premium, rationally perceived. This implies that the average equity share of agent i is $\theta_i = \frac{\bar{\pi}}{\gamma_i \sigma^2}$.

We assume that the agent has a one-period horizon, so that there is no Merton (1971) hedging demand. This is the basic model, which we will refer to as the "plain Merton model." The risk premium is assumed to mean-revert at a rate ϕ_π. Its shocks can be thought of as coming from supply or demand shocks outside that do not affect the Addepar households.[14] Then (as in Gabaix and Koijen (2023)), for such a rational investor, the risk transfer is (in

14. It would easy to augment this partial equilibrium model into a market equilibrium model, very much along the lines of the model in section D.3.2. We'd suppose that there is an outside investor, with shocks b_t to his demand (say, an AR(1)), which then change the price and equity premium in equilibrium.

the limit of small time intervals):

$$\Delta q_{it} = -\zeta_i \Delta p_t, \qquad \zeta_i = 1 - \theta_i + \kappa_i (\delta + \phi_\pi), \qquad \kappa_i = \frac{1}{\bar{\pi}}, \tag{9}$$

where ζ_i is the elasticity of the demand for stocks (the Marshallian demand, which takes into account wealth effects), and $\kappa_i = \frac{\partial \ln \theta_{it}}{\partial \pi_t}$ is the sensitivity to the risk premium. Very importantly, we have $\kappa_i = \frac{1}{\bar{\pi}}$ for an agent following (8). Indeed, $\theta_{it} = \frac{\pi_t}{\gamma \sigma^2}$, so that $\kappa_i = \frac{\partial \ln \theta_{it}}{\partial \pi_t} = \frac{1}{\bar{\pi}}$. This is, as we shall see later, a very high value.

So, for a group with homogeneous equity shares, the risk transfer ratio is

$$\mathcal{RTR}^{\text{Merton}} = |\zeta_g| \,.$$

Using the calibration from Gabaix and Koijen (2023) with $\theta_i = 0.8$, $\bar{\pi} = 4\%/\text{yr}$, $\delta = 4\%$, $\phi_\pi = 6\%$, so $\kappa_i (\delta + \phi_\pi) = \frac{1}{4\%} \times 10\% = 2.5$, we obtain $\zeta_g = 2.7$, hence, for a group

$$\mathcal{RTR}^{\text{Merton}} = |\zeta_g| = 270\%. \tag{10}$$

This is 30 times higher than the empirical value in (7).[15] This shows how agents in the plain Merton model are too reactive.

3.4 Risk transfer in the equilibrium model of Gârleanu-Panageas (2015)

In the Merton model above, the risk premia shocks are unexplained: outside forces that do not directly affect the Addepar investors disturb the risk premium, and we measure how agents in our sample react to it. This is a useful rational benchmark, but a special one. This is why a large literature has been devoted to explaining the origins of these risk premia shocks. It is typically with a representative agent, which would generate a risk transfer of 0. So, we take a model that generates risk premia shocks and heterogeneity, Gârleanu and Panageas (2015).[16] We chose this model because it is well-cited, compact, and successfully calibrates the variation of equity prices.

We briefly sketch the Gârleanu and Panageas (2015) model (Section D.2 of the online appendix gives details). It has two types of agents, with high versus low risk aversion. In ad-

15. We note that a "Lucas" model where the agent has also lots of labor income would lead to an even higher elasticity (by a factor of ~ 10, see Gabaix and Koijen (2023)) and risk transfer ratio.

16. We thank Nicolae Gârleanu and Stavros Panageas for discussions, and sharing their code with us.

dition, those agents have different ages (with a Poisson probability of dying) and Epstein-Zin utility functions. Productivity shocks create shocks to stock market values, and subsequently the transfers between types of agents.

Importantly, the agents are rational and frictionless: they react fully rationally to shocks, like in the simple Merton model we saw above, though with a more complex value function (as they have a hedging demand). So, one might expect that they will react a lot.

To verify this intuition, we simulate the model, using the calibration proposed in that original paper. Indeed, in the Gârleanu and Panageas (2015) model, the risk transfer is 78% at a quarterly horizon for the high risk aversion group and 3.5% for the low risk aversion group. Hence, this is much higher than in the data (about 0.65%, see (6)) for both groups.

We conclude that those agents are "too reactive" in this sophisticated model, as they were in the plain Merton model.

3.5 Risk transfer in an equilibrium model with inelastic investors

We saw that both in the plain Merton model, and in a more state-of-the-art macro model, risk transfer was too large as asset demand is too reactive to changes in the equity premium. How to fix that? Fortunately, a sizable strand of research has worked on that using behavioral inattention (see Gabaix (2019) for a survey). The key is to reduce the reactivity to prices, by some form of inattention (or prudent processing of an imperfectly understood situation), which leads to lowering elasticities of demand (Gabaix (2014), Giglio et al. (2021), Khaw, Li, and Woodford (2021), and Enke and Graeber (2023)). We operationalize that in the next model.

3.5.1 Economic environment

We now propose a model that fits the data, which is a heterogeneous-agent generalization of the representative agent model in Gabaix and Koijen (2023). Indeed, it is set up so that in the aggregate, it boils down to that model. Thus, it inherits its ability to explain standard asset pricing moments such as high and volatile risk premium and a low riskless interest rate. In addition, the present model features a heterogeneous cross-section of holdings, and proposes a calibrated economic mechanism behind a low risk transfer.

Qualitatively, the key ingredient is that agents are inelastic, even in the long run: their sensitivity to the risk premium, κ, is low compared to traditional models (around 1yr, compared to $\frac{1}{\pi} = 25\text{yr}$ in the Merton model). Second, and much less importantly, they react slowly, rather than very fast (as in Gabaix and Laibson 2001, Mankiw and Reis 2002). Chien, Cole, and Lustig (2012) also present an asset pricing model with a delayed reaction, but their investors are fully elastic in the long run. Therefore, we suspect that our model would be more consistent with long-run risk transfer if we had such data.

We next specify these ideas in detail. The risky asset gives an exogenous dividend that follows a lognormal growth process, so that $\frac{D_t}{D_{t-1}} = e^{g+\varepsilon_t^D - \frac{1}{2}\sigma_D^2}$, where $\varepsilon_t^D \sim \mathcal{N}\left(0, \sigma_D^2\right)$ is i.i.d. We write the price of the risky asset as:

$$P_t = \frac{D_t}{\delta} e^{p_t}, \tag{11}$$

where δ is the average dividend-price ratio, and p_t is the deviation of the log price-dividend ratio from its average (and will generate the "excess volatility" of the stock price), and they are both endogenous.

Asset demand Agent i has a demand Q_{it}, which reacts slowly to a "target" or "virtual" demand Q_{it}^v, as follows. Taking lower cases for logs, e.g $q_{it} = \ln Q_{it}$:

$$\Delta q_{it} = \mu_i \Delta q_{it}^v + (1-\mu_i)\, \Delta q_{it}^{v,\phi}, \qquad \Delta q_{it}^{v,\phi} := \sum_{h \geq 0} \phi\,(1-\phi)^h\, \Delta q_{i,t-h}^v, \tag{12}$$

where $\Delta q_{it}^{v,\phi}$ is a moving average with speed $\phi \in (0,1]$, and $\mu_i \in [0,1]$ (which is unitless) is the agility on impact.[17] In other terms,

$$\Delta q_{it} = \sum_{h \geq 0} a_i(h)\, \Delta q_{i,t-h}^v, \tag{13}$$

with reactivity parameter at lag h equal to:

$$a_i(h) = (1-\mu_i)\,\phi\,(1-\phi)^h + \mu_i 1_{h=0}, \tag{14}$$

which satisfy $\sum_{h=0}^{\infty} a_i(h) = 1$. So the demand change Δq_{it} is the average of the current and lagged virtual demand changes $\Delta q_{i,t-h}^v$, with weights $a_i(h)$.

We model the virtual demand as:

$$Q_{it}^v = \frac{W_{it}\theta_i}{P_t} e^{\kappa_i \hat{\pi}_t + b_t}, \tag{15}$$

where W_{it} is the agent's wealth, $\hat{\pi}_t = \pi_t - \bar{\pi}$ is the deviation of the risk premium from its

17. In the continuous time limit (hence, for a full calibration if we had high frequency data), we need some agile agents with $\mu_i > 0$ for the equilibrium to exist.

average, and b_t is a "behavioral disturbance" shock. It is an AR(1): $\Delta b_t = -\phi_b b_{t-1} + \varepsilon_t^b$, ϕ_b is the speed of mean reversion and ε_t^b i.i.d. with mean 0 and variance σ_b^2. It is a stand-in for time-varying sentiment, risk tolerance, et cetera. We find it productive to study risk transfer without taking a firm stance on the "deep" (and plausibly varied) origin of the appetite for stocks.

This demand in (12) and (15) is a moderate variation from the Merton demand (8), which is, with $\theta_i = \frac{\bar{\pi}}{\gamma\sigma^2}$,

$$Q_{it}^{\text{Merton}} = \frac{W_{it}}{P_t}\frac{\pi_t}{\gamma\sigma^2} \approx \frac{W_{it}}{P_t}\theta_i e^{\kappa^r \hat{\pi}_t}, \qquad \kappa^r = \frac{1}{\bar{\pi}}.$$

Compared to the Merton model, the main differences are (i) a lower sensitivity $\kappa_i = \frac{\partial \ln \theta_{it}}{\partial \pi_t}$ to the risk premium, as the plain Merton model predicts $\kappa^r = \frac{1}{\bar{\pi}} = 25$yr (as we saw in Section 3.3), which is too high compared to the empirical value, which is closer to $\kappa_i \simeq 1$yr (see Giglio et al. (2021), Gabaix and Koijen (2023), Dahlquist and Ibert (2024)); (ii) the behavioral shock b_t (which could be belief shocks). A more minor (but descriptive useful) difference is (iii) a slow adjustment to target / virtual demand (captured by $a_i(0) < 1$). This can be microfounded easily via e.g. inattention to the risk premium, with also noisy beliefs (Gabaix and Koijen (2023)), while the slow adjustment can come from psychological adjustment costs (see the survey in Gabaix (2019)). Here, we do not revisit those well-traveled issues of microfoundations, but rather investigate the consequence for risk exchange.

Evolution of wealth We view each agent i as a member of a vast "family" who pools consumption. Hence, each agent i manages a portfolio, but returns to the representative family the dividends and interest income from bonds. Dividend and interest income are directly passed on to the household. The wealth W_{it} of fund i evolves as:

$$\Delta W_{it} = W_{i,t-1}\left(\theta_{i,t-1}\frac{\Delta P_t}{P_{t-1}} + f_{it}\right), \qquad f_{it} = (1-\theta_{i,t-1})\frac{\Delta D_t}{D_{t-1}} + a_t + \varepsilon_{it}. \tag{16}$$

The first term, $\theta_{i,t-1}\frac{\Delta P_t}{P_{t-1}}$, indicates that the wealth changes because the equity price changes. The second term, f_{it}, is an extra flow coming from "the rest of the family," or perhaps labor income, or some other source of funds. In that flow, the term $(1-\theta_{i,t-1})\frac{\Delta D_t}{D_{t-1}}$ is helpful for the steady state. First, in the aggregate, it is necessary, in order have a balanced growth path with a constant equity share (if equities are 10% more valuable, and the equity share is 80%, then to keep a constant equity share equal to 80%, the fund needs to receive an extra 2% of cash). We also keep it this way in the cross section. It makes the analytics much simpler, as risk exchange will be expressed as a function of one shock, the "discount rate shock" or "sentiment" Δp_t, rather than also the "fundamental" Δd_t.[18]

The flow term has a random component $\varepsilon_{it} = u_{it} - u_{St}$, where u_{it} is i.i.d. with mean 0, and u_{St} is the size-weighted average (using weights proportional to $W_{i,t-1}$), so that the average ε_{it} is zero, $\varepsilon_{St} = 0$. This shock ε_{it} ensures that wealth follows a proportional random growth, which will generate the power law steady state distribution of wealth that one finds empirically (Champernowne (1953), Gabaix (2009), Benhabib, Bisin, and Zhu (2011)). The term a_t ensures an adding up constraint (34). It is does not affect the cross-sectional risk transfer, which is the core of our analysis, and which will turn out to be second order.

The rest of the model, which is mostly about aggregate quantities (e.g. production and consumption, general equilibrium, determination of the risk-free rate, steady state) is not essential to understand risk transfer, which is about the reallocation of risk across agents. Still, we detail it in the appendix (Section A) for the interested reader. We give further complements and robustness checks in the online appendix (Section D).

3.5.2 Equilibrium

The price clears the market at all dates, i.e., $\Delta q_{St} = 0$. We make the innocuous assumption that $\Delta q^{v,\phi}_{S,-1} = 0$ at the initial date (far in the past). For simplicity, we assume that all μ_i's and κ_i are equal. This leads to the following solution for prices (the proof is in Section D.1). Throughout, we linearize, for small p_t, b_t, and keep only leading order terms. In particular, we drop the terms $O\left(\sigma_b^2\right)$ and $O\left(\sigma_b, \sigma_d\right)$.

We start with a derivation of the virtual demand.[19]

Lemma 1. (Virtual demand in linearized form) *The virtual demand (15) follows:*

$$\Delta q^v_{it} = -\left(1-\theta_i\right)\Delta p_t + \kappa_i \Delta\hat{\pi}_t + \Delta b_t + \varepsilon_{it}. \tag{17}$$

Next, we lay out the full equilibrium.

Proposition 1. (Equilibrium in the inelastic model with heterogeneous agents) *The stock price is $P_t = \frac{D_t}{\delta} e^{p_t}$ where the price deviation p_t follows:*

$$p_t = \frac{1}{\zeta_S} b_t, \tag{18}$$

18. The logic the we will lay out would also work with two types of shocks, but less transparently. In addition, given that most variations are due to Δp_t rather than Δd_t (Campbell and Shiller (1988)) this is arguably not a very material assumption.

19. It reveals that the term a_t in (16) is second order, thus negligible.

where b_t is the behavioral deviation. The deviation of the risk premium from its average is $\hat{\pi}_t = -(\delta + \phi_b) e^g p_t$. The virtual demand is:

$$\Delta q_{it}^v = -\zeta_i \Delta p_t + \Delta b_t + \varepsilon_{it} = \lambda_i \Delta p_t + \varepsilon_{it}, \tag{19}$$

where the elasticity of demand ζ_i is:

$$\zeta_i = 1 - \theta_i + \kappa_i (\delta + \phi_b) e^g. \tag{20}$$

and long-run sensitivity of holdings to prices is the relative elasticity of demand:

$$\lambda_i = \zeta_S - \zeta_i. \tag{21}$$

The holdings by agent i are given by:

$$\Delta q_{it} = \sum_{h \geq 0} a_i(h) \left(\lambda_i \Delta p_{t-h} + \varepsilon_{i,t-h}\right). \tag{22}$$

Equation (21) shows that it is the relative elasticity, rather than the absolute elasticity, that matters. For instance, if there is a negative belief shock that lowers the price, more elastic agents buy, while less elastic agents sell. The first part of the proposition simply reflects the forces in the representative agent model in Gabaix and Koijen (2023), whose aggregated properties our model inherits by design.[20] The only difficulty in this proposition was to embed all those things in a general equilibrium model, while having a non-trivial cross-section.

We next turn to the key result in this section: the risk transfer in this model. For analytical clarity, we take the empirically relevant limit $\phi_b \ll \phi$, which means that at the time scale at which agents rebalance $(1/\phi)$, prices are essentially a random walk.

Proposition 2. (Risk transfer in the inelastic model above) *In the model with inelastic agents, in the limit of small time intervals, the risk transfer ratio is*

$$\mathcal{RTR}'_{gt} := \left(\frac{\mathbb{E}\left[(\Delta q_{gt})^2\right]}{\mathbb{E}\left[r_t^2\right]} \right)^{1/2} = \chi \left|\lambda_i\right| \left(\sum_{h \geq 0} a_i(h)^2 \right)^{1/2}, \tag{23}$$

where $\chi = \frac{\sigma_{\Delta p_t}}{\sigma_{r_t}}$ is the ratio of the volatility of the return due to changes in the risk premium

20. Lemma 2 in Appendix A contains further results about the aggregate behavior of this economy.

to the volatility in total returns. If shocks are all Gaussian with mean 0, this gives

$$\mathcal{RTR}_{gt} := \frac{\mathbb{E}\left[\left|\langle \Delta q_{it} \rangle_{i \in g}\right|\right]}{\mathbb{E}\left[|r_t|\right]} = \mathcal{RTR}'_{gt},$$

while the conditional risk transfer (using the unpredictable part of risk transfer and returns):

$$\mathcal{RTR}^{\mathbb{S}}_{gt} := \frac{\mathbb{E}\left[|\mathbb{S}_t\left[\Delta q_{gt}\right]|\right]}{\mathbb{E}\left[|\mathbb{S}_t\left[r_t\right]|\right]} = \chi \left|\lambda_i\right| a_i\left(0\right) = \chi \left|\lambda_i\right| \left[\left(1-\mu_i\right)\phi \Delta t + \mu_i\right]. \tag{24}$$

where we use the surprise operator $\mathbb{S}_t[X] = \mathbb{E}_t[X] - \mathbb{E}_{t-1}[X]$*, which isolates the unpredictable innovation in the expectation of a random variable* X*.*

Numerically, the two values $\mathcal{RTR}_{gt}$ and $\mathcal{RTR}^{\mathbb{S}}_{gt}$ are very close, but $\mathcal{RTR}^{\mathbb{S}}_{it}$ is easier analytically, so we start with it. Eq. (23) shows that the risk transfer ratio $\mathcal{RTR}^{\mathbb{S}}_{gt}$ is lower when agents have an elasticity close to the average (a low $|\lambda_i|$ in (21)), are more inert(lower μ_i or ϕ). The regular risk transfer $\mathcal{RTR}_{it}$, carries the same message; it simply has more lagged shocks, replacing $a_i(0)$ by $\left(\sum_{h \geq 0} a_i(h)^2\right)^{1/2}$.

3.5.3 Calibration: risk transfer in this inelastic model

We use a quarterly horizon, $\Delta t = \frac{1}{4}$yr. The annualized mean-reversion rate is $\bar{\phi} = 100\%/\text{yr}$ (as in Gabaix and Koijen 2023), so that the quarterly one is $\phi = \bar{\phi}\Delta t = 0.25$. We take an agility parameter, $\mu = 0.2$, which means that only 20% of the reaction happens on impact. From the empirical results (section 3.2), we take $\langle|\theta_i - \theta_S|\rangle = 20\%$.[21] We assume a sensitivity to the risk premium $\kappa_i = \kappa_S = 1$yr (as in the empirical evaluation of Dahlquist and Ibert (2024) and the calibration of Gabaix and Koijen (2023)). The specific value does not matter, as the κ_i are homogeneous, but the value matters if we have heterogeneous κ_i's (section Section D.3.2). Then, from (21),

$$\langle|\lambda_i|\rangle = \langle|\theta_i - \theta_S|\rangle = 0.2. \tag{25}$$

In our model, what matters is Δp_t, the part of the return coming from non-fundamental shocks. Given that this is the bulk of stock market fluctuations at short horizons, both empirically (Campbell and Shiller 1988) and in our model, we approximate it by the stock market return in excess of the risk-free rate, $\Delta p_t \simeq r_t$, so $\chi \simeq 1$. Then, the conditional risk

21. We saw that our two groups where respectively 43% and 81%. We take $\theta_S = 62\%$ to be the average, so that $\left\langle |\theta_i - \theta_S|_{i \in g} \right\rangle = \frac{81\% - 43\%}{2} \simeq 20\%$.

transfer ratio $\mathcal{RTR}_g^{\mathbb{S}} = \frac{\left|\langle \Delta q_{it} \rangle_{i \in g}\right|}{|r_t|}$ at a quarterly horizon is:

$$\mathcal{RTR}_g^{\mathbb{S}} = \chi \left|\lambda_g\right| \left[\left(1-\mu_g\right) \phi \Delta t + \mu_g\right] = 0.2 \left[0.8 \times 1 \times \frac{1}{4} + 0.2\right] = 8\%. \qquad (26)$$

The value of the unconditional risk transfer is $\mathcal{RTR}_g = 9.2\%$, computing the infinite sum (23). This is in line with the empirical value we found in (7).

We conclude that this inelastic model matches well the empirical values of risk transfer. To probe the robustness of this conclusion, Section D.3 investigates plausible variants, e.g. with different loadings of the behavioral shock. It concludes that the model still delivers the right order of magnitude of risk transfer. For this, the low sensitivity κ_i to the risk premium is crucial: a high value would create large risk transfers as the risk premium changes. Hence, we think that this simple model, and its calibration, might serve as a prototype for future macro models, and enrich old ones (as surveyed by Panageas 2020).

3.6 Risk transfer as a new target for asset pricing

We think that risk transfer should be a new target for models with heterogeneous agents, in finance and in macroeconomics. We find it to be very small empirically, but macro-finance models typically predict a very high value. One can surmise that the same reasoning will hold with more refined cuts of risk, e.g., with different types of risk and asset classes.[22] In sum, we propose that major targets for asset pricing are traditional macro-finance moments, such as the mean and volatility of returns, their predictability; inelasticity; and now risk transfer.

We have used a behavioral model to make the point. One could imagine other variants, e.g. with rational agents (as in Gârleanu and Panageas (2015)), but with a different friction, perhaps some taxes or transaction costs. However, it is unclear (and beyond the scope of this paper) whether this would work. Indeed, those models with heterogeneous agents and transaction costs are notoriously difficult to work with (e.g. because actions depends on sS shifting bands). If they then generate low medium-run elasticity of demand (and high reaction of prices to flow), they will behave similarly to the model we proposed. In any case, we submit that the new fact and challenge that we lay out will help guide the writing of the core behavior in models of asset demand.

22. The definition easily generalizes to several asset classes. The risk transfer by agent i for an asset a (or asset class a) is: $\mathcal{RT}_{agt} = \langle \Delta q_{iat} \rangle_{i \in g}$.

4 Conclusion

In this paper, we define and operationalize "risk transfer," and show how it is a very useful moment to investigate macro-finance models with heterogeneous agents. We find that risk transfer is very small in the data and that leading rational models predict a risk transfer that is counterfactually too large. This is because agents in those models are too reactive. We show how a model with more inelastic agents naturally calibrates better.

To do so, we used new monthly security-level data on portfolio holdings, flows, and returns of U.S. households to measure risk transfer. Our data feature broad coverage across the wealth distribution—including ultra-high-net-worth (UHNW) households—and span multiple asset classes, covering both public and private assets. Our data have two important advantages to traditional survey data: the coverage of a broad set of households, including over 400 billionaires, and the large number of different asset classes.

These new facts paint the picture of quite inert households (even for the extremely wealthy households), with low turnover and reaction to the aggregate stocks market developments, consistent with models of inertia, inattention, and inelasticity. This should useful to inform basic modeling of macro-finance agents, to think about the origin of financial fluctuations, and of the relocation of risk and return in the economy, inequality, and macroeconomics.

A Complements to the inelastic model

A.1 Aggregate equilibrium background, and representative investor

Here we give complements to the inelastic model of Section 3.5. The main text gave the key feature: the inelastic demand. In this section, we specify important, but more generic, details, e.g. the production and consumption, the general equilibrium background, the endogenous risk-free rate, et cetera.

We specify the general equilibrium background, paraphrasing Gabaix and Koijen (2023). The aggregate endowment Y_t follows a proportional growth process, with an i.i.d. log-normal growth rate G_t: $\frac{Y_t}{Y_{t-1}} = e^{g+\varepsilon_t^y - \frac{1}{2}\sigma_y^2}$, with $\varepsilon_t^y \sim \mathcal{N}\left(0, \sigma_y^2\right)$ is iid. Utility is $\sum_t \beta^t u\left(C_t\right)$ with $u\left(C\right) = \frac{C^{1-\gamma}}{1-\gamma}$. Bonds are in zero net supply. As dividend growth and GDP growth are not very correlated, we model that GDP Y_t is divided as $Y_t = D_t + \Omega_t$ into an aggregate dividend D_t and a residual Ω_t, where the dividend stream has i.i.d. lognormal growth, $\frac{D_t}{D_{t-1}} = e^{g+\varepsilon_t^D - \frac{1}{2}\sigma_D^2}$, where $\varepsilon_t^D \sim \mathcal{N}\left(0, \sigma_D^2\right)$ is i.i.d. an uncorrelated with ε_t^y. The "residual" Ω_t can be thought of as a combination of wages, entrepreneurial income, and so forth (and indeed it is the vast majority of GDP). The representative firm raises capital entirely through equity, and passes the endowment stream as a dividend D_t. With δ the (endogenous) average dividend-price ratio, the fundamental value of the stock market is

$$\bar{P}_t = \frac{D_t}{\delta}. \tag{27}$$

We decompose the household as a rational consumer, who only decides on consumption (so dissaving from a savings account made only of the riskless bond), and a behavioral investor, who trades between a savings account (yielding the riskless rate) and in a "fund mix" made of N funds trading trading equities and the risk-free asset. Those funds are meant to represent the accounts in our data (as well as other entities not in our data). They manage money, but they do not consume: they give all interest and dividend income to the representative household.[23]

The rational consumer part of the household chooses consumption (but not equity shares) to maximize lifetime utility, subject to the dynamic budget constraint for bonds. She takes the actions of the investor as given. As she is rational, she satisfies the Euler equation for bonds: $\mathbb{E}_t[\beta \left(C_{t+1}/C_t\right)^{-\gamma} R_{ft}] = 1$, with $C_t = Y_t$ in equilibrium. This pins down the interest rate R_{ft}, which is constant in our i.i.d. growth economy.

The behavioral investor part of the household is influenced by b_t, a behavioral disturbance, which is a stand-in for noise in institutions, beliefs, tastes, fears, and so on. We assume that the investor trades (between stocks and bonds) with a form of "narrow framing" objective function (as in Barberis, Huang, and Santos (2001)). He seeks to maximize $\mathbb{E}_t \left[V^p \left(R_{t+1}\right)\right]$ with $V^p \left(R\right) = \frac{R^{1-\gamma}-1}{1-\gamma}$ a proxy value function, on the gross return on his investments. Specifically, when $b_t = 0$, he chooses his allocation $\bar{\theta}^M$ in the fund mix as:

$$\bar{\theta}^M = \underset{\theta^M}{\operatorname{argmax}} \, \mathbb{E}\left[V^p\left(\left(1-\theta^M\right) R_{ft} + \theta^M R_{M,t+1}\right) | b_t = 0\right], \tag{28}$$

where $R_{M,t+1}$ is the stochastic rate of return of the mixed fund. This choice of a "narrow framing" benchmark is opposed to the fully rational value function, which would have all the Merton (1971)-style hedging demand terms. Instead, the above formulation with narrow

23. This sort of model where "funds" get their flows from the representative agent but to not consume is not uncommon, see e.g. Gertler and Karadi (2011). It simply helps keeping the "consumption" part of the model extremely simple (as all income ultimately is passed on to the representative consumer), while allowing for heterogeneous financial institutions (the households in our data). One could dispense with the representative consumer, but that would introduce complications that would distract from the chief goal of thinking about risk transfer.

framing will lead to a high equity premium $\bar{\pi} = \gamma\sigma_r^2$, where the σ_r^2 is the volatility of the stock market, which is affected by flow shocks.

We model the behavioral investor part of the household as rational on average, but subject to behavioral disturbances. First, if there are no behavioral disturbances, this investor wishes to maintain a constant allocation $\bar{\theta}^M$ in the fund mix and should invest via

$$\Delta \bar{F}_t = \frac{1-\theta}{\theta} \Delta \bar{P}_t, \tag{29}$$

where θ is the average equity share of existing funds (in the steady state), and $\bar{P}_t$ is the "fundamental value" of the stock (27).[24] We assume that his policy, however, is affected by the behavioral disturbance b_t, so that the actual aggregate flow in the fund mix is

$$\Delta F_t = \Delta \bar{F}_t + \frac{\lambda^f}{\theta} \Delta \left(b_t \bar{P}_t \right), \tag{30}$$

which on average differs from the baseline amount $\Delta \bar{F}_t$ by a fraction Δb_t of the "fundamental value" $\bar{P}_t$ of the equity market, times a fixed loading $\frac{\lambda^f}{\theta}$. This aggregate flow is in turn given to the various funds or families as outlined in the next section. We next turn to the cross-sectional flows into the various funds making up the fund mix.

A.2 Demand and evolution of wealth

We give a slightly more general version than the one in Section 3.5, as it helps to think about the robustness of the model, and it may be helpful in future calibrations. We use the generalized version for the virtual or target demand (15):

$$Q_{it}^v = \frac{W_{it}\theta_i}{P_t} \exp\left(\kappa_i \hat{\pi}_t + \lambda_i^d b_t + \nu_{it} \right), \tag{31}$$

where the sensitivity of demand to the behavioral disturbance, λ_i^d, could depend on i, and ν_{it} is some other demand shock, autocorrelated over time and independent across i's.

Wealth W_{it} of fund i evolves as

$$\Delta W_{it} = Q_{i,t-1} \Delta P_t + \Delta F_{it}. \tag{32}$$

24. Indeed, in the steady state, the average fund has equity share θ, so wealth $\bar{W}_t = \frac{\bar{P}_t}{\theta}$. Hence, it must have bond holdings equal in value to $\bar{B}_t = \bar{W}_t - \bar{P}_t = \left(\frac{1}{\theta} - 1\right) \bar{P}_t$, so that the inflow at t should be $\Delta \bar{F}_t = \Delta \bar{B}_t = \frac{1-\theta}{\theta} \Delta \bar{P}_t$.

The first term, $Q_{i,t-1}\Delta P_t$ indicates that the wealth grows because of capital gains and losses (recall that dividend and interest income are directly passed on to the households, and then consumed by them in the aggregate). There is also a dollar flow made of two parts, $\Delta F_{it} = \Delta \bar{F}_{it} + \Delta \hat{F}_{it}$:

$$\Delta \bar{F}_{it} = W_{i,t-1}\left(1-\theta_{i,t-1}\right)\frac{\Delta \bar{P}_t}{\bar{P}_{t-1}}, \qquad \Delta \hat{F}_{it} = W_{i,t-1}\left(\lambda_i^f \Delta b_t + \varepsilon_{it} + a_t\right), \tag{33}$$

where W_t is total wealth. The first part, $\Delta \bar{F}_{it}$, ensures that we are on a balanced growth path. On that path, we need enough new "fresh inflows", to ensure that the funds can maintain a constant equity share θ_i. The second part, $\Delta \hat{F}_{it}$, is the "random shock to inflows" part: it has some loading on the systematic behavioral shock b_t and some extra idiosyncratic shock ε_{it}.

We next discuss the a_t term. As in all heterogeneous agents economy, one needs a stabilizing force to ensure the existence of a steady state (see Gabaix (2009) for an exposition); otherwise, relative wealths diverge without bounds. We choose death. Each fund dies with a constant probability of death $\delta^\dagger$, and then it is replaced by a small fund, with size that is the average size, times a small factor $e^\dagger$ (as in *e*ndowment) less than 1, and with the same κ_i, θ_i. The remaining wealth is distributed to the other funds, proportionally to their existing wealth: this is in the a_t term in (33).[25] It is adjusted so that the total flow is equal to the aforementioned aggregate flow (30) into the fund mix:

$$\sum_i \Delta F_{it} = \frac{1-\theta}{\theta}\Delta \bar{P}_t + \frac{\lambda^f}{\theta}\Delta\left(b_t \bar{P}_t\right), \tag{34}$$

i.e. the total flow is the rational steady state flow, and the second the flow change due to the behavioral disturbance.[26] This ensures that, in the aggregate, the model behaves like the representative agent model of Gabaix and Koijen (2023), and inherits its quantitative aggregate properties. The above gives the following (the term a_t is second order, hence omitted).

Proposition 3. (Virtual demand in the generalized model) *In the model above, the change*

25. This implies that the funds collected in debt are $\delta^\dagger \langle W_{it} \rangle$, of which a fraction $e^\dagger$ is distributed to the new funds, and the rest is given to the old funds, as a proportion to their wealth W_{it}. So, each surviving fund receives a proportional extra inflow $\delta^\dagger\left(1-e^\dagger\right)$ in each period. This is captured as part of the term a_t.

26. Hence, if a fund "dies" and is reborn with the endowment of wealth described above, we have $\Delta F_{it} = e^\dagger \left\langle W_{jt^-}\right\rangle - W_{it^-}$ where $\left\langle W_{jt^-}\right\rangle$ is the average of wealths before death.

in the virtual demand is, up to higher order terms:

$$\Delta q_{it}^{v} = -\left(1-\theta_i\right)\Delta p_t + \kappa_i \Delta \hat{\pi}_t + \left(\lambda_i^d + \lambda_i^f\right)\Delta b_t + \Delta \nu_{it} + \varepsilon_{it} \tag{35}$$

So the aggregate "virtual" cumulative flow into equities is $\Delta f_t = \left(\lambda_S^d + \lambda_S^f\right)\Delta b_t + \Delta \nu_{St}$.

In the main text, we use that case of uniform loadings with $\lambda_i^f = 0$, $\lambda_i^d = 1$, $\nu_{it} = 0$, but this is for presentational ease only. Then, this gives the announced formula, (17).

Steady state distribution of wealth The small probability of death is a stabilizing force, that permits the existence of a stochastic steady state in relative wealths $S_{it} = \frac{W_{it}}{W_t}$. Indeed, we have a proportional random growth model, which has the good property of generating a power law distribution of wealth, as is relevant empirically (Champernowne (1953), Gabaix (1999), Benhabib, Bisin, and Zhu (2011), Beare and Toda (2022), and Gomez and Gouin-Bonenfant (2024)). With this model, we have a well-defined steady state: calling w_{*t} the log average wealth, $w_{it} - w_{*t} - \theta_i p_t - \lambda_i^f b_t$ has a stationary distribution. Hence, $\tilde{W}_{it} := W_{it} e^{-\theta_i p_t - \lambda_i^f b_t}$ have a Pareto right tail. And because p_t, b_t are stationary and with thin, Gaussian tails, they do not influence the power law (see Gabaix (2009) for an exposition), and W_{it} has also a Pareto tail with the same exponent as $\tilde{W}_{it}$. Hence, there is also a well-defined ergodic distribution of average equity shares, $\theta = \mathbb{E}\left[\theta_{St}\right]$.

Aggregate behavior of asset prices We record some more aggregate properties of this economy. They are directly inherited from the representative agent economy in Gabaix and Koijen 2023, whose aggregate properties, and calibration, the present model replicates by design—while adding to it the crucial innovation of a non-trivial cross-section.

Lemma 2. (Further aggregate properties of the model: average values of the aggregate stock market in the steady state) *The average dividend-price ratio is* $\delta = r_f + \bar{\pi} - g$. *With* $f_t = b_t$ *the aggregate flow in equities, the variance of stock market returns is*

$$\sigma_r^2 = var\left(\varepsilon_t^D + b_f^p \varepsilon_t^b\right), \tag{36}$$

and depends on both fundamental risk (ε_t^D) *and flow risk* (ε_t^b). *Both contribute to the average equity premium, which is:*

$$\bar{\pi} = \gamma \sigma_r^2. \tag{37}$$

Finally, the interest rate is constant, and given by the traditional consumption Euler equation:

$$r_f = -\ln \beta + \gamma g - \gamma (\gamma + 1) \frac{\sigma_y^2}{2}. \tag{38}$$

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Online Appendix

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

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B Literature review

In Table 4, we summarize related literature on portfolio choice decisions by households.

C Additional details on Addepar data

C.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 5.

Table 4: **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 (2023)	Addepar	U.S. (2016-2020)	Various	Heterogeneity in asset allocation and returns by wealth
Egan, MacKay, and Yang (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, Campbell, and Sodini (2007)	Swedish Wealth and Income Registry	Sweden (1999-2002)	Various	Efficiency of household investment decisions focusing on under-diversification and non-participation
Calvet, Campbell, and Sodini (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, Sodini, and Zhang (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, Keloharju, and Linnainmaa (2011)	Finnish Central Securities Depository	Finland (1995-2002)	Equity	Determinants of stock market participation
Anagol, Balasubramaniam, and Ramadorai (2015)	Indian National Securities Depository	India (2007-2012)	Equity	Effect of investment experiences on future investment behavior
Campbell, Ramadorai, and Ranish (2014)	Indian National Securities Depository	India (2004-2012)	Equity	Effect of investment experiences on future investment behavior
Campbell, Ramadorai, and Ranish (2019)	Indian National Securities Depository	India (2002-2011)	Equity	Relationship between return heterogeneity and equity wealth inequality
Balasubramaniam et al. (2023)	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.

Table 5: 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_inception, total_commitments, total_contributions, unfunded_commitment *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_class*, *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; *currency*, which provides the native currency of the security. In Section C.2, we provide details on how these input variables are combined to construct the asset class assignment.

C.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.

C.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 6 .

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.

Table 6: 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

Adjustments to the Addepar classification We make several adjustments to the assignment of asset classes imputed by Addepar. First, 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 or the domicile country class is United States.[27] 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 7, 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.

Table 7: 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, REITs, Other Equity
Alternatives	Private Equity & Venture, Hedge Funds, Direct Real Estate, Direct Private Companies, Fund of Funds, Real Estate Funds, Other Funds, Unknown Alts.
Other	Collectibles, Crypto, Derivatives, Liabilities, Other, Other Non-Financial Assets

C.2.2 Investment types

Although not directly used in the paper, Table 8 reports for completeness the breakdown of investment types into investment sub types observed in the dataset.

27. 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 8: 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

C.3 Additional details on cleaning steps

We provide further details on cleaning steps that are performed before aggregating the dataset at a 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 a small number of 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 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.

Fourth, 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.

D Theory complements

D.1 Omitted Proofs

Proof of Lemma 1 and Proposition 3 We prove Proposition 3, which is a generalization of Lemma 1, and does not depend on the previous propositions. Linearizing (16), with the slightly more general flow in (33) (which allows for $\lambda_i^f \neq 1$), we get for log wealth $w_{it} = \ln W_{it}$:

$$\Delta w_{it} = \theta_i \Delta p_t + \Delta d_t + \lambda_i^f \Delta b_t + \varepsilon_{it} + a_t. \tag{39}$$

So, the change in the virtual log holding of the risky asset is, using (31) and $\Delta \ln P_t = \Delta d_t + \Delta p_t$:

$$\begin{aligned} \Delta q_{it}^v &= \Delta w_{it} + \kappa_i \Delta \hat{\pi}_t + \lambda_i^d \Delta b_t + \Delta \nu_{it} - (\Delta d_t + \Delta p_t) \\ &= -(1-\theta_i)\Delta p_t + \kappa_i \Delta \hat{\pi}_t + \left(\lambda_i^d + \lambda_i^f\right)\Delta b_t + \Delta \nu_{it} + \varepsilon_{it} + a_t. \end{aligned}$$

For completeness, we show that the term a_t is second order, hence negligible. We use $\eta := \max(\sigma_d, \sigma_b, \sigma_{\varepsilon_S})$ as order of magnitude of the deviations from the steady state. First, we observe:

$$W_t = \frac{P_t}{\theta_t} = \frac{\bar{P}_t}{\theta}\frac{P_t}{\bar{P}_t}\frac{\theta}{\bar{\theta}_t} = \frac{\bar{P}_t}{\theta} e^{p_t - \kappa_S \hat{\pi}_t} = \frac{\bar{P}_t}{\theta} e^{O(\eta)}.$$

Then, (33) gives, taking the leading order terms only, so state:

$$\begin{aligned} \sum_i \Delta F_{it} &= \sum_i W_{i,t-1}\left[(1-\theta_{i,t-1})\frac{\Delta \bar{P}_t}{\bar{P}_{t-1}} + \lambda_i^f \Delta b_t + \varepsilon_{it} + a_t\right]. \\ &= W_{t-1}\left[(1-\theta_S + O(\eta))\frac{\Delta \bar{P}_t}{\bar{P}_{t-1}} + \lambda_S^f \Delta b_t + \varepsilon_{St} + a_t\right] \\ &= \frac{\bar{P}_{t-1}}{\theta} e^{O(\eta)}\left[(1-\theta + O(\eta))\frac{\Delta \bar{P}_t}{\bar{P}_{t-1}} + \lambda_S^f \Delta b_t + a_t\right] \qquad (40) \\ &= \frac{\bar{P}_{t-1}}{\theta}\left[(1-\theta)\frac{\Delta \bar{P}_t}{\bar{P}_{t-1}} + \lambda_S^f \Delta b_t + a_t + O\left(\eta^2\right)\right], \qquad (41) \end{aligned}$$

where (40) holds because as $\varepsilon_{St} = 0$, and because $W_t := \sum_i W_{it} = \frac{\bar{P}_t}{\theta}$ if there are no behavioral disturbances, as $\theta = \theta_S$ is the average equity share of the funds.

Also, by (34), we want the right-hand side to be equal to

$$\begin{aligned} \sum_i \Delta F_{it} &= \frac{1-\theta}{\theta}\Delta \bar{P}_t + \frac{\lambda^f}{\theta}\Delta\left(b_t \bar{P}_t\right) \qquad (42) \\ &= \frac{1-\theta}{\theta}\Delta \bar{P}_t + \frac{\lambda^f}{\theta}\left(\bar{P}_{t-1}\Delta b_t + b_t \Delta \bar{P}_t\right) \\ &= \frac{\bar{P}_{t-1}}{\theta}\left[(1-\theta)\frac{\Delta \bar{P}_t}{\bar{P}_{t-1}} + \lambda_S^f \Delta b_t + O\left(\eta^2\right)\right], \qquad (43) \end{aligned}$$

where we have $\lambda_S^f = \lambda_f + O(\eta)$. So equating (41) and (43) gives:

$$(1-\theta)\frac{\Delta \bar{P}_t}{\bar{P}_{t-1}} + \lambda_S^f \Delta b_t + a_t + O\left(\eta^2\right) = (1-\theta)\frac{\Delta \bar{P}_t}{\bar{P}_{t-1}} + \lambda_S^f \Delta b_t + O\left(\eta^2\right)$$

hence the term a_t is second order, so negligible:

$$a_t = O\left(\eta^2\right). \tag{44}$$

Proof of Proposition 1 We first derive the following simple result (re-using the derivation in Gabaix and Koijen 2023).

Lemma 3. *We have the following Taylor expansion of the derivation of the risk premium from its average, $\hat{\pi}_t = \pi_t - \bar{\pi}$:*

$$\hat{\pi}_t = e^g \left(\mathbb{E}_t \left[\Delta p_{t+1}\right] - \delta p_t\right) \tag{45}$$

In the limit of small time intervals (where $g = \bar{g}\Delta t$, with $\Delta t \to 0$), the term e^g in (45) becomes a 1, we get the more essential value $\hat{\pi}_t \simeq \mathbb{E}_t \left[\Delta p_{t+1}\right] - \delta p_t$, up to higher order terms.

Proof. Recall that $P_t = \frac{D_t}{\delta} e^{p_t}$ with $\mathbb{E}_t \left[\frac{D_{t+1}}{D_t}\right] = e^g$. Call $\bar{P}_t = \frac{D_t}{\delta}$. So, we have, neglecting second-order terms:

$$\begin{aligned}
1 + r_f + \bar{\pi} + \hat{\pi}_t &= 1 + r_f + \pi_t \\
&= \frac{\mathbb{E}_t \left[P_{t+1} + D_{t+1}\right]}{P_t} \\
&= \frac{\mathbb{E}_t \left[\bar{P}_{t+1} \left(1 + p_{t+1}\right) + D_{t+1} \left(1 + d_{t+1}\right)\right]}{\bar{P}_t \left(1 + p_t\right)} \\
&= \mathbb{E}_t \left[\frac{\bar{P}_{t+1}}{\bar{P}_t} \left(1 + p_{t+1} - p_t\right) + \frac{D_{t+1}}{D_t} \frac{D_t}{\bar{P}_t} \left(1 + d_{t+1} - p_t\right)\right] \\
&= \mathbb{E}_t \left[e^g \left(1 + p_{t+1} - p_t\right) + e^g \delta \left(1 + d_{t+1} - p_t\right)\right] && (46) \\
&= e^g (1 + \delta) + e^g \mathbb{E}_t \left[\Delta p_{t+1} + \delta \left(d_{t+1} - p_t\right)\right] && (47)
\end{aligned}$$

The zero-th order term gives $1 + r_f + \bar{\pi} = e^g (1 + \delta)$, which is the Gordon growth formula: writing $e^g = 1 + \bar{g}$, $r_f + \bar{\pi} - \bar{g} = (1 + \bar{g}) \delta = \frac{\mathbb{E}_t[D_{t+1}]}{P_t}$. The next order term gives (45):

$$\hat{\pi}_t = e^g \mathbb{E}_t \left[\Delta p_{t+1} - \delta p_t\right]. \tag{48}$$

□

We next move to the core of the proof of Proposition 1. First, we show that at all dates,

$\Delta q^v_{S,t} = 0$. Indeed, the market clearing condition is

$$\Delta q_{St} = 0 \tag{49}$$

at all dates. As we assumed that the μ_i are all identical to a value μ, (12) gives:

$$\Delta q_{S,t} = \mu \Delta q^v_{S,t} + (1-\mu)\,\Delta q^{v,\phi}_{S,t-1}, \tag{50}$$

$$\Delta q^{v,\phi}_{St} = \phi \Delta q^v_{St} + (1-\phi)\,\Delta q^{v,\phi}_{S,t-1}. \tag{51}$$

Also, we assumed that at the initial date, $\Delta q^{v,\phi}_{S,-1} = 0$. Hence, at time $t = 0$, (49) and (50) give $\Delta q^v_{S,0} = 0$. Then, (49) and (51) at $t = 0$ gives $\Delta q^{v,\phi}_{S,0} = 0$. But then, at time $t = 1$, (49) and (50) give $\Delta q^v_{S,1} = 0$. Reasoning similarly, and recursively, we have, for all dates $t \geq 0$, $\Delta q^v_{S,t} = \Delta q^{v,\phi}_{S,t} = 0$. We have indeed proven that $\Delta q^v_{S,t} = 0$ at all dates.

Next, we look for a solution where the price deviation from the baseline p_t depends linearly on the behavioral disturbance b_t, as in:

$$p_t = cb_t,$$

for some coefficient of proportionality c. So we have, using (45),

$$\mathbb{E}_t[\Delta p_{t+1}] = c\mathbb{E}_t[\Delta b_{t+1}] = -c\phi_b b_t = -\phi_b p_t,$$

we get, by (45):

$$\hat{\pi}_t = e^g (\mathbb{E}_t[\Delta p_{t+1}] - \delta p_t) = -e^g(\delta + \phi_b)\, p_t.$$

As a result, (17) gives rise to (19) with the announced elasticity ζ_i.

Next, using $\Delta q^v_{S,t} = 0$ and taking the size-average of (19) gives

$$0 = \Delta q^v_{St} = -\zeta_S \Delta p_t + \Delta b_t$$

As a result, $p_t = \frac{1}{\zeta_S} b_t + k$. As we set $P_t = \frac{D_t}{\delta} e^{p_t}$, which sets the constant k to be zero to ensure the normalization $\mathbb{E}[p_t] = 0$. So (18) obtains.

Next, (19) gives

$$\Delta q^v_{it} - \varepsilon_{it} = -\zeta_i \Delta p_t + \Delta b_t = -\zeta_i \Delta p_t + \zeta_S \Delta p_t = \lambda_i \Delta p_t,$$

with $\lambda_i = \zeta_S - \zeta_i$. Finally, (13) gives $\Delta q_{it} = \sum_{h \geq 0} a_i(h)(\lambda_i \Delta p_{t-h} + \varepsilon_{i,t-h})$, i.e. (22).

Proof of Proposition 2. In the limit of small time intervals, we can neglect the "drift" terms and only focus on the innovations. In addition, as we assumed that $\phi_b \ll \phi$, which means that at the time scale at which agents rebalance $(1/\phi)$, prices are essentially a random walk.

Here "i" represents a group, so the idiosyncratic effect ε_{it} cancels out. Eq. (22) gave $\Delta q_{it} = \lambda_i \sum_{h\geq 0} a_i(h)\,\Delta p_{t-h}$, hence (as the returns are assumed to be uncorrelated):

$$\mathbb{E}\left[(\Delta q_{it})^2\right] = \sigma_{\Delta p}^2 \lambda_i^2 \sum_{h\geq 0} a_i(h)^2$$

This gives

$$\mathcal{RTR}_i' := \frac{\sqrt{\mathbb{E}\left[(\Delta q_{it})^2\right]}}{\sigma_r} = \frac{\sigma_{\Delta p}}{\sigma_r}\,|\lambda_i|\left(\sum_{h\geq 0} a_i(h)^2\right)^{1/2}$$

and if the returns are Gaussian (so that $\sqrt{\mathbb{E}[X^2]} \propto \mathbb{E}|X|$), we get (23).

Eq. (22) also gives, as $\mathbb{S}_t[\Delta p_{t-h}] = 0$ for $h > 0$,

$$\mathbb{S}_t[\Delta q_{it}] = a_i(0)\,\lambda_i \mathbb{S}_t[\Delta p_t],$$

so $\mathbb{E}[|\mathbb{S}_t[\Delta q_{it}]|] = |a_i(0)\,\lambda_i|\,\mathbb{E}|\mathbb{S}_t[\Delta p_t]|$. This gives, assuming Gaussian mean 0 shocks:

$$\mathcal{RTR}_{gt}^{\mathbb{S}} = \frac{\mathbb{E}[|\mathbb{S}_t[\Delta q_{gt}]|]}{\mathbb{E}[|\mathbb{S}_t[r_t]|]} = \frac{\sigma_{\Delta p_t}}{\sigma_{r_t}}\,|a_i(0)\,\lambda_i| = \chi\,|\lambda_i|\,a_i(0).$$

(24).

Proof of Lemma 2 This comes directly from the representative agent economy in Gabaix and Koijen (2023), whose aggregate properties, and calibration, the present model replicates by design.

Proof of Proposition 4. Using our convention that $a(h) = 0$ for $h < 0$, we can write (22) as

$$\frac{\Delta q_{it}}{\lambda_i} = \sum_{h\geq 0} a_i(h)\,\Delta p_{t-h} = \sum_{s=-\infty}^{\infty} a_i(t-s)\,\Delta p_s.$$

Hence, at horizon H,

$$\begin{aligned}\Delta^{(H)} q_{it} &:= q_{it} - q_{i,t-H-1} = \sum_{h=0}^{H} \Delta q_{i,t-h} = \lambda_i \sum_{s=-\infty}^{\infty} \sum_{h'=0}^{H} a_i\left(t-h'-s\right) \Delta p_s \\ &= \lambda_i \sum_{h\geq 0}^{\infty} \sum_{h'=0}^{H} a_i\left(h-h'\right) \Delta p_{t-h},\end{aligned}$$

i.e.,

$$\Delta^{(H)} q_{it} = \lambda_i \sum_{h\geq 0}^{\infty} \left(a_i\left(h-H\right) + \cdots + a_i\left(h\right)\right) \Delta p_{t-h}. \tag{52}$$

This gives:

$$\mathbb{E}\left[\left(\Delta^{(H)} q_{it}\right)^2\right] = \lambda_i^2 \sigma_{\Delta p}^2 \sum_{h\geq 0}^{\infty} \left(a_i\left(h-H\right) + \cdots + a_i\left(h\right)\right)^2.$$

Given that $\mathbb{E}\left[\left(p_{it} - p_{i,t-H-1}\right)^2\right] = \left(H+1\right)\sigma_{\Delta p}^2$, we obtain

$$\left(\frac{\mathbb{E}\left[\left(q_{it} - q_{i,t-H-1}\right)^2\right]}{\mathbb{E}\left[\left(p_{it} - p_{i,t-H-1}\right)^2\right]}\right)^{1/2} = \left|\lambda_i\right| A_i\left(H\right).$$

Hence, under a Gaussian assumption, we get the announced value for $\mathcal{RTR}_{it}^{H}$.

If we condition (52) on $t-H-1$ information, we get

$$\mathbb{S}_{t-H-1}\left[q_{it} - q_{i,t-H-1}\right] = \lambda_i \sum_{h=0}^{H} \left(a_i\left(0\right) + \cdots + a_i\left(h\right)\right) \Delta p_{t-h}$$

hence

$$var_{t-H-1}\left(q_{it} - q_{i,t-H-1}\right) = \lambda_i^2 \sigma_{\Delta p}^2 \sum_{h=0}^{H} \left(a_i\left(0\right) + \cdots + a_i\left(h\right)\right)^2$$

which then gives the expression for $\mathcal{RTR}_{it}^{\mathbb{S},H}$.

Proof of Proposition 5. By the same reasoning as in the main text and in the proof of Proposition 1, market clearing gives $0 = \Delta q_{St}^{v} = -\zeta_S \Delta p_t + \lambda_S^{\nu} b_t$, i.e. $\Delta p_t = \frac{\lambda_S^{\nu}}{\zeta_S} b_t$. So, (76) gives $\Delta q_{it}^{v} = \left(-\zeta_i + \lambda_i^{v} \frac{\zeta_S}{\lambda_S^{v}}\right) \Delta p_t$, i.e.

$$\Delta q_{it}^{v} = \lambda_i \Delta p_t, \qquad \lambda_i := \frac{\lambda_i^{v}}{\lambda_S^{v}} \zeta_S - \zeta_i \tag{53}$$

which gives the announced value for λ_i.

D.2 Complements to the Gârleanu-Panageas (2015) model of Section 3.4

The model by Gârleanu and Panageas (2015) features two types of agents with different risk aversions in an overlapping generations framework. The model incorporates Epstein-Zin utility, heterogeneous agents, an exogenous output process, human capital, and capital markets. We show how we simulate the model, and calculate the risk transfer.[28]

D.2.1 Recap of model ingredients

We briefly describe the key ingredients of the model.

1. **Heterogeneity.** Two types of agents $i \in \{A, B\}$, with $\gamma_A \leq \gamma_B$.

2. **Utility.** At each time t, agent of type i born at time s maximizes Epstein-Zin utility adapted to continuous time

$$V_{st}^i = \mathbb{E}_t \left[\int_t^\infty f^i \left(c_{su}^i, V_{su}^i \right) du \right]$$

$$f^i (c, V) = \left(\alpha^i \right)^{-1} \left[\left(1 - \gamma^i \right) V \right]^{1 - \frac{\alpha^i}{1 - \gamma^i}} \left\{ c^{\alpha^i} - (\rho + \pi) \left[\left(1 - \gamma^i \right) V \right]^{\frac{\alpha^i}{1 - \gamma^i}} \right\}$$

   where γ_i controls risk aversion, $\frac{1}{1-\alpha^i}$ is the intertemporal elasticity of substitution, c_{st}^i denotes consumption and V_{st}^i the value function.

3. **OLG feature.** At each time t, a fraction π of agents die and they are replaced by an equivalent mass π of newly born agents. Specifically, $\pi \upsilon^A$ of newly born agents are of type A and $\pi \upsilon^B \equiv \pi \left(1 - \upsilon^A \right)$ are of type B, where $\upsilon^A \in (0, 1)$.

4. **Exogenous process.** Aggregate output Y_t evolves as a geometric Brownian motion

$$\frac{dY_t}{Y_t} = \mu_Y dt + \sigma_Y dB_t$$

5. **Human capital.** Each agent born at time s receives at time t a fraction of aggregate

28. We thank Nicolae Gârleanu and Stavros Panageas for discussions, and sharing their code with us.

output given by

$$y_{st} = \omega Y_t G\left(t-s\right) \equiv \omega Y_t \left(B_1 e^{-\delta_1(t-s)} + B_2 e^{-\delta_2(t-s)}\right) \tag{54}$$

where $\omega \in (0,1)$ and $G\left(t-s\right)$ is rescaled so that $\int_{-\infty}^{t} \pi e^{-\pi(s-t)} G\left(t-s\right) ds = 1$. It follows that a total fraction ω of aggregate output Y_t is received by agents at each time t and the remaining fraction is distributed as a dividend $D_t = \left(1-\omega\right) Y_t$.

6. **Capital markets.** Risky asset pays dividend $D_t = \left(1-\omega\right) Y_t$ and is available in unit supply with (endogenous) price process

$$\frac{dS_t + D_t dt}{S_t} = \mu_t dt + \sigma_t dB_t$$

A riskless asset is also available and guarantees a (endogenous) risk free rate r_t.

7. **Insurance.** As in Blanchard 1985, competitive insurance is available that pays πW_{st}^i until death and receives the entire financial wealth upon death. Every agent finds it optimal to enter such contract.

8. **Budget constraint.** Financial wealth W_{st}^i evolves as

$$dW_{st}^i = \left[r_t W_{st}^i + \theta_{st}^i \left(\mu_t - r_t\right) + y_{st} + \pi W_{st}^i - c_{st}^i\right] dt + \theta_{st}^i \sigma_t dB_t$$

where θ_{st}^i denotes dollar holdings of the risky asset.

9. **State variable.** Useful to define the following state variable X_t that represents the share of output Y_t consumed by agents of type A

$$X_t = \frac{1}{Y_t} \int_{-\infty}^{t} \upsilon^A \pi e^{-\pi(t-s)} c_{st}^A ds \tag{55}$$

with (endogenous) process

$$dX_t = \mu_X\left(X_t\right) dt + \sigma_X\left(X_t\right) dB_t$$

D.2.2 Solving for Risky Asset Holdings θ_{st}^i

To solve for θ_{st}^i for each $i \in \{A, B\}$, s and t, we equate the diffusion of financial wealth W_{st}^i in the budget constraint with the diffusion implied by the definition of financial wealth as the presented discounted value of future consumption net of human capital, i.e.

$$W_{st}^{i}=\mathbb{E}_{t}\left[\int_{t}^{\infty}e^{-\pi(u-t)}\frac{\xi_{u}}{\xi_{t}}c_{su}^{i}du\right]-\mathbb{E}_{t}\left[\int_{t}^{\infty}e^{-\pi(u-t)}\frac{\xi_{u}}{\xi_{t}}y_{su}du\right]$$

where ξ_t denotes the equilibrium SDF at time t.

Diffusion of wealth implied by the budget constraint The diffusion of W_{st}^{i} implied by the budget constraint is $\theta_{st}^{i}\sigma_{t}$ with solution for σ_t provided in equation (A.26) of the online appendix in Gârleanu and Panageas (2015):

$$\sigma_{t}=\frac{s'\left(X_{t}\right)}{s\left(X_{t}\right)}\sigma_{X}\left(X_{t}\right)+\sigma_{Y}$$

where $s\left(X_{t}\right)$ and $\sigma_{X}\left(X_{t}\right)$ are known functions.

Diffusion of wealth implied by the present discounted value Define $W_{1,st}^{i}\equiv\mathbb{E}_{t}\left[\int_{t}^{\infty}e^{-\pi(u-t)}\frac{\xi_{u}}{\xi_{t}}c_{su}^{i}du\right]$ and $W_{2,st}\equiv\mathbb{E}_{t}\left[\int_{t}^{\infty}e^{-\pi(u-t)}\frac{\xi_{u}}{\xi_{t}}y_{su}du\right]$ so that $W_{st}^{i}=W_{1,st}^{i}-W_{2,st}$. We need to derive the diffusion of the process

$$dW_{st}^{i}=dW_{1,st}^{i}-dW_{2,st}$$

Starting from $W_{1,st}^{i}$, we have

$$\begin{aligned}W_{1,st}^{i}&=\mathbb{E}_{t}\left[\int_{t}^{\infty}e^{-\pi(u-t)}\frac{\xi_{u}}{\xi_{t}}c_{su}^{i}du\right]\\&=c_{st}^{i}\mathbb{E}_{t}\left[\int_{t}^{\infty}e^{-\pi(u-t)}\frac{\xi_{u}}{\xi_{t}}\frac{c_{su}^{i}}{c_{st}^{i}}du\right]\\&=\frac{c_{st}^{i}}{g^{i}\left(X_{t}\right)}\end{aligned}\tag{56}$$

or equivalently

$$\log W_{1,st}^{i}=\log c_{st}^{i}-\log g^{i}\left(X_{t}\right)\tag{57}$$

where $g^{i}\left(X_{t}\right)$ is a known function obtained as solution of the ODE (A.22) in the online appendix.

By definition of the state variable X_t we have

$$X_{t}Y_{t}=\upsilon^{A}\pi\int_{-\infty}^{t}e^{-\pi(t-s)}c_{st}^{A}ds\tag{58}$$

$$(1 - X_t)\, Y_t = \upsilon^B \pi \int_{-\infty}^{t} e^{-\pi(t-s)} c_{st}^B ds \tag{59}$$

Let $\sigma_{c,t}^A$ and $\sigma_{c,t}^B$ denote the diffusion of log consumption of agents of type A and B respectively. Taking logs on both sides of (58), applying Ito's Lemma on both sides, and matching diffusion terms on both sides we have

$$\sigma_{c,t}^A = \frac{\sigma_X(X_t)}{X_t} + \sigma_Y \tag{60}$$

Repeating for equation (59)

$$\sigma_{c,t}^B = -\frac{\sigma_X(X_t)}{1 - X_t} + \sigma_Y \tag{61}$$

Using equation (57) the diffusion $\sigma_{1,t}^A$ of $\log W_{1,st}^A$ is then

$$\sigma_{1,t}^A = \sigma_{c,t}^A - \frac{g^A(X_t)'}{g^A(X_t)}\sigma_X(X_t) = \left[\frac{1}{X_t} - \frac{g^A(X_t)'}{g^A(X_t)}\right]\sigma_X(X_t) + \sigma_Y \tag{62}$$

and the diffusion $\sigma_{1,t}^B$ of $\log W_{1,st}^B$ is

$$\sigma_{1,t}^B = \sigma_{c,t}^B - \frac{g^B(X_t)'}{g^B(X_t)}\sigma_X(X_t) = \left[-\frac{1}{1 - X_t} - \frac{g^B(X_t)'}{g^B(X_t)}\right]\sigma_X(X_t) + \sigma_Y \tag{63}$$

Because $d\log W_{1,st}^i \equiv \frac{dW_{1,st}^i}{W_{1,st}^i}$, the diffusion of $dW_{1,st}^A$ is then $W_{1,st}^A \sigma_{1,t}^A$ and the diffusion of $dW_{1,st}^B$ is $W_{1,st}^B \sigma_{1,t}^B$.

Turning to $W_{2,st}$, we can use (54) together with the definition in (A.17) to derive

$$\begin{aligned} W_{2,st} &= \mathbb{E}_t\left[\int_t^\infty e^{-\pi(u-t)}\frac{\xi_u}{\xi_t} y_{su} du\right] \\ &= \mathbb{E}_t\left[\int_t^\infty e^{-\pi(u-t)}\frac{\xi_u}{\xi_t}\left[\omega Y_u\left(B_1 e^{-\delta_1(u-s)} + B_2 e^{-\delta_2(u-s)}\right)\right] du\right] \\ &= Y_t\left[e^{-\delta_1(t-s)}\phi^1(X_t) + e^{-\delta_2(t-s)}\phi^2(X_t)\right] \end{aligned} \tag{64}$$

Using Ito's Lemma and ignoring again the terms that are not part of the diffusion

$$dW_{2,st} = (\dots)\, dt + \underbrace{\left\{W_{2,st}\sigma_Y + \left[e^{-\delta_1(t-s)} Y_t \phi^{1\prime}(X_t) + e^{-\delta_2(t-s)} Y_t \phi^{2\prime}(X_t)\right]\sigma_X(X_t)\right\}}_{\sigma_{2,st}} dB_t$$

It follows that the diffusion of W_{st}^i is $W_{1,st}^i \sigma_{1,t}^i - \sigma_{2,st}$.

Solution Equating the diffusion terms of W_{st}^i obtained in Sections D.2.2 and D.2.2 we have

$$\theta_{st}^{i} = \frac{W_{1,st}^{i}\sigma_{1,t}^{i} - \sigma_{2,st}}{\sigma_t} \tag{65}$$

Aggregation Before proceeding with the simulation of the model, it is useful to derive aggregate portfolio holdings θ_t^i, financial wealth W_t^i, total wealth $W_{1,t}^i$, and human capital $W_{2,t}^i$ across all agents of type A and B. This step confers two advantages: (i) it mirrors our calculation in the Addepar data, where we construct risk exposure and risk transfer for the aggregate investor in each group; (ii) it eliminates the need to keep track of agents in different cohorts in the simulation.

Recall at time t we have a mass $\pi\nu^A e^{-\pi(t-s)}$ of agents A that were born at time s and a mass $\pi\nu^B e^{-\pi(t-s)}$ of agents B that were born at time s.

Let's start from the aggregate agent of type A. The aggregate total wealth is

$$W_{1,t}^{A} = \pi\nu^A \int_{-\infty}^{t} W_{1,st}^{A} e^{-\pi(t-s)} ds = \pi\nu^A \int_{-\infty}^{t} \frac{c_{st}^{A}}{g^A(X_t)} e^{-\pi(t-s)} ds = \frac{X_t Y_t}{g^A(X_t)} \tag{66}$$

where the first equality just aggregates wealth $W_{1,st}^{A}$ across cohorts, the second equality uses equation (56), and the third equality uses equation (55).

Aggregate human capital is

$$\begin{aligned} W_{2,t}^{A} &= \pi\nu^A \int_{-\infty}^{t} W_{2,st}^{A} e^{-\pi(t-s)} ds \\ &= \pi\nu^A Y_t \int_{-\infty}^{t} \left[e^{-\delta_1(t-s)}\phi^1(X_t) + e^{-\delta_2(t-s)}\phi^2(X_t)\right] e^{-\pi(t-s)} ds \\ &= \pi\nu^A Y_t \left[\frac{\phi^1(X_t)}{\pi+\delta_1} + \frac{\phi^2(X_t)}{\pi+\delta_2}\right] \end{aligned} \tag{67}$$

where the second equality uses (64). By definition, aggregate financial wealth is the difference between aggregate total wealth and aggregate human capital

$$W_t^A = \pi\nu^A \int_{-\infty}^{t} W_{st}^{A} e^{-\pi(t-s)} ds = \pi\nu^A \int_{-\infty}^{t} \left(W_{1,st}^{A} - W_{2,st}^{A}\right) e^{-\pi(t-s)} ds = W_{1,t}^{A} - W_{2,t}^{A} \tag{68}$$

Finally, aggregate portfolio holdings equal

$$\theta_{1,t}^{A} = \pi\nu^A \int_{-\infty}^{t} \theta_{1,st}^{A} e^{-\pi(t-s)} ds = \frac{W_{1,t}^{A}\sigma_{1,t}^{A} - W_{2,t}^{A}\sigma_Y - \pi\nu^A Y_t \left[\frac{\phi^1(X_t)'}{\pi+\delta_1} + \frac{\phi^2(X_t)'}{\pi+\delta_2}\right]\sigma_X(X_t)}{\sigma_t} \tag{69}$$

where the third equality uses the solution for $\theta_{1,st}^{A}$ in equation (65).

The same logic can be used to derive wealth and portfolio holdings for the aggregate agent of type B

$$W^B_{1,t} = \frac{(1 - X_t)\, Y_t}{g^B\,(X_t)} \tag{70}$$

$$W^B_{2,t} = \pi\nu^B Y_t \left[\frac{\phi^1\,(X_t)}{\pi + \delta_1} + \frac{\phi^2\,(X_t)}{\pi + \delta_2}\right] \tag{71}$$

$$W^B_t = W^B_{1,t} - W^B_{2,t} \tag{72}$$

$$\theta^B_{1,t} = \frac{W^B_{1,t}\sigma^B_{1,t} - W^B_{2,t}\sigma_Y - \pi\nu^B Y_t \left[\frac{\phi^1(X_t)'}{\pi+\delta_1} + \frac{\phi^2(X_t)'}{\pi+\delta_2}\right]\sigma_X\,(X_t)}{\sigma_t} \tag{73}$$

D.2.3 Simulation

Let $\mathcal{G}$ denote the set of functions describing the model equilibrium

$$\mathcal{G} = \left\{g^A\,(X)\,, g^B\,(X)\,, \phi^1\,(X)\,, \phi^2\,(X)\,, \phi^1\,(X)'\,, \phi^2\,(X)'\,, \mu\,(X)\,, \sigma_X\,(X), S\,(X)\,, \sigma\,(X)\right\}.$$

Given a solution for the functions in $\mathcal{G}$ on a discrete grid of X, we simulate the model as follows:

1. **Time periods**. Following the authors (Appendix B; Gârleanu and Panageas, 2015), we simulate the model for $T = 4,000$ years and we drop the first 3,700 years of the simulation to avoid that the results depend on the initial conditions for X and Y.
   - All exogenous parameters $\left\{\delta_1, \delta_2, \pi, \nu^A, \mu_Y, \sigma_Y\right\}$ are set as in the calibration used in the paper.
   - To match the frequency of the data in Addepar, we simulate at quarterly frequency, i.e. $\Delta t = 0.25$.
2. **Initial conditions**. We initialize X_0 at its stationary mean and we set $Y_0 = 1$.
3. **Portfolio Holdings and Wealth**. At each time t, we use linear interpolation to compute the functions $\mathcal{G}$ at the simulated value X_t. We then construct aggregate portfolio holdings and wealth for each agent A and B using equations (66)-(73).

4. **Update X and Y**. We update X and Y using a discretized version of their process

$$X_{t+1} = X_t + \mu_X (X_t) \Delta t + \sigma_X (X_t) \sqrt{\Delta t} B_{t+1}$$
$$Y_{t+1} = Y_t + \mu_Y Y_t \Delta t + \sigma_Y Y_t \sqrt{\Delta t} B_{t+1}$$

   where $B_{t+1} \sim N(0, 1)$.

5. **Repeat**. We repeat steps 3 and 4 until we reach T.

6. **Portfolio shares**. Once the simulation is over, we compute the number of shares of the risky asset held by aggregate investors A and B as dollar holdings divided by the asset price

$$Q_t^A = \frac{\theta_t^A}{S_t}, \quad Q_t^B = \frac{\theta_t^B}{S_t}$$

7. **Dollar flows**. We compute dollar flows as

$$F_t^A = \left(Q_t^A - Q_{t-1}^A\right) S_{t-1}, \quad F_t^B = \left(Q_t^B - Q_{t-1}^B\right) S_{t-1}$$

8. **Risk exposure**. We compute the risk exposure (weighted average market beta in Addepar) of the aggregate investors A and B as dollar holdings rescaled by financial wealth

$$\Theta_t^A = \frac{\theta_t^A}{W_t^A}, \quad \Theta_t^B = \frac{\theta_t^B}{W_t^B}$$

9. **Risk transfer relative to financial wealth**. We compute the market beta traded by the aggregate investors A and B as flows divided by financial wealth

$$\Phi_t^A = \frac{F_{t+1}^A}{W_t^A}, \quad \Phi_t^B = \frac{F_{t+1}^B}{W_t^B}$$

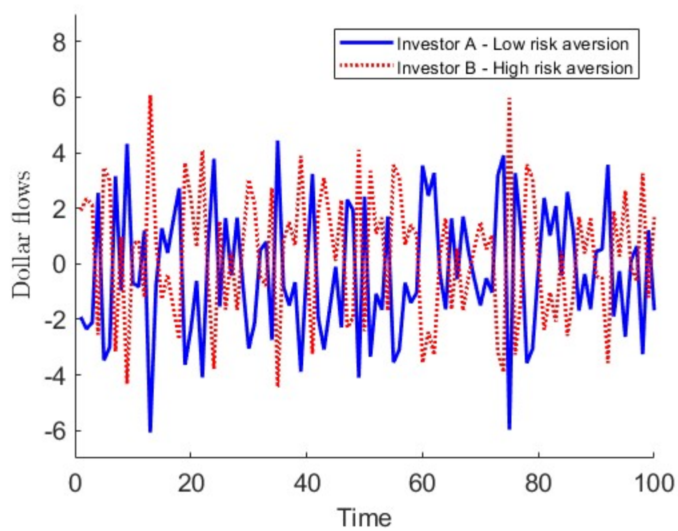
10. **Risk transfer relative to holdings in risky asset**. Finally, we compute the risk transfer relative to holdings in the risky asset as

$$\Delta q_t^A = \frac{\Phi_t^A}{\Theta_t^A}, \quad \Delta q_t^B = \frac{\Phi_t^B}{\Theta_t^B}$$

Table 9: **Summary of Results**

Variable	Groups	
	B (High risk aversion)	A (Low risk aversion)
$\mathbb{E}\left[\Theta_t^g\right]$	-0.274	1.814
$\mathbb{E}\left[\lvert\Phi_t^g\rvert\right]$	0.481	0.064
$\mathbb{E}\left[\lvert\Delta q_t^g\rvert\right]$	0.785	0.035

Figure 8: **Dollar flows of aggregate investors A and B**
This figure reports dollar flows F_t^A and F_t^B for aggregate investors A and B respectively in the simulation of Gârleanu and Panageas (2015).



D.2.4 Results

Table 9 compares the time-series average of risk exposure and risk transfer obtained from the simulation. First, it shows that the average risk transfer for both groups are much larger than what we find in the data. Second, the simulations show that the high risk aversion agents (group B) in Gârleanu and Panageas (2015) are on average short the risky asset. This is because the dividend paid out by the risk asset is perfectly correlated with the endowment received by agents. It follows that high risk averse agents use the risky asset to diversify the risk in their human capital.

As a sanity check, we also report in Figure 1 the dollar flows of aggregate investors A and B. As expected, the two aggregate investors trade against each other and dollar flows sum to zero.

D.3 Complements to the inelastic model of Section 3.5

D.3.1 Risk transfer at longer horizons

We generalize Proposition 2 to horizons greater than one period.

Proposition 4. *The following generalizes Proposition 2. Call* $\Delta^{(H)} q_{it} := q_{it} - q_{i,t-H-1}$ *and similarly for* $\Delta^{(H)} p_t$*. Assume for simplicity that all variables are jointly Gaussian. At horizon* $H \geq 0$*, we have, in the limit* $\phi_b \ll \phi$ *of a quasi-random walk in asset prices:*

$$\mathcal{RTR}_{it}^{H} := \frac{\mathbb{E}\left[\left|\left\langle \Delta^{(H)} q_{it} \right\rangle\right|\right]}{\mathbb{E}\left[\left|\Delta^{(H)} p_t\right|\right]} = \chi \left|\lambda_i\right| A_i\left(H\right), \qquad A_i\left(H\right) := \left(\frac{1}{H+1}\sum_{h\geq 0}\left(a_i\left(h-H\right)+\cdots+a_i\left(h\right)\right)^2\right)^{1/2} \tag{74}$$

$$\mathcal{RTR}_{it}^{\mathbb{S},H} := \frac{\mathbb{E}\left|\mathbb{S}_{t-H-1}\left[\Delta^{(H)} q_{it}\right]\right|}{\mathbb{E}\left|\mathbb{S}_{t-H-1}\left[\Delta^{(H)} p_t\right]\right|} = \chi \left|\lambda_i\right| A_i^{\mathbb{S}}\left(H\right), \qquad A_i^{\mathbb{S}}\left(H\right) := \left(\frac{1}{H+1}\sum_{h=0}^{H}\left(a_i\left(0\right)+\cdots+a_i\left(h\right)\right)^2\right)^{1/2} \tag{75}$$

where we use the convention that $a_i\left(h\right) = 0$ *for* $h < 0$*;* $A_i^{\mathbb{S}}\left(H\right)$ *is increasing, with* $A_i^{\mathbb{S}}\left(0\right) = \left|a_i\left(0\right)\right|$ *and* $\lim_{H\to\infty} A_i^{\mathbb{S}}\left(H\right) = 1$.

Simulated values. The values of risk transfer (in its conditional value $\mathcal{RTR}_{it}^{\mathbb{S},H}$) at horizon 0, 1, 2, 3 quarters are respectively: 8%, 9.6%, 11%, 12.1%, so that the increase with the horizon is quite moderate.

D.3.2 Generalizations of the inelastic model of Section 3.5

We next study how generalizations of this model keep robust the basic contention of low risk transfers. For instance, suppose the following generalization of (19):

$$\Delta q_{it}^{v} = -\zeta_i \Delta p_t + \lambda_i^{\nu} \Delta b_t \tag{76}$$

where λ_i^{ν} indicates potentially different loadings on the behavioral shock. In the ergodic distribution, with a large number of families, λ_S does not move appreciably. So, we assume that it does not move.

Proposition 5. *In the model with heterogeneous loadings on the behavioral shock, Proposition 1 remains true, replacing* (*21*) *by:*

$$\lambda_i = \zeta_S - \zeta_i + \frac{\lambda_i^{\nu} - \lambda_S^{\nu}}{\lambda_S^{\nu}} \zeta_S = \theta_i - \theta_S - (\kappa_i - \kappa_S)(\delta + \phi_\pi) + \frac{\lambda_i^{\nu} - \lambda_S^{\nu}}{\lambda_S^{\nu}} \zeta_S \tag{77}$$

Calibration We have $\theta_S = 0.8$, $\kappa_S = 1\text{yr}$, so $\zeta_S = 0.2$. To think about dispersions between groups, we take a moderate dispersion of 30% around the mean values: $\left\langle \frac{|\kappa_i - \kappa_S|}{\kappa_S} \right\rangle = \left\langle \left| \frac{\lambda_i^{\nu} - \lambda_S^{\nu}}{\lambda_S^{\nu}} \right| \right\rangle = 0.3$. Then, we examine the extra terms in (77):

$$|(\kappa_i - \kappa_S)(\delta + \phi)| = \left| \left(\frac{\kappa_i - \kappa_S}{\kappa_S} \right) \right| \kappa_S (\delta + \phi_\pi) = 0.3 \times 1 \times 0.1 = 3\% \tag{78}$$

$$\left| \frac{\lambda_i^{\nu} - \lambda_S^{\nu}}{\lambda_S^{\nu}} \zeta_S \right| = 0.3 \times 0.2 = 6\%. \tag{79}$$

This is compared to the initial term from the simplest version in (25):

$$|\theta_i - \theta_S| = 20\% \tag{80}$$

We conclude that the extra terms in (77) modify only very moderately the baseline estimate from our model. This is only possible because κ_S and ζ_S are small — the key features of an inelastic market. With elastic markets ($\kappa_S = \frac{1}{\pi} = 20\text{yr}$, $\zeta_S \simeq 2$), any variation around the average would create a very large amount of risk transfer, and would violate the empirical evidence.

E Computing risk transfer in Addepar data

E.1 The stock market beta of each asset class

The stock market β_n are taken in Table 10.[29]

E.2 Computing Risk Transfers with a longer horizon

In constructing multi-horizon flows, we follow these steps:

1. For each quarter t, we sum the dollar flows for quarter t and τ future quarters. For example, if $\tau = 3$, this yields the dollar flow for four consecutive quarters $t+1$, $t+2$, and $t+3$.

2. We rescale the dollar flow by the DH wealth at t, i.e. A_{gt}^{DH} to obtain $f_{g,n,t:t+\tau}^{Liq}$.

3. We then compute the multi-horizon risk transfer as:

$$\mathcal{RT}_{g,t:t+\tau} = \frac{\Phi_{g,t:t+\tau}}{\Theta_{g,t-1}^{Liq}} = \frac{\sum_n f_{g,n,t:t+\tau}^{Liq}\beta_n}{\Theta_{g,t-1}^{Liq}}$$

We generalize the earlier definitions of risk transfer to accommodate flows over multiple quarters ($\mathcal{RT}_{g,t:t+\tau}$) and compute the risk transfer ratio, as:

$$\mathcal{RTR}_{g,\tau} = \frac{\mathbb{E}\left[|\mathcal{RT}_{g,t:t+\tau}|\right]}{\mathbb{E}\left[|r_{t:t+\tau}|\right]}$$

where $r_{t:t+\tau}$ is the cumulative return from t to $t+\tau$. We report the results for $\tau = 1, 2, 3$ (i.e. two-, three-, and four-quarter flows).

Table 11 provides the equivalent statistic for multi-horizon flows of Table 3, which had a horizon of one quarter. We see an increase of the risk transfer ratio with the horizon from 1 to 2 quarters, consistent with slow and progressive rebalancing. As our time sample is short, we have only seven non-overlapping yearly changes, so we recommend taking those values are simply suggestive. It will be useful to revisit those result in say ten years, when there are many more non-overlapping periods, which will allow to measure risk transfer as truly long horizons.

29. They are taken from Blackrock: https://www.blackrock.com/institutions/en-us/insights/charts/capital-market-assumptions.

Table 10: **Beta Values for Various Asset Classes**

This table reports the market beta for various liquid asset classes, along with the intermediate values used in their calculation: correlation ρ, volatility σ_n of each asset class, and volatility $\sigma_{benchmark}$ of the benchmark asset. ρ and σ_n are sourced from BlackRock's Capital Market Assumptions as of May 2024. For asset classes not included in their capital market assumptions, the closest substitute has been used. $\sigma_{benchmark}$ is chosen to align with the volatility of global equity, as the exact benchmark index is not specified in the report. Using ρ, σ_n, and $\sigma_{benchmark}$, we construct β for each asset class.

Asset Class (n)	ρ	σ_n	$\sigma_{benchmark}$	β	Index
ABS/MBS	-0.121	0.057		-0.041	Bloomberg Barclays US MBS Index
Bond Funds	-0.066	0.051		-0.020	Bloomberg Barclays U.S. Aggregate Index
Corporate Bonds	0.236	0.060		0.084	Bloomberg Barclays Long Credit index
Developed Market Equity	0.914	0.168		0.914	MSCI World ex-US Index
Emerging Market Equity	0.780	0.203	0.168	0.943	MSCI Emerging Markets Index
Global Equity	0.914	0.168		0.914	MSCI World ex-US Index
International Government/Agency Bonds	-0.075	0.032		-0.015	Bloomberg Barclays Global Aggregate Treasury Index ex US
Municipal Bonds	-0.267	0.050		-0.080	(Not Available) – Using Bloomberg Barclays Government Index
Other Government/Agency Bonds	-0.075	0.032		-0.015	(Not Available) – Using Bloomberg Barclays Global Aggregate Treasury Index ex US
Structured Debt	0.630	0.070		0.263	(Not Available) – Using Bloomberg Barclays U.S. High Yield Index
U.S. Government/Agency Bonds	-0.267	0.050		-0.080	Bloomberg Barclays Government Index
U.S. Equity	0.879	0.177		0.926	MSCI USA Index
REITS	0.781	0.202		0.942	FTSE EPRA Nareit Developed Index (Gross)

Table 11: **Risk Exposure and Transfer: Multi-Quarter Horizon**

This table summarizes the risk exposure $\left(\Theta^{Liq}_{g,t-1}\right)$, risk transfer ($\mathcal{RT}_{gt}$), and risk transfer ratio ($\mathcal{RTR}_g$) computed using the Addepar data for multi-quarter flows. Each column denotes the group of investors.

(a) Two-Quarter ($\mathbb{E}\left[|r_t - r_{ft}|\right] = 0.116$)

Variable	Groups based risk exposure											
	High	Low	1	2	3	4	5	6	7	8	9	10
$\mathbb{E}\left[\Theta^{Liq}_{g,t-1}\right]$	0.814	0.428	0.208	0.409	0.501	0.569	0.625	0.677	0.732	0.791	0.869	0.915
$\mathbb{E}\left[\lvert\mathcal{RT}_{gt}\rvert\right]$	0.0053	0.020	0.065	0.028	0.016	0.010	0.010	0.0065	0.0089	0.0074	0.0066	0.010
$\mathcal{RTR}_g$	0.046	0.170	0.562	0.241	0.134	0.086	0.086	0.056	0.077	0.064	0.057	0.089

(b) Three-Quarter ($\mathbb{E}\left[|r_t - r_{ft}|\right] = 0.148$)

Variable	Groups based risk exposure											
	High	Low	1	2	3	4	5	6	7	8	9	10
$\mathbb{E}\left[\Theta^{Liq}_{g,t-1}\right]$	0.814	0.428	0.208	0.409	0.501	0.569	0.625	0.677	0.732	0.791	0.869	0.915
$\mathbb{E}\left[\lvert\mathcal{RT}_{gt}\rvert\right]$	0.0069	0.029	0.101	0.043	0.022	0.013	0.014	0.0082	0.011	0.010	0.0089	0.014
$\mathcal{RTR}_g$	0.047	0.195	0.684	0.289	0.153	0.090	0.094	0.055	0.076	0.067	0.060	0.092

(c) Four-Quarter ($\mathbb{E}\left[|r_t - r_{ft}|\right] = 0.185$)

Variable	Groups based risk exposure											
	High	Low	1	2	3	4	5	6	7	8	9	10
$\mathbb{E}\left[\Theta^{Liq}_{g,t-1}\right]$	0.814	0.428	0.208	0.409	0.501	0.569	0.625	0.677	0.732	0.791	0.869	0.915
$\mathbb{E}\left[\lvert\mathcal{RT}_{gt}\rvert\right]$	0.0063	0.030	0.106	0.045	0.022	0.013	0.012	0.0085	0.0093	0.010	0.0073	0.013
$\mathcal{RTR}_g$	0.034	0.163	0.573	0.243	0.121	0.071	0.065	0.046	0.050	0.054	0.039	0.072

Table 12: Classification and fraction of total wealth by broad group in SCF
This table reports the classification of items observed in SCF in six broad groups. For each broad group, we report the total population-weighted wealth in trillions of dollars. For each broad group, we further report the fraction of total wealth observed in each item. The data are based on the 2019 SCF (that is, as of December 2018).

Cash		Equities		Fixed Income	
Items	Fraction of wealth (%)	Items	Fraction of wealth (%)	Items	Fraction of wealth (%)
Savings Accounts	29.36	Businesses	56.22	Quasi-liquid Retirement Accounts	82.94
Money Market Accounts	26.74	Directly Held Stocks	17.62	Tax-free Bond Mutual Funds	6.23
Checking Accounts	21.80	Stock Mutual Funds	16.02	Directly Held Bonds	4.48
Certificate of Deposits	16.09	Trusts	7.87	Other Bond Mutual Funds	3.76
Call Accounts	5.84	Annuities	2.27	Government Bond Mutual Funds	2.17
Prepaid Cards	0.17			Savings Bonds	0.41
Total wealth ($ trillions)	6.26	Total wealth ($ trillions)	38.10	Total wealth ($ trillions)	20.01

Other Liquid Assets		Illiquid Assets		Excluded	
Items	Fraction of wealth (%)	Items	Fraction of wealth (%)	Items	Fraction of wealth (%)
Cash Value of Life Insurance	42.33	Residential Property	59.12	Primary Residence	63.16
Other Mutual Funds	31.61	Non-residential Real Estate	28.13	Total Debt	30.43
Combination Mutual Funds	26.06	Other Financial Assets	6.56	Vehicles	6.41
		Other Non-Financial Assets	6.19		
Total wealth ($ trillions)	2.36	Total wealth ($ trillions)	11.54	Total wealth ($ trillions)	45.49

F Additional details on the comparison with the SCF

F.1 Classification of SCF variables

Table 12 provides the classification of the items in the SCF into six broad groups: (i) Cash, (ii) Equities, (iii) Fixed Income, (iv) Other Liquid Assets, (v) Illiquid Assets, and (vi) Excluded. We assign to (vi) those items in the SCF that we do not observe in Addepar. For each of these categories, we report the total wealth and the fraction of total wealth for each item in Table 12. We classify Quasi-liquid Retirement Accounts as Fixed Income and we further discuss this choice in Section F.3. Based on the classification adopted in the SCF, we report in Table 13 the corresponding classification adopted on the Addepar dataset.

F.2 Variable definitions

We construct two variables to sort investors in the SCF and Addepar. For Addepar, we first construct total wealth in direct equity, $A_{it}^{\text{Eq, Dir}}$, as the sum of all positions with (i)

Table 13: Classification and fraction of total wealth by broad group in Addepar
This table reports the classification of items observed in Addepar in six broad groups. For each broad group, we report the total wealth in billions of dollars. For each broad group, we further report the fraction of total wealth observed in each item. The data are from December 2018.

Cash		**Equities**		**Fixed Income**	
Items	Fraction of wealth (%)	Items	Fraction of wealth (%)	Items	Fraction of wealth (%)
Money Market Fund	60.85	US Equity	43.51	Municipal Bonds	43.39
USD	25.46	Private Equity & Venture	27.97	U.S. Government/Agency Bonds	17.09
EUR	5.56	Direct Private Companies	12.93	Corporate Bonds	15.21
Cash	3.93	Global Equity	6.51	Bond Funds	12.93
Certificate of Deposit	1.51	Developed Market Equity	3.76	Other Debt	10.31
CAD	1.48	Other Equity	3.36	ABS/MBS	0.43
CHF	0.55	Emerging Market Equity	1.75	International Government/Agency Bonds	0.36
Commercial Paper	0.41	REITs	0.22	Structured Debt	0.21
Other Currency	0.26			Other Government/Agency Bonds	0.07
Total wealth ($ billions)	49.64	Total wealth ($ billions)	275.78	Total wealth ($ billions)	97.59

Alternatives		**Other**		**Excluded**	
Items	Fraction of wealth (%)	Items	Fraction of wealth (%)	Items	Fraction of wealth (%)
Hedge Funds	47.35	Other	85.49	Liabilities	100.00
Direct Real Estate	28.64	Crypto	5.40		
Other Funds	11.08	Collectibles	4.96		
Unknown Alts	10.19	Other Non-Financial Assets	2.40		
Real Estate Funds	1.60	Derivatives	1.74		
Fund of Funds	1.14				
Total wealth ($ billions)	115.57	Total wealth ($ billions)	42.22	Total wealth ($ billions)	1.67

instrument_type = "Common Equity" or "Preferred Equity" and (ii) *sub_asset_class* = "US Equity". We construct the corresponding measure for each household in the SCF using the variable *STOCKS*, corresponding to "Directly Held Stocks" in Table 12. We also construct total wealth in equity mutual funds and ETFs, $A_{it}^{\text{Eq, Indir}}$, in Addepar as the sum of all positions with (i) *instrument_type* = "Mutual Funds" or "ETF" or "Fund of Funds" and (ii) *sub_asset_class* = "US Equity". We construct the corresponding measure for each household in the SCF using the variable *STMUTF*, corresponding to "Stock Mutual Funds" in Table 12.

F.3 Quasi-liquid retirement accounts

We show that Quasi-liquid Retirement Accounts (*retqliq*) in the SCF likely include major positions in fixed income. We first group investors in the SCF and Addepar into four groups based on their holdings of equity mutual funds and ETFs: $A_{it}^{\text{Eq, Indir}} \in$[\$0.1m, \$1m), $A_{it}^{\text{Eq, Indir}} \in$[\$1m, \$3m), $A_{it}^{\text{Eq, Indir}} \in$[\$3m, \$10m), and $A_{it}^{\text{Eq, Indir}} \geq$\$10m. For each group, we report in the second column of Table 14, the mean (median) wealth in fixed income, A_{it}^{Fi}, that we observe in the SCF when we exclude *retqliq*. We further report in the fifth column the mean (median) of A_{it}^{Fi} observed in Addepar. For each group, wealth in fixed income observed in the SCF is small, exactly equal to zero for a large number of households and, in general, significantly lower than the corresponding number in Addepar.

For each group, we then report in the third column the mean (median) of *retqliq* observed in the SCF for each group. We compare this measure with (i) the mean (median) wealth in direct fixed income, $A_{it}^{\text{Fi, Dir}}$, in Addepar, which we report in the sixth column, and (ii) the mean (median) wealth in fixed income mutual funds and ETFs, $A_{it}^{\text{Fi, Indir}}$, in Addepar, which we report in the seventh column.[30]

Columns three and seven of Table 14 reveal that, especially based on median values, *retqliq* in the SCF aligns well with $A_{it}^{\text{Fi, Indir}}$ in Addepar (except for the wealthiest investors). Notice also that, as we are not directly sorting investors based on *retqliq* or $A_{it}^{\text{Fi, Indir}}$, the alignment between these two variables is not mechanical. This analysis suggests that *retqliq* likely includes positions in fixed income mutual funds and thus it should be included in the definition of $A_{it}^{\textbf{Fi}}$ in the SCF.

30. We compute $A_{it}^{\text{Fi, Dir}}$ in Addepar as the sum of positions in all securities characterized by: (i) **instrument_type** = "Corporate Bonds" or "Municipal Bonds" or "Government Bonds"; (ii) **output_asset_class** = "Fixed Income". We compute $A_{it}^{\text{Fi, Indir}}$ in Addepar as the sum of positions in all securities characterized by: (i) **instrument_type** = "Mutual Funds" or "ETF" or "Fund of Funds"; (ii) **output_asset_class** = "Fixed Income".

Table 14: Comparison of retirement accounts in the SCF and wealth in fixed income in Addepar

This table compares several definitions of fixed income assets in SCF and Addepar. Columns two to four focus on SCF while columns five to seven focus on Addepar data. In column two, we report the mean and median wealth in fixed income observed in the SCF before adding *retqliq*. Column three provides mean and median *retqliq* observed in the SCF. Column four reports mean and median wealth in fixed income observed in the SCF after adding *retqliq*. In columns five, six, and seven, we report wealth in fixed income, direct fixed income and fixed income mutual funds and ETFs observed in Addepar respectively. Mean and median values in the SCF are population-weighted. The means are reported in Panel A and the medians in Panel B.

Panel A. Mean

	SCF			Addepar		
Group	A_{it}^{Fi} (No *retqliq*)	*retqliq*	A_{it}^{Fi}	A_{it}^{Fi}	$A_{it}^{\text{Fi, Dir}}$	$A_{it}^{\text{Fi, Indir}}$
$A_{it}^{\text{Eq, Indir}} \in [\$0.1m, \$1m)$	0.23	0.53	0.77	0.95	0.54	0.36
$A_{it}^{\text{Eq, Indir}} \in [\$1m, \$3m)$	0.73	1.37	2.10	4.09	2.62	1.18
$A_{it}^{\text{Eq, Indir}} \in [\$3m, \$10m)$	2.06	1.60	3.66	11.64	7.85	3.03
$A_{it}^{\text{Eq, Indir}} \geq \$10m$	5.56	1.68	7.24	59.78	41.27	11.47
Total	0.52	0.77	1.28	2.94	1.90	0.80

Panel B. Median

	SCF			Addepar		
Group	A_{it}^{Fi} (No *retqliq*)	*retqliq*	A_{it}^{Fi}	A_{it}^{Fi}	$A_{it}^{\text{Fi, Dir}}$	$A_{it}^{\text{Fi, Indir}}$
$A_{it}^{\text{Eq, Indir}} \in [\$0.1m, \$1m)$	0.00	0.30	0.34	0.29	0.00	0.17
$A_{it}^{\text{Eq, Indir}} \in [\$1m, \$3m)$	0.25	0.90	1.31	1.54	0.39	0.64
$A_{it}^{\text{Eq, Indir}} \in [\$3m, \$10m)$	1.00	1.25	2.77	4.99	2.25	1.31
$A_{it}^{\text{Eq, Indir}} \geq \$10m$	2.65	1.13	5.01	16.27	6.27	3.07
Total	0.00	0.42	0.56	0.41	0.00	0.21

Table 15: Comparison between the SCF and Addepar - Mean
This table reports the mean of the variables defined in Section F.2 by wealth group for the SCF (Panel A) and Addepar (Panel B). Investors are sorted based on wealth in direct equities. The mean values in the SCF are population-weighted.

Panel A. SCF

Group	Sample size	A_{it}	A_{it}^{CEFi}	A_{it}^{Cash}	A_{it}^{Eq}	A_{it}^{Fi}
$A_{it}^{\text{Eq, Dir}} \in [\$0.1m, \$1m)$	328	2.69	2.25	0.21	1.25	0.79
$A_{it}^{\text{Eq, Dir}} \in [\$1m, \$3m)$	164	8.20	7.04	0.69	4.33	2.03
$A_{it}^{\text{Eq, Dir}} \in [\$3m, \$10m)$	142	18.37	15.55	0.72	12.03	2.80
$A_{it}^{\text{Eq, Dir}} \geq \$10m$	133	71.92	63.16	3.25	54.61	5.30
Total	767	6.07	5.18	0.39	3.54	1.25

Panel B. Addepar

Group	Sample size	A_{it}	A_{it}^{CEFi}	A_{it}^{Cash}	A_{it}^{Eq}	A_{it}^{Fi}
$A_{it}^{\text{Eq, Dir}} \in [\$0.1m, \$1m)$	10,400	4.01	3.01	0.37	1.79	0.85
$A_{it}^{\text{Eq, Dir}} \in [\$1m, \$3m)$	3,938	11.68	9.23	1.08	5.52	2.63
$A_{it}^{\text{Eq, Dir}} \in [\$3m, \$10m)$	2,011	38.12	27.33	4.17	16.28	6.88
$A_{it}^{\text{Eq, Dir}} \geq \$10m$	1,154	210.87	169.96	17.27	121.42	31.27
Total	17,503	23.29	18.21	2.08	12.18	3.95

To provide further support for this measurement assumption, we report the mean and median of $A_{it}^{\mathbf{Fi}}$ in column four of Table 14for each wealth bracket in the SCF after we include *retqliq*. Based on columns four and five, we find that the wealth in fixed income of households in the SCF now aligns well with the corresponding measure computed for Addepar households, especially when median values are considered.

F.4 Comparison

We now compare the measures defined in Section F.2 in the SCF (in Panel A) and in Addepar (in Panel B). We consider two variants. First, we sort investors based on wealth in direct equity, $A_{it}^{\text{Eq, Dir}}$, or, alternatively, we sort investors based on wealth in equity mutual funds and ETFs, $A_{it}^{\text{Eq, Indir}}$. We select these sorting variables as they are likely measured consistently in both datasets. This choice avoids that we introduce error when grouping investors. For each group of investors, we compute the mean and median of each measure defined in Section F.2.

Table 16: Comparison between the SCF and Addepar - Median
This table reports the median of the variables defined in Section F.2 by wealth group for the SCF (Panel A) and Addepar (Panel B). Investors are sorted based on wealth in direct equities. The median values in the SCF are population-weighted.

Panel A. SCF

Group	Sample size	A_{it}	A_{it}^{CEFi}	A_{it}^{Cash}	A_{it}^{Eq}	A_{it}^{Fi}
$A_{it}^{\text{Eq, Dir}} \in [\$0.1m, \$1m)$	328	1.36	1.15	0.07	0.42	0.40
$A_{it}^{\text{Eq, Dir}} \in [\$1m, \$3m)$	164	5.88	5.16	0.29	2.50	1.06
$A_{it}^{\text{Eq, Dir}} \in [\$3m, \$10m)$	142	9.06	7.94	0.31	6.00	1.06
$A_{it}^{\text{Eq, Dir}} \geq \$10m$	133	34.81	29.66	1.67	23.30	3.00
Total	767	2.27	1.91	0.11	0.70	0.55

Panel B. Addepar

Group	Sample size	A_{it}	A_{it}^{CEFi}	A_{it}^{Cash}	A_{it}^{Eq}	A_{it}^{Fi}
$A_{it}^{\text{Eq, Dir}} \in [\$0.1m, \$1m)$	10,400	1.36	1.23	0.08	0.76	0.24
$A_{it}^{\text{Eq, Dir}} \in [\$1m, \$3m)$	3,938	4.53	4.20	0.25	2.76	0.84
$A_{it}^{\text{Eq, Dir}} \in [\$3m, \$10m)$	2,011	15.04	13.03	0.69	8.86	2.15
$A_{it}^{\text{Eq, Dir}} \geq \$10m$	1,154	66.72	56.35	2.81	38.59	5.35
Total	17,503	2.79	2.49	0.15	1.54	0.42

Table 17: Comparison between the SCF and Addepar - Mean
This table reports the mean of the variables defined in Section F.2 by wealth group for the SCF (Panel A) and Addepar (Panel B). Investors are sorted based on wealth in equity mutual funds and ETFs. The mean values in the SCF are population-weighted.

Panel A. SCF

Group	Sample size	A_{it}	A_{it}^{CEFi}	A_{it}^{Cash}	A_{it}^{Eq}	A_{it}^{Fi}
$A_{it}^{\text{Eq, Indir}} \in [\$0.1m, \$1m)$	325	3.10	2.50	0.25	1.48	0.77
$A_{it}^{\text{Eq, Indir}} \in [\$1m, \$3m)$	184	8.29	7.09	0.58	4.41	2.10
$A_{it}^{\text{Eq, Indir}} \in [\$3m, \$10m)$	136	18.69	15.18	0.76	10.77	3.66
$A_{it}^{\text{Eq, Indir}} \geq \$10m$	110	52.38	46.19	1.70	37.24	7.24
Total	755	5.75	4.77	0.37	3.12	1.28

Panel B. Addepar

Group	Sample size	A_{it}	A_{it}^{CEFi}	A_{it}^{Cash}	A_{it}^{Eq}	A_{it}^{Fi}
$A_{it}^{\text{Eq, Indir}} \in [\$0.1m, \$1m)$	15,251	5.20	4.11	0.45	2.71	0.95
$A_{it}^{\text{Eq, Indir}} \in [\$1m, \$3m)$	2,720	20.98	16.11	2.62	9.40	4.09
$A_{it}^{\text{Eq, Indir}} \in [\$3m, \$10m)$	1,052	79.49	58.48	4.86	41.98	11.64
$A_{it}^{\text{Eq, Indir}} \geq \$10m$	318	312.47	232.66	16.02	156.86	59.78
Total	19,341	16.51	12.51	1.25	8.32	2.94

Table 18: Comparison between the SCF and Addepar - Median

This table reports the median of the variables defined in Section F.2 by wealth group for the SCF (Panel A) and Addepar (Panel B). Investors are sorted based on wealth in equity mutual funds and ETFs. The median values in the SCF are population-weighted.

Panel A. SCF

Group	Sample size	A_{it}	A_{it}^{CEFi}	A_{it}^{Cash}	A_{it}^{Eq}	A_{it}^{Fi}
$A_{it}^{\text{Eq, Indir}} \in [\$0.1m, \$1m)$	325	1.36	1.12	0.09	0.51	0.34
$A_{it}^{\text{Eq, Indir}} \in [\$1m, \$3m)$	184	5.50	4.68	0.19	2.21	1.31
$A_{it}^{\text{Eq, Indir}} \in [\$3m, \$10m)$	136	12.24	11.17	0.43	6.50	2.77
$A_{it}^{\text{Eq, Indir}} \geq \$10m$	110	34.34	29.66	0.89	23.30	5.01
Total	755	2.24	1.84	0.10	0.80	0.56

Panel B. Addepar

Group	Sample size	A_{it}	A_{it}^{CEFi}	A_{it}^{Cash}	A_{it}^{Eq}	A_{it}^{Fi}
$A_{it}^{\text{Eq, Indir}} \in [\$0.1m, \$1m)$	15,251	1.43	1.23	0.07	0.72	0.29
$A_{it}^{\text{Eq, Indir}} \in [\$1m, \$3m)$	2,720	8.10	6.80	0.39	3.97	1.54
$A_{it}^{\text{Eq, Indir}} \in [\$3m, \$10m)$	1,052	29.17	23.33	1.28	14.10	4.99
$A_{it}^{\text{Eq, Indir}} \geq \$10m$	318	111.73	91.40	5.16	56.92	16.27
Total	19,341	2.08	1.80	0.10	1.05	0.41

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