Do Households Matter for Asset Prices?

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Abstract

Contrary to the common assertion that households have little impact on stock prices, we find their relevance is of first order. We quantify their impact using an asset-demand system applied to the complete ownership data for all Norwegian stocks from 2007 to 2020. Households contribute the most to stock market volatility relative to their market share. Even in absolute terms, they come second, surpassed only by institutional investors. Our granular data on households reveal a strong factor structure in household demand: The demand of the rich is distinct from less affluent investors, accounts for the bulk of volatility attributable to households, tilts away from ESG, and is informative about future firm fundamentals. We conclude by using the demand system to measure the profits one can make from trading on household demand shocks.

1 Introduction

The field of household finance has made significant advances over the past few decades in our understanding of household portfolios and behavior. There is substantial evidence that many households deviate from standard textbook models, hold undiversified portfolios, and trade based on signals that are difficult to reconcile with fundamental news.[1] Despite the progress, we still know relatively little about the extent to which households influence asset prices. Perhaps due in part to this lack of evidence, many economists feel confident in neglecting households in discussions of asset price formation. The standard argument against their importance is that their portfolios are small, and any impact they might have on asset prices is likely offset by arbitrage forces.

In this paper, we provide the first systematic assessment of the importance of households for asset prices. Are households, in the aggregate, more or less important than institutions in explaining the cross-section of stock returns? To the extent that households matter for asset prices, which types of households are most important? Are households best characterized as noise traders, or do their portfolios exhibit systematic factors that drive variation in returns? What prevents sophisticated arbitrageurs from eliminating the price impact of households?

These questions are of key importance to household finance and asset pricing literature, but reliable answers have proven difficult to obtain. Two key challenges have hindered earlier progress: data and methods. Most commonly used datasets on portfolio holdings typically exclude households. For instance, researchers utilizing 13F data on institutional portfolios often define households as a residual sector.[2] This measurement of households is problematic, as it bundles households together with fundamentally different investors, such as hedge funds and small institutions. Alternative approaches that employ data from retail brokers or infer retail order flow from trade characteristics can suffer from selection biases, exclude high net-worth investors, and therefore do not accurately represent the aggregate household sector either.[3]

In terms of methodology, most existing empirical work examining household impact on

[1]See Gomes, Haliassos, and Ramadorai (2021) for a review.
[2]See, e.g., Koijen and Yogo (2019).
[3]See, e.g., Barber, Odean, and Zhu (2008).

asset prices relies on reduced-form approaches that exploit plausibly exogenous shocks—such as policy changes or technological disruptions—to household demand.[4] While these studies provide compelling evidence that households influence asset prices, the treatment effects they identify are informative only about the households directly affected. Consequently, they offer limited insight into the collective role of households. Moreover, reduced-form methods often lack sufficient statistical power to address important counterfactual questions, such as whether household demand contributes to asset pricing anomalies.

We overcome these challenges by combining comprehensive Norwegian administrative data with the demand system approach to asset pricing. Our data originate from Euronext VPS, the central securities depository, and include complete ownership records for all Norwegian stocks listed on the Oslo Stock Exchange. For each stockholder, we observe a unique identifier, end of month portfolio holdings, and categorization by investor type: individual, institutional investor (e.g. mutual fund), bank, government, foreign investors, and listed and non-listed firms. For individual investors we also observe age and gender. Our data span almost 1.5 decade, from 2007 to 2020.

Households can hold stocks both directly or via privately held companies. Using private companies is beneficial for tax reasons and is particularly common among more wealthy investors who often use family offices or personal businesses to register stock holdings. We use the Norwegian Shareholder Register to assign stock ownership by privately held companies to their beneficial household owners. The aggregate household sector has a meaningful ownership share: 18% of the Oslo Stock Exchange market capitalization on average over our sample period. It also displays a distinct investment style compared to institutional investors. For example, compared to institutions, households have about twice lower inertia, measured as fraction of stocks not traded between two months. Household portfolios have also about 50% higher turnover, measured as the fraction of inflows and outflows within the portfolio. These differences are less dramatic for the most wealthy households, whose inertia and turnover is more similar to institutions.

We use the data to estimate the demand system of Koijen and Yogo (2019). The key

[4] Foucault, Sraer, and Thesmar (2011) use a policy reform in France that increased the cost of speculative retail trading. Barber, Huang, Odean, and Schwarz (2022a) exploit Robinhood outages to identify attention-induced trading by retail investors.

advantage of this methodological approach is that it allows us to quantify how much cross-sectional variation in stock returns can be attributed to different investor types and different drivers of their demand. We identify the system following established approaches that exploit mutual fund mandates. With the estimated system in hand, we can perform counterfactual exercises. For example, we can *"freeze"* the demand of an investor—e.g., the household sector—and quantify the impact on stock returns from eliminating demand of that investor.

We document five main results. First, we quantify the relative importance of different investor types for the cross-sectional variance of stock returns. Understanding which investors are most important is informative about the drivers of cross-sectional volatility and helps to inform the discussion of which approaches to asset pricing—such as classic, intermediary, or behavioral—are likely to be most successful. We find considerable heterogeneity in the importance for stock returns across investor types. At one extreme, households account for a disproportionate fraction of cross-sectional variance relative to their market share. Despite owning 18% of the stock market, they explain about 26% (value-weighted) or 49% (equally weighted) of the cross-sectional variance of stock returns. Conversely, the public sector—with a higher ownership share than households—accounts only for 5% (value-weighted) or less than 2% (equally weighted) of the cross-sectional variance of stock returns. Institutions own about 38%, and their contribution to volatility corresponds to their ownership share (value-weighted) or about 3/4 of their ownership share (equal-weighted).

Within the household sector, the contribution to stock market volatility is, as expected, dependent on wealth. Households in the top 1% of the wealth distribution own about 80% of the stock wealth of the household sector, and contribute about 70% of the volatility attributable to households. The highest relative contribution to volatility, thus, comes from households below the top 1% and equals 1.5 of their ownership share.

In our second set of results, we examine variation in demand elasticity across investor types. Gabaix and Koijen (2021) study the surprisingly (from the perspective of classic models) low elasticity of stock prices and argue that institutional constraints, such as investment mandates, limit elasticity. Household investors are not subject to the same constraints and their elasticity has not been extensively studied.[5] We find the household sector as a whole

[5] Guiso, Fagereng, and Ring (2023) examine variation in household elasticity by exploiting tax changes.

is significantly more elastic than institutions. Within households, elasticity declines with wealth, with the most wealthy households being as inelastic as institutions. These patterns suggest that frictions other than mandates are important contributors to inelastic demand.

Third, we explore variation in investor preferences. Our demand system models preferences for size, CAPM beta, profitability, and ESG. We find relative to institutions, households prefer larger, higher beta, higher ESG and lower profitability stocks. Within the household sector, we find some evidence of more affluent investors displaying preferences that have been previously associated with better performance. For example, preference for beta and size declines with wealth, whereas preference for profitability increases with wealth. We also find decreasing preference for ESG with wealth.

In our four set of results, we analyze the latent demand of investors. Latent demand is the component of demand unexplained by preferences, and captures the role of subjective beliefs, sentiment, behavioral biases, investment constraints, and other preferences. Consistent with earlier results in Koijen and Yogo (2019), we find latent demand is by far the most important contributor to return volatility. We perform two analyses of latent demand. In the first exercise, we aim to understand whether household latent demand exhibits systematic components. The asset pricing implications of latent demand depend in part on whether investors' latent demand cancels out in the aggregate. For example, sentiment-based models as in Barberis, Shleifer, and Wurgler (2005) predict that stock returns are in part driven by systematic investor sentiment unrelated to fundamentals. We observe strong systematic components in latent demand of households below the top wealth decile. Latent demand is strongly correlated among investor groups of similar wealth, age, and gender. This indicates that households have similar demand shocks and, as a result, can impact stock market volatility despite the market value of their individual portfolios being small.

In the second analysis of latent demand, we test whether latent demand of households appears to be informed about future fundamentals. We uncover a monotonic relationship between the predictive value of latent demand on future firm fundamentals and wealth: The latent demand of wealthy households is positively associated with future firm fundamentals, while the opposite is true for households on the other side of the wealth distribution.

In our fifth set of results, we quantify the profits one can make from trading with or against the latent demand of households. These analyses speak to the various sources of limits to arbitrage—fundamental risk, noise trader risk, and implementation risk. Our empirical approach is to introduce a hypothetical "hedge fund" into the demand system that tilts their portfolios according to the latent demand of different households. This counterfactual exercise improves on the paper trading simulations common in asset pricing literature, as it accounts for any potential price impact of the hedge fund as well as demand response of other investors. Our results highlight two key frictions preventing sophisticated arbitrageurs from trading against households. First, the strategy is profitable only when arbitrageurs can separate less affluent and less sophisticated households from the rich, otherwise the strategy is exposed to a large fundamental risk. Second, the strategy is not well scaleable due to significant price impact and is profitable only on a small scale. These results help explain why professional investors generally do not trade systematically on shifts in the stock demand of households.

Taken together, our key takeaway is that households matter for stock prices, and matter by a factor of 1.5 more than what is their ownership share. Our results also reveal stark heterogeneity within households in how they trade, construct their portfolios, and how much they affect asset prices.

Our paper relates to several streams of the literature. Some of our results are consistent with earlier studies of household portfolios. For example, Kumar and Lee (2006) and Barber, Odean, and Zhu (2009) study the impact of retail trades on stock returns. Betermier, Calvet, Knüpfer, and Kvaerner (2024) and Balasubramaniam, Campbell, Ramadorai, and Ranish (2023) study systematic factors in households portfolios. Vissing-Jorgensen (2003), Calvet, Campbell, and Sodini (2007), and Grinblatt, Keloharju, and Linnainmaa (2012) study role of wealth and other household characteristics in trading behavior. Barber, Huang, Odean, and Schwarz (2022b) and Welch (2022) focus on the recent rise of Robinhood traders.

Our central contribution is to systematically quantify the extent to which different types of households and various sources of household demand influence asset prices. Contrary to the common perception that equates households with small retail investors, we find that high-net-worth (HNW) households account for the majority of the return variation attributable to households. While these households have been less extensively studied, possibly due to data limitations, our findings suggest that further research on HNW investors may yield important insights.

Our results are also relevant to the discussion on different approaches to asset pricing. The three dominant approaches to asset pricing—classic, intermediary, and behavioral—differ primarily in their focus on various investor types (households vs. intermediaries) and the frictions they emphasize (psychological biases vs. intermediary constraints). We document new stylized facts that are relevant to behavioral asset pricing models, which often make predictions about individual investor portfolio choices and seek to explain the excess volatility puzzle or anomaly returns. We focus on the effect of household demand on asset prices through their direct holdings, rather than the the indirect effect of household flows in and out of mutual funds and hedge funds which is the focus of other papers (e.g. Ben-David, Li, Rossi, and Song, 2022; Azarmsa and Davis, 2024).

A growing body of literature seeks to explain variations in stock returns using demand-based asset pricing (Koijen and Yogo, 2019; Koijen, Richmond, and Yogo, 2022; Haddad, Huebner, and Loualiche, 2021; Van der Beck and Jaunin, 2021; Chaudhry, 2023; Van der Beck, 2021). Existing research has primarily focused on the role of institutions. In contrast, our focus is on households. However, instead of ignoring the role of institutions, our paper shows that these institutional investors are insufficiently elastic to absorb the flows of households, meaning that household demand matters. This builds on the literature showing that arbitrageurs have a limited ability to absorb the flows of other investors (Davis, 2024; Davis, Kargar, and Li, 2025). Our paper departs from earlier work in three main ways. First, we are the first to apply the system in a country with complete holdings data on all participants, allowing us to characterize household demand and their impact on asset prices, taking into account how institutions react to this demand. Second, we use granular and comprehensive data on various types of households, spanning both small retail investors and high-net-worth households. Third, our findings reveal important heterogeneity across different household types, reflected in their preferences, latent demand, role in the cross-section of stock returns, and the profitability of arbitrage strategies that trade on household demand shocks.

The rest of the paper unfolds as follows. Section 2 describes our data. Section 3 presents the empirical model for asset demand and describes our estimation procedure. Section 4 presents the results and we conclude in Section 5.

2 Data

Our analysis is a result of merging several administrative datasets that allow us to construct complete ownership records of Norwegian publicly listed stocks. We now describe how we combine the datasets, classify investors and assets, and present descriptive statistics.

2.1 Holdings Data

Norwegian Central Securities Depository. Our primary data source is the Norwegian Central Securities Depository (VPS), which provides ownership data of all listed equity at the Oslo Stock Exchange (OSE) from 2007 to 2020. VPS is the only central securities depository in Norway. It provides services for the settlement of transactions in securities and the registration of ownership rights over securities. It delivers its services to investors and issuers through a network of investment banks, brokers, banks, and fund management companies. These entities, acting as account operators, are responsible for all customer relationships with investors and issuers and manage day-to-day access to VPS services.

OSE is a stock exchange within the Nordic countries and represents Norway's only regulated market for securities trading. By European standards, the OSE is a medium-sized stock exchange (Doeskeland and Hvide, 2011). We observe all trading accounts for each security that together add up to 100% ownership. Each trading account comes with an anonymized identification number and the number of shares of the account holder.

2.2 Financial Assets

We collect stock and fund prices as well as most stock characteristics from Titlon. It is a financial database accessible to higher-education institutions in Norway. For each stock, we observe the price, dividends, corporate events, shares outstanding, book value of equity, net income, and the sector code of the stock. We collect stock and industry-level ESG scores from MSCI. We use stock prices and the total number of shares held to compute portfolio value for each trading account.

We construct four stock characteristics that we use to explain variation in investor portfolios in the demand system: CAPM beta (Beta), book equity value (Equity), ESG score (ESG), and return on equity (ROE). We estimate market betas from one-year daily regressions at the stock level. We require at least 180 days of non-missing data to estimate the beta. We use an equally weighted average of the stocks as the proxy for the market portfolio and adjust for asynchronous trading by including one lag return and one forward market return following Dimson (1979). We then assign the estimated beta to the stock in the following month. In very few cases, the reported Equity value is negative. We set negative equity values to missing values and filled out all missing values with the most recent historical data. We define return on equity (ROE) as earnings net income divided by the last period's book equity. We lag ROE 12 months to ensure they are available to investors when they build their portfolios. To mitigate estimation errors, we winsorize Beta and ROE at the 5 and 95 percent level. We construct ESG scores following Pastor, Stambaugh, and Taylor (2022). Their measure of greenness includes two firm-specific variables, $Escore$, which measures how far the company is from a perfect environment score of 10, and $Eweight$, which measures how brown the firm is. Combining these measures gives the greenness of firm n at time t

$$G_{n,t} = -(10 - Escore_{n,t}) \times \frac{Eweight_{n,t}}{100} \tag{1}$$

As Pastor et al. (2022) explain, the minus sign in front of the equation makes the grenness of the company an increasing function of $G_{n,t}$. We use $Escore_{n,t}$ and $Eweight_{n,t}$ if we observe them and otherwise rely on the IVA Industry median, which we calculate across all firms (including also firms not listed at OSE). We map these sector codes to the sector definitions in Titlon. Finally, we cross-sectionally standardize the $G_{n,t}$ to have a mean of zero and a standard deviation of one in each month.

We assign securities into "inside" and "outside" assets following IO norms. Inside assets include the sample of stocks used by Betermier et al. (2024) plus new listings after their sample period (2018 and onward). These are stocks that satisfy a set of minimum criteria commonly used in empirical asset pricing. In a few cases, we observe a big difference between the total shares outstanding reported in Titlon and the sum of shares across all investors in our data. In these cases, we remove the stocks from the sample of inside assets. Outside assets consist of listed equities, not part of the inside assets. In addition, we include the holdings of bond mutual funds and money market funds as part of outside assets. We use prices obtained from Titlon to compute portfolio weights (see Appendix A.1 for details).

2.3 The Owners of the Equity Market

VPS classifies trading accounts into broad investor-type categories. We use the VPS classification to define seven broad investor types: Households, Institutions, Governments, Banks, Foreign investors, Listed firms, and Non-listed firms. The VPS classification identifies all households that hold Norwegian stocks directly, but individuals can also hold stocks through private firms. Stock holdings via private firms are widespread for wealthy households who frequently hold stocks via family offices or private family businesses. Since our goal is to provide a comprehensive account of the role of households, we complement the VPS categorization to identify household stockholdings via private firms as now describe.

Norwegian Tax Administration's Shareholder Register. We obtain data on the ownership structure of companies from the Norwegian Tax Administration's Shareholder Register. This is a comprehensive register of complete ownership records for all privately-held companies in Norway. For each firm, we observe a complete breakdown of its owners: personal characteristics (such as name and age) for individual owners and unique organization identifiers for companies. We use the information on owners to identify which companies are owned by households using the following procedure. For each company, we calculate the ownership share of each household owner. For instance, suppose 50% of company A is held by an individual and the remaining 50% is held by company B, which is equally owned by two individuals. In this case, we assign ownership of company A to three households with ownership shares of 50%, 25%, and 25%. We calculate such household ownership shares in up to five layers of ownership. We then classify trading accounts of privately-held companies as households if the ten largest household owners hold more than 50% of the company shares in any of our sample years. VPS merged this ownership information with their data using the organization number and year.

Our classification of households is conservative as some wealthy Norwegian individuals change their tax domicile to a foreign country or hold stocks via family offices incorporated abroad. These households are mostly classified as the foreign sector.

Household categories. We use the demographic variables observed in VPS for households who hold stocks directly to split the household sector into granular household categories. We split the sector by gender and ten groups sorted by age. The first age group includes investors less than 30 years old; the next nine groups are in five-year increments, and the tenth age group consists of all investors above 70 years old. Finally, we form 12 groups of investors sorted by stock market wealth in the previous month. The wealth groups consist of the first nine deciles of the net worth distribution (groups 1-9), the 90^{th}-99^{th} percentiles (group 10), the 99^{th}-99.9^{th} percentiles (group 11), and the top 0.1% (group 12). With this classification, we obtain 216 household portfolios (see Appendix A.2 for details). All households belong only to one group.

Aggregastion. We face a tradeoff between investor heterogeneity and portfolios that are large enough to estimate investor preferences relatively precisely. For that reason, we aggregate individual trading accounts into portfolios. Starting with households, we aggregate trading accounts to the 216 household categories described above. For institutional investors, we keep all individual trading accounts with at least 15 stocks, of which at least two are in the outside asset. These trading accounts together account for the majority of the institutional sector. We aggregate the remaining institutional trading accounts into three groups based on AUM. For the foreign sector, which combines both foreign institutions and households, we keep trading accounts with at least 30 inside assets and five outside assets. We aggregate the remaining accounts into six portfolios based on AUM. We aggregate the trading accounts for the remaining four investor types (listed firms, non-listed firms, banks, and governments) into one portfolio per sector.

2.4 Descriptive Statistics

Figure 1 presents the evolution of ownership shares of the Oslo Stock Exchange by broad investor types. Panel A is based on the complete ownership data, while Panel B decomposes the household sector into categories sorted by wealth.

[Insert Figure 1 here]

The institutions own about 38% of the market and the household sector 18%. The ownership share of the foreign investor group was 13% at the beginning of the period and around 19% towards the end. Governments (State and local governments) own around 20%. The State is the largest governmental owner, and its largest investment is Equinor. Banks, private non-financial firms, and listed firms hold together the rest of the market, which sums to about 5%. Panel B shows that ownership is highly right-skewed within the household sector. The bottom 90% (W10 and below) hold slightly less than 20% of the household sector's ownership of OSE. The top 1% (W11) without the top 0.1% (W12) own alone 15%, and the top 0.1% own almost 2/3 of all household wealth invested in listed stocks.

Table 1 presents complementary descriptive statistics for the same investor types. The last four columns of the table display summary statistics on the portfolio level. The mean portfolio AUM is higher than the median portfolio AUM for institutions, households, and the foreign sector, reflecting that AUM is right skewed within the sectors. The mean and median number of stocks per portfolio is similar for all investor types. A typical institutional account holds 50-60 stocks out of the about 120 stocks that make up the inside assets. The household portfolios hold, on average, about 100 stocks.

[Insert Table 1 here]

2.5 Investor Portfolios

We provide descriptive statistics on investor portfolios. Our measure of similarity is the cosine similarity.[6] We compare portfolios between the broad investor types and within sectors. The portfolios reflect holdings as of January 2010, June 2015, and March 2020. January 2010 represents regular market conditions, and March 2020, the onset of COVID-19, represents a period of uncertainty. June 2015 is somewhere in the middle.[7] This allows us to study both the cross-sectional and time-series variation in portfolios.

[6] We define cosine similarity in Appendix A.3.

[7] See, e.g., https://fred.stlouisfed.org/series/WUINOR.

The heatmap depicted in Figure 2 shows the cosine similarity of portfolio weights among broad investor types as of March 2020, June 2015, and January 2010. We split the household sector into less wealthy households (HH, defined as those in the bottom 99th percentile of the wealth distribution) and wealthy households (HW, defined as the top 1% wealthiest households). We observe both similarities and stark differences in portfolios. Foreign investors (F), governments (G), less wealthy households (HH), and institutions (I) hold similar portfolios. Wealthy households (HW), banks (B), non-listed firms (NF), and listed firms (LF) hold distinct portfolios.

[Insert Figure 2 here]

Comparing the similarity in portfolios over time suggests a collective shift in investment strategies towards more heterogeneity. For example, wealthy households (HW) have developed more distinctive investment strategies. In 2010, their portfolios were more similar to institutions (I), banks (B), and also somewhat similar to less wealthy households (HH). We observe similar patterns for banks (B), institutions (I), and foreign investors (F). Non-listed firms (NF) and listed firms (LF) have maintained distinct portfolios throughout the periods.

Figure 3 displays the cosine similarity for the 216 household portfolios.

[Insert Figure 3 here]

Several observations merit attention. First, the middle wealth groups (W4 to W10) exhibit the highest degree of similarity among themselves, indicated by the dense red clusters in the middle of the heatmap. This suggests that these groups have very similar portfolios. Second, the least wealthy groups (W1 to W3) and the wealthiest groups (W11 and W12) invest differently than the middle-wealth groups. Third, the lack of red coloring among the wealthiest (particularly in most recent periods) suggests considerable heterogeneity in portfolios within the high-wealth group. This is in contrast to the least wealthy, which hold similar portfolios as indicated by the reddish square in the top left of the graphs. Fourth, comparing household portfolios across periods suggests that wealth is a reliable predictor of differences in stock portfolios—as the cosine similarity plots are quite stable over time.

2.6 Investment Styles

We now calculate the corresponding "flow statistics" for the broad investor groups and 12 household categories based on wealth.[8] The purpose with these statistics is to shed light on differences in investment behavior. We first define the variables of interest, explain how we calculate these variables in the data, and then present the results. As standard in the literature (see, e.g., Gabaix, Koijen, Mainardi, Oh, and Yogo, 2022), we aggregate the monthly numbers to quarterly means.

Starting with inertia, we first define the following indicator variable

$$I_{i,n,t} = \begin{cases} 1, & \text{if } S_{i,n,t} = S_{i,n,t-1} \\ 0, & \text{if } S_{i,n,t} \neq S_{i,n,t-1}, \end{cases} \tag{2}$$

where $S_{i,n,t}$ is the number of shares of stock n held by investor i at month t. Thus, $I_{i,n,t}$ is set to one if the number of shares held in month t by investor i equals that of month $t-1$. We then calculate $Inertia$ at the investor level as the fraction of non-traded stocks to the number of stocks in the portfolio following Gabaix et al. (2022)

$$Inertia_{i,t} = \frac{\sum_{n \in N} I_{i,n,t}}{N_{i,t}}. \tag{3}$$

The flow from investor i to stock n at time t is

$$Flow_{i,n,t} = S_{i,n,t}P_{n,t} - S_{i,n,t-1}P_{n,t-1} - S_{i,n,t-1}\Delta P_{n,t}. \tag{4}$$

We define the aggregate flow from the investor i at time t as

$$Flow_{i,t} = \sum_{n} |Flow_{i,n,t}|. \tag{5}$$

We then calculate investor i's turnover as the flow into the stock portfolio scaled by two

[8] Portfolios 215 and 216 are excluded within the wealthiest group for household sector analysis by wealth groups. Hence, the household sector includes 214 portfolios for Table 3.

times the portfolio value at the start of the month following Gabaix et al. (2022)

$$T_{i,t} = \frac{Flow_{i,t}}{2AUM_{i,t-1}}. \tag{6}$$

Finally, we include as part of the statistics the sum of the absolute value of the change in shares held by investor i between two periods calculated as

$$\Delta S_{i,t} = \sum_{n} |S_{i,n,t} - S_{i,n,t-1}| \,. \tag{7}$$

Table 2 presents inertia, turnover, flow, and changes in shares for the broad investor types.

[Insert Table 2 here]

Governments and institutions are the most inert investors. In other words, they tend to hold on to their stocks to a larger extent than other investors. For governments, this makes intuitive sense as they often hold stocks for strategic purposes, while institutions often have strict mandates that prevent them from investing in certain stocks. The other sectors have comparable numbers.

Turnover reflects the inflow and outflow of money in the portfolio of inside assets. The informativeness of turnover regarding investor preferences and investment styles depends in part on whether flows are exogenous or endogenous. If flows are endogenous, then a high turnover means that the investor responds elastically to changes in risk and expected return on inside and outside assets. We would thus expect investors with the highest turnover to be the most elastic. If flows are exogenous, more volatile flows suggest holding larger and more liquid stocks to minimize transaction costs associated with "forced" rebalancing. Across investors, it is plausible that flows are endogenous for some (e.g., households and Governments) and exogenous for others (e.g., institutional investors).

We observe the highest turnover for foreign investors, banks, and households. Governments have practically zero turnovers. The two last columns show flows in million NOK and changes in shares. As expected, the smallest flows are for the household sector, followed by institutions. The perhaps seemingly low flow of institutions is because the flow is an equally weighted average among institutional investors, which includes many small accounts. Table

3 presents the corresponding statistics for the 12 household categories based on wealth.

[Insert Table 3 here]

The pattern for turnover is striking. The first two wealth groups have turnover several orders of magnitude higher than the household norm. The turnover of the least wealthy is, for instance, twice as high as banks, which has the highest turnover among the broad investor groups. Under the assumption that flows are endogenous, the high turnover among the low-wealth groups suggests that they are more elastic than for example wealthy households. Columns three and four show statistics on flows and changes in shares. As expected, both statistics increase monotonically in wealth. Comparing these statistics with similar statistics for the main investor groups, we see that households in the top 90-99.9% of the wealth distribution are more similar to institutions than other households. The statistics of households in the top 0.1% are the most similar to the aggregate portfolio of listed firms.

3 Estimation

We now describe the empirical implementation of the asset demand system estimation, which closely following Koijen and Yogo (2019).

3.1 The Asset Demand Equation

There are $N+1$ assets, indexed by $n = 0, 1, ..., N$. Lowercase letters denote the logarithm of the corresponding uppercase variables. Bold notation denotes vectors and matrices. We denote the vector of $K + 1$ characteristics of asset n in period t as $\boldsymbol{x}_t(n)$. The first column of $\boldsymbol{x}_t(n)$ is the log market capitalization of company n at time t, and the second is a vector of ones, capturing investor-time fixed effects. The other columns are the four stock characteristics defined earlier: log book equity (BE), CAPM-Beta, ESG, and profitability (ROE). I investors, indexed by $i = 1, ..., I$, own the N assets. An investor i can refer to one trading account or a portfolio of many accounts, as described in Section 2.3.

In any period t, we include $n = \{0, 1, 2, ...N_t\}$ assets, where $n = 0$ denotes the outside asset. Each investor invests wealth $AUM_{i,t}$ in period t across the $1 + N_{i,t}$ assets in the investor's choice set. The portfolio weight of investor i at time t scaled by the investor's weight in the outside asset $w_{i,t}(0)$ is given by

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \delta_{i,t}(n) = \exp\left(\beta_{0,i,t}\ln(ME_t(n)) + \sum_{k=0}^{K}\beta_{k,i,t}x_{k,t}(n)\right)\epsilon_{i,t}(n) \tag{8}$$

where $\delta_{i,t}(0) = 1\forall i, t$. Eq 8 is the characteristics-based demand introduced by Koijen and Yogo (2019).[9] An investor's demand depends on firm characteristics and latent demand, $\epsilon_{i,t}(n)$. Latent demand represents portfolio tilts not explained by the characteristics $\boldsymbol{x}_t(n)$. $\beta_{0,i,t}$ captures the price elasticity of investors, with lower values of $\beta_{0,i,t}$ reflecting more elastic demand. We normalize the left-hand-side of Eq. 8 to one and identify the intercept $\beta_{1,i,t}$ by setting mean latent demand, $\epsilon_{i,t}(n)$, to 1. Finally, following Koijen and Yogo (2019), we impose $\beta_{0,i,t} < 1\forall i$ in the estimation to guarantee downward sloping aggregate demand for all stocks, and, as a result, unique equilibrium prices in all counterfactual scenarios.

3.2 Implementation

We now explain how we estimate the characteristics-based demand in Eq. 8. To identify the price elasticities of different investors, we use the standard price instrument based on sticky investment mandates. The instrument depends only on the AUM and the investment universes of institutional investors. For each institutional account, we calculate the ratio of stocks in the portfolio at time t that has been in the account at least once during the previous 36 months. This ratio is one in the first period the account enters the sample. Consistent with the notion that institutional accounts have sticky investment universes, the time-series average of the ratio is ca. 98%. In constructing the instrument, we restrict the sample to $j = 1, 2, ..., J$ accounts with a ratio of at least 95% in month t. The instrumented log market value of stock n at time t for investor i is then: $\widehat{me}_{i,t}(n) = \ln\left(\sum_{j\neq i} AUM_j \frac{1}{1+N_{j,t}}\right)$. The variation in the instrument comes from cross-sectional variation in the investment universe of institutional investors. Stocks that appear in many institutional portfolios have high prices relative to book values and other characteristics in the asset demand equation. The instru-

[9] We opt for the exponential demand equation to avoid excluding zero holdings due to our relatively small cross-section of stocks.

mented log market value is specific to the institutional investor as it excludes the investor's holdings. For all other investors, we include the holdings of all institutional investors.

Figure A1 presented in Appendix B.1 show the t-statistic for the instrument in the regression of log market equity onto the instrument and characteristics. The black line shows the median t statistic, and the shaded area shows the 10–90 percentile range. For the vast majority of the periods, the range is well above the critical value for rejecting the null of weak instruments at the 5 percent level (dashed line).

We estimate the asset demand equation in Eq. 8, in which the relative portfolio weights are a non-linear function of investor preferences and beliefs, as follows: Let $\boldsymbol{z}_{i,t}$ be a matrix with $N \times (K+1)$ columns. The first column of $\boldsymbol{z}_{i,t}$ is the instrumented market value of equity, $\widehat{ME}_{i,t}(n)$, the second column is a vector of ones, and the final $K-1$ columns are stock characteristics. The vector with $K+1$ moment conditions based on Eq. 8 is:

$$g_{i,t}(\boldsymbol{w}, \boldsymbol{x}, \boldsymbol{\beta}) = \boldsymbol{z_{i,t}}' \left[\left(\frac{w_{i,t}(n)}{w_{i,t}(0)} \right) \exp\left(-\boldsymbol{\beta}_i' \boldsymbol{x}_t(n) \right) \right] - 1, \tag{9}$$

where $\boldsymbol{w} := \left(\frac{w_{i,t}(n)}{w_{i,t}(0)} \right)$. The preference parameters $\boldsymbol{\beta}$ are defined by choosing a vector of preference parameters that minimize the following objective function:

$$\boldsymbol{\beta}^{\star}(\lambda, \Omega) = \arg\min_{\boldsymbol{\beta}} \left\{ g(\boldsymbol{w}, \boldsymbol{x}, \boldsymbol{\beta})' \Omega g(\boldsymbol{w}, \boldsymbol{x}, \boldsymbol{\beta}) \right\} \tag{10}$$

where Ω is a weighting matrix, which we set to $\Omega = (\boldsymbol{z}'\boldsymbol{z})^{-1}$. We solve Eq. 10 for each investor i in each month t.

We complete the model with the market clearing condition for each asset n:

$$ME_t(n) = \sum_{i=1}^{I} AUM_{i,t} w_{i,t}(n). \tag{11}$$

The market value of shares outstanding must equal the asset-weighted sum of portfolio weights across all investors. Equilibrium prices correspond to fixed points of $f(\boldsymbol{p})$ so that

$$f(\boldsymbol{p}) = \boldsymbol{p} = \ln\left(\sum_{i=1}^{I} AUM_i \boldsymbol{w}_i(\boldsymbol{p}) \right) - \boldsymbol{s}. \tag{12}$$

Market clearing thus defines an implicit function for log price, $\boldsymbol{p_t} = g(\boldsymbol{s_t}, \boldsymbol{X_t}, \boldsymbol{AUM_t}, \boldsymbol{\beta_t}, \boldsymbol{\epsilon_t})$, that ensures prices are fully determined by: shares outstanding, characteristics, the wealth distribution, the coefficients on characteristics, and latent demand. As mentioned earlier, the assumption imposed in the estimation that the price elasticity coefficient, $\beta_{i,t}$, is smaller than one for all i investors guarantees that new equilibrium prices are unique.

4 Results

This section includes the results. We start by discussing preferences, the correlation structure of latent demand, and the informativeness of latent demand regarding future firm fundamentals. Next, we use the demand system together with market clearing to understand the relative importance of each investor in causing cross-sectional variation in stock return volatility. Then, we provide evidence of a key driver of the variation in investors' relative importance for volatility. Finally, we augment the demand system with a "hedge fund" that trades on the latent demand of households and studies its cumulative return over time.

4.1 Household Preferences

Table 4 summarizes the preferences estimated with Eq. 8. Variation in preferences across investors represents the predictable part of differences in portfolios. To condense the results, we first compute the mean coefficient for all portfolios belonging to the same investor category, and then report time-series averages of these cross-sectional averages.

[Insert Table 4 here]

The first column contains the price elasticity coefficient. The household sector is the most elastic, with an estimated price elasticity of 0.34. Governments are the least elastic (mean coefficient of 0.86), and institutions are in the middle. Listed firms, banks, and foreign investors are similar to institutions, while non-listed firms are almost as inelastic as governments. These aggregate results echo the patterns documented by (Koijen and Yogo, 2019) for U.S.: institutions and passive investors (such as governments) are the least elastic.

The remaining coefficients are the estimated preference for the four characteristics included in our demand equation: the log of book value of equity (BE), systematic risk (Beta), ESG score (ESG), and return on equity (ROE). A position coefficient means a portfolio tilt toward companies that score high on that characteristic.

The household sector as a whole has preferences for large companies, high-beta and high-ESG (green) stocks, and less profitable companies. Institutions tilt towards profitable stocks. Governments have the most extreme preferences with a strong tilt towards large, low-beta, and low-profitability stocks. We acknowledge that this is unlikely a representation of governments' preferences for these characteristics. Instead, these are the characteristics of firms the governments hold mainly for either historical, strategic reasons, or both. Interestingly, all sectors other than households have negligible ESG preferences.

As our primary interest is in households, we analyze the variation in preferences for various household categories in Figure 4. This figure plots the average coefficients by household wealth, age, and gender. We first compute a time-series average for each of the 216 household portfolios and then plot the equal-weighted average for each of the 216 categories.

In Panel A Figure 4, we find that men, wealthier, and older investors are typically less elastic. The mean elasticity coefficient is 0.2 or less for the first three wealth deciles, while it typically exceeds 0.6 for households in the top 10% of the wealth distribution; wealthy households are thus about as elastic as institutional investors.

Men, young, and less-wealthy investors have a taste for smaller and less profitable companies with higher CAPM-betas. Differences in ESG preferences are less pronounced across gender and age, while we find a dramatic decline in the preferences for ESG with wealth. The wealthiest investors have a negative preference for ESG. This declining preference for green stocks with wealth is consistent with the evidence on beliefs of German investors documented by Aron-Dine, Beutel, Piazzesi, and Schneider (2023).

[Insert Figure 4 here]

4.2 Latent Demand

Investors differ in terms of styles, information, technology, beliefs, and biases. While investors' coefficients on stock characteristics capture cross-sectional differences in preferences for specific firm characteristics, all other forms of heterogeneity are swept into latent demand (see Eq. 8). The asset pricing implications of latent demand depend in part on whether investors' latent demand cancels out in the aggregate. The rationale paradigm typically assumes biases cancel, while the behavioral finance literature has the opposite view (see, e.g., Hirshleifer, 2001). Several empirical papers focusing on households indicate that individual investors' trades are correlated (see, e.g., Kaniel, Saar, and Titman, 2008). In what follows, we study the similarity of latent demand using the cosine similarity metric.

Figure 5 shows the average similarity for the broad investor types as of January 2010 and March 2020.

[Insert Figure 5 here]

There are distinct cross-sectional patterns in latent demand. Institutions (I) and foreign investors (F) have very similar latent demands, indicated by the dark red square. Institutions (I) also have somewhat similar latent demand to households, measured by the light red squares. The latent demand of wealthy households is closest to foreign investors but also somewhat similar to less wealthy households. Governments (G), banks (B), non-listed firms (NF), and listed firms (LF) have distinct latent demands. By comparing Panel A (March 2020) with Panel B (January 2010), we see that the correlation structure in latent demand is relatively stable over time.[10] This is by no means obvious, as the two periods reflect portfolios made up of different stocks and different individual accounts but of similar characteristics.

Figure 6 displays similarity in latent demand for the 216 household portfolios. To simplify the interpretation of the figure, we organize the portfolios by wealth, gender (male and female), and age (young to old) and display tick marks for the first portfolio in each of the 12 wealth groups.

[Insert Figure 6 here]

[10] The most notable difference is the decline in similarity among wealthy households (HW), less wealthy households (HH), and institutional investors (I) from 2010 to 2020.

The heatmap reveals a factor structure in household latent demand: households that are closer in wealth distribution have more similar latent demand. The least wealthy households generally have distinct latent demand from other households. The large red area in the middle of the matrix illustrates that households just above the lowest wealth groups up to the 90 percentile have similar latent demand. This indicates that this group has similar demand shocks and, as a result, can impact stock market volatility despite the market value of the individual portfolios being small. The latent demand of the wealthiest households generally differs from the rest of the household sector.

4.3 On the Price Informativness of Latent Demand

Is the latent demand of households informative about future firm profitability? A rich literature on investor behavior documents a plethora of investment mistakes by retail investors that harm their performance. If households are systematically wrong about which stocks are good investments, we may observe a negative relation between their latent demand and future profitability. Conversely, if some household groups are sophisticated or possess private information, their latent demand may positively predict fundamentals.

We use a predictive regression to empirically test whether the latent demand of some households can explain cross-sectional variation in future firm profitability. Because profitability—measured by return on equity (ROE)—changes only once a year, we keep only the December observations. The sample runs from 2007 until 2019, as our sample ends in April 2020. We run the following regressions for each of the $i = \{1, 2, \ldots, 216\}$ household portfolios

$$ROE_{t+1}(n) = \pi_i \epsilon_{i,t}(n) + \eta_{BE} \ln(BE_t(n)) + \eta_{ROE} ROE_t(n) + \lambda_t + \lambda_n + u_{n,t+1}. \tag{13}$$

The coefficient of interest is π_i, which measures whether household i's latent demand is informative about future ROE after controlling for current ROE and book value of equity (BE). The parameters λ_t and λ_n represent year and stock fixed effects, and, as a result, only time-series variation at the stock level identifies the coefficient of interest π_i. We cluster standard errors at the stock and year level. We measure the informativeness of a particular household category as the equally weighted average $\hat{\pi}_i$ coefficient across all portfolios in the same category. Figure 7 presents informativeness by wealth, age, and gender household categories (we tabulate additional results in Table A2 in Appendix C.1).

[Insert Figure 7 here]

Panel a) of Figure 7 reveals a clear pattern of informativeness with a sharp increase in wealth. Wealth groups 10 (90-99 percentile), 11 (99-99.9), and 12 (top 0.1%) all have positive averages, as opposed to the rest of the wealth distribution, which has negative means. Within the wealthiest groups, some households have statistically significant coefficients, with a coefficient estimate of about 0.05. Among the lowest wealth groups, some households have significant negative coefficients, which means they consistently overweight stocks with relatively low ROE in the future. Panel b) and c) of Figure 7 show no apparent differences in informativeness across the age distribution and gender.

4.4 Variance Decomposition of Return Volatility

We now use the demand system together with market clearing to understand the relative contributions of different investors to cross-sectional stock return volatility. We first apply the decomposition to the broad investor types. We then use the same approach to break down the household sector's contribution to stock return volatility to the contributions of 12 household types distinguished by wealth.

[Insert Table 5 here]

Table 5 presents the results for the seven broad investor types. The columns labeled WLS weigh each stock by its free-float market capitalization, whereas the columns labeled OLS weigh each stock equally. We can broadly interpret the results for WLS as a mapping of the cross-sectional variation in stock return of large stocks to their owners' wealth and investment behavior. The OLS has a similar interpretation for a broader index of small-caps. The volatility contribution can be both positive or negative depending on the investor trades in response to changes in supply and other investors' portfolio rebalancing. If supply and stock characteristics remain unchanged, then stock prices change only if investors' wealth, preferences, or latent demand changes. Ceteris paribus, larger shareholders matter the most because the quantity of shares they wish to trade is higher. For that reason, we report both the estimated volatility contribution with its standard error and the volatility contribution scaled by market share.

The contribution of the institutional sector to the cross-sectional variance of stock returns equals its market share of 39%. Its contribution to a small-cap index is 29%, reflecting that institutions mainly invest in large firms. This result echoes Koijen and Yogo (2019), who find that the institutional sector in the U.S., and, in particular, the biggest institutions, are relative to their market share responsible for a relatively smaller share of the cross-sectional variance of stock returns.

In comparison, the household sector has a market share of 18% and contributes to 26% of the cross-sectional variance of stock returns. Relative to their market share, the ratio is 1.5 (26/18), which is considerably above the ratio of 1 for institutions. For the small-caps, the household sector is responsible for about half of the cross-sectional variance. Taken together, this shows that households play an important role in causing volatility in the stock market.

The foreign sector explains 16% and 13% of the return volatility of large and small-caps, respectively. Relative to their market share, that is about 1.4 for large caps and slightly less than one for small caps. Governments—with an ownership share above 20%, have no statistically significant impact on the cross-sectional variation in returns. The contribution of the banks and non-financial firms is between 2 and 5%.

The last row shows the impact of changes in shares outstanding and stock characteristics on cross-sectional return volatility. For large caps, supply explains, on average 8% of the cross-sectional variance. However, this estimate varies considerably over time, as reflected in high standard errors. For small stocks, changes in supply do not matter much.

Next, we decompose the contribution to the volatility of the household sector to 12 household categories based on wealth. We obtain our estimates by changing all the demand characteristics of one particular household portfolio at the time. The sum of the contribution of all the households equals the contribution of the household sector. Figure 8 presents the results. Panel a) shows the results for large caps and Panel b) for small caps. The green bars represent households at the bottom of 99th of the wealth distribution; the light blue bars represent households between 99th and 99.9th wealth percentile, and the dark blue bars represent the top 0.1% percentile.

[Insert Figure 8 here]

The importance of households to stock market volatility is, as expected, dependent on wealth. Households in the top 1% of the wealth distribution own about 80% of the stock wealth of the household sector and about 70% of the volatility attributable to households comes from them. The high relative importance of this group is true regardless of whether we look at the cross-sectional variance of small or large stocks. The second observation is that households below the top 1% of the wealth distribution matter more for volatility relative to their ownership share than the wealthiest households.

To conclude, the finding that the relative contribution of institutions to stock market volatility is smaller than that of households is similar to Koijen and Yogo (2019). Our contribution explains which non-institutional sectors contribute most to stock market volatility: wealthy households. Previous literature also documents that both retail investors (Barber et al., 2009; Foucault et al., 2011) and institutions (Ben-David, Franzoni, and Moussawi, 2018; Ben-David et al., 2022) contribute to stock market volatility. In this respect, we quantify the contribution of each investor group. These moments are useful for the literature aiming to understand the sources of cross-sectional volatility in stock returns. Our results imply that wealthy investors play a vital role in stock market volatility and highlight the importance of incorporating household heterogeneity to understand asset price dynamics.

4.5 On the Relative Importance of Households

How do household contribute to return volatlity? We hypothesize that an important reason is that they matter the most for changes in aggregate latent demand. The hypothesis is motivated by the finding in KY that demand shocks unrelated to changes in observed characteristics are the most important determinants of stock returns. In Section C.2 of the Appendix, we verify that latent demand is also the most important variable in explaining stock returns in Norway.[11] We test our hypothesis by estimating the relationship between changes in latent demand at the investor level and the aggregate level.

The setup is as follows. Let j denote a particular investor (e.g., young women or a particular fund) belonging to a broad investor group i. We then transform the latent demand from the portfolio level j to the investor group level i by calculating the share-weighted sum of the latent demand for each investor group at each date for each stock, $\epsilon_{i,t}(n) = \sum_j^J (S_{j,t}(n)/\sum_j^J S_{j,t}(n))\epsilon_{i,j,t}(n)$. Subsequently, we calculate the change in latent demand for each investor i by taking first differences, $\Delta\epsilon_{i,t}(n) = \epsilon_{i,t}(n) - \epsilon_{i,t-1}(n)$. We calculate the change in aggregate latent demand for stock n at time t via summation, $\Delta\epsilon_{\text{Market},t}(n) = \sum_i \Delta\epsilon_{i,t}(n)$. With these variables at hand, we run a time-series regression of the change in latent demand of investor group i on the change in the aggregate latent demand (similar to the cross-sectional variance decomposition).

Panel a) of Figure 9 presents the R2 from this regression, and panel b) decomposes R2 into a correlation and a relative standard deviation of latent demand (i.e., the standard deviation of the change in latent demand of investor i scaled by the corresponding standard deviation of the market.).[12]

[Insert Figure 9 here]

The household sector—with an ownership share of around 18%—explains almost 40% of the cross-sectional variation in changes in aggregate latent demand. With an ownership share of 38%, institutions come second and explain roughly 25%. The remaining sectors are less important. Panel b) of Figure 9 shows that investors other than households and institutions explain little of the change in aggregate latent demand because their demand shocks are almost uncorrelated with other investors. The standard deviation of changes in households' latent demand is comparable to foreign investors, higher than that of institutions but much lower than governments, banks, and firms.

To sum up, the fact that changes in aggregate latent demand explain most of the cross-sectional variation in return volatility, together with the above finding that changes in the

[11] Latent demand explains between 52 and 80% of the return variation depending on whether we weigh stock returns by market capitalization (52%) or equally (80%).

[12] Table 6 presents the regression output.

latent demand of households explain the largest share of fluctuations in shocks to aggregate latent demand, provide evidence for why households matter for stock market volatility.

4.6 Trading on the Latent Demand of Households

We use the demand system to show that it is generally unprofitable to trade against or on household demand shocks. We first explain our approach and then present the results.

We introduce a new long-only hedge fund, labeled HF, in the demand system. Its strategy is to trade on households' latent demand. Let $h \in H$ index any combination of the 216 households that make up the household sector (e.g., h could be a subset of wealthy households). We define the vector of latent demand of household group h as $\bar{\boldsymbol{\epsilon}}_t^h$, which corresponds to the equally weighted latent demand across all household portfolios included in h. Inspired by Brandt, Santa-Clara, and Valkanov (2009), we specify the asset demand of the new hedge fund HF that we have introduced in the demand system as

$$\boldsymbol{w}_{HF,t} = \boldsymbol{w}_{m,t} + \frac{\theta}{N_t}\bar{\boldsymbol{\epsilon}}_t^h, \tag{14}$$

where $w_{m,t}$ is a vector of market weights and N_t number of stocks at time t, exogenous to trading of the HF. At each time t, we normalize the vector $\bar{\boldsymbol{\epsilon}}_t^h$ by subtracting the mean and dividing it by its standard deviation. The parameter θ controls how aggressively the HF adjusts their portfolio weights with respect to households latent demand but does not change the mean portfolio weight because $\mathrm{E}[\bar{\epsilon}_t^h] = 0$. To stay internally consistent with our demand system, we consider a sequence of one-period optimization problems and restrict weights to be non-negative using

$$\boldsymbol{w}_{HF,t} = \frac{\max(0, \boldsymbol{w}_{HF,t})}{\sum_{n=1}^{N_t} \max(0, w_{HF,t}(n))}. \tag{15}$$

The normalization ensures that the weights are non-negative and add up to one.

We separate between gross returns and net returns. The trading cost associated with buying the portfolio makes up the difference between gross and net returns. To formally define the return on the fund from t to $t+1$, let p_t be the equilibrium price before HF

invest, let p_t^+ be the new equilibrium prices after HF invested according to Eq. 14, and denote the dividend yield by v_{t+1}. Adding up gives

$$r_{HF,t+1} = \sum_{n=1}^{N_t} w_{HF,t}^+ \left\{ \left(\exp\left(p_{t+1} + v_{t+1} - p_t^+ \right) - 1 \right) - \left(\exp\left(p_t^+ - p_t \right) - 1 \right) \right\}, \tag{16}$$

where the first is the gross return of the fund and the second term is the trading cost. We fix the scaling parameter θ, by setting: $\theta = \sqrt{\pi/2}$. With this θ, the expected deviation from the benchmark is N_t^{-1}, or $\approx 1\%$ in our sample.[13]

Figure 10 shows the cumulative log return in excess of the market for four investment strategies based on Eq. 16. The market portfolio corresponds to a portfolio with $\theta = 0$.

[Insert Figure 10 here]

In panel a) of Figure 10, we study a small HF with around 50 million NOK in AUM that only sees the aggregate latent demand of the household sector.[14] The black line represents the performance of a fund that trades with households ($\theta > 0$) and the green line represents the performance a fund that trades against households ($\theta < 0$). We observe that both portfolio strategies underperform (even before transaction costs) relative to the market, with trading against households being the least profitable. Moreover, household latent demand does not cancel in the aggregate, which would have resulted in the HF holding the market portfolio. This finding echos Barber et al. (2009), who first documented that retail trading typically does not cancel out in aggregate.

In panel b) of Figure 10, we consider a HF that can separate the latent demand of different household types. We consider two strategies motivated partly by the previous results on the informativeness of households and partly by the now extensive literature that relates the portfolio choices of individual investors to their characteristics (Barber and Odean, 2001; Kumar, 2009; Betermier et al., 2024). The first strategy trades on the latent

[13] To see this, note that the absolute value of deviation from the market is: $|w_{HF,t} - w_{m,t}| = |\theta/N_t \bar{\epsilon}_t^h|$. By the law of the expected absolute value of a normal random variable, the expected deviation from the market is $\theta/N_t\sqrt{2/\pi}$. Setting $\theta = \sqrt{\pi/2}$ implies that the expected deviation from benchmark is N_t^{-1}.

[14] The size of the fund matters not only for transaction costs but also because it impacts the size of the investment and, therefore, the fund's possibility to spread its investments across stocks that are in either high or low demand by households.

demand of senior households in the top 10 percentile of the wealth distribution (3 groups). The second strategy trades on the latent demand of young men in the bottom 30 percentile of the wealth distribution (3 groups). We observe a large spread in cumulative log returns: Trading on the latent demand of senior wealth households slightly outperforms the market, while tilting the portfolio toward young men at the bottom of the wealth distribution results in a large loss relative to the market.

Panel c) of Figure 10 shows the gross and net returns on a spread portfolio that is long senior wealthy households and short young men with little wealth (the strategies presented in Panel b Figure 10). Abstracting from costs due to the short position, we see that the spread portfolio is profitable for a small-sized HF.[15]

Panel d) of Figure 10 presents the equivalent spread to that depicted in Panel c) but for a larger HF with an AUM of roughly 500 million NOK. Increasing the size of the fund has two effects. The first effect is it forces the fund to take more concentrated positions as it can no longer fully exploit positive or negative latent demand shocks. Regarding positive latent demand shocks, a larger fund is more likely to obtain large ownership shares in small firms. Regarding negative latent demand (recall we have normalized latent demand), because the fund is long-only, it can only set the weights to zero, which has little impact on fund performance if the company has a small weight in the market portfolio. The second effect is it increases transaction costs as a fraction of the portfolio value because the fund has to trade larger quantities. We see that in the specific case of the strategy we consider in Panel c), the first effect is positive. At the same time, the difference between gross and net return is now wider due to the transaction costs that are non-linear in the traded quantity of shares.

Based on the above results, we conjecture that few hedge funds would, if they could, trade on demand shocks of households. We come to our conclusion for the following three reasons. First, it is unclear whether to trade (unconditionally) with or against the household sector. Probably, the decision to tilt towards or away from the demand shocks of households changes in an unpredictable way over time. Second, a profitable strategy seems to require close to perfect knowledge about the characteristics of the households who trade, which funds do not

[15] Because the weights in both the long and short portfolios add up to one, trading the spread portfolio in practice would come with additional fees due to security lending, which we do not consider.

possess. Third, households are active investors in small-cap stocks, which are expensive to trade, which limits the scope of scaling up the fund.

5 Conclusion

Investor demand for stocks plays a key role in leading theories of risk and return in the stock market (Campbell, 2018; Merton, 1973). Preferences, beliefs, and constraints determine investors' portfolio choices (Koijen and Yogo, 2019; Giglio, Maggiori, Stroebel, and Utkus, 2021). By combining complete ownership records of all Norwegian stocks from 2007 to 2020 with the demand system of Koijen and Yogo (2019), we shed new light on how the portfolio choices of all investors affect the cross-sectional variance of stock returns. Our results reveal stark heterogeneity within non-institutional sectors, particularly among households, in how they trade, construct portfolios, and how much they affect asset prices.

We provide several new facts about the investment behavior of households and the implications of their investment styles for volatility in the stock market. First, we find considerable heterogeneity in households' investment styles and stock portfolios. For example, less wealthy households—who can essentially trade any quantity without having a price impact—have portfolio turnover many orders of magnitude higher than the household norm. In contrast, the portfolio turnover of wealthy households is somewhere between the aggregate portfolio of firms and institutional investors. Second, the richest households are comparable elastic to institutions, overweight profitable stocks with low betas and negative ESG Scores, whereas the least wealthy households are much more elastic and have opposite preferences for firm characteristics. Third, we find a strong factor structure in household demand. Here again, we see a strong wealth gradient; households below the 90 percentile of the wealth distribution have similar latent demand, while the wealthiest households have distinct latent demand. Fourth, we uncover a monotonic relationship between the predictive value of latent demand on future firm fundamentals and wealth: The latent demand of wealthy households is positively associated with future firm fundamentals, while the opposite is true for households on the other side of wealth distribution.

Households play a first-order role in the cross-sectional variance of returns. In our sample period, they own 18% of the market but contribute to 26% of cross-sectional variance. Hence, the ratio of households' contribution to volatility relative to their ownership share is 1.5. The corresponding ratio for institutions is 1. By running time-series regressions of the change in the latent demand of investors on the change in the aggregate latent demand, we show that households explain the largest share of fluctuations in shocks to aggregate latent demand.

The observation that professional investors tend not to trade against demand shocks from retail investors and the theoretical literature on asset prices and noise traders motivate our last application: To study the financial gains from trading on household demand shocks. We do so by introducing a "hypothetical" hedge fund that trades on households' latent demand into the demand system. Three findings lead us to conclude that it is generally unprofitable to trade on household demand shocks. First, whether one should trade with or against the household sector changes over time. Second, a profitable strategy seems to require close to perfect knowledge about the characteristics of the households who trade, which funds do not possess. Third, households are active investors in small-cap stocks, which are expensive to trade, which limits the scope of scaling up the fund.

References

Aron-Dine, Shifrah, Johannes Beutel, Monika Piazzesi, and Martin Schneider, 2023, Household climate finance: Theory and survey data on safe and risky green assets, Technical report, Working Paper.

Azarmsa, Ehsan, and Carter Davis, 2024, Is asset demand elasticity set at the household or intermediary level?, *Available at SSRN* .

Balasubramaniam, Vimal, John Y Campbell, Tarun Ramadorai, and Benjamin Ranish, 2023, Who owns what? a factor model for direct stockholding, *The Journal of Finance* 78, 1545–1591.

Barber, Brad M, Xing Huang, Terrance Odean, and Christopher Schwarz, 2022a, Attention-induced trading and returns: Evidence from robinhood users, *The Journal of Finance* 77, 3141–3190.

Barber, Brad M., Xing Huang, Terrance Odean, and Christopher Schwarz, 2022b, Attention Induced Trading and Returns: Evidence from Robinhood Users, *Journal of Finance, Forthcoming* .

Barber, Brad M, and Terrance Odean, 2001, Boys Will Be Boys Gender Overconfidence and Common Stock Investment, *Quartely Journal of Economics* 32.

Barber, Brad M, Terrance Odean, and Ning Zhu, 2008, Do retail trades move markets?, *The Review of Financial Studies* 22, 151–186.

Barber, Brad M., Terrance Odean, and Ning Zhu, 2009, Do retail trades move markets?, *The Review of Financial Studies* 22, 151–186.

Barberis, Nicholas, Andrei Shleifer, and Jeffrey Wurgler, 2005, Comovement, *Journal of financial economics* 75, 283–317.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2018, Do etfs increase volatility?, *The Journal of Finance* 73, 2471–2535.

Ben-David, Itzhak, Jiacui Li, Andrea Rossi, and Yang Song, 2022, Ratings-driven demand and systematic price fluctuations, *The Review of Financial Studies* 35, 2790–2838.

Betermier, Sebastien, Laurent E. Calvet, Samuli Samuli Knüpfer, and Jens S. Kvaerner, 2024, Investor factors, *The Journal of Finance* forthcoming.

Brandt, Michael W., Pedro Santa-Clara, and Rossen Valkanov, 2009, Parametric Portfolio Policies: Exploiting Characteristics in the Cross-Section of Equity Returns, *The Review of Financial Studies* 22, 3411–3447.

Calvet, Laurent E, John Y Campbell, and Paolo Sodini, 2007, Down or out: Assessing the welfare costs of household investment mistakes, *Journal of Political Economy* 115, 707–747.

Campbell, John Y., 2018, *Financial Decisions and Markets: A Course in Asset Pricing* (Princeton University Press).

Chaudhry, Aditya, 2023, *Do Subjective Growth Expectations Matter for Asset Prices?* (The University of Chicago).

Davis, Carter, 2024, Elasticity of quantitative investment, *Review of Financial Studies, Forthcoming* .

Davis, Carter, Mahyar Kargar, and Jiacui Li, 2025, Why do portfolio choice models predict inelastic demand?, *Journal of Financial Economics, Forthcoming* .

Dimson, Elroy, 1979, Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* 7, 197–226.

Doeskeland, Trond M., and Hans K. Hvide, 2011, Do individual investors have asymmetric information based on work experience?, *Journal of Finance* 66, 1011–1041.

Foucault, Thierry, David Sraer, and David J Thesmar, 2011, Individual investors and volatility, *The Journal of Finance* 66, 1369–1406.

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

Gabaix, Xavier, Ralph SJ Koijen, Federico Mainardi, Sangmin Oh, and Motohiro Yogo, 2022, Asset demand of U.S. households Working paper.

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephen Utkus, 2021, Five facts about beliefs and portfolios, *Journal of Political Economy* 111, 1481–1522.

Gomes, Francisco, Michael Haliassos, and Tarun Ramadorai, 2021, Household finance, *Journal of Economic Literature* 59, 919–1000.

Grinblatt, Mark, Matti Keloharju, and Juhani T Linnainmaa, 2012, Iq, trading behavior, and performance, *Journal of Financial Economics* 104, 339–362.

Guiso, Luigi, Andreas Fagereng, and Marius Ring, 2023, How much and how fast do investors respond to equity premium changes? evidence from wealth taxation, Technical report, CEPR Discussion Papers.

Haddad, Valentin, Paul Huebner, and Erik Loualiche, 2021, How Competitive is the Stock Market? Theory, Evidence from Portfolios, and Implications for the Rise of Passive Investing, *Working Paper* .

Hirshleifer, David, 2001, Investor psychology and asset pricing, *The Journal of Finance* 56, 1533–1597.

Kaniel, Ron, Gideon Saar, and Sheridan Titman, 2008, Individual investor trading and stock returns, *The Journal of Finance* 63, 273–310.

Koijen, Ralph S J, Robert J Richmond, and Motohiro Yogo, 2022, Which Investors Matter for Equity Valuations and Expected Returns?, *Working Paper* 54.

Koijen, Ralph S. J., and Motohiro Yogo, 2019, A Demand System Approach to Asset Pricing, *Journal of Political Economy* .

Kumar, Alok, 2009, Who gambles in the stock market?, *The Journal of Finance* 64, 1889–1933.

Kumar, Alok, and Charles MC Lee, 2006, Retail investor sentiment and return comovements, *The Journal of Finance* 61, 2451–2486.

Merton, Robert C., 1973, An intertemporal capital asset pricing model 41, 867–887.

Pastor, Lubos, Robert Stambaugh, and Lucian A. Taylor, 2022, Dissecting green returns, *Journal of Financial Economics* 146, 403–424.

Van der Beck, Philippe, 2021, Flow-driven esg returns, *Swiss Finance Institute Research Paper* .

Van der Beck, Philippe, and Coralie Jaunin, 2021, The equity market implications of the retail investment boom, *Swiss Finance Institute Research Paper* .

Vissing-Jorgensen, Annette, 2003, Perspectives on behavioral finance: Does" irrationality" disappear with wealth? evidence from expectations and actions, *NBER macroeconomics annual* 18, 139–194.

Welch, Ivo, 2022, The Wisdom of the Robinhood Crowd, *The Journal of Finance* 77, 1489–1527.

TABLES

Table 1. Descriptive Statistics

This table reports descriptive statistics by broad investor types for three periods. The time-series (TS) average market share and its standard deviation are reported in column three and four. The number of subinvestors (portfolios) per investor type is reported in column five. The cross-sectional mean and median of the TS average of AUM of each subinvestor are in columns six and seven. AUM is in million NOK. The last two columns report the same statistics as we report for AUM but for the number of stocks held in the portfolio of inside assets.

		%Mkt Share			TS Mean AUM		TS Mean # Stocks	
	Period	Mean	SD	# Pf	Mean	Median	Mean	Median
Household sector	2007-2020	0.179	0.021	216	873	51	101	106
Institutions	2007-2020	0.386	0.021	106	2579	514	43	37
Governments	2007-2020	0.219	0.020	1	229101	229101	73	73
Banks	2007-2020	0.006	0.004	1	6160	6160	114	114
Foreign	2007-2020	0.159	0.036	19	4831	432	64	48
Listed firms	2007-2020	0.036	0.011	1	35408	35408	115	115
Non-listed firms	2007-2020	0.014	0.003	1	15005	15005	121	121
Household sector	2007-2014	0.181	0.023	216	696	43	96	100
Institutions	2007-2014	0.385	0.024	99	2676	394	40	36
Governments	2007-2014	0.229	0.013	1	195984	195984	74	74
Banks	2007-2014	0.008	0.004	1	6782	6782	116	116
Foreign	2007-2014	0.140	0.032	14	6268	507	72	67
Listed firms	2007-2014	0.043	0.008	1	35611	35611	112	112
Non-listed firms	2007-2014	0.014	0.002	1	12248	12248	119	119
Household sector	2015-2020	0.177	0.019	216	1136	63	109	114
Institutions	2015-2020	0.387	0.014	117	3555	671	47	39
Governments	2015-2020	0.204	0.018	1	278259	278259	73	73
Banks	2015-2020	0.004	0.002	1	5236	5236	110	110
Foreign	2015-2020	0.188	0.017	26	6973	492	69	49
Listed firms	2015-2020	0.026	0.003	1	35106	35106	121	121
Non-listed firms	2015-2020	0.014	0.003	1	19097	19097	125	125

Table 2. Inertia and Turnover for Broad Sectors

This table presents the time-series averages of inertia, turnover, flow, and changes in shares for each broad investor type. Each measure is computed monthly and then averaged within each quarter and subsequently averaged across all investors that belong to the same sector. The last row shows the quarterly average of all portfolio groups across all sectors. The data spans from the first quarter of 2007 to the first quarter of 2020.

	Inertia	**Turnover**	**Flow (million)**	**Δ shares (thousand)**
Household sector	0.28	0.12	47.9	2758
Institutions	0.48	0.08	325	7159
Government	0.50	0.001	480	7389
Foreign	0.30	0.24	1001	27573
Listed firms	0.35	0.02	1871	52975
Banks	0.19	0.19	2536	55331
Non-listed firms	0.16	0.08	2128	69326
Mean	0.35	0.11	203	5931

Table 3.Inertia and Turnover for Households

This table presents the time-series averages of inertia, turnover, flow, and changes in shares for 12 household categories based on wealth. Each measure is computed monthly and then averaged within each quarter and subsequently averaged across all households that belong to the same wealth group. The last row shows the average across all households. The data spans from the first quarter of 2007 to the first quarter of 2020.

	Inertia	**Turnover**	**Flow (million)**	**Δ shares (thousand)**
W1	0.54	0.43	1.1	81
W2	0.40	0.18	1.5	106
W3	0.32	0.11	2.5	164
W4	0.27	0.09	4.1	241
W5	0.24	0.08	6.4	355
W6	0.22	0.07	8.9	511
W7	0.20	0.06	12.4	763
W8	0.19	0.06	18.5	1311
W9	0.19	0.05	30.7	2118
W10	0.24	0.05	61.6	4025
W11	0.24	0.06	216	13942
W12	0.35	0.04	1196	59472
Mean	0.28	0.11	41.7	2455

Table 4. Estimation of Investor Preferences

This table summarizes the average estimated demand coefficients for each broad investor type. The table reports time-series averages. Institutions, households, and the foreign sector consist of multiple portfolios. For these sectors, the estimates are based on an equal-weighted cross-sectional estimate. ME refers to the log market value of equity. BE refers to the log book value of equity. Beta refers to the market beta of the stock. ROE is the current earnings divided by the book value of equity 12 months earlier. All characteristics are lagged by 12 months and normalized to have a mean of zero and a standard deviation of one each month. The sample frequency is monthly, and the period is from January 2007 to April 2020.

Sector	ME	BE	Beta	ESG	ROE
Household sector	0.34	0.24	0.28	0.22	-0.31
Institutions	0.62	0.11	0.11	0.04	0.79
Banks	0.71	0.06	0.34	-0.04	-0.20
Non-listed firms	0.82	-0.01	-0.33	0.03	0.63
Listed firms	0.62	0.44	-0.34	-0.06	0.40
Foreign	0.71	0.13	0.38	0.06	0.24
Governments	0.86	1.13	-1.54	0.07	-1.36

Table 5. Variance Decomposition of Stock Returns

This table reports the cross-sectional variance of monthly stock returns due to supply- and demand-side effects. Supply effects are aggregated and consist of changes in shares outstanding, stock characteristics, and dividends. Demand-side effects are reported by investor type and consist of changes in assets under management, preference parameters, and latent demand. Each coefficient ("Est") represents the share of variance due to a particular attribute listed in the first column. The coefficients are based on panel regressions with time-fixed effects from January 2007 to April 2020. Standard errors ("se") are Newey-West adjusted with a lag length of 4 ($\approx 0.75 \times 171^{1/3}$). Columns labeled by WLS are based on WLS with free-float adjusted market capitalization as weights. OLS means equal weight. The sample period is from 2007 to 2020. Households are reported by stock wealth in million NOK.

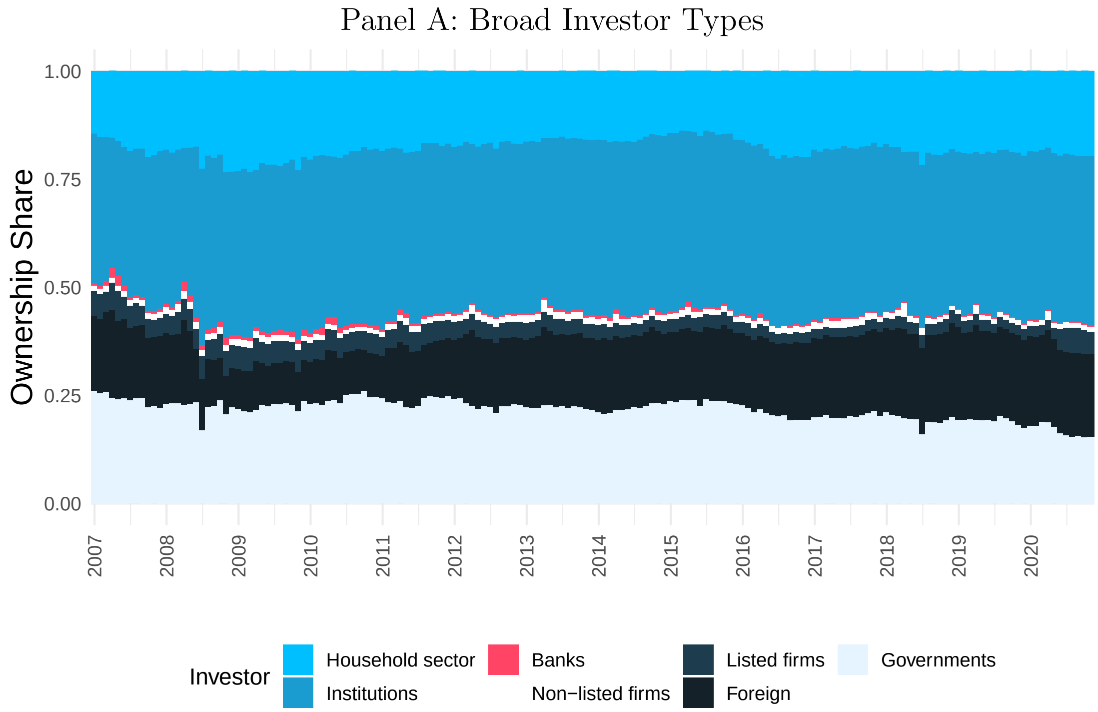
		WLS			OLS		
	%Mkt	Est	se	$\frac{\text{Est}}{\text{\%Mkt}}$	Est	se	$\frac{\text{Est}}{\text{\%Mkt}}$
Households	0.18	0.26	0.02	1.5	0.49	0.02	2.7
Institutions	0.39	0.39	0.04	1.0	0.29	0.02	0.8
Listed firms	0.04	0.02	0.01	0.5	0.03	0.01	0.9
Non-listed firms	0.01	0.05	0.01	3.5	0.03	0.01	2.4
Banks	0.01	0.02	0.01	3.8	0.03	0.01	4.4
Foreign	0.16	0.23	0.04	1.5	0.13	0.02	0.8
Governments	0.22	-0.05	0.06	-0.2	-0.00	0.01	-0.0
Supply		0.08	0.07		-0.00	0.02	

Table 6. Contribution to Latent Demand by Investor Groups

The table presents the results from a panel regression of the change in latent demand of each broad investor group on the change in the aggregate latent demand with date fixed effect. The sample frequency is monthly from January 2007 to April 2020.

	Intercept	Se	Slope	Se	R2
Household sector	0.11	0.12	0.19	0.00	0.19
Institutions	0.09	0.14	0.30	0.00	0.30
Governments	-0.03	0.10	0.10	0.00	0.10
Banks	-0.05	0.10	0.10	0.00	0.10
Foreign	-0.04	0.13	0.22	0.00	0.22
Listed firms	0.01	0.07	0.06	0.00	0.06
Non-listed firms	-0.13	0.08	0.05	0.00	0.04

FIGURES



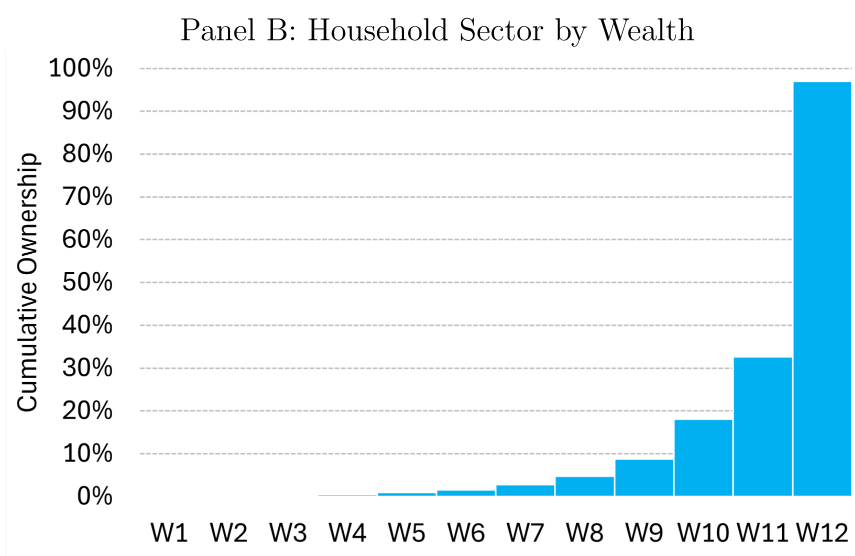
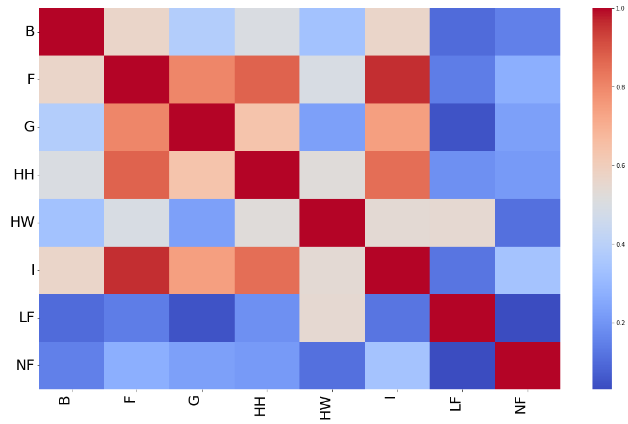
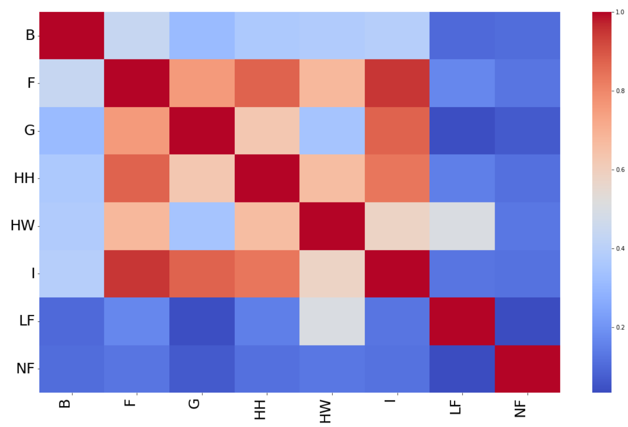


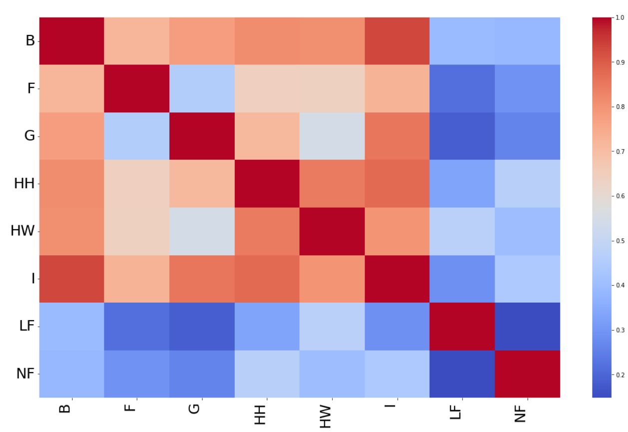
Figure 1. Ownership shares of Oslo Stock Exchange by Investor Types. Panel A shows the evolution of ownership shares for broad investor types in Norway. The sample covers the period 2007–2020, and all stocks included in the demand estimation as inside assets. Panel B plots the time-series average cumulative ownership share within the household sector by wealth groups as defined in Section 2.3. The last bar does not equal one because household groups 215 and 216 do not have a wealth category.



(a) 03-2020

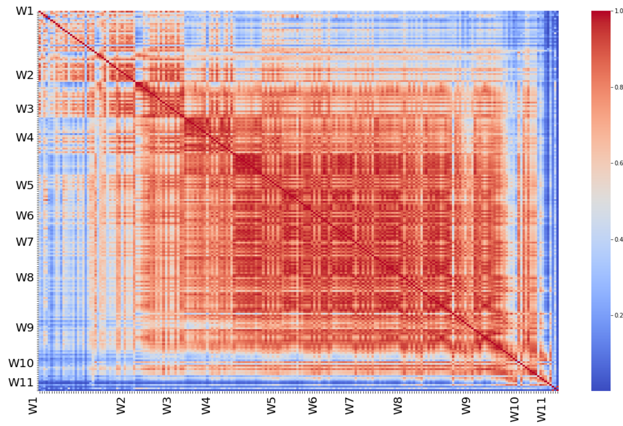


(b) 06-2015

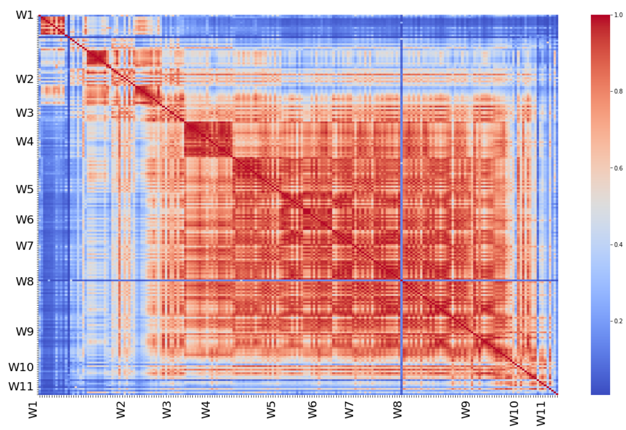


(c) 01-2010

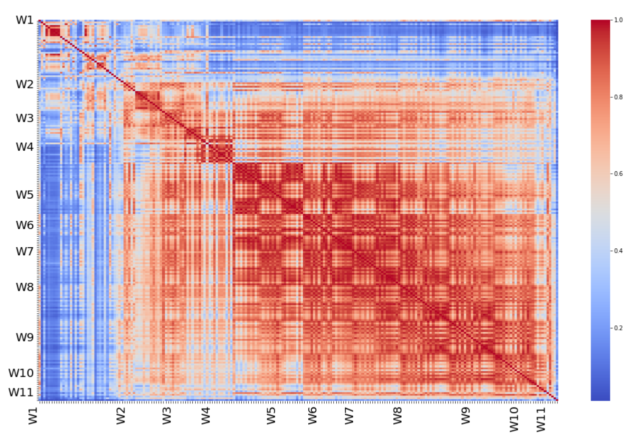
Figure 2. Cosine Similarity of Portfolio Weights by Investor Groups.
This figure displays the cosine similarity of portfolio weights among different investor groups as of March 2020, June 2015, and January 2010. The investor groups are B (banks), G (government), HH (less wealthy households), HW (wealthy households), I (institutions), F (foreign investors), NF (non-listed firms), and LF (listed firms). Red (blue) shades indicate higher (lower) similarity.



(a) 03-2020



(b) 06-2015



(c) 01-2010

Figure 3. Cosine Similarity of Portfolio Weights by Household Categories. This figure displays the cosine similarity of portfolio weights among different 216 household portfolios. The portfolios are ordered according to wealth from lowest (W1) to highest (W12). Red (blue) shades indicate higher (lower) similarity.

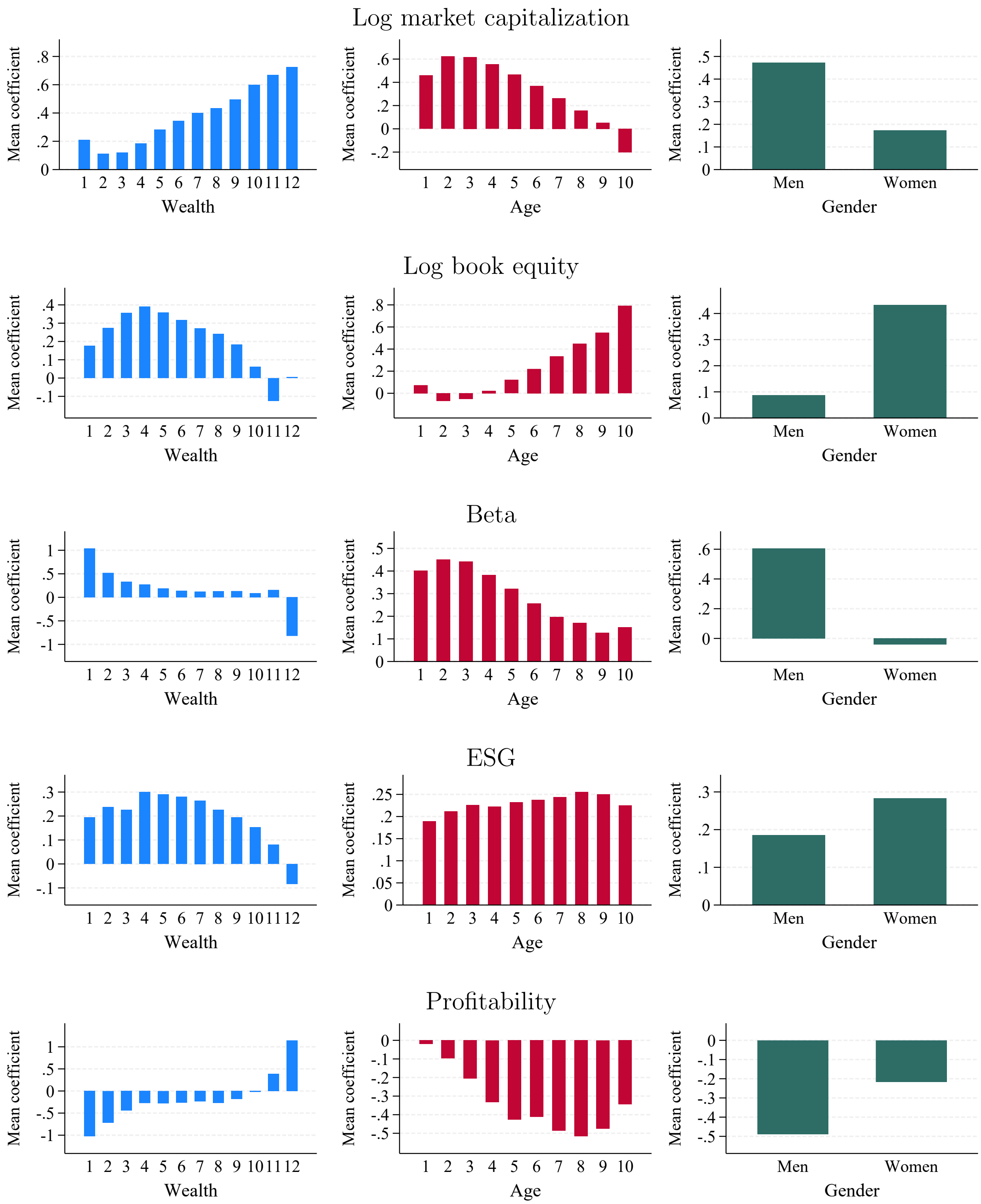
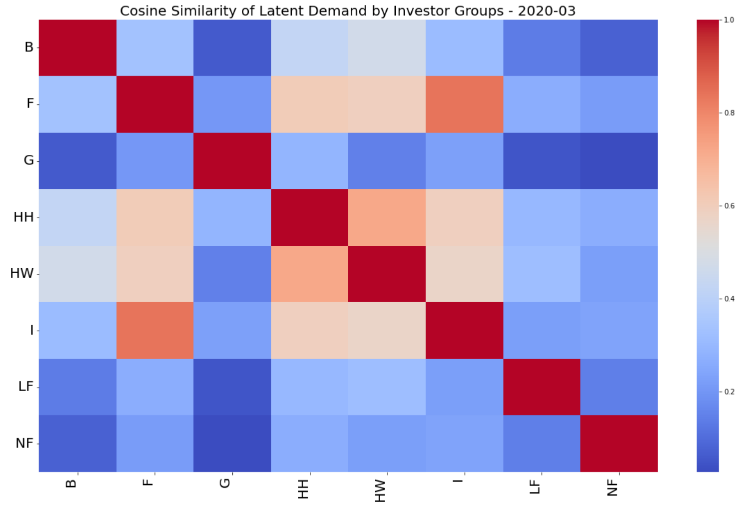
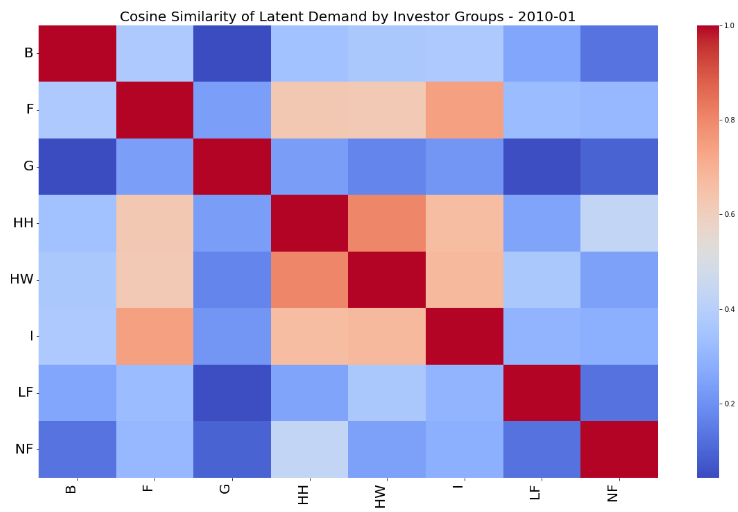


Figure 4. Demand Curve Summary by Household Categories. This figure reports the average of the estimated characteristic demand equations by household wealth, age, and gender categories. We first compute the time-series average for each of the 216 granular household portfolios. We then plot equal-weighted averages for each household category. The sample period covers 2007–2020.

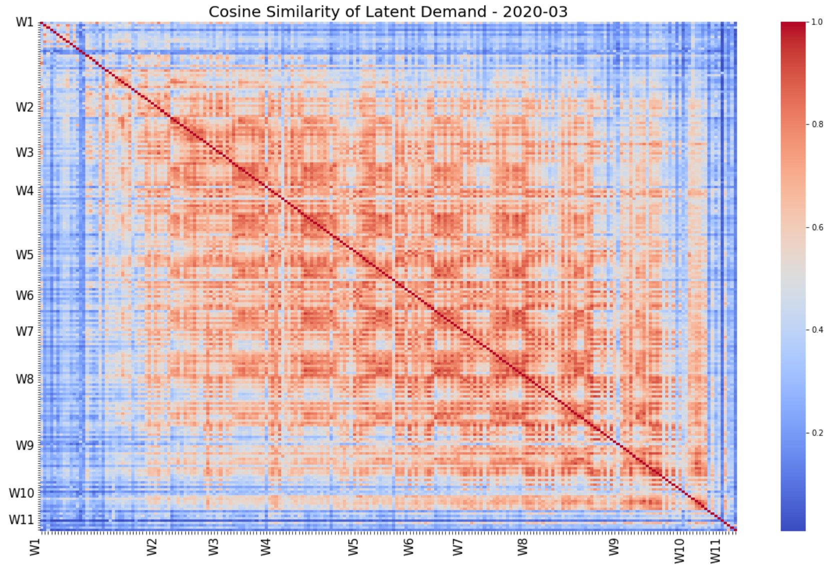


(a) CS(03-2020)

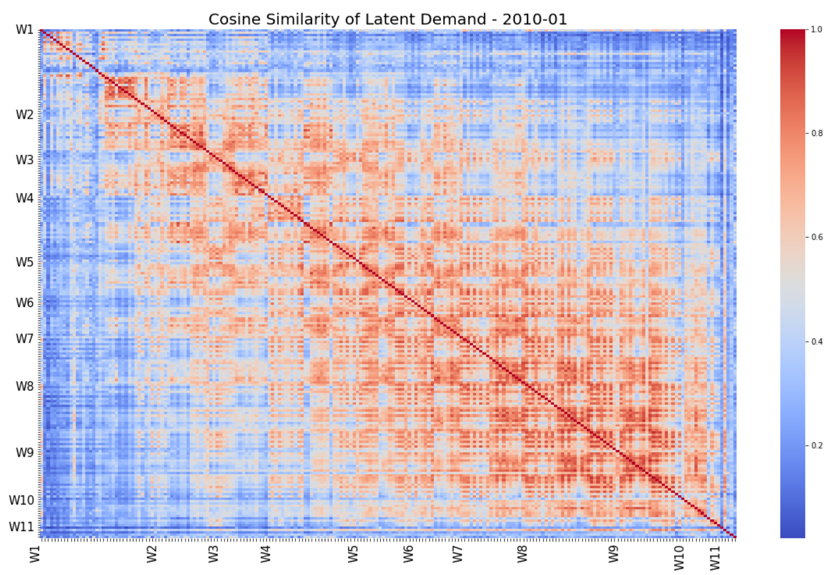


(b) CS(01-2010)

Figure 5. Cosine Similarity by Investor Groups. This figure illustrates the cosine similarity of latent demand among different investor groups as of March 2020 (Panel A) and January 2010 (Panel B). Investors include B (banks), G (government), HH (less wealthy households), HW (wealthy households), I (institutions), F (foreign investors), NF (non-listed firms), and LF (listed firms). Red (blue) shades visualize the high (low) similarity.



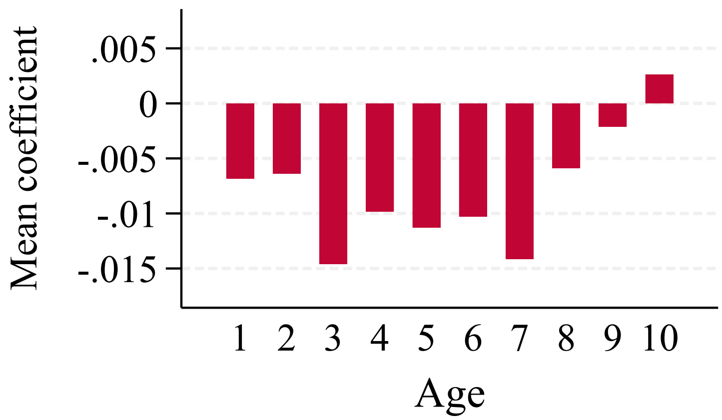
(a) CS(03-2020)



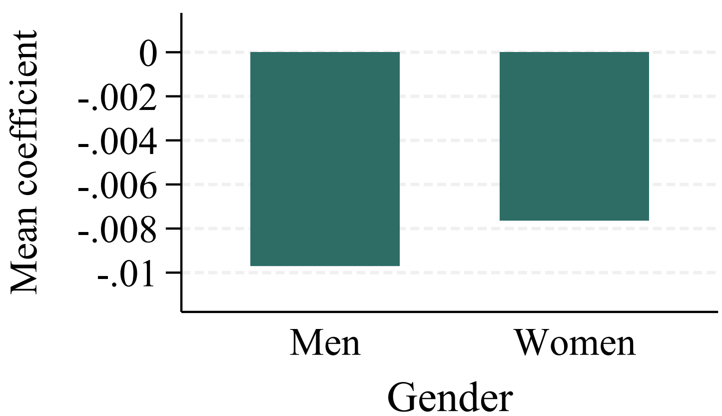
(b) CS(01-2010)

Figure 6. Cosine Similarity by Household Wealth. This figure illustrates the cosine similarity of latent demand among different investor groups as of March 2020 (Panel A) and January 2010 (Panel B). The wealth groups are labeled from W1 (least wealthy) to W12 (wealthiest). Red (blue) shades visualize the high (low) similarity.

(a) Wealth Groups

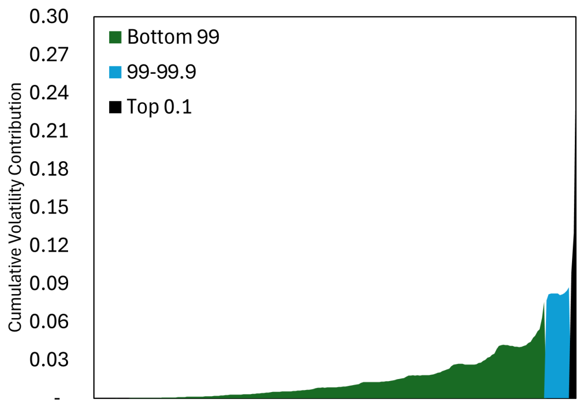


(b) Age Groups

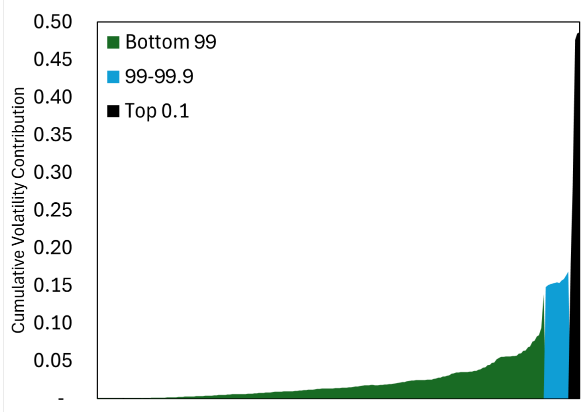


(c) Age Groups

Figure 7. Informativeness of Household Latent Demand. This figure plots the average price informativeness coefficient for three categorizations of households. Informativeness is measured by the coefficient π_i in Eq. 13.

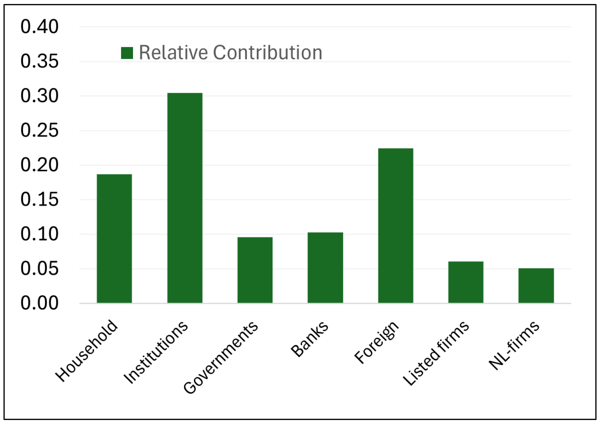


(a) WLS (Large cap)

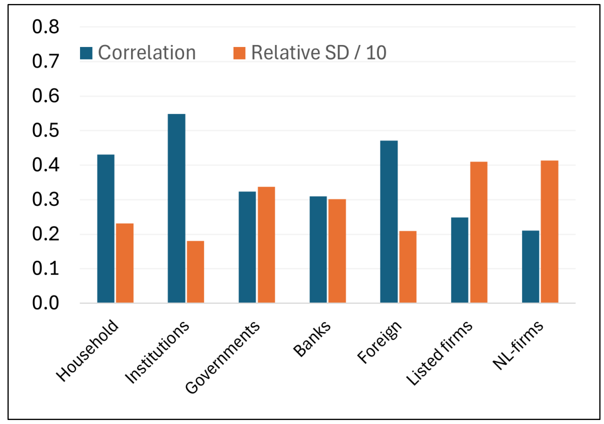


(b) OLS (Small cap)

Figure 8. Contribution to Cross-sectional Return Volatility by Household Type. This figure plots the contribution of specific households (by wealth) to the cross-sectional variance of monthly stock returns caused by the household sector. Demand-side effects consist of changes in assets under management, preferences, and latent demand. Wealth is increasing from the lowest wealth groups at the left to the highest wealth groups at the right. Each bar represents the share of variance due to a particular household group. Panel a) reports the results using WLS, and panel b reports the corresponding results using OLS.

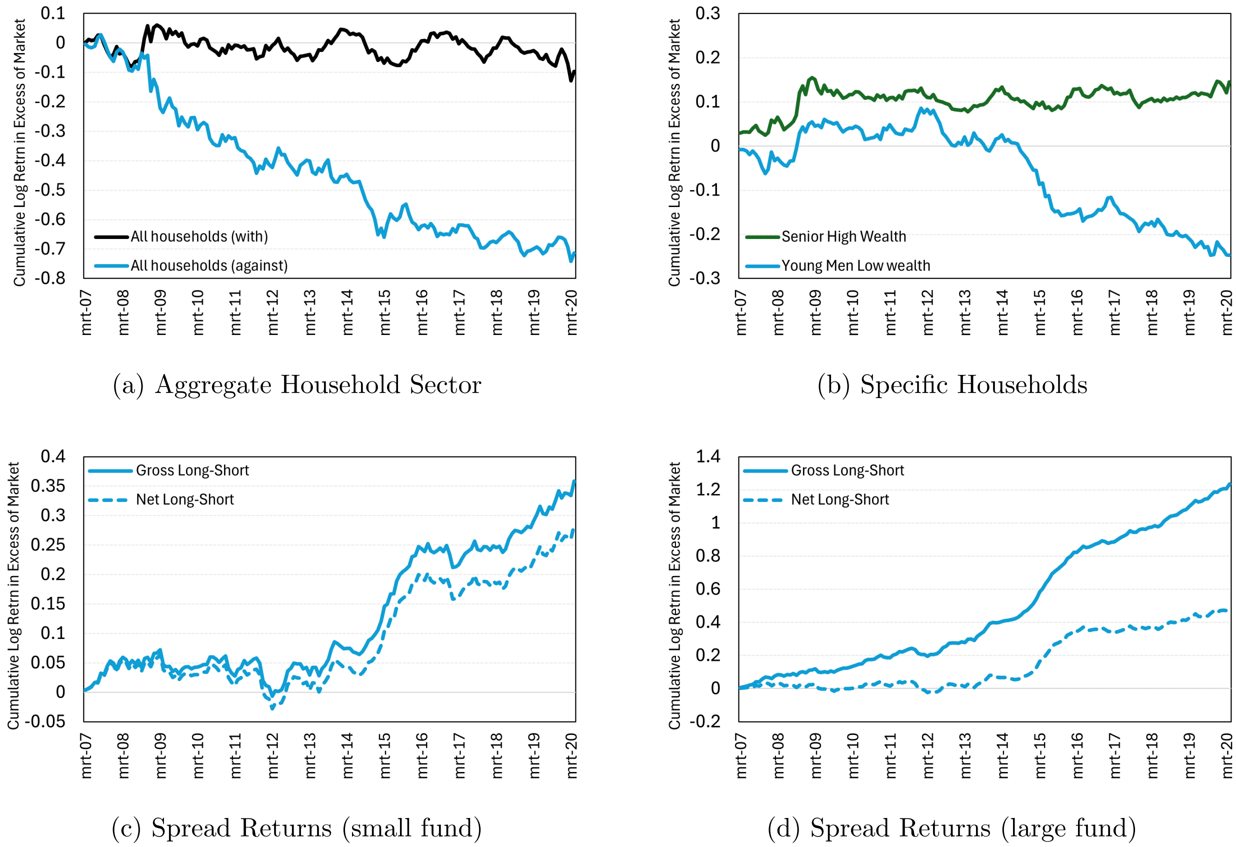


(a) R2



(b) Correlation and Standard Deviation

Figure 9. Decomposition of Changes in Aggregate Latent Demand. This figure presents the results from univariate regression of changes in latent demand for each of the seven broad investor types on changes in the aggregate latent demand. Panel a) shows the R2 from this regression, and panel b) decomposes the R2 into a correlation and a relative standard deviation (i.e., the standard deviation of the change in latent demand of an investor scaled by the corresponding standard deviation of the market).



(a) Aggregate Household Sector

(b) Specific Households

(c) Spread Returns (small fund)

(d) Spread Returns (large fund)

Figure 10. Trading on Latent Demand of Households. Panel a) plots the cumulative log return in excess of the market for two trading strategies: The first strategy trades on the latent demand of households, and the second trades against it. Pabel b) reports the corresponding returns for two strategies that trade on the latent demand of two different household groups. Panel c) reports the gross and net return (adjusted for transaction cost) on the corresponding spread strategy. Panel d) reports the cumulative log return for a spread strategy based on the same household types as in c) but for a fund that is ten times larger.

Appendix for
"Do Households Matter for Asset Prices?"

March 17, 2025

A Appendix to Section 2

A.1 Data Constructions

The primary data source of our analysis is VPS holdings data. We apply two primary filters to the universe of listed stocks. First, we compare shares outstanding in Titlon with the sum of shares reported in VPS and remove stocks with substantial differences. These are primarily tiny stocks and foreign listings. Two exceptions are Aker BP (NO0010345853) and MOWI (NO0003054108). These companies are involved in multiple restructurings which sometimes cause large differences between the VPS and Titlon shares outstanding. In less than 1% of stock-month observations, the number of shares outstanding in the Titlon database differs from the sum of shares held by investors in the VPS database. Whenever that happens, we use the sum of shares across all investors in the VPS database. Second, we intersect this sample with the sample used in Betermier et al. (2024), which has been a thorough quality check.

With a sample of inside assets, we construct assets as follows: We first remove the stocks that are part of the inside assets. These assets make up the alternative investment that is available to all investors. We complement outside equity with bond mutual and money market funds, which we get from the same database. We obtain ISIN, fund names, and prices from Titlon. We merge this data with Thomson Reuters (TR) and use the Lipper classification scheme provided by TR to classify the funds by asset class. Specifically, we organize funds into equity, bond, hybrid, and money market if the Lipper classification included the words "Equity", "Bond", "Mixed", "Money" respectively. Out of 5,536 mutual funds, we matched 4,238. Of those funds, 2,694 were equity funds, 932 were bond funds, 242 were hybrid funds, 147 were money market funds, and the rest (223) were classified as others. For the remaining 1,298 funds, we looked up the funds' names and labeled them accordingly. We kept all bond and money market funds.

A.2 Households

We construct household types following a similar grouping as Betermier et al. (2024). We split the sample by gender. We then form ten groups of investors sorted by age. The first age group includes investors less than 30, the next nine groups are in five-year increments, and the tenth age group includes all investors above 70. Finally, we form 12 groups of investors sorted by stock market wealth in the previous month. The wealth groups consist of the first 9 deciles of the net worth distribution (groups 1-9), the 90^{th}-99^{th} percentiles (group 10), the 99^{th}-99.9^{th} percentiles (group 11), and the top 0.1% (group 12). For wealth groups 1 to 10, each household group consists of a unique combination of gender, age, and wealth. For wealth group 11, we only sort by age to ensure we have enough investors in each group. For wealth group 12, we only split on age. In addition to these household portfolios, we include holding companies that only have the wealth characteristics (one for wealth group 11 and one for 12) and two other groups, which are based on investors that just entered the market and individual trading accounts with missing data on gender and age but with too little wealth to end up in wealth group 11 or above.

Table A1. Examples of granular household portfolios.

Portfolio #	Broad Type	Gender	Wealth coarse	Wealth fine	Age
1	Household sector	Man	Bottom99	W1	A1
2	Household sector	Woman	Bottom99	W1	A1
3	Household sector	Man	Bottom99	W1	A2
4	Household sector	Woman	Bottom99	W1	A2
5	Household sector	Man	Bottom99	W1	A3
6	Household sector	Woman	Bottom99	W1	A3
7	Household sector	Man	Bottom99	W1	A4
8	Household sector	Woman	Bottom99	W1	A4
9	Household sector	Man	Bottom99	W1	A5
10	Household sector	Woman	Bottom99	W1	A5
11	Household sector	Man	Bottom99	W1	A6
12	Household sector	Woman	Bottom99	W1	A6
13	Household sector	Man	Bottom99	W1	A7
14	Household sector	Woman	Bottom99	W1	A7
15	Household sector	Man	Bottom99	W1	A8
16	Household sector	Woman	Bottom99	W1	A8
17	Household sector	Man	Bottom99	W1	A9
18	Household sector	Woman	Bottom99	W1	A9
19	Household sector	Man	Bottom99	W1	A10
20	Household sector	Woman	Bottom99	W1	A10
		...			
201	Household sector		Bottom99	W11	A1
202	Household sector		Bottom99	W11	A2
203	Household sector		Bottom99	W11	A3
204	Household sector		Bottom99	W11	A4
205	Household sector		Bottom99	W11	A5
206	Household sector		Bottom99	W11	A6
207	Household sector		Bottom99	W11	A7
208	Household sector		Bottom99	W11	A8
209	Household sector		Bottom99	W11	A9
210	Household sector		Bottom99	W11	A10
211	Household sector		Bottom99	W11	
212	Household sector		Top1	W12	
213	Household sector	Man	Top1	W12	
214	Household sector	Woman	Top1	W12	
215	Household sector		Bottom99		
216	Household sector		Bottom99		

A.3 Cosine Simularity

Cosine similarity is a metric used to gauge the similarity between two vectors. It measures the cosine of the angle between the vectors, providing a value between -1 and 1: a value of 1 signifies that the vectors are perfectly aligned (cosine of 0 degrees), and a value of -1 indicates that the vectors are exactly opposite (cosine of 180 degrees). A value of 0 denotes that the vectors are orthogonal (cosine of 90 degrees). The cosine similarity between two vectors A and B is given by

$$\text{Cosine Similarity} = \frac{A \cdot B}{||A|| \times ||B||},$$

where $A \cdot B$ represents the dot product of vectors A and B, and $||A||$ and $||B||$ denote the magnitudes of A and B, respectively. Consider the vectors $A = [0.2, 0.2, 0.2, 0.2, 0.2, 0, 0, 0, 0]$ and $B = [0.2, 0.2, 0.2, 0.2, 0.2, 0, 0, 0, 0]$. The cosine similarity between these vectors is 1.0, indicating a 0-degree angle between them and a correlation of 1.0. In another instance, for the vectors $A = [0.2, 0.2, 0.2, 0.2, 0.2, 0, 0, 0, 0]$ and $B = [-0.2, -0.2, -0.2, -0.2, -0.2, 0, 0, 0, 0]$, the cosine similarity is -1.0, signifying a 180-degree angle and a correlation of -1.0. With smaller vectors, the difference between cosine similarity and correlation becomes more apparent. Consider, for example, the vectors $A = [1, 0, 0]$ and $B = [0, 1, 0]$: The cosine similarity is 0, representing a 90-degree angle and orthogonality, yet the correlation is -0.33333. In other words, cosine similarity measures similarity without being affected directly by the number of stocks in the investor's portfolio. For the same reason, it is not directly affected by time-series variation in the investment universe. In our case, we often compare relatively sparse portfolios, and the number of stocks available for investors changes over time.

B Appendix to Section 3

B.1 First-stage t-statistic

Figure A1 plots the evolution of the cross-sectional distribution of the first-stage t-statistic. It is a test of the strength of the instrument described in the main text.

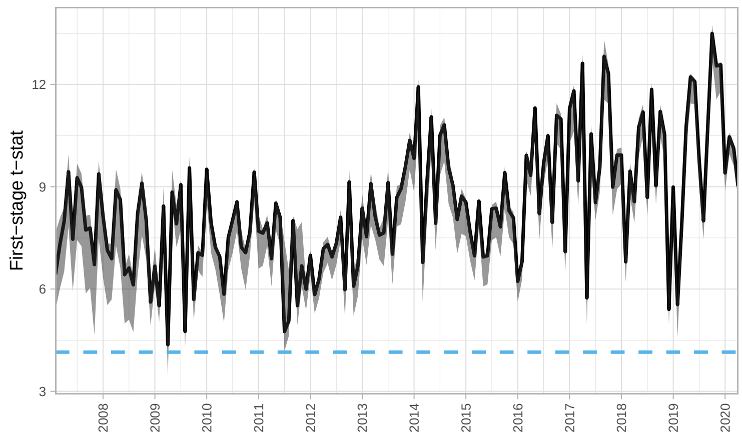


Figure A1. First-stage t-statistic. This figure shows the distribution of the first-stage t-statistic. The solid line is the median t-statistic, and the shaded area around it is the 10–90 percentile. The dashed line shows the critical value.

C Appendix to Section 4

C.1 Informativeness of Household Latent Demand

Table A2 reports the average price informativeness coefficient by wealth, age, and gender household categories. Informativeness is measured by the coefficient π_i in Eq. 13.

Table A2. Informativeness of Household Latent Demands

This table reports the average price informativeness coefficient by wealth, age, and gender household categories. Informativeness is measured by the coefficient π_i in Eq. 13. The informativeness for each household category is the equal-weighted average π_i coefficient for the category. The sample period is from January 2007 to April 2019.

Wealth Groups		Age Groups		Gender	
	Est		Est		Est
W1	-0.008	A1	-0.007	Female	-0.008
W2	-0.009	A2	-0.006	Male	-0.009
W3	-0.011	A3	-0.015		
W4	-0.011	A4	-0.010		
W5	-0.015	A5	-0.011		
W6	-0.009	A6	-0.010		
W7	-0.014	A7	-0.014		
W8	-0.010	A8	-0.006		
W9	-0.004	A9	-0.002		
W10	0.005	A10	0.003		
W11	0.009				
W12	0.016				

C.2 Variance Decomposition of Stock Returns

Koijen and Yogo (2019) introduce the following variance decomposition of stock returns to understand the relative importance of each of the exogenous variables to the demand system to cross-sectional stock return volatility (see Section V.B in their paper). We run the same variance decomposition for Norway and include the derivation of the variance decomposition here for completeness. Starting with the definition of log returns:

$$\boldsymbol{r}_{t+1} = \boldsymbol{p}_{t+1}(\boldsymbol{s_{t+1}}, \boldsymbol{X_{t+1}}, \boldsymbol{AUM_{t+1}}, \boldsymbol{\beta_{t+1}}, \boldsymbol{\epsilon_{t+1}}) - \boldsymbol{p}(\boldsymbol{s_t}, \boldsymbol{X_t}, \boldsymbol{AUM_t}, \boldsymbol{\beta_t}, \boldsymbol{\epsilon_t}) + \boldsymbol{v}_{t+1},$$

with $\boldsymbol{v}_{t+1} = \ln(\boldsymbol{1} + \boldsymbol{DP}_{t+1})$ and $\boldsymbol{DP}_{t+1}$ is a vector of the ratio of dividend payment to the ex-dividend price, The vector of capital gains equals, $\Delta\boldsymbol{p}_{t+1} = \boldsymbol{p}_{t+1} - \boldsymbol{p}_t = \Delta\boldsymbol{p}_{t+1}(k)$, where $\Delta\boldsymbol{p}_{t+1}(k)$ stand for the price change attributable to change the exogenous variable $k \in \{\boldsymbol{s}, \boldsymbol{X}, \boldsymbol{AUM}, \boldsymbol{\beta}, \boldsymbol{\epsilon}\}$ from its period t value to its value in period $t+1$. We change the variables in the order they appear in k (so first $\boldsymbol{s}$, and so on). Thus, when we reach $k = \boldsymbol{\epsilon}$ all the variables have been changed from period t values to those observed at period $t+1$, and therefore, by definition, the resultant vector of log prices, $\boldsymbol{p}_{t+1}$, corresponds to the one observed in the data. In each step k, the vector of "counterfactual prices" is unique due to the assumption imposed in the estimation that all investors have downward-sloping demand curves (i.e., $\beta_i < 1 \forall i$). We can then decompose the cross-sectional variance of log returns by regressing each of the k log price changes on the actual log price changes. It follows from the additive property of covariance that the sum of the regression slopes adds up to one. Table A3 presents the results from the estimation.

Table A3 presents the results for the variance decomposition of stock returns as a function of exogenous variables in the demand system. Panel A provides a breakdown of the variance decomposition into an explained and an unexplained part. The explained part is everything that is not latent demand, and the unexplained part is the total effect of latent demand (intensive and extensive margins). Latent demand accounts for 65% of the variance in large-cap stocks (WLS) and 85% in small-cap stocks (OLS).[16] This finding aligns with those of Koijen and Yogo (2019). They found that latent demand explains 80% of the cross-sectional

[16]The numbers do not add up to one in the table because of rounding.

Table A3. Variance Decomposition of Stock Returns

This table reports the cross-sectional variance of monthly stock returns due to supply- and demand-side effects. Supply effects consist of changes in shares outstanding, stock characteristics, and dividends. Demand-side effects consist of changes in assets under management, preference parameters, and latent demand. Each coefficient ("Est") represents the share of variance due to a particular attribute listed in the first column. The coefficients are based on panel regressions with time-fixed effects from January 2007 to April 2020. Standard errors ("se") are Newey-West adjusted with a lag length of 4 ($\approx 0.75 \times 171^{1/3}$). Columns labeled by WLS are based on WLS with free-float adjusted market capitalization as weights. OLS means equal weight. The sample period is from 2007 to 2020.

	WLS		OLS	
	Est	se	Est	se
Panel A				
Explained	0.33	0.15	0.14	0.04
Unexplained	0.65	0.15	0.85	0.04
Dividend Yield	0.00	0.00	0.00	0.00
Panel B				
Supply:				
Shares Outstanding	0.00	0.01	0.00	0.00
Stock characteristics	0.08	0.07	-0.01	0.02
Dividend Yield	0.00	0.00	0.00	0.00
Demand:				
Asset Under Management (AUM)	0.12	0.02	0.05	0.01
Coefficients on Characteristics	0.15	0.14	0.10	0.04
Latent Demand-Extensive Margin	0.01	0.04	0.10	0.04
Latent Demand-Intensive Margin	0.64	0.15	0.82	0.04

variations in stock returns. Panel B provides the full decomposition. Changes in "supply" measured by shares, stock characteristics, and dividend yield contribute modestly to cross-sectional return volatility (about 8% of large caps). Regarding "demand", assets under management account for 12% of the cross-sectional variance in stock returns and explain 15%. The remaining part is accounted for by latent demand.