Which Investors Drive Anomaly Returns and How?*

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First draft: October 2022
This version: May 2023

Abstract

We investigate the sources of time-variation in returns on anomaly portfolios, specifically examining the role of different investor types and their trading motives. Our analysis reveals that 39% of the return variation can be attributed to changes in investor demand for common stock characteristics. Flow-induced trading explains an additional 12%, while the remainder is accounted for by random demand shocks. Notably, households and small non-13F institutions have the most significant impact, whereas large 13F institutions exhibit smaller effects. These findings provide strong support for theories that underscore the role of small non-professional investors in generating anomalies, thus challenging theories that prioritize flow-induced or discretionary trading by large institutional investors.

Keywords: Factor Investing, Anomalies, Institutional Investors, Portfolio Choice.
JEL codes: G11, G12, G23.

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*We thank Azi Ben-Rephael, Foti Grigoris (discussant), Sophia Li, Ralph Koijen, Rob Richmond, Christian Wagner (discussant), Motohiro Yogo, and seminar participants at Adam Smith Spring 2023 Workshop, Citi Quantitative Research Conference 2023, MFA 2023, 11th MSUFCU Conference on Financial Institutions, and Rutgers Business School for valuable comments.

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1 Introduction

Asset pricing anomalies are patterns in asset returns which cannot be explained by the standard models of risk like the CAPM. A rich literature has documented a variety of persistent anomalies, generating a major dispute among researchers regarding their sources. The existing theories put forward several explanations which include exposure to non-standard sources of time-varying risk (Bansal and Yaron (2004); Gabaix (2012); Wachter (2013)), biased beliefs (Barberis et al. (1998), Hong and Stein (1999)), or institutional frictions (Shleifer and Vishny (1997), Lou (2012)). While some of these explanations have found empirical support, financial economists strongly disagree on which theories better fit the evidence.

Building on the pioneering work of Koijen and Yogo (2019), we propose a novel approach to decompose variation in anomaly returns into the effects of trading by different investors and into various motives behind their trades. The key innovative feature of our approach is that it allows us to directly compare the effects of investors and trading motives across a wide range of anomalies on the same scale. Since most theories make explicit assumptions about the types of investors who drive anomalies as well as the reasons behind their trades, our approach makes it possible to evaluate the contribution of different theories and shed light on their relative importance.[1]

For example, consider the momentum anomaly where stocks with higher past returns have higher future returns. Hong and Stein (1999) propose that this pattern is driven by investors who learn about stock characteristics such as fundamentals and prices. Lou (2012) argues that momentum can be explained by flow-induced trading where institutional investors have

[1]By decomposing variation in anomaly returns, our paper speaks to the vast literature on excess volatility of asset prices (Shiller et al. (1981), LeRoy and Porter (1981)). Unlike these studies, we examine long-short anomaly portfolios, netting out the market returns. Consequently, any proposed explanation for excess market volatility does not mechanically translate to any of our findings.

to change their positions due to the shocks to their assets under management. Now consider the following simple decomposition of momentum (MOM) return at time t:

$$R_{MOM,t} = R^C_{MOM,t} + R^F_{MOM,t}, \quad (1)$$

where $R^C_{MOM,t}$ is the return induced by demand for stock characteristics and $R^F_{MOM,t}$ is the return induced by flow-based trading. Therefore, the variation in momentum returns can be decomposed as:

$$Var(R_{MOM,t}) = Cov(R_{MOM,t}, R^C_{MOM,t}) + Cov(R_{MOM,t} R^F_{MOM,t}). \quad (2)$$

By dividing both sides of Equation (2) by $Var(R_{MOM,t})$, we can evaluate the relative contribution of both return components to the overall variation in momentum returns. For example, if the entire variation in momentum returns is driven by the demand for characteristics, we expect $\frac{Cov(R_{MOM,t}, R^C_{MOM,t})}{Var(R_{MOM,t})}$ to be equal one, and $\frac{Cov(R_{MOM,t}, R^F_{MOM,t})}{Var(R_{MOM,t})}$ to be equal zero. This approach also enables further decomposition into the effects by different investor groups, and it can be universally applied to any anomaly portfolio.

More generally, our methodology builds on the demand-based asset pricing framework, where stock prices are determined by the demand of a heterogeneous set of investors (Koijen and Yogo (2019)). Section 2 describes our three-step approach in great detail. Briefly, we first follow Koijen et al. (2022) and estimate demand functions across all the investors in each quarter.[2] We next decompose quarterly stock returns into the effects of various demand-driving forces by changing one element of demand at a time and calculating the

[2]Koijen and Yogo (2019) show that if expected returns and factor exposures depend on stock characteristics, investor demand also becomes a function of these characteristics. Examples of stock characteristics include market equity, book equity, investment, profitability, dividends and market beta.

counterfactual returns. We do so separately for each investor to enable the comparison across investors. Lastly, we construct the decomposed returns on anomaly portfolio by combining the components of returns for the underlying stocks and decompose the time-series variance of the total anomaly returns into the effect of various components, in the spirit of Equation (2). We examine 46 anomalies, based on the characteristics from Freyberger et al. (2020), grouping them into seven well-known categories: value, momentum, profitability, investment, issuance, size and asset tangibility. The last step is fundamentally different from the decomposition of the cross-sectional variance of individual stocks in Koijen and Yogo (2019), since we focus on the decomposition of the time-series variance of anomaly portfolios.

In Section 3 we describe our two main results. First, we uncover three major trading motives that drive anomaly returns: demand for stock characteristics, demand shocks which are unrelated to observed stock characteristics ("latent demand"), and flow-induced trading. The demand for characteristics and latent demand represent the dominant forces, each accounting for about 38% of the return variation. The flow-induced trading explains only 11% of it. The remaining variation, driven by supply-side effects (e.g. changes in shares outstanding) and model estimation errors, is minor. These findings are consistent across the anomaly groups and individual anomaly portfolios, suggesting that returns of many distinct anomalies are actually driven by common trading motives.

We also show that the effects of trading motives significantly vary over time. The demand for characteristics is more important during "normal" times while the latent demand become highly consequential in more "turbulent" times. For example, the demand for stock characteristics increases the variation in returns of the value anomaly though early 1990s, including the initial stage of the dot-com bubble (1995-1997). However, during the more explosive stage of the bubble (1997-2000), the volatility of value strategies and inflated prices of growth stocks are mostly driven by the latent demand.

Turning to momentum, the importance of demand for characteristics has been steadily growing, explaining 17% of the variation in momentum returns during the 1980-1989, and 58% over the decade of 2000-2009. Latent demand is instead the main source of return volatility during the momentum crash (Daniel and Moskowitz, 2016). It explains 60% of the variation in returns between 2009Q1 and 2009Q3, while the demand for characteristics accounts only for 38%.[3] These results suggest that the latent demand is related investor sentiment, and it drives the volatility of returns during the most unstable periods (Baker and Wurgler, 2006).

Our second set of results shows how the importance of trading motives varies across investors. We focus on seven major investor groups: investment advisors, mutual funds, banks, insurance companies, pension funds, short-sellers and non-13F investors ("households").[4] Our key finding is that much of the variation in anomaly returns is driven by households. Their demand for stock characteristics explain nearly 31% of the variation, the contribution of investment advisors, mutual funds and banks is much smaller, and the effects of other investors are barely noticeable. This result is highly consistent across anomalies, implying that the demand for characteristics of the small non-13F investors completely dominates the analogous effect of large institutions. While the latent demand of households also produces large effects, there are important differences across anomaly groups. For example, the effect

[3]These three quarters have the lowest returns on the momentum strategy in our sample.

[4]We follow the common practice in the demand-based asset pricing literature to construct the holdings of the aggregate household sector as the difference between the total shares outstanding and the aggregate holdings of institutions. This is the best practice when only the data on institutional holdings are available. See Gabaix et al. (2022) for an estimation of households' demand curves directly using disaggregated data instead.

of households' latent demand dominates that of other investors in the case of investment (36% vs. 9%); it is on par with the combined effect of latent demand by banks, mutual funds and investment advisors' for profitability (30% vs. 34%); and, it is dominated by the effect of these institutions for momentum (12% vs. 27%).

We next ask which stock characteristics are more important by decomposing the total effect of the demand for characteristics into the effects of individual characteristics. We find that the variation in demand driven by the stock's market beta explains a large fraction of the total effect. These results hold across investors, consistent with stock market beta being an important driver of demand for both institutions and individual investors (e.g. Frazzini and Pedersen (2014), Baker et al. (2011), Buffa et al. (2022), Christoffersen and Simutin (2017)). Interestingly, the effect of market beta also consistently appears across many anomalies where the underlying portfolio stocks are sorted on other stock characteristics.

Finally, we examine how the effects of the investors and their trading motives differ for explaining the systematic and idiosyncratic anomaly variance. We apply the Fama and French (1993)'s three-factor model to separate between the systematic and idiosyncratic components. Overall, the demand for stock characteristics mostly affects the systematic variance, while the latent demand has a large effect on the idiosyncratic variance. These findings suggests that preferences for stock fundamentals drive the exposure to common risk factors, while investor sentiment matters mostly for anomaly-specific variation in returns. In terms of the importance of different investors, the demand of households shows up again as the most significant factor for both systematic and idiosyncratic components.

Taken together, our results provide a novel perspective on explanations behind anomaly returns. First, our findings are inconsistent with flow-induced trading being a major driving factor.[5] They also do not support explanations which emphasize the direct role of stock characteristics (e.g., Liu et al. (2009)). In our analyses, changes in stock characteristics themselves explain only 3% of the variation in returns on the average anomaly portfolio.

Instead, our results are mostly consistent with two broad sets of theories. The importance of demand for stock characteristics supports theories where investors trade on the information about stock fundamentals. This set of anomaly theories includes: 1) behavioral theories where investors underreact or overreact to news (e.g., Hong and Stein (1999), Barberis et al. (1998) and Daniel et al. (2001)); 2) theories where investors rationally respond to new information such as productivity shocks (Kogan and Papanikolaou, 2013) or other determinants of price of risk (Lettau and Wachter, 2007).

The importance of latent demand supports the second set of theories which emphasize the role of investor sentiment and noise trading, rather than the demand for fundamentals, in explaining the variation in returns (e.g., De Long et al. (1990), Baker and Wurgler (2006)). We note that this interpretation comes with a caveat, because changes in latent demand can also represent the variation in unobserved characteristics which are not included in our empirical model. This alternative interpretation suggests that a considerable fraction of variation in anomaly returns is explained by factors yet to be discovered.

Additionally, our results emphasize a dominant role of direct trading by households relative to trading by institutional investors.[6] If small non-13F investors are viewed as less sophisticated, this finding further reinforces the behavioral theories. Moreover, this result is

[5]While flows appear to be important in explaining aggregate market fluctuations (Gabaix and Koijen, 2021) and matter to some extent for returns on anomaly portfolios (Lou (2012), Akbas et al. (2015), Ben-David et al. (2022)), their *relative* role in explaining variation in anomaly returns is much less significant.

[6]Other recent studies also suggest that households can play an important role in determining asset prices. Balasubramaniam, Campbell, Ramadorai and Ranish (2023) estimate a factor model of direct stock holdings. Gabaix, Koijen, Mainardi, Oh and Yogo (2022) study the rebalancing behavior of U.S. households across the wealth distribution and find that ultra-high-net-worth households stabilize market fluctuations.

in line with the idea that many institutional investors are limited by benchmarking, which may discourage pursuing arbitrage-based strategies (Lewellen (2011), Baker et al. (2011)). Our findings are also less supportive of the view that more sophisticated investors such as short-sellers play a major role in determining anomaly returns. While trading by sophisticated investors weakens anomalies (e.g. Hanson and Sunderam (2014), Chen et al. (2019)), it appears to make a very modest contribution to their overall returns' variation.

Our study also speaks to the recent work by Lochstoer and Tetlock (2020) who examine the effects of cash flow and discount rate news on the variation in anomaly returns. They find that the cash flow news are especially important. Our results complement their work by dissecting the variation in returns by investors and their trading motives, rather than by type of news. Our methodology makes it possible to study how investors respond to news and which investors are more important, further enriching our understanding on who transmits the information into financial markets and how.

2 Variance Decomposition of Anomaly Returns

In this section, we describe how we decompose variation in anomaly returns building on the demand system approach from Koijen and Yogo (2019). We also describe several datasets we use in this study.

2.1 Demand Estimation

In our first step, we estimate the investors' demand curves. In the characteristics-based demand system, the investor demand curves are given by:

$$\frac{w_{i,t}(n)}{w_{i,t}(0)} = \delta_t(n) = \exp\left(\beta_{0,i,t} me_t(n) + \sum_{k=1}^{6} \beta_{k,i,t} x_{k,t}(n) + \beta_{7,i,t}\right) \epsilon_{i,t}(n) \tag{3}$$

where $w_{i,t}(n)$ denotes the portfolio weight of investor i at date t for stock n, and $\epsilon_{i,t}(n)$ denotes latent demand.[7]

Stock Characteristics. We first include the standard set of characteristics $x_{k,t}(n)$ from Koijen and Yogo (2019): log market equity, log book equity, dividends to book equity, profitability, investment, and market beta. Since our model differs from Koijen and Yogo (2019)'s setup in that it features a short-selling sector, we also include accruals as an additional characteristic (Sloan, 1996). Including the same set of baseline characteristics enables easier comparison of our results to prior work, while including accruals is consistent with the studies that show how the demand for shorting is related to discretionary accruals (Kolasinski et al. (2013), Mainardi (2021)).

Investor Holdings. Using Thomson Reuters Institutional Ownership S34 database, we obtain the holdings of all 13F institutional investors from 1980 to 2019.[8] We follow Koijen and Yogo (2019), applying the same filters to the data and the same classification of all

[7] Koijen and Yogo (2019) show that the demand function $w_i(n) = \exp^{\beta_{0,i} P(n) + \beta_i x(n) + \epsilon_i}$ can be derived from mean-variance portfolio choice under the assumption of a factor structure in the covariance matrix in returns and assuming linearity of expected returns and factor loadings in x. Koijen et al. (2022) justify the demand function for an investor with CARA utility over wealth and time-varying investment opportunities.

[8] We use the updated and partially regenerated version of the S34 dataset which includes corrections to errors, previously identified by researchers (for example, Ben-David et al. (2021)). See https://wrds-www.wharton.upenn.edu/documents/952/S12_and_S34_Regenerated_Data_2010-2016.pdf for details.

13F investors. We first classify investors into six groups: investment advisors, mutual funds, banks, insurance companies, pension funds and other 13F institutions (e.g., endowments, foundations, and non-financial corporations). Unlike Koijen and Yogo (2019), we also add short sellers as a seventh investor category as in Mainardi (2021). To do so, we obtain the firm-level short interest from Compustat, Supplemental Short Interest File. At the end of each quarter, we calculate the dollar value of short interest for each stock. The assets under management for the short-selling sector is the sum of these dollar holdings. We attribute the rest of the holdings to the residual investors which we call "households". To compute the household holding for a given stock, we follow the common practice in the demand-based asset pricing literature, and subtract the total number of shares held by all other seven investor groups from the total number of shares outstanding.[9] As a result, the aggregate "households" sector captures both direct holdings by households as well as holdings of small, non-13F institutions.

Estimation Procedure. We use the same set of instruments as in Koijen and Yogo (2019), and follow the two-step estimation procedure proposed by Koijen et al. (2022). In the first step, we construct one representative investor for each aforementioned group in each quarter, and estimate demand curves for these "aggregate" investors.[10] In the second step, we estimate demand curves for each individual investor within each group by introducing a ridge penalty. Our procedure shrinks the individual investor's estimates towards the group-level estimates from the first-step. We determine the shrinkage parameter using cross-validation as

[9]Mainardi (2021) follows a different approach, adding short interest in each quarter to the original household holdings which increases the total number of shares outstanding. When we compute the counterfactual prices under this approach, the difference in shares outstanding generates an extra price gap between the actual and counterfactual prices. Since we seek to minimize the price gap, we do not follow Mainardi (2021)'s approach.

[10]We restrict $\beta_{0,t} > 1$ for the short-selling sector to obtain an upward-sloping demand curve, and we impose $\beta_{0,t} \leq 1$ for all other investors.

in Koijen et al. (2022).[11] Using this two-step procedure is important since Koijen et al. (2022) document substantial heterogeneity in demand curves of institutional investors within and across groups. This fact is relevant for our analysis since a too-coarse, group-level estimates curve could mask important variation. For example, if we only used the first-step group-level estimates for all the mutual funds, we would mix the different effects of passive and active mutual funds.

By design, our methodology allows for a rich heterogeneity in the demand curves of 13F investors, and does not allow for any heterogeneity for households, because all the non-13F investors are treated as a single investor due to the data limitations. As a result, our estimates provides a lower bound on the effect coming from the demand of the non-13F investors for which we do not have disaggregated, investor-level data.

2.2 Decomposition of Stock Returns

Koijen and Yogo (2019) show that the equilibrium log stock price $\mathbf{p}_t$ is a function of the log shares outstanding $\mathbf{s}_t$, the firms' characteristics x_t, the investors' assets under management (AUM) $\mathbf{A}_t$, the investors' coefficients on characteristics β_t ("demand for characteristics") and the investor-specific latent demand ϵ_t:

$$\mathbf{p}_t = \mathbf{g}(\mathbf{s}_t, x_t, \mathbf{A}_t, \beta_t, \epsilon_t). \tag{4}$$

Define the log returns: $r_{t+1} = \mathbf{p}_{t+1} - \mathbf{p}_t + \mathbf{v}_{t+1}$, where $\mathbf{v}_{t+1} = \log\left(1 + \exp\left(\frac{\mathbf{d}_{t+1}}{\mathbf{p}_{t+1}}\right)\right)$ is the

[11] The penalty is specified as $\lambda_{i,t} = \lambda\,|\mathcal{N}_{i,t}|^{-\xi}$ where $|\mathcal{N}_{i,t}|$ denotes the number of holdings. The cross-validation procedure selects $\lambda = 20$ and $\xi = 0$.

dividend yield. The realized log capital gain can be decomposed as:

$$\mathbf{p}_{t+1}-\mathbf{p}_t = \Delta\mathbf{p}_{t+1}(\mathbf{s})+\Delta\mathbf{p}_{t+1}(\mathbf{x})+\Delta\mathbf{p}_{t+1}(\mathbf{A_t^{CF}})+\Delta\mathbf{p}_{t+1}(\mathbf{A_{t+1}})+\Delta\mathbf{p}_{t+1}(\beta)+\Delta\mathbf{p}_{t+1}(\epsilon)+\psi_{\mathbf{t+1}} \tag{5}$$

where

$$\begin{aligned}
\Delta\mathbf{p}_{t+1}(\mathbf{s}) &= \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_t, \mathbf{A}_t, \beta_t, \epsilon_t\right) - \mathbf{p}_t \\
\Delta\mathbf{p}_{t+1}(\mathbf{x}) &= \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_t, \beta_t, \epsilon_t\right) - \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_t, \mathbf{A}_t, \beta_t, \epsilon_t\right) \\
\Delta\mathbf{p}_{t+1}(\mathbf{A_{t+1}^{CF}}) &= \mathbf{g^{CF}}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}^{CF}, \beta_t, \epsilon_t\right) - \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_t, \beta_t, \epsilon_t\right), \\
\Delta\mathbf{p}_{t+1}(\mathbf{A_{t+1}}) &= \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}, \beta_t, \epsilon_t\right) - \mathbf{g^{CF}}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}^{CF}, \beta_t, \epsilon_t\right), \\
\Delta\mathbf{p}_{t+1}(\beta) &= \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}, \beta_{t+1}, \epsilon_t\right) - \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}, \beta_t, \epsilon_t\right), \\
\Delta\mathbf{p}_{t+1}(\epsilon) &= \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}, \beta_{t+1}, \epsilon_{t+1}\right) - \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}, \beta_{t+1}, \epsilon_t\right) \\
\boldsymbol{\psi}_{t+1} &= \mathbf{p_{t+1}} - \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}, \beta_{t+1}, \epsilon_{t+1}\right)
\end{aligned} \tag{6}$$

Decomposition by Trading Motives. Equations (5) and (6) allow for the decomposition of return by trading motives, using a series of counterfactual experiments. We change one component at a time in the order presented in Equation (6), and recalculate the counterfactual equilibrium stock price.[12] We repeat the process for all the components until we fully decompose the change in log prices between every two quarters. Since we use numerical approximations when calculating counterfactual prices, a difference between the actual and counterfactual prices (denoted by $\boldsymbol{\psi}_{t+1}$) remains even after we change all the price determinants (see Appendix B.1 for detail). In terms of magnitude, this difference is small and does not play an important role in our results.

[12]We later show that the order of return decomposition does not affect our main results.

Effect of Fund Flows. Since we are interested in the effects of flow-induced trading, we decompose the effects of the total change in the investor's AUM into the effects of fund flows and other effects. Let us define the next period's AUM of investor i as:

$$A_{i,t+1} = A_{i,t} R^{P}_{i,t+1} + F_{i,t+1}, \tag{7}$$

where $R^{P}_{i,t+1}$ is the investor's portfolio return and $F_{i,t+1}$ is the fund flow. We first neutralize the effect of flows by setting $F_{i,t+1} = 0$, which results in the counterfactual AUM:

$$A^{CF}_{i,t+1} = A_{i,t} R^{P,CF}_{i,t+1}. \tag{8}$$

Note that the return in the counterfactual scenario with no flows $R^{P,CF}_{i,t+1}$ is not equal to $R^{P}_{i,t+1}$, since flows affect equilibrium prices. To obtain $R^{P,CF}_{i,t+1}$, we conduct a "repricing" exercise where we calculate counterfactual prices under the assumption of no flows. Using these counterfactual prices, we compute the counterfactual market capitalization for each stock $ME^{CF}_{t}(n)$. As a result, the counterfactual portfolio return is given by:

$$R^{P,CF}_{i,t} = \sum_{n} w_{i,t}(n) \frac{ME^{CF}_{t}(n)}{ME_{t}(n)}. \tag{9}$$

Having calculated the counterfactual returns, we can compute the counterfactual AUM $A^{CF}_{i,t+1}$ and decompose the change in prices into the effect of returns ($\Delta \mathbf{p}_{t+1}(A^{CF}_{t+1})$ in Equation (6)) and the effect of realized flows ($\Delta \mathbf{p}_{t+1}(\mathbf{A_{t+1}})$ in Equation (6)).

Decomposition by Investors. To further decompose returns by investor group, we change a single component for all investors within the given group from time t to $t+1$. For example, consider the effect of demand for stock characteristics $\Delta \mathbf{p}_{t+1}(\beta)$, and denote with

$\beta^{g}_{i(g),t}$ the coefficients on characteristics of investor i within group g at time t. Suppose that we are interested in the effect of mutual funds ($g = \mathbf{MF}$), and assume there are I_{MF} mutual funds in total. To calculate the return due to changes coefficients for MF, $\Delta p_{t+1}(\beta^{\mathbf{MF}})$, we change $\beta_{i(MF),t}$ to $\beta_{i(MF),t+1}$ for all the investors classified as a mutual fund company $i = 1, ..., I_{MF}$ *at once* (while keeping everything else at time t unchanged).

More generally, the composition of the effect of demand for stock characteristics by investor group takes the following form:

$$
\begin{aligned}
&\Delta \mathbf{p}_{t+1}(\beta^{\mathbf{HH}}) = \mathbf{g}\left(\cdots, \beta^{HH}_{t+1}, \beta^{g\neq HH}_{i(g),t}, \cdots, \right) - \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}, \beta_t, \epsilon_t\right) \\
&\Delta \mathbf{p}_{t+1}(\beta^{\mathbf{Banks}}) = \mathbf{g}\left(\cdots, \beta^{Banks}_{i(Banks),t+1}, , \beta^{HH}_{t+1}, \beta^{g\neq HH, Banks}_{i(g),t}, \cdots, \right) - \mathbf{g}\left(\cdots, \beta^{HH}_{t+1}, \beta^{g\neq HH}_{i(g),t}, \cdots, \right) \\
&\cdots \\
&\Delta \mathbf{p}_{t+1}(\beta^{Short-sellers}) = \mathbf{g}\left(\cdots, \beta_{t+1}, \cdots, \right) - \mathbf{g}\left(\cdots, \beta^{g\neq Short-sellers}_{t+1}, \beta^{Short-sellers}_{t}, \cdots, \right)
\end{aligned} \tag{10}
$$

where "HH" denotes households.[13]

2.3 Decomposition of Anomaly Returns

Portfolio return decomposition. We start by developing a general approach for decomposition of log returns on any portfolio and then apply it to anomaly portfolios. Let $R^{(k)}_{t+1}$ be the simple portfolio return induced by a change in a component k, where $k \in \{s, x, A^{CF}_{t+1}, A_{t+1}, \beta, \epsilon, v\}$. To calculate $R^{(k)}_{t+1}$, we first apply the exponential transformation to obtain simple returns of the underlying stocks, induced by a change in k, and then value-weight these returns. Therefore, $R^{(k)}_{t+1}$ is defined as:

[13]The notation for the households and short-sellers emphasizes that we only have a single aggregate investor for these investor groups.

$$R_{t+1}^{(k)} = \sum_{i=1}^{N} w_{i,t}(e^{\Delta p_{i,t+1}(k)} - 1), \quad k \in \{s, x, A_{t+1}^{CF}, A_{t+1}, \beta, \epsilon, v\} \tag{11}$$

where $w_{i,t}$ is the portfolio weight of stock i at time t, and $\Delta p_{i,t+1}(v) \equiv v_{i,t+1}$ is the stock-level dividend yield.

We next decompose the total portfolio log return. Let $r_{t+1}^{(k)} = \log(1+R_{t+1}^{(k)})$ be the portfolio log return, induced by a change in k. The total portfolio log return is given by:

$$r_{t+1} = \sum_{k=1}^{K} r_{t+1}^{(k)} + u_{t+1}, \quad k \in \{s, x, A_{t+1}^{CF}, A_{t+1}, \beta, \epsilon, v\}. \tag{12}$$

where u_{t+1} is the portfolio-level residual return. This residual bundles together two components. The first one is the difference between the actual and the counterfactual prices which arises from the decomposition of returns and equals the portfolio-level analog of $\boldsymbol{\psi}_{t+1}$ from Equation (6). The second component is the difference between the total portfolio log return and the sum of log component-induced returns, which arises from log-transformation (see Appendix B.1 for detail). We refer to u_{t+1} as "Residual" and later show that it does not materially affect our results.[14]

Anomaly Portfolios. Following Freyberger et al. (2020), we create anomaly portfolios based on 46 characteristics and categorize them in seven broad groups: value, momentum, profitability, investment, issuance, size and tangibility. Appendix Table A.1 provides details. We follow Lochstoer and Tetlock (2020) and define anomaly returns as the value-weighted returns of stocks ranked in the highest quintile of a given firm characteristic minus the

[14]Note that our approach does not require observing how much capital investors allocate to different anomaly portfolios. Instead, we calculate the decomposed anomaly portfolio returns "bottom-up", starting with the portfolio weights on individual stocks which reflect the allocations of stocks to various investment strategies.

value-weighted returns of stocks ranked in the lowest quintile. Quintiles are computed using NYSE breakpoints at each June, and portfolios are rebalanced every year. For momentum portfolio, we use the 12-month strategy as in Jegadeesh and Titman (1993).

We report our results both by anomaly groups (e.g., "value") and by individual anomaly portfolios within each group (e.g., "book-to-market" or "cash-to-assets"). To construct the group-level anomaly portfolios, we follow Keloharju et al. (2021) and use the following procedure. We first convert all the firm characteristics in a given group into percentile ranks to make them comparable. We then sign firm characteristics such that higher values correspond to higher average returns, based on the original study. A stock's combined signal is the average of its non-missing percentile ranks.[15] Lastly, we construct the group-level portfolio by applying the aforementioned sorting procedure to the combined signal.

2.4 Time-Series Variance Decomposition

Following the decomposition of total portfolio log return in Equation (12), we decompose the times-series variance of portfolio log returns as:

$$
\begin{aligned}
\operatorname{Var}\left(r_{t+1}\right) = & \underbrace{\operatorname{Cov}\left(r_{t+1}^{(\beta)}, r_{t+1}\right)}_{\text{Demand for Characteristics}} + \underbrace{\operatorname{Cov}\left(r_{t+1}^{(\epsilon)}, r_{t+1}\right)}_{\text{Latent Demand}} + \underbrace{\operatorname{Cov}\left(r_{t+1}^{(\mathbf{A_{t+1}})}, r_{t+1}\right)}_{\text{Flow-Induced Trading}} \\
& + \underbrace{\operatorname{Cov}\left(r_{t+1}^{(\mathbf{s})}, r_{t+1}\right) + \operatorname{Cov}\left(r_{t+1}^{(\mathbf{x})}, r_{t+1}\right) + \operatorname{Cov}\left(r_{t+1}^{(\mathbf{A_{t+1}^{CF}})}, r_{t+1}\right) + \operatorname{Cov}\left(\mathbf{v}_{t+1}, r_{t+1}\right)}_{\text{Other Effects}} \\
& + \underbrace{\operatorname{Cov}\left(u_{t+1}, r_{t+1}\right)}_{\text{Residual}}.
\end{aligned} \tag{13}
$$

[15]For example, in the value group we have 14 predictors (see Table A.1); if a firm has non-missing values for all of them, its "value" signal is the average percentile rank of these 14 predictors.

For ease of exposition, we bundle together the effects of several components because their impact tends to be small. In particular, we combine the effects of changes in stock characteristics, changes in shares outstanding, the return-driven changes in AUM, and the effects of dividend yield. We label the combined effect as "Other Effects" when we present our results.

To conduct the decomposition, we regress the component of log returns on the raw (not decomposed) log return r_{t+1}:

$$r_{t+1}^{(k)} = \alpha_k + \beta_k r_{t+1} + u_{k,t+1}. \tag{14}$$

The percentage of the covariance of portfolio log return with the log return induced by each component k a given component is given by:

$$\beta_k = \frac{\text{Cov}\left(r_{t+1}^{(k)}, r_{t+1}\right)}{Var(r_{t+1})}. \tag{15}$$

Since Equation (13) implies that the estimates of β_k's add up to one, our approach enables the full decomposition of the time-series variance of portfolio returns.

3 Empirical Results

3.1 Which Trading Motives Drive Anomaly Returns?

Figure 1 reports the results of the baseline decomposition by trading motives, without conditioning on particular investor group. For each anomaly category, we report the estimates of β_k's - the contributions in percentages of various factors to the total anomaly portfolio variance.

[Insert Figure 1 about here]

It is immediately apparent that the demand for stock characteristics and latent demand drive most of the variation in anomaly returns. Averaging across all anomalies, the demand for stock characteristics and latent demand explain 38.9% and 38.3% of the time-series variation in portfolio returns, respectively. By contrast, flow-induced trading accounts only for 11.2%. The combined importance of the demand for characteristics and the latent demand shows up consistently across anomalies, while the effects of the remaining components are comparatively small.

Table 1 summarizes the decomposition for each anomaly portfolio in a given group. The estimated effects of demand for stock characteristics, latent demand and flow-induced trading are statistically significant at the 5% level for most of the individual anomalies.[16] The effect of the other driving forces is statistically insignificant in most of the cases. Table 1 also shows that the contribution of different forces vary within the anomaly categories across the underlying individual anomaly portfolios. For example, within the value category, the importance of preferences for stock characteristics varies from 23% of the variation (sales-to-price, "sp", portfolio) to 52% (payout, "O2P", portfolio). Within the same value group, the importance of flow-induced trading ranges from 6% to 20%, whereas the latent demand can explain 24%-53% of the variation.

[Insert Table 1 about here]

While we find some variation across anomaly groups and the individual portfolios, the

[16] We calculate the Newey-West adjusted t-statistics with one-period lag for β_k in Equation (14). In Table 1, bold values indicate statistical significance at the 5% level.

differences mostly arise from the relative contribution of the demand for characteristics and the latent demand. The effect of demand for characteristics is typically between 23%-57%, and the effect of latent demand is within a similar range (22%-68%). By contrast, the effect of flows is almost never above 20%.

In sum, most of the variation in anomaly returns is driven by direct trading due to changes in the investors' demand for stock characteristics and their latent demand. These results are generally consistent with theories where anomalies are driven by demand for fundamentals (e.g., Hong and Stein (1999), Barberis et al. (1998), Daniel et al. (2001), Lettau and Wachter (2007), Kogan and Papanikolaou (2013)) or by sentiment (e.g., De Long et al. (1990), Baker and Wurgler (2006)). Flow-induced trading matters, consistent with prior works (e.g., Lou (2012), Akbas et al. (2015)), but it does not appear to be a major factor. We also do not find that changes in stock characteristics themselves are fundamentally important (Liu et al. (2009)). Below we discuss several baseline robustness checks for these results.

Order of Decomposition. Equation (6) shows that we follow a certain order when decomposing returns - we start with the change in stock characteristics and end with the residual component. Appendix Figure C.1 shows that our conclusions are robust to changes in the order of decomposition, when we start with the demand for characteristics instead.

Long and Short Legs. Appendix Figures C.3 and C.4 provide separate decomposition for long and short legs, net of the market returns. The results for each anomaly leg are generally in line with our baseline results on the standard long-short portfolios. For the average long-leg portfolio, the demand for stock characteristics, the latent demand and the flow-induced trading explain 36%, 41% and 13%, respectively. The analogous results for the average short leg are 35%, 43% and 11%.[17]

[17] While we find significant effects of the investor demand within the short leg, we later show that the effects

Comparison with Koijen and Yogo (2019). Our approach uncovers a different pattern from the Koijen and Yogo (2019) who find that the residual component together with the latent demand explain 80.8% of the cross-sectional variance of *individual* stock returns, while the demand for characteristics explains only 4.7%. There are three main differences between our methodology and theirs: 1) the decomposition of the time-series rather than cross-sectional variance; 2) the analysis of portfolios rather than individual stocks; 3) the focus on the specialized anomaly portfolios rather than on any "non-specialised" portfolio. We makes these three adjustment sequentially to understand what exactly drives the differences in our findings.

The results in Appendix Figure C.2 show that the differences arise from our focus on portfolio analysis and, more specifically, on anomaly portfolios. Starting with the decomposition of the times-series variance at the individual stock level (second bar from the right in Appendix Figure C.2), we observe a negligible role of the demand for characteristics, as in Koijen and Yogo (2019). Differently from Koijen and Yogo (2019), however, most of the variation is driven by the effects of the investor-specific latent demand and flows rather than by the residual component.[18]

To examine the role of portfolio analysis, we generate multiple random long-short portfolios and decompose the variation in their returns. Appendix B.2 provides details on the simulation procedure. For the average random portfolio, the demand for stock characteristics accounts only for 13% of the return variation, and the residual component together with

of the short-sellers are small. These findings imply that the variation within the short-leg is primarily driven by the long-only investors. In line with this idea, Betermier et al. (2017) show that households progressively shift their allocation from growth to value as they age, thus generating the variation in both legs of the value anomaly. More generally, we do not require the existence of the short-selling sector to have a variation in the anomaly's short leg.

[18] Koijen and Yogo (2019) call the residual component "the intensive margin of latent demand".

the latent demand account for 77%. This result suggests that the effects of characteristics start to appear at the portfolio level, but their role for the average random portfolio is small. Lastly, the comparison of this result with our main results (leftmost bar in Appendix Figure C.2) reveals that the transition to the anomaly portfolios from a random portfolio further boosts the role of the demand for stock characteristics. We conclude that our results are not driven by a mechanical effect of portfolio diversification but rather arise from "specialness" of anomaly portfolios.

3.1.1 How Do the Effects of Trading Motives Vary over Time?

We next investigate how the contribution of the key effects changes over time. Figure 2 presents the results across the anomaly groups. The shaded areas represent the 95% confidence intervals. These results illustrate three key patterns.

[Insert Figure 2 about here]

First, we find substantial time-variation in the effect of preferences for stock characteristics and latent demand, and much less variation for the effects of flow-induced trading. The estimated effects are statistically different from zero over most of our sample period across all the components, thus confirming the prominent role played by these effects for the variability of anomalies featuring in state-of-the-art factor models.

Second, the relative role of the demand for stock characteristics and the latent demand varies over time without clear trend. The correlation between these two effects is large and negative at -69% (average across groups), suggesting that they tend to substitute each other. This result implies that at times when the demand for fundamentals is more important, the effects of sentiment are much weaker.

Focusing on specific anomalies and market events further helps to understand this relation. Start with value anomaly from panel (a). The contribution of demand for characteristics is large and increasing outside the dot-com bubble in the late 1990s and the Great Recession of 2007-2009. This effect peaks at 82% in 1997Q1 and declines afterwards. Our model thus attributes the volatility of value strategies and inflated prices of growth stocks during the early part of the dot-com bubble (1995-2000) to the demand for specific stock characteristics. By contrast, the latent demand picks up most of the return variation during the late part of the dot-com bubble as well as during the Great Recession of 2007-2009.

Next consider the momentum anomaly (panel (b)). Overall, the importance of demand for stock characteristics is increasing over time. For example, this effect explains 58% of the variation in returns over the decade of 2000-2009 but only 17% for the 1980-1989 decade. However, we find sudden and large bursts in the effect of latent demand during the most unstable periods. In particular, latent demand is the main source of return variation during the momentum crash (Daniel and Moskowitz (2016)). Between 2009Q1 and 2009Q3 (the three worst quarters for momentum returns in our sample), latent demand explains 60%, with demand for characteristics picking up the remaining variability (38%).[19]

The results for value and momentum support the idea that investor sentiment, a share of the demand unexplained by stock characteristics, drives the returns during the most turbulent periods (Baker and Wurgler, 2006). Additionally, the importance of latent demand for investment, issuance, size and tangibility displays an increasing trend in the last decade (panels (c), and (e)-(g)). Its contribution is greater than 80% for investment, issuance and tangibility during the period 2010-2019, suggesting a key role of investor sentiment to explain

[19]During March 2009 to March 2013, the largest sustained draw-down period for the momentum strategy Daniel and Moskowitz (2016), the latent demand explain 41%, while the demand for characteristics accounts for 56%.

the variability in returns on these anomalies in the recent years.

Finally, Figure 2 shows that the effect of flow induced trading is not only smaller relative to the two other effects, but also more stable over our sample period. This effect is the largest for the value and issuance anomalies at about 20% relative to a smaller contribution of about 10% for momentum, profitability, and size. The time-variation is limited and mostly concentrated in the profitability and issuance anomalies for which we observe a more sizable effect of flow-induced trading after 2010.

3.2 Which Investors Drive Anomaly Returns?

We next examine which investors are responsible for the variation in anomaly returns. We dissect the effects of the demand for characteristics, latent demand and flow-induced trading by each investor type and report the results in Figure 3. The number at the top of each bar shows the total effects from Figure 1, and the colors indicate the relative contribution of each investor type.[20]

[**Insert Figure 3 about here**]

Figure 3 conveys three main patterns. First, the variation in the demand of households represents the key driving factor behind the variation in anomaly returns. The decomposition of the demand for stock characteristics in panel (a) shows that the effects of households are not only vastly larger than the effects of the institutions, but they are also remarkably stable across anomaly groups. For example, households' demand for characteristics explains

[20]The use of log returns induces small differences between the total effect (e.g., demand for stock characteristics) in Figure 1, and the same effect obtained by summing across investors in Figure 3. We explain and precisely quantify these very minor differences in Appendix B.3.

55% of the return variation in the size anomaly. This effect is also large for value (32%), momentum (31%), profitability (30%), and issuance (37%). While the effect is smaller for investment and tangibility anomalies (20% and 17%), it still remains sizable and larger than the analogous effect from other institutional investors. For comparison, the demand for characteristics by banks explains only 3%-5% of the variation in anomaly returns, and the effects of mutual funds and investment advisors are the largest for momentum anomaly at 3% and 7%, respectively. Table 2 presents the results for individual anomaly portfolios, further confirming that contribution of households' demand for stock characteristics is large and statistically significant for almost all of the anomalies considered. This effect is the largest for payout ratio (45%) and earnings per share (49%), as well as for anomalies in the size and issuance groups.

[Insert Table 2 about here]

Second, households' latent demand also represents an important source of variation in anomaly returns (panel (b)). However, in this case, we find important differences across anomaly groups. The effect of households' latent demand dominates the effects of the institutions for investment (36%), issuance (19%), and tangibility (33%) anomalies. At the same time, the combined effect of banks, mutual funds and investment advisors' plays a more important role for momentum (27% against 12% by households) and profitability (34% against 30% by households).[21]

While Table 3 shows similar patterns across individual anomaly portfolios overall, we also find rich heterogeneity within anomaly groups. For example, 1-year net-share-issuance

[21] The effect of the short-selling sector is small. It is somewhat meaningful only for profitability through demand for characteristics (panel (a)) and for momentum and size through latent demand (panel (b)).

(NSI) and 5-year composite-share-issuance (CSI) are combined in the recent behavioral factor model proposed by Daniel et al. (2020) to capture overconfidence-driven mispricing. Our results show that these two anomalies display similar fractions of variance explained by households' latent demand, but different fractions by institutional latent demand. Banks and mutual funds' latent demand accounts for 28% of NSI variance, and for only 5% of CSI variance. The more sizable role played by latent demand for NSI over CSI suggests that the NSI factor may capture the behavioral phenomena better that the CSI factor.

[Insert Table 3 about here]

Third, panel (c) of Figure 3 shows that the effect of flow-induced trading is primarily driven by mutual funds and investment advisors. The combined effect of these institutional investors ranges from 5% (Tangibility) to 27% (Issuance). Table 4 conveys a similar pattern and also shows that these effects are statistically significant in most cases. This result provides further validation to our empirical approach, since our model attributes most of the effects of flow-induced trading to the "usual suspects" such as mutual funds and investment advisors (Lou (2012), Akbas et al. (2015) and Ben-David et al. (2022))).

[Insert Table 4 about here]

3.3 Which Stock Characteristics Are More Important?

We next examine the role of individual stock characteristics. We decompose the total effect of demand for characteristics from Figure 1 into the effect of individual characteristics, presenting the results in Figure 4.[22] Given our prior results on the importance of different

[22]The effect of the constant is small at -5% , and not reported for ease of exposition.

investors, we focus on households, mutual funds and investment advisors (panel (a), (b) and (c), respectively).

We find three main patterns. First, the variation in the coefficient on stock market beta explains the largest fraction of the total effect. This result is consistent with multiple mechanisms that create demand for stocks with different market betas such the effects of leverage constraints (Frazzini and Pedersen, 2014), the effects of benchmarking (Baker et al. (2011) and Buffa et al. (2022)), as well as the incentives provided by pension plan sponsors to mutual funds (Christoffersen and Simutin, 2017). The next most important characteristic is the stock's book-to-market ratio (BM), and the effects of the other characteristics are minor.

Second, the overall importance of market beta and BM relative to other characteristics does not vary across investor types and anomaly groups. For households, the combined effects of market beta and BM are much larger then the combined effects of the other stock characteristics across all the anomalies. The same pattern holds for mutual funds and investment advisors in terms of the absolute magnitudes.

Third, the results show some major differences in how the demand for market beta and BM by different investors affects the variation in anomaly returns. The returns induced by changes in demand for market beta positively correlate with anomaly returns. This pattern holds both across anomalies and investors types, suggesting that the demand for beta increases the variation in anomaly returns. By contrast, the effects of BM vary across investors. The households' demand for BM primarily increase the variation, while the analogous effect of the institutional investors reduces it.

These patterns are novel, and they represent a challenge for the theories of anomalies.

In particular, a plausible theory needs to explain why different anomalies are driven by the demand for same underlying stock characteristics, and why the role of market beta and BM differs across investor types.

3.4 Systematic vs. Idiosyncratic Variance

A natural question to ask is whether the demand for stock characteristics, flow-induced trading, and latent demand mostly contribute to systematic or idiosyncratic variance of anomaly returns. To address this question, we implement the following approach. Denote raw returns R_t and, without loss of generality, let's focus on two components X and Y (e.g., X could be demand for characteristics and Y flow-induced trading). We have that $R_t = R_t^X + R_t^Y$. It is standard to decompose the variance of R_t into systematic and idiosyncratic components by running a regression:

$$R_t = \beta \mathbf{F}_t + u_t \tag{16}$$

where $\mathbf{F}_t$ are the systematic factors. By OLS properties, we have

$$\operatorname{Var}(R_t) = \underbrace{\operatorname{Var}(\beta \mathbf{F}_t)}_{\text{systematic}} + \underbrace{\operatorname{Var}(u_t)}_{\text{idiosyncratic}} \tag{17}$$

Our interest lies in understanding if R_t^X contributes to the systematic of idiosyncratic variance of R_t. To this end, note that

$$\operatorname{Var}(\beta \mathbf{F}_t) = \operatorname{Cov}\left(\beta \mathbf{F}_t, R_t^X\right) + \operatorname{Cov}\left(\beta \mathbf{F}_t, R_t^Y\right)$$

since by OLS $\text{Cov}\left(\beta \mathbf{F}_t, \epsilon_t\right) = 0$. Analogously, we have that

$$\text{Var}\left(u_t\right) = \text{Cov}\left(u_t, R_t^X\right) + \text{Cov}\left(u_t, R_t^Y\right)$$

Practically, we adopt the Fama and French (1993) three-factor model, use the specification from Equation (16) to estimate $\widehat{\beta}\mathbf{F}_t$ and $\widehat{u}_t$, and then compute the contribution of component X (e.g., the part of return driven by demand for stock characteristics) to systematic and idiosyncratic variance as $\frac{\text{Cov}\left(R_t^X,\ \beta \mathbf{F}_t\right)}{\text{Var}(R_t)}$ and $\frac{\text{Cov}\left(R_t^X, u_t\right)}{\text{Var}(R_t)}$.

Figure 5 report the results across anomaly groups. The key pattern is that the demand for stock characteristics mostly affects systematic variance, while the latent demand mostly generates idiosyncratic variation. Panel (a) shows that the demand for characteristics generates especially strong impact on the systematic variance of value, size and profitability anomalies. By contrast, panel (b) illustrates that much of the variation induced by the latent demand is idiosyncratic with large effects across all the anomalies except the size anomaly. The figure also shows that the flow-induced trading contributes more or less equally to the systematic and idiosyncratic variance across most of the anomaly groups.

[Insert Figure 5 about here]

Figures 6-8 report similar decomposition by investor type.[23] The results on the demand for characteristics in Figure 6 show that the effect of households makes roughly equal contribution to the systemic and idiosyncratic variance, with some differences across anomaly groups. Households' demand for characteristics mostly induces systematic variation in value,

[23] In Figures 6-8, the number at the top of each bar shows the total systematic (see panel (a)) and idiosyncratic (see panel (b)) variance contribution. In line with equation (17), the sum of these systematic and idiosyncratic effects for a given trading motive (e.g., demand for stock characteristics) coincides (up to the portfolio residual return) with the number reported in the respective panel of Figure 3.

size and issuance anomalies; it generates comparable impact on the systematic and idiosyncratic variance for profitability and investment anomalies, and mostly affects idiosyncratic variance for momentum.

The results on the latent demand in Figure 7 show that this component mostly contributes to idiosyncratic variation. This finding again supports the idea that the latent demand can be interpreted as investor sentiment. The effect of latent demand is particularly strong for households contributing 16% to the idiosyncratic variation across anomalies, as opposed to only 4% to the systematic volatility. For comparison, the average contribution of latent demand across anomalies by banks, mutual funds, and investment advisors equals 6% for systematic variance and 12% for idiosyncratic variance.

Figure 8 shows the effects of flow-induced trading. Given our prior results on the importance of investment advisors and mutual funds for the effects of flows, we focus our discussion on these investors. We find that their flow-induced trading mostly affects systematic variance. For example, for value anomaly, the contribution of mutual funds and investment advisors to systematic variation equals 8% and 5%, respectively. By contrast, their contribution to the idiosyncratic component is minor, being equal to only 2% and 1%. We obtain similar results for the profitability anomaly where the contribution to systematic variation equals 5% for mutual funds and 8% for investment advisors, relative to 3% and 3% for the idiosyncratic component.

[Insert Figure 6–8 about here]

3.5 Do Macroeconomic News Drive the Effects of Trading Motives?

We conclude by examining the sources of information which drive the trading motives of different investors. We consider the following macroeconomic variables as potential drivers of investor trading: (1) innovations in industrial production and inflation, the two most common macroeconomic risk factors (Chen et al., 1986); (2) macroeconomic uncertainty index (Jurado et al., 2015)[24]; (3) two subjective cash flow measures (De La O and Myers, 2021); and (4) a measure of 1-year-ahead stock return expectations implied by surveys (Nagel and Xu, 2022).

We estimate the effects of macroeconomic variables on anomaly returns by using pooled regressions of the form:

$$r_{p,t}^{(k)} = a_p + bZ_t + \varepsilon_{p,t},$$

where $r_{p,t}^{k}$ denotes the log return component k of anomaly p, Z_t represents the vector of the candidate explanatory variables, and a_p stands for anomaly fixed effects. For brevity, we focus only on the most important investors (households, mutual funds and investment advisors).

The results in Table 5 show several major patterns. Overall, the macroeconomic variables are uncorrelated with the total anomaly returns, with the subjective dividend growth being the only exception. This result is in line with the prior work which documented low the correlations between asset returns and macroeconomic predictors.

[24] Jurado et al. (2015) examine three different uncertainty indices, but we only include the macroeconomic uncertainty index in our analysis. We do so because the correlations between the indices are high, and we seek to avoid the multicollinearity problem.

[Insert Table 5 about here]

However, our return decomposition reveals much more powerful and consistent correlations between certain macro-variables and decomposed anomaly returns. First, macroeconomic uncertainty is strongly correlated with the effects of the demand for stock characteristics (panel (a)) and the latent demand (panel (b)). The negative coefficient on the returns from the combined demand from characteristics of all investors equals -0.125, and it is entirely driven by the effects of households (-0.123). By contrast, the coefficient on the effects of latent demand equals 0.178, suggesting that macroeconomic uncertainty is positively related to the effect of latent demand. In this case, each investor type matters, albeit the effect of households is again the largest.

Additionally, we find strong correlations of both demand components with subjective expectations of earnings growth. Relative to the effects of uncertainty, the effect of expectation work in the opposite direction. At times of high expectations, the effect of the demand for characteristics boosts the anomaly returns, and this effect is again entirely driven by households. By contrast, the effects of latent demand reduces the variability of anomaly returns through the trading by institutions.

Lastly, our results in panel (c) show that flow-induced trading positively contributes to the anomaly returns at time of high subjective expectations of dividend growth. Consistent with our prior results, the effect of flows only comes from the institutions.

Our exercise leads to several conclusions. First, while the anomaly returns appear to be disconnected from the macroeconomic fundamentals on the surface, decomposition by trading motives and investors reveals a much more nuanced picture. In particular, the impact of macroeconomic information has strong but opposite effects on different components of demand, and these effects cancel each other out at the aggregate level. Second, subjective expectations of fundamentals together with the macroeconomic uncertainty appear to be the most important drivers of the effects of investor demand on anomalies. High uncertainty is associated with stronger sentiment effects and weaker effects of the demand for stock fundamental characteristics. By contrast, the expectations of earnings growth increase the effect of the demand for characteristics but reduce the effects of latent demand.

We note that our results are just a first step toward understanding the effects of macroeconomic information on various drivers of anomaly returns. However, we believe that zooming into the trading motives of different investors provides useful information to calibrate or test theories linking asset returns, macroeconomic information and expectations.

4 Conclusions

We draw two conclusions. First, the demand for stock characteristics and the latent demand are the most important factors in explaining variation in anomaly returns. The narrow set of well-known observed stock characteristics is a good proxy for the features that matter to investors, since it explains as much variation as all the unobserved characteristics combined. These findings favor the theories of anomalies that feature fundamental-based or sentiment-based direct trading, as opposed to mechanical flow-induced trading.

Second, small non-13F investors drive most of the variation in anomaly returns. The effects of direct trading by this group are not only much larger on average, relative to the effects of large institutional investors, but they also remain remarkably persistent despite the increase in holdings by institutions over time. Our results set a new benchmark for theories of anomalies, suggesting that direct trading by small investors should be a key ingredient in such theories.

References

Akbas, Ferhat, Will J Armstrong, Sorin Sorescu, and Avanidhar Subrahmanyam (2015) "Smart money, dumb money, and capital market anomalies," *Journal of Financial Economics*, Vol. 118, No. 2, pp. 355–382.

Baker, Malcolm and Jeffrey Wurgler (2006) "Investor sentiment and the cross-section of stock returns," *The Journal of Finance*, Vol. 61, No. 4, pp. 1645–1680.

Baker, Malcolm, Brendan Bradley, and Jeffrey Wurgler (2011) "Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly," *Financial Analysts Journal*, Vol. 67, No. 1, pp. 40–54.

Balasubramaniam, Vimal, John Y. Campbell, Tarun Ramadorai, and Benjamin Ranish (2023) "Who Owns What? A Factor Model for Direct Stock Holding," *Journal of Finance*.

Bansal, Ravi and Amir Yaron (2004) "Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles," *The Journal of Finance*, Vol. 59, No. 4, pp. 1481–1509.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny (1998) "A model of investor sentiment," *Journal of Financial Economics*, Vol. 49, No. 3, pp. 307–343.

Ben-David, Itzhak, Francesco Franzoni, Rabih Moussawi, and John Sedunov (2021) "The granular nature of large institutional investors," *Management Science*, Vol. 67, No. 11, pp. 6629–6659.

Ben-David, Itzhak, Jiacui Li, Andrea Rossi, and Yang Song (2022) "Ratings-driven demand and systematic price fluctuations," *The Review of Financial Studies*, Vol. 35, No. 6, pp. 2790–2838.

Betermier, Sebastien, Laurent E Calvet, and Paolo Sodini (2017) "Who are the value and growth investors?" *The Journal of Finance*, Vol. 72, No. 1, pp. 5–46.

Buffa, Andrea M., Dimitri Vayanos, and Paul Woolley (2022) "Asset Management Contracts and Equilibrium Prices," *Journal of Political Economy*, Vol. 130, No. 12, pp. 3146–3201.

Chen, Yong, Zhi Da, and Dayong Huang (2019) "Arbitrage trading: The long and the short of it," *The Review of Financial Studies*, Vol. 32, No. 4, pp. 1608–1646.

Chen, Nai-Fu, Richard Roll, and Stephen A Ross (1986) "Economic forces and the stock market," *Journal of business*, pp. 383–403.

Christoffersen, Susan E. K. and Mikhail Simutin (2017) "On the Demand for High-Beta Stocks: Evidence from Mutual Funds," *The Review of Financial Studies*, Vol. 30, No. 8, pp. 2596–2620, 04.

Daniel, Kent and Tobias J Moskowitz (2016) "Momentum crashes," *Journal of Financial Economics*, Vol. 122, No. 2, pp. 221–247.

Daniel, Kent D., David Hirshleifer, and Avanidhar Subrahmanyam (2001) "Overconfidence, Arbitrage, and Equilibrium Asset Pricing," *Journal of Finance*, Vol. 56, No. 3, pp. 921–965, June.

Daniel, Kent, David Hirshleifer, and Lin Sun (2020) "Short- and Long-Horizon Behavioral Factors [Financial intermediaries and the cross-section of asset returns]," *Review of Financial Studies*, Vol. 33, No. 4, pp. 1673–1736.

De La O, Ricardo and Sean Myers (2021) "Subjective cash flow and discount rate expectations," *The Journal of Finance*, Vol. 76, No. 3, pp. 1339–1387.

De Long, J Bradford, Andrei Shleifer, Lawrence H Summers, and Robert J Waldmann (1990) "Noise trader risk in financial markets," *Journal of Political Economy*, Vol. 98, No. 4, pp. 703–738.

Fama, Eugene F. and Kenneth R. French (1993) "Common risk factors in the returns on stocks and bonds," *Journal of Financial Economics*, Vol. 33, No. 1, pp. 3 – 56.

Frazzini, Andrea and Lasse Heje Pedersen (2014) "Betting against beta," *Journal of Financial Economics*, Vol. 111, No. 1, pp. 1–25.

Freyberger, Joachim, Andreas Neuhierl, and Michael Weber (2020) "Dissecting characteristics nonparametrically," *The Review of Financial Studies*, Vol. 33, No. 5, pp. 2326–2377.

Gabaix, Xavier (2012) "Variable Rare Disasters: An Exactly Solved Framework for Ten Puzzles in Macro-Finance," *The Quarterly Journal of Economics*, Vol. 127, No. 2, pp. 645–700.

Gabaix, Xavier and Ralph SJ Koijen (2021) "In search of the origins of financial fluctuations: The inelastic markets hypothesis," *Working Paper*.

Gabaix, Xavier, Ralph S. J. Koijen, Federico Mainardi, Sangmin Oh, and Motohiro Yogo (2022) "Asset Demand of U.S. Households," *Working Paper*.

Hanson, Samuel G and Adi Sunderam (2014) "The growth and limits of arbitrage: Evidence from short interest," *The Review of Financial Studies*, Vol. 27, No. 4, pp. 1238–1286.

Hong, Harrison and Jeremy C Stein (1999) "A unified theory of underreaction, momentum trading, and overreaction in asset markets," *The Journal of Finance*, Vol. 54, No. 6, pp. 2143–2184.

Jacobs, Heiko and Alexander Hillert (2016) "Alphabetic Bias, Investor Recognition, and Trading Behavior," *Review of Finance*, Vol. 20, No. 2, pp. 693–723.

Jegadeesh, Narasimhan and Sheridan Titman (1993) "Returns to buying winners and selling losers: Implications for stock market efficiency," *The Journal of Finance*, Vol. 48, No. 1, pp. 65–91.

Jurado, Kyle, Sydney C Ludvigson, and Serena Ng (2015) "Measuring uncertainty," *American Economic Review*, Vol. 105, No. 3, pp. 1177–1216.

Keloharju, Matti, Juhani T. Linnainmaa, and Peter Nyberg (2021) "Long-term discount rates do not vary across firms," *Journal of Financial Economics*, Vol. 141, No. 3, pp. 946–967.

Kogan, Leonid and Dimitris Papanikolaou (2013) "Firm characteristics and stock returns: The role of investment-specific shocks," *The Review of Financial Studies*, Vol. 26, No. 11, pp. 2718–2759.

Koijen, Ralph SJ and Motohiro Yogo (2019) "A demand system approach to asset pricing," *Journal of Political Economy*, Vol. 127, No. 4, pp. 1475–1515.

Koijen, Ralph SJ, Robert J Richmond, and Motohiro Yogo (2022) "Which investors matter for equity valuations and expected returns?" *Working Paper*.

Kolasinski, Adam C, Adam V Reed, and Matthew C Ringgenberg (2013) "A multiple lender approach to understanding supply and search in the equity lending market," *The Journal of Finance*, Vol. 68, No. 2, pp. 559–595.

LeRoy, Stephen F and Richard D Porter (1981) "The present-value relation: Tests based on implied variance bounds," *Econometrica*, pp. 555–574.

Lettau, Martin and Jessica A Wachter (2007) "Why is long-horizon equity less risky? A duration-based explanation of the value premium," *The Journal of Finance*, Vol. 62, No. 1, pp. 55–92.

Lewellen, Jonathan (2011) "Institutional investors and the limits of arbitrage," *Journal of Financial Economics*, Vol. 102, No. 1, pp. 62–80.

Liu, Laura Xiaolei, Toni M Whited, and Lu Zhang (2009) "Investment-based expected stock returns," *Journal of Political Economy*, Vol. 117, No. 6, pp. 1105–1139.

Lochstoer, Lars A and Paul C Tetlock (2020) "What drives anomaly returns?" *The Journal of Finance*, Vol. 75, No. 3, pp. 1417–1455.

Lou, Dong (2012) "A flow-based explanation for return predictability," *The Review of Financial Studies*, Vol. 25, No. 12, pp. 3457–3489.

Mainardi, Federico (2021) "A Demand-Based Approach for Short-Selling," *Working Paper*.

Nagel, Stefan and Zhengyang Xu (2022) "Asset pricing with fading memory," *The Review of Financial Studies*, Vol. 35, No. 5, pp. 2190–2245.

Shiller, Robert J et al. (1981) "Alternative tests of rational expectations models: The case of the term structure," *Journal of Econometrics*, Vol. 16, No. 1, pp. 71–87.

Shleifer, Andrei and Robert W Vishny (1997) "The limits of arbitrage," *The Journal of finance*, Vol. 52, No. 1, pp. 35–55.

Sloan, Richard G (1996) "Do stock prices fully reflect information in accruals and cash flows about future earnings?" *The Accounting Review*, pp. 289–315.

Wachter, Jessica A. (2013) "Can Time-Varying Risk of Rare Disasters Explain Aggregate Stock Market Volatility?" *The Journal of Finance*, Vol. 68, No. 3, pp. 987–1035.

Tables and Figures

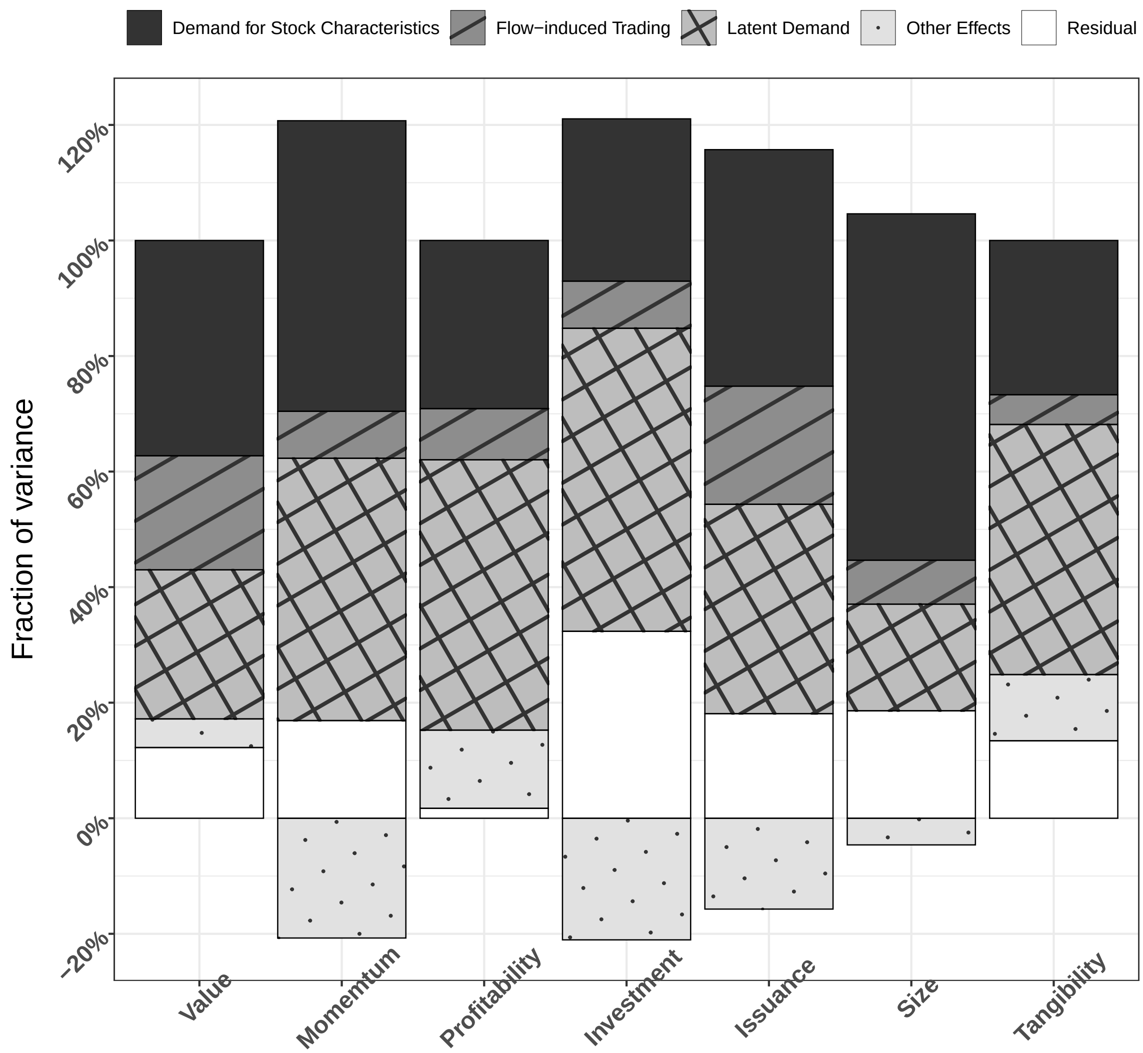
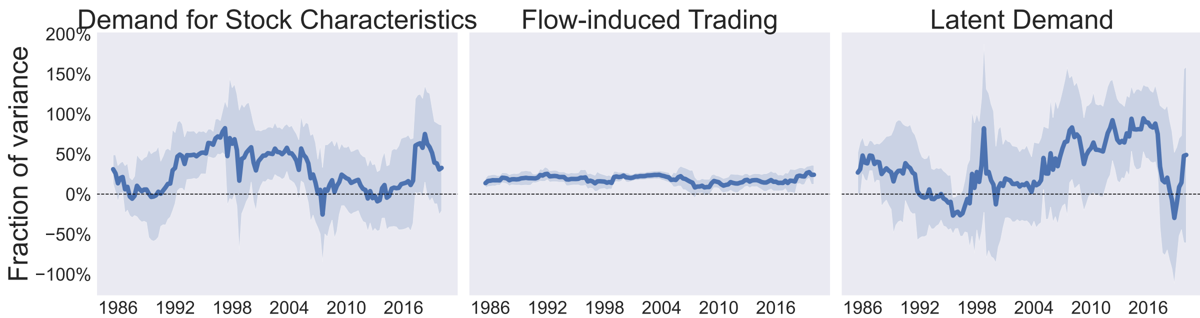
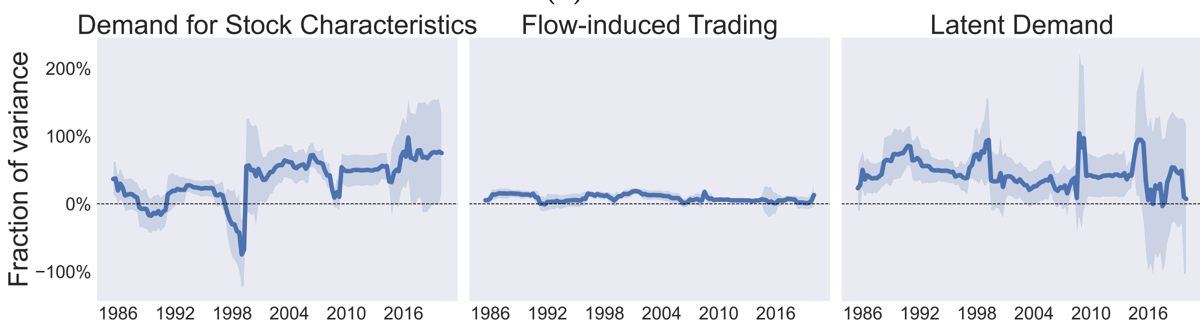


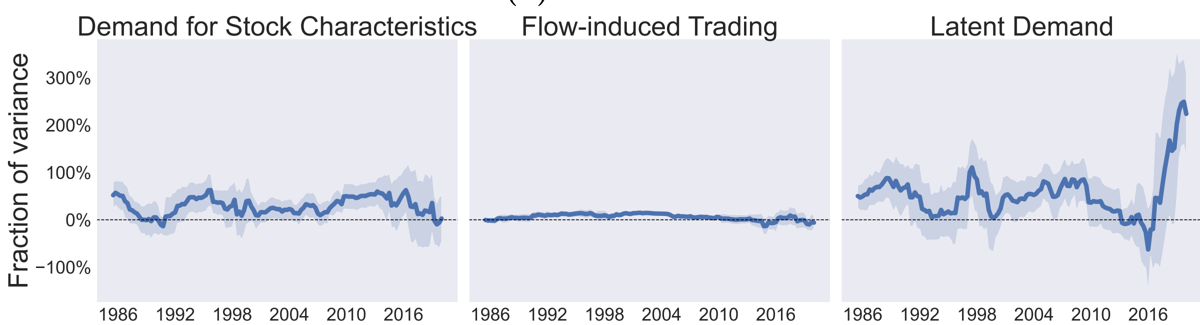
Figure 1: Variance Decomposition: Each bar refers to a given anomaly group. We assign stocks into quintiles, based on a combination of equal-weighted ranked return predictors within the group. Appendix Table A.1 describes which anomalies are included in a given group. The bars show the contribution of demand for stock characteristics, flow-induced trading, and latent demand to return variation. Other Effects include the effect of supply-side components as well as changes in AUM. Residual includes the effect of log transformation and model error. The sample period is 1980 to 2019.



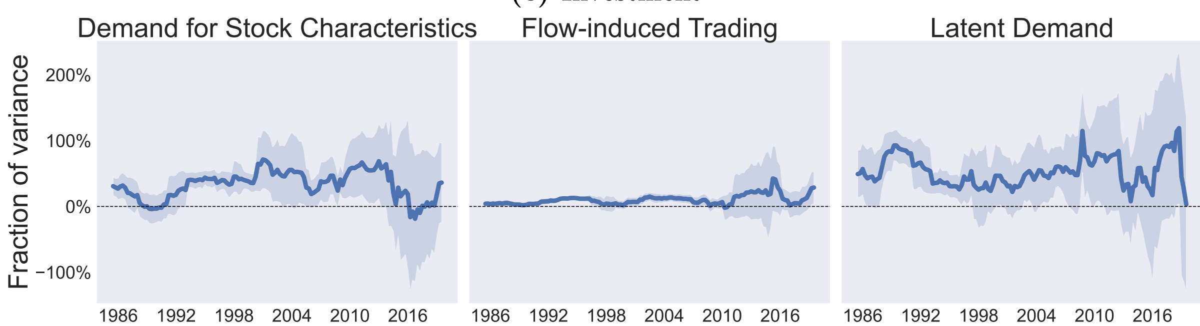
(a) Value



(b) Momentum

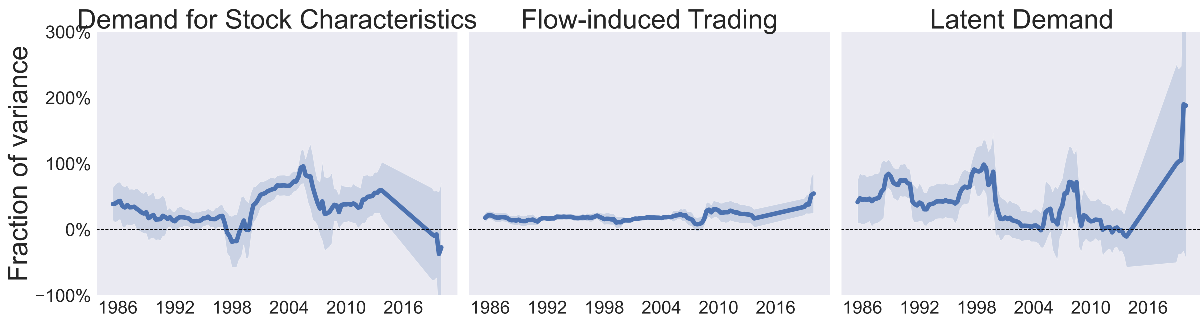


(c) Investment

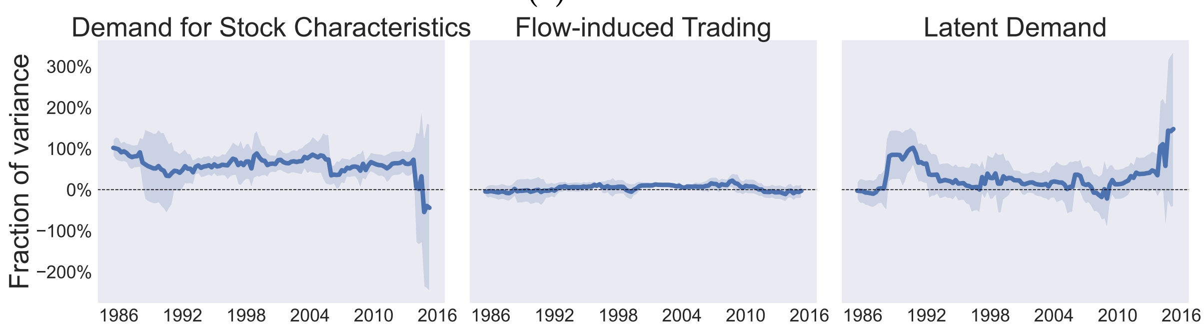


(d) Profitability

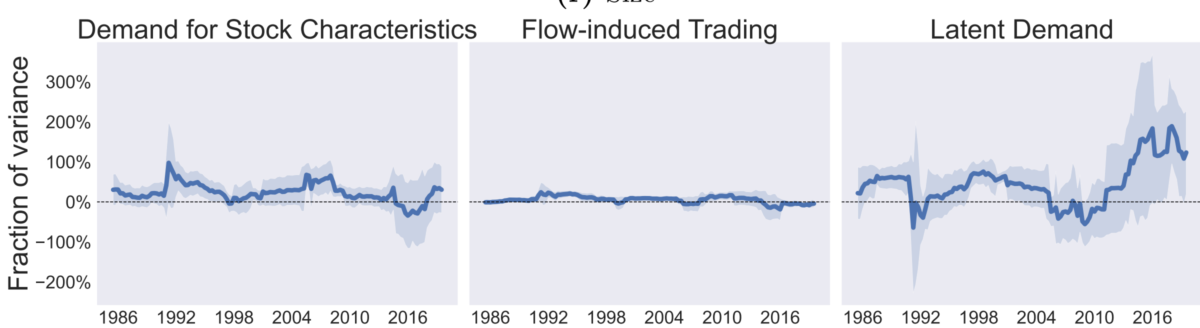
Figure 2: Variance Decomposition Over Time: Each row refers to an anomaly group. From panel (a) to (g), we have value, momentum, investment, profitability, issuance, size, and tangibility. Each column refers to the return induced by a specific component. From left to right, we have the effects of the demand for stock characteristics, flow-induced trading, and latent demand. The sample period is 1980 to 2019.



(e) Issuance

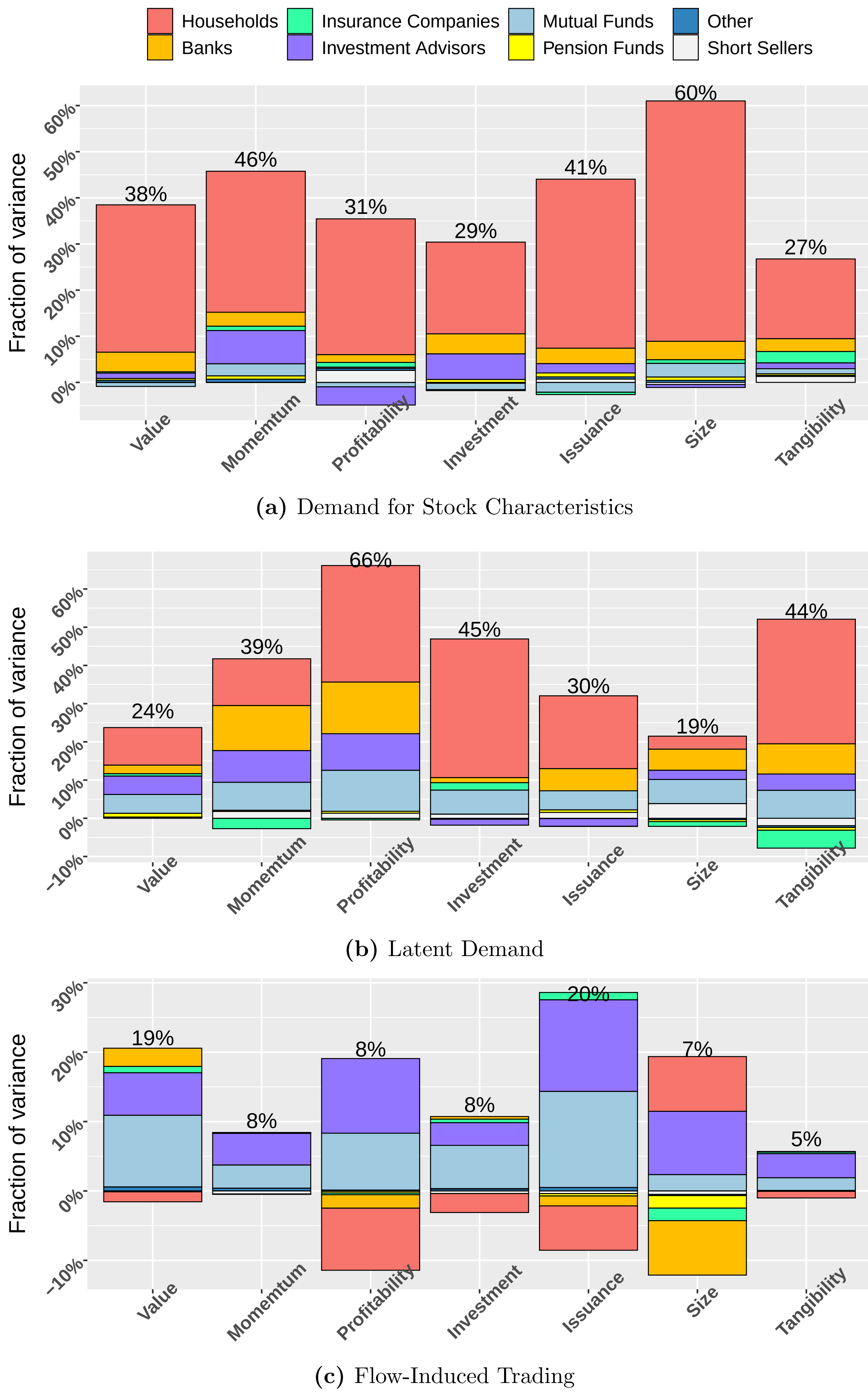


(f) Size



(g) Tangibility

Figure 2: Variance decomposition over time (*continued*)

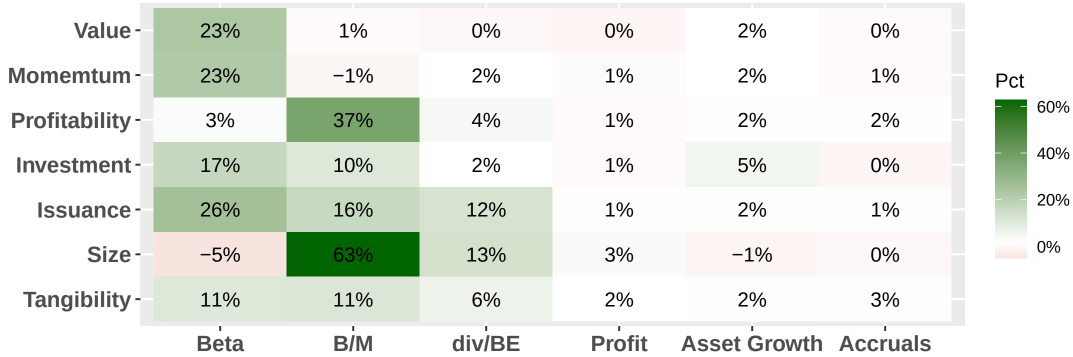


(a) Demand for Stock Characteristics

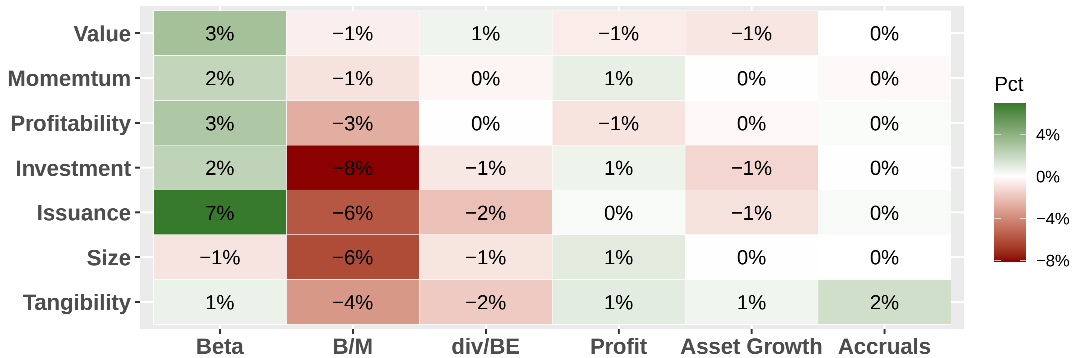
(b) Latent Demand

(c) Flow-Induced Trading

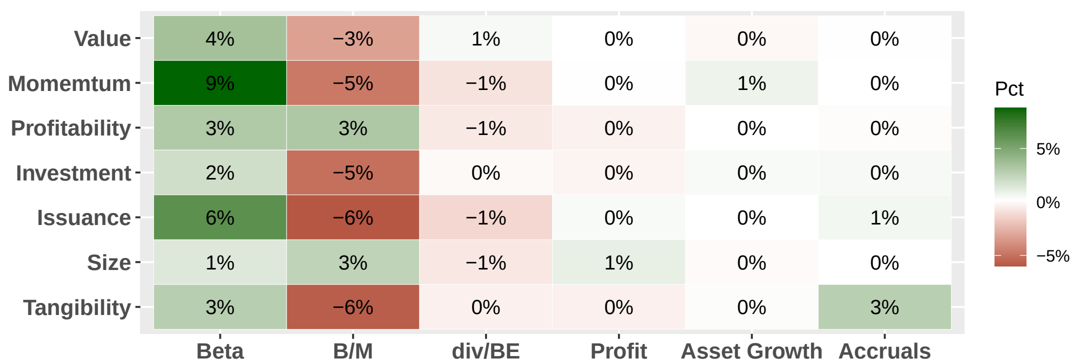
Figure 3: Variance Decomposition by Investor Each bar refers to a given anomaly group. The bars show the contribution of each investor type to the return variation. Panel (a) shows the effects of demand for stock characteristics, panel (b) shows the effects of latent demand, and panel (c) shows the effect of flow-induced trading. The sample period is 1980 to 2019.



(a) Household

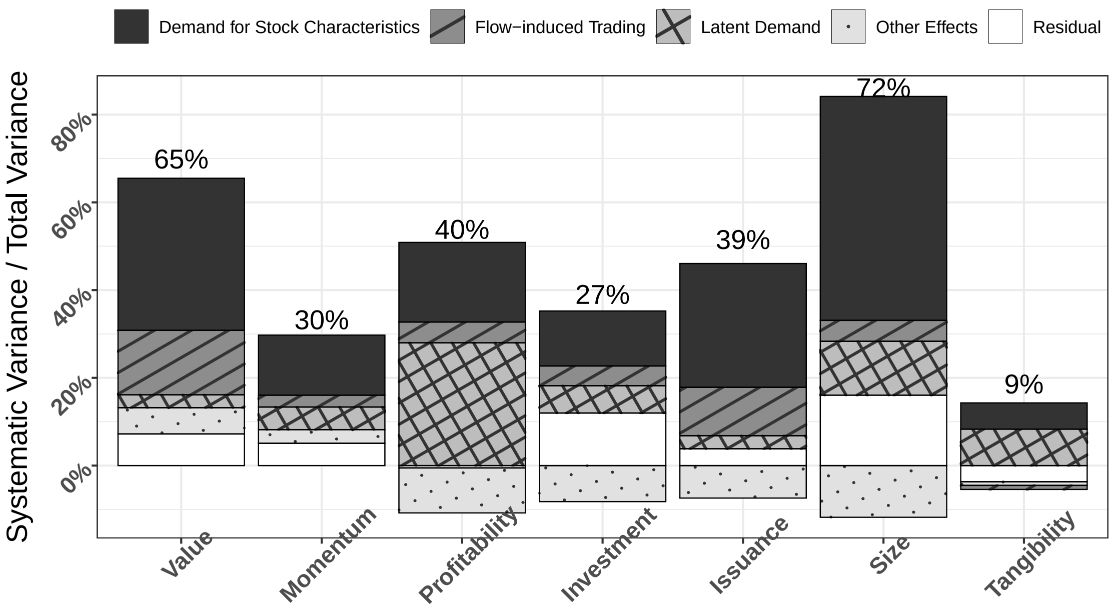


(b) Mutual Funds

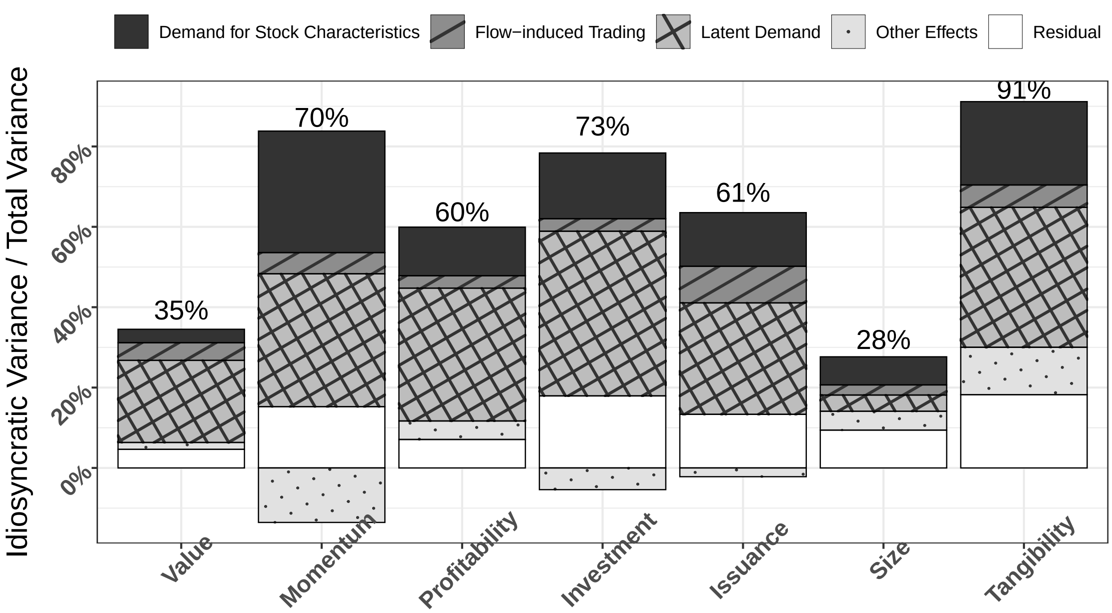


(c) Investment Advisors

Figure 4: Variance Decomposition by Individual Characteristics Each row refers to a given anomaly group. The elements within each row show the contribution of demand for different characteristics to return variation. Panel (a) shows the effects of household demand for stock characteristics, panel (b) shows the effects of mutual funds' demand for stock characteristics, and panel (c) shows the effect of investment advisors' demand for stock characteristics. We report the total effect of log book-to-market equity, instead of log book equity and log market equity separately. The sample period is 1980 to 2019.

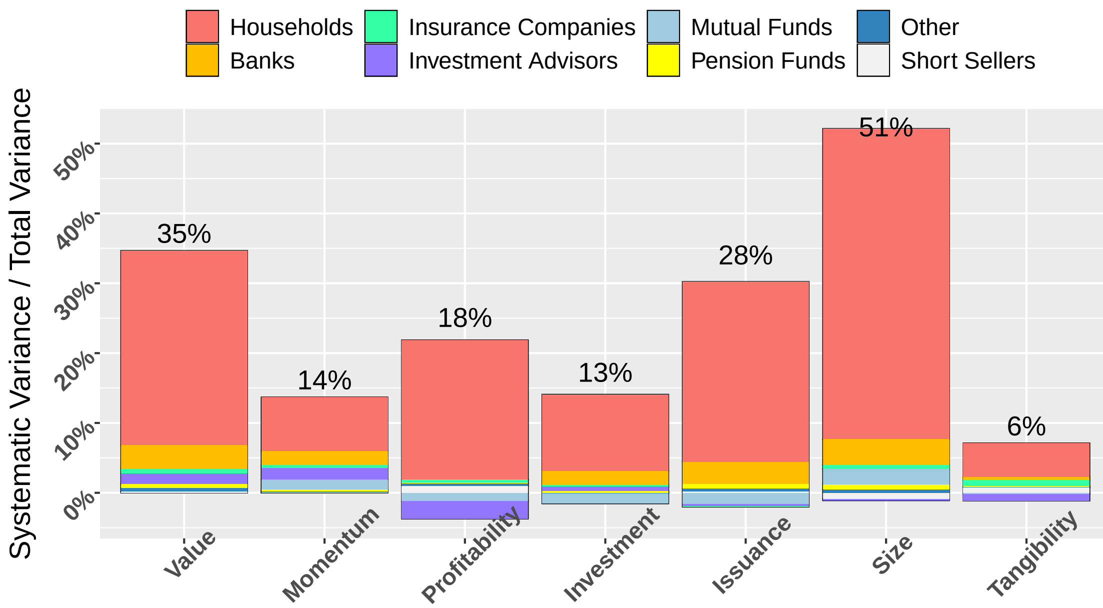


(a) Systematic Variance

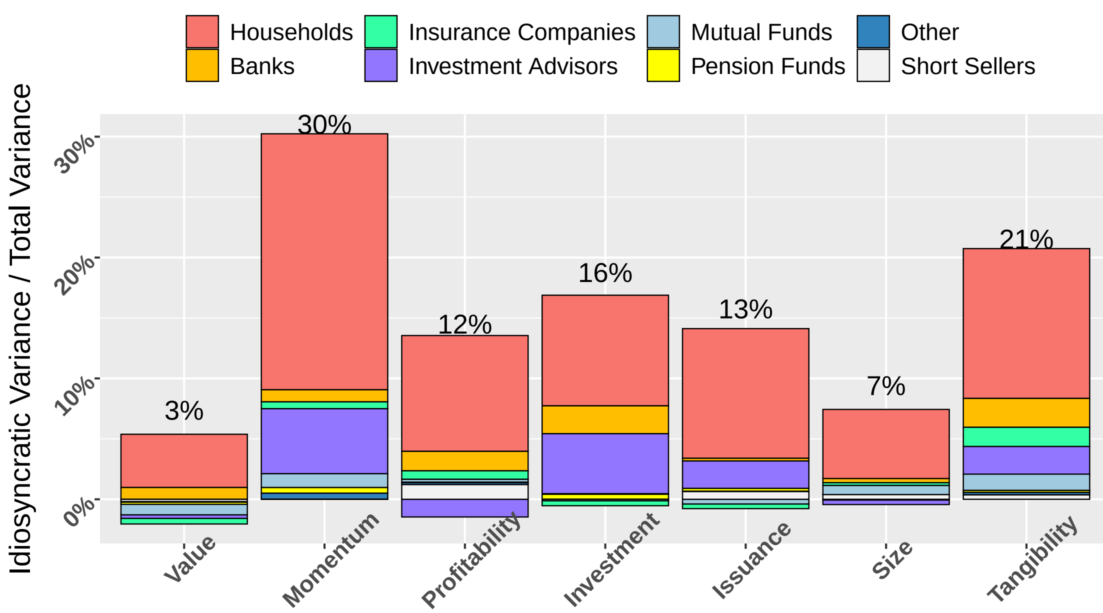


(b) Idiosyncratic Variance

Figure 5: Systematic and Idiosyncratic Variance Decomposition Each bar refers to a given anomaly group. The bars show the contribution of the demand for stock characteristics, flow-induced trading, and latent demand to return variation. Panel (a) shows the decomposition of systematic variance, and panel (b) shows the decomposition of idiosyncratic variance. The sample period is 1980 to 2019.

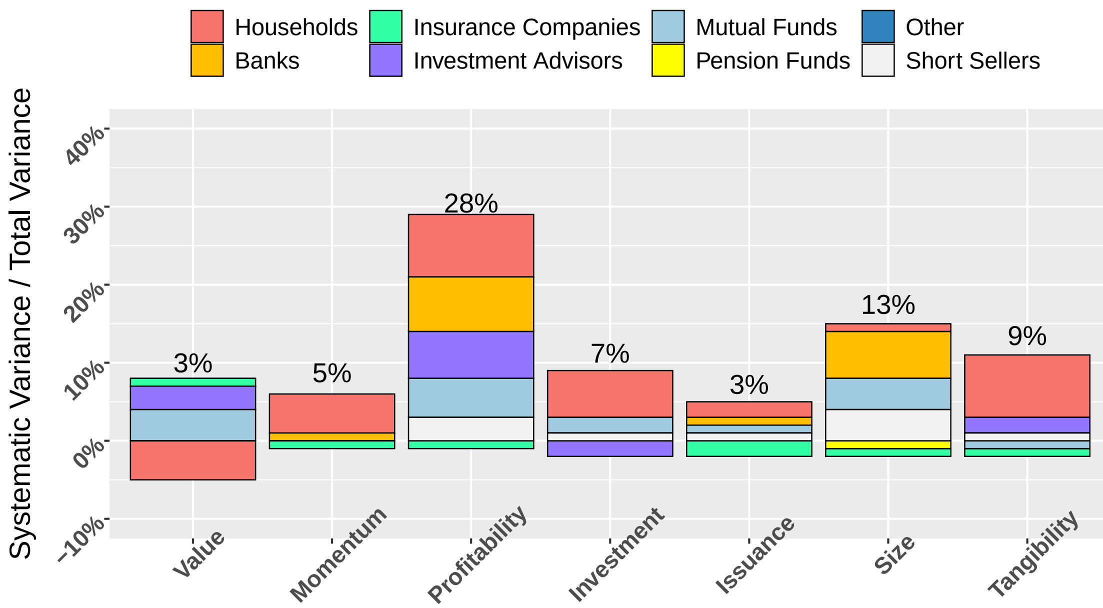


(a) Systematic Variance

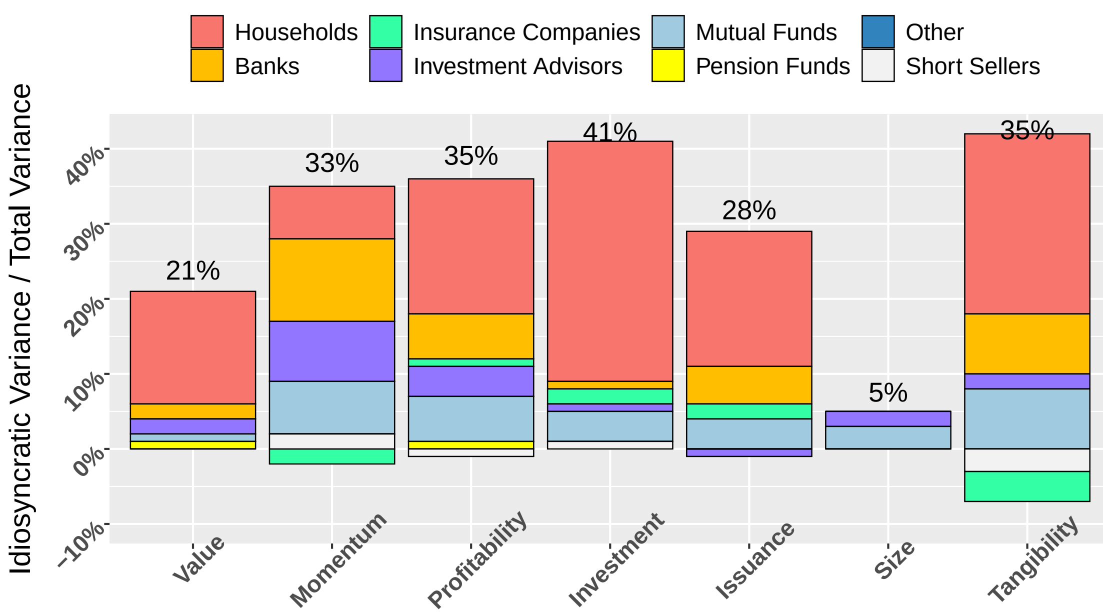


(b) Idiosyncratic Variance

Figure 6: Effects of the Demand for Stock Characteristics on Systematic and Idiosyncratic Variance We decompose the effects of the demand for stock characteristics into its effects on systematic and idiosyncratic variance. Each bar refers to a given anomaly group. The bars show the contribution of each investor type to return variation. Panel (a) shows the decomposition of systematic variance, and panel (b) shows the decomposition of idiosyncratic variance. The sample period is 1980 to 2019.

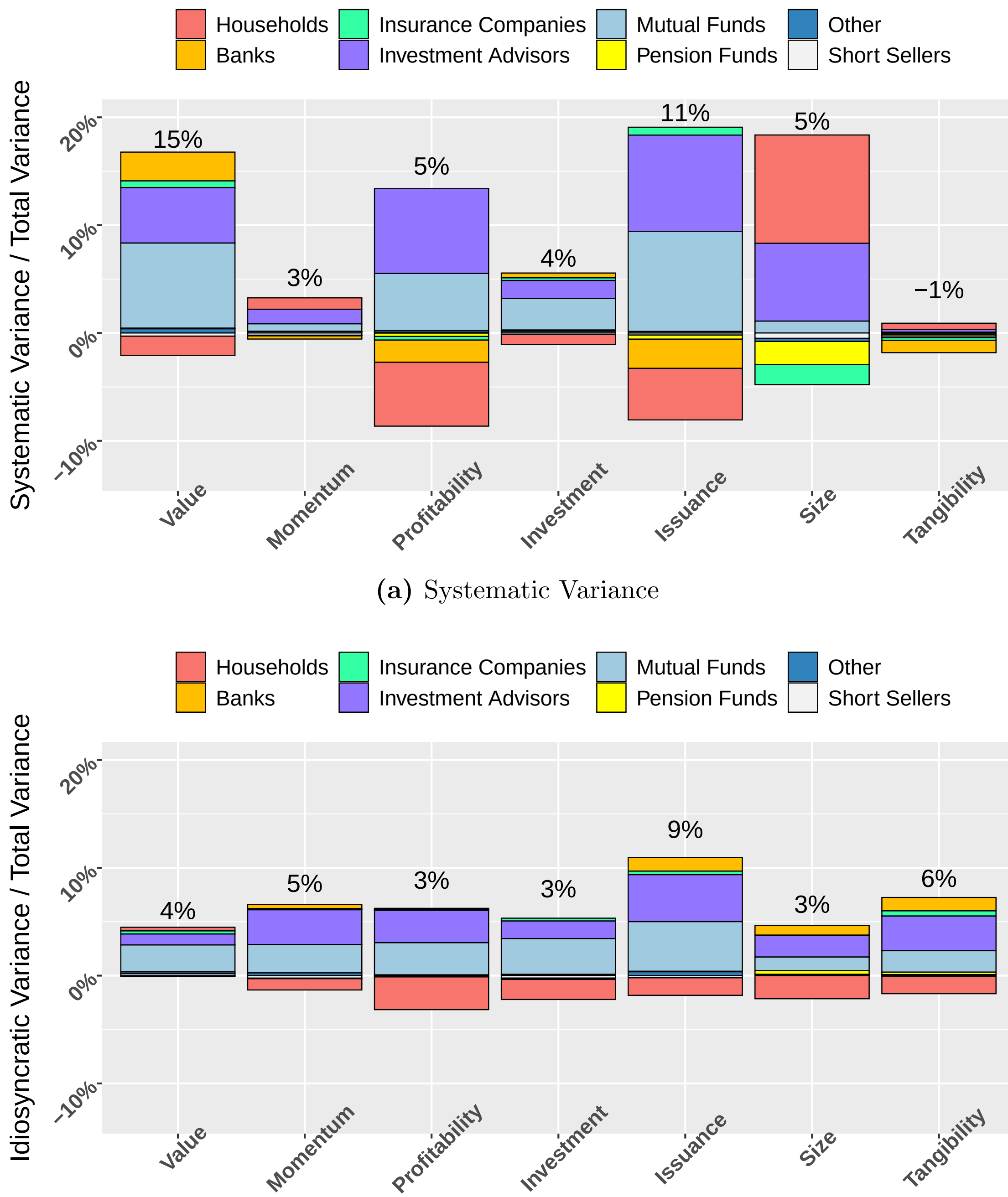


(a) Systematic Variance



(b) Idiosyncratic Variance

Figure 7: Effects of the Latent Demand on Systematic and Idiosyncratic Variance
We decompose the effects of latent demand into its effects on systematic and idiosyncratic variance. The bars show the contribution of each investor type to return variation. Panel (a) shows the decomposition of systematic variance, and panel (b) shows the decomposition of idiosyncratic variance. The sample period is 1980 to 2019.



(a) Systematic Variance

(b) Idiosyncratic Variance

Figure 8: Effects of the Flow-induced Trading on Systematic and Idiosyncratic variance We decompose the effects of flow-induced trading into its effects on systematic and idiosyncratic variance. Each bar refers to a given anomaly group. The bars show the contribution of each investor type to return variation. Panel (a) shows the decomposition of systematic variance, and panel (b) shows the decomposition of idiosyncratic variance. The sample period is 1980 to 2019.

Table 1: Variance Decomposition of Anomaly Returns

This table reports variance decomposition of 46 anomaly portfolios, grouped into 7 categories. Appendix Table A.1 describes which anomalies are included in a given category. We report the decomposition of the time-series variance into the effects of demand for stock characteristics, flow-induced trading, latent demand, residual effects, and other effects. Numbers marked in bold indicate statistical significance at the 5% level.

Anomalies	Demand for Stock Characteristics	Flow-Induced Trading	Latent Demand	Residual Effects	Others
Mean	39%	12%	42%	19%	-11%
A. Value					
Total assets (AT) over market equity (ME)	**34%**	**10%**	**44%**	9%	2%
Book equity (BE) over ME	**38%**	**16%**	**37%**	12%	-3%
Industry-adjusted bm	**35%**	**19%**	28%	8%	10%
Cash+Short-term Investments (CHE) over AT	**43%**	**15%**	**38%**	7%	-3%
Cash flow to total liabilities (LT)	**32%**	**6%**	**62%**	13%	-14%
Log change in the shares outstanding	**45%**	**18%**	**57%**	**23%**	-42%
Debt to Price	**34%**	**11%**	**41%**	13%	2%
Earnings Yield	**31%**	**17%**	**53%**	1%	-1%
Cash flow to BE	**32%**	**20%**	24%	**41%**	-17%
Net payout ratio	**48%**	**20%**	**39%**	**18%**	-25%
Payout ratio	**52%**	**16%**	**32%**	11%	-11%
Tobin's Q	**39%**	**17%**	**32%**	7%	5%
Sales (SALE) to ME	**23%**	**15%**	**61%**	10%	-9%
Sales growth	**39%**	**13%**	**36%**	**28%**	-17%
B. Momentum					
12-months Momentum	**50%**	**8%**	**45%**	**17%**	-21%
C. Profitability					
Net sales over lagged NOA	**32%**	**10%**	**46%**	18%	-7%
SALE over lagged AT	**40%**	**9%**	**48%**	**24%**	-21%
Delta Gross Margin - Delta SALE	**34%**	**5%**	**68%**	-7%	0%
Earnings per share	**58%**	**14%**	**24%**	17%	-13%
Pre-tax income (PI) to SALE	**39%**	**15%**	**32%**	**20%**	-5%
Price-to-cost margin	**38%**	**12%**	**41%**	**33%**	-25%
Profit margin	**43%**	**9%**	**38%**	**22%**	-11%
Industry-adjusted PM	**34%**	**10%**	**62%**	5%	-11%
Gross Profitability	**47%**	**10%**	26%	**29%**	-13%
Return on net operating assets	**31%**	**8%**	**41%**	**53%**	-33%
Return on assets	**43%**	**12%**	**39%**	7%	-1%
(ME+long-term debt -AT)/CHE	**31%**	**16%**	**39%**	17%	-3%
Return on equity	**38%**	**13%**	**43%**	**28%**	-23%
Return on invested capital	**56%**	**7%**	**38%**	**18%**	-19%
Sales to cash	**38%**	**14%**	**49%**	-10%	9%
SALE over AT	**39%**	**6%**	**46%**	**23%**	-14%
Quality minus junk	**47%**	**11%**	14%	**36%**	-8%
D. Investment					
Asset Growth	**50%**	**13%**	**27%**	**21%**	-12%
Change in the book value of equity (CEQ)	19%	**7%**	**69%**	-5%	10%
Change in PP&E over lagged AT	**23%**	**13%**	**63%**	-4%	5%
Change in inventories over average AT	**38%**	**9%**	**52%**	**27%**	-26%
Net operating assets	**41%**	4%	**28%**	**37%**	-11%
E. Issuance					
1-year Horizin CSI excluding dividends	**33%**	**16%**	**68%**	**21%**	-38%
5-year growth in ME - 5-year return	**41%**	**27%**	**33%**	54%	-55%
F. Size					
Total Assets	**49%**	**18%**	15%	18%	0%
Size	**63%**	2%	17%	9%	9%
Industtry-adjusted Size	**42%**	**16%**	**37%**	**38%**	-33%
G. Tangibility					
Absolute value of operation accruals (OA)	**33%**	**6%**	**49%**	17%	-5%
Operating leverage	**27%**	**5%**	**43%**	**28%**	-3%
Sloan's operation accruals	**26%**	**7%**	**54%**	**23%**	-9%

Table 2: The Effects of Demand for Stock Characteristics By Investor

This table reports the decomposition of the effects of demand for stock characteristics by investors. Numbers marked in bold indicate statistical significance at the 5% level.

Anomaly	Households	Mutual Funds	Investment Advisors	Banks	Insurance Companies	Pension Funds	Other	Short Sellers
Mean	28%	2%	3%	4%	1%	1%	0%	0%
A. Value								
Total assets (AT) over market equity (ME)	**17%**	**4%**	**7%**	**5%**	**1%**	1%	**1%**	0%
Book equity (BE) over ME	**23%**	**3%**	**7%**	**4%**	1%	1%	1%	0%
Industry-adjusted bm	**27%**	1%	**6%**	2%	-1%	**1%**	0%	0%
Cash+Short-term Investments (CHE) over AT	**34%**	**3%**	**3%**	**3%**	0%	**1%**	0%	1%
Cash flow to total liabilities (LT)	**15%**	**3%**	**5%**	**5%**	**1%**	0%	0%	0%
Log change in the shares outstanding	**35%**	2%	**4%**	3%	0%	**1%**	0%	-1%
Debt to Price	**17%**	**4%**	**6%**	**6%**	**2%**	1%	1%	**-1%**
Earnings Yield	**19%**	**1%**	**3%**	**5%**	**2%**	0%	1%	0%
Cash flow to BE	**32%**	**-4%**	**-1%**	**4%**	0%	**1%**	0%	-1%
Net payout ratio	**43%**	**0%**	**1%**	**5%**	1%	**1%**	0%	0%
Payout ratio	**45%**	**-1%**	**1%**	**5%**	1%	**1%**	0%	1%
Tobin's Q	**27%**	**0%**	**5%**	**5%**	1%	**1%**	1%	0%
Sales (SALE) to ME	10%	**3%**	**5%**	**5%**	1%	1%	0%	-1%
Sales growth	**29%**	**0%**	**2%**	**6%**	1%	**1%**	0%	1%
B. Momentum								
12-months Momentum	**31%**	**3%**	**7%**	**3%**	**1%**	**1%**	**1%**	0%
C. Profitability								
Net sales over lagged NOA	**27%**	0%	**2%**	3%	**2%**	0%	0%	-1%
SALE over lagged AT	**30%**	**1%**	**3%**	**3%**	**2%**	0%	0%	0%
Delta Gross Margin - Delta SALE	**19%**	**3%**	**6%**	**3%**	**1%**	0%	**1%**	2%
Earnings per share	**49%**	**1%**	**2%**	**5%**	**1%**	**1%**	**1%**	-1%
Pre-tax income (PI) to SALE	**32%**	**0%**	**1%**	**6%**	**1%**	0%	**1%**	-2%
Price-to-cost margin	**21%**	**4%**	5%	**7%**	0%	1%	0%	0%
Profit margin	**33%**	**3%**	**1%**	**4%**	**2%**	**1%**	0%	0%
Industry-adjusted PM	**24%**	**1%**	3%	**4%**	1%	0%	0%	0%
Gross Profitability	**34%**	3%	5%	3%	1%	1%	0%	0%
Return on net operating assets	**18%**	**3%**	**4%**	**7%**	1%	1%	0%	-2%
Return on assets	**26%**	**3%**	**4%**	**8%**	**2%**	**1%**	1%	0%
(ME+long-term debt -AT)/CHE	**20%**	**2%**	4%	**4%**	1%	1%	0%	0%
Return on equity	**23%**	**2%**	**3%**	**8%**	**1%**	1%	1%	0%
Return on invested capital	**30%**	**7%**	**7%**	**7%**	**2%**	**1%**	**1%**	0%
Sales to cash	**28%**	**3%**	**3%**	**3%**	0%	**1%**	0%	1%
SALE over AT	**26%**	**3%**	**4%**	**3%**	**1%**	0%	0%	0%
Quality minus junk	**25%**	**5%**	**7%**	**7%**	1%	1%	**1%**	-1%
D. Investment								
Asset Growth	**37%**	**1%**	**5%**	**6%**	**1%**	0%	0%	1%
Change in the book value of equity (CEQ)	12%	1%	4%	1%	0%	0%	0%	0%
Change in PP&E over lagged AT	**20%**	**-1%**	0%	**4%**	0%	1%	1%	0%
Change in inventories over average AT	**24%**	**3%**	**6%**	**4%**	1%	**1%**	0%	-1%
Net operating assets	**30%**	**3%**	**2%**	**5%**	0%	**1%**	0%	-1%
E. Issuance								
1-year Horizin CSI excluding dividends	**25%**	1%	**4%**	2%	0%	**1%**	**0%**	-1%
5-year growth in ME - 5-year return	**47%**	**-6%**	**0%**	**3%**	-1%	**1%**	0%	-1%
F. Size								
Total Assets	**47%**	**-2%**	**-2%**	**4%**	**1%**	**1%**	**0%**	-1%
Size	**56%**	2%	0%	2%	1%	0%	**0%**	0%
Industtry-adjusted Size	**32%**	**5%**	2%	**4%**	0%	0%	0%	-1%
G. Tangibility								
Absolute value of operation accruals (OA)	**24%**	**-1%**	-1%	**5%**	2%	0%	0%	2%
Operating leverage	**18%**	**2%**	**3%**	**3%**	1%	0%	**0%**	0%
Sloan's operation accruals	**16%**	**-1%**	3%	**5%**	2%	0%	0%	1%

Table 3: The Effects of Demand for Latent Demand By Investor

This table reports the decomposition of the effects of latent demand by investors. Numbers marked in bold indicate statistical significance at the 5% level.

Anomaly	Households	Mutual Funds	Investment Advisors	Banks	Insurance Companies	Pension Funds	Other	Short Sellers
Mean	22%	6%	2%	6%	0%	0%	0%	1%
A. Value								
Total assets (AT) over market equity (ME)	**22%**	**7%**	4%	**7%**	**0%**	1%	0%	0%
Book equity (BE) over ME	18%	4%	6%	5%	2%	1%	0%	2%
Industry-adjusted bm	11%	**3%**	1%	**7%**	3%	0%	0%	1%
Cash+Short-term Investments (CHE) over AT	**21%**	**4%**	**6%**	**6%**	**1%**	**1%**	**1%**	-1%
Cash flow to total liabilities (LT)	**34%**	**7%**	5%	4%	**1%**	1%	0%	0%
Log change in the shares outstanding	**21%**	**6%**	1%	**14%**	2%	1%	0%	4%
Debt to Price	16%	**9%**	**5%**	**6%**	**0%**	**1%**	0%	0%
Earnings Yield	**17%**	**12%**	**11%**	**7%**	**0%**	1%	0%	**1%**
Cash flow to BE	**29%**	3%	-15%	4%	0%	0%	0%	3%
Net payout ratio	**20%**	**6%**	0%	0%	**1%**	0%	0%	1%
Payout ratio	9%	**10%**	1%	2%	**2%**	1%	0%	1%
Tobin's Q	7%	6%	7%	7%	2%	0%	0%	**3%**
Sales (SALE) to ME	**18%**	**13%**	**14%**	**10%**	**2%**	1%	-1%	2%
Sales growth	20%	2%	**8%**	**3%**	-3%	0%	1%	0%
B. Momentum								
12-months Momentum	12%	**7%**	**8%**	**12%**	**-3%**	0%	0%	2%
C. Profitability								
Net sales over lagged NOA	19%	**8%**	**6%**	**12%**	**-1%**	**1%**	0%	-1%
SALE over lagged AT	**27%**	3%	4%	3%	-1%	0%	0%	-1%
Delta Gross Margin - Delta SALE	**48%**	**7%**	**8%**	**11%**	**1%**	**1%**	0%	1%
Earnings per share	**20%**	0%	-3%	3%	0%	0%	0%	**4%**
Pre-tax income (PI) to SALE	**27%**	6%	-8%	5%	3%	0%	0%	4%
Price-to-cost margin	10%	**7%**	**10%**	**10%**	**-3%**	**1%**	0%	2%
Profit margin	**24%**	5%	1%	3%	2%	0%	0%	4%
Industry-adjusted PM	**22%**	**14%**	**11%**	**11%**	**1%**	**1%**	0%	1%
Gross Profitability	24%	-3%	-4%	2%	2%	0%	**1%**	0%
Return on net operating assets	7%	**8%**	**0%**	7%	**4%**	1%	1%	0%
Return on assets	**39%**	**8%**	-14%	6%	**1%**	0%	0%	5%
(ME+long-term debt -AT)/CHE	9%	**6%**	**7%**	**10%**	**-1%**	1%	1%	0%
Return on equity	**39%**	4%	-7%	2%	3%	0%	-1%	**5%**
Return on invested capital	**30%**	2%	-9%	0%	1%	0%	0%	2%
Sales to cash	55%	**5%**	**6%**	**6%**	**3%**	**1%**	1%	-2%
SALE over AT	**26%**	4%	4%	3%	1%	0%	0%	-1%
Quality minus junk	**21%**	-1%	**-14%**	**4%**	1%	0%	-1%	3%
D. Investment								
Asset Growth	16%	3%	**5%**	**2%**	-3%	0%	0%	0%
Change in the book value of equity (CEQ)	**28%**	**11%**	**12%**	**7%**	**0%**	1%	0%	1%
Change in PP&E over lagged AT	65%	1%	**11%**	**1%**	-4%	0%	-1%	0%
Change in inventories over average AT	18%	**3%**	**13%**	**10%**	1%	1%	0%	1%
Net operating assets	**22%**	1%	1%	6%	1%	0%	1%	0%
E. Issuance								
1-year Horizin CSI excluding dividends	**21%**	**10%**	**1%**	**18%**	**3%**	**1%**	0%	4%
5-year growth in ME - 5-year return	**21%**	2%	-28%	3%	-1%	1%	0%	1%
F. Size								
Total Assets	6%	**7%**	0%	4%	**-2%**	0%	0%	2%
Size	3%	**6%**	3%	5%	**0%**	-1%	0%	2%
Industtry-adjusted Size	14%	6%	3%	8%	-1%	0%	0%	6%
G. Tangibility								
Absolute value of operation accruals (OA)	**29%**	**10%**	8%	**10%**	**-2%**	1%	0%	0%
Operating leverage	**22%**	**5%**	**5%**	**6%**	**2%**	**1%**	1%	-1%
Sloan's operation accruals	17%	**11%**	**11%**	**15%**	**-1%**	0%	0%	0%

Table 4: The Effects of Flow-Induced Trading By Investor

This table reports the decomposition of the effects of flow-induced trading by investors. Numbers marked in bold indicate statistical significance at the 5% level.

Anomaly	Households	Mutual Funds	Investment Advisors	Banks	Insurance Companies	Pension Funds	Other	Short Sellers
Mean	-2%	6%	7%	0%	0%	0%	0%	0%
A. Value								
Total assets (AT) over market equity (ME)	1%	**4%**	**4%**	**1%**	**0%**	**0%**	**0%**	0%
Book equity (BE) over ME	**-4%**	**7%**	**6%**	**4%**	**1%**	**0%**	**1%**	0%
Industry-adjusted bm	-3%	**9%**	**6%**	**4%**	**1%**	0%	**1%**	0%
Cash+Short-term Investments (CHE) over AT	0%	**7%**	**5%**	**2%**	**0%**	0%	**0%**	**0%**
Cash flow to total liabilities (LT)	1%	**2%**	**4%**	**-1%**	**0%**	0%	0%	-1%
Log change in the shares outstanding	-2%	**9%**	**11%**	**0%**	**0%**	**0%**	**1%**	-1%
Debt to Price	2%	**3%**	**4%**	**1%**	**0%**	**0%**	**0%**	0%
Earnings Yield	-2%	**9%**	**6%**	**2%**	**1%**	**0%**	**1%**	0%
Cash flow to BE	**-8%**	**14%**	**15%**	**-2%**	**1%**	0%	**0%**	0%
Net payout ratio	-4%	**13%**	**11%**	**-1%**	**1%**	**0%**	**0%**	0%
Payout ratio	-1%	**11%**	**9%**	**-2%**	**0%**	**-1%**	0%	0%
Tobin's Q	**-5%**	**9%**	**7%**	**3%**	**1%**	**0%**	**1%**	0%
Sales (SALE) to ME	-4%	**8%**	**8%**	**1%**	**0%**	**0%**	**1%**	0%
Sales growth	0%	**7%**	**5%**	**0%**	**1%**	0%	0%	0%
B. Momentum								
12-months Momentum	0%	**3%**	5%	**0%**	0%	0%	**0%**	0%
C. Profitability								
Net sales over lagged NOA	**-5%**	**6%**	**4%**	**3%**	**0%**	**1%**	**0%**	0%
SALE over lagged AT	-2%	**5%**	**3%**	**1%**	**1%**	0%	**0%**	0%
Delta Gross Margin - Delta SALE	2%	**1%**	2%	**0%**	0%	0%	0%	0%
Earnings per share	-5%	**9%**	**13%**	**-3%**	**0%**	**-1%**	0%	-1%
Pre-tax income (PI) to SALE	-8%	**9%**	**16%**	**-1%**	**0%**	0%	**1%**	-1%
Price-to-cost margin	0%	**5%**	**6%**	**0%**	**0%**	0%	**0%**	-1%
Profit margin	**-9%**	**8%**	**11%**	**-2%**	**0%**	0%	**0%**	0%
Industry-adjusted PM	0%	**5%**	**5%**	**0%**	**0%**	0%	**0%**	0%
Gross Profitability	**-5%**	**5%**	**5%**	**3%**	**0%**	0%	0%	0%
Return on net operating assets	1%	**3%**	**3%**	**0%**	**0%**	0%	0%	0%
Return on assets	-6%	**7%**	**12%**	**-1%**	**0%**	0%	**1%**	-1%
(ME+long-term debt -AT)/CHE	2%	**6%**	**4%**	**4%**	**0%**	0%	**0%**	**0%**
Return on equity	**-11%**	**10%**	**13%**	**1%**	**0%**	0%	**1%**	-1%
Return on invested capital	-2%	**3%**	**7%**	**-1%**	**0%**	0%	**0%**	-1%
Sales to cash	**5%**	**5%**	**4%**	**0%**	**0%**	0%	0%	0%
SALE over AT	-1%	**3%**	**2%**	**1%**	**1%**	0%	0%	0%
Quality minus junk	**-6%**	**6%**	**12%**	**-2%**	**0%**	0%	0%	-1%
D. Investment								
Asset Growth	3%	**5%**	**4%**	**0%**	**1%**	0%	**0%**	0%
Change in the book value of equity (CEQ)	-1%	**5%**	**3%**	**0%**	**0%**	0%	0%	0%
Change in PP&E over lagged AT	-6%	**8%**	**8%**	**1%**	**1%**	0%	**0%**	0%
Change in inventories over average AT	**-5%**	**7%**	**5%**	**1%**	**1%**	0%	**0%**	0%
Net operating assets	2%	**5%**	**4%**	**-5%**	**0%**	**-1%**	0%	0%
E. Issuance								
1-year Horizin CSI excluding dividends	0%	**7%**	**10%**	**0%**	**0%**	**0%**	**1%**	-1%
5-year growth in ME - 5-year return	-6%	**17%**	**15%**	**-1%**	**2%**	0%	0%	0%
F. Size								
Total Assets	2%	**11%**	**15%**	**-7%**	**-1%**	**-2%**	0%	0%
Size	**10%**	**-1%**	**3%**	**-6%**	**-1%**	**-2%**	0%	0%
Industtry-adjusted Size	-1%	**7%**	**14%**	**-4%**	**-1%**	-1%	**0%**	0%
G. Tangibility								
Absolute value of operation accruals (OA)	0%	**4%**	**5%**	**-1%**	**0%**	**0%**	0%	0%
Operating leverage	0%	2%	1%	0%	0%	0%	0%	0%
Sloan's operation accruals	-1%	**4%**	**3%**	**0%**	**0%**	0%	0%	0%

Table 5: Macro News and Trading Motives

This table reports the estimates from the pooled regression with the anomaly fixed effects. Numbers marked in bold indicate statistical significance at the 5% level.

	Industrial Production	Inflation	Stock Return Expectations	Macro Uncertainty	Subjective Dividend Growth	Subjective Eearnings Growth
Total Return	0.054	-0.380	-0.059	-0.002	**0.040**	0.005
A. Demand For Stock Characteristics						
Households	-0.094	-0.376	-0.097	**-0.123**	0.017	**0.023**
Investment Advisors	**0.061**	-0.081	0.022	0.007	0.002	0.003
Mutual Funds	-0.004	-0.089	0.014	-0.005	0.005	0.002
Total Investor	-0.020	-0.876	-0.001	**-0.125**	0.015	**0.029**
B. Latend Demand						
Households	0.141	-0.795	0.052	**0.077**	0.024	-0.009
Investment Advisors	0.030	-0.169	**-0.134**	**0.048**	-0.015	**-0.014**
Mutual Funds	0.018	**0.423**	-0.031	**0.029**	-0.004	**-0.007**
Total Investor	**0.226**	0.414	-0.233	**0.178**	0.014	**-0.027**
C. Flow-Induced Trading						
Households	-0.011	-0.028	0.019	0.004	0.003	-0.002
Investment Advisors	0.012	-0.159	-0.005	-0.002	**0.012**	0.001
Mutual Funds	0.001	0.010	0.019	-0.002	**0.010**	**0.004**
Total Investor	-0.026	-0.216	0.027	0.006	**0.023**	0.002

Online Appendix

A Anomaly Groups Definition

Table A.1: Firm characteristics by category

Momemtum:		**Profitability:**	
mom12	Return from 12 to 2 months before prediction	aturnover_soliman	Sales to lagged net operating assets
		CTO	Sales to lagged total assets
Investment:		d_dgm_dsales	Δ(Δ%GM and Δ% Sales)
agrowth	% change in AT	EPS	Earnings per share
d_ceq	% change in BE	IPM	Pretax income over sales
investment_K	Change in PP&E and inventory over lagged AT	PCM	Sales minus costs of goods sold to sales
IVC	Change in inventory over average AT	PM	OI after depreciation over sales
noa_w	Net-operating assets over lagged AT	PM_adj	Industry-adjusted Profit margin
		prof_W	Gross profitability over BE
Intangibles:		RNA	OI after depreciation to lagged NOA
AOA	Absolute value of operating accruals	roaa_W	IB to lagged AT
OL	Costs of goods solds + SG&A to total assets	ROC	Return on Cash
TAN	Tangibility	roea_W	IB to lagged BE
OA	Operating accruals	ROIC	Return on invested capital
		S2C	Sales to cash
Value:		SAT	Sales to total assets
A2ME	Total assets to Size		
bm	Book to market ratio	**Size:**	
bm_adj	Industry-adjusted BEME	AT	Total assets
C	Cash to AT	LME	Price times shares outstanding
C2D	Cash flow to total liabilities	LME_adj	Industry-adjusted Size
nissa_FF	Log change in split-adjusted shares outstanding		
Debt2P	Total debt to Size	**Issuance:**	
ep_FF	Income before extraordinary items to Size	NSI_comp	CISS
FCF	Free cash flow to BE	CSI_DHS	5-year composite-share-issuance
NOP	Net payouts to Size		
O2P	Operating payouts to market cap	**Quality:**	
Q_junME	Tobin's Q	QMJ	Quality-minus-Junk
sp	Sales to price		
Sales_g	Sales growth		

B Technical Details about the Decomposition

B.1 The "residual" component

Our approach generates a gap between the sum of decomposed portfolio return $\sum_k r_{t+1}^{(k)}$ and the realized portfolio return r_{t+1}. This gap, which we call the "residual", is caused by two effects.

First, there is model error since the market clearing condition is not imposed when estimating investors' demand function. If there are I investors, and the demand functions for $I-1$ investors have already been estimated, then the market clearing condition implies that the demand for the last investor is already determined. However, their demand may not follow the functional form assumed in Equation (3). At the stock-level, this model-induced error is labeled as $\psi_{\mathbf{t+1}}$ in Equation (5).[25]

Second, at the stock-level, the log stock return is a linear combination of the decomposed log returns (see Equation (5)). However, this does not hold at the portfolio level due to the effect of log-transformation:

$$r_{t+1} = log(1 + \sum_i w_{i,t}(e^{r_{i,t}} - 1)) \neq \sum_{k \in \left\{s,x,A_{t+1}^{CF},A_{t+1},\beta,\epsilon,v\right\}} \log(1 + R_{t+1}^{(k)}) \tag{B.1}$$

where $r_{i,t+1}$ is the total log return for stock i at time $t+1$ and $R_{t+1}^{(k)}$ has been defined in Equation (11). In our analysis, we bundle the effects of model error and log-transformation into the "residual" component of log returns u_{t+1}.

[25] Koijen and Yogo (2019) call this effect intensive latent demand, and contrast it to the effect of extensive demand ($\Delta p_{t+1}(\epsilon)$, in our notation).

B.2 Construction of Random Portfolios

We describe the procedure to generate random portfolios. We use the CRSP MSENAMES file, which allows for time-varying names, and we transform the company name to lower cases. We then create a mapping from $[a - z] + [0 - 9]$ to $[0 - 25] + [26 - 35]$. E.g., Apple is converted to $[0, 15, 15, 11, 4]$. We then reshuffle this mapping by sampling numbers from $[0 - 35]$ without replacement. E.g., the reshuffled mapping could be such that $[0, 15, 15, 11, 4]$ is mapped into "zywwx", which is the new name for Apple. We then rank the firms based on their new names. Finally, each June, we use NYSE breakpoints calculated on the new name rankings to create the quantile portfolios.

We prefer using this reshuffled mapping compared to a simple A-Z sorts because Jacobs and Hillert (2016) show that the U.S. stocks that appear near the top of an alphabetical listing have about 5–15% higher trading activity and liquidity than stocks that appear toward the bottom. In other words, investors may have some preference for those stocks.

B.3 Decomposition into Subcomponents

Table B.1 shows that, averaging across anomalies, the difference between the effect in Figure 1 and the same effect obtained by summing across investors in Figure 3 is 0.2%, 0.6%, and 0.2%, for demand for stock characteristics, flow-induced trading, and latent demand, respectively.

Table B.1: Difference between a given effect and the aggregated subcomponents

This table compares the effect in Figure 1 with the same effect obtained by summing across investors in 3a.

	Demand for Stock Characteristics		Flow-induced Trading		Latent Demand	
	Figure 1	Figure 3	Figure 1	Figure 3	Figure 1	Figure 3
Value	37%	38%	20%	19%	26%	24%
Momemtum	50%	46%	8%	8%	45%	39%
Profitability	29%	31%	9%	8%	47%	66%
Investment	28%	29%	8%	8%	52%	45%
Issuance	41%	41%	20%	20%	36%	30%
Size	60%	60%	8%	7%	18%	19%
Tangibility	27%	27%	5%	5%	43%	44%

Table B.2 shows that the effect of decomposing variance across investors is even smaller in the case of systematic and idiosyncratic variance.

Table B.2: Differences between Figure 5 and Figure 6-8

This table compares the systematic (and idiosyncratic) variance in Figure 5 with the same effect obtained by summing across investors.

	Demand for Stock Characteristics		Flow-induced Trading		Latent Demand	
	Figure 5	Figure 6	Figure 5	Figure 7	Figure 5	Figure 8
Value	35%	35%	15%	15%	3%	3%
Momentum	14%	14%	3%	3%	5%	5%
Profitability	18%	18%	5%	5%	28%	28%
Investment	13%	13%	4%	4%	6%	7%
Issuance	28%	28%	11%	11%	3%	3%
Size	51%	51%	5%	5%	12%	13%
Tangibility	6%	6%	-1%	-1%	8%	9%

(a) Systematic Variance

	Demand for Stock Characteristics		Flow-induced Trading		Latent Demand	
	Figure 5	Figure 6	Figure 5	Figure 7	Figure 5	Figure 8
Value	3%	3%	4%	4%	20%	21%
Momentum	30%	30%	5%	5%	33%	33%
Profitability	12%	12%	3%	3%	33%	35%
Investment	16%	16%	3%	3%	41%	41%
Issuance	13%	13%	9%	9%	28%	28%
Size	7%	7%	3%	3%	4%	5%
Tangibility	21%	21%	6%	6%	35%	35%

(b) Idiosyncratic Variance

C Additional Evidence

C.1 Changing the Order of Decomposition

In this section, we show that the effect of demand for stock characteristics is robust to changes in the order of decomposition. To this end, we now calculate the return induced by the demand for stock characteristics before changing the effects of the characteristics themselves, AUM and flows:

$$
\begin{aligned}
&\Delta \mathbf{p}_{t+1}(\mathbf{s}) = \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_t, \mathbf{A}_t, \beta_t, \epsilon_t\right) - \mathbf{p}_t \\
&\Delta \mathbf{p}_{t+1}(\beta) = \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_t, \mathbf{A}_t, \beta_{t+1}, \epsilon_t\right) - \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_t, \mathbf{A}_t, \beta_t, \epsilon_t\right), \\
&\Delta \mathbf{p}_{t+1}(\mathbf{x}) = \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_t, \beta_{t+1}, \epsilon_t\right) - \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_t, \mathbf{A}_t, \beta_{t+1}, \epsilon_t\right) \\
&\Delta \mathbf{p}_{t+1}(\mathbf{A^{CF}_{t+1}}) = \mathbf{g^{CF}}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}^{CF}_{t+1}, \beta_{t+1}, \epsilon_t\right) - \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_t, \beta_{t+1}, \epsilon_t\right), \\
&\Delta \mathbf{p}_{t+1}(\mathbf{A_{t+1}}) = \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}, \beta_{t+1}, \epsilon_t\right) - \mathbf{g^{CF}}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}^{CF}_{t+1}, \beta_{t+1}, \epsilon_t\right), \\
&\Delta \mathbf{p}_{t+1}(\epsilon) = \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}, \beta_{t+1}, \epsilon_{t+1}\right) - \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}, \beta_{t+1}, \epsilon_t\right) \\
&\boldsymbol{\psi}_{t+1} = \mathbf{p_{t+1}} - \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}, \beta_{t+1}, \epsilon_{t+1}\right)
\end{aligned}
\tag{C.1}
$$

Averaging across all anomalies, we now find that latent demand and the demand for stock characteristics explain 37% and 38% of the time-series variance of portfolio returns, respectively. Flow-induced trading accounts for 10% of the variance, instead. The contribution of coefficients on characteristics is sizable within each anomaly group: e.g., in the value, profitability and investment categories, it explains 37%, 26%, and 32%, of the variance, respectively. Overall, these numbers are almost the same as in our benchmark case reported in Figure 1.

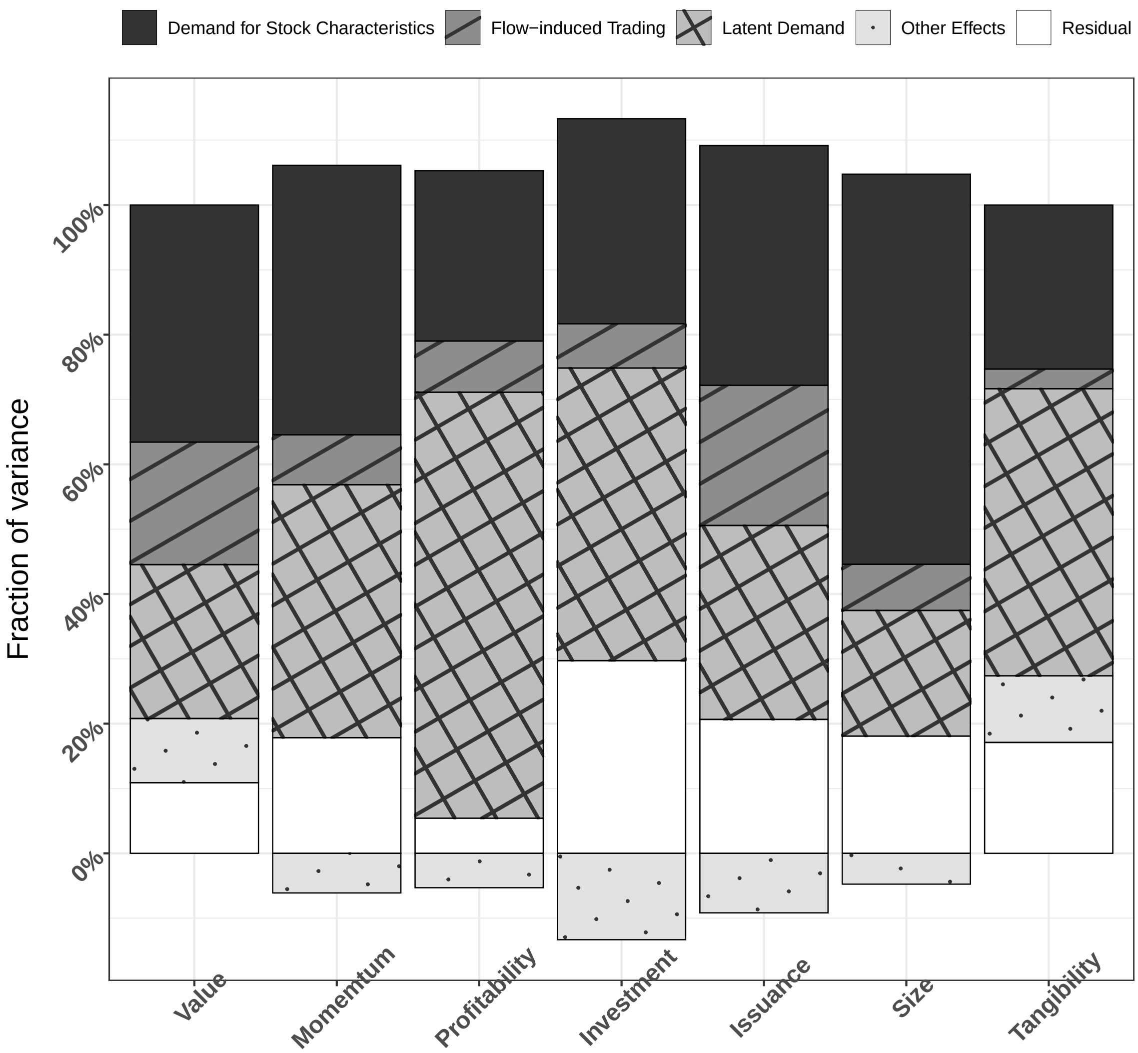


Figure C.1: Variance Decomposition: In this figure, we change the decomposition order. We now decompose the return induced by the demand for characteristics before changing the characteristics themselves, AUM and flows. Each bar refers to a given anomaly group. The bars show the contribution of demand for stock characteristics, flow-induced trading, and latent demand to return variation. Other Effects include the effects of supply-side components as well as changes in AUM. Residual include the effects of log transformation and model error. The sample period is 1980 to 2019.

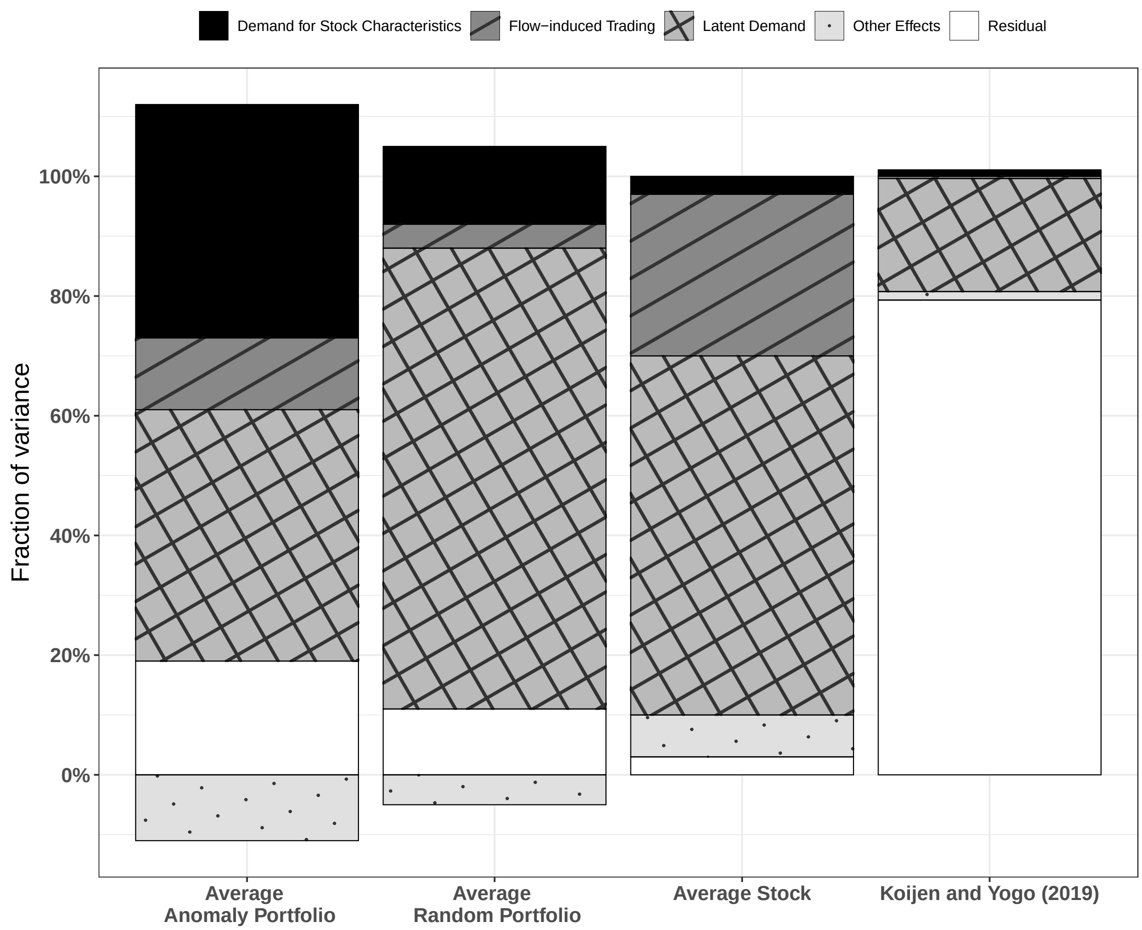


Figure C.2: Difference between Our Approach and Koijen and Yogo (2019): In this figure, we compare the times-series variance decomposition for the average anomaly portfolio, the average random portfolio, individual stocks and the cross-sectional decomposition results from Koijen and Yogo (2019). The sample period is 1980 to 2019.

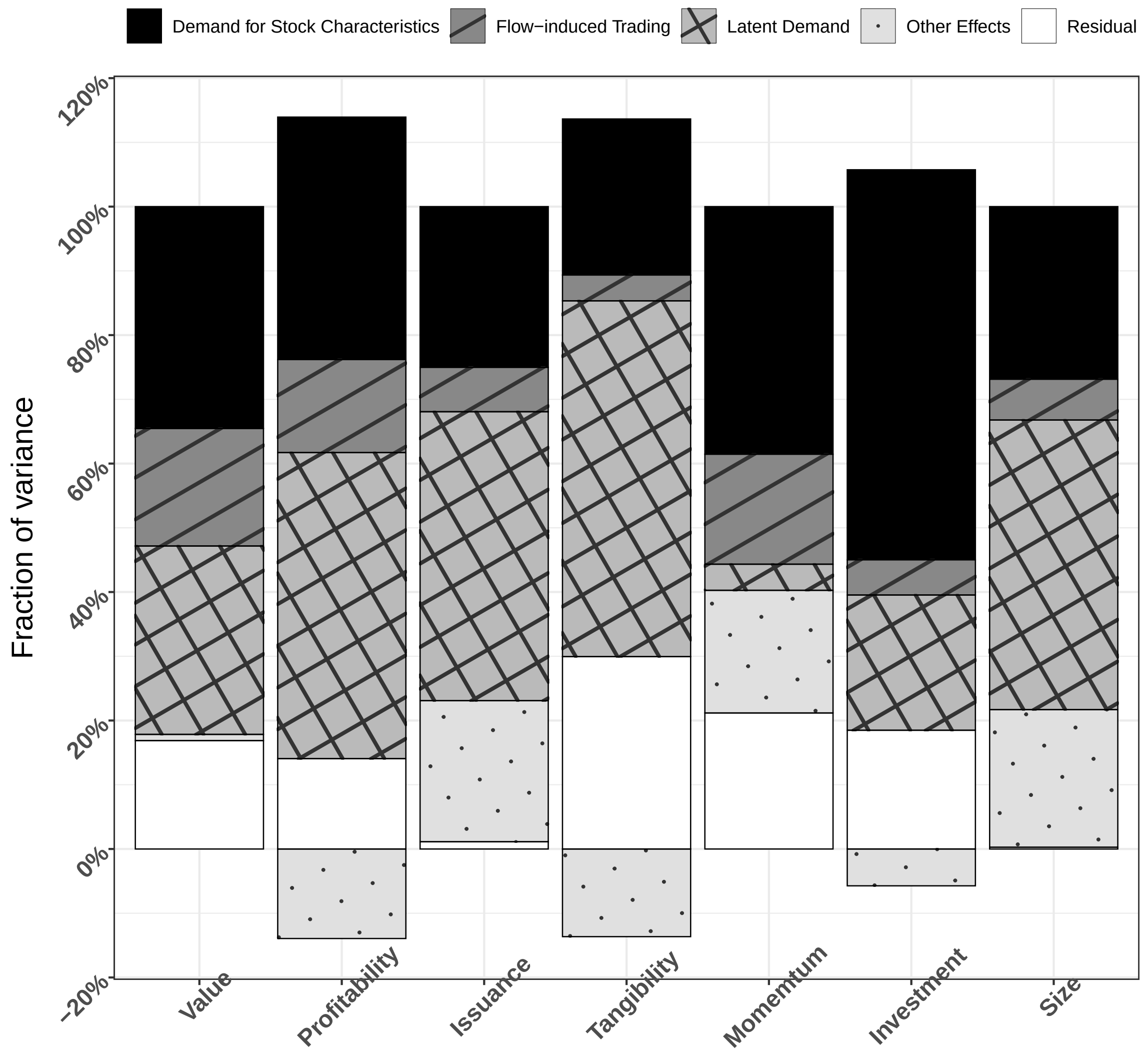


Figure C.3: Variance Decomposition (Long Leg): The bars show the contribution of demand for stock characteristics, flow-induced trading, and latent demand to return variation. Other Effects include the effects of supply-side components as well as changes in AUM. Residual include the effects of log transformation and model error. The sample period is 1980 to 2019.

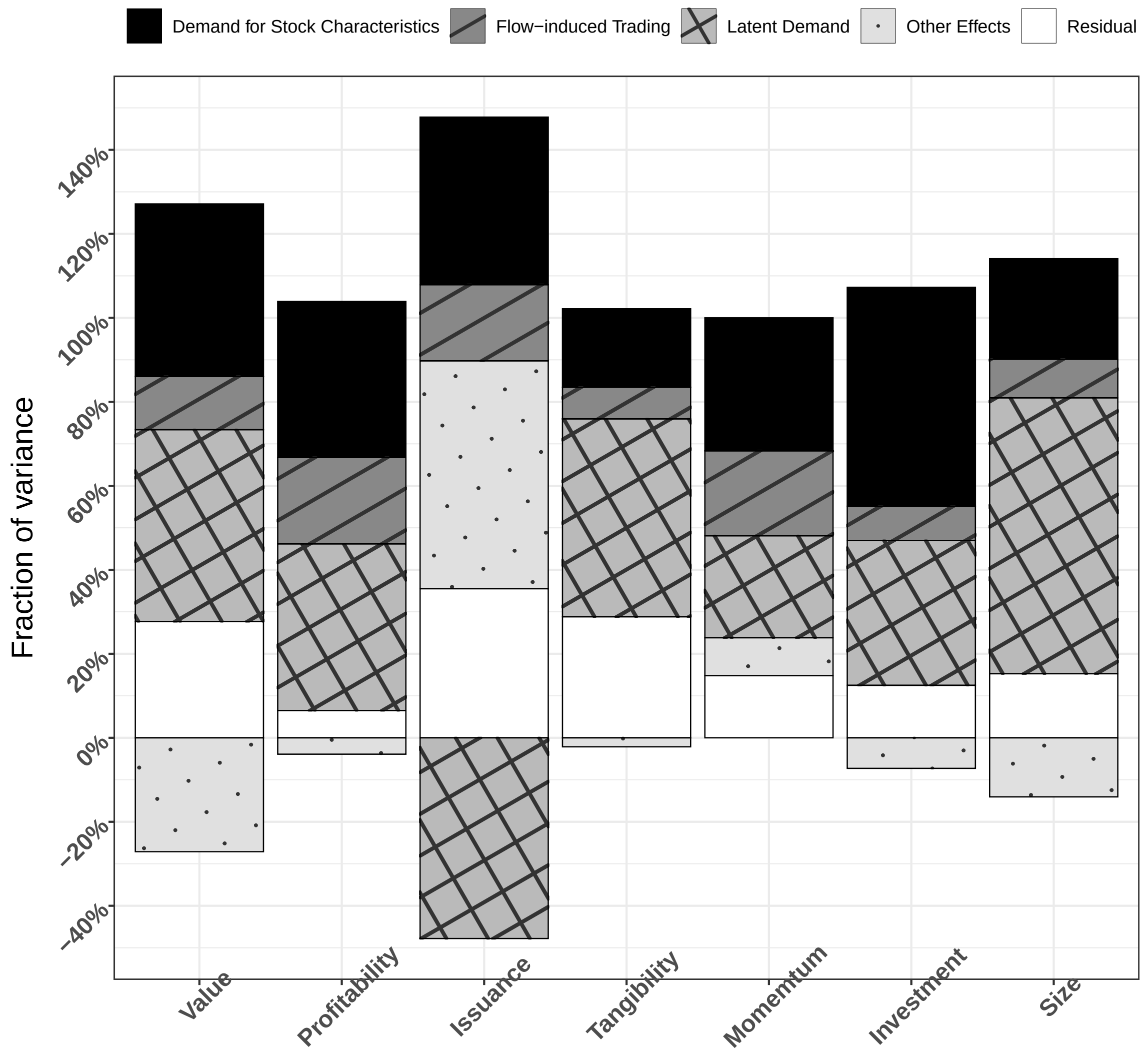


Figure C.4: Variance Decomposition (Short Leg): The bars show the contribution of demand for stock characteristics, flow-induced trading, and latent demand to return variation. Other Effects include the effects of supply-side components as well as changes in AUM. Residual includes the effect of log transformation and model error. The sample period is 1980 to 2019.