Which Investors Drive Anomaly Returns and How?*

Yizhang Li† Stanislav Sokolinski‡ Andrea Tamoni§

First draft: October 2022
This version: October 2022

Abstract

We decompose the time-variation in returns on anomaly portfolios into the effects of different investor types and their trading motives. Trading due to changes in investor preferences for observed stock characteristics explains nearly 50% of the variation, while the effects of changes in stock characteristics themselves account only for 3%. Flow-induced trading explains 15% of the variation, and the remaining part is mostly driven by unobserved characteristics. Households are the most consequential investors, since changes in their preferences account for approximately 40% of the variation in returns on the average anomaly portfolio. These findings support theories of anomalies where information-based trading by less sophisticated investors plays an important role. Our results are inconsistent with theories which emphasize the importance trading by institutions, including flow-induced trading.

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

---

*We thank Azi Ben-Rephael, Sophia Li, Ralph Koijen, Motohiro Yogo, and seminar participants at Rutgers Business School for valuable comments.

†Rutgers Business School. Address: Department of Finance, 1 Washington Pl, Newark, NJ 07102. E-mail: yl1277@scarletmail.rutgers.edu.

‡Rutgers Business School. Address: Department of Finance, 1 Washington Pl, Newark, NJ 07102. E-mail: ssokolinski@business.rutgers.edu. Web: https://stanislavsokolinski.wordpress.com.

§Rutgers Business School. Address: Department of Finance, 1 Washington Pl, Newark, NJ 07102. E-mail: andrea.tamoni.research@gmail.com. Web: https://andreatamoni.meltinbit.com.

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 innovative work of Koijen and Yogo (2019), we propose a demand-based asset pricing approach to decompose variation in anomaly returns into the effects of trading by different investors and to evaluate the relative importance of various motives behind investor trades.[1] Our approach allows us to address two principal questions in the anomaly literature that remain largely unresolved. The first question is which driving forces of anomaly returns are more important. Most of the studies test a single theory, but the existing methodologies are typically not suited to quantify the contribution of one theory relative to others. The second question is how the effects of different driving forces vary across anomalies. Do theories that explain one anomaly, also explain the others? This question became especially important in the recent decades as the empirical literature kept uncovering additional anomalies and populating the "anomaly zoo" (Cochrane, 2011).

To see how our approach addresses these questions, consider the momentum anomaly

[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 this literature, 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.

where stocks with higher past returns have higher future returns. Hong and Stein (1999) propose that this pattern is driven by investor trading due to new information. Lou (2012) argues that momentum can be explained by flow-induced trading where institutional investors have to change their positions due to the shocks to their assets under management. Now consider the following simple decomposition of momentum (MOM) return in time t:

$$R_{MOM,t} = R^I_{MOM,t} + R^F_{MOM,t}, \tag{1}$$

where $R^I_{MOM,t}$ is the return induced by information-based trading and $R^I_{MOM,t}$ is the return induced by flow-based trading. Therefore, the variation in momentum returns can be decomposed as:

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

By dividing both sides of the 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 information-based trading, we expect $\frac{Cov(R_{MOM,t},R^I_{MOM,t})}{Var(R_{MOM,t})}$ 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.

We design our methodology building on the pioneering demand-based asset pricing framework, developed by Koijen and Yogo (2019). The key idea behind this framework is that stock prices are determined by the demand of a heterogeneous set of investors. Under the assumption that expected returns and and factor exposures depend on a narrow set of stock characteristics (i.e., market equity, book equity, investment, profitability, dividends, and market beta), investor demand also becomes a function of these characteristics. By structurally estimating the demand functions across investors, we can recover their preferences for the characteristics and calculate the counterfactual prices from changing one demand component at a time. This approach enables the decomposition of stock returns into components coming from various demand-driving forces such as the changes in the preferences for stock characteristics or in the stock characteristics themselves, as well as the changes in the investor's asset under management. We also augment the basic Koijen and Yogo (2019)'s framework by introducing the effects of the variation in investor flows as well as the short-selling sector, as in Mainardi (2021).

Using this methodology, we examine 46 anomaly portfolios, grouping them into eight well-known categories: value, size, profitability, investment, momentum, asset tangibility, issuance and quality-minus-junk. We present several new results which not only shed light on the relative importance of the existing anomaly theories but also provide new evidence, requiring further explanation.

First, we uncover three major trading motives that drive anomaly returns: changes in preferences for stock characteristics, latent demand and flow-induced trading. The changes in preferences for the observed characteristics are the dominant force, accounting for nearly 50% of the variation. The changes associated with unobserved characteristics (i.e. the "latent demand") explain around 35%-40%, and flow-induced trading accounts for nearly 10%-15% of the variation. The remaining variation is minor, and it is mostly explained by the supply side effects such as changes in shares outstanding. These findings are generally consistent across the anomaly groups and their underlying portfolios, suggesting that anomaly returns are driven by common trading motives. We also find modest differences in the relative importance of these sources across anomalies, implying that some distinct driving factors can be in play. For example, flow-induced trading drives 20% of the value and 23% of the issuance effects, while explaining less than 10% of the size, profitability and tangibility effects. Changes in characteristics tend to be more important for momentum, size and quality-minus-junk factors, explaining nearly 70% of the variation.

Second, the relative contribution of the three major sources significantly varies over time. The importance of trading due to changes in preferences for observed characteristics has been steadily growing from 1980 to 2019 across the four well-known anomalies: value, momentum, profitability and investment. The returns induced by changes in the preferences for characteristics negatively covary with the raw (i.e., not decomposed) anomaly returns during the financial crises of 2002 and 2008, suggesting that the preference-based trading is pro-cyclical. The effect of flow-induced trading show less time-variation relative to preference-induced trading, but it also appears to include a business cycle component. For example, flow-induced trading had a stronger effects on momentum returns during the 2008 financial crisis.

Third, the importance of trading motives considerably varies across investors. We focus on seven major investor groups: investment advisors, mutual funds, banks, insurance companies, pension funds, short-sellers and households. Changes in preferences of households explain nearly 40% of the variation in anomaly returns, being especially important for issuance (42%) and size (55%). The contribution of investment advisors, mutual funds and banks is much smaller, and the effects of other investors are barely noticeable. These findings are consistent across anomalies, implying that the direct trading by households due to the changes in their preferences represents one of the dominant sources of variation in anomaly returns. We also find that this effect significantly varies over time, becoming more important over the recent years. Contrary to this, the effects of the preference-based institutional trading show much less time variation. Furthermore, the decomposition of the flow-induced trading across investors suggests that the effects of flows mostly come from investment advisors and mutual funds. The role of investment advisors' flows is increasing, while there is no clear trend in the role of mutual fund flows.

Finally, we examine how the variation in macroeconomic variables interacts with the preference-based and flow-induced trading motives. We focus on the role of inflation and industrial production in the variation of value and momentum returns. We find a non-trivial correlation between both trading motives and macroeconomic variables, suggesting that these anomalies may be driven by the effects of macro news. For example, for the value strategy, we observe a positive correlation of flow-induced trading with industrial production and a negative one with inflation. Investors also show time-varying preferences for trading based on macro news. For example, households' preference-based trades always respond to changes in industrial production in the same way, while mutual funds interpret this information differently in different time periods. This result is consistent with the view that investors can have heterogeneous interpretation of the same information (Cookson and Niessner (2020)).

Our results help understand the relative importance of different anomaly explanations. First, our findings are inconsistent with flow-induced trading being a major driving force behind the anomaly returns (Shleifer and Vishny, 1997). 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.

Our findings are also inconsistent with explanations which emphasize the direct role of stock characteristics, such as Liu et al. (2009). In our analyses, changes in characteristics explain only 3% of the variation in returns on the average anomaly portfolio. The major driving factor behind variation in anomaly returns is trading due to changes in preferences for stock characteristics, rather than changes in characteristics themselves. Such trading can be interpreted as being information-based. The arrival of new signals causes investors to reallocate holdings across different types of stocks, affecting stock prices. This result is consistent with theories where investors trades are driven by new information on macro-economy or on specific stocks. For example, it is in line with the behavioral theories of anomalies where investors underreact or overreact to news (e.g. Hong and Stein (1999), Barberis et al. (1998) and Daniel et al. (2001)). We can also interpret these findings as being supportive of theories where investors rationally respond to new information: for example, about productivity shocks (Kogan and Papanikolaou, 2013) or about other macroeconomic variables which determine the price of risk (Lettau and Wachter, 2007).

Second, another important driving factor of anomaly returns is the variation in latent demand. This variation is unrelated to a narrow parsimonious set of observed stock characteristics and can be possibly interpreted as changes in investor sentiment. Our findings on the importance of latent demand are thus consistent with theories which emphasize the role of sentiment in explaining the variation in returns (e.g. De Long et al. (1990), Baker and Wurgler (2006)). This interpretation, however, comes with a caveat. In particular, changes in latent demand can also represent the variation in unobserved characteristics which are not included in our empirical model. This alternative interpretation would suggests that a considerable fraction of variation in anomaly returns is explained by factors yet to be discovered.

Third, our results emphasize a dominant role of direct trading by households relative to trading by institutional investors. If households are viewed as less sophisticated investors who process the information less rationally, this finding further reinforces the behavioral theories. Additionally, this result is consistent with the idea that many institutional investors are limited by benchmarking which may discourage pursuing arbitrage-based strategies (Lewellen (2011), Baker et al. (2011)) It is 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 into the overall variation in their returns.

Our study is also related to the recent work by Lochstoer and Tetlock (2020) who examine the effects of cash flow and discount rate news on anomaly returns. They find that cash flow news are especially important in explaining the variation in returns on anomalies. Our results complement Lochstoer and Tetlock (2020) 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 how the news are transmitted into financial markets.

Section 2 provides a description of our methodology. In Section 3, we describe our main empirical results. Section 4 concludes.

2 Return Variation through the Lens of Demand-based Asset Pricing

In this section, we describe how we decompose variation in anomaly return using the demand system approach in Koijen and Yogo (2019). We also discuss how we construct an aggregate short-selling sector.

2.1 Setup

The characteristics-based demand system reads:

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

where $w_{i,t}(n)$ denotes the portfolio weight of investor i at date t for stock n. We include the following characteristics $x_{k,t}(n)$: accruals (Sloan, 1996), log market equity, log book equity, dividends to book equity, profitability, investment, and market beta.[2]

We impose the same filters as Koijen and Yogo (2019), and extend their holding dataset until the end of 2019. Differently from Koijen and Yogo (2019), we also add short sellers as an aggregated sector following Mainardi (2021). In particular, 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. To compute the household holding for a given stock, we subtract from the total shares outstanding the total number of

[2]Several papers such as Kolasinski et al. (2013) and Mainardi (2021), show that the demand for short-selling is significantly related to discretionary accruals.

shares held by all other investors, including the short-selling sector.[3] 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 sum, our sample includes eight investors' groups as in Koijen and Yogo (2019): households, banks, mutual funds, insurance companies, pension funds, investment advisors, short-sellers, and other 13F institutions (e.g., endowments, foundations, and nonfinancial corporations).

We use the same set of instruments as in Koijen and Yogo (2019) and estimate the system investor-by-investor for investors with more than 1,000 holdings. For institutions with fewer than 1,000 holdings, we pool them with similar institutions in order to estimate their coefficients.

2.2 Stock-level return decomposition

Koijen and Yogo (2019) show that, in equilibrium, the log stock price $\tilde{p}_t$ is a function of several components such as log shares outstanding s_t, firm characteristics x_t, investors' AUM A_t, investors' loadings on characteristics β_t and the extensive latent demand ε_t:

$$\tilde{p}_t = g(s_t, x_t, A_t, \beta_t, \varepsilon_t) \tag{4}$$

Following Koijen and Yogo (2019) and Koijen et al. (2020), the realized log capital gain can

[3] Mainardi (2021) adjusts the household holding by adding short interest in each quarter to the original household holding. This adjustment may be problematic when calculating the counterfactual price because it increases the total number of shares and, in the market clearing condition, generate a price gap due to the difference in shares outstanding.

be decomposed as:

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

where

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

We conduct a repricing exercise when calculating the AUM and the flow effect with endogenized asset distribution as in Koijen et al. (2020). We first create a counterfactual where there are no fund flows. We define the next period's AUM as $A_{i,t+1} = A_{i,t}R^P_{i,t+1} + F_{i,t+1}$. We then neutralize the effect of flows by setting $F_{i,t+1} = 0$ which results in the counterfactual AUM $A^{CF}_{i,t+1} = A_{i,t}R^{P,CF}_{i,t+1}$. The counterfactual investor's portfolio return equals $R^{P,CF}_{i,t} = \sum_n w_{i,t}(n)\frac{ME^{CF}_t(n)}{ME_t(n)}$ where the counterfactual market capitalization's are based on the counterfactual prices. Therefore, the change in prices $\Delta\mathbf{p}_{t+1}(A^{CF}_{t+1})$ captures the effect of changes in asset under management from returns. The remaining effect is defined as $\Delta\mathbf{p}_{t+1}(\mathbf{A_{t+1}})$ which is the change in prices due to the realized flow F_{t+1}.

To further attribute the return to different investor groups, each time, we only change investors loadings (and flows) for a certain group from time t to $t+1$. Taking $\Delta \mathbf{p}_{t+1}(\beta)$ as an example, we can further decompose the return due to changes in investor loadings into investor groups as follows:

$$
\begin{aligned}
&\Delta \mathbf{p}_{t+1}(\beta^{\textbf{Households}}) = \mathbf{g}\left(\cdots, \beta_{t+1}^{Households}, \beta_{k,t}^{k\neq HH}, \cdots,\right) - \mathbf{g}\left(\mathbf{s}_{t+1}, \mathbf{x}_{t+1}, \mathbf{A}_{t+1}, \beta_t, \epsilon_t\right)\\
&\Delta \mathbf{p}_{t+1}(\beta^{\textbf{Banks}}) = \mathbf{g}\left(\cdots, \beta_{t+1}^{HH,Banks}, \beta_{k,t}^{k\neq HH,Banks}, \cdots,\right) - \mathbf{g}\left(\cdots, \beta_{t+1}^{Households}, \beta_{k,t}^{k\neq HH}, \cdots,\right)\\
&\cdots\\
&\Delta \mathbf{p}_{t+1}(\beta^{Others}) = \mathbf{g}\left(\cdots, \beta_{t+1}, \cdots,\right) - \mathbf{g}\left(\cdots, \beta_{k,t+1}^{k\neq Others}, \beta_{t}^{Others}, \cdots,\right)
\end{aligned}
\tag{7}
$$

2.3 Portfolio-level return decomposition

We calculate the portfolio return due to a change in a given component as the value-weighted return of the underlying stocks:

$$
R_{t+1}^{k} = \sum_{i=1}^{N} w_{i,t}(e^{\Delta \mathbf{p}_{t+1}(k)} - 1), \quad k \in \{dividend, s, x, A_{t+1}^{CF}, A_{t+1}, \beta, \epsilon^{E}\} \tag{8}
$$

We correct the intensive latent demand component at the portfolio-level so that the product of portfolio-level return components equal to the total portfolio return. The anomaly return for each component is defined as the difference in returns between the long and short leg of that component. The long and short legs includes the stocks in the top and bottom quintiles, respectively. We conduct a standard sorting of stocks such that the stocks at the top quintile have higher future average returns. For example, for the value anomaly, the top quintile includes value stocks and the bottom quintile includes growth stocks.

2.4 Variance Decomposition

The variance of portfolio log returns can be decomposed as

$$\begin{aligned}\text{Var}\left(\mathbf{r}_{t+1}\right) = &\text{Cov}\left(\Delta\mathbf{p}_{t+1}(\mathbf{s}), \mathbf{r}_{t+1}\right) + \text{Cov}\left(\Delta\mathbf{p}_{t+1}(\mathbf{x}), \mathbf{r}_{t+1}\right) + \text{Cov}\left(\mathbf{r}_{t+1}^{Div}, \mathbf{r}_{t+1}\right) \\ &+ \text{Cov}\left(\Delta\mathbf{p}_{t+1}(\mathbf{A}_{\mathbf{t+1}}^{\mathbf{CF}}), \mathbf{r}_{t+1}\right) + \text{Cov}\left(\Delta\mathbf{p}_{t+1}(\mathbf{A}_{\mathbf{t+1}}), \mathbf{r}_{t+1}\right) \\ &+ \text{Cov}\left(\Delta\mathbf{p}_{t+1}(\epsilon), \mathbf{r}_{t+1}\right) + \text{Cov}\left(\Delta\mathbf{p}_{t+1}(\beta), \mathbf{r}_{t+1}\right)\end{aligned} \tag{9}$$

To conduct the decomposition, we run the time-series regression Eq.10, regressing the component-induced log return on the total anomaly log return r_{t+1}. The total percentage covariance contribution for a given component equals to $\beta_k = \frac{\text{Cov}(\Delta\mathbf{p}_{t+1}(k), \mathbf{r}_{t+1})}{Var(r_{t+1})}$.

$$\Delta\mathbf{p}_{t+1}(\mathbf{k}) = \alpha_k + \beta_k r_{t+1} + u_{k,t+1} \tag{10}$$

3 Empirical Results

3.1 Data

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

Following Freyberger et al. (2020), we categorize anomalies in eight groups: value, momentum, profitability, investment, issuance, quality-minus-junk, size and tangibility. Appendix Table A.1 describes which anomalies are included in a given group.

3.2 Variance Decomposition of Anomaly Returns

We start with an unconditional decomposition of time-series variance of anomaly returns, as described in Section 2. Figure 1 shows the results. The x-axis displays the anomaly categories. For each category, we report the contribution in percentages of various factors to the portfolio variance.[4] It is immediately apparent the changes in demand due to changes in preferences for stock characteristics and due to latent demand drive most of the variation in returns. Interestingly, whereas Koijen and Yogo (2019) find that latent demand explains most of the cross-sectional variance of stock returns, we instead document that demand-side effects due to changes in the coefficients on characteristics are the most important factor explaining the time-series variance of anomalies. Averaging across all anomalies, we find that flows explain 14%, latent demand explains 43.6%, and the coefficients on characteristics explain 51.5% of the time-series variance of portfolio returns. The contribution of coefficients on characteristics is particular important for portfolios in the value, momentum and size categories, explaining 48%, 69%, 72%, of the variance, respectively.

[**Insert Figure 1 about here**]

Table 1 summarizes the decomposition across anomaly portfolios, showing that the estimated effects of changes in preferences, latent demand and flows are statistically significant at the

[4] The "Others" category includes supply-side effects such as changes in shares outstanding, changes in characteristics, and the dividend yield, but it also includes the changes in assets under management due to returns which is a demand-effect. Section 2.2 describes how we separate the effect of returns from the effect of flows.

5% level for most of the individual anomalies. The effect of the other forces is statistically insignificant in most of the cases. Table **??** also shows that the contribution of different forces vary within an anomaly category across the underlying individual anomaly portfolios. For example, within the value category, the importance of preferences for stock characteristics varying from explaining 37% of the variation ("sp" portfolio) to 65% ("O2P" portfolio). The importance of flow-induced trading ranges from 9.9% to 29%, and the latent demand can explain 21%-55% of the variation.

While we can observe similar variations within other broadly-defined anomalies, we can also see that the importance of the three factors is relatively stable across individual portfolios. For example, the effect of flows is almost never above 20%. The effect of changes in preferences is typically between 40%-60%, and the effect of latent demand is within the same range. These results again support the relative importance of preferences for stock characteristics against the mechanical flow-induced trading.

In sum, most of the variation in anomaly returns is driven by direct trading due to changes in investor preferences for stock characteristics and the latent demand. These results are generally consistent with both behavioural and rational theories where anomalies are driven by information-based trading (e.g., Hong and Stein (1999), Barberis et al. (1998), Daniel et al. (2001), Lettau and Wachter (2007), Kogan and Papanikolaou (2013)).

[Insert Table 1 about here]

3.3 Time-Varying Effects

We next investigate how the contribution of the three major demand-side effects to the anomaly return variance changes over time. For ease of exposition, we focus on the four most prominent anomaly portfolios sorted on book-to-market, asset growth, profitability (Fama and French (2015); Novy-Marx (2013)), and momentum (Jegadeesh and Titman (1993)). Figure 2 shows the results. For book-to-market (Panel (a)) and momentum (Panel (b)) portfolios, we observe that the contribution of coefficients on characteristics is large and increasing outside the dot-com bubble in the late 1990s and the Great Recession of 2007-2009. During the crises, the latent demand picks up most of the return variation. This result is consistent with 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). For profitability (Panel (d)), we observe a clear upward trend in the importance of coefficients on characteristics at the cost of latent demand. For asset growth (Panel (c)), the contribution of latent demand seems to become more substantial after 2008. Figure 2 also shows that the effect of flows is relatively small over our sample period. While this effect is more stable relative to the two other effects, it also shows some variation over time. For example, the importance of flows for momentum and investment anomalies increases over the Great Recession of 2007-2009, when investors traded funds very actively.

[Insert Figure 2 about here]

Table 2 shows the contribution to anomaly variance of coefficients, flows and latent demand over non-overlapping decades. The table confirms the economically large and statistically significant role played by changes in coefficients for the variability of prominent anomalies featuring in the state-of-the-art factor models. Over the decade of 2010-2019, the trading due to changes in coefficients on stock characteristics explains 92% and 99% of the variation in returns of value and momentum anomalies, respectively. Since the relevant numbers for the 1980-1989 decade are 27% and 25%, this result highlights the growing importance of preference-based trading over time.

The importance of flows is also generally increasing. For the momentum anomaly, flow-induced trading explains 15.5% of the variation in returns over 2010-2019, but only 8.2% of the variation in returns in 1980-1989. For value and asset growth anomalies, we also observe increases from 11.7% to 13.3%, and from 5.5% to 13.7%. The effect of flows is the largest for value anomaly over 2000-2010 (26.4%) and for asset growth anomaly over the same period (35.6%).

[**Insert Table 2 about here**]

Table 2 also illustrates the variation in the effects of latent demand, which can be viewed as changes in investor sentiment or unobserved characteristics. The effects of latent demand significantly vary across anomalies and time periods. For example, latent demand explains 61.9% of the variation in profitability anomaly over 1980-1989, and it negatively co-moves with anomaly returns in 2010-2019, generating a normalized covariance of -51.4%. For the value anomaly, the effect of latent demand noticeably declined. During the 2000-2010 decade which includes the dot-com bubble with inflated prices of growth stocks, changes in latent demand explained 55% of the variation. On contrary, in the last decade of 2010-2019, changes in latent demand explain only 19% of the variation. These findings are consistent with interpreting latent demand as investor sentiment which was an important driving force behind trading during the dot-com bubble. The importance of latent demand for asset growth has also declined to 12.1% over the 2010-2019 decade, but its importance for momentum has increased to 50.1%.

3.4 Which investors drive anomaly returns?

We next examine which investors are responsible for the variation in anomaly returns. In particular, we quantify the contribution to the total variance of changes in flows and in coefficients on characteristics due to each investor type. Figure 3 shows the results. Focusing on Panel (a), it is clear that changes in households' coefficients on characteristics are responsible for a large fraction of total variation in anomaly returns. For example, they explain almost 55% of the return variation in the size anomaly. This effect is also large for issuance (nearly 45%) and profitability (nearly 40%). The investment anomaly exhibits the smallest effect of changes in coefficients on characteristics which equals approximately 20%. The next most important investors are mutual funds and investor advisors: their preference-based tradings explains 3%-15% of the variation in anomaly returns. The effect is the largest for quality-minus-junk and momentum, and the smallest for profitability and tangibility. The effects of other investors appear to be negligible.[5] Turning to Panel (b), the decomposition of the flow-induced trading across investors suggests that the effects of flows mostly come from investment advisors and mutual funds.

[Insert Figure 3 about here]

Table 3 shows how the effect of preference-based changes in demand varies in magnitude across investors, anomalies and time periods. The effect of households is increasing over time for each anomaly group. For value anomaly, it becomes 51% in 2010-2019, relative to only

[5] In line with Figure 2, the importance of changes in households coefficients is decreasing during the the dot-com bubble in the late 1990s and Great Recession (2007-2009). During these episodes, it is latent demand that drives the variation in anomaly returns.

13% in 1980-1989 (see also Appendix Figure A.3, left column, for a graphical representation). We can observe similar increases among other anomalies: 24%-61% for profitability, 18%-31% for momentum and 24%-40% for investment. These results show how the effect of direct trading by households is growing over time. If household are considered being unsophisticated investors, our results provide support for behavioral theories where investor trade stocks based on new information, but they form biased beliefs (Hong and Stein (1999), Barberis et al. (1998), Daniel et al. (2001)). If households trade rationally, for example, based on information that determines the price of risk, these results support the rational theories of anomalies as in Lettau and Wachter (2007) and Kogan and Papanikolaou (2013).

[Insert Table 3 about here]

The effects of preference-based trading by other investors are smaller and also not always statistically significant at the 5% level. Trading by investment advisors appears to be important for momentum and profitability, while the effects of trading by mutual funds are more important for profitability, especially in the recent sample years. The effects of other investors are noticeably smaller.

Table 4 shows the relative importance of the flow effect by investor.[6] The effects of flows to investment advisors and mutual funds play the most important role. While this finding is less surprising, it shows how our structural approach picks up the known fact on the relative importance of flows to professional asset managers. The effect of flows to investment advisors vary from 2% to 11%, becoming more important in the recent years. The effect of mutual fund flows is between 1% and 9%. The effects of flows to other investors are smaller and less likely to be statistically significant at the 5% level.

[6] See also the right column in Appendix Figures A.3 and A.4 for the case of value and momentum.

[**Insert Table 4 about here**]

3.5 Macro News and Trading Motives

What sort of information, if any, is driving the (preference-based and flow-induced) trading motives of different investors? To answer this question, we focus on innovations in two key macroeconomic risk factors: macroeconomic activity and inflation. Interestingly, while the correlation between asset returns and macroeconomic series have often been found weak in the data, our analysis can shed new light on the sources of macro-finance comovement (or absence thereof). For example, it could be the case that by separating the variability of returns due to different components - coefficients vs flows - one would find stronger correlation with the macro factors for one of these components.

We start by investigate the comovement between macroeconomic variables and the component of return induced by changes in either preferences or flows. Figures 4 and 5 show the results for the value and momentum anomalies, respectively. The left column shows the correlation of a given anomaly return component with inflation while the right column displays the correlation with industrial production growth.[7] From top to bottom we have returns due to changes in coefficients on characteristics, flows and latent demand. Each panel also overlays the correlation between raw returns and macro factor to the correlation obtained using the return component instead.

[**Insert Figure 4 about here**]

[7]Following Guo et al. (2017), we obtain the industrial production (IP) and the Consumer Price Index (CPI) for all urban consumers (all items) from the Federal Reserve Bank of St. Louis. We then compute the year-over-year log changes.

Start with the value anomaly. Figure 4 shows several interesting facts. First, the rather weak correlation between inflation and value returns (-0.08) is mostly attributable to the variation in returns generated by coefficients. On the contrary, flows generate a much larger and consistently negative comovement (at about -.35) which would make the value strategy considerably riskier. The latent demand component also co-moves with inflation in the same direction as the observed characteristics. Turning to industrial production, we see again that changes in flows make the value strategy riskier, by generating positive comovement (of about 0.30) until 2000. However, such pattern reverses afterwards (correlation of -0.17).[8]

[Insert Figure 5 about here]

Turning to momentum, Figure 5 shows that the component of returns due to flows is positively correlated with inflation until 2016, but this correlation flips sign after 2016.[9] This suggests that flows-induced returns made momentum a hedge for inflation before 2016, but a risky bets in the more recent environment. The correlation with industrial production (second column) wonders around zero, with infrequent episodes characterized by large negative values (see 2016 in particular). This is the case for returns induced by flows and as well as by changes in coefficients. These large negative correlations make consumption-based risk explanations problematic for momentum.

Tables 5 and 6 zoom into the value anomaly, and show the role of different investors' trading motives in generating comovement between returns and macro variables. Whereas in Figure 4 (top right panel) it was difficult to identify a clear pattern between preference-based trading and industrial production, the disaggregation by investor types in Table 5

[8]Using 2000 as the split point, the pre- and post-correlation between returns induced by changes in coefficients on characteristics and industrial production are 0.1 and -0.03.

[9]The correlations are 0.2 and -0.68, pre- and post-2016.

uncovers a positive correlation with the preference-based trading by households and banks, and a negative correlation with investment advisor trades and mutual funds. The effects of flows across investors are also (generally) positive correlated with industrial production until 2000: for example, the correlations equal to 33%-49% for mutual funds and 21%-33% for investment advisors.

[Insert Table 5 about here]

The results for inflation in Table 6 show little to no effect of inflation on direct trading. The effect of flows, however, strongly responds to inflation. The correlation ranges from -20% to -27% for investment advisors, and -10% to -24% for mutual funds. The correlations with inflation are also negative and statistically significant for banks and insurance companies.

[Insert Table 6 about here]

The combined results for both value and momentum suggest that a certain fraction of both direct and indirect investor trading arises from consuming macro news. While the correlation between macroeconomic information and returns are low on average, they show noticeable time and across-investor variation, suggesting that macro news can be more important in certain time periods for some investors.

4 Conclusions

We draw two conclusions. First, trading due to changes in preferences over stock characteristics is the most important factor 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 more variation than all the unobserved characteristic combined. These findings favor the theories of anomalies that feature information-based or sentiment-based direct trading, as opposed to mechanical flow-induced trading.

Second, households are the most important investors which drives the variation in anomaly returns. The effects of direct trading by households are not only much larger on average, relative to the institutional investors, but these effects tend to grow over time. These results set a new benchmark for theoretical literature on anomalies, suggesting that we need new theories where the direct trading by households plays a more prominent role.

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.

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, 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.

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.

Cochrane, John H. (2011) "Presidential Address: Discount Rates," *The Journal of Finance*, Vol. 66, No. 4, pp. 1047–1108.

Cookson, J Anthony and Marina Niessner (2020) "Why don't we agree? Evidence from a social network of investors," *The Journal of Finance*, Vol. 75, No. 1, pp. 173–228.

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.

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 (2015) "A five-factor asset pricing model," *Journal of Financial Economics*, Vol. 116, No. 1, pp. 1–22.

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*.

Guo, Hui, Chaojiang Wu, and Yan Yu (2017) "Time-varying beta and the value premium," *Journal of Financial and Quantitative Analysis*, Vol. 52, No. 4, pp. 1551–1576.

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.

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.

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 (2020) "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*.

Novy-Marx, Robert (2013) "The other side of value: The gross profitability premium," *Journal of Financial Economics*, Vol. 108, No. 1, pp. 1–28.

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

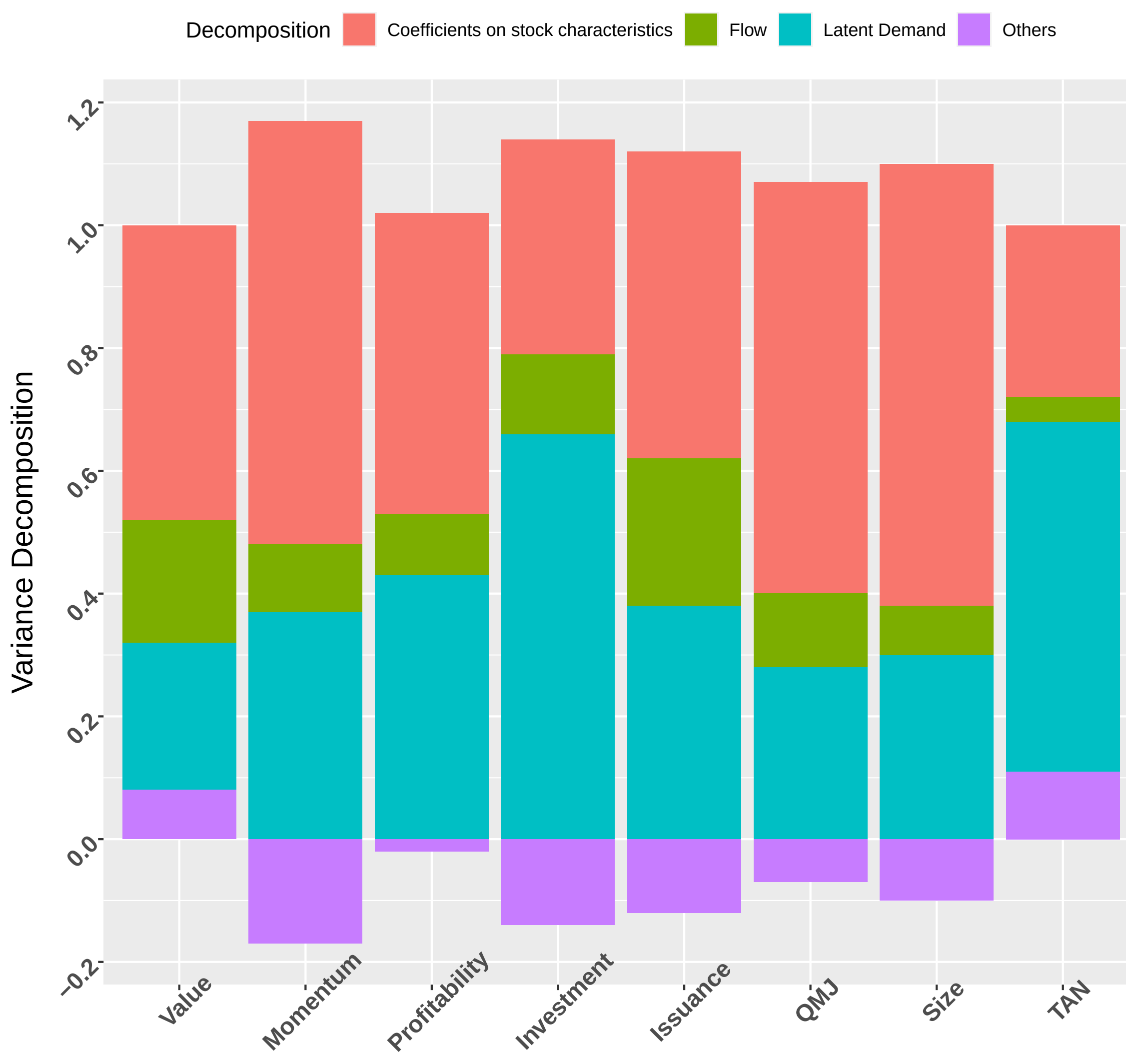
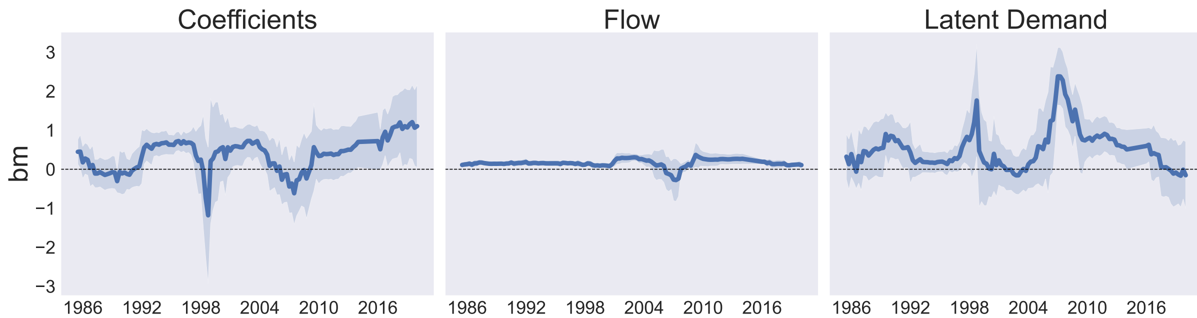
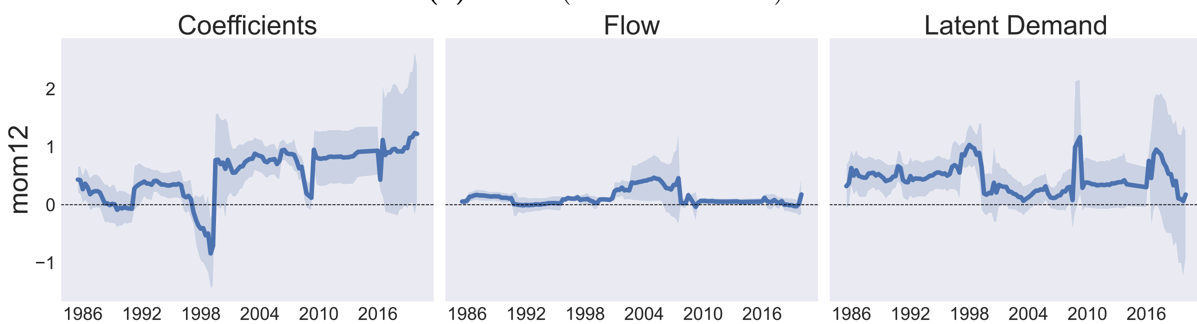


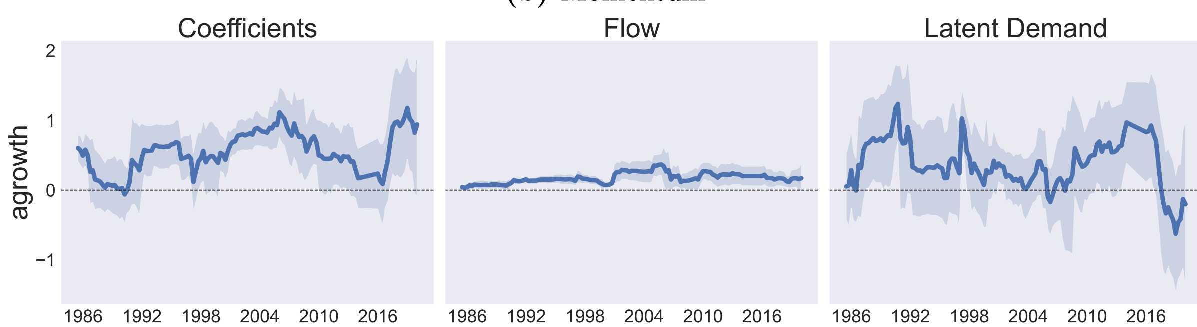
Figure 1: Variance decomposition: Each bar refers to a given anomaly group. Appendix Table A.1 describes which anomalies are included in a given group. The bars show the contribution (averaged across anomalies in a given group) of changes in coefficients, flows, latent demand to return variation. Others include the effect of supply-side components as well as changes in AUM. The sample period is 1980 to 2019.



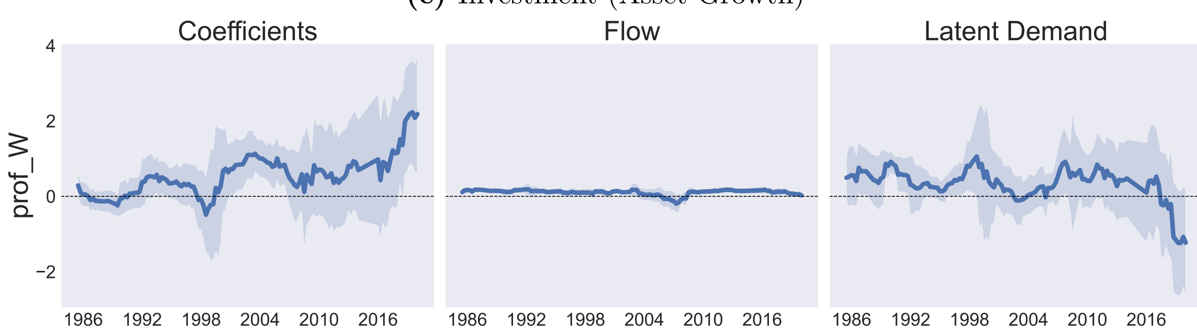
(a) Value (Book-to-Market)



(b) Momentum

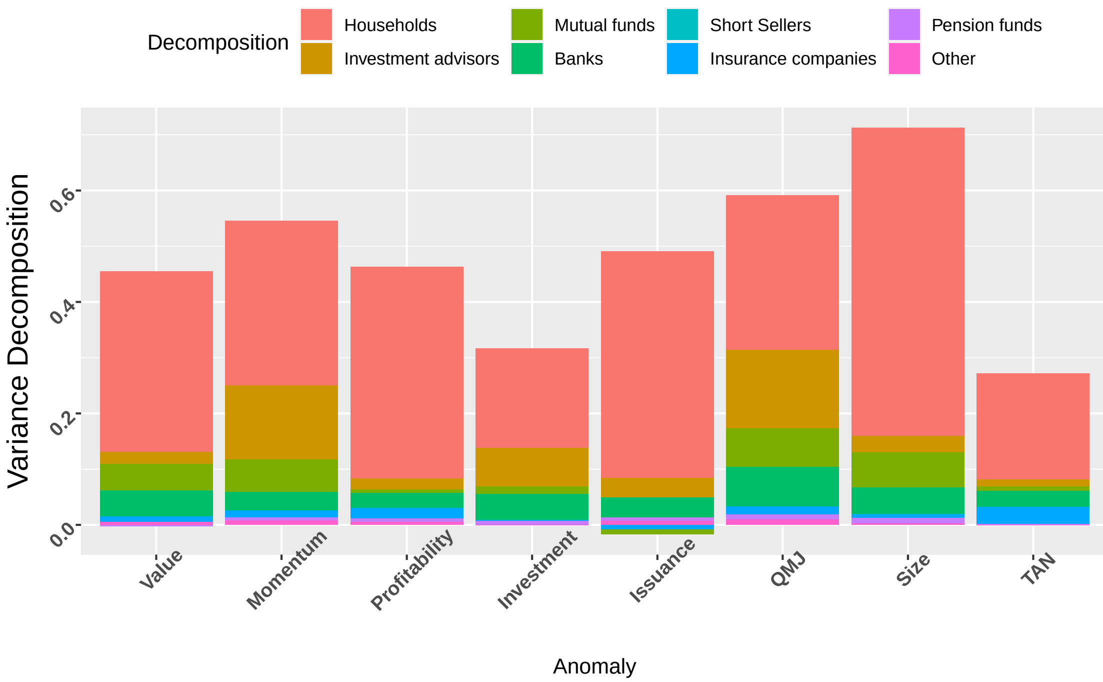


(c) Investment (Asset Growth)

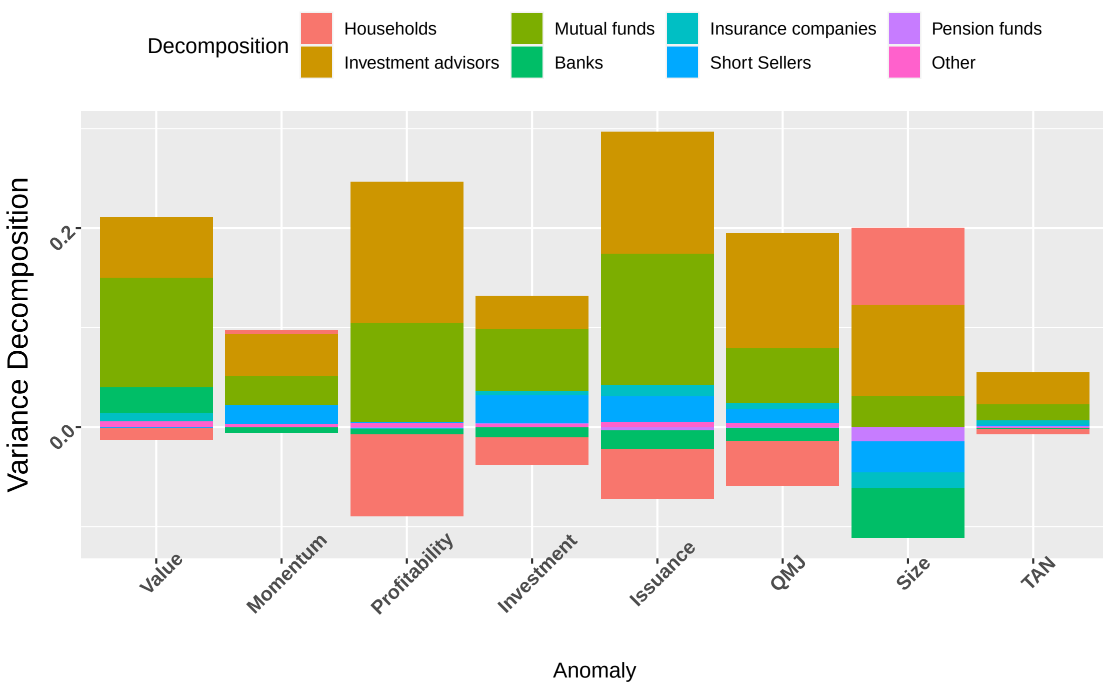


(d) Profitability

Figure 2: Variance decomposition over time: Each row refers to an anomaly portfolio. From top to bottom, we have value, momentum, investment, and profitability. Each column refers to the return induced by a specific component. From left to right, we have returns induced by changes in coefficients, flows, and latent demand. The sample period is 1980 to 2019.



(a) Coefficients



(b) Flow

Figure 3: Variance decomposition by investor Each bar refers to a given anomaly group. Appendix Table A.1 describes which anomalies are included in a given group. The bars show the contribution of each investor type to return variation. Panel (a) shows the effects of changes in coefficients, and Panel (b) shows the effects of flows.The sample period is 1980 to 2019.

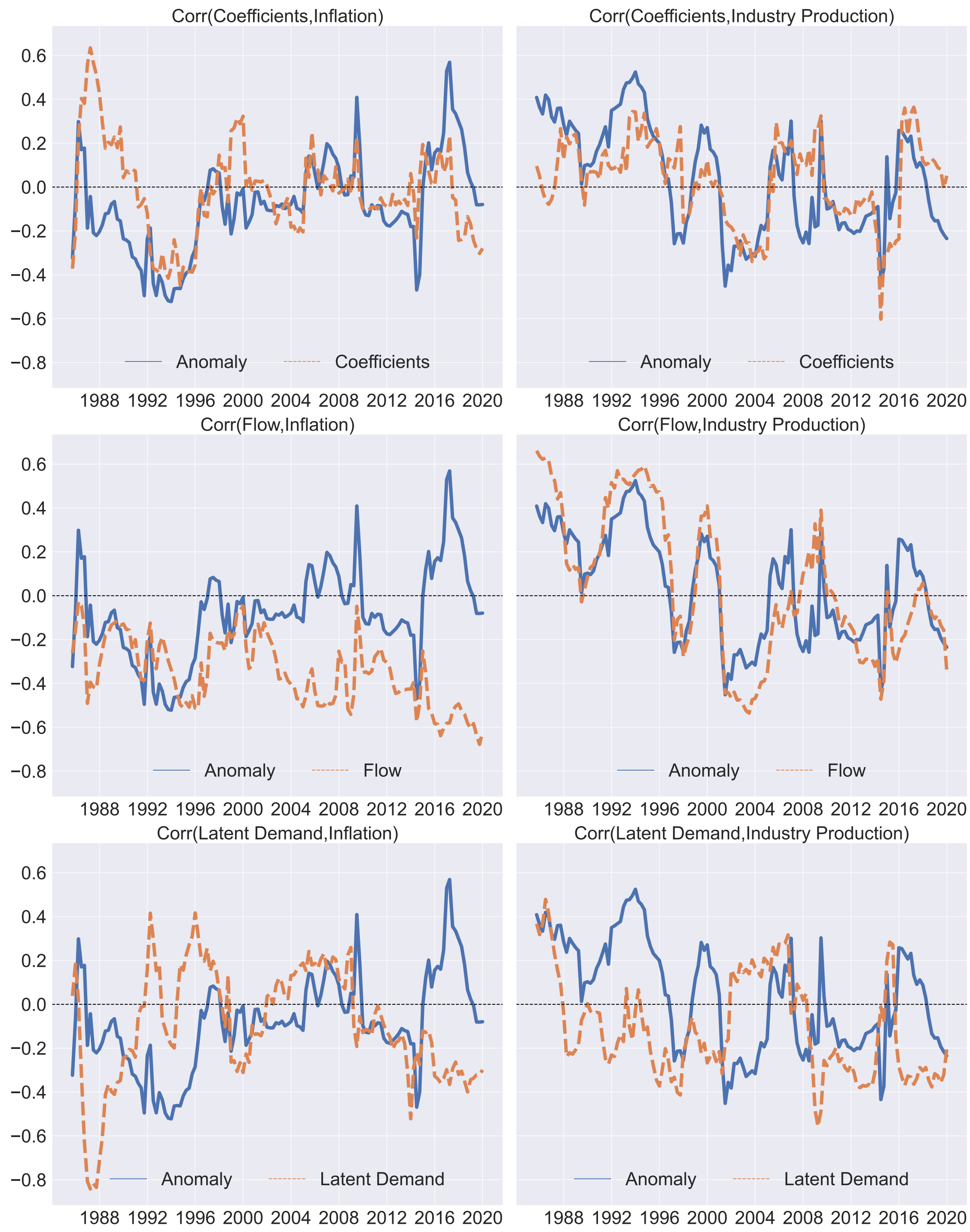


Figure 4: Correlation between macro variables and the value strategy: Each panel shows the correlation between a component of value returns with inflation (left column) and industrial production (right column). From top to bottom we have returns induced by changes in coefficients, returns induced by changes in flows, and returns induced by demand. The correlations are computed suing a rolling 5-years window. The sample period is 1980 to 2019.

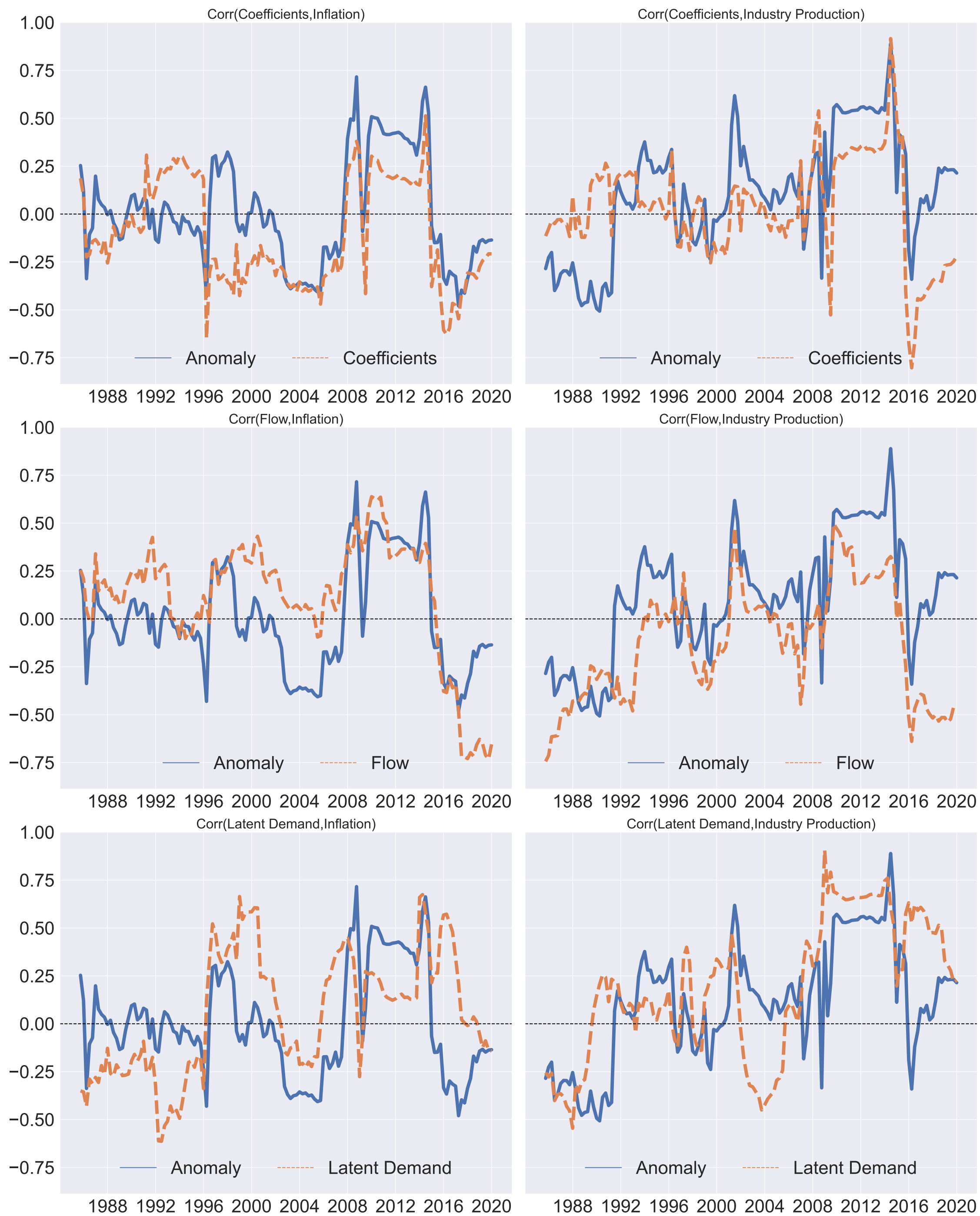


Figure 5: Correlation between macro variables and the momentum strategy: Each panel shows the correlation between a component of value returns with inflation (left column) and industrial production (right column). From top to bottom we have returns induced by changes in coefficients, returns induced by changes in flows, and returns induced by demand. The correlations are computed suing a rolling 5-years window. 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 8 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 changes in coefficients on stock characteristics, flows, changes in shares outstanding, changes in stock characteristics, changes in investor AUM due to past returns, changes in due to dividend and changes in latent demand. Numbers marked in bold indicate statistical significance at the 5% level.

Anomalies	Coefficients	Flow	Shares outstanding	Characteristics	AUM	Dividend	Latent Demand
A. Momentum							
mom12	68.5%	10.7%	-4.2%	-9.3%	-0.6%	-0.1%	36.5%
B. Investment							
agrowth	**68.6%**	**19.1%**	-2.4%	-0.3%	-0.8%	-0.2%	20.6%
d_ceq	24.8%	**12.6%**	9.5%	12.2%	0.0%	**-0.2%**	**47.0%**
investment_K	**31.0%**	**18.9%**	1.2%	-6.0%	**-0.8%**	**-0.1%**	**59.6%**
IVC	**42.8%**	**11.5%**	-11.7%	-4.6%	-0.8%	**-0.6%**	**64.2%**
noa_w	**55.1%**	4.7%	-9.1%	-3.3%	-0.3%	**-0.1%**	**51.2%**
C. Profitability							
aturnover_soliman	**36.8%**	**10.5%**	-10.3%	0.3%	-0.1%	-0.4%	**64.4%**
CTO	**48.0%**	**8.1%**	-7.2%	-2.0%	**-0.5%**	-0.3%	**53.6%**
d_dgm_dsales	**36.7%**	**7.7%**	3.1%	-10.0%	0.2%	-0.1%	**64.6%**
EPS	**76.5%**	**12.8%**	-12.1%	-3.2%	-0.2%	0.4%	23.3%
IPM	**58.1%**	19.3%	-8.3%	-5.6%	-0.2%	0.0%	**38.0%**
PCM	**53.0%**	**12.4%**	-9.9%	-10.7%	-0.6%	-0.6%	**55.0%**
PM	**58.5%**	6.0%	-7.8%	0.0%	-1.5%	-0.2%	**39.3%**
PM_adj	**43.7%**	**14.2%**	1.9%	-10.8%	**-1.2%**	-0.3%	**53.9%**
prof_W	**61.0%**	**11.6%**	-5.8%	0.8%	-0.5%	**-1.3%**	**34.8%**
RNA	**44.3%**	**9.4%**	-13.6%	-7.0%	-0.3%	-0.4%	**68.6%**
roaa_W	**60.8%**	10.6%	-6.0%	-0.4%	0.4%	-0.3%	31.9%
ROC	**44.2%**	**19.6%**	0.8%	2.7%	-0.4%	-0.4%	36.2%
roea_W	**57.0%**	9.4%	**-28.6%**	-1.1%	-0.2%	-0.3%	**58.9%**
ROIC	**73.5%**	**6.9%**	-7.1%	2.0%	-0.3%	**-0.5%**	22.0%
S2C	**48.9%**	**15.2%**	-4.7%	-12.4%	0.1%	-0.1%	**53.3%**
SAT	**48.7%**	**6.7%**	-8.7%	1.6%	-0.5%	-0.4%	**53.1%**
D. Intangibles							
AOA	**49.6%**	**10.4%**	-10.8%	0.3%	-0.5%	-0.1%	**54.4%**
OL	**33.6%**	4.2%	-5.7%	8.9%	-0.1%	0.1%	**58.1%**
TAN	**27.6%**	3.8%	3.1%	8.0%	0.0%	0.0%	**56.5%**
OA	**39.4%**	**8.4%**	-7.1%	6.0%	-0.2%	-0.5%	**55.2%**

Table 1: Variance Decomposition of Anomaly Returns (continued)

Anomalies	Coefficients	Flow	Shares outstanding	Characteristics	AUM	Dividend	Latent Demand
E. Value							
A2ME	**44.2%**	**14.2%**	4.1%	3.3%	**-0.5%**	-0.2%	**37.7%**
bm	**52.4%**	**19.4%**	0.3%	-1.0%	-0.5%	-0.2%	**32.4%**
bm_adj	**52.0%**	**19.1%**	8.0%	1.2%	-0.1%	**-0.7%**	21.1%
C	**55.2%**	**16.1%**	3.6%	-7.7%	0.3%	-0.1%	**34.4%**
C2D	**44.5%**	**9.9%**	3.3%	-2.9%	-0.5%	-0.2%	**47.6%**
nissa_FF	**61.8%**	**29.0%**	**-23.7%**	-14.5%	**-1.8%**	-0.2%	**55.6%**
Debt2P	**45.9%**	**15.6%**	4.6%	5.0%	**-0.6%**	-0.3%	**32.9%**
ep_FF	**42.8%**	**17.7%**	9.1%	-6.0%	-0.5%	0.2%	**36.5%**
FCF	**47.8%**	**19.1%**	-14.4%	-3.4%	-0.5%	-0.1%	**47.7%**
NOP	**63.6%**	**20.6%**	-2.9%	-14.9%	-0.3%	0.2%	**32.8%**
O2P	**65.3%**	**16.5%**	6.2%	-13.0%	-0.2%	0.3%	**23.6%**
Q_junME	**53.7%**	**18.0%**	3.5%	2.4%	-0.4%	-0.6%	**24.4%**
sp	**37.1%**	**14.8%**	-2.9%	-4.0%	-0.8%	-0.5%	**54.3%**
Sales_g	**53.2%**	**18.4%**	-10.6%	2.8%	-0.4%	-0.3%	**41.6%**
F. Size							
AT	**62.1%**	**18.1%**	-10.0%	5.1%	0.2%	0.4%	20.8%
LME	**67.7%**	4.5%	6.9%	-3.5%	1.5%	0.4%	25.5%
LME_adj	**61.5%**	**21.3%**	-31.5%	-2.4%	-0.4%	-0.2%	**55.7%**
G. Issuance							
NSI_comp	**47.4%**	**25.9%**	**-23.5%**	-6.6%	**-1.8%**	-0.3%	**64.1%**
CSI_DHS	**54.2%**	**30.0%**	**-14.3%**	-8.7%	-0.5%	0.2%	**36.9%**
H. Quality							
QMJ	**27.6%**	**12.0%**	-7.7%	0.3%	-0.3%	**-0.6%**	**27.5%**

Table 2: Variance Decomposition By Decades

This table reports variance decomposition for value, momentum, profitability and investment anomalies by decades. Panel (a) reports the variation by investors coefficients on firm characteristics. Panel (b) reports the variation accounted by flow. Panel (c) reports the variation by aggregated latent demand. Numbers marked in bold indicate numbers that are significant on the 95% confidence limit.

Decade	1980-1989	1990-1999	2000-2010	2010-2019
Value (bm)	27.1%	**62.9%**	23.5%	**92.0%**
Momentum (mom12)	**24.5%**	**48.1%**	**78.2%**	**99.5%**
Profitability (prof_W)	17.0%	34.1%	**80.8%**	**145.4%**
Investment (agrowth)	**40.0%**	**61.3%**	**81.6%**	**77.8%**

(a) Coefficients

Decade	1980-1989	1990-1999	2000-2010	2010-2019
Value (bm)	**11.7%**	**13.1%**	**26.4%**	**13.3%**
Momentum (mom12)	**8.2%**	**6.7%**	**13.8%**	15.5%
Profitability (prof_W)	**11.3%**	**12.6%**	6.7%	7.8%
Investment (agrowth)	**5.5%**	**11.7%**	**35.6%**	**13.7%**

(b) Flow

Decade	1980-1989	1990-1999	2000-2010	2010-2019
Value (bm)	42.6%	12.5%	55.5%	19.0%
Momentum (mom12)	**41.0%**	**38.3%**	**32.5%**	50.1%
Profitability (prof_W)	**61.9%**	15.6%	30.0%	-51.4%
Investment (agrowth)	30.6%	21.7%	38.4%	12.1%

(c) Latent Demand

Table 3: The Effects of Changes in Coefficients on Stock Characteristics By Investor

This table reports the effects of changes in coefficients on stock characteristics across investors for value, momentum, profitability and investment anomalies by non-overlapping decades. Appendix Table A.1 describes which anomalies are included in a given category. Numbers marked in bold indicate statistical significance at the 5% level

Decades	Investment advisors	Mutual funds	Households	Banks	Short Seller	Insurance	Pension funds	Other
1980-1989	0.01	-0.05	0.13	0.09	0.00	**0.04**	0.01	**0.02**
1990-1999	**0.10**	**0.19**	0.26	**0.09**	0.00	0.01	-0.01	-0.01
2000-2009	0.09	0.08	0.08	0.03	0.00	-0.01	0.01	0.00
2010-2019	0.11	0.06	0.51	**0.05**	**0.00**	**0.01**	**0.03**	0.03

(a) Value (bm)

Decades	Investment advisors	Mutual funds	Households	Banks	Short Seller	Insurance	Pension funds	Other
1980-1989	0.00	-0.02	0.18	**0.06**	0.00	**0.02**	0.01	**0.00**
1990-1999	**0.07**	0.04	0.25	0.06	0.00	0.01	0.01	0.00
2000-2009	**0.16**	**0.08**	**0.33**	**0.03**	0.00	**0.01**	**0.01**	**0.01**
2010-2019	**0.22**	0.02	0.31	0.02	0.00	0.00	0.01	0.05

(b) Momentum (mom12)

Decades	Investment advisors	Mutual funds	Households	Banks	Short Seller	Insurance	Pension funds	Other
1980-1989	**-0.07**	-0.06	**0.24**	0.00	0.00	0.03	-0.01	0.01
1990-1999	**0.05**	0.05	0.26	0.00	0.00	-0.01	0.01	-0.01
2000-2009	0.06	**0.18**	**0.39**	**0.08**	0.00	0.00	0.01	0.00
2010-2019	**0.38**	**0.10**	0.61	**0.09**	0.00	**0.03**	**0.03**	0.01

(c) Profitability (prof_W)

Decades	Investment advisors	Mutual funds	Households	Banks	Short Seller	Insurance	Pension funds	Other
1980-1989	0.03	-0.03	**0.24**	**0.09**	0.00	**0.02**	0.01	**0.01**
1990-1999	**0.04**	0.05	**0.44**	**0.07**	0.00	0.00	-0.01	0.00
2000-2009	**0.13**	**0.10**	**0.42**	0.04	0.00	0.04	0.00	-0.01
2010-2019	0.04	0.05	0.40	**0.05**	0.00	0.01	**0.02**	0.00

(d) Investment (agrowth)

Table 4: The Effects of Flows by Investor

This table reports the effects of flows across investors for value, momentum, profitability and investment anomalies by non-overlapping decades. Appendix Table A.1 describes which anomalies are included in a given category. Numbers marked in bold indicate statistical significance at the 5% level.

Decades	Investment advisors	Mutual funds	Households	Banks	Short Seller	Insurance	Pension funds	Other
1980-1989	**0.05**	**0.07**	**-0.12**	**0.10**	0.00	**0.01**	**0.01**	**0.01**
1990-1999	**0.02**	**0.08**	0.00	**0.07**	0.00	**0.01**	0.00	**0.00**
2000-2009	**0.08**	**0.09**	-0.02	-0.01	0.00	-0.01	0.00	**0.01**
2010-2019	**0.10**	0.01	0.00	-0.01	-0.01	0.00	0.00	**0.01**

(a) Value (bm)

Decades	Investment advisors	Mutual funds	Households	Banks	Short Seller	Insurance	Pension funds	Other
1980-1989	**0.02**	**0.04**	0.01	0.02	**-0.01**	**0.00**	0.00	0.00
1990-1999	**0.03**	**0.06**	0.00	-0.01	0.01	0.00	**0.00**	0.00
2000-2009	**0.04**	0.02	0.02	-0.01	0.02	0.00	0.00	**0.00**
2010-2019	0.11	0.01	-0.01	-0.04	0.07	0.00	0.00	0.01

(b) Momentum (mom12)

Decades	Investment advisors	Mutual funds	Households	Banks	Short Seller	Insurance	Pension funds	Other
1980-1989	**0.06**	**0.07**	**-0.13**	**0.09**	0.01	**0.01**	**0.01**	**0.01**
1990-1999	**0.03**	**0.06**	-0.02	0.05	0.00	0.01	**0.01**	**0.00**
2000-2009	**0.07**	0.03	0.02	**-0.08**	0.01	0.00	-0.01	0.00
2010-2019	0.05	0.03	0.00	-0.03	0.04	0.00	0.00	0.00

(c) Profitability (prof_W)

Decades	Investment advisors	Mutual funds	Households	Banks	Short Seller	Insurance	Pension funds	Other
1980-1989	**0.02**	0.03	**-0.03**	0.01	0.01	0.00	0.00	0.00
1990-1999	**0.04**	**0.08**	0.00	0.01	0.00	**0.01**	0.00	0.00
2000-2009	0.02	**0.06**	**0.11**	**-0.06**	**0.06**	0.00	0.00	0.00
2010-2019	**0.10**	0.02	-0.03	-0.02	0.02	0.00	0.00	**0.01**

(d) Investment (agrowth)

Table 5: Correlation between Industrial Production and Decomposed Returns on Value Anomaly

This table reports the correlations between decomposed returns on value anomaly and industrial production across investors by non-overlapping decades. Value anomaly is captured by book-to-market sort (see Appendix Table A.1). The decomposed returns are returns induced by changes in coefficients on stock characteristics and flow-induced returns. Numbers marked in bold indicate statistical significance at the 5% level.

	Investment advisors	Mutual funds	Households	Banks	Short Seller	Insurance	Pension funds	Other
1980-1989	**-0.06**	**-0.09**	**0.11**	**0.11**	**0.17**	-0.07	-0.03	**0.13**
1990-1999	-0.03	**0.09**	**0.17**	**0.13**	0.10	0.03	**0.07**	-0.01
2000-2009	**-0.10**	-0.05	**0.09**	**0.09**	**-0.07**	**-0.08**	-0.01	**0.10**
2010-2019	**-0.28**	**-0.16**	**0.16**	**-0.07**	-0.03	-0.08	**-0.22**	**-0.07**

(a) Coefficients

	Investment advisors	Mutual funds	Households	Banks	Short Seller	Insurance	Pension funds	Other
1980-1989	**0.21**	**0.49**	**-0.39**	**0.29**	**0.42**	**0.42**	**0.41**	**0.14**
1990-1999	**0.33**	**0.33**	**-0.10**	0.08	**0.12**	**0.18**	**0.07**	**0.26**
2000-2009	0.09	-0.10	-0.03	-0.11	**-0.26**	-0.03	-0.03	0.02
2010-2019	**-0.13**	-0.05	**0.23**	**-0.17**	**-0.01**	**0.13**	**0.18**	**0.12**

(b) Flow

Table 6: Correlation between Inflation and Decomposed Returns on Value Anomaly

This table reports the correlations between decomposed returns on value anomaly and inflation across investors by non-overlapping decades. Value anomaly is captured by book-to-market sort (see Appendix Table A.1). The decomposed returns are returns induced by changes in coefficients on stock characteristics and flow-induced returns. Numbers marked in bold indicate statistical significance at the 5% level.

	Investment advisors	Mutual funds	Households	Banks	Short Seller	Insurance	Pension funds	Other
1980-1989	0.01	-0.01	**0.24**	0.10	-0.02	**-0.17**	0.17	0.05
1990-1999	-0.05	-0.05	**-0.17**	0.00	-0.07	0.03	0.09	0.03
2000-2009	-0.01	0.06	-0.02	0.28	0.02	0.08	0.18	0.19
2010-2019	**-0.14**	**-0.22**	0.20	0.08	-0.03	-0.04	**-0.08**	-0.03

(a) Coefficients

	Investment advisors	Mutual funds	Households	Banks	Short Seller	Insurance	Pension funds	Other
1980-1989	**-0.27**	**-0.10**	0.12	-0.12	**-0.18**	**-0.15**	-0.01	**-0.22**
1990-1999	**-0.21**	**-0.24**	0.32	**-0.27**	**-0.25**	**-0.15**	-0.01	**-0.40**
2000-2009	0.27	**-0.12**	**-0.29**	**-0.38**	**-0.17**	**-0.30**	**-0.17**	0.14
2010-2019	**-0.20**	0.03	0.15	**-0.34**	-0.11	0.19	0.19	0.16

(b) Flow

Online Appendix

A Additional Evidence

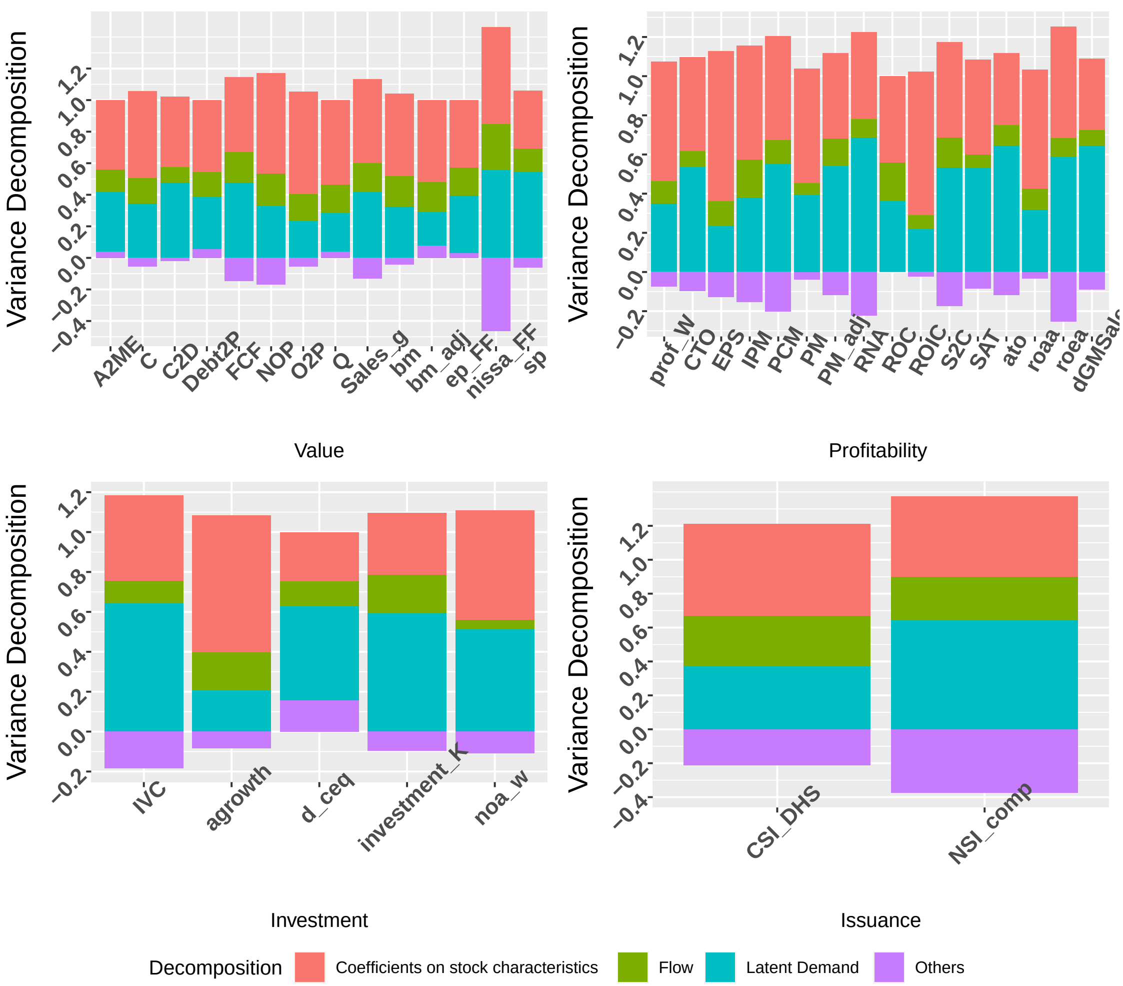


Figure A.1: Variance decomposition: individual anomaly portfolios Each bar refers to a given anomaly portfolio. Appendix Table A.1 describes the construction of anomaly portfolios. The bars show the contribution (averaged across anomalies in a given group) of changes in coefficients, flows, latent demand to return variation. Others include the effect of supply-side components as well as changes in AUM. The sample period is 1980 to 2019.

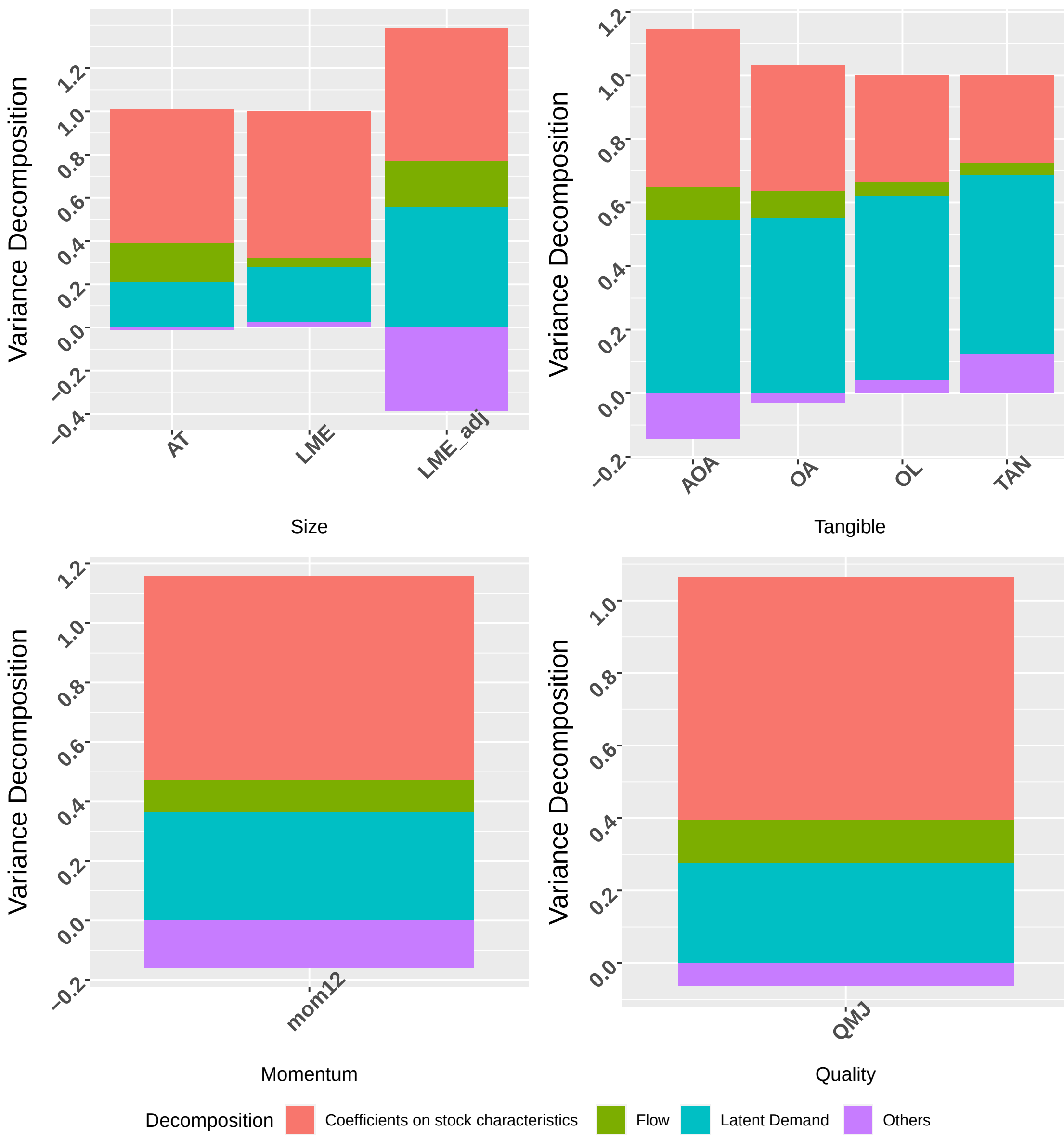


Figure A.2: Variance decomposition: individual anomaly portfolios Each bar refers to a given anomaly portfolio. Appendix Table A.1 describes the construction of anomaly portfolios. The bars show the contribution (averaged across anomalies in a given group) of changes in coefficients, flows, latent demand to return variation. Others include the effect of supply-side components as well as changes in AUM. The sample period is 1980 to 2019.

A.1 The role of flows and coefficients over time and by investors

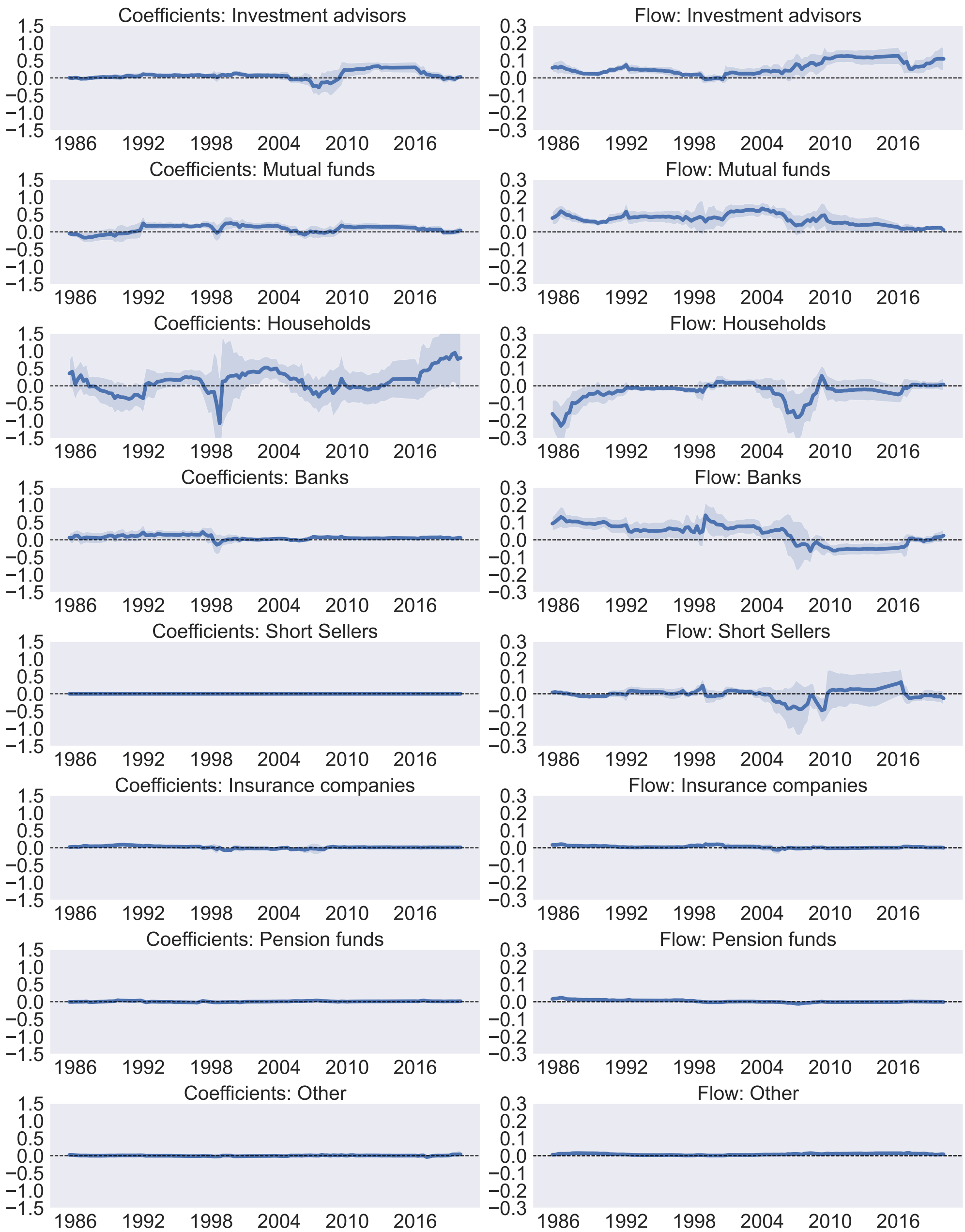


Figure A.3: Variance Decomposition over time and by investors: Value Anomaly. The figure shows the contribution of changes in coefficients (left column) and flows (right column) to variation in value returns. Each row refers to one of the eight investor groups. The sample period is 1980 to 2019.

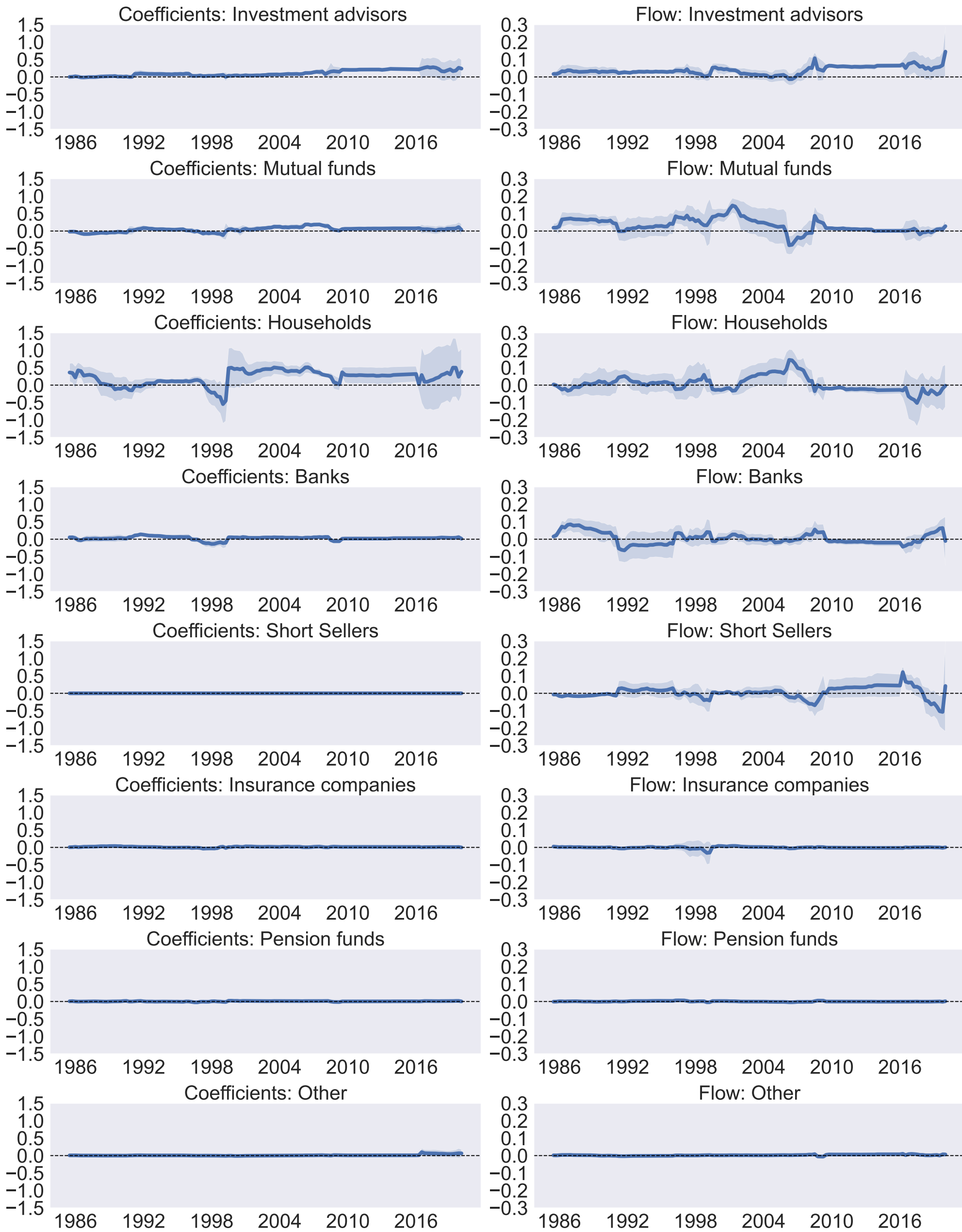


Figure A.4: Variance Decomposition over time and by investors: Momentum Anomaly. The figure shows the contribution of changes in coefficients (left column) and flows (right column) to variation in value returns. Each row refers to one of the eight investor groups. The sample period is 1980 to 2019.

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	Tobins Q	QMJ	Quality-minus-Junk
sp	Sales to price		
Sales_g	Sales growth		