Inelastic Demand at the Extensive and Intensive Margins

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Abstract

We decompose investor demand into its extensive margin—initiating or liquidating a position—and intensive margin—scaling an existing position. Extensive demand is economically large, accounting for 40% of institutional and 80% of retail flows, and its estimated price elasticity is closer to zero and often positive. Extensive demand is primarily driven by past returns and attention, whereas intensive demand reflects fundamentals. To account for these findings, we develop a Grossman–Stiglitz-style model of inelastic markets in which extensive flows act as unobservable endogenous demand shocks and investors learn from prices based on their subjective expectations about these flows. Learning from prices leads to a more inelastic, and even upward-sloping, extensive demand curve. Embedding the model in an asset demand system, we structurally estimate both elasticities under alternative specifications of flow expectations and find that extrapolative expectations best fit the data. Reduced-form evidence and counterfactual analysis both show that as the share of extensive demand rises, prices, volatility, and firm-specific price informativeness increase, while market-wide informativeness declines.

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1 Introduction

A growing body of work estimates investor demand for assets directly from portfolio holdings, recovering demand elasticities that reveal how much demand responds to changes in prices (Koijen and Yogo, 2019). A central finding of this literature is that demand is inelastic: estimated elasticities are far below what frictionless models predict (Gabaix and Koijen, 2021), and they vary substantially across investors (Haddad, Huebner, and Loualiche, 2025). The same literature also faces several open challenges. Roughly 20 percent of investor-by-cross-section estimations yield positive price elasticities, which contradict the downward-sloping demand curves imposed in the current estimation framework. At the same time, asset demand systems admit a large share of "residual demand," leaving roughly 80 percent of the variation in investor demand unexplained. Something important is missing from how we model investor demand.

Building on previous work, this paper studies investor demand and its heterogeneity through two novel perspectives. First, we decompose investor demand into its extensive and intensive margins: extensive flows are trades associated with investors' entry into or exit from stocks, while intensive flows are quantity adjustments to existing holdings. Our empirical evidence indicates that extensive and intensive flows have differential origins and impacts. And such distinctions likely originate from the heterogeneity in the informational content of these flows. Therefore, our second perspective highlights information dispersion as one important source of demand heterogeneity. We focus on a specific mechanism in which investors infer information about fundamentals from prices (Grossman and Stiglitz, 1980; Mendel and Shleifer, 2012; Banerjee and Green, 2015; Eyster, Rabin, and Vayanos, 2019; Bastianello and Fontanier, 2025). In our framework, changes in prices not only affect investors' demand along a given demand curve but also shift the curve itself by altering investors' perceived information content of asset prices.

We first establish the empirical relevance of decomposing demand into extensive and intensive margins. We measure extensive and intensive demand using institutional holdings from Thomson Reuters and retail holdings from Barber and Odean (2000). Four facts stand out. First, flows concentrate at the endpoints of holding cycles: institutions deploy 70 percent of their peak position on entry and liquidate 60 percent on exit; retail investors deploy 77 and 71 percent at those same endpoints. Second, the extensive margin makes up a large share of total activity—38 percent

for investment advisors, roughly 25 percent for pension funds and insurance companies, and 84 percent for retail investors. Third, in the aggregate, extensive flows average 40 percent of quarterly institutional flow and 80 percent of monthly retail flow. These magnitudes alone justify treating the extensive margin as a separate dimension of investor demand. Finally, yet potentially most interestingly, extensive and intensive flows relate to returns in different ways. Net extensive flows are positively associated with contemporaneous returns but negatively with next-quarter returns; by contrast, net intensive flows are negatively associated with contemporaneous returns and display a weak positive relation with future returns. These facts highlight the conceptual and empirical differences between the extensive and intensive margins of investor demand.

We use a within-portfolio design to trace why investors choose to trade at the extensive versus the intensive margin. Regressing the probability of an extensive trade on time-varying stock characteristics—controlling for investor-stock and investor-time fixed effects—reveals a sharp informational divide. Extensive flows respond strongly to social media attention and to lagged price movements, but not to earnings news. Intensive flows respond to news media coverage and to earnings news (standardized unexpected earnings). A Shapley-Owen R^2 decomposition indicates that the choice of margin is primarily an investor trait, while the amount to trade at the extensive margin is driven by time-varying stock-level shocks. Extensive flows are attention- and momentum-driven, while intensive flows are fundamental-driven.

Higher extensive flow intensity—measured as the share of a stock's quarterly trading at the extensive margin—raises both contemporaneous returns and idiosyncratic volatility. In panel regressions with stock and time fixed effects and comprehensive controls, a one-percentage-point increase in the extensive share raises the quarterly return by roughly four basis points and quarterly return volatility by roughly five basis points. The volatility effect is entirely idiosyncratic, consistent with our model later in which signals pertain to the idiosyncratic component of dividends.

Extensive flow share also amplifies how prices respond to news. At the sample mean extensive share of 30 percent, a one-percentage-point increase in SUE raises the contemporaneous return by 0.23 percentage points in a baseline specification and by an additional 0.09 percentage points when interacted with the extensive share—a 39 percent amplification. The same increase in SUE reduces volatility by 8.7 basis points in the baseline, with an additional reduction of 6.0 basis points from the interaction—a 69 percent amplification.

The effect on price informativeness is state-dependent. On average, a one-percentage-point increase in the extensive share raises stock-specific price informativeness (Dávila and Parlatore, 2025) by 0.3 percentage points (a 3.4 percent increase relative to the mean). In already-informative states this effect is strongly positive; in low-informativeness states it reverses, with the same increase reducing informativeness by 0.03 percentage points. The model explains the asymmetry: it is easier for extensive investors to extract fundamental signals from an already-informative price, so flow amplifies informativeness when prices are revealing and obscures it when they are not.

To organize these facts, we develop a stylized model in the spirit of Grossman and Stiglitz (1980) to highlight how learning from prices, information heterogeneity, attention, and specialization (Van Nieuwerburgh and Veldkamp, 2010; Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016) naturally lead to investor capital reallocation at the extensive margin. There are two risky assets, two investor types, and three periods. "Intensive investors" hold both assets simultaneously and observe noisy fundamental signals. "Extensive investors" hold at most one asset and switch between them, generating entry and exit flows that are unobservable in real time. As a result, investors, when inferring information from prices, need to disentangle price movements driven by changes in fundamentals from those originating from flow fluctuations, based on their subjective expectations about these flows. Because this price-implied signal is contaminated by unobservable flow noise, their posterior precision is lower than that of intensive investors. Three consequences follow. First, demand at the extensive margin is strictly more inelastic—price is simultaneously a cost signal and an information signal, and the two effects partially offset. Second, when investors underestimate inflows, they over-attribute price increases to fundamentals and cut demand less or even increase it, generating upward-sloping demand. Third, extensive inflows compress the residual supply absorbed by intensive investors, raising contemporaneous prices and reversing future returns.

Our model highlights two opposing effects of price movements: a standard substitution effect, which results in a downward sloping demand curve (Shleifer, 1986), and an information effect, which arises when investors infer fundamentals from prices (Grossman and Stiglitz, 1980) and pushes towards an upward sloping demand curve. Intuitively, after a price increase, the stock becomes "more expensive" to investors, so they want to substitute away and hold less of it. At the same time, investors also interpret the observed price increase as a positive signal on the stock's fundamentals, so they believe the stock is "better" than previously expected and want to hold more

of it. Taken together, when investors determine how to shift their demand for an asset after a price increase, they face a tradeoff: the asset is now "better" but also "more expensive." As a result, when investors learn from prices, the demand curve becomes steeper and potentially upward sloping.

The model also predicts the news-amplification and state-dependent informativeness patterns we empirically find in the data. Higher extensive flow raises the price loading on fundamentals when investors attribute more of any price increase to fundamental news. Whether this raises or lowers price informativeness depends on whether flow tightens or widens residual belief dispersion among current holders—a state-dependent force we formalize and test.

Finally, we extend the stylized model to a multi-asset demand system in which investor demand is a linear function of prices, subjective flow expectations, public payoff signals, and stock characteristics. We model flow expectations under several specifications of belief formation, including statistically optimal beliefs based on public information (Bianchi, Ludvigson, and Ma, 2022), extrapolative beliefs (Barberis et al., 2015, 2018), and beliefs proxied by social media attention (Cookson et al., 2024). We estimate the model on quarterly institutional holdings using the optimal granular instrumental (GIV) proposed by Chaudhary, Fu, and Zhou (2024), which extends the approach of Gabaix and Koijen (2024). Two structural findings stand out. Price elasticity at the extensive margin (mean -0.34) is less negative than at the intensive margin (mean -0.43), with more mass in the positive region. And demand falls when investors anticipate higher extensive inflows: a one-percentage-point increase in flow expectations reduces demand by 0.8 percentage points. Both findings confirm the mechanism. Extrapolative expectations fit the data better than a rational benchmark, suggesting investors overreact to recent realized flows when forming beliefs about future flows.

A budget-neutral counterfactual—shifting 10 percent of AUM from intensive to extensive investors—raises annualized returns by 3.3 percentage points and annualized volatility by 3.7 percentage points. Stock-specific price informativeness (Dávila and Parlatore, 2025) rises by 0.4 percentage points on average (9.3 percent relative to the mean), with a one-percentage-point increase for already-informative stocks and a 0.2-percentage-point decline for less-informative ones. Market-wide informativeness, measured following Bai, Philippon, and Savov (2016), falls across all horizons of one, three, and five years. The two informativeness measures move in opposite directions because they capture different aspects of price discovery: stock-specific informativeness

gauges within-stock accuracy; market-wide informativeness gauges how well prices rank stocks by future fundamentals across the cross-section. More extensive activity introduces unobservable demand shocks that impair cross-sectional ranking even as it sharpens within-stock accuracy in high-informativeness states.

Related literature.

Demand system asset pricing. Koijen and Yogo (2019) develop a framework for measuring investor demand and its price impacts; Gabaix and Koijen (2021) establish that markets are inelastic relative to frictionless benchmarks. Subsequent work estimates demand systems in richer environments (Haddad et al., 2025; He, Kondor, and Li, 2025; Koijen and Yogo, 2025; van Binsbergen, David, and Opp, 2025) and documents substantial heterogeneity in elasticities (Haddad, Huebner, and Loualiche, 2025). We provide an information-based microfoundation for low—and positive—price elasticity rooted in the extensive margin. Chaudhry and Li (2025) find that price multipliers shrink for larger demand shocks; our framework is complementary but operates along a different dimension: holding shock size fixed, the presence of extensive investors mechanically lowers effective elasticity. He, Kondor, and Li (2025) show that static systems identify short-run elasticities; we share this interpretation explicitly. Graves (2025) recovers investor beliefs from holdings and distinguishes owners from non-owners, an angle directly analogous to the intensive-extensive split.

Learning from prices. Grossman and Stiglitz (1980) and Hellwig (1980) show that prices cannot fully reveal private information in equilibrium; our extensive investors are an endogenous version of the noise traders that impede full revelation. Eyster, Rabin, and Vayanos (2019) study markets where investors neglect the informational content of prices; Bastianello and Fontanier (2025) examine markets where investors neglect that others also learn from prices; Schmidt-Engelbertz and Vasudevan (2025) show that higher-order beliefs amplify excess volatility. Our mechanism is distinct: extensive investors correctly understand the inference structure but face irreducible uncertainty about unobservable flow—an identification problem that is micro-founded in who holds what.

Flow-based price pressure. Event studies around index changes establish downward-sloping demand and sizable price impacts from non-fundamental flows (Shleifer, 1986; Harris and Gurel, 1986; Chen, Noronha, and Singal, 2004). A broader literature documents that institutional and fund

flows generate price pressure, fragility, and return predictability (Coval and Stafford, 2007; Lou, 2012; Pavlova and Sikorskaya, 2023; Hartzmark and Solomon, 2025). We decompose total flow into extensive and intensive components and show that the two have opposite return implications—a distinction that aggregate flow measures mask.

Investor heterogeneity. Micro evidence documents systematic differences in who trades and how those trades affect prices (Barber and Odean, 2000, 2008; Kaniel, Saar, and Titman, 2008; Kelley and Tetlock, 2013). The extensive-intensive decomposition maps directly onto participation margins—entry and exit versus rebalancing—and helps explain why reallocations by certain investor groups generate stronger short-run return and volatility dynamics.

2 Data and Motivating Stylized Facts

Four stylized facts motivate our analysis: flows concentrate at the start and end of holding cycles; the extensive margin accounts for a large share of trading for every investor type; extensive flows average 40 percent of aggregate institutional flow and 80 percent of retail flow; and extensive and intensive flows relate to returns with opposite signs. This section describes the data and sample construction underlying these facts, then documents each in turn.

2.1 Data Sources

Our data on investor holdings come from two sources: Thomson Reuters for institutional holdings, as used in Koijen and Yogo (2019), and a large discount broker for retail trading, as used in Barber and Odean (2000). We use CRSP, Compustat, and IBES to construct characteristics, data shared by Cookson et al. (2024) for social media attention and sentiment, and RavenPack for news coverage and news sentiment.

We obtain institutional stock holdings data from Thomson Reuters Institutional Holdings Database (S34) from 1980 to 2022. This database compiles the quarterly 13F filings from the Securities and Exchange Commission (SEC). All institutional investors with assets under management (AUM) above $100 million must file the form to report stock positions. Institutional holdings data are merged with CRSP and Compustat data by CUSIP. Dollar holdings are computed as price times shares held. We follow Koijen and Yogo (2019) to classify institutional investors into six

types based on their reported institution type in the Thomson Reuters database: investment advisors, mutual funds, pension funds, insurance companies, banks, and other 13F institutions. Investment advisors are firms that register with SEC Form ADV. Mutual funds are separated from investment advisors and form their own group. Other 13F institutions include endowments, foundations, and nonfinancial corporations. We define the household shares for any given stock as the difference between the total shares outstanding and the total shares held by all other 13F institutions. The household sector comprises direct household holdings and smaller institutions that are exempt from filing Form 13F.

We also draw on the retail investor dataset used in Barber and Odean (2000), which provides detailed trading records for a large set of self-directed brokerage accounts between 1991 and 1996. The sample allows us to observe how retail investors adjust their holdings at both the extensive and intensive margins. The retail holdings data complements our analyses on the institutional investors and strengthens the external validity of the results presented in this paper.

2.2 Sample and Variable Construction

We build three data sets: an investor-by-stock quarterly panel for holdings of institutional investors, an investor-by-stock monthly panel for holdings of retail investors, and a quarterly panel of stocks that aggregates investor holdings and augments stock and firm characteristics.

Investor demand. Our central classification separates the decision of whether to hold a stock from the decision of how much to hold. Using the holdings data described above, we categorize each position (i.e., an investor-stock-time observation) into one of five types: extensive in, extensive out, intensive in, intensive out, and no trading. Extensive in means an investor opens a new position in a stock in this period. Similarly, extensive out means an investor exits a stock. Intensive in and out represent an investor's continuing holdings of a stock, with buying or selling shares in this period, respectively. No trading indicates an investor has a position in a stock whose shares do not change. We then calculate the dollar value and the number of shares for each holding.

Based on holdings data, the flow measures are constructed as changes in holdings relative to the previous period's holdings. Net flow is the difference between buying flows and selling flows, in both dollar value and number of shares. To obtain the percentage net flows, we normalize dollar

net flows by the stock's lagged market capitalization and normalize share net flows by the stock's lagged total shares outstanding.

For each institutional investor, we follow Koijen, Richmond, and Yogo (2024) and construct their active shares. The active share is defined as the total share of the investor's portfolio that deviates from the market weights (Cremers and Petajisto, 2009). Specifically, the active share is calculated as one-half the sum of the absolute differences between the portfolio weights and the market weights for the set of stocks in the investor's investment universe. We then average an investor's active share measures over time to generate an investor-level, time-invariant average activeness measure, which we use to study investor heterogeneity.

Finally, we aggregate variables constructed above from the level of investor holdings (i.e., investor-stock-quarter) to the level of stocks (i.e., stock-quarter). We obtain stock-level measures of aggregate investor demand and flows, such as percentage net flows, by demand type, including extensive in/out and intensive in/out. The composition of flows is defined as the percentage of extensive and intensive flows in shares, divided by the number of shares of total flows. As a result, the compositions of extensive flows and intensive flows always sum up to one hundred percent by definition.

Stock characteristics. We use CRSP, Compustat, and IBES to construct stock characteristics. Stock size is measured by the log of a stock's market capitalization. B/M is the ratio of book equity to market equity. Profitability is measured by operating cash flow to assets, following Bouchaud et al. (2019). Standardized unexpected earnings (SUE) is calculated as unexpected earnings (IBES actual earnings minus consensus analyst earnings forecast)[1] divided by fiscal-quarter-end market capitalization, following Rendleman Jr, Jones, and Latane (1982).

We use data from Cookson et al. (2024) on social media attention and sentiment. Both indices are standardized to have a mean of zero and a standard deviation of one. RavenPack provides measures of news coverage and news sentiment. News coverage is the log of the number of news articles covering a stock in a quarter. We focus on news articles with a relevance score above 75 in the RavenPack sample. Following Cookson et al. (2024), we use the Event Sentiment Score (ESS) calculated by Ravenpack as our measure for news sentiment.

[1] If the consensus analyst earnings forecast is not available, then use the seasonally differenced quarterly earnings before extraordinary items from Compustat quarterly file

For each stock in a given quarter, we calculate realized total volatility as the annualized monthly average of the standard deviation of cum-dividend daily stock returns from CRSP. Idiosyncratic volatility is constructed as the standard deviation of residuals in a regression of daily returns on daily market returns for the three years preceding the quarter end (Ali, Hwang, and Trombley, 2003).

We construct stock-specific price informativeness, which was recently developed by Dávila and Parlatore (2023, 2025). The data and programs are downloaded from the author's webpage. We extend the sample to 2022 using the programs shared by the authors. Under the framework of Dávila and Parlatore (2025), price informativeness τ_s measures the relative precision of information that asset prices contain about future payoffs. The measure is identified by comparing the R^2 from two OLS regressions of log-price changes (Δp_t) on contemporary and future log-payoff changes (Δx_t and Δx_{t+1}, with $\Delta \chi_t$ as the change in public signals):

$$\Delta p_t = \overline{\beta} + \beta_0 \Delta x_t + \beta_1 \Delta x_{t+1} + \beta_2 \cdot \Delta \chi_t + e_t, \tag{2.1}$$

$$\Delta p_t = \overline{\zeta} + \zeta_0 \Delta x_t + \zeta_2 \cdot \Delta \chi_t + e_t^{\zeta}. \tag{2.2}$$

After collecting $R^2_{\Delta x, \Delta x'}$ and $R^2_{\Delta x}$ from the two regressions, the relative price informativeness is calculated as the normalized difference:

$$\tau_s = \frac{R^2_{\Delta x, \Delta x'} - R^2_{\Delta x}}{1 - R^2_{\Delta x}} \tag{2.3}$$

The numerator captures the percentage reduction in uncertainty about future payoffs after observing the price, while the denominator represents the residual uncertainty about future payoffs not explained by current public information and the realized payoff.

Table 1 presents the descriptive statistics for investor holdings (i.e., the investor-stock-quarter panel) in Panel (a) and stocks (i.e., the stock-quarter panel) in Panel (b). All variables are winsorized at the 1% and 99% cutoffs.

[Insert Table 1 Here.]

2.3 Motivating Stylized Facts

Using the samples constructed above, we document the following four stylized facts on investor extensive and intensive flows.

Fact 1: Extensive flow is large within a stock holding cycle.

We begin by examining the size of extensive and intensive flows at the finest level: stock holding cycles. We define a stock holding cycle as an array of an investor's consecutive holdings in the same stock, which always begins with an extensive inflow and ends with an extensive outflow. We normalize the holdings in shares by the maximum shares held within a stock holding cycle. Figure 1 presents how flows distribute within an average holding cycle.

[Insert Figure 1 Here.]

A strong empirical pattern emerges for both institutional investors in Panel (a) and retail investors in Panel (b). Extensive flows dominate in size within a stock holding cycle: flows are concentrated in the first and the last periods (F1 and L1 in the graphs) when an investor enters or exits a stock. When an institutional investor decides to enter a stock, she, on average, buys around 70% of her shares in the first period. Similarly, when she decides to exit a stock, she sells around 60% of her shares in the last period. The magnitude is even larger for retail investors, who buy 77% via extensive inflows and sell 71% via extensive outflows. As a robustness check, we exclude holding cycles that consist of only one buying observation and one selling observation. The results are presented in Figure A1. Although the magnitudes are slightly smaller, the conclusion remains unchanged: extensive flows still dominate within an average holding cycle.

Fact 2: Extensive flow is large in percentage composition.

We now turn to the level of investor holdings (i.e., investor-stock-time observations). We calculate the average dollar values and the percentage composition of extensive and intensive flows. Table 2 presents these statistics by investor type in Panel (a) and by active share quintile in Panel (b). To make the results more intuitive, we also visualize the percentage composition of flows in Figure 2.

[Insert Table 2 and Figure 2 Here.]

Retail investors own the largest share of the extensive demand, around 84%, indicating that they frequently switch stocks in their potentially underdiversified portfolios. For institutional investors, investment advisors implement more extensive trading, comprising 38%. Namely, around one-third of investment advisors' trading involves entering a new stock or completely exiting a stock in their portfolios. The extensive demand remains considerable, even for relatively passive investors such as pension funds and insurance companies, whose extensive investment compositions are 25% and 22%, respectively. Figure A2 presents graphs of the average dollar values of extensive and intensive flows, supporting the observation that extensive demand plays an important role in both institutional and retail investor holdings.

Fact 3: Extensive flow is large in aggregate.

We then aggregate investor holdings to the market level. We construct the quarterly time series of aggregate dollar values and the percentage composition of extensive and intensive flows. Figure 3 presents the aggregate flow percentage composition.

[Insert Figure 3 Here.]

For institutional investors in Panel (a), extensive demand accounts for up to 50%, with an average of around 40% across quarters. Extensive demand is more salient for retail investors in Panel (b), taking up to 90% of the total flow, with an average of around 80%. The large magnitude of extensive flows highlights the importance of decomposing total flows into extensive and intensive components and studying them separately. Figure A3 presents the time series of the aggregate dollar values, yielding a similar conclusion.

Fact 4: Extensive and intensive flows relate to stock returns differently.

The last but potentially the most interesting fact associates net percentage flows of extensive and intensive demand with contemporaneous and future returns. For each stock in a quarter, we construct net percentage extensive (intensive) flows as the number of shares bought minus those sold by extensive (intensive) investors, scaled by the lagged total number of shares outstanding for that stock. We then estimate the specification below on a stock (n)-by-quarter (t) panel to link demand flows to returns.

$$\text{Return}_{n,t+h} = \beta^h \cdot \text{Net Flow}_{nt} + \gamma \cdot \text{Controls}_{nt} + \alpha_n + \alpha_t + \epsilon_{nt}, \tag{2.4}$$

for $h = 0$ (contemporaneous returns) and $h = 1$ (returns next quarter). The controls include standardized unexpected earnings (SUE), size, book-to-market ratio, lagged return, and profitability. We also include stock fixed effects (α_n) and quarter fixed effects (α_t). β^h is the coefficient of interest, capturing how net extensive and intensive flows relate to returns in the h-th period. We present the binned scatterplots in Figure 4 to illustrate the relationship between returns and net extensive and intensive flows. In Section 3.3, we implement this intuitive regression specification (2.4) using a local projection framework and estimate the orthogonalized impulse response functions (IRFs). The results are similar, qualitatively and quantitatively.

[Insert Figure 4 Here.]

Figure 4 Panel (a) presents the results on contemporaneous returns: net extensive flows are significantly positively correlated with contemporaneous returns, while the intensive flows exhibit a significant negative association with returns. However, when we implement the same specification on future returns in Panel (b), the signs above flip. Net extensive flows are significantly negatively correlated with future returns, while the intensive flows are now positively related to future returns. Such a contrast highlights the distinction between extensive and intensive flows, suggesting different information content and asset pricing implications. Together with Facts 1–3, these stylized empirical patterns motivate our empirical analyses in Section 3.

3 Empirical Analysis

Extensive and intensive flows differ in both origin and impact. Extensive flows are driven by past returns and attention, while intensive flows respond to fundamentals. Stocks with a higher composition of extensive demand have higher returns and volatility, and the relation between extensive composition and price informativeness is positive when informativeness is high and negative when it is low. We establish these results in this section, closing with a local projection analysis of the dynamic two-way relationship between net flows and returns.

3.1 The Origin of Extensive and Intensive Flows

We implement the analyses in this subsection at the level of holdings. To fix ideas, the data consist of investor (i)-stock (n)-time (t) observations, with t being a quarter for institutional holdings and a month for retail holdings.

3.1.1 Variation Decomposition

To understand what drives extensive and intensive flows, we begin by decomposing their variation. The decomposition delivers a clear division of labor: the choice between extensive and intensive trading is primarily an investor trait, whereas the dollar amount traded at the extensive margin responds to time-varying, stock-specific shocks. To show this, we estimate OLS regressions of the flow type (i.e., indicator variables of whether a flow is extensive or intensive) and flow intensity (i.e., a flow's dollar value) on a comprehensive list of fixed effects, including time fixed effects (η_t), investor fixed effects (α_i), stock fixed effects (α_n), investor-time fixed effects (η_{it}), stock-time fixed effects (η_{nt}), and investor-stock fixed effects (α_{in}). To evaluate the independent contribution of each set of fixed effects to the variations in flows, we implement a Shapley-Owen variance decomposition (Audoly et al., 2025; Shorrocks et al., 2013). Intuitively, the procedure considers all possible orderings of introducing the fixed effects into the OLS regressions and averages their incremental contributions to the model fit (R^2), ensuring that no set of fixed effects is given undue priority simply because of the order in which it is added.

[Insert Figure 5 Here.]

Figure 5 visualizes the variation explained for flow type in Panel (a) and for the dollar values of extensive flows in Panel (b) and intensive flows in Panel (c). Investor-related dimensions account for the majority of the variation in flow type: investor, investor-time, and investor-stock fixed effects together contribute 34 percentage points of the 41 percent of total variation explained in Panel (a), whereas stock and stock-time fixed effects contribute only 7 percentage points. Whether investors constantly switch across stocks ("extensive trading") or maintain a diversified portfolio and rebalance ("intensive trading") is thus largely an investor trait. The picture reverses for trade size. For the dollar value of extensive flows in Panel (b), stock-time fixed effects alone contribute

11.3 of the 16.3 percentage points of explained variation—roughly 70 percent—while all investor-related dimensions combined contribute 4 percentage points. In short, who trades at the extensive margin is an investor characteristic, but how much is traded responds to time-varying, stock-specific shocks. This pattern motivates our analysis below to discover which dimensions of time-varying stock heterogeneity drive investor flows.

3.1.2 Relations to Sentiment, Attention, Returns, and Fundamentals

We augment investor holdings data with time-varying stock characteristics to study which factors drive investors' decisions in trading at the extensive or intensive margins. We focus on stock-level attention and sentiment from social media and news media, past price movement (e.g., the absolute value of lagged returns), and changes in fundamentals (e.g., standardized unexpected earnings). We estimate the specification below, linking these stock characteristics to the flow type at the level of investor holdings, using the investor (i)-stock (n)-time (t) observations.

$$\mathbf{1}(\text{Extensive/Intensive})_{int} = \beta \cdot X_{nt} + \eta_{it} + \alpha_{in} + \epsilon_{int}, \tag{3.1}$$

where $\mathbf{1}(\text{Extensive/Intensive})_{int}$ represents indicator variables in percentage terms for whether investor i's demand for stock n at time t is extensive or intensive. X_{nt} is the explanatory variable, such as social media attention and sentiment from Cookson et al. (2024), news coverage and sentiment from RavenPack, and lagged absolute values for stock returns and standardized unexpected earnings (SUE). Social media attention and sentiment, as well as news media sentiment, are standardized to have a mean of zero and a standard deviation of one. News coverage is measured by the log of the number of news articles covering a stock in a quarter. We include α_{in}, investor-stock fixed effects, accounting for unobserved time-invariant factors affecting investor i's demand on stock n, such as preferences, the time-invariant component of beliefs, proximity, and investor habitats. We also include η_{it} investor-time fixed effects, which capture investor-level shocks, such as liquidity, fund flows, fund structure, and investor-specific exposure to market fluctuations. By adding investor-time fixed effects, we effectively estimate a within-portfolio effect, which compares the same investor's choices between extensive and intensive trading, within the same period and within her portfolio, but across different stocks that have varying levels of attention, sentiment, price movement, and

changes in fundamentals.

[Insert Table 3 Here.]

Table 3 reveals three main findings on the different origins of extensive and intensive flows. First, the extensive flow is significantly driven by social media attention and sentiment, as shown in Column (1). However, this social media pathway is muted for the intensive flow in Column (5). In terms of the magnitude, social media attention has a sizable impact: a one-standard-deviation increase in social media attention increases the probability of a flow being extensive by 0.68 percentage points, a 3% rise relative to the sample mean of 20.4 percentage points.

Second, both flow types react to news coverage and news sentiment, as presented in Columns (2) and (6). The intensive flow reacts more strongly to news media, suggesting a high sensitivity to asset fundamentals. Finally, the extensive flow is driven by past returns while the intensive flow reflects changes in fundamentals. For example, Column (3) shows a significant positive relationship between the probability of extensive flows and the size of past price movement, measured by the absolute values of lagged returns—the larger a stock's price moved last quarter, the higher the probability for an investor to enter or exit that stock, relative to other stocks in her portfolio with smaller price movement. By contrast, the intensive flow has a significantly positive relationship with changes in fundamentals, as captured by the absolute values of standardized unexpected earnings (SUE). SUE measures the difference between realized earnings and the consensus analyst forecasts, which can be viewed as an unexpected shock to stock fundamentals. Column (8) indicates that a one-percentage-point increase in SUE results in a positive effect of 1.3 percentage points on the intensive flow probability.

Taken together, empirical results suggest that extensive and intensive flows originate from different sources and may have distinct information contents, with extensive flows driven by attention and past returns, and intensive flows reflecting asset fundamentals. Such findings motivate our stylized and estimation models and support the modeling assumptions on the distinction between extensive and intensive flows.

3.2 The Impact of Extensive and Intensive Flows

In this section, we examine the impacts of extensive and intensive flows on stock returns, volatility, and price informativeness. We aggregate investor holdings to the stock level, yielding a stock (n)-by-time (t) panel data for empirical analysis. The main finding is that the flow composition of a stock explains its return, volatility, and price informativeness—the larger the portion of extensive flows, the higher the contemporaneous return and volatility. The impact of extensive flow composition on price informativeness depends on the level of price informativeness itself. If a stock's price informativeness is high, extensive flow is positively correlated with informativeness. By contrast, if a stock's price informativeness is low, extensive flow is negatively correlated with informativeness.

3.2.1 Relations to Returns and Volatility

We first examine how the composition of investor flow relates to stock returns and volatility by estimating the specification below.

$$Y_{nt} = \beta \cdot \text{Composition}_{nt} + \gamma \cdot \text{Controls}_{nt} + \alpha_n + \alpha_t + \epsilon_{nt}, \tag{3.2}$$

where the outcome variable Y_{nt} is stock return, total volatility, and idiosyncratic volatility. The flow composition Composition_{nt} is the percentage composition of extensive flows. The percentage composition of intensive flow is omitted due to its perfect colinearity with extensive flow composition. We include stock fixed effects (α_n) and time fixed effects (α_t). Control variables include standardized unexpected earnings (SUE), size, book-to-market ratio, lagged return, and profitability.

[Insert Table 4 Here.]

Panel (a) in Table 4 shows the results. From Column (1) to Column (3), a consistent pattern emerges: a rise in the composition of extensive flows significantly increases contemporaneous return, volatility, and idiosyncratic volatility. Quantitatively, a one-percentage-point rise in extensive flow composition is associated with a four-basis-point increase in quarterly return and a five-basis-point increase in return volatility. If we shift the level of extensive flow composition from its 25th percentile, 19%, to its 75th percentile, 42%, the effect on return is 0.87 percentage

points (i.e., a 32.5% increase from the sample mean of 2.68%) and the effect on volatility is 1.15 percentage points (i.e., a 2.45% increase from the sample mean of 46.96%). These results show that the composition of flows, not just their level, has significant implications for asset pricing.

3.2.2 Relation to Price Informativeness

We now turn to the impact of flow composition on price informativeness, using the same specification (3.2) in the previous section. We focus on the stock-specific price informativeness (Dávila and Parlatore, 2023, 2025) whose construction is discussed in detail in Section 2.2.

Panel (b) in Table 4 displays the relationship between flow composition and price informativeness. We estimate the same regression specification first on the full sample and then on the samples with above-median price informativeness (the "high" sample) and below-median price informativeness (the "low" sample). Column (1) presents results estimated on the full sample, indicating a weakly positive relationship between extensive flow composition and price informativeness. If we focus on the sample of high informativeness, this positive relationship is strengthened significantly. A one-percentage-point increase in extensive flow is associated with a 0.3-percentage-point increase in price informativeness, representing a 3.4% increase from the sample mean. However, this positive relation flips sign in the sample of low informativeness—extensive flow is negatively correlated with price informativeness. A one-percentage-point increase in extensive flow is now associated with a 0.03-percentage-point decline in price informativeness, indicating a 4.5% decrease from the sample mean. Such a contrast between high- and low-informativeness samples is consistent with Dávila and Parlatore (2023): the papers argue that volatility and informativeness have a positive (negative) correlation when informativeness is sufficiently high (low). This argument naturally extends to our setting of extensive flows and corroborates our empirical findings, as we have shown in Panel (a) of Table 4 that extensive composition is positively correlated with volatility.

3.2.3 Flow Composition as Stock Heterogeneity

So far, we have been using flow composition as an explanatory variable for stock prices. Besides its direct impact on return and volatility, can flow composition function as a dimension of stock heterogeneity and alter how prices react to shifts in fundamentals? To answer this question, we estimate the regression specification below, which interacts flow composition with fundamentals

and ties both to returns and volatility.

$$\begin{aligned} Y_{nt} = \beta_0 \cdot \text{SUE}_{nt} + \beta_1 \cdot \text{Composition}_{nt} + \beta_2 \cdot \text{SUE}_{nt} \times \text{Composition}_{nt} \\ + \gamma \cdot \text{Controls}_{nt} + \alpha_n + \alpha_t + \epsilon_{nt}, \end{aligned} \tag{3.3}$$

where the outcome variable Y_{nt} is stock return, total volatility, and idiosyncratic volatility. We measure a stock's changes in fundamentals by standardized unexpected earnings (SUE). We then include the percentage composition of extensive flow and interact it with SUE. The flow composition Composition_{nt} is the percentage composition of extensive flows. The percentage composition of intensive flow is omitted due to its perfect colinearity with extensive flow composition. We include stock fixed effects (α_n) and time fixed effects (α_t). Control variables include size, book-to-market ratio, lagged return, and profitability.

The coefficient of interest is β_2, the one for the interaction term of SUE and flow composition. β_2 captures the heterogeneous effects of SUE on outcomes with varying levels of extensive flows, in addition to SUE's baseline effect on outcomes, β_0.

[Insert Table 5 Here.]

Table 5 documents that the extensive flow composition, as a measure for stock heterogeneity, amplifies the effect of SUE on returns and volatility—all coefficients for the interaction term are highly statistically significant. In terms of the magnitudes, for a stock with the average extensive flow composition around 30 percentage points, a one-percentage-point increase in SUE will raise returns by 0.23 percentage points through its baseline effect, as well as by an additional 0.09 (=0.003×30×1) percentage points through the amplifying heterogeneous effect via extensive flow composition. As such, the average extensive flow composition amplifies the impact of fundamentals on returns by 39% (=0.09/0.23). Similarly, for a stock with the average extensive flow composition, a one-percentage-point increase in SUE will lower volatility by 8.7 basis points through its baseline effect, as well as by an additional 6.0 (=0.002×30×1) basis points through the amplifying heterogeneous effect via extensive flow composition. As such, the average extensive flow composition amplifies the impact of fundamentals on volatility by 69% (=6.0/8.7).

3.3 Dynamic Flow-Return Relation: Local Projections

In the final part of this section, we use local projections to study the dynamic two-way relationship between stock returns and net extensive and intensive flows. We use the following specification to estimate the orthogonalized impulse response functions (IRFs).

$$Y_{n,t+h} = \beta^h \cdot X_{nt} + \sum_{\tau=1}^{L} \psi^\tau \cdot Y_{n,t-\tau} + \sum_{\tau=1}^{L} \phi^\tau \cdot X_{n,t-\tau} + \gamma \cdot \text{Controls}_{nt} + \alpha_n + \alpha_t + \epsilon_{nt}, \tag{3.4}$$

for $h \in \{0, 1, ..., 6\}$ and $L = 3$. Y and X are returns, net extensive flows, and net intensive flows. The coefficients of interest are $\{\beta^h\}_{h=1}^6$, which capture the dynamic effects of net extensive and intensive flows on stock returns in the next h quarter or the effects in the other direction. The specification includes stock fixed effects (α_n) and time fixed effects (α_t), and controls for standardized unexpected earnings (SUE), size, book-to-market ratio, and profitability. We present the estimated effects visually in Figure 6.

[Insert Figure 6 Here.]

Figure 6 plots the orthogonalized impulse response functions (IRFs) of returns to a one-percentage-point increase in net extensive and intensive flows in Panel (a), and net extensive and intensive flows to a one-percentage-point increase in returns in Panel (b).

The figure reveals three main findings. First, the contemporaneous relationship between net flows and returns is strong, with high statistical significance and large economic magnitude. Panel (a) indicates that a one-percentage-point increase in net extensive flows leads to an immediate positive effect of 1.2 percentage points on stock return. In the other direction, Panel (b) shows that a one-percentage-point increase in stock returns results in an immediate positive effect of two basis points on net extensive flows, and such an effect persists for at least one quarter.

Second, the effects for extensive and intensive flows generally have opposite signs. Take the contemporaneous effects of flows on returns in Panel (a) as an example. The extensive flows are positively related to stock returns, while a rise in net intensive flows has a negative, though relatively small, impact on stock returns. This finding is consistent with the motivating empirical Fact 4 presented in the previous section.

Finally, effects for extensive flows are strong in the short run but exhibit a reversal in the long run. As Panel (a) indicates, the effect of extensive flows on returns is positive in the same period, but the effects on future returns all turn negative. A similar pattern holds for the effect of returns on extensive flows: it is significantly positive within the first three periods but becomes negative starting from the fourth period, suggesting potential overshooting over the short run and then reversal over the long run.

4 Stylized Model

This section develops a three-date model of extensive and intensive demand for two risky assets, in the spirit of Grossman and Stiglitz (1980). It preserves the two ingredients emphasized in the data and carried into the structural model: (i) an information gap between extensive and intensive investors, and (ii) unobserved extensive reallocation that is impounded into prices and cannot be perfectly disentangled from fundamentals. The same environment also yields comparative statics that map directly into our reduced-form evidence on returns, volatility, and price informativeness.

4.1 Setup

There are two risky assets, A and B, each in unit supply, and a risk-free asset with zero net return. Time is $t \in \{1, 2, 3\}$: investors allocate capital at $t = 1$ before any information arrives, trade again at $t = 2$ after signals arrive and prices adjust, and collect dividends at $t = 3$. Asset $n \in \{A, B\}$ pays dividend

$$d_n = \mu_n + \varepsilon_n, \qquad \varepsilon_n \sim \mathcal{N}(0, \sigma_n^2),$$

with $\varepsilon_A \perp \varepsilon_B$. At $t = 2$, an asset-specific signal arrives:

$$\eta_n = d_n + e_n, \qquad e_n \sim \mathcal{N}(0, \sigma_{\eta,n}^2),$$

where all shocks are mutually independent unless stated otherwise.

Intensive investors have mass $1 - \phi$, where $\phi \in (0, 1)$, and can hold both risky assets simultaneously. Extensive investors have mass ϕ and take a position in at most one risky asset at a time.

At $t = 2$, intensive investors observe η_A and η_B; extensive investors do not observe these signals and infer fundamentals from prices instead.

All investors have CARA utility over terminal wealth:

$$V_t = \mathbb{E}_t[W_3] - \frac{\gamma}{2}\mathrm{Var}_t(W_3),$$

where $\gamma > 0$ is common risk aversion.

Let $E_{n,t}$ denote the set of extensive investors holding asset n at time t, with mass $\theta_{n,t}$ and $\theta_{A,t} + \theta_{B,t} = \phi$. Aggregate extensive holdings of asset n are

$$Q^E_{n,t} \equiv \int_{E_{n,t}} q^{E,i}_{n,t}\, di.$$

The net extensive reallocation into asset n at $t = 2$ is

$$m_n \equiv Q^E_{n,2} - Q^E_{n,1}.$$

Noise-trader demand at $t = 2$ is $z_n \sim \mathcal{N}(0, \sigma_z^2)$, independent across assets and of fundamentals.

Each extensive investor i holds a subjective belief $\tilde{m}_{n,i}$ about net extensive flow into asset n. For holder sets with $\theta_{n,2} > 0$, the cross-sectional mean belief is

$$\bar{m}_n \equiv \frac{1}{\theta_{n,2}} \int_{E_{n,2}} \tilde{m}_{n,i}\, di.$$

4.2 Equilibrium

4.2.1 Pre-signal allocation

At $t = 1$ no signal has arrived. Both investor types who hold asset n share the same prior, so each solves

$$U^I_{n,1}(q^I_{n,1}) = q^I_{n,1}(\mu_n - p_{n,1}) - \frac{\gamma}{2}(q^I_{n,1})^2\sigma_n^2,$$

with first-order condition

$$\mu_n - p_{n,1} - \gamma\sigma_n^2 q^I_{n,1} = 0,$$

giving

$$q^I_{n,1} = \gamma^{-1}\sigma_n^{-2}(\mu_n - p_{n,1}).$$

The extensive investor's problem is identical at $t = 1$, yielding the same quantity:

$$q^E_{n,1} = \gamma^{-1}\sigma_n^{-2}(\mu_n - p_{n,1}).$$

An extensive investor first chooses an asset, then quantity. Substituting the optimal demand, the maximized utility from choosing asset n is

$$U^E_{n,1} = \frac{1}{2}\gamma^{-1}\sigma_n^{-2}(\mu_n - p_{n,1})^2.$$

Interior choice requires $U^E_{A,1} = U^E_{B,1}$, or equivalently

$$\frac{\mu_A - p_{A,1}}{\sigma_A} = \frac{\mu_B - p_{B,1}}{\sigma_B} > 0.$$

Using $Q^E_{n,1} = \theta_{n,1} q^E_{n,1}$, market clearing is

$$(1-\phi)q^I_{n,1} + Q^E_{n,1} = 1,$$

which gives

$$\left[(1-\phi) + \theta_{n,1}\right]\gamma^{-1}\sigma_n^{-2}(\mu_n - p_{n,1}) = 1.$$

Together with $\theta_{A,1} + \theta_{B,1} = \phi$, these conditions pin down the holder-set masses and equilibrium prices.

Assumption 1 (Interior pre-signal allocation)**.** $\sigma_A > (1-\phi)\sigma_B \qquad \textit{and} \qquad \sigma_B > (1-\phi)\sigma_A.$

Proposition 1 (Pre-signal equilibrium)**.** *Under Assumption 1, there is a unique interior equilibrium at $t = 1$. For each asset $n \in \{A, B\}$, let $-n$ denote the other asset and let $\sum_n \sigma_n \equiv \sigma_A + \sigma_B$. Then*

$$q^I_{n,1} = q^E_{n,1} = \frac{\sum_n \sigma_n}{(2-\phi)\sigma_n}, \tag{4.1}$$

$$p_{n,1} = \mu_n - \frac{\gamma\left(\sum_n \sigma_n\right)\sigma_n}{2-\phi}. \tag{4.2}$$

Moreover,

$$\theta_{n,1} = \frac{\sigma_n - (1-\phi)\sigma_{-n}}{\sum_n \sigma_n},$$
$$Q^E_{n,1} = \theta_{n,1} \frac{\sum_n \sigma_n}{(2-\phi)\sigma_n}. \tag{4.3}$$

Before signals arrive both groups share the same prior, so any investor who chooses asset n holds the same quantity (4.1). The pre-signal price (4.2) and extensive holdings (4.3) serve as benchmarks for period-2 returns and reallocation. Assumption 1 ensures both assets attract a positive extensive mass.

4.2.2 Intensive investors at t=2

At $t = 2$, an intensive investor observes η_n and $p_{n,2}$. Joint normality gives a posterior mean and precision:

$$\hat{\mu}_n = \mu_n + g_n(\eta_n - \mu_n), \qquad g_n = \frac{\sigma^{-2}_{\eta,n}}{\sigma^{-2}_n + \sigma^{-2}_{\eta,n}}, \qquad \hat{\sigma}^{-2}_n = \sigma^{-2}_n + \sigma^{-2}_{\eta,n}. \tag{4.4}$$

Hence $\mathrm{Var}(\hat{\mu}_n) = g_n\sigma^2_n = \sigma^2_n - \hat{\sigma}^2_n$.

Since dividend shocks are independent across assets, the period-2 problem separates by asset. Optimizing

$$U^I_{n,2}(q^I_{n,2}) = q^I_{n,2}(\hat{\mu}_n - p_{n,2}) - \frac{\gamma}{2}(q^I_{n,2})^2\hat{\sigma}^2_n$$

gives optimal intensive demand

$$q^I_{n,2} = \gamma^{-1}\hat{\sigma}^{-2}_n(\hat{\mu}_n - p_{n,2}). \tag{4.5}$$

Define

$$\lambda_{z,n} \equiv \frac{\gamma}{(1-\phi)\hat{\sigma}^{-2}_n}, \tag{4.6}$$

the price impact of one unit of residual supply on the $1-\phi$ mass of intensive investors.

4.2.3 Extensive investors at t=2

An extensive investor does not observe η_n directly. Investor i's period-2 information set consists of $p_{n,2}$, the pre-signal holdings $Q^E_{n,1}$, model primitives, and a subjective belief $\tilde{m}_{n,i}$ about net extensive reallocation into asset n. Let $\bar{m}_n$ denote the holder-average belief.

Under investor i's subjective model, period-2 market clearing is

$$(1-\phi)\gamma^{-1}\hat{\sigma}_n^{-2}(\hat{\mu}_n - p_{n,2}) + Q^E_{n,1} + \tilde{m}_{n,i} + z_n = 1. \tag{4.7}$$

Rearranging (4.7) and using (4.6),

$$p_{n,2} = \hat{\mu}_n - \lambda_{z,n}\big(1 - Q^E_{n,1} - \tilde{m}_{n,i} - z_n\big).$$

Isolating the fundamental component gives the price-implied signal

$$\eta^p_{n,i} \equiv p_{n,2} + \lambda_{z,n}\big(1 - Q^E_{n,1} - \tilde{m}_{n,i}\big). \tag{4.8}$$

In investor i's subjective model,

$$\eta^p_{n,i} = \hat{\mu}_n + \lambda_{z,n} z_n. \tag{4.9}$$

Bayesian updating places weight κ_n on the price-implied signal, where

$$\kappa_n \equiv \frac{g_n(\lambda^2_{z,n}\sigma_z^2)^{-1}}{\sigma_n^{-2} + g_n(\lambda^2_{z,n}\sigma_z^2)^{-1}}.$$

Investor i's posterior mean is

$$\mathbb{E}_i[d_n \mid p_{n,2}, \tilde{m}_{n,i}] = \mu_n + \kappa_n\big(\eta^p_{n,i} - \mu_n\big). \tag{4.10}$$

The price-implied signal can be written as

$$\eta^p_{n,i} = \mu_n + g_n(d_n - \mu_n) + g_n e_n + \lambda_{z,n} z_n,$$

or equivalently

$$\mu_n + g_n^{-1}\left(\eta_{n,i}^{p} - \mu_n\right) = d_n + e_n + g_n^{-1}\lambda_{z,n} z_n.$$

Price therefore supplies a noisy signal of the dividend with effective noise variance

$$\sigma_{p,n}^2 \equiv \sigma_{\eta,n}^2 + \left(\frac{\lambda_{z,n}}{g_n}\right)^2 \sigma_z^2,$$

and posterior precision

$$\hat{\sigma}_{n,E}^{-2} \equiv \mathrm{Var}_i(d_n \mid p_{n,2}, \tilde{m}_{n,i})^{-1} = \sigma_n^{-2} + \sigma_{p,n}^{-2}. \tag{4.11}$$

This signal is noisier than the intensive investor's private signal because price embeds both signal noise and residual-supply noise. Using (4.4) and (4.6),

$$\hat{\sigma}_{n,E}^{-2} = \sigma_n^{-2} + \left[\sigma_{\eta,n}^2 + \frac{\gamma^2\sigma_{\eta,n}^4}{(1-\phi)^2}\sigma_z^2\right]^{-1} = \frac{(\sigma_n^2 + \sigma_{\eta,n}^2)(1-\phi)^2 + \gamma^2\sigma_{\eta,n}^4\sigma_z^2}{\sigma_n^2\sigma_{\eta,n}^2\left[(1-\phi)^2 + \gamma^2\sigma_{\eta,n}^2\sigma_z^2\right]}.$$

Optimizing investor i's expected utility

$$U_{n,2}^{E,i}(q_{n,2}^{E,i}) = q_{n,2}^{E,i}\Big(\mathbb{E}_i[d_n \mid p_{n,2}, \tilde{m}_{n,i}] - p_{n,2}\Big) - \frac{\gamma}{2}(q_{n,2}^{E,i})^2\hat{\sigma}_{n,E}^2$$

gives the first-order condition

$$\mathbb{E}_i[d_n \mid p_{n,2}, \tilde{m}_{n,i}] - p_{n,2} - \gamma\hat{\sigma}_{n,E}^2 q_{n,2}^{E,i} = 0.$$

Substituting (4.10) gives individual demand; plugging back into the objective gives the maximized utility (4.13) that governs sorting across assets.

Proposition 2 (Period-2 extensive demand)**.** *Fix an asset n and an extensive investor i. Then*

$$q_{n,2}^{E,i} = \gamma^{-1}\hat{\sigma}_{n,E}^{-2}\Big[(1-\kappa_n)(\mu_n - p_{n,2}) + \kappa_n\lambda_{z,n}\big(1 - Q_{n,1}^{E} - \tilde{m}_{n,i}\big)\Big]. \tag{4.12}$$

The corresponding maximized expected utility at $t = 2$ is

$$U_{n,2}^{E,i} = \frac{1}{2}\gamma^{-1}\hat{\sigma}_{n,E}^{-2}\left[(1-\kappa_n)(\mu_n - p_{n,2}) + \kappa_n\lambda_{z,n}\left(1 - Q_{n,1}^{E} - \tilde{m}_{n,i}\right)\right]^2. \tag{4.13}$$

The holder sets satisfy

$$E_{A,2} = \{i : U_{A,2}^{E,i} \geq U_{B,2}^{E,i}\}, \qquad E_{B,2} = \{i : U_{B,2}^{E,i} > U_{A,2}^{E,i}\}. \tag{4.14}$$

Extensive demand (4.12) combines two channels. The first term is a substitution channel: a higher price lowers the expected excess return and reduces demand. The second term is a learning channel: the investor's flow belief $\tilde{m}_{n,i}$ determines how much of the price she attributes to fundamentals rather than flow pressure, so a higher subjective inflow belief lowers demand. The price-signal weight κ_n governs the relative strength of the two channels.

Assumption 2 (Local post-signal sorting region)**.** *At the realized post-signal state, the expected-utility inequalities in* (4.14) *are strict. Hence there is a neighborhood of the state in which the holder sets $E_{n,2}$ and their masses $\theta_{n,2}$ remain fixed.*

This assumption is a simplifying device: it lets us characterize prices and demand within a fixed sorting region without tracking the measure-zero set of investors who switch assets at the margin.

4.2.4 Aggregate extensive demand at t=2

Assumption 2 fixes the holder set locally, so aggregate extensive demand depends only on the mean belief $\bar{m}_n$ among current holders. Integrating (4.12) over $E_{n,2}$ and using $\int_{E_{n,2}} \tilde{m}_{n,i}\, di = \theta_{n,2}\bar{m}_n$ gives:

Proposition 3 (Aggregate extensive demand)**.** *Under Assumption 2, fix a holder set $E_{n,2}$ with mass $\theta_{n,2}$ and mean belief $\bar{m}_n$. Aggregate extensive demand is*

$$Q_{n,2}^{E} = \gamma^{-1}\hat{\sigma}_{n,E}^{-2}\left[\theta_{n,2}(1-\kappa_n)(\mu_n - p_{n,2}) + \theta_{n,2}\kappa_n\lambda_{z,n}\left(1 - Q_{n,1}^{E} - \bar{m}_n\right)\right]. \tag{4.15}$$

Within a fixed sorting region, disagreement affects aggregate extensive demand only through the holder-average belief $\bar{m}_n$.

4.2.5 Equilibrium price at t=2

Market clearing at $t = 2$ requires

$$(1 - \phi)q^I_{n,2} + Q^E_{n,2} + z_n = 1. \tag{4.16}$$

Substituting (4.5),

$$p_{n,2} = \hat{\mu}_n - \lambda_{z,n}\big(1 - Q^E_{n,2} - z_n\big) = -\lambda_{z,n}\big(1 - Q^E_{n,1}\big) + \hat{\mu}_n + \lambda_{z,n}(m_n + z_n). \tag{4.17}$$

Price equals cash-flow news minus the discount needed to induce intensive investors to absorb residual supply. Extensive inflows and noise-trader demand enter symmetrically — both reduce the residual quantity that intensive investors must absorb.

Substituting (4.15) into (4.16) and collecting terms in $p_{n,2}$:

Proposition 4 (Local price equation)**.** *Under Assumption 2, fix a holder set $E_{n,2}$ with mass $\theta_{n,2}$ and mean belief $\bar{m}_n$. The local equilibrium price is*

$$p_{n,2} = a_n + b_n\hat{\mu}_n + c_n z_n - \delta_n \bar{m}_n, \tag{4.18}$$

where

$$\begin{aligned}
D_n &\equiv (1 - \phi)\hat{\sigma}_n^{-2} + \theta_{n,2}(1 - \kappa_n)\hat{\sigma}_{n,E}^{-2}, \\
a_n &\equiv \frac{\theta_{n,2}\left[(1 - \kappa_n)\mu_n + \kappa_n\lambda_{z,n}(1 - Q^E_{n,1})\right]\hat{\sigma}_{n,E}^{-2} - \gamma}{D_n}, \\
b_n &\equiv \frac{(1 - \phi)\hat{\sigma}_n^{-2}}{D_n}, \\
c_n &\equiv \frac{\gamma}{D_n}, \\
\delta_n &\equiv \frac{\theta_{n,2}\kappa_n\lambda_{z,n}\hat{\sigma}_{n,E}^{-2}}{D_n}.
\end{aligned}$$

Higher cash-flow news and stronger noise-trader demand both raise price; a higher mean flow belief lowers it, as extensive investors attribute more of the price increase to flow pressure rather

than fundamentals.

4.3 Implications

4.3.1 Demand elasticities

Proposition 5 (Demand elasticities)**.** *For any interior holder of asset n at t = 2,*

$$\mathcal{E}_n^I \equiv \frac{\partial q_{n,2}^I}{\partial p_{n,2}} = -\gamma^{-1}\hat{\sigma}_n^{-2}, \qquad \mathcal{E}_n^E \equiv \frac{\partial q_{n,2}^{E,i}}{\partial p_{n,2}} = -\gamma^{-1}\hat{\sigma}_{n,E}^{-2}\Big[(1-\kappa_n) + \kappa_n\lambda_{z,n}\psi_n\Big],$$

where $\psi_n = \frac{\partial \tilde{m}_n}{\partial p_n}$*. Hence,*

$$|\mathcal{E}_n^I| > |\mathcal{E}_n^E|, \tag{4.19}$$

and the extensive demand elasticity $\mathcal{E}_n^E$ *is positive if* $\psi_n < (1-\kappa_n^{-1})\lambda_{z,n}$*.*

Intensive investors observe η_n directly, so a higher price lowers only expected excess return. Extensive investors learn from price, so part of a price increase signals better cash flows — making demand less elastic in absolute value.

Prediction 1. *Extensive demand is less price-elastic than intensive demand, and can be upward-sloping when investors' flow beliefs comove negatively with prices.* Section 6 tests this prediction with structurally estimated elasticities at both margins (Table 6).

Proposition 6 (Flow-belief sensitivity)**.** *For any extensive investor i and asset n,*

$$\frac{\partial q_{n,2}^{E,i}}{\partial \tilde{m}_{n,i}} = -\gamma^{-1}\kappa_n\lambda_{z,n}\hat{\sigma}_{n,E}^{-2} < 0.$$

If investor i expects stronger inflows, a given price more likely reflects flow pressure and less likely signals strong cash flows, so desired holdings fall.

4.3.2 Returns and volatility

Proposition 7 (Extensive flow and returns)**.** *For each asset n, define the contemporaneous and next-period returns by*

$$r_{n,2} \equiv p_{n,2} - p_{n,1}, \qquad r_{n,3} \equiv d_n - p_{n,2}.$$

Then

$$\frac{\partial r_{n,2}}{\partial m_n} = \lambda_{z,n} > 0, \qquad \frac{\partial r_{n,3}}{\partial m_n} = -\lambda_{z,n} < 0.$$

Intensive investors are the residual price-setters. Extensive inflows reduce the quantity they absorb, raising price on impact; the compressed dividend-price spread then lowers subsequent returns.

Aggregate intensive net flow is

$$m_n^I \equiv (1-\phi)\left(q_{n,2}^I - q_{n,1}^I\right) = -m_n - z_n,$$

so, holding z_n fixed,

$$\frac{\partial r_{n,2}}{\partial m_n^I} = -\lambda_{z,n} < 0, \qquad \frac{\partial r_{n,3}}{\partial m_n^I} = \lambda_{z,n} > 0.$$

The intensive-flow signs mirror the extensive-flow signs: high intensive net buying reflects greater residual supply absorption, so prices are lower on impact and higher subsequently.

Prediction 2. *Net extensive inflows raise contemporaneous returns and lower next-period returns; net intensive flows display the opposite signs.* This is Fact 4 (Figure 4), and the local projections in Section 3.3 confirm the dynamics.

Proposition 8 (Contemporaneous return variance decomposition)**.** *Conditioning on time-*1 *information,*

$$\mathrm{Var}(r_{n,2} \mid t=1) = \mathrm{Var}(\hat{\mu}_n) + \lambda_{z,n}^2 \mathrm{Var}(m_n + z_n) + 2\lambda_{z,n}\mathrm{Cov}(\hat{\mu}_n, m_n). \tag{4.20}$$

The three terms are fundamental news, non-fundamental price pressure from $m_n + z_n$, and the news-amplification channel. Noise-trader demand is non-fundamental by assumption; extensive reallocations move prices through market clearing regardless of their informational content. Return volatility rises when extensive flow covaries positively with cash-flow news.

4.3.3 Extensive flow share and news amplification

Holder-average beliefs determine how strongly price loads on fundamentals. The following results trace that channel through news amplification, volatility resolution, and price informativeness.

Assumption 3 (Price-based holder-average beliefs)**.** *Within a fixed sorting region, the holder-weighted mean post-price belief of extensive investors who hold asset n satisfies*

$$\bar{m}_n = \alpha_n(m_n) + \xi_n(m_n)p_{n,2} + \nu_n(m_n), \tag{4.21}$$

where α_n and ξ_n are continuously differentiable, $\xi_n(m_n) \geq 0$, $1 + \delta_n\xi_n(m_n) > 0$, and $\nu_n(m_n)$ satisfies

$$\mathbb{E}[\nu_n(m_n) \mid \hat{\mu}_n] = 0, \qquad \mathrm{Cov}(\hat{\mu}_n, \nu_n(m_n)) = 0, \qquad \mathrm{Cov}(z_n, \nu_n(m_n)) = 0.$$

The coefficient $\xi_n(m_n)$ measures how strongly current holders interpret a higher price as evidence of greater flow pressure. The term $\nu_n(m_n)$ captures residual holder-average belief variation orthogonal to both cash-flow news and noise-trader demand. The affine functional form is for tractability; the economic content is that holders may read part of a higher price as flow pressure ($\xi_n \geq 0$).

Substituting (4.21) into the local price equation (4.18) gives

$$p_{n,2} = \tilde{a}_n(m_n) + \tilde{b}_n(m_n)\hat{\mu}_n + \tilde{c}_n(m_n)z_n - \tilde{d}_n(m_n)\nu_n(m_n), \tag{4.22}$$

where

$$\begin{aligned}
\tilde{a}_n(m_n) &\equiv \frac{a_n - \delta_n\alpha_n(m_n)}{1 + \delta_n\xi_n(m_n)}, \\
\tilde{b}_n(m_n) &\equiv \frac{b_n}{1 + \delta_n\xi_n(m_n)}, \\
\tilde{c}_n(m_n) &\equiv \frac{c_n}{1 + \delta_n\xi_n(m_n)}, \\
\tilde{d}_n(m_n) &\equiv \frac{\delta_n}{1 + \delta_n\xi_n(m_n)}.
\end{aligned}$$

Equation (4.22) shows how extensive flow shifts the loadings of price on fundamentals, noise trading, and residual belief dispersion.

Assumption 4 (Extensive-flow price attribution)**.** *Under Assumption 3, the price-attribution coef-*

ficient is continuously differentiable and decreasing in extensive flow:

$$\xi_n'(m_n) < 0.$$

With more extensive flow, investors attribute a larger share of any price increase to fundamentals rather than flow pressure. For two nearby flow realizations with $m_n^H > m_n^L$ and two news realizations $\hat{\mu}_n^H > \hat{\mu}_n^L$, define the within-flow news spread

$$\Delta r_{n,2}(m_n) \equiv r_{n,2}(\hat{\mu}_n^H \mid m_n) - r_{n,2}(\hat{\mu}_n^L \mid m_n). \tag{4.23}$$

Proposition 9 (Extensive flow and news amplification)**.** *Suppose Assumptions 3 and 4 hold. Then*

$$\frac{\partial r_{n,2}}{\partial \hat{\mu}_n} = \tilde{b}_n(m_n) = \frac{b_n}{1 + \delta_n \xi_n(m_n)}, \tag{4.24}$$

$$\Delta r_{n,2}(m_n^H) > \Delta r_{n,2}(m_n^L). \tag{4.25}$$

Higher extensive flow strengthens the return response to news (4.24): when investors attribute less of a price increase to flow pressure, good news generates a larger contemporaneous return (4.25).

Prediction 3. *A higher extensive flow share amplifies the response of returns to fundamental news.* Table 5 tests this with regressions that interact the extensive flow composition with earnings surprises.

Proposition 10 (Extensive flow and volatility resolution)**.** *Suppose Assumptions 3 and 4 hold. Define*

$$\Delta\mathrm{Var}(r_{n,2} \mid t = 1, m_n) \equiv \mathrm{Var}(r_{n,2} \mid t = 1, m_n) - \mathrm{Var}(r_{n,2} \mid \hat{\mu}_n, m_n). \tag{4.26}$$

Then, conditional on extensive flow m_n, contemporaneous return variance is

$$\mathrm{Var}(r_{n,2} \mid t = 1, m_n) = \tilde{b}_n(m_n)^2 \mathrm{Var}(\hat{\mu}_n) + \tilde{c}_n(m_n)^2 \sigma_z^2 + \tilde{d}_n(m_n)^2 \mathrm{Var}\big(\nu_n(m_n)\big),$$

while conditioning on fundamental news leaves

$$\mathrm{Var}(r_{n,2} \mid \hat{\mu}_n, m_n) = \tilde{c}_n(m_n)^2\sigma_z^2 + \tilde{d}_n(m_n)^2\mathrm{Var}\big(\nu_n(m_n)\big). \tag{4.27}$$

Hence the amount of contemporaneous volatility resolved by fundamentals is

$$\Delta\mathrm{Var}(r_{n,2} \mid t = 1, m_n) = \tilde{b}_n(m_n)^2\mathrm{Var}(\hat{\mu}_n) = \frac{b_n^2}{\big[1 + \delta_n\xi_n(m_n)\big]^2}\mathrm{Var}(\hat{\mu}_n), \tag{4.28}$$

and for any two sufficiently close realizations with $m_n^H > m_n^L$,

$$\Delta\mathrm{Var}(r_{n,2} \mid t = 1, m_n^H) > \Delta\mathrm{Var}(r_{n,2} \mid t = 1, m_n^L).$$

Higher extensive flow raises the share of contemporaneous return variance attributable to fundamentals. More volatility is resolved once news arrives because a larger fraction of the prior price movement reflects fundamentals.

4.3.4 Price informativeness

For the local equilibrium indexed by m_n, stock-level informativeness is

$$\mathcal{I}_n^{stock}(m_n) \equiv \frac{\mathrm{Var}\big(\mathbb{E}[d_n \mid p_{n,2}, m_n] \mid m_n\big)}{\mathrm{Var}(d_n \mid m_n)}.$$

Price attribution rescales every loading in (4.22) by the same denominator $1 + \delta_n\xi_n(m_n)$, which cancels in the informativeness ratio. The remaining state variable is residual holder-belief dispersion $\mathrm{Var}(\nu_n(m_n))$.

Assumption 5 (Gaussian residual belief dispersion)**.** *Fix a local equilibrium state indexed by m_n. Conditional on that state, $\nu_n(m_n)$ is Gaussian with mean zero and independent of $(\hat{\mu}_n, z_n)$.*

Under Assumption 5, $(d_n, p_{n,2})$ is jointly Gaussian within each local state, so $\mathbb{E}[d_n \mid p_{n,2}, m_n]$ is linear in price.

Assumption 6 (High- and low-informativeness states)**.** *Fix two sufficiently close extensive-flow realizations with $m_n^H > m_n^L$. In the high-informativeness state, higher extensive flow reduces*

residual holder-belief dispersion. In the low-informativeness state, higher extensive flow raises residual holder-belief dispersion:

$$\mathrm{Var}\big(\nu_n(m_n^H)\big) < \mathrm{Var}\big(\nu_n(m_n^L)\big) \quad \textit{in the high-informativeness state,}$$

and

$$\mathrm{Var}\big(\nu_n(m_n^H)\big) > \mathrm{Var}\big(\nu_n(m_n^L)\big) \quad \textit{in the low-informativeness state.}$$

In the high-informativeness state, more extensive flow tightens post-price belief alignment, reducing residual disagreement. In the low-informativeness state, it widens disagreement. This assumption is the model's key state-dependence ingredient rather than a derived result; Prediction 4 below makes it testable.

Proposition 11 (Extensive flow and price informativeness)**.** *Suppose Assumptions 3, 5, and 6 hold. Then*

$$\mathcal{I}_n^{stock}(m_n) = \frac{\mathrm{Var}(\hat{\mu}_n)^2 b_n^2}{\sigma_n^2\left[\mathrm{Var}(\hat{\mu}_n) b_n^2 + c_n^2\sigma_z^2 + \delta_n^2 \mathrm{Var}\big(\nu_n(m_n)\big)\right]}. \tag{4.29}$$

Moreover,

$$\begin{aligned} &\mathcal{I}_n^{stock}(m_n^H) > \mathcal{I}_n^{stock}(m_n^L) && \textit{in the high-informativeness state,} \\ &\mathcal{I}_n^{stock}(m_n^H) < \mathcal{I}_n^{stock}(m_n^L) && \textit{in the low-informativeness state.} \end{aligned}$$

Higher extensive flow can raise or lower price informativeness, depending on whether it compresses or widens residual holder-belief dispersion. The price-attribution coefficient $\xi_n(m_n)$ generates no separate comparative static — it rescales signal and noise proportionally and cancels in the ratio.

Prediction 4. *Higher extensive flow raises stock-specific price informativeness when informativeness is high and lowers it when informativeness is low.* Panel (b) of Table 4 tests exactly this state dependence.

A complementary market-level measure is

$$\mathcal{I}_n^{market}(m_n) \equiv \sqrt{\mathrm{Var}\big(\mathbb{E}[d_n \mid p_{n,2}, m_n] \mid m_n\big)}.$$

Unlike $\mathcal{I}_n^{stock}(m_n)$, this measure is not unit-free — it inherits the units of the dividend.

Corollary 12 (Level price informativeness)**.** *Suppose Assumptions 3 and 5 hold. Then*

$$\mathcal{I}_n^{market}(m_n) = \frac{\mathrm{Var}(\hat{\mu}_n)|b_n|}{\sqrt{\mathrm{Var}(\hat{\mu}_n)b_n^2 + c_n^2\sigma_z^2 + \delta_n^2\mathrm{Var}\big(\nu_n(m_n)\big)}} = \sigma_n\sqrt{\mathcal{I}_n^{stock}(m_n)}.$$

Therefore $\mathcal{I}_n^{market}(m_n)$ *depends on extensive flow only through* $\mathrm{Var}\big(\nu_n(m_n)\big)$*. Under Assumptions 3, 5, and 6,*

$$\begin{aligned} &\mathcal{I}_n^{market}(m_n^H) > \mathcal{I}_n^{market}(m_n^L) && \textit{in the high-informativeness state,} \\ &\mathcal{I}_n^{market}(m_n^H) < \mathcal{I}_n^{market}(m_n^L) && \textit{in the low-informativeness state.} \end{aligned}$$

The two measures share the same state ranking. For a given asset σ_n^2 is fixed, so they differ only in scale: $\mathcal{I}_n^{stock}$ is unit-free while $\mathcal{I}_n^{market}$ measures the level of cash-flow variation revealed by price.

5 Structural Estimation

In this section, we extend the two-asset stylized model in Section 4 to a more general setting with multiple assets and heterogeneous investors. Our goal is to obtain a tractable asset demand system that (i) preserves the core economic mechanisms distinguishing extensive from intensive demand and (ii) can be empirically estimated using stock characteristics and portfolio holdings.

Our structural model shares the same spirit but extends the characteristics-based demand system in Koijen and Yogo (2019) and Koijen, Richmond, and Yogo (2024). Specifically, we embed learning from prices (Grossman and Stiglitz, 1980) and subjective expectations about flows into a demand system. Expectations about extensive flows shape their demand by altering how they interpret the informational content of prices. We next present the full model setup and solve for investor demand and equilibrium prices. We then describe how we empirically estimate such a characteristics-based demand system, under alternative specifications of flow expectations.

5.1 Model Setup and Solution

We consider a static, two-period model ($t \in \{0, 1\}$). The economy consists of N risky assets and one riskless asset. The riskless asset offers a gross return R_f and is in perfectly elastic supply. Each risky asset n pays a dividend $d(n)$ at $t = 1$. The vector of dividends for all N assets, d, is determined by a factor model:

$$d = \mu + \rho F + \varepsilon \tag{5.1}$$

where d, μ, and ε are $N \times 1$ vectors. μ is the vector of expected dividends. F is a scalar systematic factor, assumed to follow a standard normal distribution, $F \sim N(0, 1)$. ρ is an $N \times 1$ vector of factor loadings. ε is an $N \times 1$ vector of idiosyncratic shocks. The shocks are normally distributed, $\varepsilon \sim N(0, \Sigma_\varepsilon)$, where $\Sigma_\varepsilon = \sigma_\varepsilon^2 I$ is a diagonal covariance matrix. The supply of risky assets is normalized to $\mathbf{1}$.

Investors. There is a continuum of investors, indexed by i. All investors have constant absolute risk aversion (CARA) utility over the period-1 wealth W_{1i}, with a risk aversion coefficient of γ_i. Their objective is to:

$$\max_{q_i} E[-\exp(-\gamma_i W_{1i}) | \mathcal{I}_i] \tag{5.2}$$

where q_i is the vector of asset holdings for investor i and $\mathcal{I}_i$ is their information set.

At the beginning of $t = 0$, investors hold a subset of the risky assets. We denote the subset of assets that investor i holds as $\mathcal{N}_{0i} \subseteq \{1, ..., N\}$ and define a selection vector s_i where $s_i(n) = 1$ if $n \in \mathcal{N}_{0i}$ and 0 otherwise. The corresponding selection matrices are $s_i^I = \text{diag}(s_i)$ and $s_i^E = \text{diag}(\mathbf{1} - s_i)$.[2] For an asset n, investor i is classified as an "intensive investor" if $n \in \mathcal{N}_{0i}$ and as an "extensive investor" if $n \notin \mathcal{N}_{0i}$. The period-1 wealth is

$$W_{1i} = R_f(W_{0i} - p'q_i) + q_i'd = R_f W_{0i} + q_i'(d - R_f p). \tag{5.3}$$

Information gap between investors. A key feature of this model is the information gap between extensive and intensive investors: for each asset, investors who hold it receive a private signal, while investors who do not must learn from prices. Intensive investors of asset n receive a noisy signal,

[2] For each investor, we sort the assets so that the non-zero diagonal elements of s_i^I are concentrated in the top-left block.

$\eta(n)$, about the idiosyncratic shock to the asset payoff, $\varepsilon(n)$. We write the signals of different assets in vector form:

$$\eta = \varepsilon + e, \quad \text{where } e \sim N(0, \Sigma_\eta). \tag{5.4}$$

The noise for each asset's signal is independent of the factor and uncorrelated across assets, so the covariance matrix is diagonal, $\Sigma_\eta = \sigma_\eta^2 I$, with signal-noise variance σ_η^2 for each asset.

Belief updating. Investors update their beliefs about ε using their signals and, in the case of extensive investors, the information from prices. Extensive investors infer information from market prices based on their perceived extensive flows. Following the setup in Section 4, the extensive flow of a stock is defined as the total quantity (shares) held by the extensive investors. An extensive investor i forms a subjective expectation about this extensive flow. Let $\tilde{m}_i = \left[\tilde{m}_i(1), \tilde{m}_i(2), \ldots, \tilde{m}_i(N)\right]^\top$ denote the vector of investor i's subjective expectations. The perceived price signal by extensive investor i is denoted by η_{p_i}; as in the stylized model, the investor nets her perceived flow pressure out of the observed price and treats the remainder as news about fundamentals.

In vector-matrix form, the posterior beliefs for any investor i are:

$$E[\varepsilon|\mathcal{I}_i] = \hat{\varepsilon}_i = \hat{\Sigma}_{\varepsilon i}\Sigma_{\bar{\eta}_i}^{-1}\bar{\eta}_i \tag{5.5}$$

$$\text{Var}(\varepsilon|\mathcal{I}_i) = \hat{\Sigma}_{\varepsilon i} = (\Sigma_\varepsilon^{-1} + \Sigma_{\bar{\eta}_i}^{-1})^{-1} \tag{5.6}$$

where $\bar{\eta}_i = s_i^I \eta + s_i^E \eta_{p_i}$ and $\Sigma_{\bar{\eta}_i}$ can be written as the sum of a diagonal matrix, Σ_η and a block matrix, $\Sigma_{\eta p,i}^E$, which has support only on assets that investor i does not hold at $t = 0$: $\Sigma_{\bar{\eta}_i} = s_i^I \Sigma_\eta s_i^I + s_i^E \Sigma_{p_i} s_i^E = \Sigma_\eta + \Sigma_{\eta p,i}^E$. The definition and derivation of η_{p_i} and $\Sigma_{\eta p,i}^E$ are in Appendix B.

The conditional moments of the full dividend vector d are:

$$E[d|\mathcal{I}_i] \equiv \hat{\mu}_{di} = \mu + \hat{\varepsilon}_i \tag{5.7}$$

$$\text{Var}(d|\mathcal{I}_i) \equiv \hat{\Sigma}_{di} = \rho\rho' + \hat{\Sigma}_{\varepsilon i} \tag{5.8}$$

Noise Traders. A unit measure of noise traders trade for non-information reasons, e.g., hedging needs, liquidity shocks, or fund flows. They buy z shares of the risky asset in period 0, where

$z \sim N(0, \Sigma_z)$. z is independent of other shocks. The noise demand is assumed to be independent across assets, and thus $\Sigma_z = \sigma_z^2 I$ is a diagonal covariance matrix.

Equilibrium. An equilibrium is a set of price functions p and investors' portfolio choices $\{q_i\}$, such that

1. Given the information set $\mathcal{I}_i$ and their subjective expectations about extensive flows $\tilde{m}_i$, each investor i chooses asset demand q_i to maximize expected utility (5.2), subject to the budget constraint (5.3).

2. Markets clear. The vector of price function p equates all investors' demand to the supply:

$$\int q_i di + z = \mathbf{1}. \tag{5.9}$$

Solving investor demand. By substituting the posterior beliefs (5.7) and (5.8) into the first order conditions, we obtain the expression of investors' optimal demand.

Proposition 1 (Optimal Demand)**.** *Investors' optimal demand is*

$$q_i = \gamma_i^{-1} \hat{\Sigma}_{di}^{-1} \left((I - \kappa_i) \mu + g(\tilde{m}_i) + \hat{\Sigma}_{\varepsilon i} \Sigma_{\bar{\eta}_i}^{-1} s_i^I \eta - (I - \kappa_i) R_f p \right). \tag{5.10}$$

The detailed proof is in Appendix B.1. Demand has the same structure as in the stylized model: a substitution component in prices, a learning component governed by the price-signal weight κ_i, a private-signal component carried only by intensive positions, and a flow-expectation component $g(\tilde{m}_i)$. $\kappa_i = \hat{\Sigma}_{\varepsilon i} \Sigma_{\bar{\eta}_i}^{-1} s_i^E \Sigma_\eta \hat{\Sigma}_{\varepsilon I}^{-1}$ is the loading on the signal inferred from prices by investor i.[3] If κ_i is higher, the investor perceives that the price is more informative and she puts more weight on the price signal. The term $g(\tilde{m}_i) = \kappa_i \bar{\gamma}_{iI} \hat{\Sigma}_{dI} (\mathbf{1} - \tilde{m}_i)$ captures the perceived level shift of prices driven by the extensive flow. $\hat{\Sigma}_{\varepsilon I} = (\Sigma_\varepsilon^{-1} + \Sigma_\eta^{-1})^{-1}$ and $\hat{\Sigma}_{dI} = \rho\rho' + \hat{\Sigma}_{\varepsilon I}$ denote the posterior covariance matrices of a hypothetical fully diversified intensive investor who directly observes the signal for every asset. We use $\bar{\gamma}_{iI}^{-1}$ to denote investor i's perceived aggregate risk tolerance supplied by intensive investors, and $\bar{\gamma}_{iI}$ for its component-wise reciprocal.

[3] κ_i is a block matrix which has support only on assets that investor i does not hold at $t = 0$.

Solving equilibrium prices. The objective market clearing condition can be written as:

$$\int q_i di = \int \gamma_i^{-1} \hat{\Sigma}_{di}^{-1} (\hat{\mu}_{di} - pR_f) di = \mathbf{1} - z \tag{5.11}$$

Define a matrix Ω as the risk-tolerance-weighted average posterior precision of all investors:

$$\Omega = \int \gamma_i^{-1} \hat{\Sigma}_{di}^{-1} di$$

The term Ω captures the aggregate sensitivity of investors' demands to expected excess returns, given their information sets and subjective beliefs. The aggregate demand can then be written as:

$$\int q_i di = \Omega(\mu - pR_f) + \int \gamma_i^{-1} \hat{\Sigma}_{di}^{-1} \hat{\varepsilon}_i di \tag{5.12}$$

The second term captures the demand component driven by information about the idiosyncratic shocks. Imposing market clearing gives the following proposition.

Proposition 2 (Equilibrium Prices)**.** *Solving for the equilibrium price p gives the final linear price function:*

$$p = \frac{1}{R_f} \left[\mu - (\Omega - \Omega_p)^{-1} \left(\mathbf{1} - \Omega_m(\tilde{m}) \right) + (\Omega - \Omega_p)^{-1} \Omega_\eta \eta + (\Omega - \Omega_p)^{-1} z \right] \tag{5.13}$$

The proof and definitions of Ω_p, Ω_η, and $\Omega_m(\tilde{m})$ are in Appendix B.2. The equilibrium price is a function of expected payoffs (μ), aggregate information about idiosyncratic shocks (η), the aggregated effect of subjective expectations about extensive flows ($\Omega_m(\tilde{m})$), and the noise-trader demand (z).

5.2 Characteristics-Based Demand System

Following Koijen and Yogo (2019), we assume that expected dividends $\mu(n)$ and factor loadings $\rho(n)$ can be represented as functions of observable characteristics, $x(n)$:

$$\mu(n) = \Phi'_\mu x(n) + \xi_\mu, \tag{5.14}$$

$$\rho(n) = \Phi'_\rho x(n) + \xi_\rho, \tag{5.15}$$

where Φ_μ and Φ_ρ are vectors of coefficients on stock characteristics, and ξ_μ and ξ_ρ are scalars that are constant across assets.

Rewriting investors' optimal demand in Proposition 1 into a form that separates own and cross-asset substitutions, and combining it with equations (5.14) and (5.15), gives the following corollary to Proposition 1.

Corollary 1. *Investor i's optimal demand in Proposition 1 admits the linear form*

$$\begin{aligned} q_i(n) =& \gamma_i^{-1}\left(\hat{\sigma}_{\varepsilon I}^2 + (\hat{\sigma}_{\varepsilon i}^{E,d})^2\right)^{-1}\Bigg[\underbrace{-(1-\kappa_i^{E,d})R_f p(n)}_{\text{price term}} + \underbrace{\kappa_i^{E,d}\bar{\gamma}_{iI}\hat{\sigma}_{\varepsilon I}^2(1-\tilde{m}_i(n))}_{\text{flow expectation term}} + \\ & \underbrace{\left((1-\kappa_i^{E,d})\Phi_\mu - \Phi_\rho\left(c_{i\rho,0} + c_{i\rho,1}s_i(n)\right)\right)x(n)}_{\text{characteristics term}} + \underbrace{\hat{\sigma}_{\varepsilon I}^2\sigma_\eta^{-2}s_i(n)\eta(n)}_{\text{signal term}} + \underbrace{\zeta_{i0} + \zeta_{i1}s_i(n)}_{\text{investor specific scalars}}\Bigg]. \end{aligned} \tag{5.16}$$

The proof and the definitions of $(\hat{\sigma}_{\varepsilon i}^{E,d})^2$, $\kappa_i^{E,d}$, $c_{i\rho,0}$, $c_{i\rho,1}$, ζ_{i0}, and ζ_{i1} are in Appendix B.3. We separate the posterior variance of idiosyncratic shocks, $\hat{\Sigma}_{\varepsilon i}$, into a diagonal matrix, $\hat{\Sigma}_{\varepsilon i}^{E,d}$, and a block matrix with only the bottom-right block being non-zero. This remaining block captures the posterior covariance among assets induced by learning from prices. We obtain a similar separation of κ_i, whose diagonal part is denoted by $\kappa_i^{E,d}$. In equation (5.16), $(\hat{\sigma}_{\varepsilon i}^{E,d})^2$, $\kappa_i^{E,d}$, $\bar{\gamma}_{iI}$, and $\hat{\sigma}_{\varepsilon I}^2$ are shorthand for the relevant own-asset diagonal entries. The investor-specific vectors ζ_{i0}, and ζ_{i1} capture the remaining cross-asset substitution induced by investors' posterior beliefs, including the part of the flow-expectation channel that does not load one-for-one on own-asset expected flows.

Following Haddad et al. (2025), we interpret the "price term" as the "relative" elasticity, under the assumption of homogeneous substitution conditional on observables. The "characteristics term" is standard in the literature, except that our variant embeds the heterogeneity introduced by extensive demand. The innovation of our model is reflected in the "signal" and "flow expectation" terms. The "signal" term captures the information gap between extensive and intensive investors, through the effect of the payoff signal received only by intensive investors. The "flow expectation" term captures the effect of subjective expectations about flows.

5.3 Flow Expectations

A key component in our demand system is investor i's expectation about the contemporaneous extensive flow into stock n at time t, $\tilde{m}_{it}(n)$. The actual extensive flow $m_{it}(n)$ is not observable within period t at the time of the portfolio choice. In this section, we first discuss how subjective expectations about extensive flows affect investor demand and its price elasticity. And then, we model flow expectation $\tilde{m}_{it}(n)$ using several specifications of belief formation widely studied and used in the literature.

Extensive flow expectations and demand function. Investors' extensive flow expectations enter their demand function (5.16) through the "flow expectation" term below:

$$\underbrace{\gamma_i^{-1}}_{\text{Risk tolerance}} \underbrace{\left(\hat{\sigma}_{\varepsilon I}^2 + (\hat{\sigma}_{\varepsilon i}^{E,d})^2\right)^{-1}}_{\text{Posterior precision}} \underbrace{\kappa_i^{E,d} \bar{\gamma}_{iI} \hat{\sigma}_{\varepsilon I}^2}_{\text{Kalman gain}} (1 - \tilde{m}_i(n))$$

The demand sensitivity to flow expectations is determined by risk tolerance, posterior precision, and the Kalman gain, which is the precision weight investors use to update their posterior beliefs about fundamentals using price signals in Bayesian updating. Flow expectations $\tilde{m}_i(n)$ enter the term negatively through $1 - \tilde{m}_i(n)$, which represents the perceived total intensive demand for the stock.

Intuitively, when investors believe that extensive inflows are large, they view a price increase as being less driven by intensive demand. Therefore, when investors interpret the informational content of prices, they effectively net out this uninformed component, which lowers their expectation

about fundamentals and leads them to hold less of the stock. Together, there is a negative relation between extensive flow expectation and investor demand, as shown in the equation above.

We next describe three different specifications of flow expectations that we use in structural estimation.

Specification 1: Statistically optimal expectations.

We begin with a rational benchmark and assume investors form extensive flow expectations based on statistically optimal forecasts (Bianchi, Ludvigson, and Ma, 2022). The forecasting model, estimated using rolling windows on historical data, uses a wide range of available information to predict contemporaneous extensive flows.

Specifically, we estimate a forecasting model on a training sample of past observations:

$$m_{it}(n) \;=\; h_{\theta,t}(y_{i,t}(n), z_t) + \varepsilon_{i,t},$$

where $h_\theta(\cdot)$ is the LASSO prediction of extensive flow. $y_{i,t}$ denotes stock-level characteristics (e.g., size, valuation, profitability, growth, recent returns), past extensive flows, and let z_t denote market variables (e.g., market returns and risk-free rates). The predictor set we use consists of contemporaneous and up to four quarterly lags of each characteristic, as well as lagged quarterly market returns and the risk-free rate. We estimate the forecasting model's parameters, θ, using a rolling LASSO over a 5-year (20-quarter) window. For each prediction quarter t, the model is trained on the most recent 20 quarters. The penalty parameter is selected via a simple time-series validation step that reserves the most recent year within the window and chooses the ℓ_1 penalty minimizing validation MSE. The LASSO is refit on the full training window with the selected penalty and used to generate cross-sectional forecasts $h_{\theta,t}(y_{i,t}(n), z_t)$ for all stocks in quarter t.

We allow investors to have heterogeneous expectations based on the statistically optimal forecasts. We assume their flow expectations follow an affine function of the forecasts. In period t, the investor i's flow expectation is

$$\tilde{m}^{\text{stat}}_{i,t}(n) = a^{\text{stat}}_{i,t} + b^{\text{stat}}_{i,t}\widehat{h}_{\widehat{\theta}}(y_{i,t}, z_t).$$

The heterogeneity in expectations is captured by the coefficient on statistically optimal forecasts, $b_{i,t}^{\text{stat}}$, and an intercept, $a_{i,t}^{\text{stat}}$. This specification provides a benchmark in which investors process public information efficiently through a stable forecasting technology.

Specification 2: Extrapolative expectations.

We now turn to cases where investors form subjective beliefs and potentially deviate from the rational benchmark. We first consider extrapolative belief, a psychologically founded belief formation widely studied and documented in the literature (Barberis et al., 2015, 2018; Da, Huang, and Jin, 2021). This specification assumes investors extrapolate from past realizations of extensive flows. Let $m_{t-\ell}(n)$, $\ell = 1, 2, \ldots$, be lagged extensive flows observed at the time of decision. We model expectations as a weighted average of past realizations, following a constant-gain learning rule (Malmendier and Nagel, 2016):

$$\tilde{m}_t^{\text{extrp, avg}} = \sum_{\ell=1}^{L} \omega_\ell m_{t-\ell}, \qquad \omega_\ell \geq 0, \quad \sum_{\ell=1}^{L} \omega_\ell = 1,$$

where

$$\omega_\ell = \nu(1-\nu)^{\ell-1} / \sum_{k=1}^{L} \nu(1-\nu)^{k-1}.$$

ν is the constant gain parameter. We set $\nu = 0.018$ and $L = 20$.[4] With $\nu = 0.018$, the weights decline slowly with the lag—the most recent quarter receives about 6 percent of the total weight and the twentieth lag about 4 percent—so perceived flows respond sluggishly to recent realizations. We interpret these expectations as the average expectations across investors at time t. This specification emphasizes persistence and trend-chasing in flows: recent inflows raise perceived contemporaneous inflows, with the sensitivity governed by ν.

Similarly, we allow investors to have heterogeneous expectations based on the average extrapolative expectations.

$$\tilde{m}_{i,t}^{\text{extrp}} = a_{i,t}^{\text{extrp}} + b_{i,t}^{\text{extrp}} \tilde{m}_t^{\text{extrp, avg}}$$

The heterogeneity in expectations is captured by the sensitivity to the average extrapolative expec-

[4] Malmendier and Nagel (2016) show that $\nu = 0.018$ for quarterly data matches the average belief in survey data of inflation expectations, and lies within the range of estimates from household investment decisions in Malmendier and Nagel (2011).

tations, $b_{i,t}^{\text{extrp}}$, and an intercept, $a_{i,t}^{\text{extrp}}$.

Specification 3: Subjective expectations proxied by social media attention.

Finally, we use the social media attention index (Cookson et al., 2024; Liu and Yin, 2025) as a proxy for investors' subjective expectations about contemporaneous extensive flows. We use the attention index shared by Cookson et al. (2024), which has a mean of zero and standard deviation of one. The idea is that extensive flow is driven by other investors' contemporaneous participation decisions. Social media attention indicates whether other investors are paying attention to the stock. Therefore, the attention index captures investors' overall participation and serves as a natural proxy for the expectation of extensive flows.

Operationally, we treat social media attention as an observable signal, $h_t^{\text{att}}(n)$, that is increasing in the perceived strength of contemporaneous inflows into stock n. We allow investors to have heterogeneous expectations based on the social media attention:

$$\tilde{m}_{i,t}^{\text{att}}(n) \;\equiv\; a_{i,t}^{\text{att}} + b_{i,t}^{\text{att}}\, h_t^{\text{att}}(n),$$

with $a_{i,t}^{\text{att}}$ and $b_{i,t}^{\text{att}}$ absorbing scale differences relative to the flow measures and capturing heterogeneity in investor expectations.

5.4 Estimating the Asset Demand System

We now derive the estimation equation by collecting terms and rearranging (5.16):

$$\begin{aligned} q_{i,t}(n) =& \beta_{i,t}^{m} \mathbf{1}_{i,t}^{E}(n) \tilde{m}_{i,t}(n) + \left[\mathcal{E}_{0,i,t} + \mathcal{E}_{1,i,t}\mathbf{1}_{i,t}^{E}(n)\right] p_t(n) \\ &+ \left[\beta_{0,i,t}^{x} + \beta_{1,i,t}^{x}\mathbf{1}_{i,t}^{E}(n)\right]' x_t(n) + \alpha_{0,i,t} + \alpha_{1,i,t}\mathbf{1}_{i,t}^{E}(n) + u_{i,t}(n), \end{aligned} \tag{5.17}$$

where $\mathbf{1}_{i,t}^{E}(n)$ is a dummy variable which takes the value of one if this demand is at the extensive margins, and zero otherwise. $\tilde{m}_{i,t}(n)$ is investor i's expectation of extensive flow into stock n at time t. $x_t(n)$ is the vector of characteristics of stock n at time t. In our cross-sectional estimation (and thus omitting subscript t), $\alpha_{0,i,t}$ denotes investor fixed effects, while $\alpha_{1,i,t}\mathbf{1}_{i,t}^{E}(n)$ captures the wedge in those fixed effects between extensive and intensive demand. $u_{i,t}(n)$ represents the uncorrelated

residual demand shocks. They are assumed to be conditionally mean-independent across investors.

For the demand at the intensive margins ($\mathbf{1}^E_{i,t}(n) = 0$), the price elasticities reduce to $\mathcal{E}_{0,i,t}$. $\mathcal{E}_{1,i,t}$ captures the wedge in elasticities between demand at extensive and intensive margins. A $\mathcal{E}_{1,i,t}$ larger than zero means the price elasticities of extensive demand are larger than those of intensive demand. Similarly, the coefficients on stock characteristics reduce to $\beta^x_{0,i,t}$ for intensive demand, and $\beta^x_{1,i,t}$ shows the difference in the coefficients on stock characteristics across the two margins.

Granular instrumental variables (GIV). The main identification challenge to estimate the demand equation above is that demand and prices are jointly determined in equilibrium. Price $p_t(n)$ is endogenous and is correlated with investor i's demand shock. Therefore, we need an instrument for prices. This type of instrument is difficult to find. One workhorse approach in the literature is to search for idiosyncratic demand shocks from some investors to instrument for prices in another investor's demand equation (Gabaix and Koijen, 2024). We follow Chaudhry and Li (2025) to use the optimal granular instrumental variables (GIV) methodology in Chaudhary, Fu, and Zhou (2024) to estimate price elasticities and other demand coefficients.

Our identification assumption is the conditional independence of residual demand shocks across investors:

$$\mathbb{E}\left[u_{i,t}(n)u_{j,t}(n)\right] = 0, \quad \forall i \neq j, \forall t, \forall n,$$

$u_{i,t}(n)$ and $u_{j,t}(n)$ are residual demand shocks of different investors for stock n. Based on this assumption, we construct the GIV for prices using the combination of other investors' residual demand shocks: $z_{i,t}(n) = \sum_{j\neq i} u_{j,t}(n)$. Given this construction of GIV, we obtain the equivalent moment conditions:

$$\mathbb{E}\left[u_{i,t}(n)z_{i,t}(n)\right] = 0. \tag{5.18}$$

We estimate the demand system cross-section by cross-section. Investors' residual demand shocks are constructed based on the demand elasticities, which are the variables that need to be estimated. Following the procedure in Chaudhary, Fu, and Zhou (2024), we jointly estimated the residual demand shocks and the price elasticities.

Instead of filling zero holdings of all stocks in the investment universe defined above, we focus only on one specific type of "zero holdings": extensive out, i.e., stocks that were held in the

previous period but are fully liquidated in the current period. This approach allows us to better capture investors' extensive margin decisions as discussed in the previous sections. Thus, we construct the estimation sample by including all positive holdings and extensive out observations for each investor in each quarter.[5]

Stock characteristics. The characteristics for each stock other than the market equity that we include in the estimation are log book equity, profitability, investment, dividend ratio, and market beta. Book equity represents firm size. We follow Fama and French (2015) to construct the characteristics of profitability and investment. Profitability is measured as operating profit scaled by book equity. Operating profit to equity is measured as revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense. Investment is calculated as the yearly change in total assets. Dividend ratio is measured as the sum of total dividends over the past year divided by book equity. Market beta is estimated from the 60-month rolling regression of excess stock returns on excess market returns.

6 Structural Estimation Results and Counterfactuals

This section presents the structural estimates and a counterfactual, under the specifications of extensive flow expectations developed in Section 5.3. Three findings stand out. Extensive demand is less price-elastic than intensive demand. Demand falls when investors expect higher extensive inflows, and this relation is most consistent under extrapolative expectations. And reallocating capital from intensive to extensive investors raises returns, volatility, and firm-specific price informativeness while lowering market-wide informativeness.

6.1 Estimated Price Elasticities

Extensive demand is less price-elastic than intensive demand, confirming Prediction 1. Under the statistically optimal expectations specification, the mean price elasticity is -0.34 for extensive

[5] Koijen and Yogo (2019) compare linear GMM estimates (excluding zero holdings) to non-linear GMM estimates (including zero holdings) and document that the latter tend to yield more negative demand elasticities, especially for small institutions. Our notion of "extensive out" focuses on stocks that were held in the previous period but are fully exited in the current period, which is conceptually different from including all zero positions in the estimation sample.

demand and −0.43 for intensive demand (Table 6); the wedge of 0.09 is roughly one-fifth of the intensive elasticity. The same ranking holds at every reported percentile and under both subjective expectations specifications: the means are −0.31 versus −0.41 under extrapolative expectations and −0.28 versus −0.38 under expectations proxied by social media attention. Both magnitudes are below one, consistent with the inelastic range documented by the demand-system literature (Koijen and Yogo, 2019; Gabaix and Koijen, 2021; Haddad, Huebner, and Loualiche, 2025).

[Insert Table 6 Here.]

Figure 7 Panel (a) plots the overall distributions of estimated price elasticities for extensive and intensive demand, under the statistically optimal expectations specification. The distribution for extensive demand is shifted to the right relative to the distribution for intensive demand. Another salient feature of the graph is the non-trivial mass of estimates with positive price elasticities. The fraction of positive elasticities is visibly larger for extensive demand than for intensive demand, indicating that upward-sloping demand is more prevalent along the extensive margin. Figure 7 Panel (b) shows the time series of yearly average elasticities, estimated under the same flow expectation specification. The panel reveals that the average extensive demand elasticity is consistently higher than the average intensive demand elasticity. This pattern holds almost universally across the entire sample period. The magnitude of the difference between the two elasticities varies over time. In several years, the gap in magnitudes is sizable.

[Insert Figure 7 Here.]

These findings are consistent with the implications of our model. Because investors have less information about assets at the extensive margin and therefore rely more heavily on prices, learning from prices attenuates the magnitude of their price elasticity. As a result, extensive demand is less downward sloping than intensive demand. Furthermore, the model predicts that extensive demand elasticities can become positive. This occurs when investors' subjective expectations about extensive flows decrease as prices rise. If this is the case, investors overreact to the perceived price signals, which can push the elasticity into the positive regime. Our estimates show a non-trivial mass of positive extensive demand elasticities, aligning well with this theoretical prediction. Our findings differ from Koijen and Yogo (2019) and Koijen, Richmond, and Yogo (2024), who restrict

price elasticities to be non-positive during estimation. We show, both theoretically and empirically, that the price elasticity of extensive demand can be positive. As illustrated above, this occurs when investors believe the extensive flow is negatively correlated with prices.

Table 7 shows the descriptive statistics of estimated price elasticities by active share quintile. In general, more passive investors (those with lower active share) tend to have price elasticities closer to zero. For the most passive group (quintile 1), the extensive demand elasticity is −0.280, while the intensive demand elasticity is −0.219. However, the trend beyond the first quintile differs by demand type. For extensive demand, the elasticity becomes more negative after the first quintile. After this initial drop, the elasticity remains relatively flat, ranging from −0.340 to −0.376 across quintiles 2 through 5. This flatness suggests a similar level of information scarcity for investors who trade at the extensive margin. Conversely, the price elasticity of intensive demand decreases significantly and monotonically with activeness. The elasticity falls from −0.219 for the most passive group to −0.638 for the most active group. This result supports the interpretation that more active investors are likely to be more informed, leading to a more negative price elasticity for intensive demand. Most importantly, the wedge between extensive and intensive elasticities becomes more salient from passive to active investors (from roughly the same to a gap of 0.3). Such a pattern is consistent with our information-based mechanism—active investors actively trade on their information, amplifying the information gap between extensive and intensive demand.

[Insert Table 7 Here.]

6.2 Demand Sensitivity to Extensive Flow Expectations

Table 6 also presents the estimates of demand sensitivity to extensive flow expectations under different specifications. We begin with the rational benchmark in which investors form extensive flow expectations based on statistically optimal forecasts (Panel (a)). The mean of estimates is −0.076, which indicates that if the extensive flow expectation goes up by one percentage point, investors reduce their demand by 0.076 percentage points. This negative relation is consistent with our mechanism of investor learning from prices. When investors believe that extensive inflows are driving prices up, they do not update their beliefs about fundamentals, or they update them downward. As a result, they reduce their demand for the stock. We find this negative relation for a

large proportion of the estimates, but it also delivers a subset of sensitivity estimates with a positive sign. The 75% percentile of the estimates is 0.409. This pattern suggests that we may misspecify flow expectations—investors may deviate from the statistically optimal forecasting rule and instead form beliefs that are not fully rational.

Motivated by this evidence, we consider two alternative specifications of expectation formation. First, we draw on the behavioral finance literature and adopt the widely studied extrapolative beliefs. We find that estimation results based on extrapolative expectations are most consistent with our framework. The mean of the estimates is -0.812, indicating that a one-percentage-point increase in extensive flow expectations is associated with a 0.8-percentage-point decline in investor demand—roughly ten times the sensitivity under statistically optimal expectations. The estimates are also much more tightly distributed (a standard deviation of 0.39, versus 0.79 under the rational benchmark), and all reported percentiles are negative. Together, these findings suggest that investors overreact to recent realized flows when forming expectations.

We also take a data-driven approach and incorporate additional information plausibly relevant for belief formation. Specifically, we use social media attention as a proxy for investors' perceptions of market participation and interest (Cookson et al., 2024; Liu and Yin, 2025). The idea is that heightened discussion of a stock on social media may lead investors to infer that other market participants are entering the stock, generating extensive inflows. The estimation results under this specification are broadly consistent with our framework. The mean of the estimates is -0.719, which is close to that under extrapolative expectations. However, a non-trivial proportion of estimates remain positive. The 75% percentile of the estimates is 0.804. Overall, among the specifications we consider, extrapolative expectations appear most consistent with our framework.

6.3 Counterfactual: Reallocating Capital from Intensive to Extensive Investors

What happens to prices, volatility, and informational efficiency if the market's capital shifts toward extensive investors? To answer this question, we simulate a budget-neutral reallocation that raises the assets under management of the most extensive-heavy investors by 10%, financed pro rata by all other investors. The counterfactual is based on the estimation under the specification of statistically

optimal flow expectations.

In the analysis, we reallocate capital from intensive to extensive investors. We first classify investors by their share of extensive demand. For each investor i at time t, we calculate their extensive demand proportion as the number of positive extensive positions divided by the total number of positions. We then average this proportion across time for each investor to generate a single, time-invariant measure. Based on this measure, we divide investors into five quintiles and label the top quintile as "extensive investors."

Next, we implement a budget-neutral reallocation. We increase the total AUM of extensive investors by 10% by reallocating capital from other investors. The reallocation is financed by an AUM haircut on investors in the other four quintiles. Specifically, we reduce the AUM of each other investor by a fixed percentage such that the total reduction in AUM across all other investors equals 10% of the total AUM of extensive investors. The reduced AUM from intensive investors is then proportionally allocated to extensive investors based on their initial AUM. This process captures a market-wide shift in capital from intensive to extensive demand.

After the reallocation, we recalculate the equilibrium prices based on market clearing conditions. We assume firm characteristics and shares outstanding do not change. We also hold investors' demand coefficients and extensive flow expectations unchanged. Finally, we compute changes in stock returns, volatility, and price informativeness using counterfactual prices.

We choose to use the statistically optimal flow expectation here because it provides a natural, rational, and robust benchmark that is transparent and easy to interpret. It shuts down the channel of biased beliefs, so that the counterfactual isolates the effect of reallocating capital toward investors with higher extensive demand, the focus of this counterfactual analysis. Using alternative behavioral expectation specifications is more difficult in this setting. A large reallocation could change the belief-formation process itself, so treating behavioral expectations as invariant under the counterfactual may be less realistic. Implementing such counterfactuals would require direct investor–stock-level data on flow expectations, which we typically do not observe. Furthermore, the data do not identify how beliefs themselves would adjust to a large reallocation, so any adjustment rule we imposed would be arbitrary. Nevertheless, we implement these specifications, and the results are available upon request.

6.3.1 Impact on Return and Volatility

Panel (a) of Table 8 shows results on return and volatility. Reallocating capital from intensive to extensive demand leads to significant increases in average stock returns and in return volatility. The average annualized return increases by 3.3 percentage points, an 18 percent increase relative to the sample mean of 18.8 percent. The average return volatility across stocks increases by 3.7 percentage points, or 7.5 percent of its mean. These results are consistent with our empirical findings in Section 3.2 that the percentage composition of extensive flow is positively correlated with stock return and volatility.

[Insert Table 8 Here.]

6.3.2 Impact on Price Informativeness

We next examine the impact of the reallocation on price informativeness. We consider two measures of price informativeness: stock-specific price informativeness (Dávila and Parlatore, 2025) and market price informativeness (Bai, Philippon, and Savov, 2016).

Stock-specific price informativeness. We first calculate stock-specific price informativeness based on actual prices and counterfactual prices using equations (2.1) to (2.3). Panel (b) of Table 8 shows the comparison between actual and counterfactual price informativeness. Reallocating capital from intensive to extensive demand leads to a significant increase in price informativeness. The average price informativeness across stocks increases by 0.4 percentage points in the full sample, a 9.3 percent increase relative to the mean of 4.5 percent. However, the reallocation has heterogeneous impacts across stocks. For stocks with already high price informativeness (above-median actual price informativeness), the reallocation leads to a further increase of 1.0 percentage points, or 12 percent of the subsample mean. In contrast, for stocks with low actual price informativeness (below-median), the reallocation leads to a decrease of 0.2 percentage points—a 27 percent decline relative to the subsample mean of 0.6 percent. These findings are consistent with our empirical results in Section 3.2, which show that extensive flow is positively correlated with price informativeness for stocks with high actual price informativeness but negatively correlated for stocks with low actual price informativeness.

This stock-specific price informativeness captures how changes in prices reflect changes in future earnings at the individual stock level. When prices are very informative, extensive investors can better learn information from prices. This learning limits the role of their subjective beliefs about extensive flow, makes their demand move more closely with future fundamentals, and thus increases price informativeness. By contrast, when prices are noisy, extensive investors place more weight on their subjective beliefs about extensive flow. This causes their demand to deviate further from future fundamentals and to distort prices more.

Market price informativeness. Following Bai, Philippon, and Savov (2016), we estimate the market-wide price informativeness by first running cross-sectional regressions of future earnings on current market prices:

$$\frac{E_{i,t+h}}{A_{i,t}} = a_{t,h} + b_{t,h} \log\left(\frac{M_{i,t}}{A_{i,t}}\right) + c_{t,h}\left(\frac{E_{i,t}}{A_{i,t}}\right) + d^s_{t,h}\mathbf{1}^s_{i,t} + \epsilon_{i,t,h}, \tag{6.1}$$

where h represents different horizons of future earnings, $\mathbf{1}^s_{i,t}$ is the indicator of sector (one-digit SIC code). The measure of price informativeness is calculated as

$$\tau_m = b_{t,h} \times \sigma_t(\log(M/A)), \tag{6.2}$$

where $\sigma_t(\log(M/A))$ is the cross-sectional standard deviation of $\log(M/A)$ at time t.

[Insert Figure 8 Here.]

We compute market price informativeness based on actual and counterfactual prices. Figure 8 plots the time series of actual and counterfactual market price informativeness for different horizons. Reallocating capital from intensive to extensive demand lowers market price informativeness: the counterfactual series lies below the actual series in most years, and the gap widens in the second half of the sample. The decline does not contradict our findings on stock-specific price informativeness, because the two measures capture different aspects of price discovery. Stock-specific informativeness gauges, within a stock, how well price changes anticipate that stock's future earnings. Market price informativeness gauges, in the cross-section, how well the level of prices ranks stocks by future earnings. More extensive demand introduces unobservable demand

shocks that differ across stocks; these shocks impair the cross-sectional ranking even as sharper within-stock learning raises stock-specific informativeness for already-informative stocks.

7 Conclusion

Who trades, and at which margin, shapes how demand moves asset prices. Using institutional and retail holdings, we show that entry and exit trades account for 40 percent of institutional and 80 percent of retail flow, that attention and past returns drive these extensive flows while fundamentals drive intensive flows, and that a stock's flow composition predicts its return, volatility, and price informativeness. The informativeness relation is state-dependent: extensive flows sharpen prices that are already informative and distort prices that are not. Local projections reveal a strong two-way interaction between extensive flows and returns—a one-percentage-point net extensive inflow raises the contemporaneous return by 1.2 percentage points—with effects that reverse over longer horizons. Flow composition, rather than flow levels alone, is thus a key state variable for the relation between investor demand and asset prices.

Guided by these facts, we develop a Grossman–Stiglitz–style model with unobserved extensive flows and subjective beliefs about them, and we embed it in a characteristics-based demand system that allows distinct elasticities at the two margins. The structural estimates confirm the model's core predictions: extensive demand is substantially less downward-sloping—and often upward-sloping—than intensive demand, reflecting learning from prices with potentially inaccurate beliefs about unobserved flows, and extrapolative flow expectations fit the data best. In the counterfactual, shifting capital from intensive to extensive investors raises average returns and volatility, improves stock-specific price informativeness where prices are already informative, and degrades it where they are not, while market-wide informativeness declines.

The broader message is that the composition of investors across trading margins is central to volatility, comovement, and the informational efficiency of prices. Regulation, market structure, and information technologies that shift capital between extensive and intensive investors—the growth of commission-free retail platforms is a leading example—will therefore move not only prices but also how much information prices reveal. Measuring these feedback effects with the demand-system decomposition developed here is a natural next step.

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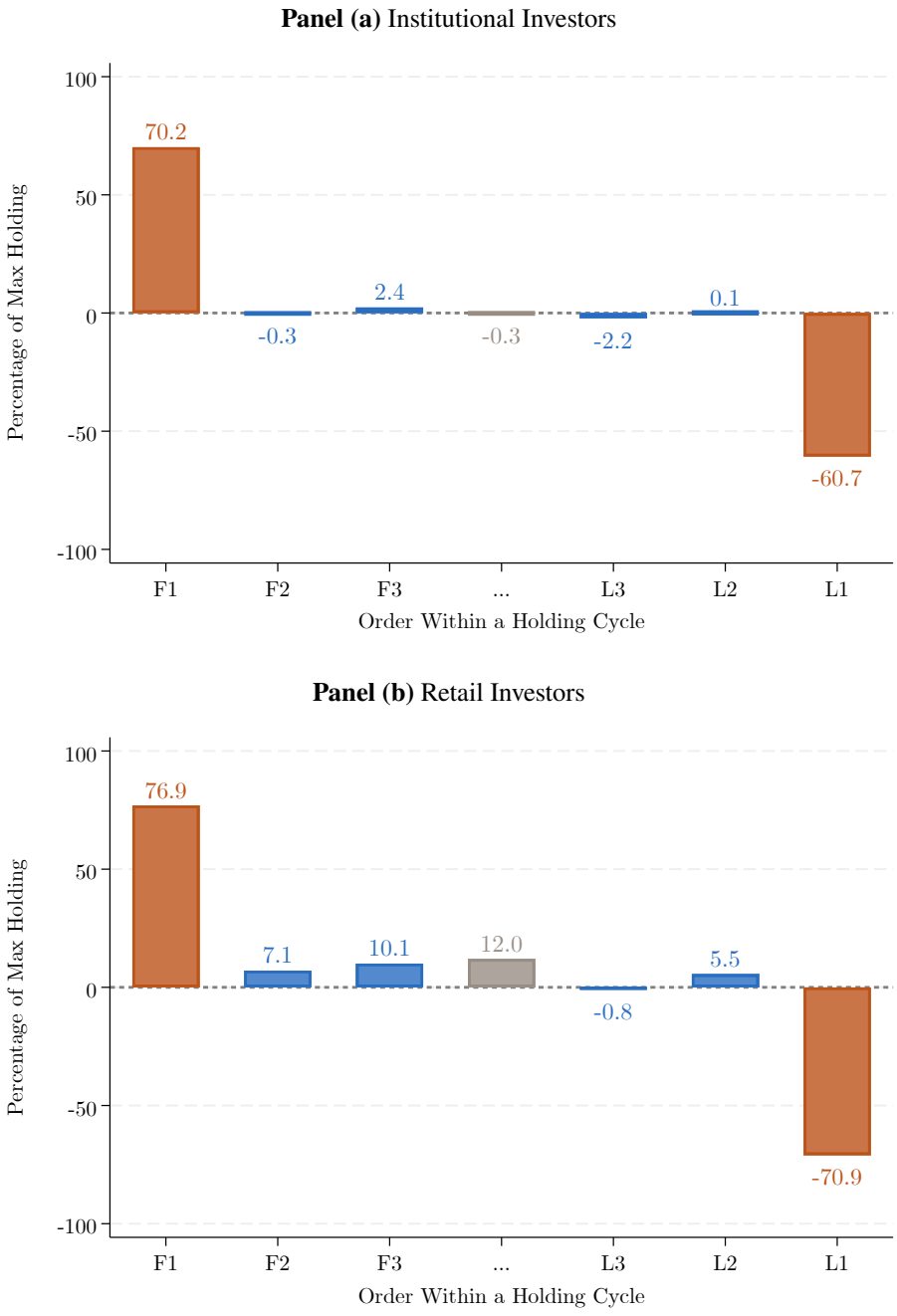
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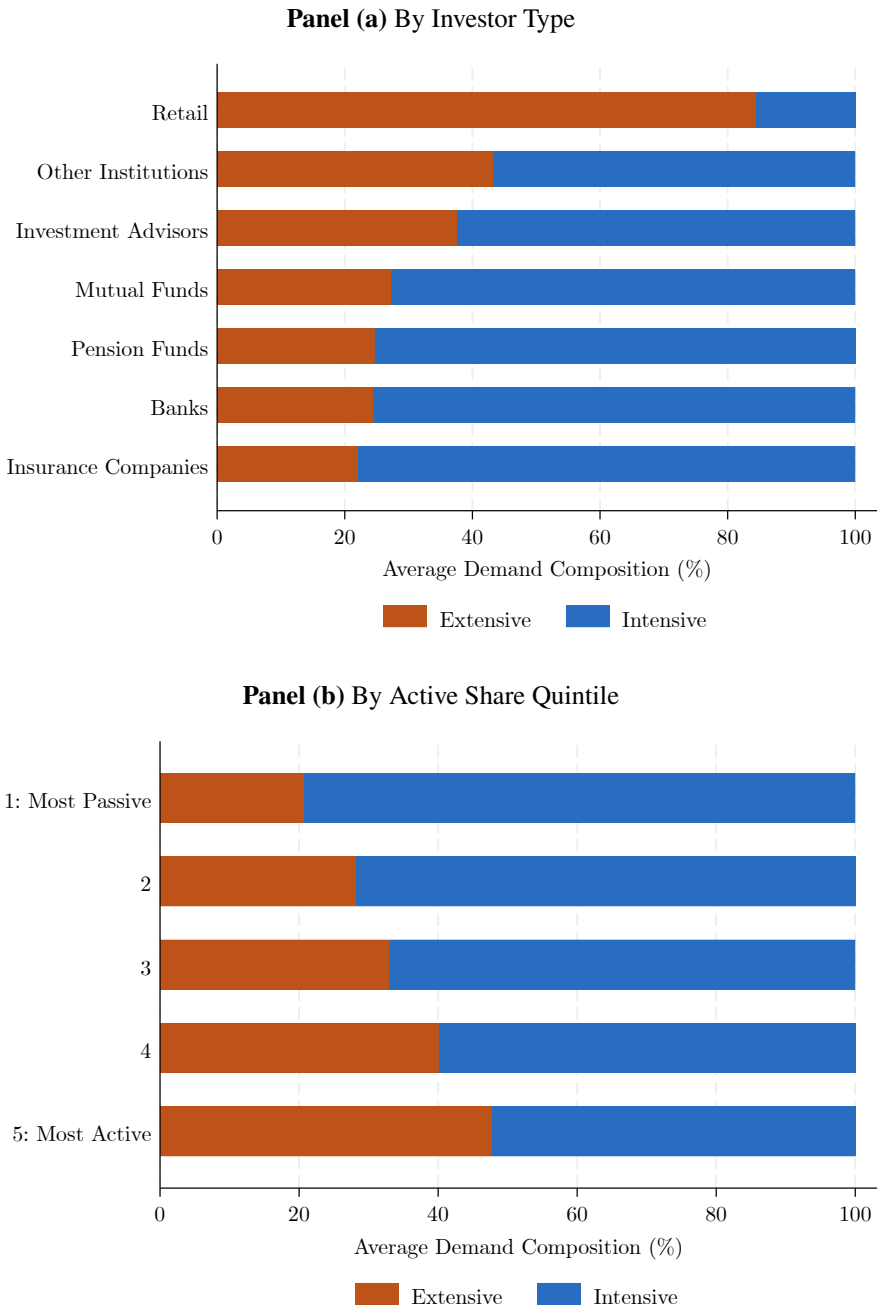
Figures

Figure 1. Flow Distribution Within a Holding Cycle



Notes. This figure plots the distribution of flows as a percentage of the maximum position within an average holding cycle, using the institutional investor sample (1980–2022, quarterly) in Panel (a) and the retail investor sample (1991–1996, monthly) in Panel (b). F1–F3 denote the first, second, and third periods of the cycle, while L1–L3 correspond to the last, second-to-last, and third-to-last periods. Red bars indicate extensive flows, whereas blue and gray bars represent intensive flows.

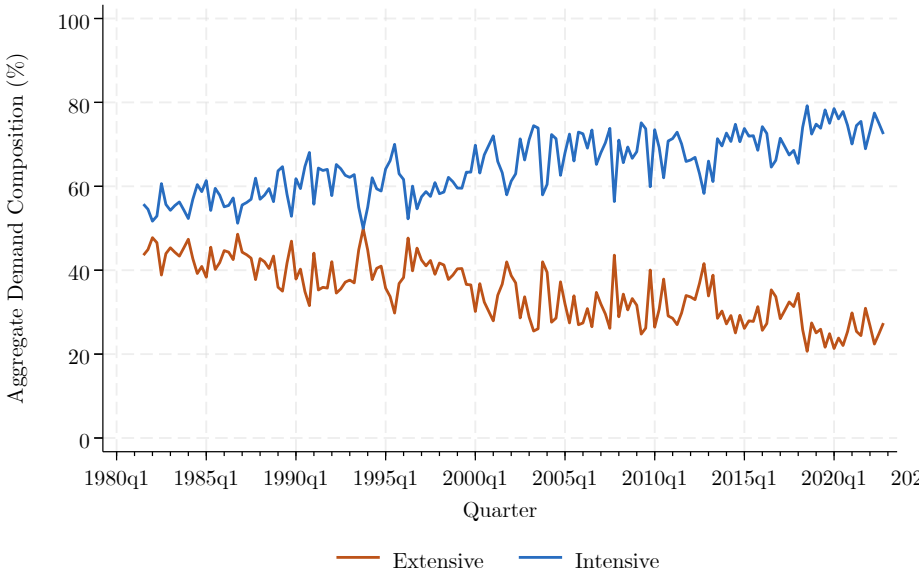
Figure 2. Compositions of Extensive and Intensive Flows



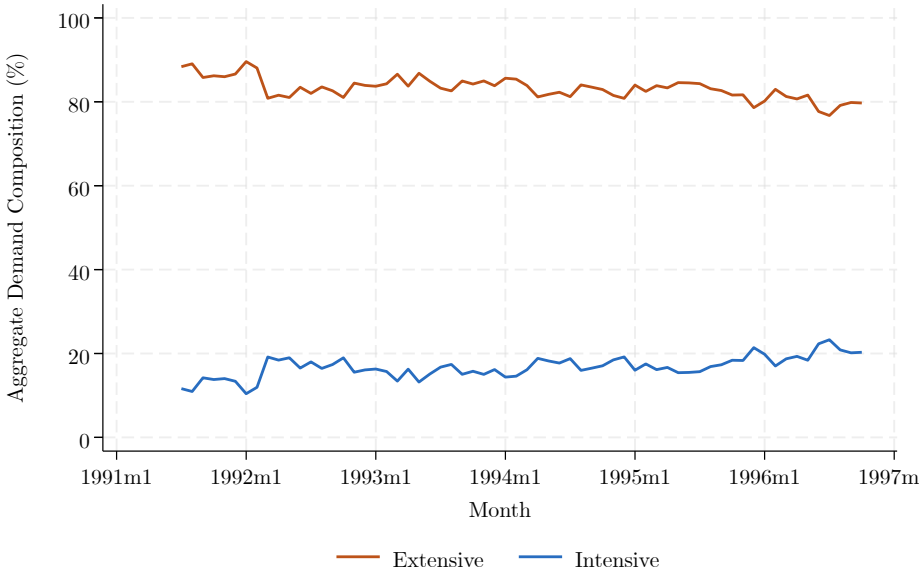
Notes. This figure plots the percentage composition of extensive flows (the sum of extensive in and out) and intensive flows (the sum of intensive in and out), by investor type in Panel (a) and by active-share quintile in Panel (b). Institutional categories are computed on the institutional investor sample (1980–2022); the retail category in Panel (a) uses the retail sample (1991–1996).

Figure 3. Compositions of Aggregate Flows

Panel (a) Institutional Investors



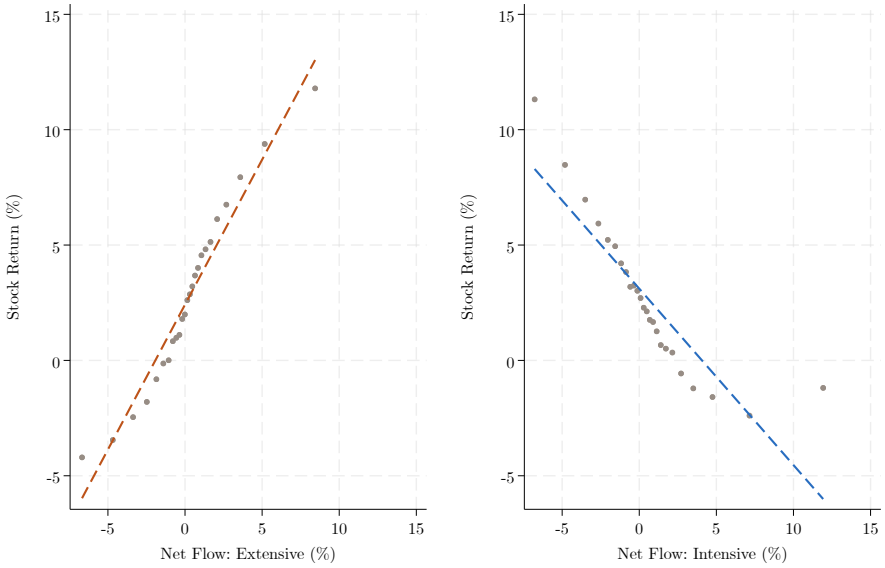
Panel (b) Retail Investors



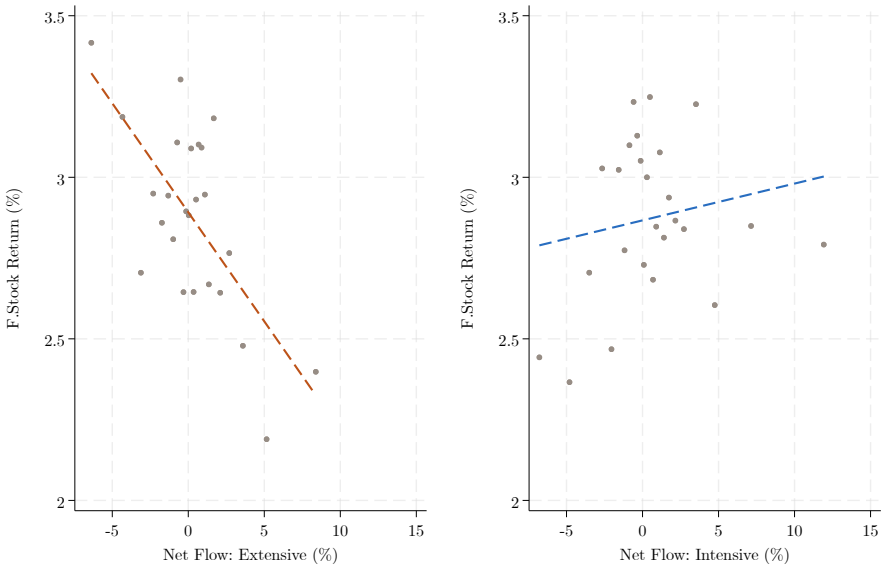
Notes. This figure plots the time series of the percentage composition of aggregate extensive flows (the sum of extensive in and out) and intensive flows (the sum of intensive in and out), using the institutional investor sample (1980–2022, quarterly) in Panel (a) and the retail investor sample (1991–1996, monthly) in Panel (b).

Figure 4. Relationship Between Net Flows and Stock Returns

Panel (a) Contemporaneous Stock Return



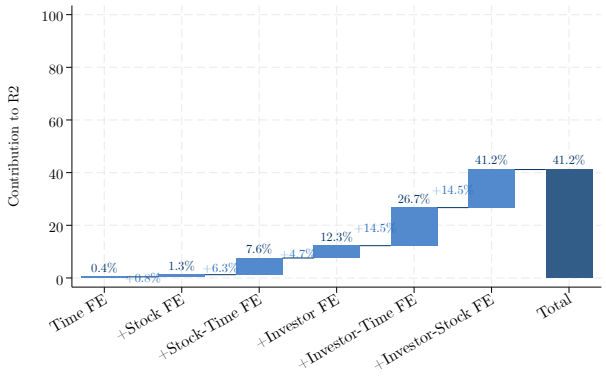
Panel (b) Future Stock Return



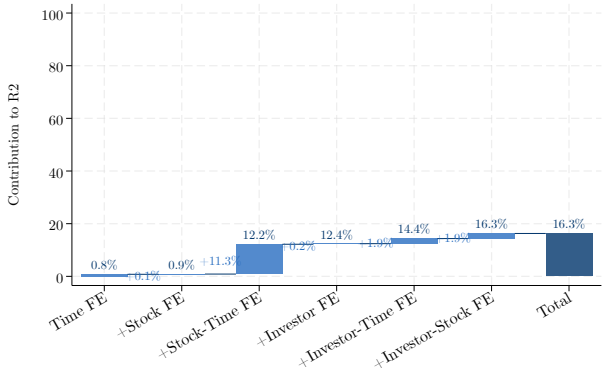
Notes. This figure plots binned scatterplots of the relationship between quarterly net flows and stock returns, showing contemporaneous returns in Panel (a) and next-quarter returns in Panel (b). The underlying regression specification (3.2) includes stock fixed effects, quarter fixed effects, as well as controls for standardized unexpected earnings (SUE), size, book-to-market ratio, lagged return, and profitability.

Figure 5. Decomposing Variations of Extensive and Intensive Flows

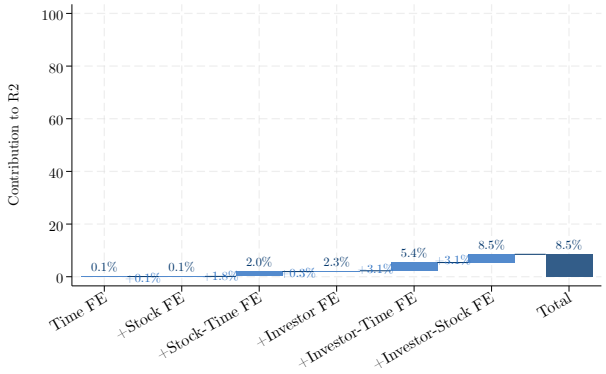
Panel (a) Type: Extensive or Intensive



Panel (b) Dollar Value: Extensive



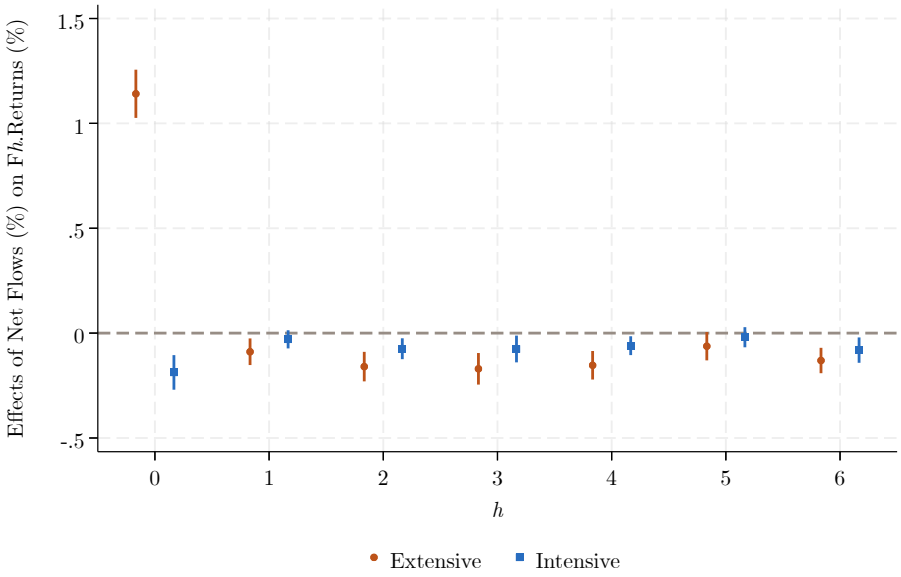
Panel (c) Dollar Value: Intensive



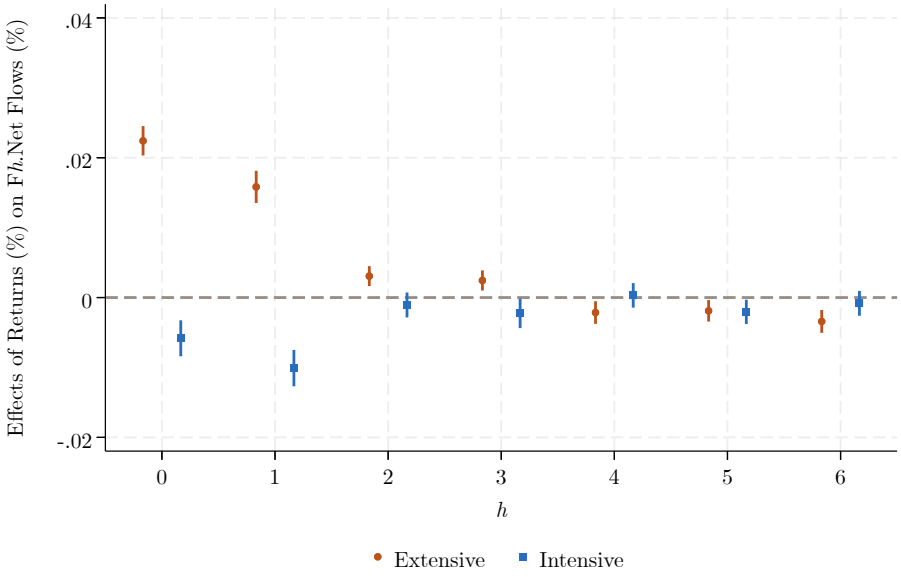
Notes. This figure plots the share of variation in flow type and dollar value explained by different fixed-effect specifications. Panel (a) decomposes the variation in whether a flow is extensive or intensive, while Panels (b) and (c) show the corresponding decompositions for the dollar value of extensive and intensive flows. The figure is based on a Shapley–Owen decomposition using an investor–stock–time panel, considering time, investor, stock, investor–time, stock–time, and investor–stock fixed effects.

Figure 6. Local Projection Orthogonalized IRFs

Panel (a) Net Flows$_t$ (%) → Returns$_{t+h}$ (%)



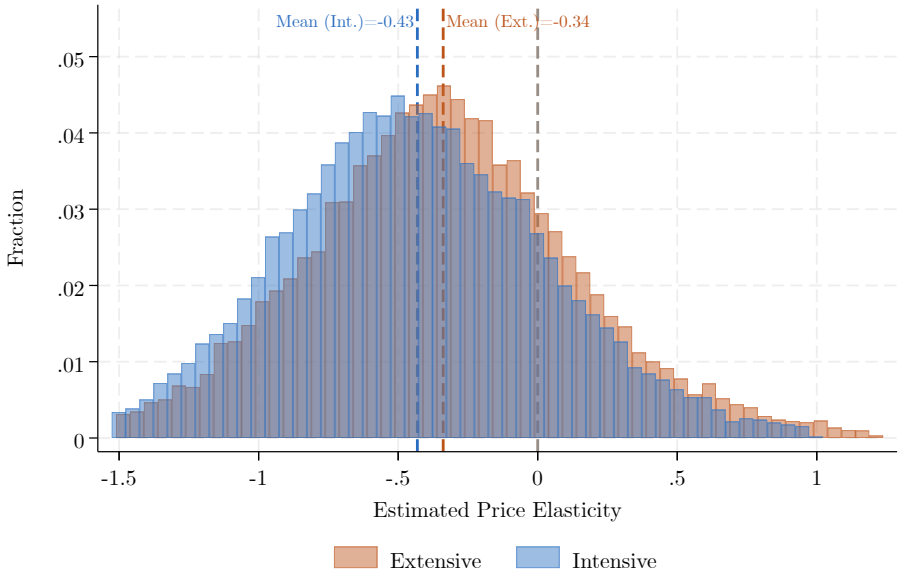
Panel (b) Returns$_t$ (%) → Net Flows$_{t+h}$ (%)



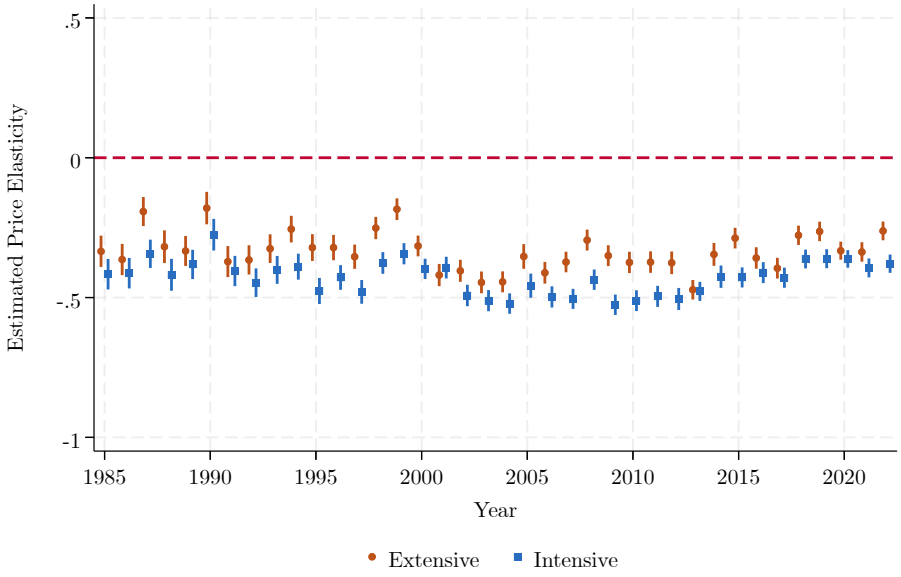
Notes. This figure plots orthogonalized impulse response functions (IRFs). Panel (a) shows the responses of stock returns to a one-percentage-point increase in net extensive or intensive flows, while Panel (b) shows the responses of net flows to a one-percentage-point increase in returns. The IRFs are estimated using local projections (3.4) with three lags, controlling for time fixed effects, stock fixed effects, lagged dependent and independent variables, standardized unexpected earnings (SUE), size, book-to-market ratio, and profitability.

Figure 7. Estimated Price Elasticities of Extensive and Intensive Demand

Panel (a) Overall Distribution

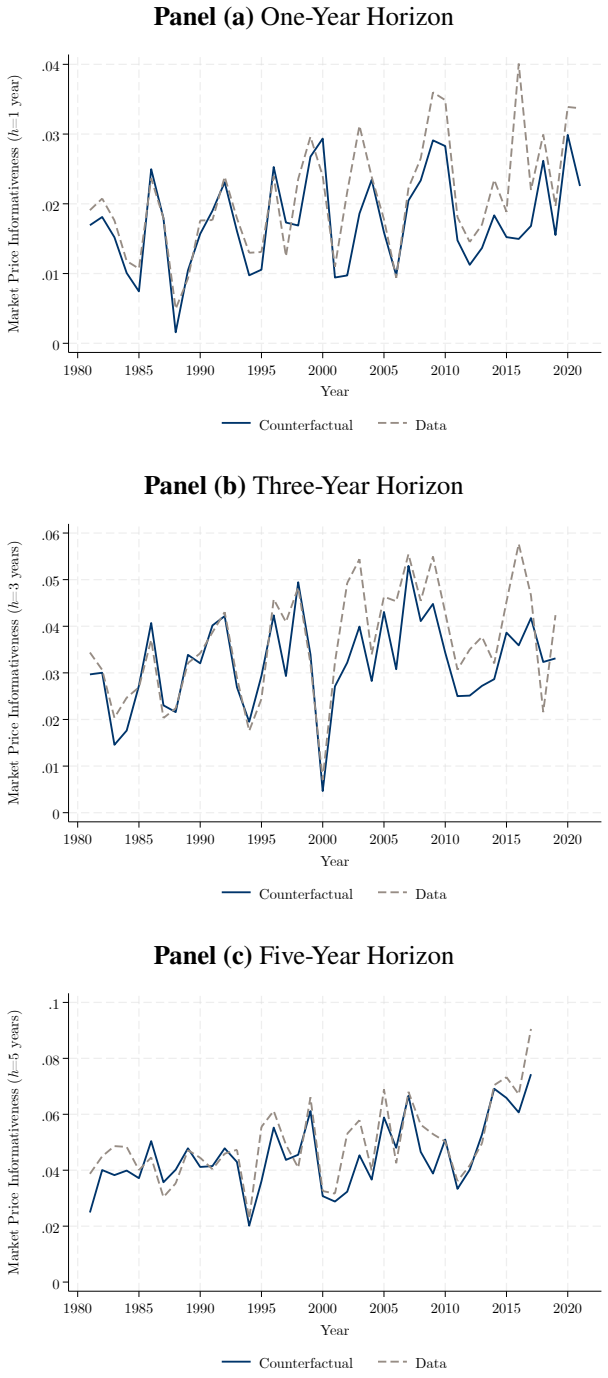


Panel (b) Time Series of Yearly Averages



Notes. This figure plots the distribution and time series of the estimated price elasticities of extensive and intensive demand, under the specification of statistically optimal extensive flow expectations. Panel (a) shows the cross-sectional distribution, and Panel (b) reports the annual time series of mean elasticities with 95% confidence intervals.

Figure 8. Counterfactual: Market Price Informativeness



Notes. This figure plots the time series of market price informativeness, comparing the data with the counterfactual. Following Bai, Philippon, and Savov (2016), market price informativeness is constructed from the cross-sectional regressions in (6.1) and computed using (6.2). Panels (a)–(c) present the results for the one-, three-, and five-year horizons, respectively. The blue solid lines depict the market informativeness of counterfactual prices, while the dashed gray lines depict that of actual prices.

Tables

Table 1. Descriptive Statistics

Panel (a) Investor-Stock-Quarter Panel

	N	Mean	SD	25%	50%	75%
1(Extensive) (%)	93,117,390	25.608	43.646	0.000	0.000	100.000
1(Intensive) (%)	93,117,390	55.048	49.745	0.000	100.000	100.000
Extensive Flow ($ M)	23,845,210	5.424	112.225	0.177	0.484	2.017
Intensive Flow ($ M)	51,259,456	5.377	106.079	0.055	0.277	1.562
Active Share (%)	93,117,390	46.352	16.203	36.678	47.020	57.661
Social Media: Attention (z)	11,427,940	0.000	1.000	−0.709	−0.346	0.326
Social Media: Sentiment (z)	11,427,940	0.000	1.000	−0.628	0.058	0.655
News Media: Coverage	45,648,742	227.623	539.468	43.000	106.000	208.000
News Media: Sentiment (z)	45,648,742	0.000	1.000	−0.439	0.107	0.596
Return (%)	93,117,390	2.809	17.255	−7.854	2.720	13.332
abs(Return) (%)	93,117,390	13.741	10.808	4.869	10.883	20.577
SUE (%)	45,582,021	0.003	0.937	−0.036	0.038	0.164
abs(SUE) (%)	45,582,021	0.391	0.851	0.037	0.113	0.320

Panel (b) Stock-Quarter Panel

	N	Mean	SD	25%	50%	75%
Net Flow: Extensive (%)	235,315	0.201	3.266	−1.118	0.000	1.332
Net Flow: Intensive (%)	235,315	0.578	4.031	−1.295	0.045	1.741
Composition: Extensive (%)	235,315	31.128	17.801	19.046	29.787	41.676
Composition: Intensive (%)	235,315	68.872	17.801	58.324	70.213	80.954
Return (%)	235,315	2.669	21.561	−9.957	1.990	14.319
Volatility (%)	235,191	47.099	28.864	26.445	38.516	58.182
Idiosyncratic Volatility (%)	235,191	41.433	27.349	21.991	33.115	51.278
SUE (%)	235,315	−0.212	4.426	−0.204	0.035	0.282
Size	235,315	6.230	2.120	4.731	6.191	7.639
B/M	235,315	0.679	0.524	0.297	0.543	0.891
Profitability (%)	235,315	−0.012	9.028	−3.058	−0.013	2.952
Stock-Specific Price Informativeness (%)	93,468	4.750	6.828	0.480	2.150	6.159

Notes. This table reports descriptive statistics for quarterly institutional investor holdings (an investor-stock-quarter panel) in Panel (a) and for the quarterly stock panel in Panel (b). The sample covers 1980–2022. Stock-specific price informativeness follows Dávila and Parlatore (2023, 2025). All variables are winsorized at the 1% and 99% cutoffs.

Table 2. Magnitudes of Extensive and Intensive Flow

Panel (a) By Investor Type

	Flow Type			
Investor Type	Extensive In	Extensive Out	Intensive In	Intensive Out
Retail ($K)	9.63 [54.14%]	11.29 [30.35%]	10.35 [10.98%]	12.68 [4.53%]
Banks	4.36 [12.74%]	4.96 [11.76%]	3.33 [37.78%]	3.27 [37.73%]
Insurance Companies	4.16 [11.62%]	4.78 [10.53%]	3.30 [42.58%]	3.91 [35.27%]
Investment Advisors	3.91 [20.09%]	3.85 [17.56%]	3.07 [31.41%]	3.20 [30.94%]
Mutual Funds	7.54 [14.2%]	7.96 [13.15%]	7.48 [37.97%]	8.03 [34.68%]
Pension Funds	6.64 [13.12%]	6.95 [11.59%]	2.05 [36.87%]	2.35 [38.42%]
Others	4.64 [23.29%]	3.94 [20.03%]	4.14 [29.03%]	4.49 [27.65%]

Panel (b) By Active Share Quintile

	Flow Type			
Active Share Quintile	Extensive In	Extensive Out	Intensive In	Intensive Out
1: Most Passive	8.57 [11.44%]	8.61 [9.36%]	5.65 [42.64%]	5.82 [36.57%]
2	3.90 [15.01%]	4.14 [13.18%]	3.02 [35.62%]	3.42 [36.19%]
3	4.13 [17.29%]	4.14 [15.71%]	3.00 [33.2%]	3.48 [33.8%]
4	4.29 [20.95%]	4.11 [19.15%]	3.00 [29.92%]	3.54 [29.98%]
5: Most Active	5.14 [24.79%]	4.87 [22.92%]	2.92 [25.45%]	3.39 [26.83%]

Notes. This table reports the average dollar value (in millions, except for retail investors, whose unit is thousands) and the corresponding percentage share (shown in square brackets below the dollar value) of extensive and intensive inflows and outflows, by investor type in Panel (a) and by active-share quintile in Panel (b). Inflows and outflows are reported separately to show the asymmetry between entry and exit trades.

Table 3. Origins of Extensive and Intensive Flows

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1(Extensive) (%)				**1**(Intensive) (%)			
Social Media: Attention	0.678***				0.246			
	(0.246)				(0.238)			
Social Media: Sentiment	−0.194*				0.034			
	(0.099)				(0.087)			
News Media: Coverage		0.243***				0.922***		
		(0.084)				(0.124)		
News Media: Sentiment		−0.805***				0.406***		
		(0.046)				(0.039)		
L.abs(Return) (%)			0.087***				−0.036***	
			(0.004)				(0.004)	
L.abs(SUE) (%)				−1.685***				1.320***
				(0.066)				(0.061)
Investor-Stock FE	Y	Y	Y	Y	Y	Y	Y	Y
Investor-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	11,427,940	45,648,742	93,117,390	45,582,021	11,427,940	45,648,742	93,117,390	45,582,021
No. of Investors	7,467	8,705	12,158	8,704	7,467	8,705	12,158	8,704
R^2	0.529	0.502	0.485	0.503	0.506	0.476	0.452	0.476
Mean of Dep. Var.	20.396	23.438	25.512	23.440	59.046	58.315	55.134	58.323

Notes. This table examines the determinants of investor flow type (extensive or intensive) by estimating specification (3.1) on an investor (i)-stock (n)-quarter (t) panel. The dependent variables are indicator variables (in percentage terms) for whether a holding is extensive or intensive. Independent variables include a stock's standardized social media attention and sentiment indices from Cookson et al. (2024), news coverage, standardized news sentiment from RavenPack, and the lagged absolute values of returns and standardized unexpected earnings (SUE). News coverage is measured as the log of the number of news articles covering a stock within a quarter. Standard errors are double-clustered by stock and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Impacts of Extensive and Intensive Flows

Panel (a) Return and Volatility

	(1)	(2)	(3)
	Return (%)	Total Volatility (%)	Idiosyncratic Volatility (%)
Composition: Extensive (%)	0.038***	0.050***	0.051***
	(0.004)	(0.005)	(0.004)
Stock FE	Y	Y	Y
Time FE	Y	Y	Y
Controls	Y	Y	Y
Observations	234,334	234,230	234,230
No. of Stocks	7,080	7,076	7,076
R^2	0.342	0.697	0.704
Mean of Dep. Var.	2.676	46.963	41.285

Panel (b) Stock-Specific Price Informativeness

	(1)	(2)	(3)
	Stock-Specific Price Informativeness (%)		
	Full Sample	High	Low
Composition: Extensive (%)	0.209*	0.304***	−0.031***
	(0.123)	(0.063)	(0.008)
Stock FE	Y	Y	Y
Time FE	Y	Y	Y
Controls	Y	Y	Y
Observations	93,468	46,734	46,734
No. of Stocks	3,116	2,575	2,583
R^2	0.496	0.552	0.229
Mean of Dep. Var.	4.752	8.843	0.672

Notes. This table examines the impact of flow composition on stock returns and volatility in Panel (a), and on stock-specific price informativeness in Panel (b), following Dávila and Parlatore (2023, 2025). The specification (3.2) is estimated on a stock (n)-quarter (t) panel, where the dependent variable is the percentage composition of extensive flows. The intensive-flow composition is omitted because it is perfectly collinear with the extensive-flow measure. In Panel (a), independent variables include stock return, total volatility, and idiosyncratic volatility. In Panel (b), the same specification is estimated for the full sample, for stocks with above-median price informativeness ("High"), and for those with below-median informativeness ("Low"). All regressions include time and stock fixed effects, lagged dependent and independent variables, standardized unexpected earnings (SUE), size, book-to-market ratio, and profitability. Standard errors are double-clustered by stock and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Flow Composition as Stock Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
	Return (%)		Total Volatility (%)		Idiosyncratic Volatility (%)	
SUE (%)	0.313***	0.231***	−0.154***	−0.087**	−0.162***	−0.095***
	(0.025)	(0.026)	(0.028)	(0.033)	(0.031)	(0.035)
Composition: Extensive (%)		0.040***		0.049***		0.050***
		(0.004)		(0.005)		(0.004)
Composition: Extensive (%) × SUE (%)		0.003***		−0.002***		−0.002***
		(0.000)		(0.001)		(0.001)
Stock FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	234,334	234,334	234,230	234,230	234,230	234,230
No. of Stocks	7,080	7,080	7.076	7.076	7,076	7,076
R^2	0.340	0.342	0.697	0.697	0.704	0.704
Mean of Dep. Var.	2.676	2.676	46.963	46.963	41.285	41.285

Notes. This table examines how a stock's flow composition affects the relation between stock prices and fundamentals, estimating specification (3.3) on a stock (n)-quarter (t) panel. Independent variables include stock return, total volatility, and idiosyncratic volatility, while dependent variables include standardized unexpected earnings (SUE), the percentage composition of extensive flows, and their interaction term. The intensive-flow composition is omitted because it is perfectly collinear with the extensive-flow measure. All regressions include time and stock fixed effects, lagged dependent and independent variables, size, book-to-market ratio, and profitability. Standard errors are double-clustered by stock and time. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Price Elasticities and Demand Sensitivity to Extensive Flow Expectations

Panel (a) Statistically Optimal Expectations

	N	Mean	SD	25%	50%	75%
Price Elasticity						
Extensive	19,445	−0.339	0.475	−0.656	−0.351	−0.040
Intensive	19,445	−0.431	0.462	−0.753	−0.451	−0.122
Pooled	38,890	−0.385	0.471	−0.709	−0.400	−0.079
Demand Sensitivity to						
Flow Expectation ($\beta^m_{i,t}$)	19,445	−0.076	0.791	−0.659	−0.209	0.409

Panel (b) Extrapolative Expectations

	N	Mean	SD	25%	50%	75%
Price Elasticity						
Extensive	20152	−0.309	0.473	−0.626	−0.322	−0.013
Intensive	20152	−0.412	0.456	−0.731	−0.431	−0.111
Pooled	40304	−0.360	0.467	−0.682	−0.376	−0.061
Demand Sensitivity to						
Flow Expectation ($\beta^m_{i,t}$)	20152	−0.812	0.388	−1.072	−0.810	−0.550

Panel (c) Expectations Proxied by Social Media Attention

	N	Mean	SD	25%	50%	75%
Price Elasticity						
Extensive	5842	−0.280	0.460	−0.578	−0.294	0.002
Intensive	5842	−0.384	0.471	−0.712	−0.387	−0.070
Pooled	11684	−0.332	0.468	−0.647	−0.336	−0.033
Demand Sensitivity to						
Flow Expectation ($\beta^m_{i,t}$)	5842	−0.719	2.520	−2.303	−0.733	0.804

Notes. This table reports the estimated price elasticities of extensive and intensive demand, as well as the estimated sensitivity of demand to expected extensive flows, $\beta^m_{i,t}$, from specification (5.17). Each panel presents results under a different belief specification described in Section 5.3. Within each panel, estimates are reported separately for extensive demand, intensive demand, and the pooled sample, along with the sensitivity to expected extensive flows. The panels report the number of investor-quarter estimates (N), the mean, the standard deviation, and the 25th, 50th, and 75th percentiles of the estimates.

Table 7. Price Elasticities of Extensive and Intensive Demand by Active Share Quintile

	Demand Type	
Active Share Quintile	Extensive	Intensive
1: Most Passive	−0.280	−0.219
	[0.466]	[0.411]
2	−0.376	−0.362
	[0.467]	[0.440]
3	−0.345	−0.409
	[0.489]	[0.452]
4	−0.340	−0.509
	[0.480]	[0.456]
5: Most Active	−0.349	−0.638
	[0.466]	[0.441]

Notes. This table reports the estimated price elasticities of extensive and intensive demand across quintiles of active share, under the specification of statistical optimal extensive flow expectations. The first quintile corresponds to the most passive investors and the fifth to the most active. Standard deviations are shown in square brackets.

Table 8. Counterfactual: Return, Volatility, and Stock-Specific Price Informativeness

Panel (a) Return and Volatility (%)

	Data	Counterfactual	Difference
Return (%)	18.790	22.127	3.337***
	(0.136)	(0.146)	(0.041)
Volatility (%)	48.781	52.434	3.653***
	(0.195)	(0.219)	(0.070)

Panel (b) Stock-Specific Price Informativeness

	Data	Counterfactual	Difference
Full Sample	4.520	4.941	0.421***
	(0.015)	(0.012)	(0.013)
High	8.388	9.406	1.018***
	(0.023)	(0.029)	(0.022)
Low	0.640	0.468	−0.172***
	(0.002)	(0.004)	(0.012)

Notes. This table compares return, volatility, and stock-specific price informativeness between the data and the counterfactual. The counterfactual implements a budget-neutral reallocation that raises the AUM of extensive investors (the top quintile of investors by extensive demand share) by 10%, financed pro rata by all other investors, holding demand coefficients and flow expectations fixed. Panel (a) reports annualized returns and volatilities, while Panel (b) reports stock-specific price informativeness following Dávila and Parlatore (2023, 2025). Price informativeness is reported in percentages. The first row shows estimates for the full sample, and the second and third rows show estimates for subsamples with above-median ("High") and below-median ("Low") price informativeness, respectively. Standard errors are reported in brackets.

Internet Appendix

Inelastic Demand at the Extensive and Intensive Margins

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A Stylized Model Proofs

A.1 Proof of Proposition 1

Let $\Delta_n \equiv \mu_n - p_{n,1}$. Both investor classes who hold asset n choose

$$q^I_{n,1} = q^E_{n,1} = \gamma^{-1}\sigma_n^{-2}\Delta_n.$$

Market clearing implies

$$\left[(1-\phi) + \theta_{n,1}\right]\gamma^{-1}\sigma_n^{-2}\Delta_n = 1. \tag{A1}$$

An extensive investor who chooses asset n attains

$$U^E_{n,1} = \frac{1}{2}\gamma^{-1}\sigma_n^{-2}\Delta_n^2.$$

Interior choice requires $U^E_{A,1} = U^E_{B,1}$, so

$$\frac{\Delta_A}{\sigma_A} = \frac{\Delta_B}{\sigma_B} > 0. \tag{A2}$$

Writing $M_n \equiv (1-\phi) + \theta_{n,1}$, (A1) gives $\Delta_n = \gamma\sigma_n^2/M_n$. Substituting into (A2) yields $\sigma_A/M_A = \sigma_B/M_B$. Together with $M_A + M_B = 2 - \phi$,

$$M_A = \frac{(2-\phi)\sigma_A}{\sigma_A + \sigma_B}, \qquad M_B = \frac{(2-\phi)\sigma_B}{\sigma_A + \sigma_B}.$$

Hence

$$\theta_{A,1} = M_A - (1-\phi) = \frac{\sigma_A - (1-\phi)\sigma_B}{\sigma_A + \sigma_B}, \qquad \theta_{B,1} = M_B - (1-\phi) = \frac{\sigma_B - (1-\phi)\sigma_A}{\sigma_A + \sigma_B},$$

which is interior exactly under Assumption 1. Substituting back gives (4.2); premultiplying by $\gamma^{-1}\sigma_n^{-2}$ gives (4.1); multiplying by $\theta_{n,1}$ gives (4.3). □

A.2 Proof of Proposition 2

For intensive investors, (4.4) is the standard Gaussian updating formula, and the first-order condition gives (4.5).

For extensive investor i, (4.7) implies (4.8) and (4.9). Using (4.4),

$$\eta^p_{n,i} = \mu_n + g_n(d_n - \mu_n) + g_n e_n + \lambda_{z,n} z_n.$$

Because $(d_n, \eta^p_{n,i})$ are jointly Gaussian,

$$\mathbb{E}_i[d_n \mid \eta^p_{n,i}] = \mu_n + \frac{\mathrm{Cov}(d_n, \eta^p_{n,i})}{\mathrm{Var}(\eta^p_{n,i})}\left(\eta^p_{n,i} - \mu_n\right),$$

with

$$\mathrm{Cov}(d_n, \eta^p_{n,i}) = g_n \sigma_n^2, \qquad \mathrm{Var}(\eta^p_{n,i}) = g_n \sigma_n^2 + \lambda_{z,n}^2 \sigma_z^2,$$

so the projection coefficient equals κ_n. This gives (4.10). Next normalize the price-implied signal:

$$\mu_n + g_n^{-1}\left(\eta^p_{n,i} - \mu_n\right) = d_n + e_n + g_n^{-1}\lambda_{z,n} z_n.$$

The effective noise variance is $\sigma^2_{\eta,n} + (\lambda_{z,n}/g_n)^2 \sigma_z^2$, which implies (4.11). The extensive investor's first-order condition gives

$$q^{E,i}_{n,2} = \gamma^{-1} \hat{\sigma}^{-2}_{n,E}\left(\mathbb{E}_i[d_n \mid p_{n,2}, \tilde{m}_{n,i}] - p_{n,2}\right),$$

which yields (4.12) after substituting (4.10). Plugging the optimal quantity back gives (4.13). The sorting rule (4.14) follows from the single-asset constraint. □

A.3 Proof of Proposition 3

Under Assumption 2, integrating (4.12) over $E_{n,2}$ gives

$$Q^E_{n,2} = \gamma^{-1} \hat{\sigma}^{-2}_{n,E}\left[\theta_{n,2}(1 - \kappa_n)(\mu_n - p_{n,2}) + \kappa_n \lambda_{z,n} \int_{E_{n,2}} \left(1 - Q^E_{n,1} - \tilde{m}_{n,i}\right) di\right].$$

Since $\int_{E_{n,2}} 1\, di = \theta_{n,2}$ and $\int_{E_{n,2}} \tilde{m}_{n,i}\, di = \theta_{n,2}\bar{m}_n$, this becomes (4.15). □

A.4 Proof of Proposition 4

Under Assumption 2, actual market clearing is

$$(1-\phi)\gamma^{-1}\hat{\sigma}_n^{-2}(\hat{\mu}_n - p_{n,2}) + \gamma^{-1}\hat{\sigma}_{n,E}^{-2}\Big[\theta_{n,2}(1-\kappa_n)(\mu_n - p_{n,2}) + \theta_{n,2}\kappa_n\lambda_{z,n}\big(1 - Q_{n,1}^E - \bar{m}_n\big)\Big] + z_n = 1.$$

Multiplying by γ and collecting terms in $p_{n,2}$:

$$\left[(1-\phi)\hat{\sigma}_n^{-2} + \theta_{n,2}(1-\kappa_n)\hat{\sigma}_{n,E}^{-2}\right] p_{n,2} = (1-\phi)\hat{\sigma}_n^{-2}\hat{\mu}_n + \theta_{n,2}(1-\kappa_n)\hat{\sigma}_{n,E}^{-2}\mu_n + \theta_{n,2}\kappa_n\lambda_{z,n}\hat{\sigma}_{n,E}^{-2}(1 - Q_{n,1}^E - \bar{m}_n) - \gamma + \gamma z_n.$$

Dividing by $D_n \equiv (1-\phi)\hat{\sigma}_n^{-2} + \theta_{n,2}(1-\kappa_n)\hat{\sigma}_{n,E}^{-2}$ yields (4.18) with coefficients as stated. □

A.5 Proof of Proposition 5

Differentiating (4.5) gives $\mathcal{E}_n^I = -\gamma^{-1}\hat{\sigma}_n^{-2}$. Differentiating (4.12) gives $\mathcal{E}_n^E = -\gamma^{-1}(1-\kappa_n)\hat{\sigma}_{n,E}^{-2}$. Since

$$\sigma_{\eta,n}^2 + \left(\frac{\lambda_{z,n}}{g_n}\right)^2 \sigma_z^2 > \sigma_{\eta,n}^2,$$

equation (4.11) implies $\hat{\sigma}_{n,E}^{-2} < \hat{\sigma}_n^{-2}$. Because $\kappa_n \in (0,1)$,

$$(1-\kappa_n)\hat{\sigma}_{n,E}^{-2} < \hat{\sigma}_n^{-2},$$

which is equivalent to (4.19). □

A.6 Proof of Proposition 6

The result follows directly from differentiating (4.12):

$$\frac{\partial q_{n,2}^{E,i}}{\partial \tilde{m}_{n,i}} = -\gamma^{-1}\kappa_n\lambda_{z,n}\hat{\sigma}_{n,E}^{-2} < 0.$$

□

A.7 Proof of Proposition 7

Equation (4.17) gives $\partial p_{n,2}/\partial m_n = \lambda_{z,n}$. Since $p_{n,1}$ is fixed,

$$\frac{\partial r_{n,2}}{\partial m_n} = \lambda_{z,n}, \qquad \frac{\partial r_{n,3}}{\partial m_n} = -\lambda_{z,n}.$$

□

A.8 Proof of Proposition 8

From (4.17),

$$r_{n,2} = -p_{n,1} - \lambda_{z,n}\big(1 - Q^E_{n,1}\big) + \hat{\mu}_n + \lambda_{z,n}(m_n + z_n).$$

Conditioning on $t = 1$ information, the first two terms are fixed. Taking variances:

$$\mathrm{Var}(r_{n,2} \mid t = 1) = \mathrm{Var}(\hat{\mu}_n) + \lambda^2_{z,n}\mathrm{Var}(m_n + z_n) + 2\lambda_{z,n}\mathrm{Cov}\big(\hat{\mu}_n, m_n + z_n\big).$$

Since z_n is independent of fundamentals, $\mathrm{Cov}(\hat{\mu}_n, z_n) = 0$, so $\mathrm{Cov}(\hat{\mu}_n, m_n + z_n) = \mathrm{Cov}(\hat{\mu}_n, m_n)$, yielding (4.20). □

A.9 Derivation of intensive-flow return signs

Subtracting the $t = 1$ market-clearing condition from the $t = 2$ condition gives

$$m^I_n = (1 - \phi)\big(q^I_{n,2} - q^I_{n,1}\big) = -(Q^E_{n,2} - Q^E_{n,1}) - z_n = -m_n - z_n.$$

Holding z_n fixed, $m_n = -m^I_n - z_n$, so

$$\frac{\partial r_{n,2}}{\partial m^I_n} = -\lambda_{z,n}, \qquad \frac{\partial r_{n,3}}{\partial m^I_n} = \lambda_{z,n}.$$

A.10 From local belief aggregation to a state-indexed price system

Substituting (4.21) into (4.18):

$$p_{n,2} = a_n + b_n\hat{\mu}_n + c_n z_n - \delta_n\alpha_n(m_n) - \delta_n\xi_n(m_n)p_{n,2} - \delta_n\nu_n(m_n).$$

Collecting terms in $p_{n,2}$:

$$\big[1 + \delta_n\xi_n(m_n)\big]p_{n,2} = a_n - \delta_n\alpha_n(m_n) + b_n\hat{\mu}_n + c_n z_n - \delta_n\nu_n(m_n).$$

Dividing by $1 + \delta_n\xi_n(m_n)$ gives (4.22) with the coefficient definitions in the text. The stability condition $1 + \delta_n\xi_n(m_n) > 0$ ensures the local price system is well defined.

A.11 Proof of Proposition 9

From (4.22),

$$r_{n,2} = \tilde{a}_n(m_n) - p_{n,1} + \tilde{b}_n(m_n)\hat{\mu}_n + \tilde{c}_n(m_n)z_n - \tilde{d}_n(m_n)\nu_n(m_n).$$

The coefficient on $\hat{\mu}_n$ gives (4.24). Differentiating with respect to m_n:

$$\tilde{b}_n'(m_n) = -\frac{b_n\delta_n\xi_n'(m_n)}{\big[1 + \delta_n\xi_n(m_n)\big]^2}.$$

Under Assumption 4, $\tilde{b}_n'(m_n) > 0$, so $m_n^H > m_n^L$ implies $\tilde{b}_n(m_n^H) > \tilde{b}_n(m_n^L)$ locally. Then (4.23) gives

$$\Delta r_{n,2}(m_n) = \tilde{b}_n(m_n)(\hat{\mu}_n^H - \hat{\mu}_n^L).$$

Since $\hat{\mu}_n^H - \hat{\mu}_n^L > 0$, this gives (4.25). □

A.12 Proof of Proposition 10

From (4.22), with $\hat{\mu}_n$, z_n, and $\nu_n(m_n)$ pairwise orthogonal under Assumption 3:

$$\mathrm{Var}(r_{n,2} \mid t = 1, m_n) = \tilde{b}_n(m_n)^2\mathrm{Var}(\hat{\mu}_n) + \tilde{c}_n(m_n)^2\sigma_z^2 + \tilde{d}_n(m_n)^2\mathrm{Var}\big(\nu_n(m_n)\big).$$

Conditioning on $\hat{\mu}_n$ removes the fundamental component:

$$\mathrm{Var}(r_{n,2} \mid \hat{\mu}_n, m_n) = \tilde{c}_n(m_n)^2\sigma_z^2 + \tilde{d}_n(m_n)^2\mathrm{Var}\big(\nu_n(m_n)\big),$$

which gives (4.27). Subtracting and using (4.26) yields (4.28). Since $\tilde{b}'_n(m_n) > 0$ under Assumption 4, $m_n^H > m_n^L$ implies $\Delta\mathrm{Var}(r_{n,2} \mid t = 1, m_n^H) > \Delta\mathrm{Var}(r_{n,2} \mid t = 1, m_n^L)$. □

A.13 Proof of Proposition 11

Fix a local state indexed by m_n; all moments are taken under the associated equilibrium distribution.

From (4.22), write $d_n = \hat{\mu}_n + \varepsilon_n^{d|2}$, where $\varepsilon_n^{d|2}$ is the residual dividend innovation, Gaussian, mean zero, and independent of $\hat{\mu}_n$ by (4.4). With Assumption 5, $(d_n, p_{n,2})$ is jointly Gaussian in this local state. So

$$\mathrm{Cov}(d_n, p_{n,2} \mid m_n) = \tilde{b}_n(m_n)\mathrm{Var}(\hat{\mu}_n),$$

and

$$\mathrm{Var}(p_{n,2} \mid m_n) = \tilde{b}_n(m_n)^2\mathrm{Var}(\hat{\mu}_n) + \tilde{c}_n(m_n)^2\sigma_z^2 + \tilde{d}_n(m_n)^2\mathrm{Var}\big(\nu_n(m_n)\big).$$

Joint normality gives

$$\mathbb{E}[d_n \mid p_{n,2}, m_n] = \mathbb{E}[d_n \mid m_n] + \frac{\mathrm{Cov}(d_n, p_{n,2} \mid m_n)}{\mathrm{Var}(p_{n,2} \mid m_n)}\Big(p_{n,2} - \mathbb{E}[p_{n,2} \mid m_n]\Big).$$

Taking the variance:

$$\mathrm{Var}\big(\mathbb{E}[d_n \mid p_{n,2}, m_n] \mid m_n\big) = \frac{\mathrm{Var}(\hat{\mu}_n)^2\tilde{b}_n(m_n)^2}{\mathrm{Var}(\hat{\mu}_n)\tilde{b}_n(m_n)^2 + \tilde{c}_n(m_n)^2\sigma_z^2 + \tilde{d}_n(m_n)^2\mathrm{Var}\big(\nu_n(m_n)\big)}.$$

Since the local state indexes beliefs rather than dividend realizations, $\mathrm{Var}(d_n \mid m_n) = \sigma_n^2$. Substituting the definitions of $\tilde{b}_n$, $\tilde{c}_n$, and $\tilde{d}_n$, the factor $[1 + \delta_n\xi_n(m_n)]^{-2}$ cancels, giving (4.29).

Since $\mathrm{Var}(\nu_n(m_n))$ enters only the denominator of (4.29), lower dispersion raises $\mathcal{I}_n^{stock}$ and higher dispersion lowers it. Assumption 6 then gives the stated rankings. □

A.14 Proof of Corollary 12

From the proof above,

$$\mathrm{Var}\big(\mathbb{E}[d_n \mid p_{n,2}, m_n] \mid m_n\big) = \frac{\mathrm{Var}(\hat{\mu}_n)^2 b_n^2}{\mathrm{Var}(\hat{\mu}_n) b_n^2 + c_n^2 \sigma_z^2 + \delta_n^2 \mathrm{Var}\big(\nu_n(m_n)\big)}.$$

Taking square roots and using (4.29) gives $\mathcal{I}_n^{market}(m_n) = \sigma_n \sqrt{\mathcal{I}_n^{stock}(m_n)}$. Hence $\mathcal{I}_n^{market}$ inherits the same state dependence as $\mathcal{I}_n^{stock}$, and since σ_n is fixed, Assumption 6 implies the stated rankings. □

B Structural Model Proofs

B.1 Proof of Proposition 1

Proof. The proof has two parts. We first recover the signal that investor i extracts from prices under her subjective market-clearing condition, and then substitute that signal into the posterior mean. For investor i, the CARA-normal problem implies

$$q_i = \gamma_i^{-1} \hat{\Sigma}_{di}^{-1} (\hat{\mu}_{di} - R_f p).$$

It is therefore enough to rewrite the posterior mean $\hat{\mu}_{di} = \mu + \hat{\varepsilon}_i$.

A fully diversified intensive investor observes the private signal for every asset. Hence

$$\hat{\varepsilon}_I = \hat{\Sigma}_{\varepsilon I} \Sigma_\eta^{-1} \eta, \qquad \hat{\Sigma}_{\varepsilon I} = (\Sigma_\varepsilon^{-1} + \Sigma_\eta^{-1})^{-1}, \qquad \hat{\Sigma}_{dI} = \rho \rho' + \hat{\Sigma}_{\varepsilon I}.$$

Investor i perceives intensive investors as supplying aggregate risk tolerance $\bar{\gamma}_{iI}^{-1}$. Under those beliefs, the subjective market-clearing condition is

$$\tilde{m}_i + \bar{\gamma}_{iI}^{-1} \hat{\Sigma}_{dI}^{-1} (\mu + \hat{\varepsilon}_I - R_f p) + z = \mathbf{1}.$$

Solving for price gives the linear pricing rule perceived by investor i:

$$p = \frac{1}{R_f}\left[\mu + \hat{\Sigma}_{\varepsilon I}\Sigma_\eta^{-1}\eta - \bar{\gamma}_{iI}\hat{\Sigma}_{dI}(\mathbf{1} - \tilde{m}_i - z)\right].$$

Rearranging isolates the part of price that is informative about fundamentals:

$$\eta_{p_i} \equiv \Sigma_\eta \hat{\Sigma}_{\varepsilon I}^{-1}\left[pR_f - \mu + \bar{\gamma}_{iI}\hat{\Sigma}_{dI}(\mathbf{1} - \tilde{m}_i)\right] = \eta + \Sigma_\eta \hat{\Sigma}_{\varepsilon I}^{-1}\bar{\gamma}_{iI}\hat{\Sigma}_{dI} z. \tag{A1}$$

The second equality shows that the perceived price signal equals the underlying payoff signal plus a term generated by noise-trader demand. Since z is independent of η, the covariance matrix of the price-implied signal is

$$\Sigma_{p_i} = \Sigma_\eta + \bar{\gamma}_{iI}^2\left(\Sigma_\eta \hat{\Sigma}_{\varepsilon I}^{-1}\hat{\Sigma}_{dI}\right)\Sigma_z\left(\Sigma_\eta \hat{\Sigma}_{\varepsilon I}^{-1}\hat{\Sigma}_{dI}\right)'. \tag{A2}$$

Combining direct signals and price-implied signals gives

$$\bar{\eta}_i = s_i^I \eta + s_i^E \eta_{p_i}, \qquad \Sigma_{\bar{\eta}_i} = s_i^I \Sigma_\eta s_i^I + s_i^E \Sigma_{p_i} s_i^E = \Sigma_\eta + \Sigma_{\eta p,i}^E.$$

Bayesian updating then yields

$$\hat{\varepsilon}_i = \hat{\Sigma}_{\varepsilon i}\Sigma_{\bar{\eta}_i}^{-1}\bar{\eta}_i, \qquad \hat{\Sigma}_{\varepsilon i} = (\Sigma_\varepsilon^{-1} + \Sigma_{\bar{\eta}_i}^{-1})^{-1}.$$

Substituting $\bar{\eta}_i$ and (A1) into the posterior mean gives

$$\begin{aligned}\hat{\varepsilon}_i &= \hat{\Sigma}_{\varepsilon i}\Sigma_{\bar{\eta}_i}^{-1} s_i^I \eta + \hat{\Sigma}_{\varepsilon i}\Sigma_{\bar{\eta}_i}^{-1} s_i^E \Sigma_\eta \hat{\Sigma}_{\varepsilon I}^{-1}\left[pR_f - \mu + \bar{\gamma}_{iI}\hat{\Sigma}_{dI}(\mathbf{1} - \tilde{m}_i)\right] \\ &= \hat{\Sigma}_{\varepsilon i}\Sigma_{\bar{\eta}_i}^{-1} s_i^I \eta - \kappa_i(\mu - R_f p) + \kappa_i \bar{\gamma}_{iI}\hat{\Sigma}_{dI}(\mathbf{1} - \tilde{m}_i),\end{aligned}$$

where

$$\kappa_i \equiv \hat{\Sigma}_{\varepsilon i}\Sigma_{\bar{\eta}_i}^{-1} s_i^E \Sigma_\eta \hat{\Sigma}_{\varepsilon I}^{-1}, \qquad g(\tilde{m}_i) \equiv \kappa_i \bar{\gamma}_{iI}\hat{\Sigma}_{dI}(\mathbf{1} - \tilde{m}_i).$$

Hence the posterior mean of dividends can be written as

$$\hat{\mu}_{di} - R_f p = (I - \kappa_i)\mu + g(\tilde{m}_i) + \hat{\Sigma}_{\varepsilon i}\Sigma_{\bar{\eta}_i}^{-1} s_i^I \eta - (I - \kappa_i)R_f p.$$

Plugging this expression into the first-order condition proves Proposition 1. Because s_i^E has support only on assets outside the investor's initial portfolio, κ_i has the same support. □

B.2 Proof of Proposition 2

Proof. Substitute the demand system in Proposition 1 into objective market clearing and collect the aggregate terms that multiply expected payoffs, price-implied signals, and flow expectations. Proposition 1 gives

$$q_i = \gamma_i^{-1}\hat{\Sigma}_{di}^{-1}\left[(I-\kappa_i)(\mu - R_f p) + g(\tilde{m}_i) + \hat{\Sigma}_{\varepsilon i}\Sigma_{\bar{\eta}_i}^{-1}s_i^I\eta\right].$$

Aggregating across investors gives

$$\int q_i\, di = (\Omega - \Omega_p)(\mu - R_f p) + \Omega_\eta \eta + \Omega_m(\tilde{m}),$$

where

$$\begin{aligned}
\Omega &\equiv \int \gamma_i^{-1}\hat{\Sigma}_{di}^{-1}\, di,\\
\Omega_p &\equiv \int \gamma_i^{-1}\hat{\Sigma}_{di}^{-1}\kappa_i\, di,\\
\Omega_\eta &\equiv \int \gamma_i^{-1}\hat{\Sigma}_{di}^{-1}\hat{\Sigma}_{\varepsilon i}\Sigma_{\bar{\eta}_i}^{-1}s_i^I\, di,\\
\Omega_m(\tilde{m}) &\equiv \int \gamma_i^{-1}\hat{\Sigma}_{di}^{-1}g(\tilde{m}_i)\, di\\
&= \int \gamma_i^{-1}\hat{\Sigma}_{di}^{-1}\kappa_i\bar{\gamma}_{iI}\hat{\Sigma}_{dI}(\mathbf{1}-\tilde{m}_i)\, di.
\end{aligned}$$

Objective market clearing requires

$$\int q_i\, di + z = \mathbf{1},$$

or equivalently

$$(\Omega - \Omega_p)(\mu - R_f p) + \Omega_\eta \eta + \Omega_m(\tilde{m}) = \mathbf{1} - z.$$

Solving for price yields

$$p = \frac{1}{R_f}\left[\mu - (\Omega - \Omega_p)^{-1}(\mathbf{1} - \Omega_m(\tilde{m})) + (\Omega - \Omega_p)^{-1}\Omega_\eta \eta + (\Omega - \Omega_p)^{-1} z\right],$$

which is the expression in Proposition 2. □

B.3 Proof of Corollary 1

Proof. Impose the restriction that $\bar{\gamma}_{iI}$ is scalar across assets and define

$$h_i \equiv s_i^E \rho.$$

The proof proceeds by showing that, under this restriction, the matrices that matter for demand all reduce to a diagonal part plus a rank-one correction supported on the extensive block. That structure implies that the remaining cross-asset terms can be absorbed into grouped coefficients multiplying $\rho(n)$. Start from Proposition 1:

$$q_i = \gamma_i^{-1}\hat{\Sigma}_{di}^{-1}\left[(I - \kappa_i)\mu + g(\tilde{m}_i) + \hat{\Sigma}_{\varepsilon i}\Sigma_{\bar{\eta}_i}^{-1} s_i^I \eta - (I - \kappa_i) R_f p\right].$$

Because $\Sigma_\eta = \sigma_\eta^2 I$, $\Sigma_z = \sigma_z^2 I$, $\hat{\Sigma}_{\varepsilon I} = \hat{\sigma}_{\varepsilon I}^2 I$, and $\hat{\Sigma}_{dI} = \hat{\sigma}_{\varepsilon I}^2 I + \rho\rho'$, equation (A2) implies that

$$\Sigma_{\eta p,i}^E \equiv s_i^E(\Sigma_{p_i} - \Sigma_\eta) s_i^E = a_i s_i^E + b_i h_i h_i'$$

for some scalars a_i and b_i. Hence

$$\Sigma_{\bar{\eta}_i} = D_{\eta i} + b_i h_i h_i', \qquad D_{\eta i} \equiv \Sigma_\eta + a_i s_i^E.$$

Applying the Sherman-Morrison formula gives

$$\Sigma_{\bar{\eta}_i}^{-1} = D_{\eta i}^{-1} - c_i D_{\eta i}^{-1} h_i h_i' D_{\eta i}^{-1}$$

for some scalar c_i.

Since $\hat{\Sigma}_{\varepsilon i}^{-1} = \Sigma_{\varepsilon}^{-1} + \Sigma_{\bar{\eta}_i}^{-1}$ and $\Sigma_\varepsilon = \sigma_\varepsilon^2 I$, the same argument yields

$$\hat{\Sigma}_{\varepsilon i} = D_i + d_i h_i h_i', \qquad D_i \equiv \hat{\Sigma}_{\varepsilon I} + \hat{\Sigma}_{\varepsilon i}^{E,d},$$

for some scalar d_i, where $\hat{\Sigma}_{\varepsilon i}^{E,d}$ is diagonal and supported on the extensive block. Its nth diagonal entry is denoted by $(\hat{\sigma}_{\varepsilon i}^{E,d})^2$; this entry is zero on intensive assets.

Using $\hat{\Sigma}_{\varepsilon i}\Sigma_{\bar{\eta}_i}^{-1} = I - \hat{\Sigma}_{\varepsilon i}\Sigma_{\varepsilon}^{-1}$, we can similarly write

$$\kappa_i = \kappa_i^{E,d} + f_i h_i h_i'$$

for some scalar f_i, where

$$\kappa_i^{E,d} \equiv (I - D_i\Sigma_\varepsilon^{-1}) s_i^E \Sigma_\eta \hat{\Sigma}_{\varepsilon I}^{-1}$$

is diagonal, zero on intensive assets, and constant across extensive assets. As in the main text, we use $\kappa_i^{E,d}$ to denote the relevant diagonal entry.

Since

$$\hat{\Sigma}_{di} = \rho\rho' + \hat{\Sigma}_{\varepsilon i} = D_i + \rho\rho' + d_i h_i h_i',$$

it is a diagonal matrix plus two rank-one terms. Woodbury's identity therefore implies

$$\hat{\Sigma}_{di}^{-1} = D_i^{-1} + M_i,$$

where M_i belongs to the span of

$$\rho\rho', \qquad \rho h_i', \qquad h_i\rho', \qquad h_i h_i'.$$

Consequently, for any vector x, there exist scalars $m_i^I(x)$ and $m_i^E(x)$ such that

$$e_n' M_i x = \left[m_i^I(x) s_i(n) + m_i^E(x)(1 - s_i(n))\right] \rho(n).$$

This follows because $h_i(n) = 0$ on intensive assets and $h_i(n) = \rho(n)$ on extensive assets.

Define the bracketed term in Proposition 1 by

$$w_i \equiv (I - \kappa_i)\mu + \kappa_i \bar{\gamma}_{iI} \hat{\Sigma}_{dI}(\mathbf{1} - \tilde{m}_i) + \hat{\Sigma}_{\varepsilon i} \Sigma_{\bar{\eta}_i}^{-1} s_i^I \eta - (I - \kappa_i) R_f p.$$

The signal term simplifies exactly. Because h_i has support only on the extensive block,

$$\Sigma_{\bar{\eta}_i}^{-1} s_i^I = \sigma_\eta^{-2} s_i^I \qquad \text{and} \qquad \hat{\Sigma}_{\varepsilon i} s_i^I = \hat{\Sigma}_{\varepsilon I} s_i^I.$$

Hence

$$\hat{\Sigma}_{\varepsilon i} \Sigma_{\bar{\eta}_i}^{-1} s_i^I \eta = \hat{\sigma}_{\varepsilon I}^2 \sigma_\eta^{-2} s_i^I \eta,$$

so the own-asset signal component is exactly $\hat{\sigma}_{\varepsilon I}^2 \sigma_\eta^{-2} s_i(n)\eta(n)$.

For the flow term, use $\hat{\Sigma}_{dI} = \hat{\sigma}_{\varepsilon I}^2 I + \rho\rho'$. The diagonal part of κ_i contributes the exact own-asset component

$$\kappa_i^{E,d} \bar{\gamma}_{iI} \hat{\sigma}_{\varepsilon I}^2 (1 - \tilde{m}_i(n)).$$

Every remaining part of the flow term is proportional to $(1 - s_i(n))\rho(n)$: this is immediate for $\kappa_i^{E,d} \bar{\gamma}_{iI} \rho\rho'(\mathbf{1} - \tilde{m}_i)$, and it also holds for the rank-one piece $f_i h_i h_i' \bar{\gamma}_{iI} \hat{\Sigma}_{dI}(\mathbf{1} - \tilde{m}_i)$ because h_i is proportional to $s_i^E \rho$. Combining those pieces with the cross-asset correction from M_i, there exist scalars c_i^I and c_i^E such that

$$\begin{aligned} q_i(n) = \gamma_i^{-1} D_i(n,n)^{-1} \Big[& -(1 - \kappa_i^{E,d}) R_f p(n) + \kappa_i^{E,d} \bar{\gamma}_{iI} \hat{\sigma}_{\varepsilon I}^2 (1 - \tilde{m}_i(n)) \\ & + (1 - \kappa_i^{E,d}) \mu(n) - \left[c_i^I s_i(n) + c_i^E (1 - s_i(n)) \right] \rho(n) \\ & + \hat{\sigma}_{\varepsilon I}^2 \sigma_\eta^{-2} s_i(n) \eta(n) \Big]. \end{aligned}$$

It remains to substitute the characteristic representations

$$\mu(n) = \Phi_\mu' x(n) + \xi_\mu, \qquad \rho(n) = \Phi_\rho' x(n) + \xi_\rho.$$

Define

$$c_{i\rho,0} \equiv c_i^E, \qquad c_{i\rho,1} \equiv c_i^I - c_i^E, \qquad \zeta_{i0} \equiv (1 - \kappa_i^{E,d})\xi_\mu - c_i^E \xi_\rho, \qquad \zeta_{i1} \equiv \kappa_i^{E,d} \xi_\mu - (c_i^I - c_i^E)\xi_\rho.$$

Since $D_i(n,n) = \hat{\sigma}^2_{\varepsilon I} + (\hat{\sigma}^{E,d}_{\varepsilon i})^2$, collecting terms yields

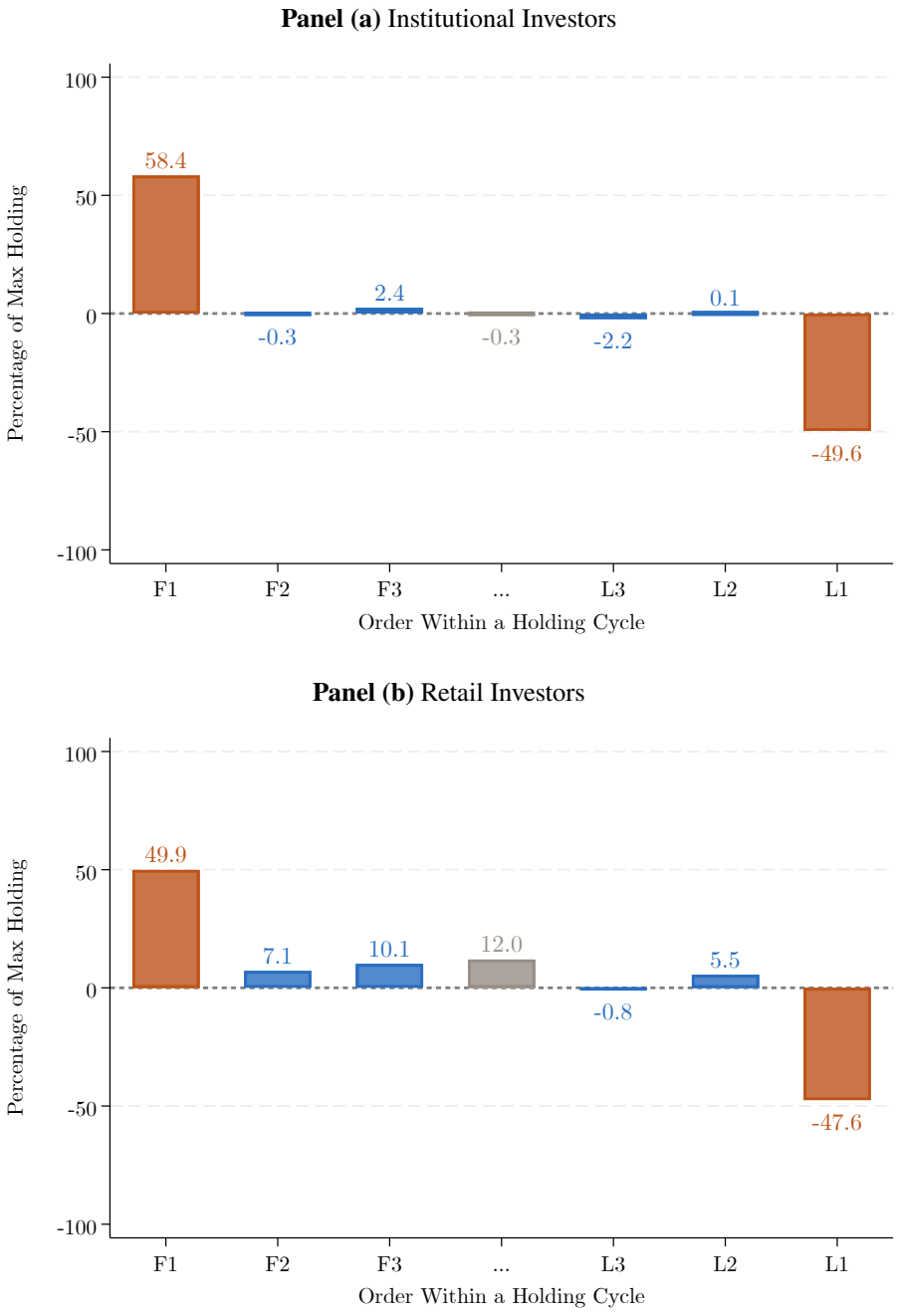
$$\begin{aligned} q_i(n) = \gamma_i^{-1} \left(\hat{\sigma}^2_{\varepsilon I} + (\hat{\sigma}^{E,d}_{\varepsilon i})^2\right)^{-1} \Big[& -(1-\kappa_i^{E,d}) R_f p(n) + \kappa_i^{E,d} \bar{\gamma}_{iI} \hat{\sigma}^2_{\varepsilon I} (1-\tilde{m}_i(n)) \\ & + \left((1-\kappa_i^{E,d})\Phi_\mu - \Phi_\rho \left(c_{i\rho,0} + c_{i\rho,1} s_i(n)\right)\right) x(n) \\ & + \hat{\sigma}^2_{\varepsilon I} \sigma_\eta^{-2} s_i(n)\eta(n) + \zeta_{i0} + \zeta_{i1} s_i(n) \Big], \end{aligned}$$

which is equation (5.16).

□

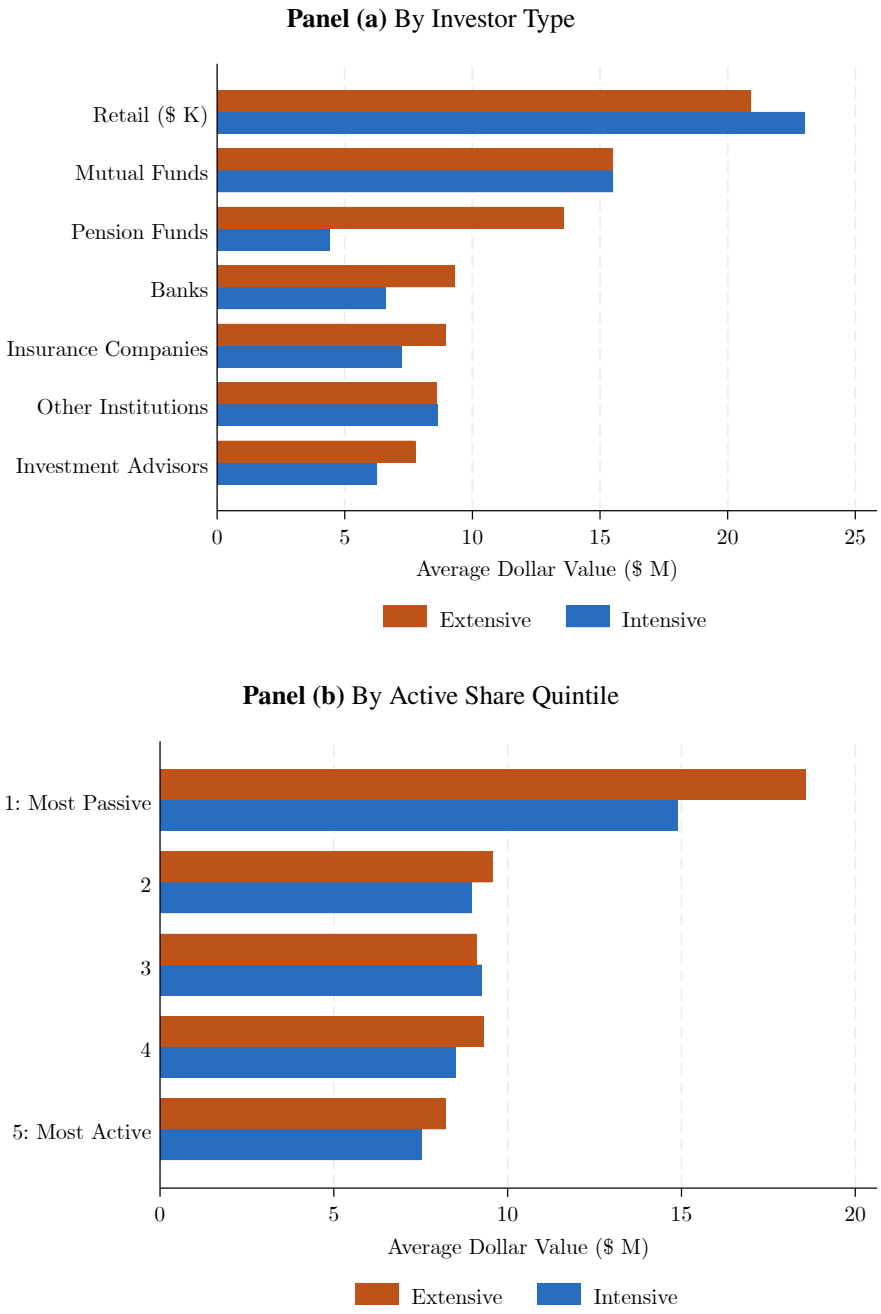
C Appendix Figures

Figure A1. Flow Distribution Within a Holding Cycle
(Excluding One-Buy-One-Sell)



Notes. This figure plots the distribution of flows as a percentage of the maximum position within an average holding cycle, using the institutional investor sample in Panel (a) and the retail investor sample in Panel (b). Both samples exclude holding cycles that contain only one buy and one sell observation. F1–F3 denote the first, second, and third periods of the cycle, while L1–L3 correspond to the last, second-to-last, and third-to-last periods. Red bars indicate extensive flows, whereas blue and gray bars represent intensive flows.

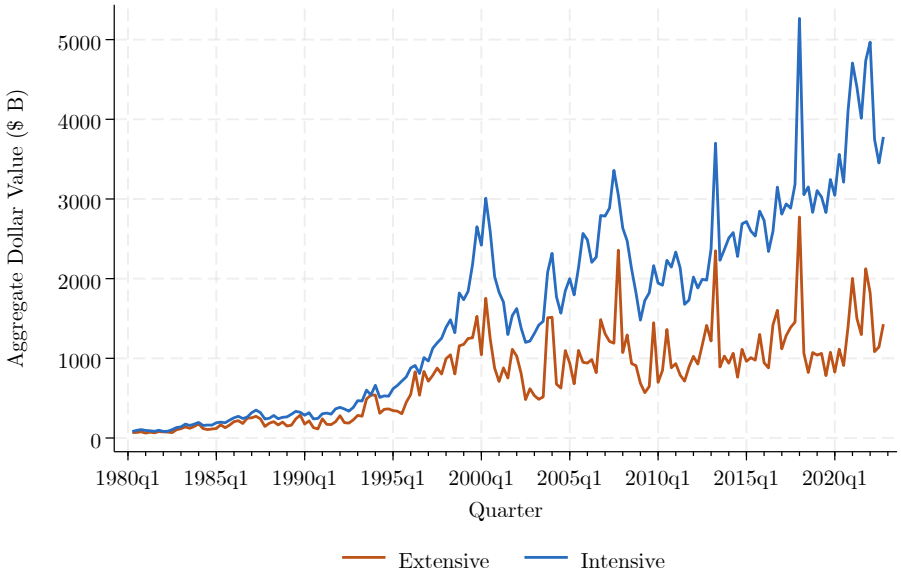
Figure A2. Dollar Values of Extensive and Intensive Flows



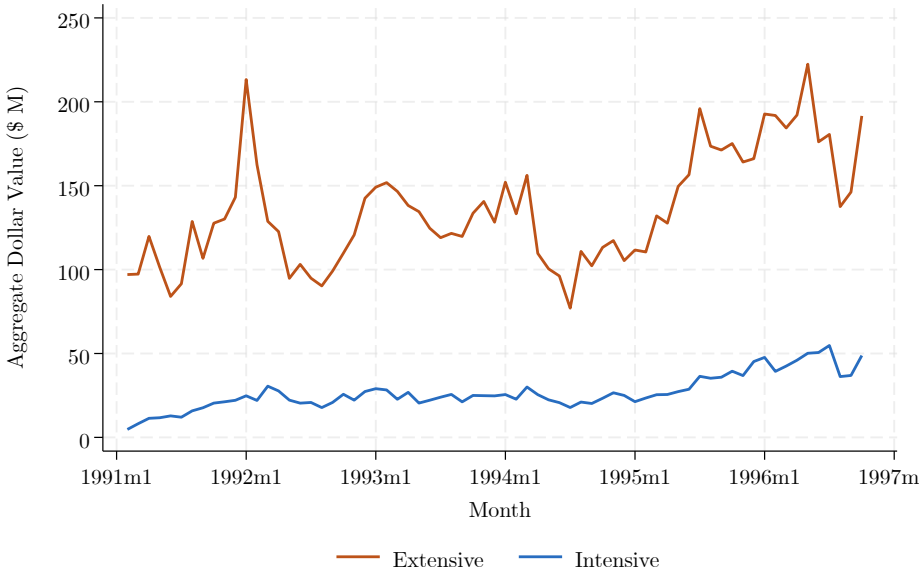
Notes. This figure plots the average dollar value of extensive flows (the sum of extensive in and out) and intensive flows (the sum of intensive in and out), by investor type in Panel (a) and by active–share quintile in Panel (b).

Figure A3. Dollar Values of Aggregate Flows

Panel (a) Institutional Investors



Panel (b) Retail Investors



Notes. This figure plots the time series of the aggregate dollar value of extensive flows (the sum of extensive in and out) and intensive flows (the sum of intensive in and out), using the institutional investor sample in Panel (a) and the retail investor sample in Panel (b).