Capital Flow Dynamics and Strategic Risk Management in Mutual Funds: Deciphering Managerial Decision-Making

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Abstract

This study investigates the relationship between mutual fund capital flows and managers' risk management decisions, presenting an original methodology to distinguish active managerial choices from passive portfolio segments. We introduce a set of metrics—Risk-Attitude-Purchases (RAP), Risk-Attitude-Sales (RAS), and Risk-Attitude-Trades (RAT)—to discern risk preferences under varying capital conditions, focusing on ESG compliance, Illiquidity, and Mispricing. Our findings demonstrate that managers strategically adjust their holdings from asset characteristics in response to capital inflows or withdrawals, optimizing between immediate fund performance and long-term potential. The research further explores how these risk-adjustment strategies vary between funds with different investor bases, revealing a tailored approach to the distinct expectations of retail versus institutional clients. The analysis confirms the validity of our findings, mitigating concerns about portfolio manipulation and window dressing. This contribution aids in understanding the complex strategies underpinning fund management in an ever-changing financial landscape.

Keywords: Mutual Fund Risk Management, Capital Flow Dynamics, trades, Managerial Decision-Making, Risk Preferences, Mispricing, Illiquidity, ESG, Investment Strategies, and Risk Shift.

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[2]Please ensure that you are referring to the most recent version of this paper before proceeding. I regularly update the content to refine the analysis and incorporate new data. The latest version and R statistical code for replicating the study's analyses are available on my GitHub repository. Access it directly by clicking HERE.

1 Introduction

The mutual fund industry perennially grapples with the fickle nature of capital flows, a reality laid bare by moments of significant market stress. Events such as the 2008 financial crisis, the S&P 500's volatility in November 2018, and the March 2020 market disruption triggered by COVID-19 have underscored the profound effects of swift capital movement. The industry is still reeling from the repercussions of 2003's market-timing and late-trading scandals, which eroded trust and decimated fund values. These fluctuations extend beyond performance metrics, signaling market recalibrations with multibillion-dollar stakes, warranting rigorous regulatory and investor scrutiny.

Academic discourse has illuminated the impact of capital flows on mutual fund performance, focusing on the mitigating role of liquidity buffers and management strategies (Sirri and Tufano 1998; Edelen 1999; Zheng 1999; Coval and Stafford 2007; Chen et al. 2010; Lou 2012; Agarwal et al. 2020). Nevertheless, an analysis gap persists: the literature is scant on how fund managers recalibrate portfolios amid the tumult of capital variation, a process critical to understanding risk attitude shifts that bear upon long-term fund resilience and the nuanced evaluation of managerial performance.

While some research threads have started to untangle the web of portfolio adjustments in response to capital flow pressures (Coval and Stafford 2007; Evans et al. 2019), they often stop short of an exhaustive investigation into how these adjustments inform broader diversification strategies and risk-taking behavior. To fill this void, a granular examination of risk attitudes is imperative. The literature lacks clear and straightforward mechanisms that can help reveal fund managers' deliberate and strategic choices in pursuit of portfolio optimization amidst the unpredictable waves of investor sentiment. The in-depth analysis of risk management at the organizational level provides a window into the strategic acumen fund managers exhibit, adding a dimension of value to investment stewardship beyond mere short-term gains.

This study introduces a refined identification strategy that meticulously separates the manageable facets of fund managers' decisions from the unpredictable exogenous shocks and market-wide externalities that often cloud traditional performance metrics. This approach promises a more precise evaluation of asset management efficacy during extreme capital flow movements, providing insights beyond the usual narratives of underperformance or the so-called "smart money" effect.

Our analytical framework is pioneering in recognizing the complex investment terrain navigated by fund managers. By casting light on the strategic underpinnings of their actions, we offer a detailed perspective on how they contend with and often outmaneuver volatile market conditions. Hence, through a comprehensive examination of mutual fund portfolio reallocation strategies, our paper expands the discourse on how fund managers respond to capital flow pressures. Therefore, by answering how mutual fund managers' risk management strategies and portfolio reallocation decisions respond to extreme capital flow pressures, we underscore the finesse fund managers operate to mitigate adverse price impacts while safeguarding and growing the invested capital.

We pioneer in scrutinizing portfolio reallocation dynamics, considering portfolio features and manager risk attitudes in fluctuating capital flow environments. Our detailed analysis encompasses three critical factors frequently discussed in finance literature: overpricing, illiquidity, and Environmental, Social, and Governance (ESG) considerations. By examining how these factors influence equity stock returns and managerial trading choices, we shed light on the sophisticated risk-return calculus that guides fund managers (Pástor and Stambaugh 2003; Gibson Brandon et al. 2021).

Our research transcends conventional analysis by employing an original set of metrics—Risk-Attitude-Purchases (RAP), Risk-Attitude-Sales (RAS), and Risk-Attitude-Trades (RAT)—to dissect mutual fund managers' risk attitudes in the face of variable capital flows. This novel approach reveals the strategic layers of decision-making and the nuanced risk preferences that underlie portfolio allocation strategies. Hence, we discovered that fund managers tend to divest from ESG-compliant assets in extreme capital withdrawals, preferring to retain assets characterized by higher illiquidity and overpricing. This behavior suggests prioritizing short-term portfolio value over long-term stability. Conversely, when funds experience extreme capital injections, managers strategically incorporate ESG-intense, more liquid, and less overpriced assets, favoring long-term stability over immediate gains or yields. These insights demonstrate a sophisticated balancing act executed by managers to navigate the conflicting demands of performance and stability.

Further deepening our analysis, we investigated how investor profiles impact managerial strategies. Our evidence suggests that managers tailor their behaviors to their investor base, exhibiting a less short-term focused risk attitude during outflows when dealing with retail investors, potentially due to a lower likelihood of performance-based penalties in the short term. This finding speaks to the complex relationship between investor expectations and fund management tactics. In addition, to address potential confounds and ensure the integrity of our results, we conducted robustness tests to distinguish genuine managerial skill from possible manipulation of reported performance. Previous research suggests managers may manipulate portfolios to project false performance signals (Agarwal et al. 2014; Patel and Sarkissian 2020). To counter this, we excluded data from the last quarter to isolate our analysis from any end-of-year window dressing effects and from the first quarter to eliminate any distortions from post-performance adjustments. These tests affirm that the sophisticated risk allocation strategies we observed do not result from manipulative practices but rather reflect a genuine alignment of fund management with investor needs and fund stability.

Our paper enriches the vast literature on mutual funds by dissecting the relationship between capital flows and managerial risk-taking. To our knowledge, this paper is the first to systematically examine fund managers' risk attitudes using a framework that captures the subtleties of their response to capital flow volatility, a perspective not previously explored in such depth. Our identification strategy provides fresh insights into the risk preferences of mutual fund managers, offering a more nuanced understanding of asset management practices in extreme market conditions. Our results have practical implications for policymakers and regulators seeking to ensure market stability and protect investor interests. By revealing how fund managers' strategies vary with investor composition and capital flow pressures, our analysis informs the ongoing debate on fund liquidity regulation and the need for transparency in fund operations.

The subsequent sections of this paper systematically build upon our introductory framework. Section 2 grounds our research in institutional knowledge and related studies, framing our innovative hypotheses. Section 3 delves into the methodological backbone of our work, presenting the variables and data that support our investigation. Section 4 showcases the empirical rigor of our regression analysis, bolstering confidence in our findings through extensive robustness checks. Section 5 synthesizes these findings, extrapolating their implications for the financial industry and suggesting fertile ground for future inquiries into asset management's evolving landscape.

2 Institutional Background, Related Literature, and Hypothesis Development

Mutual funds specialize as investment vehicles that offer unmatched liquidity through the subscription and redemption of shares.[3] Investors can freely inject or withdraw capital. When investors introduce new money, the fund issues a new share and typically buys securities expected to yield appropriate returns.[4] While managers can keep these inflows as cash and avoid immediate trading, it's important to note that investors usually pay management fees to benefit from skillful capital allocation. If managers only hold cash, investors could do the same without incurring these fees. On the other hand, when investors redeem shares and pull out their investments, managers must sell assets to meet these demands. If the cash buffer doesn't cover the redemptions, managers might have to sell assets at less favorable prices, affecting the portfolio's value.

Managers of mutual funds follow a dual mandate: to maintain portfolio value and strive for value creation. When buying or selling assets, managers can choose from various strategies. They can continue investing in stocks they know well or diversify by adding new stocks to their portfolio. Similarly, they can sell parts of multiple holdings during sales or exit specific positions completely. Managers make these decisions based on their market outlook and particular securities. However, they also consider broader portfolio management goals like risk mitigation and profitability. According to Markowitz's portfolio theory, portfolio optimization involves skill in forecasting price movements to maximize returns while minimizing risk. Therefore, a comprehensive understanding of a manager's behavior requires considering their value-generating ability and risk management strategies.

The academic discourse around mutual funds has concentrated mainly on the interplay between fund flows and performance. Initial studies, such as those by Edelen (1999) and Chen et al. (2010), examined how fund flows impact performance and how performance, in turn, influences future flows. Subsequent research extended this line of inquiry by incorporating variables like investor type and fund-specific attributes. Works by Sirri and Tufano (1998), Guercio and Tkac

[3]This fluid exchange is facilitated through an unlimited number of shares, which provide investors with the right to redeem their deposits at will, as per Section 22 of the Investment Company Act of 1940.

[4]The value of these shares is inherently tied to the overall portfolio value. As delineated in Section 2, numerals 32 and 33 of the Investment Company Act 1940, any redeemable share proffers a proportionate slice of the fund's portfolio based on the net asset value.

(2002), and Ferreira et al. (2012) delve into how these factors mediate the flow-performance relationship. In addition, scholars like Alexander et al. (2007) and Coval and Stafford (2007) have shifted the focus toward understanding how managers' trading activities impact their portfolios. However, one notable gap in the literature is the limited exploration of risk management, an integral component of portfolio management.

Another significant strand of literature investigates how fund flows affect managers' risk-taking behaviors. Chevalier and Ellison (1997) and Ha and Ko (2017) found that managers adjust portfolio risk profiles to attract additional inflows. Conversely, Basak et al. (2007) provide theoretical evidence that managers willingly modify asset allocation to increase the chances of securing future flows. This body of work presents a nuanced understanding of how fund flows influence managerial decisions around risk. A noteworthy contribution from Huang et al. (2011) suggests that managers who adjust their risk profiles to compete for flows may erode future performance, signaling a potential lack of skill.

The notion of tournaments in mutual funds has garnered academic attention as an extension of the flow-performance relationship. Researchers such as Busse (2001), Hvide (2002), Taylor (2003), and Kempf and Ruenzi (2008) explore how underperforming funds, categorized by past returns, engage in riskier strategies to attract more capital. However, Qiu (2003) offers a more nuanced perspective by arguing that only those closer to top-performing funds will take this gamble. Funds at the bottom are constrained by the risks associated with potential termination, limiting their propensity to engage in riskier asset allocations.

Our research uniquely positions itself by examining managers' attitudes toward specific portfolio characteristics—namely, Illiquidity, Overpricement, and ESG—in the context of extreme fund flows. While no existing studies directly investigate how managers reallocate these specific characteristics in response to flows, there is relevant literature. For instance, we adopt Amihud (2002) measure for Illiquidity and Stambaugh and Yuan (2017) measure for Overpricement. In the case of ESG, we employ a composite score based on KLD and Asset 4 datasets, as suggested by Gibson Brandon et al. (2022). According to Pástor and Stambaugh (2003), Sadka (2006), Gibson Brandon et al. (2021), these risk factors significantly influence stock returns and thus should form an essential part of managers' trading decisions.

The concept of mutual fund fragility, particularly in illiquid stocks, offers crucial insights into the dynamic between portfolio liquidity and fund flows. Studies by Chen et al. (2010) and Goldstein et al. (2017) find that portfolios with higher illiquidity are more susceptible to outflows, especially during adverse market conditions. However, the literature must address how managers adapt or reallocate illiquid assets in response to such flow-driven pressures, leaving a gap that our research aims to fill.

Several studies have probed the relationship between overpricement, ESG, and fund flows, albeit in a different manner than our research focus. Akbas et al. (2015) discuss how inflows can mitigate or exacerbate market mispricing, depending on the fund's investment strategies. Sulaeman and Wei (2019) add another layer by showing that sell-side analysts often issue price-correcting recommendations due to flow-driven mispricing. Yet, these works must investigate how managers realign their portfolios based on these dynamics.

In ESG, Bollen (2007) find that Socially Responsible Investment (SRI) funds, which perform well on ESG metrics, are more likely to attract future capital. Hartzmark and Sussman (2019) build on this by showing that high sustainability levels can lead to inflows, regardless of performance. These findings underscore the increasing importance investors place on sustainability, aligning well with our research objectives to explore the reallocation behavior of ESG factors under extreme flow conditions.

Despite extensive studies on fund flows and their impact on portfolio management, a gap remains. There needs to be more research on how managers actively respond to extreme flow situations, such as large inflows or outflows. Our paper aims to contribute to the field by focusing on the portfolio rebalancing strategies managers employ when facing significant shifts in fund flows. This inquiry is especially relevant in understanding how managers adapt their portfolios concerning risky attributes like illiquidity, overpricement, and ESG factors.

Our study can be contextualized within broader financial theories. For instance, literature on household finance, such as the work by Calvet et al. (2009), explores how individuals adjust their risk profiles based on changes in wealth. In mutual funds, our research seeks to uncover similar behavioral traits among fund managers. Additionally, our work is a specialized application of prospect theory. While the thesis primarily deals with how individuals make choices between probabilistic alternatives involving risk, we extend this to examine how fund managers might adjust their portfolios in response to extreme flow conditions. Importantly, our focus is not on individual stock performance—winners versus losers—but on how managers adjust risk levels in their portfolios. Cici (2012) found that mutual funds are more likely to sell winning stocks under outflows; our research takes this a step further by examining whether managers prefer stocks with higher or lower risk premiums under different flow dynamics.

Investors allocate capital to mutual funds, expecting managers to make informed rebalancing decisions to maximize returns. Berk and Green (2004) argue that this capital provision operates on a rational dynamic where investors entrust their money based on the present value of opportunities. When managers decide to trade, they weigh various risk factors. For instance, a purchase could introduce a new stock to the portfolio or increase the weight of an existing one. In both scenarios, the trade alters the portfolio's risk profile. The manager accepts more risk if the new or reinforced stock comes with a higher risk than the rest of the portfolio. Conversely, when incoming stocks are less risky, it indicates a strategic move toward a low-risk portfolio. Sales also follow the same principle: offloading high-risk stocks reduces the portfolio's overall risk exposure, while selling low-risk stocks increases it.

Our central hypothesis posits that managers adjust their risk profiles based on the extreme fund flow levels they experience. Specifically, we hypothesize that managers lean towards assets considered less risky or of better quality during large inflows, including those with strong ESG characteristics. ESG characteristics can attract more flows, irrespective of performance. Conversely, managers will likely opt for riskier assets, including those with low ESG scores during large outflows. In terms of pricing, we hypothesize that managers aim to reduce mispricing during periods of high inflows and increase it during large flows. Regarding illiquidity, we posit that managers will prefer less illiquid stocks during periods of large subscriptions and more illiquid stocks during significant redemptions.

Understanding these behavioral patterns among fund managers can offer investors and finance professionals crucial insights. It aids in making more informed choices in fund selection and risk management. Our research emphasizes the need to consider fund flow dynamics when evaluating risk management strategies within mutual funds. By focusing on how managers respond to extreme flow situations, we contribute a new layer of understanding to the existing body of literature, particularly in risk management and capital allocation.

2.1 Risk Preferences: A Comparative Approach on Trading Attitudes

The mutual fund industry grapples with the ongoing challenges of capital flows. Investors can subscribe or redeem shares at will, creating a fluid landscape that fund managers must navigate adroitly. Although fee structures like front and back loads offer some relief, the industry lacks effective strategies for managing extreme capital movements—large inflows or outflows. These scenarios mandate astute portfolio allocation of risk to safeguard fund value and meet investment objectives.

Existing literature offers limited perspectives on the intricate relationship between capital flow dynamics and risk preferences in mutual funds. While some studies focus on how diversification contracts or expands under varying flow conditions (Coval and Stafford 2007; Evans et al. 2019), others, like Huang et al. (2011), concentrate solely on the implications of risk-shifting for fund performance, no work has examined whether risk-shifting patterns differ between inflow and outflow scenarios. Furthermore, the current body of research is notably silent on extending the concept of risk-shifting beyond return volatility, for example, by exploring the allocation of characteristics such as illiquidity, overpricing, and Environmental, Social, and Governance (ESG) factors that have been shown to have a connection with prices and risk premiums (Pástor and Stambaugh 2003; Chen and Pennacchi 2009; Stambaugh and Yuan 2017; Maiti 2021; Bofinger et al. 2022; Cao et al. 2023).

Our research introduces a paradigmatic shift in methodological focus, targeting the uncharted territory of fund managers' risk attitudes. We scrutinize managers' specific trading decisions under extreme capital flow conditions, thereby gaining a more nuanced understanding of their risk preferences. Our methodology employs a suite of newly designed equations that yield three key metrics: Risk-Attitude-Purchases (RAP), Risk-Attitude-Sales (RAS), and Risk-Attitude-Trades (RAT). These metrics directly indicate a manager's risk attitudes, significantly improving existing measures that often confound managerial decisions with broader market dynamics.

What sets our approach apart is its focus on isolating managers' trading decisions during specific quarters. This temporal focus eradicates distortions caused by external factors, giving a crystal-clear understanding of a manager's risk preferences. Our methodology bridges existing gaps and lays a foundation for future research in this domain. Our study radically enhances the analytical toolbox for dissecting complex risk-management strategies, especially under high-pressure conditions. By delivering a more nuanced understanding of risk, we furnish invaluable insights for investors, regulators, and the academic community.

We focus on delineating how portfolio risk dynamics evolve due to trading decisions made by fund managers. Specifically, we assess the risk disparities between assets that have been traded and those that remain static within a given timeframe. Each quarter, for every fund, we distinguish between the risk elements attributable to trades and those resulting from time trends.[5] To concretize our identification strategy, we categorize assets within the portfolio into two distinct sub-portfolios: purchases and sales. These categories are derived based on the change in the number of shares for each asset ($\Delta Shares$). We then compute value-weighted average risks for these sub-portfolios. The mathematical formulation to identify these sub-portfolios and calculate their corresponding weights is as follows:

$$\Delta_{stock,t}^{Purchase} = \begin{cases} \Delta Shares_t, & \text{if } \Delta Shares_t > 0 \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

$$\Delta_{stock,t}^{Sale} = \begin{cases} \Delta Shares_t, & \text{if } \Delta Shares_t < 0 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

Our approach necessitates a value-weighted average over risk measures. Given that any coherent risk measure is always positive, the weights are also constrained to be positive. The weight equations for Purchase Trading characteristic PTR and Sale Trading characteristic STR are as follows and denote the average value of a particular characteristic for all the stocks that managers buy or sell in a specific quarter. It is essential to point out that for both types of weights ($W^{Purchase}, W^{Sale}$), the corresponding sum must be equal to one ($\sum_s^n W_s^{Purchase} = \sum_s^n W_s^{Sale} = 1$).

[5] This solely emphasizes intra-period risk variations, excluding time trend changes, which are not necessarily indicative of managerial discretion.

$$W^{Purchase}_{stock,t} = \frac{\Delta^{Purchase}_{stock,t} \times Price_{stock,t}}{\sum_{stock,t} \Delta^{Purchase}_{stock,t} \times Price_{stock,t}}, \quad W^{Purchase}_{stock,t} \in (0,1] \tag{3}$$

$$W^{Sale}_{stock,t} = \frac{\Delta^{Sale}_{stock,t} \times Price_{stock,t}}{\sum_{stock,t} \Delta^{Sale}_{stock,t} \times Price_{stock,t}}, \quad W^{Sale}_{stock,t} \in (0,1] \tag{4}$$

$$PTR^{fund}_t = \sum_{stock} W^{Purchase}_{stock,t} \times Char_{stock,t} \tag{5}$$

$$STR^{fund}_t = \sum_{stock} W^{Sale}_{stock,t} \times Char_{stock,t} \tag{6}$$

Previously, we concentrated on identifying the weights of each stock within trading sub-portfolios. Our focus then shifts to those assets that remain stable in their shareholdings, which serve as key indicators of risk preferences influenced by trading activity. These stable assets comprise a sub-portfolio, denoted as NTR, an acronym for "Non-Trading Characteristic." This sub-portfolio signals the fund managers' intention to maintain the existing risk profile of these assets into the upcoming financial quarter. To provide a more granular analysis, we establish a benchmark sub-portfolio composed of stock that managers decide not to trade. We introduce a dummy variable, D^{NT}, that flags these non-traded securities. This variable is set to one when there is no change in the number of shares between two consecutive quarters ($\Delta \text{Shares} = 0$). We carefully generate the weights for these non-traded assets to compute the value-weighted average measure for the NTR sub-portfolio. In this regard, $W_{t,\text{stock}}$ represents the proportion of each stock's monetary value within the entire portfolio, a method that aligns with existing literature. We then normalize these weights to center our analysis solely on the assets that have not been traded. Notably, the normalized weights, W^{NT}_{stock}, are designed to be positive, and their sum is constrained to be one ($\sum_{\text{stock}} W^{NT}_{\text{stock}} = 1$).

$$D_{t,\text{stock}}^{NT} = \begin{cases} 1, & \text{if } \Delta\text{Shares}_t = 0 \\ 0, & \text{otherwise} \end{cases}, \tag{7}$$

$$W_{t,\text{stock}}^{NT} = \frac{W_{t,\text{stock}} \times D_{t,\text{stock}}^{NT}}{\sum_{\text{stock}} W_{t,\text{stock}} \times D_{t,\text{stock}}^{NT}} \tag{8}$$

$$NTR_t^{\text{fund}} = \sum_{\text{stock}} W_{\text{stock}}^{\text{NT}} \times \text{Char}_{\text{stock},t} \tag{9}$$

Our approach uniquely categorizes assets into three distinct sub-portfolios based on managerial decisions: PTR, STR, and NTR. This categorization allows us to scrutinize the immediate choices made by managers under specific time constraints and capital flow pressures without the confounding influence of past decisions or long-term holdings. In this framework, PTR and STR focus on the assets traded within a specific quarter, offering a snapshot of the risk landscape as the managers actively shape it. In contrast, NTR reflects asset managers deliberately choose not to trade, giving a window into their risk attitudes for assets they intend to hold long-term. Importantly, these sub-portfolios offer a more targeted perspective than traditional portfolio-wide metrics, effectively isolating the managers' decision-making process.[6] After identifying the characteristic risk measures for PTR, STR, and NTR, we further refine our analysis by introducing three key variables: RAP, RAS, and RAT. These variables are calculated as follows:

$$\begin{aligned} RAP_t^{\text{fund}} &= PTR_t^{\text{fund}} - NTR_t^{\text{fund}}, \\ RAS_t^{\text{fund}} &= NTR_t^{\text{fund}} - STR_t^{\text{fund}}, \\ RAT_t^{\text{fund}} &= RAP_t^{\text{fund}} + RAS_t^{\text{fund}}. \end{aligned} \tag{10}$$

Our three pivotal variables, RAP, RAS, and RAT serve to elucidate managerial attitudes toward risk within the complex landscape of asset management. Unlike conventional metrics that capture only the net alterations in portfolio risk, these variables offer nuanced insights into risk preferences influenced by active managerial decisions. For example, RAP gives insights into the incremental risk managers are willing to assume through their purchasing activities relative

[6] It's worth noting that these sub-portfolios don't represent the entire asset holding structure but aim to capture the essence of managers' decisions during specific periods.

to a stable, non-trading baseline; meanwhile, RAS reflects the magnitude of risk mitigation achieved through selling activities, and finally, RAT provides an aggregated perspective on the net risk posture adopted by fund managers. Although these values may not quantitatively align with the total portfolio's risk profile, they serve as qualitative indicators of managerial behavior. Specifically, a negative value over RAP or RAS signals a penchant for risk aversion. These metrics are instrumental in dissecting administrative strategies and can be a critical tool for academic inquiry and practical applications.

3 Data

3.1 Data Description

Our study employs a robust and comprehensive dataset that includes 4,533 mutual funds active in the asset management industry from 2000 to 2020. We derive this data from a leading financial database that compiles fund attributes such as performance metrics, capital flows, and organizational features. The CRSP Mutual Fund database is our primary source for essential fund characteristics like net returns, turnover ratios, and investment styles. All data from CRSP comes at the share-class level. Still, we adjust this to the fund level by summing the total net assets and value-weighting attributes of share-classes at the portfolio level.[7]

To delve into the intricacies of fund managers' trading decisions, we examine changes in portfolio holdings every quarter. This information comes from both Thomson Reuters S12 and CRSP databases.[8] Additionally, Morningstar Direct supplements our main dataset by providing detailed information about fund managers and advisors, such as career timelines and fund tenures. We meticulously link CRSP and Thomson Reuters via MFLINKS, while Morningstar Direct data aligns with our main dataset through tickers and ncusip codes.[9]

Our sample focuses exclusively on capitalization, growth, and income style-oriented funds, excluding sector, international, and index funds (e.g., EDCS, EDCM, EDCL, EDYG, EDYB, EDYI objectives CRSP codes). We winsorize the data at the 1st and 99th percentiles to mitigate the influence of outliers. We also eliminate funds with less than two years of data or less than \$10 million in assets under management, as Evans (2010) recommended, to avoid incubation bias and the impact of unusual capital flows.

In line with the core focus of our study, we pay special attention to three well-known factors in the literature: Mispricing as defined by Stambaugh and Yuan (2017), Illiquidity following Amihud (2002), and ESG metrics as described by Gibson Brandon et al. (2022). We derive data for these factors from multiple sources. Specifically, we access mispricing metrics from the author's web-page, while illiquidity measures follow the methodology of Amihud (2002). For ESG metrics, we combine data from MSCI (previously known as KLD) and Thomson Reuters

[7] A mapping file from CRSP provider streamlines this aggregation over time.

[8] We adhere to Chernenko and Sunderam (2020) methodology to merge these datasets into a comprehensive and up-to-date view of portfolio holdings.

[9] The mapping file facilitates this fund-level linkage.

(formerly Asset 4) to provide a comprehensive view.[10] By adhering to this rigorous data collection and cleaning process, we ensure the reliability and comprehensiveness of our dataset, setting the stage for the following empirical analyses.

3.2 Relevant Variables

In our research, we employ several variables instrumental to our identification strategy. These variables are grounded in established literature and are instrumental in deciphering the intricate dynamics of what we want to explore within mutual funds and managers' decision-making. Below, we elucidate these variables:

3.2.1 Net-Flows

Mutual funds frequently report share subscriptions and redemptions. Nonetheless, in line with the existing literature on mutual funds, we estimate net flows through the variation in assets under management, as done in studies by Sirri and Tufano (1998), Coval and Stafford (2007), and others. We denote the net flow as the change in assets under management not explained by the returns. The following equation describes the calculus process:

$$\begin{aligned} NetFlows_{f,t} &= \frac{TNA_{f,t} - TNA_{f,t-1}(1 + R_{f,t})}{TNA_{f,t-1}}, \\ R_{f,t} &= \frac{NAV_{f,t} - NAV_{f,t-1} + D_{f,t-1}}{NAV_{f,t-1}}. \end{aligned} \tag{11}$$

Our concentration lies in scrutinizing quarterly net flows within the range of -50 and 200 percent (Coval and Stafford 2007). By understanding the dynamics of inflows (subscriptions) and outflows (redemptions), we aim to shed light on their implications for decision-making in the mutual fund arena under flow dynamics.

3.2.2 Stock Characteristics Measures

- **Mispricing**: Stambaugh and Yuan (2017) propose a mispriced stock measure. This measure averages eleven market anomalies, providing an overpriced score for each stock. The subsequent ranking process results in scores within a uniform distribution [0,100], where

[10]These additional databases help us in generating risk factors at the stock level and serve as crucial elements in our empirical analyses.

higher ranks indicate relative overpricing. Readers are referred to the detailed methodology available on Robert F. Stambaugh's web page for a comprehensive understanding.

- **Illiquidity**: Illiquidity delineates the challenges inherent in stock trading. Guided by the methodologies introduced by Amihud (2002), we harness daily trading data to ascertain the price's responsiveness to trading volume. Nevertheless, Amihud's measure presents interpretative challenges. Its pronounced skewness and proximity to zero hinder its numerical interpretability. While lower values indicate diminished illiquidity—attributed to a reduced price reaction to trades—the measure's structure complicates its practical application. We introduce a scoring mechanism to enhance its utility and address its limitations. By ranking stocks based on their Amihud values within each period, we derive a score ranging from 0 to 100. A higher score indicates increased illiquidity; conversely, a lower score suggests more fluid trading conditions. Notably, this scoring transformation aligns the numerical interpretation of Amihud's measure with scores representing Mispricing, facilitating a more intuitive and actionable understanding for financial practitioners.

- **ESG**: Understanding a firm's stance on environmental, social, and governance (ESG) factors is crucial for assessing its sustainability practices and future performance. However, the ESG landscape is fraught with inconsistencies and divergent methodologies across various data providers (Berg et al. 2022). Our study adopts a harmonized approach by averaging ESG scores from two leading databases: MSCI (previously KLD) and Thomson Reuters (Asset 4). Following Gibson Brandon et al. (2022), this strategy enhances our measure's reliability and mitigates the biases often inherent in single-source ESG scores.

  MSCI, formerly known as KLD, offers a nuanced view by providing "strengths" and "concerns" across seven ESG categories. However, it lacks an aggregate ESG score. To address this, we use the methodology proposed by Lins et al. (2017) to calculate a comprehensive ESG score that nets these strengths against concerns. We then normalize each firm's strengths and concerns by dividing them by the maximum number of strengths or concerns in that category for the given year. In contrast, Thomson Reuters offers a straightforward, relative ESG score that ranges from zero to 100. This measure covers roughly 80% of the global market capitalization and is updated annually. The directness of this score complements the multi-dimensionality of the MSCI metrics, providing a more rounded view. We employ a weighted averaging method to harmonize these disparate scores into a single, robust ESG metric. The mathematical representation is as follows:

$$\text{ESG Score}_{it} = \frac{I_{A4,it} \times z_t(\text{A4}_{it}) + I_{MSCI,it} \times z_t(\text{MSCI}_{it})}{I_{A4,it} + I_{MSCI,it}} \tag{12}$$

After obtaining the Z-score for this consensus ESG measure, we take another step to enhance its interpretability and comparability with other risk factors in our study. Specifically, we rank companies each period based on their Z-scores, transforming these into a percentile ranking that ranges between 0 and 100. This final scoring step aligns our ESG measure with other risk factors like Mispricing and Illiquidity, which are also scored on a percentile basis. This uniformity ensures that our ESG Score seamlessly integrates into our broader research framework and provides a consistent metric for evaluating mutual fund managers' risk-taking behaviors.

3.3 Summary Statistics

Panel A of Table 1 serves as a treasure trove of insights into managerial attitudes toward asset trading. Our focus on Purchase and Sale Attitudes is vital because these variables serve as barometers of risk preference for specific asset characteristics. A positive value implies a risk-friendly stance, whereas a negative value indicates risk aversion.

The data presents a compelling story of diverging preferences. When managers decide to purchase assets, they exhibit a conservative outlook towards mispricing and illiquidity risks, as indicated by the negative means of -0.33% and -0.96%, respectively. This conservative stance suggests a risk-mitigating strategy crucial for portfolio performance. However, the narrative takes a twist when we look at ESG factors. The negative mean of -0.43% in purchase attitudes toward ESG implies that managers, on average, are willing to ignore downside risks associated with poor ESG when buying assets. This finding is particularly noteworthy given the surging global emphasis on sustainable investing.

The Sale Attitudes reveal a contrasting picture. Here, we find positive means of 1.02% and 2.20% for mispricing and illiquidity, respectively, indicating that managers are generally optimistic about retaining assets with these characteristics in their portfolios. Again, the ESG narrative is flipped. Managers appear more eager to divest from assets with poor ESG scores, ignoring the downside risks of holding onto such assets. This divergence in attitudes towards buying and selling across different asset characteristics underscores the complexity of mutual fund trading behaviors.[11]

Panel B shifts our attention to the control variables, whose statistical properties harmonize with prior literature, thereby adding an extra layer of robustness to our study. Quarterly Flows, Returns, and Cash distribution align well with Agarwal et al. (2020). The mean values are in the ballpark of what one would expect: 0.3552% for Quarterly Flows, 2.27% for Returns, and 3.67% for Cash. These metrics will serve as essential controls in our analysis and add depth to our understanding of fund dynamics. Our data also dovetails with Chernenko and Sunderam (2020) regarding Fund and Family Size, represented in logarithmic terms; the mean values are 5.6729 and 9.0337, respectively. With a mean of 15.3443 years, the Fund Age encapsulates a wide array of fund maturities, from fledgling to well-established entities. Lastly, the Expense Ratio and Management Fee are consistent with Dong et al. (2017) and Cremers and Pareek (2016) findings. With mean values of 1.0191% and 0.6438%, these metrics will enable us to control for fund operating efficiency in our subsequent analyses.

Table 1: Summary Statistics

	Mean	Median	Std.Dev	Min	P10	P90	Max
Panel A: Managerial Attitudes							
Trading (ESG)	-1.0258	-0.9262	11.8277	-43.0951	-15.0743	12.8751	47.2654
Purchase (ESG)	-0.4306	-0.3889	14.8728	-50.9863	-18.6323	17.7998	48.5225
Sale (ESG)	-0.5636	-0.4891	14.8305	-49.5266	-18.7400	17.3551	48.4032
Trading (Illiquidity)	1.2600	1.0436	5.0160	-21.5314	-4.4382	7.2334	26.2498
Purchase (Illiquidity)	-0.9657	-0.2642	6.6825	-34.8105	-9.0168	6.1490	26.8117
Sale (Illiquidity)	2.2040	1.2933	6.7839	-20.1942	-4.9537	10.6256	35.0959
Trading (OverPricing)	0.6878	0.4290	6.1193	-22.0280	-6.4975	8.2858	23.3978
Purchase (OverPricing)	-0.3346	-0.1843	7.3859	-28.1476	-9.3145	8.4951	23.9202

[11] Please refer to Appendix A for a comprehensive graphical analysis of the density distributions of managerial trading attitudes. This supplementary section expands on our discussion by providing a visual representation of the attitudes towards ESG, Illiquidity, and Mispricing, offering further insights into the nuanced risk preferences that underlie managerial decision-making processes.

Sale (OverPricing)	1.0246	0.8234	7.4275	-25.7865	-7.8759	10.0885	27.6671
Panel B: Fund Charateristics							
Quarterly Flows (%)	0.3552	-1.5127	12.9069	-49.9975	-7.6650	9.1129	199.7015
Quarterly Returns (%)	2.2722	3.1395	9.6586	-58.7264	-10.6441	12.7344	64.1723
Cash (%)	3.6713	1.8000	7.0778	0.0000	0.0500	7.8010	102.2784
Management Fee	0.6993	0.7260	0.2923	0.0000	0.2880	1.0120	1.6544
Deferred Load	0.0128	0.0100	0.0157	0.0000	0.0000	0.0401	0.0550
Redemption Load	0.0051	0.0000	0.0081	0.0000	0.0000	0.0200	0.0349
Front Load	0.0489	0.0550	0.0147	0.0000	0.0329	0.0575	0.0847
Turnover Ratio	0.7530	0.5400	0.8074	0.0000	0.1500	1.5200	11.2078
Expenses Ratio	0.0111	0.0110	0.0045	0.0000	0.0053	0.0165	0.0329
Fund Size	5.6729	5.6280	1.8352	-2.3026	3.2847	8.0466	13.8931
Family Size	9.0337	9.3495	2.5912	-2.3026	5.3181	12.1510	15.1366
Age	15.3444	13.0412	10.7190	2.0000	4.4313	28.0288	55.4258
Team	0.7657	1.0000	0.4235	0.0000	0.0000	1.0000	1.0000
Team Size	3.2688	2.0000	3.2781	1.0000	1.0000	6.0000	71.0000

Note: The data in this table is winsorized at the 1% and 99% levels to mitigate the impact of extreme outliers. Variables 'Fund Size' and 'Family Size' are log-transformed values of total assets, providing a more normalized distribution for analytical rigor. The variable 'Age' represents the number of years since the fund's oldest share class was first offered to investors, indicating fund maturity. The variable 'Team' is a binary indicator, with a value of 1 denoting that a team of professionals manages the fund. 'Team Size,' on the other hand, quantifies the number of managers involved in trading decisions within a fund, offering an additional layer of granularity. Managerial attitudes are captured in a two-fold manner. The variables 'Purchase' and 'Sale' encapsulate attitudes toward buying and selling, respectively, while 'Trading' provides an aggregated view across all trades. These attitudes serve as vital indicators of risk preferences during trading activities and are evaluated across three well-established risk-associated characteristics: Mispricing, Illiquidity, and ESG. The table presents a comprehensive statistical overview of these variables.

A Graphical Exploration of Trading Attitudes and Capital Flows

Our investigation explores mutual fund managers' nuanced decision-making landscape, mainly through the lens of risk characteristics—Mispricing, Illiquidity, and ESG—that fundamentally influence portfolio value in adverse market conditions. We delve into the strategic reallocations managers undertake in response to the flow of capital, scrutinizing the variance in their risk preferences within the spectrum of flow dynamics.

The core of our initial inquiry is to unconditionally scrutinize the prevailing trading attitudes across the capital flow distribution segmented into deciles (Di). Figure 1 is our empirical compass. It dissects mutual fund managers' risk preference adjustments—buying, selling, or net trading—in response to the changing tides of capital flows. Initially, we observe a discernible pattern in managerial attitudes: they are not monolithic but fluctuate with the direction and magnitude of capital flows. We encounter a dichotomy in purchase scenarios: a concave pattern in Mispricing and Illiquidity versus a convex trend in ESG attitudes. At the epicenter of flow distribution—where decisions are not pressure-cooked by extreme capital movements—managers prefer Mispricing and Illiquidity. At the same time, their appetite for ESG appears minimal. However, when we turn to sales, the narrative inverts; ESG attitudes form a concave pattern, while Mispricing and Illiquidity trend convexly—albeit with a less pronounced curvature for Mispricing, suggesting that managers engage in a delicate balancing act, simultaneously buying and selling securities with similar risk profiles, thereby maintaining a steady exposure to these characteristics within the portfolio.

In examining the flow distribution extremities, we observe managerial attitudes' crystallization. The steepness of the trading attitude curves in Figure 1 divulges the managers' intrinsic preferences, particularly when faced with the pressures of substantial subscriptions or redemptions. In these moments of forced trades, their predilections are most pronounced, sculpting the fund's stability with discerning transactions.

A cohesive story takes shape as we synthesize the array of trading behaviors. The previously noted concave and convex tendencies of individual trade attitudes converge into a consistent pattern across the flow distribution. ESG attitudes, for instance, demonstrate a robust, positive correlation with net inflows, ascending notably in the upper quantile. This pattern suggests that managers strategically channel funds into securities boasting high ESG ratings when flush with capital due to substantial inflows. Such a trend implies a preference for securities that are not just marketable but also align with trending sustainability considerations—choices that may not always be linked to superior immediate returns but reflect a longer-term, risk-averse strategy. In addition, the attitudes towards Mispricing and Illiquidity reveal an inverse relationship with inflows. This negative correlation signals a cautious approach; managers tend to shy away from these characteristics as capital inflows increase. Instead, they opt for investments that, while potentially less lucrative in terms of immediate returns, offer a safer bet in the volatile dance of market demands and risks. This conservative shift in attitude underscores a strategic emphasis on stability over speculative gains, particularly in inflow-heavy contexts..

On the flip side, attitudes during extreme outflows present a different narrative. Here, managers exhibit a riskier stance, particularly towards Illiquidity and Mispricing factors. This may be driven by an urgent need for liquidity to meet enormous redemption demands. Interestingly, attitudes toward ESG factors also lean risky, indicating a preference for maintaining low ESG stocks. These observations open the door for a nuanced discussion on how short-term liquidity needs might influence risk preferences.

In an aggregated view, the chart reveals that attitudes aren't strictly linear functions of net flows. For instance, while there's a clear trend for increasing affinity toward ESG factors with higher inflows, attitudes toward Mispricing and Illiquidity are more ambiguous. Notably, a risk preference for liquidity and fewer Mispricing becomes evident in the upper quantile, where managers receive significant inflows.

The previous analysis sets the stage for a rigorous examination of the nuanced interplay between capital flows and managerial risk attitudes. Our initial findings hint at a dynamic where managerial behaviors are influenced by the ebb and flow of capital, with a tendency to favor specific risk attributes under varying flow conditions. These patterns, while indicative, warrant a more profound statistical validation to determine their true nature and driving factors.

In the upcoming "Empirical Procedure" section, we will apply regression analysis to dissect these relationships further, enabling us to assess the statistical significance of our preliminary insights and to explore whether these behaviors are consistent across different fund characteristics, family affiliations, or investment styles. Additionally, we will investigate whether these managerial attitudes are more pronounced under certain conditions that may amplify the expression of their risk preferences. This transition from descriptive to inferential analysis is crucial for academic rigor and practical relevance. By uncovering the underlying trends in managerial decision-making under various capital flow scenarios, we aim to provide investors and regulators with more precise insights into the risk profiles that managers navigate, especially in the face of forced trades.

This knowledge could be instrumental in shaping investment strategies and regulatory policies responsive to fund management practices' realities.

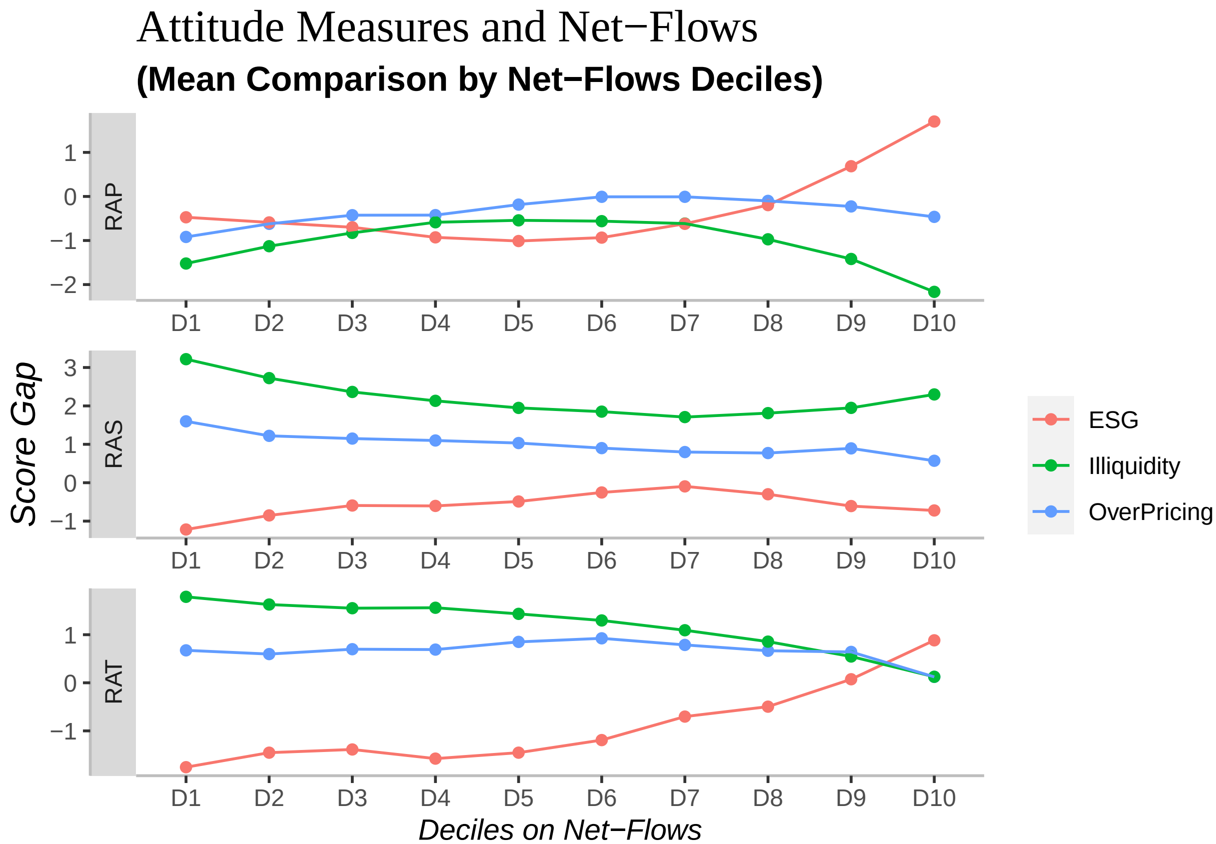

Figure 1:

4 Empirical Procedure

4.1 Decoding Managerial Risk Preferences Under Portfolio Pressures: A Tail-specific Analysis

Understanding how mutual fund managers respond to portfolio allocation pressures is crucial for predicting fund performance and risk exposure. This subsection delves into the risk preferences exhibited by managers when faced with extreme capital flows—both outflows and inflows—that place their funds at the far ends of the liquidity spectrum when compelled to execute trades that may not be information-driven, compared to scenarios where they have the flexibility to use cash reserves to meet investor demands . Specifically, we examine the tendencies toward Environmental, Social, and Governance (ESG) criteria, stock illiquidity, and asset mispricing under the strain of significant capital movements within a quarter.

We dissect the nature of these preferences by contrasting managerial behaviors during periods of large flow dynamics against those in more stable times. Our empirical approach employs Ordinary Least Squares (OLS) regression with dual fixed effects to isolate fund-specific responses from broader market trends and style influences. The attitudes are quantified into three distinct metrics—Risk Attitude on aggregated Trades (RAT), Risk Attitude on Purchases (RAP), and Risk Attitude on Sales (RAS)—and each is analyzed as a dependent variable within its own regression framework to ensure a comprehensive understanding of trading behaviors across different risk dimensions. The empirical model is specified as follows:

$$
\begin{aligned}
\{RAT_{f,t}, RAP_{f,t}, RAS_{f,t}\} =& \lambda_{\text{Time}\times\text{Style}} + \lambda_{\text{Fund}} \\
&+ \beta\,\text{LargeOutflows}(p)_{f,t} + \text{LargeInflows}(p)_{f,t} \\
&+ \gamma\,\text{Controls}_{f,t-1} + \epsilon_{f,t}
\end{aligned}
\tag{13}
$$

The "LargeOutflows" and "LargeInflows" variables represent extreme tails of the capital flow distribution, enabling us to pinpoint the nuances in managerial attitudes within these critical thresholds. Controls are incorporated for fund characteristics such as Returns, Cash holdings, Load fees, Management Fees, Fund Age, and Size, using lagged data to account for the delayed impact of these factors. In operationalizing this approach, we define "p" as the percentage size of the tail under examination.

Table 2 unpack the intertwined effects of extreme flow conditions and ESG alignment, illiquidity, and mispricing on the trading decisions within mutual funds. The significant coefficients for large outflows and inflows across different thresholds suggest that fund managers respond asymmetrically to the pressures of capital mobility, with risk attitudes varying markedly between purchases and sales.

ESG

Panel A of Table 2 provides a nuanced view of how fund managers handle ESG assets during distinct capital flow scenarios. The findings illuminate a twofold strategy: managers tend to divest ESG-aligned assets in response to large outflows, evidenced by the significant negative score gaps of -1.2037 and -0.6137 when outflows reach the 10% and 25% thresholds. This divestment occurs more markedly than during less turbulent times, indicating a link between outflow pressures and the urgency to sell. Conversely, a surge of inflows triggers an acquisition mode for managers, where they actively seek out and invest in assets with robust ESG ratings because the score gap increases by 2.6246 and 1.8377 at the respective flow thresholds.

This behavior is not merely reactive; it reflects a strategic alignment with liquidity conditions. While there is no legal compulsion to reinvest inflows immediately, industry norms dictate prompt action to avoid signaling incompetence or damaging a manager's standing. The managers' readiness to adapt their ESG positions based on liquidity mirrors their active risk management and investment strategy rather than a fixed preference for ESG.

The linear trend in managers' responses to capital flow pressures is also telling. As inflows grow, so does the affinity for ESG investment, suggesting a proactive selection of ESG assets when funds are ample. Contrastingly, managers exhibit a reverse trend when facing outflows, offloading ESG assets more readily. These shifts suggest that managers' risk preferences are fluid, adapting to the current financial landscape's needs and the broader implications of holding or selling ESG assets.

Thus, the data underscores a dynamic adjustment in risk appetite about liquidity. During times of cash abundance, managers' preference for ESG investments becomes pronounced, possibly as a means to bolster the fund's social responsibility profile or to align with investor preferences, even though ESG assets may not always guarantee superior returns. However, in the face of redemption stress, the same managers demonstrate a clear tendency to sacrifice ESG quality for liquidity, possibly due to the relative ease of selling ESG assets or other market dynamics. This adaptable approach to ESG asset management reveals the strategic complexity with which fund managers navigate varying market conditions, balancing immediate liquidity needs against pursuing ESG-aligned investment goals.

Illiquidity

Panel B of Table 2 sheds light on the intricacies of fund manager behavior about asset illiquidity during periods of large capital flows. Illiquidity presents a nuanced challenge for fund managers. While highly liquid assets are more accessible to trade without impacting the market price, illiquid assets can offer higher returns but come with increased risk, particularly during portfolio stress when assets need to be sold quickly.

The data presented in Panel B reveals an intriguing counterintuitive trend. Contrary to the expected behavior of safeguarding liquidity by holding more liquid assets during outflows, managers tend to retain more illiquid securities. Specifically, managers' sales are skewed towards more liquid assets during the largest capital withdrawals, as shown by a positive illiquidity score differential on selling attitudes of 0.8645 and 0.6798 score units under the bottom 10 and 25 percent, compared to flow's centralized scenarios. This suggests a tactical choice to dispose of assets that can be sold more readily, possibly to mitigate the impact of sales on market prices or to meet redemption requests efficiently.

Conversely, during large capital inflows, one might anticipate a strategy favoring the purchase of illiquid assets to exploit potential risk premiums, given the context of high investors' trust. However, the evidence indicates that managers adopt a more conservative stance, preferring less illiquid investments, as reflected by the lower illiquidity scores gaps on purchases of -1.1386 and -0.4121 score units during inflow peaks of 10 and 25 percent, compared to non-extreme flow dynamics. This traditional approach during inflows aligns with a risk-averse strategy, complementing some literature that posits managers may increase the risk to attract inflows. Here, instead of keeping in competition, once managers receive high rewards, they opt for securities with less illiquidity to expand the portfolio.

This conservative reallocation suggests that managers are not merely competitive yield-seekers but are also driven by a prudential approach to risk management, especially when managing large inflows. It highlights a preference for maintaining portfolio stability and a readiness to adjust the liquidity profile of assets in response to the liquidity environment.

When connecting these findings with ESG results, a pattern emerges. Managers prioritize selling more accessible assets to liquidate—presumably those with better ESG ratings or more favorable liquidity profiles—during outflows. In times of inflow, pursuing growth gives way to a more measured investment strategy, emphasizing long-term stability rather than immediate yield enhancement.

These insights into fund manager strategies provide a more dynamic understanding of how portfolio allocations shift in response to market pressures. Far from adhering to a singular risk preference, managers' behaviors are complex and responsive to the capital flow landscape, balancing immediate liquidity demands against the pursuit of prudent long-term fund management. The observed allocation strategies offer a fresh perspective on the traditional views of risk-taking in asset management, suggesting that managers may prioritize liquidity and stability over high-risk, high-return strategies during varying portfolio size pressures.

OverPricing

Panel C of Table 2 delves into the domain of Overpricing and empirically examines fund managers' strategic responses to overpriced stocks during extreme capital flow conditions. This analysis segment interlinks with our earlier discussions on ESG and Illiquidity, further unraveling the complexity of managerial behavior under portfolio stress.

The notion of mispricing refers to the discrepancy between the market price and the intrinsic value of a stock, which can result from various market anomalies. Overpriced stocks, therefore, carry the risk of a price correction and may be perceived as having a high return potential until that correction occurs. Managing such assets, especially in periods of financial duress, is a delicate balance between exploiting potential returns and mitigating the risk of a downturn in value.

Our findings indicate that managers prefer to retain overpriced stocks during significant capital outflows, suggesting a strategy that leans towards maintaining or potentially increasing exposure to assets that are likely overvalued by the market. This tendency is quantified by the superior positive score gaps units selling attitudes of 0.3967 and 0.3287 in the bottom 10 and 25 percent of flows' distribution, compared to the non-extreme part of the distribution, indicating that the managers sell less overpriced stocks than those they keep. The rationale behind this may be multifaceted: managers could aim to sustain portfolio performance metrics or find these stocks harder to sell without incurring losses due to inflated valuations.

When the tide turns, and managers face large inflows, the strategy shifts markedly. Instead of seeking out overpriced stocks, managers prefer acquiring assets with more modest mispricing scores. In panel C, it is possible to observe an inferior attitude on purchases through lower score gap units of -0.5890 and -0.4006 for the top 10 and 25 percent of flows' distribution, compared to the non-extreme part. This cautious approach during capital abundance suggests that managers are hedging against the risk of future price corrections by choosing less overpriced stocks, thereby avoiding the pitfalls of market overvaluation. This behavior aligns with a conservative investment philosophy prioritizing long-term stability and prudent capital allocation over speculative, short-term gains. However, the response to overpricement is not as predictable or linear as it is with ESG alignment or liquidity characteristics. The analysis demonstrates non-statistical results for aggregated trading attitudes in large withdrawals.

In summary, exploring ESG, Illiquidity, and OverPricement dynamics within Table 2 underscores a strategic dichotomy: a move towards risk aversion in the wake of capital infusions and a tilt towards risk tolerance during redemption episodes. This adaptability evidences a sophisticated grasp of market psychology and a proactive stance in portfolio management. Managers' decisions reflect a deep consideration of current market conditions and anticipatory strategies for future volatility, suggesting an elevated level of finesse in navigating the risk-reward paradigm.

Table 2: Managerial Attitudes and Large Flows Dynamics

	(RAT)	(RAP)	(RAS)	(RAT)	RAP	RAS
Panel A: ESG						
L. Outflows (10%)	-0.8616***	0.2844	-1.2037***			
	(0.2128)	(0.3375)	(0.3255)			
L. Inflows (10%)	2.0605***	2.6246***	-0.5784			
	(0.2945)	(0.3905)	(0.3977)			
L. Outflows (25%)				-0.3483**	0.2626	-0.6137***
				(0.1554)	(0.2144)	(0.2108)
L. Inflows (25%)				1.5326***	1.8377***	-0.2294
Observations	37905	37658	37617	37905	37658	37617
Adjusted R2	0.034	0.063	0.062	0.034	0.063	0.062
Panel B: Illiquidity						
L. Outflows (10%)	0.3165***	-0.5571***	0.8645***			
	(0.0869)	(0.1406)	(0.1372)			
L. Inflows (10%)	-0.9873***	-1.1386***	0.1726			
	(0.1137)	(0.1554)	(0.1664)			
L. Outflows (25%)				0.2802***	-0.4121***	0.6798***
				(0.0650)	(0.0906)	(0.0934)
L. Inflows (25%)				-0.7156***	-0.7923***	0.0791
				(0.0808)	(0.1017)	(0.1063)
Observations	38730	38555	38545	38730	38555	38545
Adjusted R2	0.060	0.137	0.161	0.061	0.137	0.161
Panel C: OverPricing						
L. Outflows (10%)	0.0720	-0.3203*	0.3967**			
	(0.1231)	(0.1871)	(0.1774)			
L. Inflows (10%)	-0.7724***	-0.5890***	-0.2348			
	(0.1483)	(0.2045)	(0.2183)			
L. Outflows (25%)				0.0425	-0.2969**	0.3287***
				(0.0901)	(0.1268)	(0.1249)

L. Inflows (25%)				-0.4596***	-0.4606***	-0.0189
				(0.1102)	(0.1404)	(0.1453)
Observations	31314	31112	31123	31314	31112	31123
Adjusted R2	0.099	0.064	0.072	0.099	0.065	0.072
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time x Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents regression outcomes for examining managerial attitudes during periods of large capital flows. The dependent variables—Risk Attitude on aggregated Trades (RAT), purchases (RAP), and sales (RAS)—are modeled against large outflows and inflows as percentiles of the fund's net flows distribution, accompanied by a set of control variables from the prior period. These controls include Returns, Cash reserves, Total Loads, Management Fees, Fund Age, and the Fund and its Family sizes, expressed in the natural logarithm of their total net assets (TNA). Asset-specific characteristics are investigated in separate panels: ESG, Illiquidity, and Overpricing, as defined by respective scholarly work: Stambaugh and Yuan (2017) for Overpricing, Amihud (2002) for Illiquidity, and Gibson Brandon et al. (2022) for ESG, which integrates KLD and Asset4 ratings. Large outflows and inflows are categorized by the extremities of net flow distributions—either bottom or top decile (quantile). Parenthesized standard errors are clustered at the fund level to address potential correlations within the funds' time-series data. Significance levels are marked with asterisks (*** for 1%, ** for 5%, and * for 10%). The comprehensive regression model incorporates fixed effects for time crossed with investment style and at the fund level, ensuring the robustness of our findings against unobserved heterogeneity. Further methodological details, including control variable relevance, are provided in Appendix B.

4.2 Differentiating Managerial Attitudes by Clientele Type

The interdependence between mutual fund performance and investor constituency is an enduring and evolving area of inquiry within financial asset management. The division between institutional and retail investors embodies a crucial determinant in the strategic maneuvers of fund managers, particularly when navigating the volatile tides of capital flows. Institutional investors, recognized for their discerning acumen, impose a distinct brand of scrutiny upon fund managers, compelling a measured and informed response to shifting market conditions. Conversely, retail investors, driven by sentiment and a propensity for less technical engagement with portfolio strategy, exert a different form of influence, characterized by volume and trend-driven behavior that molds the landscape of flow-performance interactions. This subsection aims to peel back the layers of this relationship, particularly in the high-stakes environment of extreme capital flows, to understand better how a fund's clientele shapes a manager's strategic approach to portfolio allocation.

The strategic behavior of mutual fund managers under the microscope of capital flow extremes provides a window into their adaptive risk management strategies. Moreover, the complexity added by the needs of their clients also helps us understand managerial sophistication in understanding the forces hitting the value of their decisions. Table 3 presents a discerning look at the interplay between investor types and mutual fund managers' strategic decisions under severe capital flow conditions. The data delineate a marked divergence in managerial actions during substantial capital outflows and inflows, providing insight into how client composition informs these decisions.

In extreme outflow conditions, managers' preference to divest from ESG-favored stocks and retain those characterized by higher illiquidity and potential mispricing exhibit an additional complexity depending on the assessment clients pose to managers. On the one hand, in the context of ESG, the divestment is moderated when retail investors primarily hold the portfolio. The reduced score gap of 0.5623 units suggests that managers are less inclined to sell off ESG assets aggressively, perhaps because retail investors have a less pronounced reaction to value dilution under withdrawals. This inference supports the idea that managers might not prioritize short-term gains as urgently when their client base is less attuned to the nuances of asset reallocation. On the other hand, in illiquidity, the trend holds even with a retail-dominated clientele but with a lower effect of 0.8413 score units, reinforcing the idea of having a less intense attitude due to the fewer worries from clients. In the case of mispricing, the trend reverses with an unexpected net negative score gap change of 0.0552 units (0.3085-0.3633) but still reinforces the notion of not caring too much about the dilution of value in the short term.

In extreme inflow conditions, the attitude on total trades heightened the acquisition of assets with less intense overpricing and illiquidity and with more ESG, ushering the long-term view on portfolio management. However, in Table 3, we provide evidence that contrarian to large withdrawals where client structure shapes the attitudes of managers, we observe no different responses on their behavior toward Illiquidity and Mispricing, meaning that independent if clients are retail, as long as managers receive their trust expressed in large inflows, they avoid short-term alpha-seeking behavior, focusing in characteristics, that leads to lower yields but are robust against future uncertainty; however, managers are more prone for acquiring assets with superior ESG with the large deposit of the retail clients, perhaps because managers know, that retail likes this kind of behavior, and is marketable because it feeds sentiments, news, and trends.

The current findings uncover the critical role of investor composition in shaping trading and risk management strategies, reflecting managers' astute capacity to adapt to a competitive and volatile market. Our findings demonstrate managers' adeptness in adjusting their portfolios in response to capital flows and investor behavior. We provide direct evidence of how managers adeptly navigate flow dynamics and investor preferences, showing their strategic realignment of assets to meet diverse challenges and opportunities.

Table 3: Client Types Versus Capital Flow Responses

	RAT		
	ESG	ILL	OVP
L. Outflows (25%)	-0.7175***	0.5140***	0.3085**
	(0.2548)	(0.1183)	(0.1439)
L. Inflows (25%)	0.5962*	-0.8413***	-0.3633**
	(0.3084)	(0.1311)	(0.1741)
L. Outflows (25%) x Retail	0.5623*	-0.2554*	-0.3251**
	(0.2906)	(0.1316)	(0.1611)
L. Inflows (25%) x Retail	0.7092**	0.1426	0.0573
	(0.3483)	(0.1478)	(0.1949)
Retail	0.0979	-0.4401*	-0.7647*
	(0.6532)	(0.2559)	(0.4158)
Observations	73820	75641	60108
Adjusted R2	0.026	0.065	0.101
Time x Style fixed effects	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes

Note: This table examines the influence of client type on mutual fund managers' trading behavior during significant capital flow events, focusing on asset-specific characteristics. The dependent variable, Risk Attitude on Aggregated Trades (RAT), reflects managerial decision-making in the face of the top and bottom quartiles of capital flow extremes, categorized as large outflows and inflows. The columns represent the emphasis on Environmental-Social-Governance (ESG), Illiquidity (ILL), and Overpricing (OVP), with foundational measures referenced from Stambaugh and Yuan (2017) for Overpricing, Amihud (2002) for Illiquidity, and recent integrations by Gibson Brandon et al. (2022) for ESG, utilizing KLD and Asset4 ratings. The interaction with the retail dummy variable (indicative of funds primarily held by retail investors) provides additional granularity on the clientele effect. The dummy equals one for funds designated as retail by CRSP and not simultaneously classified as institutional, thereby sharpening the contrast between investor types. The same analysis corroborates these effects with the standard CRSP classifications, yielding consistent results. Standard errors, presented in parentheses, are clustered by fund to mitigate within-group correlations. Asterisks denote statistical significance levels: *** p<0.01, ** p<0.05, and * p<0.1. Including time and style fixed effects, alongside fund-specific fixed effects, underpins the regression analysis' rigor against latent variable bias.

4.3 Robustness

4.3.1 Separating Managerial Strategy from Window Dressing Effects

The credibility of fund performance is often marred by the specter of window dressing, where fund managers may alter portfolio compositions to present an inflated view of year-end performance. This misrepresentation can cloud the proper risk profile of funds and obscure the actual understanding of fund managers. We have refined our analysis method to counter these practices and validate our study's conclusions. By omitting transactions from typically manipulative periods—Q4 and Q1—, we aim to discern the actual strategic behavior of fund managers in the face of capital flows unperturbed by seasonal distortions. We exclude Q4 because it is the period where managers may have incentives to manipulate and Q1 to test if managers' attitudes are influenced by any portfolio adjustments to align with the new fiscal landscape.[12]

[12] Agarwal et al. (2014) state that a window dresser can benefit from investor flows.

Our analysis, as presented in Table 4, illustrates that mutual fund managers employ a calculated strategy when facing extreme capital outflows. They prefer divesting from assets with high ESG ratings or lower liquidity and mispricing levels. This reflects a nuanced approach to maintaining value and suggests a strategic, albeit short-term, perspective rather than opportunistic trading. The continuity of this strategy, irrespective of the exclusion of data from the fourth or first quarters, provides evidence against the practice being solely a result of window dressing. These consistent strategies across various investment characteristics—such as ESG, liquidity, and pricing—validate the fund managers' proficiency in dealing with market complexities. Furthermore, the lower selling attitudes coefficients after excluding Q4, and conversely, the higher Coefficients after excluding Q1, may suggest a heightened strategic focus during the end-of-year reporting period, underscoring sophisticated and context-sensitive managerial conduct.

Fund managers' penchant for acquiring assets with robust ESG ratings and less pronounced illiquidity and mispricing is evident in the context of significant capital inflows. Contrary to the short-term gains associated with window dressing, this proactive approach reflects a commitment to shaping the portfolio for long-term stability. The consistency in strategic response, even when Q4 and Q1 data are excluded, underscores the absence of manipulative influence in these investment decisions.

The strategic posturing of fund managers diverges across the quarters, revealing a less pronounced intensity in portfolio adjustments outside the fiscal year-end. The comparative analysis of coefficient magnitudes affirms that strategic dispositions during fiscal year-ends are more acute, reflecting an intensive reallocation to prepare for annual reports. The patterns observed suggest that the strategic realignments undertaken by managers are conscientious responses to the subscriptions and withdrawals of capital rather than the result of opportunistic window dressing.

The robustness of our findings lays the groundwork for reasserting the skill and foresight of mutual fund managers, dispelling the illusion that their performance is simply a byproduct of manipulation. Our analysis serves as empirical validation of fund managers' sophistication, fortifying the position of mutual funds as a viable option for prudent long-term investment and supporting the evolution of financial markets towards practices rooted in genuine expertise.

Table 4: Capital Flow Effects on Fund Management: Robustness Without Seasonal Bias

	Without Q4			Without Q1		
	(RAT)	(RAP)	(RAS)	(RAT)	(RAP)	(RAS)
Panel A: ESG						
Extreme Outflows (25%)	-0.3219*	0.1843	-0.4988**	-0.2721	0.4356*	-0.7433***
	(0.1782)	(0.2527)	(0.2449)	(0.1811)	(0.2442)	(0.2360)
Extreme Inflows (25%)	1.4013***	1.7963***	-0.3198	1.4067***	1.8242***	-0.3878
	(0.2301)	(0.2790)	(0.2981)	(0.2366)	(0.2816)	(0.3133)
Observations	28486	28313	28262	29010	28820	28791
Adjusted R2	0.036	0.066	0.062	0.035	0.064	0.065
Panel B: Illiquidity						
Extreme Outflows (25%)	0.2183***	-0.4016***	0.6058***	0.2475***	-0.4671***	0.7027***
	(0.0754)	(0.1047)	(0.1080)	(0.0719)	(0.1020)	(0.1026)
Extreme Inflows (25%)	-0.6146***	-0.6595***	0.0541	-0.7088***	-0.8055***	0.1081
	(0.0919)	(0.1165)	(0.1216)	(0.0898)	(0.1163)	(0.1184)
Observations	29115	28985	28971	29645	29508	29509
Adjusted R2	0.063	0.135	0.160	0.063	0.135	0.163
Panel C: OverPricing						
Extreme Outflows (25%)	0.0275	-0.2822*	0.3098**	0.0623	-0.2848**	0.3421**
	(0.1025)	(0.1466)	(0.1451)	(0.1008)	(0.1404)	(0.1372)
Extreme Inflows (25%)	-0.4058***	-0.4198***	-0.0099	-0.3509***	-0.4006**	0.0464
	(0.1253)	(0.1597)	(0.1650)	(0.1233)	(0.1578)	(0.1596)
Observations	23360	23229	23209	24129	23966	23985
Adjusted R2	0.094	0.061	0.070	0.099	0.061	0.069
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time x Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table investigates the impact of capital flows on fund management decisions without the influence of year-end window dressing. The analysis aims to isolate the fund managers' responses to capital flows from potential seasonal biases by excluding the last and first quarters' data. The regression models the Risk Attitudes on aggregated Trades (RAT), Purchases (RAP), and Sales (RAS) against large capital movements, defined by the extremities of net flow distributions, and adjusts for various control variables. These include previous period returns, cash reserves, total loads, management fees, fund age, and size measures. Asset-specific characteristics are investigated in separate panels: ESG, Illiquidity, and Overpricing, as defined by respective scholarly work: Stambaugh and Yuan (2017) for Overpricing, Amihud (2002) for Illiquidity, and Gibson Brandon et al. (2022) for ESG, which integrates KLD and Asset4 ratings. Standard errors are adjusted for fund-level clustering to account for intra-fund correlation. Significance levels are marked with asterisks (*** for 1%, ** for 5%, and * for 10%). The comprehensive regression model incorporates fixed effects for time crossed with investment style and at the fund level, ensuring the robustness of our findings against unobserved heterogeneity.

5 Conclusions

Our investigation into the strategic responses of mutual fund managers to extreme capital flow conditions has bridged a significant gap in existing financial literature. By focusing on the decisions made during the tails of capital flow distributions, we provide empirical evidence that risk preferences among mutual fund managers are far from static; they are instead dynamically responsive to the inflows and outflows of fund capital. Our research offers a window into managers' nuanced approaches, highlighting their adaptability under investor pressure.

The conservative inclination exhibited by managers during periods of heavy inflow—preferring assets with strong ESG credentials and avoiding highly illiquid or overpriced assets—signals a prioritization of long-term portfolio health over short-term performance spikes. This tendency serves as a testament to the strategic foresight of managers, using heavy subscriptions as an opportunity to fortify their portfolios' foundation. On the flip side, a strategy shift is noticeable during large outflows, with managers displaying a pragmatic stance by divesting assets to prevent portfolio value dilution, even though such decisions may carry future performance risks.

Our findings substantiate the sophistication of fund managers in navigating the complexities of capital flows and investor profiles. The observed strategic behavior stands regardless of client sophistication, underscoring a deep-seated understanding of investors' criteria to assess portfolio management, influencing managers to allocate portfolio assets, especially pertinent in large outflow situations. Furthermore, our analysis reaffirms the strategic grounding of fund managers' actions at fiscal year-ends, challenging the notion that performance metrics at these times are primarily driven by opportunistic window dressing. The insights gained from excluding first and last-quarter data bolster this argument, suggesting consistency in strategic adjustment that transcends the immediate pressures of reporting periods.

Looking ahead, the paths laid out by our research pave the way for subsequent studies to dissect transaction-level strategies during extreme market conditions. Moreover, investigating the possibility of a mean-reversion tactic during post-peak competition periods and the variance of these strategies during market downturns presents exciting future research prospects. Such inquiries could greatly enrich our understanding of the temporal stability of mutual fund management strategies.

In practical terms, this study provides actionable intelligence for a broad spectrum of financial market participants. It underscores the critical role of capital flow dynamics in assessing mutual fund strategies and the importance of a flexible, forward-looking management approach that balances immediate market realities with long-term portfolio objectives. As the financial landscape continues to evolve, the enduring relevance of our findings is assured, with implications that will continue to inform risk management and asset allocation decisions within the mutual fund industry.

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Appendix

A Analysis of Managerial Attitudes and Trading Behaviors

In the following appended section, we delve into the granular details of the variables that capture the essence of managerial attitudes toward risk during trading activities. This part of our work is pioneering in its approach, utilizing a fresh methodology to decode fund managers' preferences at critical decision-making junctures. As our analytical lens, we leverage the discrete nature of trades that are potent indicators of a manager's market and portfolio expectations. While previous research has utilized trading data to infer managerial performance, our study breaks new ground by using it to infer risk preferences—a dimension hitherto unexplored within this context.

The methodology we introduce here harnesses the power of transaction data, combined with portfolio characteristics associated with specific risks, to illuminate managerial preferences in distinct temporal segments. We draw on the existing literature to connect specific portfolio characteristics—such as stock liquidity and ESG factors—with risk premiums and portfolio performance. For instance, while illiquid stocks are known to offer a risk premium balanced by potential costs during crises or liquidity shortfalls (Pastor and Stambaugh, 2003; Chen et al., 2010; Dong et al., 2017), the correlation between ESG factors and risk is less straightforward and remains a subject of ongoing debate in the scholarly community.However, in downward periods or crisis periods, portfolios tagged with these characteristics mitigate erosion in performance(Nofsinger and Varma, 2014).

Our approach identifies managerial attitudes by contrasting the average scores of traded stocks against those that remain static within the portfolio. These scores, bounded between zero and one, represent the intensity of the risk characteristics in question and are derived from percentile rankings within the stock universe at given times. This method allows for a dynamic and condition-sensitive perspective on risk preferences, moving beyond the static aggregate score analysis prevalent in much of the existing literature. By focusing on the differences in scores during the actual reshaping of the portfolio, we offer a more nuanced and precise measure of managerial expectations regarding risk-associated characteristics. Such an approach enables us to capture the often-overlooked adjustments made within a given period, providing a more straightforward window into the strategic underpinnings of fund management. In the following subsections, we will present the density distributions of the Risk Attitudes on Purchases (RAP), Sales (RAS), and aggregate Trades (RAT) variables, further illuminating the distinct behaviors and preferences of fund managers as they navigate the complex landscape of market risks.

In supplementing the quantitative data laid out in Table 1, through an analysis of density functions, which offers a visual representation of the data's distribution, Figure 2 depicts the density functions of the trading attitudes with a precision that numbers alone cannot convey. The centrality of observations around the zero mark, manifesting in a bell-shaped curve for each characteristic, captures the essence of managerial neutrality. This neutrality, however, is nuanced by the skewness and kurtosis specific to each risk characteristic.

In purchases, Mispricing and Illiquidity characteristics show a propensity for negative skewness, albeit with varying intensity. The long left tails of the distribution signal a pervasive risk aversion among managers, with Mispricing and Illiquidity exhibiting pronounced reticence. Such trends are particularly telling of the underlying conservatism that influences trading decisions in the face of potential valuation errors or liquidity constraints. On the other hand, the ESG-related attitudes, while also skewed negatively, reveal a wider dispersion, indicative of a platykurtic distribution, suggesting that attitudes towards ESG factors are more varied among managers, which may reflect a sector still grappling with integrating sustainability measures into traditional risk assessment frameworks. The pronounced tail, reaching a nadir of -50.52 percent, highlights a significant subset of managers who heavily underweight ESG considerations, perhaps indicative of an industry yet to embrace the protective potentials of sustainability fully. In sales, the data exhibits a distinctive pattern, with Mispricing and Illiquidity displaying heavier right tails. ESG attitudes take on an interesting counterpose, with the left bottom being pronounced, suggesting a readiness to sell ESG- assets. Such a pattern could imply a strategic deprioritization of ESG factors in sales decisions.

Figure 2, with its comprehensive visualization of trading attitudes, provides a substantive complement to the data presented in the body of this study. By revealing the shape and spread of managerial attitudes towards risk characteristics, it imparts a deeper understanding of the strategic nuances that guide trading behaviors. This analysis not only enhances the academic discourse on organizational risk preferences but also holds the potential to inform practical applications in portfolio management and regulatory oversight.

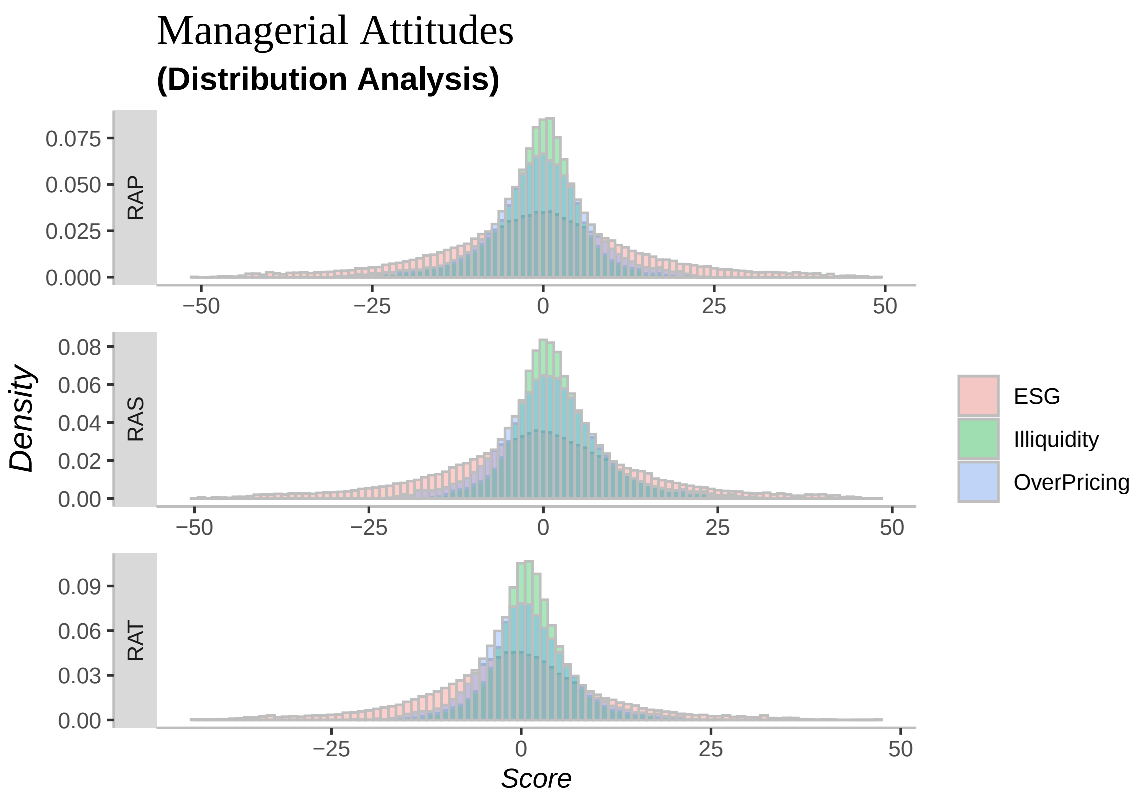

Figure 2: Density Distribution of Managerial Attitudes

B Extended Regressions

B.1 ESG Attitudes

Table 5: ESG Attitude and Flows

	Attitudes					
	(RAT)	(RAP)	(RAS)	(RAT)	(RAP)	(RAS)
Extreme Outflows (10%)	-0.8616***	0.2844	-1.2037***			
	(0.2128)	(0.3375)	(0.3255)			
Extreme Inflows (10%)	2.0605***	2.6246***	-0.5784			
	(0.2945)	(0.3905)	(0.3977)			

Extreme Outflows (25%)				-0.3483**	0.2626	-0.6137***
				(0.1554)	(0.2144)	(0.2108)
Extreme Inflows (25%)				1.5326***	1.8377***	-0.2294
				(0.2058)	(0.2478)	(0.2705)
Returns	-5.7249**	-4.3381	-0.4287	-6.4649***	-4.7939*	-0.8063
	(2.2737)	(2.8102)	(2.8510)	(2.2802)	(2.8239)	(2.8674)
Cash	0.0150	0.0291	-0.0125	0.0120	0.0272	-0.0138
	(0.0128)	(0.0206)	(0.0225)	(0.0127)	(0.0206)	(0.0224)
Loads	-7.0005	-32.5047**	24.2908*	-6.7725	-32.5048**	24.6070*
	(9.2745)	(15.0641)	(14.6799)	(9.2421)	(15.0088)	(14.6935)
Management Fee	-4.9499	-1.3713	-3.8050	-4.9413	-1.3174	-3.8251
	(3.2489)	(4.5656)	(4.2661)	(3.2379)	(4.5644)	(4.2643)
Age	0.1096*	0.1843**	-0.0827	0.1135**	0.1871**	-0.0816
	(0.0573)	(0.0777)	(0.0825)	(0.0565)	(0.0770)	(0.0821)
Fund Size	0.0421	0.2953*	-0.2254	0.0024	0.2484	-0.2163
	(0.1153)	(0.1786)	(0.1694)	(0.1131)	(0.1766)	(0.1679)
Family Size	-0.1006	0.0753	-0.1888	-0.1136	0.0665	-0.1952
	(0.1834)	(0.2677)	(0.2525)	(0.1826)	(0.2679)	(0.2528)
Observations	37905	37658	37617	37905	37658	37617
Adjusted R2	0.034	0.063	0.062	0.034	0.063	0.062
Time x Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table examines the relationship between extreme capital flow percentiles and ESG-related trading attitudes, using RAT, RAP, and RAS to represent attitudes on aggregated trades, purchases, and sales, respectively. These attitudes are evaluated under conditions of large fund outflows and inflows, defined by the lower and upper 10th and 25th percentile thresholds of the NetFlow distribution. The analysis extends the summary in Panel A of Table 2 by isolating ESG dynamics. Controls included in the regression are fund Returns, Cash holdings, Load fees, Management Fees, Fund Age, and the logarithmically transformed Total Net Assets (TNA) for Fund and Family Size to account for size effects. Standard errors are reported in parentheses and are clustered at the fund level to address autocorrelation concerns. The model adjusts for Time x Style, and Fund-level fixed effects, ensuring consistency with the comprehensive modeling approach detailed in the main text. Significance levels are indicated by ***, **, and *, corresponding to 1%, 5%, and 10% thresholds, respectively. The ESG scores are adopted from Gibson et al. (2022), integrating data from "MSCI" (formerly KLD) and "Thomson Reuters Asset 4" to capture the ESG dimension in trade decision-making robustly.

B.2 Illiquidity Attitude

Table 6: Illiquidity Attitude and Flows

	Attitudes					
	(RAT)	(RAP)	(RAS)	(RAT)	(RAP)	(RAS)
Extreme Outflows (10%)	0.3165***	-0.5571***	0.8645***			
	(0.0869)	(0.1406)	(0.1372)			
Extreme Inflows (10%)	-0.9873***	-1.1386***	0.1726			
	(0.1137)	(0.1554)	(0.1664)			
Extreme Outflows (25%)				0.2802***	-0.4121***	0.6798***
				(0.0650)	(0.0906)	(0.0934)
Extreme Inflows (25%)				-0.7156***	-0.7923***	0.0791
				(0.0808)	(0.1017)	(0.1063)
Returns	-0.7690	4.6755***	-5.7809***	-0.1274	4.5769***	-5.0361***
	(1.0761)	(1.3539)	(1.3501)	(1.0866)	(1.3452)	(1.3535)
Cash	-0.0113	-0.0006	-0.0121	-0.0097	-0.0006	-0.0105
	(0.0078)	(0.0104)	(0.0108)	(0.0077)	(0.0103)	(0.0108)
Loads	-1.5372	10.8478*	-12.1656*	-1.6183	10.9540*	-12.3591*
	(3.3544)	(6.4665)	(7.0323)	(3.3586)	(6.4791)	(7.0667)
Management Fee	-0.5390	-0.8143	0.2782	-0.4702	-0.8943	0.4168
	(1.3867)	(1.8568)	(2.0951)	(1.3893)	(1.8540)	(2.0900)
Age	0.0119	-0.0718	0.0757	0.0082	-0.0718	0.0720
	(0.0181)	(0.0494)	(0.0498)	(0.0182)	(0.0491)	(0.0495)
Fund Size	0.1558***	0.2052**	-0.0342	0.1757***	0.2229***	-0.0329
	(0.0577)	(0.0858)	(0.0867)	(0.0568)	(0.0856)	(0.0864)
Family Size	-0.0730	0.0848	-0.1383	-0.0626	0.0838	-0.1264
	(0.0906)	(0.1278)	(0.1338)	(0.0899)	(0.1281)	(0.1336)
Observations	38730	38555	38545	38730	38555	38545
Adjusted R2	0.060	0.137	0.161	0.061	0.137	0.161
Time x Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table examines the relationship between extreme capital flow percentiles and Liquidity-related trading attitudes, using RAT, RAP, and RAS to represent attitudes on aggregated trades, purchases, and sales, respectively. These attitudes are evaluated under conditions of large fund outflows and inflows, defined by the lower and upper 10th and 25th percentile thresholds of the NetFlow distribution. The analysis extends the summary in Panel B of Table 2 by isolating Illiquidity dynamics. Controls included in the regression are fund Returns, Cash holdings, Load fees, Management Fees, Fund Age, and the logarithmically transformed Total Net Assets (TNA) for Fund and Family Size to account for size effects. Standard errors are reported in parentheses and are clustered at the fund level to address autocorrelation concerns. The model adjusts for Time x Style, and Fund-level fixed effects, ensuring consistency with the comprehensive modeling approach detailed in the main text. Significance levels are indicated by ***, **, and *, corresponding to 1%, 5%, and 10% thresholds, respectively. The illiquidity scores are constructed by percentiles ranking from the standardized Amihd (2002) measures that indicate the sensitive prices to trades.

B.3 OverPricement Attitude

Table 7: Over-Pricement Attitude and Extreme Flows

	Over-Pricement Attitude					
	(RAT)	(RAP)	(RAS)	(RAT)	RAP	RAS
Extreme Outflows (10%)	0.0720	-0.3203*	0.3967**			
	(0.1231)	(0.1871)	(0.1774)			
Extreme Inflows (10%)	-0.7724***	-0.5890***	-0.2348			
	(0.1483)	(0.2045)	(0.2183)			
Extreme Outflows (25%)				0.0425	-0.2969**	0.3287***
				(0.0901)	(0.1268)	(0.1249)
Extreme Inflows (25%)				-0.4596***	-0.4606***	-0.0189
				(0.1102)	(0.1404)	(0.1453)
Returns	0.6645	3.2472*	-2.6455	0.7823	3.1394*	-2.4476
	(1.4006)	(1.6890)	(1.6907)	(1.4042)	(1.6881)	(1.6828)
Cash	-0.0108	0.0029	-0.0144	-0.0104	0.0029	-0.0140
	(0.0071)	(0.0099)	(0.0092)	(0.0072)	(0.0099)	(0.0092)
Loads	7.2215	6.7305	0.6194	7.2619	6.7470	0.6522
	(5.0637)	(6.5565)	(7.0540)	(5.0581)	(6.5311)	(7.0629)
Management Fee	2.4894	2.5461	0.1273	2.4720	2.4383	0.2021
	(1.8055)	(2.3712)	(2.5786)	(1.8154)	(2.3778)	(2.5831)
Age	-0.0152	-0.0742	0.0562	-0.0165	-0.0731	0.0540
	(0.0326)	(0.0452)	(0.0371)	(0.0325)	(0.0452)	(0.0372)
Fund Size	0.0258	0.0132	0.0222	0.0455	0.0257	0.0311
	(0.0712)	(0.0948)	(0.1051)	(0.0709)	(0.0946)	(0.1051)
Family Size	-0.2060*	0.0545	-0.2510*	-0.2044*	0.0513	-0.2467
	(0.1107)	(0.1433)	(0.1506)	(0.1109)	(0.1427)	(0.1507)
Observations	31314	31112	31123	31314	31112	31123
Adjusted R2	0.099	0.064	0.072	0.099	0.065	0.072
Time x Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table examines the relationship between extreme capital flow percentiles and OverPricement (Initially known as Mispricing) related trading attitudes, using RAT, RAP, and RAS to represent attitudes on aggregated trades, purchases, and sales, respectively. These attitudes are evaluated under conditions of large fund outflows and inflows, defined by the lower and upper 10th and 25th percentile thresholds of the NetFlow distribution. The analysis extends the summary in Panel C of Table 2 by isolating OverPricement dynamics. Controls included in the regression are fund Returns, Cash holdings, Load fees, Management Fees, Fund Age, and the logarithmically transformed Total Net Assets (TNA) for Fund and Family Size to account for size effects. Standard errors are reported in parentheses and are clustered at the fund level to address autocorrelation concerns. The model adjusts for Time x Style, and Fund-level fixed effects, ensuring consistency with the comprehensive modeling approach detailed in the main text. Significance levels are indicated by ***, **, and *, corresponding to 1%, 5%, and 10% thresholds, respectively. The authors construct the OverPricement or Mispricing scores available on Stambaugh's web page.