Unveiling the Winning Edge: How Team-Managed Mutual Funds Outsmart the Market in Flow Dynamics

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Abstract

This study delves into the performance predictability and competitive behavior of mutual funds based on their organizational structure and flow dynamics. It examines the contrasting outcomes of team vs. individual-managed funds during periods of outflows and inflows, focusing on their decision-making processes and value generation. Results reveal a compelling competitive advantage wielded by team-managed funds in effectively navigating the challenges posed by redemptions. Specifically, funds managed by teams showcase a remarkable ability to make astute trading decisions that preserve and enhance their performance, reflecting their adeptness in handling pressure and maintaining their competitive edge. Interestingly, an intriguing paradox emerges when examining the performance of such funds during inflow periods: despite their strengths, they struggle to capitalize on new subscriptions, facing hurdles in expanding their portfolios and making informed investment choices. Our analysis sheds light on the pivotal role of fund shareholders in shaping the competitive actions of fund managers. We underscore the critical importance of diligent monitoring of team-managed funds during inflows to proactively address potential agency issues and exploit the full potential of their informed decision-making. Moreover, we highlight the significance of team composition, with larger, older, and more diverse experienced teams demonstrating superior competitiveness. However, cautionary notes arise concerning diverse ethnic and interconnected teams as they threaten valuable portfolio growth. We suggest that investors consider team characteristics before subscribing or redeeming a fund; in the case of regulators, we draw attention to the need to supervise management companies when they place their managers to run multiple portfolios simultaneously, as this harms the capability of funds in delivering competitive outcomes.

Keywords: Mutual funds, flow dynamics, performance predictability, team characteristics

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1 Introduction

The mutual fund industry, a cornerstone of global finance, channels trillions of dollars into diverse asset classes, making it a vital avenue for investors seeking returns. Central to this industry are the mutual fund managers entrusted with generating risk-adjusted excess returns. Their effectiveness in executing value-enhancing trades defines the competitive landscape within this sector. In this paper, we unravel the intricate link between mutual fund organizational structures and the competitive decision-making of fund managers, shedding light on the subtleties that underpin their actions.

The challenge of delivering consistent performance within the mutual fund industry has persisted for years. Navigating this challenge involves a complex interplay of market dynamics, investor behavior, and organizational configurations. This paper addresses this challenge directly by spotlighting a critical yet understudied aspect—the impact of organizational structures, specifically team-managed and individual-managed funds, on competitive behavior and the predictability of fund performance.

The behavior of mutual fund managers has long held a central place in finance literature. These managers shoulder a fiduciary duty towards investors and must exercise prudence, especially in the face of liquidity constraints. Investor monitoring plays a pivotal role, where investors reward managers with increased subscriptions for astute decisions or impose penalties through redemptions. Capital flows, whether inflows or outflows, significantly influence fund performance. Research by Edelen (1999) highlights how outflows correlate with decreased performance, manifested in abnormal returns. Coval and Stafford (2007) demonstrates how outflows pressure managers into liquidating securities at discounted values, eroding portfolio worth. Alexander et al. (2007) underscores that, even amid outflow pressures, managers retain the capacity for quality decisions involving motivational trades. In essence, the ebb and flow of funds represent a critical variable in analyzing manager behavior.

Within mutual funds, managerial structures come in varying forms, with individuals and teams taking the helm of portfolios. Over the past two decades, the landscape has seen a notable surge in team-based management structures. Investment companies have increasingly offered these team-based approaches to fund investors, with the proportion of such structures nearly doubling from 30 percent in 2002 to 75 percent in 2022.

However, despite the burgeoning popularity of team structures, a fundamental question lingers: under what circumstances do these teams provide more excellent value to investors compared to individual managers? While it seems intuitive that two or more heads could make better investment decisions than a solitary individual, the efficacy of teams hinges on the synergy among their members and the absence of friction within their cohesive efforts, as Kelly and Karau (1999) underscored. Recent empirical evidence hints at an intriguing distinction—individual fund managers tend to exhibit competitive behavior. In contrast, their counterparts within mutual fund teams often lean toward a cooperative approach, particularly within a family of mutual funds (Evans et al. 2020).

Evaluating mutual fund managers' competence in augmenting portfolio value is a multifaceted challenge. Traditional performance metrics, the bedrock of assessment, often need to catch up in encapsulating the full spectrum of managerial skills. These metrics fixate primarily on the net portfolio value, inadvertently sidelining critical dimensions. They frequently neglect to account for opportunity costs from inaction or alternative investment decisions. Moreover, these metrics need to recognize the potential value that managers can create at specific junctures or in response to distinct market conditions.

On the other hand, the literature has acknowledged the pivotal role of investor flows as a potential driver of performance variations in mutual funds. However, a conspicuous void exists in our comprehension of how diverse organizational structures within mutual funds—those entrusted to teams of managers and those guided by individuals—react to these flows. This gap, regrettably, has persisted unaddressed for some time, leaving investors and regulators with a fragmented understanding of the intricate mechanisms governing mutual fund performance. This study surges beyond the assessment of individual managerial competence and ventures into the realm of mutual fund organizational structures. We scrutinize how these structures may influence a manager's capacity to foster portfolio value, subsequently echoing across the competitive landscape of the mutual fund industry.

Our investigation uncovers a critical dimension that significantly influences the behavior of mutual fund managers—liquidity constraints. Specifically, we find that the response of fund teams to liquidity-motivated trades differs significantly based on the circumstances. When faced with outflows, team-managed funds exhibit competitive behavior, making wise decisions to safeguard portfolio value. However, when the challenge shifts to managing inflows, these funds behave more cooperatively. In addition, this research challenges conventional wisdom by highlighting the complexities inherent in managing capital injections and the critical role of team composition. We reveal that larger teams excel under outflows, except when they exhibit significant ethnic diversity. Conversely, teams comprising older members with similar experiences outshine more diverse teams during inflows.

Furthermore, we delve into the role of investor monitoring, a key influence on managerial behavior. Our exploration of the flow-performance relationship reveals that positive past performance bolsters future net flows, while negative past performance triggers withdrawals. Interestingly, during outflows, team-managed funds demonstrate a stronger flow-performance relationship when underperforming, suggesting that investors closely monitor team-managed funds during discharges but grant them more flexibility during inflows. These insights illuminate the differentiated behavior of team-managed funds based on flow dynamics and emphasize the pivotal role of investor monitoring.

Finally, to ensure the robustness of our findings, we consider alternative hypotheses that could explain the differences between team-managed and individual-managed funds. Our analysis reveals that team-managed funds are motivated by factors beyond competition on their purchasing decisions when dealing with inflows, as instead of making informed choices, they opt for speculative-initiated assets when expanding the portfolio. Importantly, our research also investigates cash holdings as a potential explanatory factor for performance differences, revealing that the decision-making performed by teams is independent of cash holdings or the strategy to avoid poor trades.

Our research breaks new ground in the mutual fund performance discourse, examining how organizational structures influence competitive behavior and performance predictability. This knowledge equips investors and regulators. In the subsequent sections, we delve into our research question, understanding organizational structures and flow dynamics in the mutual fund realm. We begin with Section 2, which provides essential institutional context and outlines our key hypotheses. Then, Section 3 elaborates on our dataset, while Section 4 presents the core results alongside robustness analyses. Finally, Section 5 encapsulates our conclusions, summarizing key findings and their implications.

2 Institutional background and testable hypotheses

Mutual funds are extensively utilized by investors seeking professional asset management services. However, one of the most crucial challenges confronted by mutual fund managers arises because investors can subscribe to or redeem shares at any time. This dynamic decision-making process does not necessarily lead to an optimal and efficient allocation of assets within the fund's portfolio. Therefore, analyzing how managers address such uncertainty in fund flows and deliver investment performance that surpasses their competitors is imperative. Understanding the behavior of management in this regard holds significant importance.

The mutual fund industry is structured as investment management companies offering various portfolio styles. Each portfolio is designed and managed by the respective asset manager or managers. In other words, the managerial structure is characterized by individuals or teams. Within a fund family, a manager may belong to multiple teams or choose to manage a portfolio independently. Considering managers' diverse objectives and challenges, team-based structures have become increasingly popular. The literature on team vs. individual management structures exhibits mixed results in terms of performance: First, when teams overperform Patel and Sarkissian (2017); Adams et al. (2018).[2] Second, when they underperform (Chen et al. 2004; Karagiannidis 2010).[3] Finally, when there are no differences in absolute terms (Prather and Middleton 2002; Bliss et al. 2008). Alternatively, other studies find that teams allocate their portfolios better than individuals; meanwhile, they are not good at market timing Dass et al. (2013). Finally, Evans et al. (2020) recently introduced a new dimension comparing teams and individuals by stating that teams are generally cooperative, finding that companies associated with cooperative structures exhibit lower performance and dispersion over their affiliated funds. However, the impact of outflows on team management structures' cooperative behavior is still unclear. This is a crucial gap in the literature because mutual fund companies use team management structures to manage their portfolios more often. Our research aims to fill this gap by exploring the relationship between capital flows and team decision-making processes in the active asset management industry. Specifically, we propose the following research question: Does team management structure's cooperative behavior change based on the direction of capital

[2]Conclusions depend on a performance assessed through a prospectus benchmark or when teams operate through an independent board.

[3]Comparisons based on portfolios with similar size or when funds face bear markets.

flows? We hypothesize that team management structures become more competitive under outflow dynamics and more cooperative under inflow dynamics. Our hypothesis is based on the previous literature that shows that teams are generally cooperative and that spirit leads to not performing optimally (Evans et al. 2020). According to Brown and Goetzmann (1995), and Elton et al. (1996), poor performance increases the probability of liquidation. Furthermore, Chen et al. (2010) shows that when funds experience outflows, investors react more strongly by withdrawing larger amounts of capital from funds whose managers are more likely to erode performance. Thus, cooperative behavior can not be static because shareholders can discipline managerial choices through outflows, forcing managers to improve their decision-making activity and become more competitive to avoid future withdrawals, loss of reputation and income from management fees, and the opportunity to keep managing a fund.

We state that under inflow pressures, as long as investors do not reward or penalize the correct allocation of new liquid resources, teams can always behave cooperatively by picking new stocks that do not add value to the portfolio. Nevertheless, when confronted with outflow pressures, the cooperative incentives deteriorate as investors can intensify the magnitude of penalization through larger future withdrawals in response to portfolio value erosion by managers. In summary, mutual fund managers are primarily responsible for executing investment decisions that affect the financial assets of the fund's shareholders. Their duties encompass identifying and capitalizing on attractive investment opportunities through strategic trades. However, it is important to recognize that managerial interests are not aligned solely with the fund's long-term performance, as managers may have divergent motivations. For instance, they may be employees of investment management firms, and their stock selection within the portfolio could be influenced by fund-family considerations to advance their careers within this institutional arrangement. Additionally, managers have the freedom to operate multiple portfolios, enabling them to leverage the inflow of capital into one specific portfolio to bolster the value of securities held in various other baskets.

Our research also sheds light on the complex interplay between team characteristics and the variation around the value that decision-making generates. For instance, we ask how specific team characteristics promote or inhibit competitive or cooperative behavior. We hypothesize that specific team characteristics, such as large team size, managerial age, and experience, promote more competitive behavior through trading decisions that ex-post generate value. In contrast, other features like ethnicity and interconnection may lead to less competitive behavior due to social conflicts and incentives to cooperate. As far as we know, these hypotheses have not been directly tested in the literature but are related to different topics in managerial finance. According to Lazear (1999), team decision quality depends on complementary skills and effective communication. In addition, polarization theory explores group decision-making through two hypotheses leading to gains and losses. First, when members are influenced by social comparison and normative processes: they deviate from the optimal isolated preference as long as they can be accepted within the organization and, with it, accept the social choice (Myers 1978; Mumford 1983; Goethals and Darley 1987). Second, group members deliberately use persuasive dynamics through novelty and valid arguments to make a consensus and shift the individual choice into a more informed decision (Vinokur 1971; Burnstein et al. 1973; Burnstein and Vinokur 1973, 1975, 1977). For example, we posit the hypothesis that larger teams can yield advantages due to their heightened probability of possessing diverse alternative arguments and complementary skills during discussions, thereby increasing the likelihood of generating informed choices. Furthermore, we hypothesize that effective communication is more probable when group members are older and possess ample experience. These attributes facilitate a deliberation process within groups that rely on an informed and diverse array of beliefs, thereby reducing reliance on normative social norms that may penalize and isolate individuals for diverging and expressing alternative opinions.

Other characteristics affecting communication may generate a contrary effect. Sutter and Strassmair (2009) found that communication between competing teams generates incentives for reducing effort, which may erode a decision-making process.[4] Besides, differences in ethnic identity among group members may raise social conflicts and ineffective communication that diminish productivity as long as it becomes harder to find consensus (Charness and Chen 2020).[5]

The literature on mutual funds has focused on understanding the role of team characteristics in the behavior of portfolio managers. About the influence of ethnic diversity within teams on risk-adjusted performance, systematic risk, and idiosyncratic risk (Bär et al. 2011; Evans et al. 2019) find no significant impact[6]. In contrast, the study by Karagiannidis (2012) delves

[4]Following a lab setting, the authors find that communication boosts the effort inside teams.

[5]Result from other studies imply that teams exhibit delays in decision-making due to coordination costs that can be explained by diversity in personal objectives (Sah and Stiglitz 1991; Becker and Murphy 1992).

[6]The authors extend their analysis to other dimensions like gender and education and find similar results.

into the relationship between team size, age diversity, turnover, and portfolio holdings. The findings indicate a negative association between age diversity and portfolio holdings. Conversely, team size exhibits a positive association with portfolio holdings[7]. However, there is a gap in the existing literature regarding including ex-ante trading decisions as a reflection of managerial behavior, particularly in studies that compare the decision-making processes of individuals and teams. This gap becomes more significant when considering that the impact of subscriptions and redemptions on managerial perceptions influences these decisions.

Our research aims to contribute to the mutual fund literature through different branches. First, we complement the literature on current valuation, stating that skills are better identifiable through current ex-ante trades (Chen et al. 2000; Alexander et al. 2007). By exploring the differences between teams and individuals, we bring a unique understanding of the capability of organizations to generate expectations in future prices. Second, by refining our analysis based on flow dynamics, we unveil a helpful alternative to identify the value managers add to the portfolio without incurring misinterpretation from flow pressures in security prices. Addressing this question is complex; according to Edelen (1999), it's unclear whether the managers added value to the portfolio or if the flows drive the returns when risk-adjusted performance is analyzed. For instance, we uniquely highlight teams' potential role when funds face outflows or inflows. Third, we extend recent literature associating mutual fund teams with cooperative behavior (Evans et al. 2020). Through the linkage of cooperative behavior with decision-making quality, we introduce a novel dimension wherein cooperation diminishes when funds face outflows, consequently learning that teams adopt a competitive stance contingent upon implementing control mechanisms by the fund's investors on their actions. Moreover, this paper contributes to the literature investigating individual characteristics within team dynamics. To the best of our knowledge, this study represents the first documented evidence of the substantial influence of ethnic diversity on organizational outcomes within funds. By examining the current ex-ante trading decisions, we introduce a novel framework that aligns with the social conflict hypothesis derived from prior research on organizational structures (Lazear 1999; Charness and Chen 2020). Furthermore, this study is a pioneer for including team size, experience, and age as crucial factors outside the confines of a laboratory setting, thereby empirically documenting the theory of polarization that promotes persuasive deliberation for informed decision-making within teams (Burnstein et al.

[7] The authors also explore gender and tenure without seeing significant results.

1973; Burnstein and Vinokur 1975, 1977). Finally, we shed light on the cooperative behavior of teams within funds by conducting the first empirical test of the assumption that the level of interconnectedness indicates cooperation (Evans et al. 2020). To test our hypothesis, we will use a rich dataset that relates organizational structure characteristics with real-life trading decisions and their corresponding quality on performance. Our research will provide a novel understanding of an industry phenomenon in which teams and individuals coexist and compete. Moreover, our findings may help investors make better investment decisions, shed light on the complex interplay between team dynamics and variation in decision-making, and provide implications for industry practices.

3 Data

3.1 Data Description

The data used in this study consists of a comprehensive dataset of 4533 mutual funds operating in the active asset management industry. The dataset covers 20 years, from 2000 to 2020, and includes information on fund characteristics, performance metrics, capital flows, and organization characteristics. The primary data source is a leading financial database aggregating information from various mutual fund sources. First, funds' information comes from the CRSP mutual fund, which includes: reporting net returns, turnover ratio, expenses, cash, loads, dividends, total assets, family affiliation, and investment style. The information reported in CRSP comes at the share-class level; since our analysis is at the fund level, we aggregate share classes by summing total net assets (TNA) and value-weighting all the information that appears at the share-class level.[8] Second, to analyze managers' decision-making process, we identify the realized trades within a portfolio by observing the changes in portfolio holdings. For instance, to obtain funds' transactions, we use quarterly information related to portfolio holdings through Thomson Reuters S12 and CRSP.[9] Third, organizational characteristics, reported by Morningstar Direct (MsD), deliver detailed information related to managers and advisors. Specifically, the names of funds' managers and advisors, the periods in which they start in the asset management industry,

[8]We define a fund as a portfolio that can have different share classes. Fortunately, CRSP has a mapping file that makes the aggregation easy over time.

[9]Following Chernenko and Sunderam (2020), we obtain the most comprehensive and up-to-date data on portfolio holdings by combining Thomson Reuters S12 and CRSP holdings.

and when they enter or depart from a fund.

We employed a matching procedure that linked the data sources using various trackers to ensure data consistency and accuracy. We connected CRSP and Thomson Reuters data through MFLINKS, while Morningstar Direct data was linked using tickers and ncusip. This linkage at the fund level was facilitated by mapping share classes to their respective funds. We excluded sector, international, and index funds from our sample, focusing on capitalization-based and style funds (e.g., EDCS, EDCM, EDCL, EDYG, EDYB, EDYI) to maintain consistency in our analysis. The data frequency for our analysis is set to quarterly, as the decision-making process is observable only when there are changes in portfolio holdings. To mitigate the influence of extreme outliers, we winsorized the data at the 1st and 99th percentiles. Furthermore, we excluded funds with less than two years of available data and less than ten million assets under management to avoid incubation bias and atypical flows (Evans 2010).

In addition to the primary database, secondary data sources were utilized to support our analysis. The CRSP Stock database was used to identify the performance metrics of individual stocks held by the funds through their trading decisions.[10] To gather information on individual managerial characteristics such as age, education, and gender, biographical data was collected by scraping LinkedIn profiles and extracting information from Morningstar webpages and Principia CD (Cici et al. 2020).[11] The meticulous collection, cleaning, and merging of data from various sources ensure the reliability and accuracy of our dataset. By incorporating a wide range of fund-level, performance, and organizational characteristics, our analysis aims to provide robust and meaningful insights into the relationship between team characteristics, decision-making, and capital flows in mutual funds.

3.2 Variables

3.2.1 Net-Flows

Although mutual funds directly report subscriptions and redemptions of shares, we follow the literature in mutual funds and estimate flows using the variation in assets under management

[10] We also use Compustat and the K-R French library as both provide necessary information to create benchmark portfolios for performance comparison, defining quality (Daniel et al. 1997; Da et al. 2011; Alexander et al. 2007).

[11] In our work, we build measures based on ethnicity. However, this is not directly observable-so, we deduce it by using a classification algorithm based on names and surnames (Ye et al. 2017; Ye and Skiena 2019)

(Sirri and Tufano 1998; Coval and Stafford 2007; Chen et al. 2010; Ferreira et al. 2012; Lou 2012; Agarwal et al. 2020). Net flow, denoted as NetFlow_t, is calculated as the percentage change in assets under management from one period to another, excluding changes related to the fund manager's ability to affect capital value. This measure captured the relative change in total net assets (TNA) without considering the net returns delivered to investors and reinvested in the fund.

Our analysis focuses on quarterly net flows ranging between -50% and 200% (Coval and Stafford 2007). Negative net flows indicate outflows or redemptions when investors withdraw their investments from the fund. On the other hand, positive net flows signal inflows or subscriptions, signifying when new investors contribute capital to the fund. By examining the dynamics of inflows and outflows, we aim to understand how these capital flow patterns impact decision-making and performance in the mutual fund industry.

$$\begin{aligned} \text{NetFlows}_{f,t} &= \frac{TNA_{f,t} - TNA_{f,t-1}(1 + R_{f,t})}{TNA_{f,t-1}} \\ R_{f,t} &= \frac{NAV_{f,t} - NAV_{f,t-1} + D_{f,t-1}}{NAV_{f,t-1}} \end{aligned} \tag{1}$$

Returns $R_{f,t}$ are the percentage changes in net asset value NAV, taking into account the dividend payments D.

3.2.2 Decision-Quality: Trading Selectivity Measures

To assess the decision quality of fund managers, we construct trading selectivity measures based on realized purchases and sales transactions within each period. Following the methodology of Daniel et al. (1997) and Da et al. (2011), we calculate the trading selectivity measures as follows:

$$PR_t^{fund} = \sum_{\text{stock}} W_{\text{stock},t}^{\text{Purchase}}(R_{\text{stock},t+1} - R_{\text{stock},t+1}^{\text{Benchmark}}) \tag{2}$$

$$SR_t^{fund} = \sum_{\text{stock}} W_{\text{stock},t}^{\text{Sale}}(R_{\text{stock},t+1} - R_{\text{stock},t+1}^{\text{Benchmark}}) \tag{3}$$

Where PR_t^{fund} represents the purchase return and SR_t^{fund} represents the sale return for the fund in period t.[12] The weights $W_{\text{stock},t}^{\text{Purchase}}$ and $W_{\text{stock},t}^{\text{Sale}}$ are determined based on the transaction size and the price of each stock. The weights on purchases ($W_{\text{stock},t}^{\text{Purchase}}$) and sales ($W_{\text{stock},t}^{\text{Sale}}$) are calculated as follows:

$$W_{\text{stock},t}^{\text{Purchase}} = \frac{\Delta_{\text{stock},t}^{\text{Purchase}} \times \text{Price}_{\text{stock},t}}{\sum_{\text{stock},t} \Delta_{\text{stock},t}^{\text{Purchase}} \times \text{Price}_{\text{stock},t}} \quad \text{where} \quad W_{\text{stock},t}^{\text{Purchase}} \in (0,1] \tag{4}$$

$$W_{\text{stock},t}^{\text{Sale}} = \frac{\Delta_{\text{stock},t}^{\text{Sale}} \times \text{Price}_{\text{stock},t}}{-\sum_{\text{stock}} \Delta_{\text{stock},t}^{\text{Sale}} \times \text{Price}_{\text{stock},t}} \quad \text{where} \quad W_{\text{stock},t}^{\text{Sale}} \in [-1,0) \tag{5}$$

The weights reflect each transaction's value proportion within the corresponding transaction basket (e.g., purchases or sales). The values of $W_{\text{stock},t}^{\text{Purchase}}$ and $W_{\text{stock},t}^{\text{Sale}}$ determine the significance of each transaction in calculating the trading selectivity measures. A positive weight on purchases indicates a correct decision by the manager to select stocks that outperform the benchmark. In contrast, a negative weight on sales reflects the right decision to sell underperforming stocks.

Suppose we buy a stock that generates a 5 percent return in the next quarter, and the profitability of a comparable benchmark asset with similar characteristics is 2 percent. In this case, a positive weight would not affect the conclusion that the manager makes a correct decision.[13] Similarly, if the analysis explores negative returns, a positive weight would not affect the conclusion that the manager made an incorrect decision.[14]

On the contrary, the weight on sales must be negative to reflect a satisfactory conclusion on the decision quality realized by managers. For example, imagine that the manager sells a stock that, in the upcoming quarter, produces a 15 percent return, while an asset with similar characteristics generates 3 percent. In this case, a negative weight will reflect that the manager makes a mistake by quitting and missing out on the 12 percent excess return.[15] Likewise, if the identification

[12] $R_t^{Benchmark}$ is the result of building 125 portfolios across all stocks. To define portfolios, we sort stocks on 5 (Market-Cap) x 5 (Book-to-Market)x 5 (momentum) factors, using K.R French Breakpoints (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

[13] If $W^{Purchase} > 0$, and $\{r_{stock} = 5\%, r_{stock}^{benchmark} = 2\%\}$, then $PR = W^{Purchase} \times (5\% - 2\%) > 0$, which identifies that the manager makes a good decision.

[14] If $W^{Purchase} > 0$, and $\{r_{stock} = -5\%, r_{stock}^{benchmark} = -2\%\}$, then $PR = W^{Purchase} \times (-5\% - (-2\%)) < 0$, which identifies that the manager makes a wrong decision.

[15] If $W^{Sale} < 0$, and $\{r_{stock} = 15\%, r_{stock}^{benchmark} = 3\%\}$, then $SR = W^{Sale} \times (15\% - 3\%) < 0$, which identifies that the manager makes a poor quality decision by quitting and missing out on the potential gain of 12 percent.

explores negative returns, a negative weight would imply that the manager made a good decision by quitting from a future loss. For example, suppose a manager sells a stock that, in the next period, delivers a -15 percent return, while an asset with similar characteristics produces a -5 percent return. In this case, a negative weight would reflect a correct decision by avoiding the potential loss of 10 percent.[16]

By constructing the trading selectivity measures and considering the weights associated with purchases and sales, we capture the decision quality of fund managers in selecting securities that outperform the benchmark. The trading selectivity measures provide insights into the managers' ability to generate excess returns by making informed trading decisions. These measures allow us to examine the association between team characteristics and decision-making under capital flows in mutual funds.

3.2.3 Out of Sample Alpha (α^{OS})

Alpha performance is estimated by following the literature on asset pricing (Carhart 1997). The *Carhart* model uses monthly fund net returns above the riskless rate as a dependent variable. The model also employs risk factors as explanatory variables, where RMF represents market return, SMB size, HML value, and WML momentum.

$$r_{f,t} - r_t = \alpha + \beta_1 \text{RMF}_t + \beta_2 \text{SMB}_t + \beta_3 \text{HML}_t + \beta_4 \text{WML}_t + \epsilon_{f,t} \quad \text{(Carhart)} \tag{6}$$

$$\tilde{r_{f,t}} = \alpha + \beta X_t + \epsilon_{f,t} \quad \text{(Abstract Carhart)} \tag{7}$$

The abstract Carhart model provides a simplified representation, where α represents the abnormal return component and βX accounts for the theoretical variation from the model that explains the return. To infer out-of-sample abnormal returns (α^{OS}), we follow these steps: First, we employ an OLS regression that re-estimates all the parameters each month, using a moving window of 24 periods. Next, we calculate the expected return ($E[\tilde{r_{f,t+1}}|_t]$) for the following period, using the estimated parameters obtained from the moving average estimation.

[16]If $W^{Sale} < 0$, and $\{r_{stock} = -15\%, r_{stock}^{benchmark} = -5\%\}$, then $SR = W^{Sale} \times (-15\% - (-5\%)) > 0$, which identifies that the manager makes a correct decision by quitting and avoiding the potential loss of 10 percent.

$$E[\tilde{r}_{f,t+1}|I_t] = \hat{\alpha}_t + \hat{\beta}_t X_t \quad \text{(Expected Return)} \tag{8}$$

In summary, the expected return for tomorrow is a combination of today's abnormal return and what is anticipated based on the theoretical model's risk factors. We subtract the realized and expected excess returns to calculate the out-of-sample performance measure. Finally, We follow Agarwal et al. (2020) to obtain quarterly out-of-sample Alpha by compounding the monthly estimators within each quarter.

$$\alpha_{t+1}^{\text{OS}} = \tilde{r}_{f,t+1} - E[\tilde{r}_{f,t+1}|I_t] \tag{9}$$

Examining the implications of managerial decisions on investor interests becomes particularly relevant when aiming to explore the distinctions between teams and individuals in their decision-making processes amidst flow dynamics. In this context, inferring out-of-sample performance holds significance as it enables us to explore the consequences of such decisions and their impact on investor interests. We use unexpected performance to avoid confounding effects on the profitability delivered to investors explained from the realized flows (Edelen 1999).

3.2.4 Team Characteristics

Our data on the management structure of each mutual fund is sourced from Morningstar Direct (MsD)[17]. This data source provides us with the dates of entry and exit for all managers involved in a fund, enabling us to track fund managers' tenure and the management team's changes over time.

However, MsD does not provide demographic information on fund managers. To overcome this limitation, manual searches were conducted on the Morningstar website[18]. This allowed us to access the managers' education information, including their highest level of study, field of study, graduation year, and the institutions they attended. To supplement any missing information, we employed the method proposed by Cici et al. (2020) of using LinkedIn to search for managers by

[17]Morningstar Direct (www.morningstar.com/products/direct) is a subscription-based product from Morningstar. It provides comprehensive reports and data on mutual funds in a user-friendly format.

[18]We conduct manual searches for portfolio managers on the Morningstar webpage (https://www.morningstar.com). We start by searching for fund names, then delve into the "People" section, where we can find historical data on portfolio managers.

name.

To ensure the reliability of this data, we cross-verified the fund advisor's name provided in MsD with the employment experience stated on LinkedIn. This allowed us to mitigate the risk of misidentification due to common names—the following list details how we calculated the variables that describe the funds' managerial structure and characteristics.

- **Team:** This binary variable takes a value of one when a fund is managed by a team (two or more managers) in a particular period. This variable can change over time, reflecting the dynamic nature of fund management.
- **Team Size:** This variable represents the total number of managers in a fund during a specific period. Like the *Team* variable, *Team Size* can also change over time. Complementary, we define a binary variable *Large Team* that equals one when the number of managers within a fund is larger than fourth, and zero otherwise.

Our data allow us to identify various characteristics of fund managers, including their professional experience, tenure, compensation, affiliations, co-managing history, and personal demographic attributes such as age, gender, and ethnicity. However, we focus on the fund's overall characteristics, not individual managers. Therefore, we aggregated the personal features to create average and diversity measures for each fund management team.

- **Team Age:** This variable represents the average age of all managers in a fund. We estimate the age of managers based on the year they obtained their bachelor's degree, assuming they were 21 at that time, following the method proposed by Chevalier and Ellison (1999). This variable can change over time due to changes in the management team. In addition, we calculate Team Age (Older) as a dummy that equals one when the Team Age overcomes the 40-year-old rank.
- **Team Experience:** This variable represents the average years of professional experience of all managers in a fund. We consider the years since the manager's first job after graduation as professional experience. This variable changes over time due to changes in the management team and the continuous professional expertise of the existing managers.
- **Interconnected (Co-Management):** This variable represents the proportion of managers within a fund with co-management activities. Co-management occurs when a manager

performs administrative activities in multiple portfolios simultaneously.

- **Diverse Team (Experience):** We utilize the **Coefficient of Variation (CV)** as a measure of diversity in our study.[19] Specifically, we apply the CV to analyze experience diversity within a team, denoted as *Diverse Team (Experience).* The CV is calculated as the standard deviation of a given attribute, scaled by its arithmetic mean. In our context, the higher the CV value, the greater the heterogeneity or diversity among the managers in terms of their experience.

- **Diverse Team (Ethnicity):** *Diverse Team (Ethnicity)* measurse the degree of ethnic diversity within a team. Unfortunately, the biographical data we obtained from Morningstar and LinkedIn does not include specific ethnicity information. To overcome this, we use a classification algorithm to infer ethnicity, as Ye et al. (2017) and Ye and Skiena (2019) suggested. Using these inferred ethnicity values, we calculate ethnic diversity using Blau's Index.[20] This diversity measure is based on the Herfindahl Concentration Index (*HInx*). It was initially designed to quantify the concentration or homogeneity of attributes within groups. However, our research focuses on measuring heterogeneity or diversity, for which the Blau's Index is particularly suitable. The index is calculated as one minus the *HInx*, and similar to the Coefficient of Variation, higher values signify greater diversity[21].

This approach enables us to create a dynamic, comprehensive, and multidimensional picture of the management team of each mutual fund. It allows us to track the changing structure and characteristics of the management team over time and to analyze the potential impact of these changes on fund performance.

3.2.5 Controls

- **Portfolio Illiquidity Measure (AMI)**: Illiquidity, a significant risk factor in trading stocks, is defined by the difficulty or cost incurred when trying to trade. Indicators of illiquidity risk include substantial price impacts due to trades. We employ methodologies proposed by Amihud (2002) to evaluate this risk at the individual stock level. These stock-specific measures are then aggregated at the portfolio level by taking a value-weighted

[19] Baer et al. (2009) proposed the measure on education.

[20] Harvey et al. (2021) originally proposed using the Blau's Index for measuring diversity in educational fields.

[21] It's worth noting that while *HInx* measures concentration, Blau's Index, by being one minus *HInx*, effectively measures dispersion or diversity.

average to generate a portfolio-wide illiquidity measure. These measures are critical in portfolio decision-making as high illiquidity can lead to potential losses. For instance, a portfolio manager may be compelled to sell a highly illiquid asset at a lower price quickly, resulting in a loss.

3.3 Summary Statistics

The provided summary in table 1 reveals insightful patterns in the asset management industry, particularly underlining the dynamics between team-managed and individually-managed funds. For example, Team management is significantly more prevalent in the industry, accounting for approximately 76.62 % of the management structures. Furthermore, the average team size stands at 3.22 members, with teams showing interconnectedness regarding co-management (64.67 % of cases). This trend aligns with the observations from the biennial comparison figure 1 that showed an increasing trend of team-managed funds over the past decades, reaching 85.38 % by 2020. Yet, it's worth noting that individual structures still operate in the industry, representing 14.62 % of the active mutual fund market.

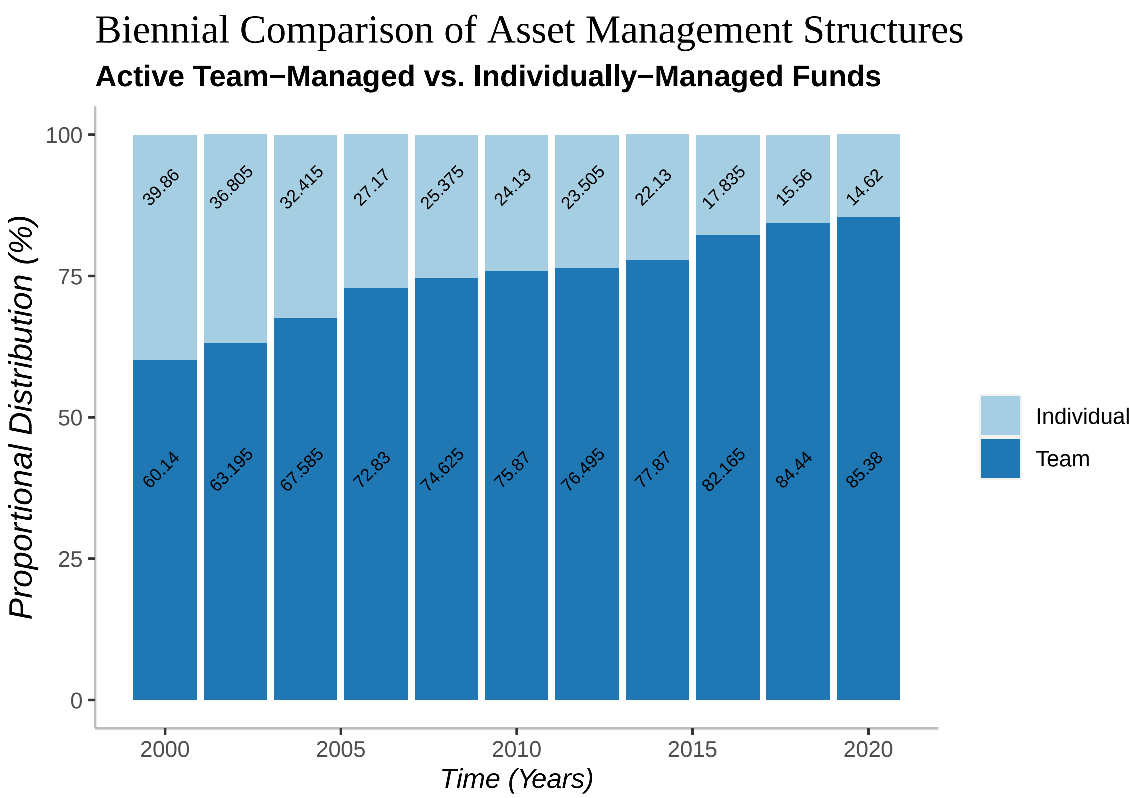

Figure 1:

Figure 1 vividly portrays the evolution of management structures in the mutual fund market over the past two decades, from 2000 to 2020. During this period, team-managed funds have significantly increased in prevalence, indicating a notable shift in the industry's preference toward team structures. In 2000, team-managed funds accounted for 60.14% of all management structures, reflecting a slightly higher prevalence than individual structures. However, the proportion of team-managed funds grew substantially over the years, reaching a peak of 85.38% in 2020. This steady rise in the popularity of team structures could indicate a perceived advantage in such arrangements. Looking closely at the distribution over time, we observe several fluctuations in the proportion of individual and team-managed funds. A significant increase in team-managed funds was noted between 2005 and 2010, followed by a minor decrease in their balance between 2010 and 2015. Despite these variations, the overarching trend leans toward a growing dominance of team-managed funds over the past two decades.

Regarding size, we can observe in table 2 that team-managed funds tend to be larger (average Fund Size of 5.7822, on a natural logarithm total assets scale) than individually-managed funds (5.3896). This aligns with the figure 2 findings, highlighting the larger responsibility of teams in managing portfolios of higher market value, though with a significant variation observed over time. In economic terms, active team structures operate more than 1.2 billion dollars from the equity market compared to less than 0.3 billion driven by individual managers. The previous results underline regulators' concerns in understanding the consequences of team-managed decisions for market stability.

Figure 2 compares assets under management (AUM) between team-managed and individually managed funds over time. The figure demonstrates the dynamic nature of the mutual fund industry and the impact of macroeconomic events such as the 2008 financial crisis. Initially, team-managed funds held a larger share of AUM, indicating that larger portfolios were typically entrusted to teams. However, the financial crisis in 2008 significantly impacted these team-managed funds, substantially reducing their AUM. This period saw a narrowing of the gap between team and individual managers in terms of AUM. In the aftermath of the crisis, team-managed funds rebounded swiftly, recovering their AUM without much sustainability. Interestingly, a shift occurred around 2017 when individual managers began managing a greater share of AUM despite representing only 14.62% of the industry's management structures. This indicates a trend of larger funds potentially showing preference towards individual managers.

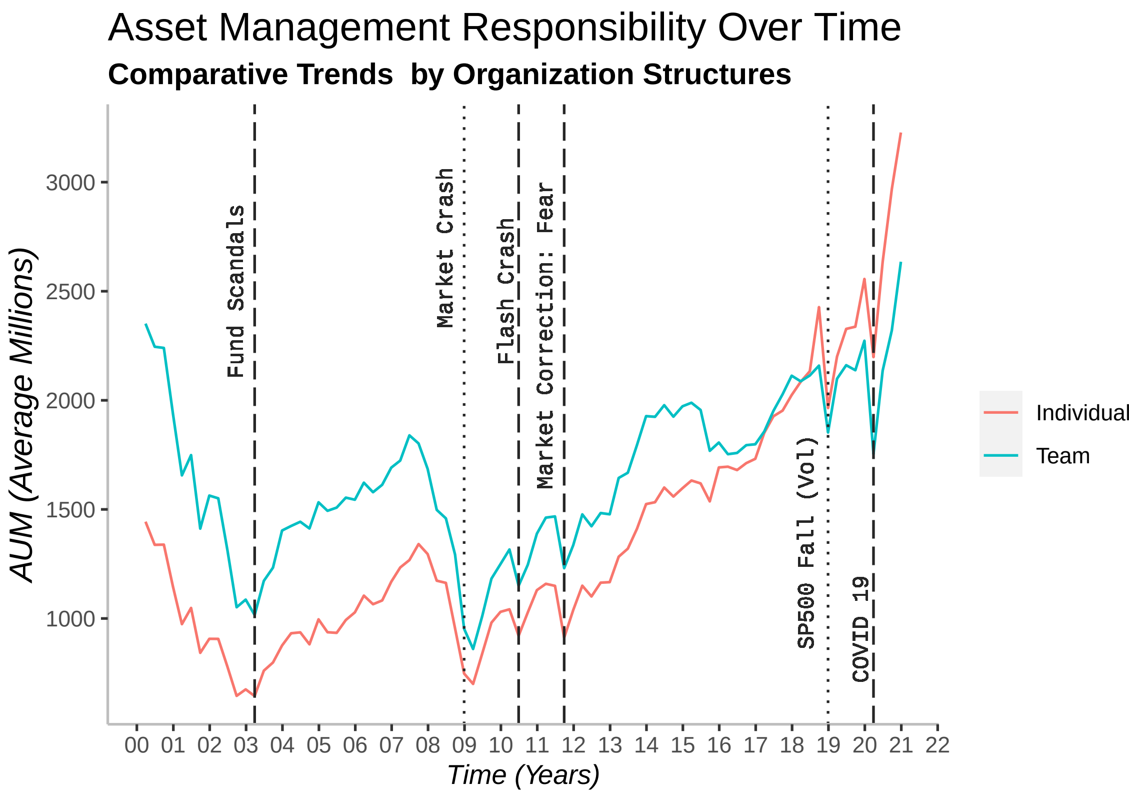

Figure 2:

Figure 2 elucidates the sensitivity of AUM distribution between the team and individually managed funds to market conditions. During bear markets, team-managed funds appear more susceptible, implying these structures might engage in higher-risk strategies or are more exposed to market downturns. The recent shift towards individual managers handling larger AUM may indicate that investors realized that individual managers maintain discipline during challenging bear markets or they exhibit a better ability to time the market or mitigate the effects of diseconomies of scale (Chen et al. 2004; Karagiannidis 2010; Dass et al. 2013). Figure 2 underscores the relevance of examining the differences between team and individually managed funds. Understanding the impact and effectiveness of different management structures is crucial for investors. It aids in their decision-making process, allowing them to align their choices with their preferences for resource accessibility and market condition responsiveness.

On the other hand, our data capture the statistical properties of other studies in the mutual fund industry, ensuring our analysis's consistency and reliability. Table 1 Panel A presents a detailed overview of fund characteristics that form the basis of our study, consistent with previous research. Notably, Quarterly Flows, Returns, and Cash, representing the proportion of money flows, net returns, and cash in the portfolio, reveal distributions similar to Agarwal et al. (2020). The mean values for Quarterly Flows and Returns are 0.7175% and 2.27%, respectively, while for Cash, it is 3.0794%. About Fund Size and Family Size, our data aligns closely with the analysis of Chernenko and Sunderam (2020). The natural logarithm of total assets is represented for these variables, averaging 5.6729 for Fund Size and 9.0337 for Family Size. The Fund Age, calculated as the number of years since the oldest share class of the portfolio was first offered to investors, has a mean of 14.7543 years, also indicating a diverse range of fund lifespans in the dataset. The Expense Ratio and Management Fee, expressed annually, align with the findings of Dong et al. (2017)and Cremers and Pareek (2016). The mean values are 1.0191% and 0.6438%, respectively.

Our analysis focuses on two critical decision-making and managerial selectivity variables: SR and PR. A positive value in these variables indicates proficient selectivity in purchasing and selling stocks. The average SR is 1.4229%, while the mean PR is -0.9454%. These values suggest that, on average, managers have demonstrated their ability to select stocks that outperform a pool of stocks with similar risks in the subsequent period. Interestingly, our findings reveal a discrepancy in managers' performance between selling and buying actions. Managers appear to excel in selling decisions while facing more challenges in purchasing decisions. This pattern aligns with the notion of informed decisions.

On the one hand, regarding selling, managers demonstrate an enhanced understanding of their portfolios' top-performing and underperforming stocks. This insight is derived from continuous monitoring and follow-up processes, enabling them to make more informed choices. On the other hand, buying decisions involve a more extensive set of options and may be influenced by various factors, making it more complex. Managers may have limited attention capacity when selecting from a wide range of potential stocks, leading to suboptimal outcomes in some cases. Hence, the average data suggests managers perform better in selling than buying. Moreover, the data indicate that the disparity between buying and selling performance may be driven by the left tail of the distribution, where significant differences are more pronounced. When managers make poor decisions, the subsequent market prices penalize buying actions more severely than selling activities. This suggests managers may have missed opportunities to include more favorable alternatives in their portfolios after making suboptimal decisions. Our analysis highlights managers' strengths in selling decisions and sheds light on their challenges when making buying decisions. These findings provide valuable insights into the decision-making process and emphasize the importance of understanding the underlying dynamics contributing to managers' performance.

Table 1: Summary Statistics

	Mean	Median	Std.Dev	Min	P10	P90	Max
Panel A: Fund Charateristics							
Quarterly Flows (%)	0.7175	-1.2700	13.6487	-49.9975	-7.7630	10.0558	199.9955
SR (%)	1.4229	1.1324	5.3206	-29.7186	-4.0514	7.3457	36.5270
PR (%)	-0.9454	-0.8979	5.7115	-35.2322	-7.2235	5.2594	37.6908
OS Alpha - α^{OS} (%)	0.0880	0.0459	1.9969	-19.1611	-2.0602	2.2940	16.6099
Quarterly Returns (%)	2.2722	3.1395	9.6586	-58.7264	-10.6441	12.7344	64.1723
Cash (%)	3.0794	1.5400	4.8126	0.0000	0.0200	7.2977	39.9900
Illiquidity: Amihud*10^7	0.0528	0.0067	0.1310	0.000001	0.0007	0.1402	1.3868
Deferred Load (%)	1.2322	1.0000	1.5477	0.0000	0.0000	4.0000	5.5000
Redemption Load (%)	0.5077	0.0000	0.8049	0.0000	0.0000	2.0000	3.4884
Front Load (%)	4.8514	5.5000	1.4909	0.0000	3.0000	5.7500	8.4674
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
Fund Age	14.7543	12.5495	10.3410	2.0000	4.2555	26.7225	55.4258
Expenses Ratio (%)	1.0191	1.0376	0.5000	0.0000	0.2677	1.6271	3.2919
Management Fee (%)	0.6438	0.6860	0.3200	0.0000	0.1500	1.0000	1.6544
Panel B: Team Charateristics							
Team	0.7662	1.0000	0.4233	0.0000	0.0000	1.0000	1.0000
Team Size	3.2221	2.0000	3.1858	1.0000	1.0000	6.0000	71.0000
Interconnected (Co-Management)	0.6467	1.0000	0.4547	0.0000	0.0000	1.0000	1.0000
Team Age	31.7078	40.0000	20.1343	0.0000	0.0000	51.0000	75.0000
Diverse Team (Experience)	0.3698	0.2407	0.4126	0.0000	0.0000	0.9744	3.0000
Diverse Team (Ethnicity)	0.0563	0.0000	0.1444	0.0000	0.0000	0.3750	0.6667

Note: Data used in the table is winsorized at the 1% and 99% levels to limit the effect of extreme values. Our measure for risk-adjusted performance, OS Risk-Adjusted Performance, is derived from Carhart's out-of-sample quarterly alphas. These quarterly alphas are obtained by compounding monthly alphas within each quarter. Furthermore, Quarterly Flows and Cash represent the proportion of money flows and cash in the portfolio, respectively, both presented as percentages. Our illiquidity measure uses a portfolio-level, value-weighted average based on Amihud (2002). We have multiplied the illiquidity measure by 10^7 to facilitate interpretation. Fund Size and Family Size denote the natural logarithm of total assets, while Fund Age represents the number of years since the oldest share class of the portfolio was first offered to investors. Please note that certain variables are expressed in percentage terms for readability.

3.3.1 Mean Differences between Team and Individual Fund Characteristics

Table 2: Mean Differences

	Individual	Team	Team-Ind
Quarterly Flows (%)	0.9626	0.7176	-0.2449 ***
Quarterly Returns (%)	1.8918	2.1844	0.2927 ***
Cash (%)	4.0830	3.9207	-0.1623 ***
Illiquidity: Amihud*10^7	0.0654	0.0544	-0.0110 ***
Deferred Load (%)	1.2044	1.2274	0.0229 ***
Redemption Load (%)	0.6373	0.4654	-0.1718 ***
Front Load (%)	4.8435	4.8515	0.0080 ***
Fund Size	5.3896	5.7822	0.3926 ***
Fund Age	14.2444	14.2740	0.0297 ***
Expenses Ratio (%)	1.1526	1.0261	-0.1266 ***
Management Fee (%)	0.7032	0.6525	-0.0507 ***

Note:

The data used in this analysis is winsorized at the 1% and 99% levels to mitigate the impact of extreme values. The type of test conducted is the Wilcoxon test, a non-parametric statistical hypothesis test. The significance levels are denoted by ***, **, and *, indicating significance at the 1%, 5%, and 10% levels, respectively. The Wilcoxon test is chosen as our data often exhibit high skewness and positive asymmetry, resulting in a non-normal distribution with heavy tails. Using a non-parametric approach, we can accurately assess the significance of mean differences between team and individual structures without relying on assumptions about the underlying distribution.

Our findings are consistent with previous studies in the literature that explore the differences between team-managed and individual-managed mutual funds. These studies have shown that, in unconditional terms, teams tend to exhibit lower cash holdings, net flows, expenses, and loads compared to individuals (Han et al. 2017; Patel and Sarkissian 2017, 2020). Our findings are consistent with the results of prior studies.

We observe significant differences between team and individually managed funds across various factors by analyzing the mean differences in Table 2. For instance, team-managed funds have lower average Quarterly Flows, representing the proportion of money flows, compared to individual-managed funds (0.7176% vs. 0.9626%). This difference of -0.2449% is statistically significant, indicating that the inflow dynamics of funds vary depending on the management structure. However, it is important to interpret the economic significance of these differences with caution. Although individuals receive a higher percentage of money flows, their actual financial inflows are smaller than those of teams due to the smaller size of their portfolios. For example, on average, team-managed funds receive 2.3284 million per quarter, while individuals receive 2.1002 million, representing a difference of 760,000 dollars.

Regarding performance metrics, team-managed funds exhibit slightly higher average Quarterly Returns (2.1844%) than individual-managed funds (1.8918%), suggesting potentially better performance for team-managed funds. However, it is essential to note that this performance is not adjusted for risk factors or conditioned to specific market states. Furthermore, the two management structures have significant differences in cash holdings. On average, team-managed funds hold slightly less cash (3.9207%) than individual-managed funds (4.0830%). This discrepancy may indicate distinct investment strategies or risk management approaches adopted by the two groups. Lastly, team-managed funds demonstrate a lower average expenses ratio (1.0261%) and management fees (0.6525%) compared to individual-managed funds (1.1526% and 0.7032%, respectively). This suggests potentially higher cost efficiency in team-managed funds, which can have a material impact on investment returns.

These findings emphasize the importance of studying the decision-making differences between teams and individuals in the asset management industry. The statistically significant and economically meaningful differences in fund flows, returns, cash holdings, fund size, and cost structure have implications for industry practitioners, regulators, and investors when selecting and evaluating fund management structures. Controlling for these fund characteristics in any research that analyzes the differences between team-managed and individual-managed funds is crucial to ensure unbiased statistical inference. Moreover, these findings open avenues for further exploration of the underlying mechanisms driving these differences and their broader implications.

4 Empirical Procedure

4.1 Money Flows and Competitive Skills Across Mutual Fund Organization Structures

This section examines the intricate relationship between mutual fund organizational structures and the competitive landscape of financial performance. Our investigation is grounded in the hypothesis that the competitiveness of the mutual fund industry can be effectively evaluated through a fund manager's adeptness in executing value-enhancing trades. This notion aligns with the core principles of investment management, where fund managers play a pivotal role in making investment decisions aimed at generating alpha or risk-adjusted excess returns. Nevertheless, quantifying the added value resulting from a manager's decisions presents a significant challenge in this highly competitive environment, particularly when performance assessment predominantly centers around net portfolio value.

Standard performance metrics often neglect the opportunity costs of inaction or alternative decisions. Furthermore, portfolio evaluation typically concentrates on cumulative managerial decisions, overlooking the potential value generated at specific moments or market conditions. Factors like those, combined with the challenges of disentangling returns from capital flow dynamics (Edelen 1999), make it difficult to accurately assess managerial skill and competitive behavior. Our identification strategy employs regression analysis in order to explore the connections between trade decisions, capital flows, and fund structures. By focusing on decision-making under specific capital flow dynamics, we can measure the value generated by managerial choices under different pressures. For instance, a portfolio might exhibit a negative alpha, suggesting poor performance, but this may not necessarily reflect a poor manager's decision-making - it could simply mean that the right choices were insufficient to offset adverse market conditions. Conversely, a positive alpha value might mask sub-optimal decisions, creating a false impression of managerial skill.

Our research aims to resolve this ambiguity by using selectivity measures that focus on the value generated by managers under specific capital flows. This allows us to more accurately assess the true competitive behavior of managers, irrespective of overall portfolio performance. Furthermore, we strive to understand how fund structures might influence a manager's ability to create portfolio value and impact industry competition. Our findings are valuable to industry participants, regulators, and academic researchers alike, aiding in understanding how fund structures shape competitive dynamics within the mutual fund industry.

4.1.1 Team vs. individual funds' management

Our analysis aims at understanding the decision-making process behind the dynamics of capital flows in mutual funds. We build upon the research conducted by Alexander et al. (2007), who found that, on average, fund managers cannot make liquidity-motivated trades that outperform a pool of similar securities, except for small sales during heavy outflows. However, their identification strategy is vulnerable to various issues. The authors combine dollar flows with transactions, and the resulting outcome is expressed in percentage of total assets, making it challenging to differentiate between valuable and liquidity-motivated trades.[22] Furthermore, they do not consider relevant factors influencing managers' buying and selling decisions, such as illiquidity exposure, investment style, or affiliation with a particular parent management company. Additionally, they overlook the potential impact of organizational structures on the vulnerability of portfolio values to industry-wide flow dynamics.

In contrast, our identification strategy allows us to separate transactions from flows, enabling us to explore all decisions independent of the dollar-size trading orders. Moreover, we ensure the robustness of our results by accounting for various fund characteristics that may influence the quality of managerial decisions. As an illustration, our analysis considers various factors, including historical returns, the necessity of compelled trades caused by exposure to illiquid assets, safeguards against flow pressures, fund size, management fees, and the impact of the parent company. By incorporating these controls, we capture the multifaceted nature of decision-making in mutual funds, as highlighted in prior studies (Chen et al. 2010; Chernenko and Sunderam 2016; Pástor et al. 2020; Agarwal et al. 2020; Gomez et al. 2020; Evans et al. 2020). Additionally, we go a step further by controlling for common variations within the investment style and family structure, mitigating cross-subsidization within conglomerates and industry disadvantages (Bhattacharya et al. 2013; Goncalves-Pinto and Schmidt 2013; Agarwal and Zhao 2019).

[22] The authors separate transactions based on the size from the combined metric. In the case of outflows, small sales lay down on expectations conditioned on the informative value; meanwhile, large sales respond to liquidity expectations. The previous is not always accurate and forces the authors to ignore large purchases on inflows and large sales on outflows.

To conduct a fair statistical inference and test our hypotheses, we employ an ordinary least squares (OLS) regression, comparing the trading decisions of team-managed funds versus individually-managed funds. We analyze these decisions under conditions of outflows and inflows to accurately distinguish between liquidity-motivated and value-motivated trades. Hence, the dependent variables are liquidity-motivated sales (SR) and purchases (PR). Our regression model includes control variables such as returns, cash, ease of trading (Amihud), loads, fund size, and family size. We incorporate fixed effects related to investment style, time, and family to address any confounding effects from unobserved common characteristics that may impact decision quality. Finally, we cluster standard errors at the fund level to support our hypothesis and ensure reliable statistical inference. The following equation describes our identification strategy and the incorporation of fixed effects in our regression analysis:

$$\begin{aligned}\{SR_{f,t}, PR_{f,t}\} = \lambda_{\text{Time}\times\text{Style}} + \lambda_{\text{Family}} + \beta \cdot \text{Team}_{f,t} \\ + \gamma \cdot \text{Controls}_{f,t-1} + \epsilon_{f,t}\end{aligned} \tag{10}$$

Table 3 presents the results of our regression analysis. For outflows, the coefficient of the "Team" variable is positive and statistically significant concerning liquidity-motivated sales. In the case of inflows, the coefficient of the "Team" variable about liquidity-motivated purchases is negative and statistically significant. On the one hand, our main findings indicate that compared to individual-managed, team-managed funds exhibit a superior ability to avoid possible losses in 11,49 basis points when they sell stocks to satisfy redemption claimants. The magnitude is economically significant compared to its standard deviation, representing approximately 216 basis points of the total variation from Sale selectivity.[23] We know that team-managed funds, on average, control portfolios appraised at 324.47 million; imagine that the fund needs to sell 5% of its assets to match withdrawals and, by doing it, deal with a loss of 2%, ending up with a portfolio of 301.75 million. However, team-managed funds can avoid losses that would be 2.1149 %, hence adding a value of $ 372 818 dollars, more than one-third of a million in a quarter, which is not observable when we follow the variation in the portfolio's value. If we would like to interpret the economic impact of the decision-making process in a hypothetical scenario where the portfolio needs to be liquidated, ceteris paribus, the process carried out by team-managed

[23]Given the nature of selectivity measures we follow Mitton (2022), and calculate the economic impact of the percentage of the standard deviation.

funds would avoid losses of around \$ 7 007 078 dollars. This value preservation is crucial for investors seeking to redeem their shares at the highest possible value.

On the other hand, our main findings in table 3 also show that the advantages perceived by team-managed funds under an outflow dynamic disappear when flows go in the opposite direction and even more exhibit disadvantages. Compared to individuals, the purchase decisions performed by groups produce lower quality in terms of opportunity costs as they include in the portfolio stocks generating 36,44 lower basis points than other available securities with similar risk characteristics. The magnitude is economically significant in approximately 638 basis points relative to its standard deviation. Suppose a team-managed fund receives 5% of its portfolio in cash due to new investors subscribing to the fund; let us assume that the team decides to use all the money to buy stocks instead of keeping a part as cash (zero opportunity cost), 16.223 million approximately. Then, instead of picking the best options available in the market, they decide to buy securities, generating 2% of profitability; consequently, the portfolio ends up with a value of 347.185 million instead of 348.367 million (a difference of \$ 1 182 377). If we would like to give an economic interpretation to the estimate in a hypothetical scenario, keeping everything else equal, a team-managed fund receiving money by the 100% of its current assets would quit earning \$ 20 701 687 dollars.

Furthermore, our analysis of control variables reveals additional insights.[24] For example, returns are positively associated with liquidity-motivated sales; meanwhile, the association is negative for liquidity-motivated purchases, indicating more persistence in the decisions at outflow dynamics. Higher cash holdings also contribute to greater selectivity in liquidity-motivated transactions, suggesting that managers with more cash can make better decisions. When examining the impact of illiquidity, we find that it does not significantly influence liquidity-motivated purchases. Fund size exhibits a positive and statistically significant impact, suggesting that larger funds tend to have higher selectivity on liquidity-motivated purchases. Finally, neither loads (which include redemption, deferred, and front loads), management fees, nor family size significantly influences selectivity measures.

The implications of our findings are twofold. First, team-managed funds demonstrate a superior

[24]It is important to note that our control variables should be interpreted cautiously, as they may have confounding effects due to correlated omitted variables. We aim to compare the differences between team-managed and individually-managed funds rather than explore how these control variables directly affect decision-making.

ability to avoid losses when selling stocks to satisfy redemption claimants during outflows. This indicates that the competitive decision-making process within teams enables them to make more informed and selective sales, protecting the portfolio from potential losses. On the other hand, team-managed funds face challenges in making high-quality purchase decisions under inflows, as they tend to include securities with lower profitability compared to individually-managed funds. This suggests that teams may struggle to identify the best investment opportunities when faced with a large cash inflow or that their investment targets differ from performing competitively around performance.

Table 3: Influence of Outflows and Inflows on Selectivity Measures

	Outflows		Inflows	
	(SR)	(SR)	(PR)	(PR)
Team	0.1259*	0.1149*	-0.2502	-0.3644**
	(0.0698)	(0.0691)	(0.1671)	(0.1723)
Returns	12.9329***	13.3688***	-4.8705***	-5.3304***
	(0.9986)	(1.0006)	(1.6386)	(1.6028)
Cash	0.0126**	0.0096*	0.0262***	0.0164**
	(0.0060)	(0.0054)	(0.0089)	(0.0078)
Illiquidity	0.1161***	0.0867***	-0.0089	0.0259
	(0.0175)	(0.0163)	(0.0368)	(0.0337)
Loads	-3.0610*	-1.8792	-4.5388	0.2059
	(1.7540)	(1.9213)	(3.7567)	(4.3564)
Fund Size	0.0063	0.0090	0.1502***	0.1446***
	(0.0224)	(0.0231)	(0.0430)	(0.0459)
Management Fee	0.6174	0.6892	-2.0395	-1.1765
	(0.6367)	(0.7412)	(1.3234)	(1.5035)
Family Size	-0.0011	0.0140	0.0090	0.0006
	(0.0201)	(0.0708)	(0.0427)	(0.1221)
Observations	31271	31271	14653	14653
Adjusted R2	0.131	0.143	0.111	0.146
Time x Style fixed effects	Yes	Yes	Yes	Yes
Family fixed effects	No	Yes	No	Yes

Note: The dependent variable in this analysis measures the selectivity of fund managers in terms of liquidity-motivated trades. Specifically, SR represents liquidity-motivated sales (sales under outflows), while PR indicates liquidity-motivated purchases (purchases under inflows). Outflows refer to current net flows ranging from 0% to -50%, while inflows correspond to current net flows ranging from 0% to 200%. Standard errors are provided in parentheses and are clustered at the fund level to account for potential within-fund correlation. Significance levels are denoted as *** for 1%, ** for 5%, and * for 10%. Control variables in the analysis are lagged by one period to capture the effect of past factors on the decision-making process. Fund Size and Family Size represent the natural logarithm of Total Net Assets (TNA), measuring the fund's size. Illiquidity is computed as the portfolio-weighted average of the Amihud (2002) illiquidity measure, which captures the level of illiquidity in the fund's holdings. To enhance interpretability, the Amihud measure is included in logarithmic form. Loads, including Redemption, Deferred, and Front loads, are combined to represent the cost associated with the fund's share classes. Management Fee is expressed quarterly, obtained by dividing the reported annual management fee by 4. By including these variables and fixed effects, we aim to control for potential biases in our statistical inference and provide a comprehensive analysis of the differences in decision-making between team-managed and individual funds.

4.1.2 Trading decisions with mediation by team characteristics

We explore now the mediating effects of team characteristics on the selectivity measures of team-managed funds. We aim to understand how these characteristics, such as Large Team Size, Ethnic Diversity, Team Age, Interconnected (Co-Management) Team, and Diverse Team Experience, mediate the ability of teams to generate value through their decision-making process, particularly in the context of liquidity-motivated trades.

To investigate this, we employ the same identification strategy used in the previous subsection, which compares the decision-making process of individual-managed and team-managed funds. The following equation describes the regression we employ to incorporate the characteristics of teams in the analysis. $SR_{f,t}$ and $PR_{f,t}$ represent liquidity-motivated sales and purchases respectively, $\lambda_{Time \times Style}$ and λ_{Family} denote time and investment style fixed effects, $Team_{f,t}$ represents a dummy variable indicating whether the fund is team-managed, $TeamChar_{f,t}$ represents the team characteristics, $Controls_{f,t-1}$ means the control variables lagged by one period, and $\epsilon_{f,t}$ is the error term. The variable $TeamChar_{f,t}$ takes a value of 0 if the fund is individually managed. This allows us to investigate the mediating effects of team characteristics.

$$
\begin{aligned}
\{SR_{f,t}, PR_{f,t}\} = \lambda_{\text{Time}\times\text{Style}} + \lambda_{\text{Family}} + \text{Team}_{f,t} + \\
\text{TeamChar}_{f,t} + \text{Controls}_{f,t-1} + \epsilon_{f,t} \\
\text{TeamChar}_{f,t} = \begin{cases} \neq 0, & \text{if Fund}_t \text{ is managed by a team} \\ 0, & \text{if Fund}_t \text{ is managed individually} \end{cases}
\end{aligned} \tag{11}
$$

As in the previous section, the same control variables are included and we set fixed effects set to ensure unbiased and reliable inference. Standard errors are clustered at the fund level to account for potential within-fund correlation. We present two tables in this subsection. The Table 1, "Mediating Effect of Large Team Size and Ethnic Diversity on Selectivity Measures," examines the mediating effects of Large Team Size and Ethnic Diversity on the selectivity measures of team-managed funds. The second table, "Impacts of Team Age, Diverse Experience, and Co-Management Connectivity on Selectivity Measures," explores the impacts of Team Age, Diverse Team Experience, and Interconnected (Co-Management) Team on the selectivity measures of team-managed funds.

Large Team size and Ethnic Diversity

This subsection explores the mediating effects of Large Team Size and Ethnic Diversity on the selectivity measures of team-managed funds, specifically in the context of liquidity-motivated sales (sales under outflows). We examine how these team characteristics influence the difference between team-managed and individual-managed funds around the decision-making process. Table 4 presents the regression analysis. The "Large Teams" coefficient in columns (1) and (3) shows a positive and statistically significant effect on liquidity-motivated sales. This suggests that team-managed funds with a larger team size have a greater ability to make decisions that generate value in the portfolio and be more competitive. For example, a team-managed fund with a team size of more than four managers exhibits a 0.1371% higher spread difference in liquidity-motivated sales than an individually-managed fund. This indicates that the presence of a larger team enhances the team's ability to make more selective sales decisions under the need to raise cash to satisfy withdrawal claimants.

Table 4 in columns (2) and (4) examines the mediating effect of "Diverse Team (Ethnicity)" on liquidity-motivated sales. The negative and statistically significant coefficient indicates that team-managed funds with greater ethnic diversity exhibit a lower competitive behavior than individuals, as their decisions add lower value to the portfolio. A team-managed fund with higher ethnic diversity, measured by the Blaus index, shows a 0.3455% smaller spread difference in liquidity-motivated sales. This suggests that a diverse ethnic team erodes the ability of teams to make selective sales when funds deal with outflows. These results support the social conflict theory and highlight the importance of effective communication in decision-making processes.

Furthermore, the coefficients for "Team" in columns (1) to (4) are no longer statistically significant when Large Team Size and Ethnic Diversity are included as mediating variables. This suggests that the significant variation in selectivity measures observed for team-managed funds disappears when considering team characteristics. These results indicate that small and homogeneous teams may still perform better liquidity-motivated sales than individuals, but the evidence is not strong enough to support these hypotheses. Overall, our findings suggest that Large Team Size and Ethnic Diversity mediate and even explain the decision-making process of team-managed funds, particularly in liquidity-motivated sales during outflows. Teams with a larger size and greater ethnic diversity exhibit a higher and smaller competitive behavior, respectively, compared to individually-managed funds. These results contribute to a better understanding of how team characteristics influence the differences observed between team-managed and individual-managed funds and highlight the importance of considering team composition in investment decision-making when funds deal with outflows.

Table 4: Team Characteristics and Liquidity-Motivated Sales

	Outflows			
	(1)	(2)	(3)	(4)
Large Teams	0.1371*		0.1371*	
	(0.0757)		(0.0757)	
Diverse Team (Ethnicity)		-0.3455*		-0.3455*
		(0.1827)		(0.1827)
Team	0.0520	0.1041	0.0520	0.1041
	(0.0701)	(0.0708)	(0.0701)	(0.0708)
Controls	Yes	Yes	Yes	Yes

Observations	31261	31409	31261	31409
Adjusted R2	0.141	0.151	0.141	0.151
Time x Style fixed effects	Yes	Yes	Yes	Yes
Family fixed effects	No	Yes	No	Yes

Note: The dependent variable in this analysis is SR representing liquidity-motivated sales (sales under outflows). Outflows pertain to current net flows from 0% to -50%. Standard errors are provided in parentheses and are clustered at the fund level. Significance levels are denoted as: *** for 1%, ** for 5%, and * for 10%. A large Team is a dummy equal to one when the number of managers within a team is superior to the fourth. Diverse Team (Ethnicity) indicates the Blaus index measure for ethnicity based on six categories (white, black, Indian and Pacific, Hispanic, Asian, and other). Control variables are lagged by one period. The controls included in the regression are Illiquidity (Ammihud), Return, Cash, Loads, Management Fee, Fund Size, and Family Size. Fund and Family Size represent the natural logarithm of Total Net Assets (TNA). Illiquidity represents the portfolio-weighted average of the Amihud (2002) illiquidity measure. For interpretability, we include Amihud in logarithms. Loads are computed as the sum of Redemption, Deferred, and Front loads. Management Fee is incorporated in quarterly dividing by four the annually reported information.

Impacts of Team Age, Diverse Experience, and Comanagement Connectivity on Investment Decisions

Table 5 presents the results of our regression analysis examining the relationship between team characteristics and liquidity-motivated purchases (purchases under inflows) in team-managed funds. We explore the impact of Team Age (Older), Interconnected (Co-Management) Team, and Diverse Team (Experience) on the selectivity measures. In Columns (1) and (4), we examine the effect of "Team Age" on liquidity-motivated purchases. The positive and statistically significant coefficients indicate that team-managed funds with older members exhibit a higher ability to make valuable buys than individuals. For example, our findings show that a team-managed fund with a more mature team exhibits a 0.0261% higher spread difference in liquidity-motivated purchases. This suggests that older teams better understand market dynamics and make more informed investment decisions, leading to competitive outcomes. Conversely, younger teams perform less competitively than individuals, with a spread difference of less than 1.28%. These results highlight the importance of maturity in investment decision-making.

Columns (2) and (5) focus on the effect of "Interconnected (Co-Management) Team" on selectivity measures. The negative and statistically significant coefficient indicates that team-managed funds with managers involved in co-management activities tend to erode their competitive outcomes in liquidity-motivated purchases. Specifically, for each one percent increase in managers engaged in co-management, the spread difference in purchases decreases by more than 0.50%. This suggests that communication and collaboration among team members closely related to competitors may hinder decision-making and result in less informative and value-generating decisions. On the other hand, while lacking statistical significance, the findings indicate that teams without managers overseeing other portfolios exhibit competitive behavior and contribute value through their purchasing decisions. These findings support the idea that effective communication and collaboration within the team, rather than with competitors, contribute to better investment decision-making.

Finally, in columns (3) and (6), we explore the impact of "Diverse Team (Experience)" on selectivity measures. The positive and statistically significant coefficients indicate that team-managed funds with diverse team members in terms of experience have a higher competitive behavior and generate value through their purchasing decisions compared to individuals. For each one percent increase in the experienced diverse index within teams, the spread difference in purchases increases by more than 0.38%. Conversely, completely homogeneous teams exhibit a spread difference of more than 0.52% lower than individuals, indicating poorer performance in generating value. These results suggest that teams with diverse experiences bring heterogeneous perspectives and approaches to investment decisions, enhancing the overall decision-making process and leading to competitive outcomes.

Overall, the results from Table 5 provide insights into the influence of team characteristics on the selectivity measures of team-managed funds during inflows. Team Age, Interconnected (Co-Management) Team, and Diverse Team (Experience) all play a role in determining the spread difference in liquidity-motivated purchases. These findings highlight the importance of team composition and dynamics in shaping the decision-making process and suggest that team characteristics can either increase or decrease the differences between team-managed and individual-managed funds. The results support existing theories around polarization, social comparisons, and persuasive argumentation. In addition, it also provides empirical evidence on the impact of age, experience, and team communication on investment decision outcomes.

Table 5: Team Characteristics and Liquidity-Motivated Purchases

	Inflows					
	(1)	(2)	(3)	(4)	(5)	(6)
Team Age (Older)	0.0261**			0.0215*		
	(0.0108)			(0.0113)		
Interconnected (Co-Management) Team		-0.5030**			-0.5005**	
		(0.2099)			(0.2248)	
Diverse Team (Experience)			0.4459**			0.3822**
			(0.2000)			(0.1930)
Team	-1.3746***	0.1749	-0.5219**	-1.2817**	0.0672	-0.5927***
	(0.5045)	(0.2411)	(0.2085)	(0.5225)	(0.2601)	(0.2141)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13978	14882	11222	13978	14882	11222
Adjusted R2	0.110	0.111	0.105	0.142	0.146	0.141
Time x Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Family fixed effects	No	No	No	Yes	Yes	Yes

Note: The dependent variable in this analysis is PR, indicating liquidity-motivated purchases (Purchases under inflows). Inflows correspond to current net flows within the range of 0% to 200%. Standard errors are provided in parentheses and are clustered at the fund level. Significance levels are denoted as *** for 1%, ** for 5%, and * for 10%. Team Age (Older) is a dummy that equals one when the Team Age overcomes the 40-year-old rank. An interconnected (Co-Management) Team is the proportion of managers with co-management activities. A diverse Team is the coefficient of variation around experience, i.e., the number of years a manager is in the asset management industry. Control variables are lagged by one period. The controls included in the regression are Illiquidity (Ammihud), Return, Cash, Loads, Management Fee, Fund Size, and Family Size. Fund and Family Size represent the natural logarithm of Total Net Assets (TNA). Illiquidity represents the portfolio-weighted average of the Amihud (2002) illiquidity measure. For interpretability, we include Amihud in logarithms. Loads are computed as the sum of Redemption, Deferred, and Front loads. Management Fee is incorporated quarterly by dividing the annual reported information into four.

4.2 Swaying Managerial Behavior: Unleashing the Influence of Investor Flows in Team-Managed Funds

In this subsection, we explore the economic mechanisms that explain the differentiated results between team-managed and individual-managed structures within the active mutual fund industry, specifically regarding their ability to make value-adding decisions for the portfolio. We investigate the power of investors to discipline managers through capital flows, which can influence the portfolio's value and subsequently impact managers' reputations, compensation, and job security.

The literature has examined various mechanisms for monitoring managers to protect investors' interests. The mechanisms explored include investment constraints, the role of the board of directors, and the free movement of capital. Team structures, in particular, may be prone to agency problems between managers and investors, as it can be challenging for investors to assess the behavior of each team member. This can lead to shared responsibilities and the sharing of costs and benefits arising from their actions. Previous studies have found that teams may be more constrained in their trading actions, such as short-selling, margin purchases, borrowing money, investing in derivatives, and dealing with restricted securities (Almazan et al. 2004). However, other research has shown that teams operating under independent boards can be more competitive than individuals and generate superior performance outcomes (Adams et al. 2018).

We analyze the influence of investors on managerial behavior through the dynamics of capital flows, regardless of whether managers are constrained or operating under the supervision of independent boards. Importantly, our differentiated results between teams and individuals regarding liquidity-motivated trades are independent of investment constraints or the effectiveness of board monitoring. This is because our selectivity measures focus solely on purchasing and selling stocks, so ignoring the role of constraints or the board does not impact our findings. We find that team-managed funds exhibit better decision-making during outflows, even though some teams may face more constraints in managing liquidity claimants. Additionally, if teams have more effective board monitoring, this should manifest in outflows and inflows. However, our findings indicate that the decision-making of teams during inflows does not add value to the portfolio, suggesting that the role of boards cannot explain our results. Instead, we argue that the behavior of managers is influenced by the direct monitoring role exercised by investors.

We follow the literature to explore this monitoring mechanism and examine the flow-performance relationship. This relationship helps us understand when managers are disciplined and which organizational structure is more likely to be monitored by investors. Previous studies have shown that future flows depend on past performance and that the relationship is often convex, meaning that overperformers are rewarded more than underperformers (Sirri and Tufano 1998; Guercio and Tkac 2002). However, there is also a clientele effect, where the relationship can be reversed depending on the type of investors involved. Sophisticated investors may penalize underperformers more than reward overperformers in a competitive market (Ferreira et al. 2012). Moreover, the liquidity of stocks within the portfolio and the availability of liquidity management tools like redemption-in-kind can influence how investors discipline managers (Chen et al. 2010; Agarwal et al. 2020).

Despite previous research on the flow-performance relationship, no study has explored how investors penalize or reward different organizational structures based on the performance outcomes resulting from managerial activities. By examining the flow-performance relationship, we aim to understand how investors react to the observable consequences of managerial decisions. We seek to explain why team-managed funds exhibit differences in their ability to make valuable liquidity-motivated trades based on flow dynamics. Although investors may not directly observe the value generated from these actions, it is crucial to understand the significance of managerial decisions in the stability and growth of a portfolio. The unobserved consequences may not directly explain the flow dynamics, but the direction of flows can provide insights into the value of those decisions.

The identification strategy for estimating the relationship between net flows and past performance, considering the influence of team management, can be expressed as follows: The dependent variable is the net flows of fund f at time $t+1$ denoted as $NetFlows_{f,t+1}$. We include fixed effects to control for time and investment style variations ($\lambda_{Time \times Style}$) and family-level variations (λ_{Family}). The variable $Team_{f,t}$ equals one when two or more managers manage the portfolio. We consider two components of past performance: negative performance ($NegPerf_{f,t}$) and positive performance ($PosPerf_{f,t}$). These components capture the effects of past performance on net flows. If the risk-adjusted performance ($\alpha^4_{f,t}$) is negative, we assign its value to $NegPerf_{f,t}$; otherwise, $NegPerf_{f,t}$ is set to zero. Similarly, if $\alpha^4_{f,t}$ is positive, we assign its value to $PosPerf_{f,t}$; otherwise, $PosPerf_{f,t}$ is set to zero. We include interaction terms between performance components and team management: $NegPerf_{f,t} \times Team_{f,t}$ and $PosPerf_{f,t} \times Team_{f,t}$. These terms capture the differential effects of performance on net flows for team-managed funds compared to individually managed funds.

By estimating this model, we aim to understand how net flows respond to past performance and team management while controlling for other influential factors and unobserved variations. The coefficients of interest are those associated with the interaction terms, which indicate the differential impact of performance on net flows for team-managed funds compared to individually managed funds. This identification strategy provides a robust method for analyzing the specific effects of past performance and team management on net flows, contributing to our understanding of investor behavior and the competitive dynamics between team-managed and individually managed funds.

$$
\begin{aligned}
\text{NetFlows}_{f,t+1} = &\lambda_{\text{Time}\times\text{Style}} + \lambda_{\text{Family}} + \text{Team}_{f,t} + \\
&\text{NegPerf}_{f,t} + \text{PosPerf}_{f,t} + \\
&\text{NegPerf}_{f,t} \times \text{Team}_{f,t} + \\
&\text{PosPerf}_{f,t} \times \text{Team}_{f,t} + \\
&\text{Controls}_{f,t} + \epsilon_{f,t}
\end{aligned}
\tag{12}
$$

$$
\begin{aligned}
\text{NegPerf}_{f,t} &= \begin{cases} \alpha^4_{f,t}, & \text{if } \alpha^4_{f,t} < 0 \\ 0, & \text{if } \alpha^4_{f,t} \geq 0 \end{cases} \\
\text{PosPerf}_{f,t} &= \begin{cases} \alpha^4_{f,t}, & \text{if } \alpha^4_{f,t} > 0 \\ 0, & \text{if } \alpha^4_{f,t} \leq 0 \end{cases}
\end{aligned}
\tag{13}
$$

Table 6 presents the regression analysis results examining the impact of past performance and team management on future net flows in the mutual fund industry. The table is divided into redemptions (outflows) and subscriptions (inflows). The coefficients for the variables "NegPerf" and "PosPerf" indicate the relationship between past performance and future net flows. Both sections' coefficients are highly significant and positive, suggesting that past performance plays a significant role in attracting future net flows. Specifically, investors tend to redeem from funds with negative past performance and subscribe to funds with positive past performance.

The interaction terms "NegPerf x Team" and "PosPerf x Team" examine the influence of team management on the flow-performance relationship. In the redemptions section, team-managed funds exhibit a stronger flow-performance relationship than individually managed funds when experiencing inadequate performance. This finding aligns with the notion that teams require stricter monitoring rules. However, in the subscriptions section, team-managed funds are not penalized differently from individually managed funds when exhibiting differentiated performance. This suggests that investors do not adequately reward team-managed funds for their competitive behavior during inflows.

The coefficient for the variable "Team" represents the overall effect of team management on future net flows. Although positive, the impact of team management on net flows is minimal compared to other factors, indicating that team management alone does not significantly influence the flow-performance relationship. Control variables such as "Flows," "Fund Size," "Age," "Expense Ratio," and "Loads" are included to account for other factors affecting future net flows. These variables exhibit associations with net flows consistent with prior research, such as persistent flows, greater flows for younger funds, size constraints on fund growth, and investor preference for lower expense ratio funds (Sirri and Tufano 1998; Chen et al. 2004).

In summary, the results indicate that positive past performance positively affects future net flows, while negative past performance negatively impacts. Team management does not significantly impact the flow-performance relationship during inflows. However, during outflows, team-managed funds exhibit a stronger flow-performance relationship when experiencing inadequate performance and a weaker relationship when performing well. This suggests that investors closely monitor team-managed funds during outflows but gain more flexibility in their actions during inflows, as investors neither penalize nor reward their competitive behavior. These findings provide insight into the differentiated behavior of team-managed funds based on the flow dynamics and highlight the role of investor monitoring in shaping their behavior.

Table 6: Past Performance and Team Management on Future Net Flows

	Future NetFlows					
	Redemptions			Subscriptions		
	(1)	(2)	(3)	(4)	(5)	(6)
NegPerf	0.8727***	0.9168***	0.8927***	1.5643***	1.5917***	1.3992***
	(0.1602)	(0.1633)	(0.1607)	(0.3170)	(0.3363)	(0.3606)
PosPerf	1.6934***	1.7091***	1.7278***	2.1692***	2.2220***	2.4094***
	(0.5277)	(0.5311)	(0.5307)	(0.3735)	(0.3798)	(0.3687)
NegPerf x Team	0.4055**	0.4285**	0.3733**	0.5464	0.5598	0.3329
	(0.1872)	(0.1878)	(0.1839)	(0.3910)	(0.4025)	(0.4164)
PosPerf x Team	-1.0272*	-1.0065*	-0.9242	0.3723	0.3479	0.0804
	(0.5595)	(0.5656)	(0.5669)	(0.4439)	(0.4461)	(0.4307)
Team	0.0020	0.0022	0.0011	0.0036	0.0038	0.0048
	(0.0022)	(0.0022)	(0.0024)	(0.0039)	(0.0040)	(0.0043)
Flows	0.1726***	0.1690***	0.1586***	0.2075***	0.2048***	0.1951***
	(0.0276)	(0.0275)	(0.0226)	(0.0161)	(0.0159)	(0.0153)
Fund Size	-0.0035***	-0.0034***	-0.0058***	-0.0040***	-0.0042***	-0.0109***
	(0.0004)	(0.0005)	(0.0006)	(0.0007)	(0.0008)	(0.0010)
Age	-0.0019*	-0.0018*	-0.0013	-0.0171***	-0.0169***	-0.0127***
	(0.0010)	(0.0010)	(0.0012)	(0.0019)	(0.0019)	(0.0020)
Expense Ratio	-0.3977*	-0.2990	-0.8095***	-0.6851**	-0.8343**	-0.1916
	(0.2064)	(0.2366)	(0.2323)	(0.3248)	(0.3662)	(0.4143)
Loads	0.0623**	0.0670**	-0.0077	-0.1606***	-0.1649***	-0.2954***
	(0.0274)	(0.0280)	(0.0397)	(0.0580)	(0.0584)	(0.0768)
Observations	45275	45275	45275	25059	25059	25059
Adjusted R2	0.028	0.029	0.047	0.116	0.119	0.143
Time x Style fixed effects	No	Yes	Yes	No	Yes	Yes
Family fixed effects	No	No	Yes	No	No	Yes
Year fixed effects	Yes	No	No	Yes	No	No

Note:

This regression analysis examines the flow-performance relationship and investigates how future net flows respond to past performance measures, considering team management's influence. Standard errors are provided in parentheses and are clustered at the fund level. Significance levels are denoted as *** for 1%, ** for 5%, and * for 10%. Following Agarwal et al. (2020), we divide performance into negative ($NegPerf$) and positive ($PosPerf$) components to capture both effects. The overall performance (α^4) is the sum of these two components. We estimate α^4 using Carhart (1997)fourth-factor model, where the intercept represents the risk-adjusted performance. Our analysis focuses on how investors react to managers' past performance, considering whether the funds are team-managed or individually managed. The variable "Team" equals one when two or more managers manage a portfolio. We control for various factors such as flows, fund size, age, expense ratio, and loads, following prior literature (Sirri and Tufano 1998; Guercio and Tkac 2002; Chen et al. 2010; Ferreira et al. 2012). Flows are expressed as quarterly net flows; fund size and age are the natural logarithm of total net assets and the years since the first share class was offered, respectively. The expense ratio is expressed annually; loads represent the sum of the front, deferred, and redemption loads. We incorporate fixed effects at the time, investment style, family, and year levels to control for unobserved confounding variations.

4.3 Organizational structure, competitive behavior, and future performance

This subsection explores the competitive dynamics between organizational structures, specifically team-managed structures, and their impact on fund performance according to flow dynamics. Compared to individual-managed, team-managed structures exhibit a more competitive behavior when dealing with redemptions, making trading decisions that add value to the portfolio. This pattern suggests that team-managed funds can generate better risk-adjusted performance than individual-managed funds.

We employ an identification strategy to investigate the implications of this competitive behavior on future performance. The dependent variable, α^{OS}, represents the out-of-sample future performance of a mutual fund at the time (t+1). Our identification includes fixed effects at the time and family levels to account for time and family-specific factors that may influence fund performance. On the right-hand side of our regression, we introduce Outflows, a binary variable that captures whether the fund experienced net outflows during the current period. Additionally, we consider the variable Team, which indicates whether the fund is team-managed or not. The interaction term Team $\times$ Outflows examines whether the effect of outflows on performance differs between team-managed and individual-managed funds. To ensure the robustness of our analysis, we incorporate control variables suggested by Agarwal et al. (2020). These variables include returns, fund size, and expense ratio, which help account for other factors affecting fund performance.

This regression analysis aims to shed light on the relationship between team-managed structures, their competitive behavior in response to redemptions, and the subsequent risk-adjusted performance delivered to investors. Through an in-depth exploration of this relationship, we validate our initial findings concerning competitive behavior and gain valuable insights into the implications for investors and the effectiveness of investor monitoring mechanisms. Overall, our study provides a comprehensive analysis of the impact of organizational structures and investor flows on fund performance, contributing to a better understanding of the dynamics within the mutual fund industry.

$$\begin{aligned} \alpha^{OS}_{f,t+1} = \lambda_{\text{Time}\times\text{Style}} + \lambda_{\text{Family}} + \text{Outflows}_{f,t} + \\ \text{Team}_{f,t} + \text{Team}_{f,t} \times \text{Outflows}_{f,t} + \text{Controls}_{f,t} + \epsilon_{f,t} \\ \text{Outflows}_{f,t} = \begin{cases} 1, & \text{if NetFlows}_{f,t} < 0 \\ 0, & \text{if NetFlows}_{f,t} \geq 0 \end{cases} \end{aligned} \tag{14}$$

Table 7 presents results from a regression analysis examining the performance predictability of mutual funds, focusing on performance before and after expenses. The variable "Outflows" demonstrates a significant negative coefficient across all models. This indicates that funds experiencing redemptions face a worrisome erosion in the upcoming risk-adjusted performance, with an average impact exceeding 0.36%. This represents a staggering economic impact of 18.73% of the total performance variation. These results highlight the detrimental effect of unhappy departing investors on the portfolio's value, regardless of whether managers operate alone or within groups. Importantly, this result is consistent with prior literature, underscoring the strong predictive power of outflows on future fund performance (Edelen 1999; Coval and Stafford 2007; Chen et al. 2010; Agarwal et al. 2020).

The interaction term "Team x Outflows", indicates that team-managed funds outperform individually managed funds under similar outflows conditions. On average, team-managed funds mitigate the erosion dynamic by more than 0.10%, reducing the economic impact by approximately 8% of the total variation in risk-adjusted performance. These findings confirm the competitive behavior of team-managed funds when faced with redemptions and highlight the advantages of having differentiated behavior compared to individual-managed structures. Investors in team-managed funds can benefit from a protective bonus over their capital.

The coefficient for the variable "Team" reveals a significant negative effect, indicating that team-managed funds exhibit lower risk-adjusted upcoming performance compared to individually managed funds in the absence of outflows, such as during periods of inflows. On average, managers operating within groups are associated with a decline in risk-adjusted performance by more than 0.063%, representing an economic impact of 3.15% of the total performance variation. These findings suggest a lack of competition within team-managed structures when they receive new subscriptions, highlighting the importance of monitoring their behavior even in such circumstances. Importantly, these results remain robust after controlling for expenses, indicating that the impact on performance is primarily driven by the behavioral patterns of team-managed structures rather than expense-related factors. On the other hand, including control variables further underscores the relevance of certain factors in signaling a manager's future performance. For instance, the persistence of returns, even over six months, indicates the ability of managers to consistently align their actions with investors' interests in the short term. Additionally, the non-linear relationship between portfolio size and performance is important in predicting upcoming performance.

Our findings provide valuable insights into the significance of organizational structures in explaining managerial behavior and the associated costs and benefits based on flow dynamics. Compared to individual-managed funds, team-managed funds incur performance variation costs/benefits of approximately 3%/8% under inflows/outflows dynamics, resulting in an overall benefit of 5%. This finding helps explain the growing popularity of team-managed funds over the past two decades. It is essential to acknowledge the challenge of directly connecting the value generated from managerial decisions to the risk-adjusted performance that investors face and observe. However, our analysis of organizational structures sheds light on the non-observable opportunity cost not incorporated within the portfolio, highlighting its tremendous implications for stability and emphasizing the need for caution among investors and regulators when evaluating the behavior of fund managers. These results underscore the intricate dynamics and provide valuable insights for informed decision-making.

Overall, the results highlight the importance of team-managed structures within mutual funds and how teams provide advantages to investors despite the existing costs and benefits from the flow dynamics. However, it also reinforces the importance of monitoring and understanding the behavior of fund managers in the face of investor flows to ensure their performance aligns with investors' interests, even during inflows. The results have significant implications for industry practitioners and regulatory bodies, emphasizing the need to carefully consider organizational structures and their potential impact on fund performance.

Table 7: Performance Predictability:Organizational Structures and Outflows Pressure

	Net Performance		Gross Performance	
	(1)	(2)	(3)	(4)
Outflows	-0.3606***	-0.3827***	-0.3637***	-0.3864***
	(0.0221)	(0.0228)	(0.0226)	(0.0233)
Team x Outflows	0.1080***	0.1145***	0.1069***	0.1148***
	(0.0239)	(0.0245)	(0.0244)	(0.0250)
Team	-0.0733***	-0.0632***	-0.0730***	-0.0633***
	(0.0169)	(0.0182)	(0.0170)	(0.0183)
Returns	2.1238***	2.2915***	2.2206***	2.3856***
	(0.2008)	(0.2048)	(0.2081)	(0.2127)
One Lag Returns	4.4865***	4.5646***	4.2255***	4.3142***
	(0.2153)	(0.2186)	(0.2151)	(0.2186)
Fund Size Squared	0.0125***	0.0228***	0.0128***	0.0229***
	(0.0011)	(0.0014)	(0.0011)	(0.0014)
Expense Ratio	9.8681***	5.9151***	34.3507***	30.5048***
	(0.9879)	(1.2746)	(0.9898)	(1.2911)
Observations	155479	155479	151504	151504
Adjusted R2	0.152	0.153	0.153	0.154
Time x Style fixed effects	Yes	Yes	Yes	Yes
Family fixed effects	No	Yes	No	Yes

Note:

The table presents the results of a regression analysis examining the performance predictability of mutual funds. The dependent variable is the out-of-sample Carhart Risk-Adjusted return in the following period α_{t+1}^{OS}. The table is divided into two sections: net performance and gross performance, allowing us to assess the managers' ability to generate performance and its impact on investors' interests separately. Standard errors are provided in parentheses () and are clustered at the fund level. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively. "Outflows" is a binary variable equal to one when net flows range from 0% to -50%, capturing the impact of outflow pressure on performance. "Team" is a binary variable that equals one when two or more managers manage activities within the portfolio, indicating team management. Control variables include "Returns," "One Lag Returns," "Fund Size Squared," and "Expense Ratio," following the approach of Agarwal et al. (2020). Returns are expressed quarterly by monthly, compounding the reported returns, and the lag on returns is included to control for performance predictability. Fund Size is squared to capture the potential non-linear relationship between performance and fund size. The Expense Ratio is expressed in annual terms. The table includes fixed effects for time, style, and family, accounting for their impact on performance.

4.4 Robustness

4.4.1 Informative Decisions and the Correct Assessment of Managerial Competition

We address alternative hypotheses that could potentially explain the differences between team-managed and individual-managed funds, focusing on the ability of fund managers to generate value through their trading decisions. We aim to confirm that the observed differences in performance between these two types of funds are not spurious but result from an informed decision-making process. We conduct a specialized analysis focusing on a subset of transactions under specific flow dynamics to test this hypothesis. Specifically, we narrow our focus to two types of transactions: liquidation sales and initiation purchases. By examining these specific transactions, we can gain insights into the informative nature of managers' trading decisions.

In the case of liquidation sales, it is known that less desirable stocks are more difficult to liquidate due to higher trading execution costs. Skillful managers, who follow an informed decision-making process, are expected to avoid aggressive selling in the market and instead opt for partial sales of these stocks to reduce exposure and minimize losses. This strategic approach allows managers to meet redemptions while maintaining portfolio value. Thus, if managers' selling decisions reflect an informative process, we should observe a higher proportion of partial sales for less desirable stocks. Regarding initiation purchases, managers often invest in their most promising ideas based on superior information. As funds grow and managers receive more capital, they may continue investing in familiar stocks or explore new stocks in which they lack experience. Initiation purchases reflect managers' informed decisions at the moment of stock selection. If these decisions result in value generation ex-post, it suggests that the decision to invest in a new stock was supported by valuable information. Conversely, if the outcome of these purchases is negative, the decisions may have been speculative or influenced by factors unrelated to value generation.

We capture the value generated by this subset of transactions by focusing on these special transactions and examining the selectivity measures, namely Liquidation-Sale Return (LSR) and Initiation-Purchase Return (IPR). Our analytical model incorporates fixed effects to control for time variations and investment style differences among fund families. This allows us to isolate the influence of our main variable of interest, whether the fund is team-managed or individually managed. Additionally, we include a set of control variables to account for other potential factors that may influence the decision-making process. We believe that this identification strategy provides a robust method for understanding the specific impacts of team versus individual management on the subset of special transactions within mutual funds. By focusing on these transactions and employing our informative process-based model, we aim to shed light on the distinct effects of team and individual management on fund performance.

$$\begin{aligned} \{LSR_{f,t}, IPR_{f,t}\} = \lambda_{\text{Time}\times\text{Style}} + \lambda_{\text{Family}} + \beta \cdot \text{Team}_{f,t} \\ + \gamma \cdot \text{Controls}_{f,t-1} + \epsilon_{f,t} \end{aligned} \tag{15}$$

Table 8 presents regression analysis that examine the differences in informative liquidity-motivated trades between team-managed and individual funds. The dependent variable measures the selectivity of fund managers in terms of special informative liquidity-motivated trades.

In the first two columns of the table, we focus on the effect of team management on liquidity-motivated liquidation sales (LSR) under outflows. The coefficient for the variable "Team" is positive but not statistically significant. This suggests no significant difference in selectivity measures between team-managed and individual-managed funds during outflows. The lack of significance indicates that team management does not directly impact the ability to liquidate stocks. Instead, the disparities observed in stock selection for selling can be ascribed to the dynamics of portfolio contraction, wherein managers strategically divest from stocks they perceive as less valuable without resorting to drastic selling measures that might undervalue the assets. These findings support the idea that team-managed funds, compared to individual-managed funds, exhibit a competitive advantage in utilizing information within their decision-making process to raise cash.

Moving on to the last pair of columns, we focus on team management's effect on liquidity-motivated initiation purchases (IPR) under inflows. Here, the variable "Team" coefficient is negative and statistically significant. This indicates that team-managed funds exhibit lower selectivity in purchasing decisions than individual-managed funds during inflows. The results suggest that team-managed funds, relative to their individual-managed counterparts, are less capable of expanding their portfolios and accommodating subscriptions in a way that adds value. This implies that the decision to incorporate new stocks into the portfolio by utilizing the investor's new money is driven by factors other than competition and an informed decision-making process.

In summary, the findings from Table 8 reveal that team management does not significantly affect the selectivity measures in liquidity-motivated liquidation sales during outflows. However, team-managed funds exhibit lower selectivity in liquidity-motivated initiation purchases during inflows than individual-managed funds. These results suggest that team-managed funds may face challenges in generating value through their purchasing decisions when dealing with inflows due to factors beyond competition influencing their decision-making process.

Table 8: Informative Liquidity Motivated Trades: Individual-managed vs Team-management Funds

	Outflows		Inflows	
	(LSR)	(LSR)	(IPR)	(IPR)
Team	0.0996	0.0535	-0.4144*	-0.5363**
	(0.1253)	(0.1253)	(0.2139)	(0.2273)
Returns	9.9064***	10.6700***	-3.3371	-3.3738
	(1.6409)	(1.6554)	(2.5332)	(2.5243)
Cash	0.0287***	0.0256***	0.0320***	0.0247**
	(0.0085)	(0.0076)	(0.0124)	(0.0112)

Illiquidity	0.1714***	0.1307***	0.0674	0.1134**
	(0.0279)	(0.0256)	(0.0516)	(0.0504)
Loads	-8.4323***	-4.2016	0.9327	7.6804
	(2.7551)	(2.9267)	(4.9191)	(6.6875)
Fund Size	0.0003	0.0063	0.0825	0.0703
	(0.0384)	(0.0397)	(0.0583)	(0.0649)
Management Fee	0.2053	0.0771	1.6286	2.0262
	(1.1156)	(1.2327)	(1.7047)	(2.0769)
Family Size	0.0632*	0.1184	0.0695	0.1188
	(0.0327)	(0.1239)	(0.0568)	(0.1651)
Observations	29897	29897	14033	14033
Adjusted R2	0.057	0.068	0.058	0.079
Time x Style fixed effects	Yes	Yes	Yes	Yes
Family fixed effects	No	Yes	No	Yes

Note:

The dependent variable in this analysis measures the selectivity of fund managers in terms of Special informative liquidity-motivated trades. Specifically, LSR represents liquidity-motivated Liquidation Sales (liquidate sales under outflows), while PR indicates liquidity-motivated Initiation Purchases (initiative purchases under inflows). Outflows refer to current net flows ranging from 0% to -50%, while inflows correspond to current net flows ranging from 0% to 200%. Standard errors are provided in parentheses and are clustered at the fund level to account for potential within-fund correlation. Significance levels are denoted as *** for 1%, ** for 5%, and * for 10%. Control variables in the analysis are lagged by one period to capture the effect of past factors on the decision-making process. Fund Size and Family Size represent the natural logarithm of Total Net Assets (TNA), measuring the fund's size. Illiquidity is computed as the portfolio-weighted average of the Amihud (2002) illiquidity measure, which captures the level of illiquidity in the fund's holdings. To enhance interpretability, the Amihud measure is included in logarithmic form. Loads, including Redemption, Deferred, and Front loads, are combined to represent the cost associated with the fund's share classes. Management Fee is expressed quarterly, obtained by dividing the reported annual management fee by 4. By including these variables and fixed effects, we aim to control for potential biases in our statistical inference and provide a comprehensive analysis of the differences in decision-making between team-managed and individual funds.

4.4.2 Cash intensity

Our study examines the liquidity-motivated trading behavior of team-managed funds compared to individual-managed funds. We find that team-managed funds exhibit better liquidity-motivated trades during outflows and poorer liquidity-motivated purchases than individual-managed funds. This suggests that team-managed funds alter their trading decisions in response to investor redemptions, indicating a behavioral change driven by investor discipline. However, it is important to consider alternative explanations for these findings. Instead of team-managed funds making superior or inferior trading choices, they could avoid making poor selling decisions by reducing their cash holdings to meet withdrawal demands. Conversely, individual-managed funds may avoid making poor purchasing decisions by accumulating more cash during inflows. This raises the question of whether the differences in competitiveness and value generation between team-managed and individual-managed funds are influenced by how they manage their cash holdings in response to flow dynamics.

We have conducted a comprehensive analysis to investigate the adjustment of cash holdings in team-managed and individual-managed funds. Our primary objective was to determine whether the observed differences in performance and competitive behavior between these two types of funds were driven by deliberate trading strategies or cash-holding advantages. We aimed to uncover the underlying mechanisms behind these differences by examining their response to flow dynamics.

To achieve this, we explored several scenarios. First, we considered the possibility that individual-managed funds, with their greater flexibility in holding larger cash positions, significantly reduced their cash holdings during redemptions compared to team-managed funds. If this were the case, and team-managed funds still exhibited superior trading decisions, it would suggest that the advantage lies in their informational superiority. Conversely, if team-managed funds reduced their cash holdings more than individual-managed funds during redemptions, it could imply that their better decision-making stemmed from avoiding poor sales by decreasing cash holdings. However, we anticipate this scenario as unlikely, as team-managed funds generally hold less cash and have limited flexibility to employ such a strategy.

We also considered the behavior of team-managed funds in response to subscriptions. Given that team-managed funds typically hold less cash than individual-managed funds, we explored whether they responded to capital injections by accumulating more cash. Such a defensive move could indicate a reluctance to expand the portfolio through valuable and informed investment decisions. Conversely, if team-managed funds accumulated less cash than individual-managed funds during capital injections, it would suggest that their inferior competitive behavior resulted from individual-managed funds strategically accumulating cash to avoid poor trades. However, this scenario is unlikely due to the constraints faced by individual-managed funds, as holding excessive cash could send negative signals to investors about their ability to invest in equity stocks effectively.

Drawing from the research conducted by Chernenko and Sunderam (2016, 2020), we employed regression analysis to examine the adjustment of cash holdings in response to flow dynamics. The dependent variable in our study was the changes in cash holdings (Δ^{Cash}) between consecutive periods. We defined redemptions and subscriptions as negative and positive net flows, respectively. Additionally, we incorporated a binary variable, "Team," which takes a value of one when two or more managers oversee the same portfolio. We interacted with the "Team" variable with "Redemptions" and "Subscriptions" to assess differences in cash accommodation based on flow dynamics. To control for any unobserved confounding effects, we included a set of fixed effects in our analysis.

$$\begin{aligned}\Delta^{\text{Cash}}_{f,t} = {} & \text{Redemptions}_{f,t} + \text{Subscriptions}_{f,t} \\ & + \text{Redemptions}_{f,t} \times \text{Team}_{f,t} + \text{Subscriptions}_{f,t} \times \text{Team}_{f,t} \\ & + \text{Team} + \epsilon_{f,t}\end{aligned} \tag{16}$$

Table 9 presents the relationship between cash holdings and flow dynamics for team-managed and individual-managed funds. The findings show that funds experiencing withdrawals reduce their cash holdings by more than 0.98%, while funds receiving injections increase their cash holdings by more than 0.86%. These results are consistent with previous research conducted by Chernenko and Sunderam (2016), which supports the link between cash holdings and flow dynamics in mutual funds.

Examining the differences between team-managed and individual-managed funds, we observe that team-managed funds exhibit a reduction in cash holdings of more than 0.27% when facing outflows. Despite having less cash available, team-managed funds intensify their use of cash during outflows, although this result lacks statistical significance. Consequently, we cannot definitively attribute the better performance of team-managed structures to their ability to avoid poor sales by reducing cash holdings. However, the results indicate that team-managed funds are superior to individual-managed funds in making informed selling decisions, which their investors closely monitor.

On the other hand, individual-managed funds increase their cash holdings by less than 0.36% when dealing with inflows compared to team-managed funds. This suggests that team-managed funds increase their cash holdings to a lesser extent when receiving injections of money, despite holding less cash overall. The negative coefficient implies that the lower competitive behavior of team-managed funds during subscriptions may be influenced by a cash management strategy employed by individual-managed funds to avoid poor purchases. However, further analysis is required to draw definitive conclusions as we don't find enough statistical evidence. Nevertheless, the results emphasize that the inferior competitive behavior of team-managed funds during subscriptions can be attributed to uninformative choices that their investors do not monitor closely.

The findings indicate no significant differences in cash intensity between team-managed and individual-managed funds in response to flow dynamics. This suggests that the ability of team-managed funds to differentiate their decision-making is not driven by a strategy to avoid poor trades based on cash holdings. The insights provided by Table 9 contribute to our understanding of the relationship between cash intensity and flow dynamics in different types of fund management. While the coefficients for "Redemptions" and "Subscriptions" reveal the impact of withdrawals and injections on cash holdings, the non-significant results for "Redemptions x Team" and "Subscriptions x Team" suggest that the decision-making behavior of team-managed funds is not influenced by cash intensity as a response to flow dynamics.

Table 9: Cash Intensity and Flow Pressures: Team-managed and Individual-managed Differences

	Changes in Cash Holdings					
	(1)	(2)	(3)	(4)	(5)	(6)
Redemptions	0.9815**	1.2221**	0.9507**	1.1903**	0.9851**	0.9907**
	(0.4741)	(0.5452)	(0.4740)	(0.5446)	(0.4974)	(0.5003)
Subscriptions	0.8612***	1.0371***	0.8718***	1.0497***	0.8858***	0.9114***
	(0.1852)	(0.2132)	(0.1853)	(0.2128)	(0.1922)	(0.1926)
Redemptions x Team	0.3031	0.2714	0.3320	0.2949	0.3336	0.3598
	(0.5239)	(0.5912)	(0.5239)	(0.5912)	(0.5418)	(0.5440)
Subscriptions x Team	-0.2825	-0.3546	-0.2944	-0.3699	-0.2946	-0.3134
	(0.2248)	(0.2534)	(0.2242)	(0.2524)	(0.2319)	(0.2312)

Team	0.0276	0.0137	0.0292	0.0151	0.0265	0.0243
	(0.0193)	(0.0282)	(0.0194)	(0.0283)	(0.0215)	(0.0217)
Observations	130176	130176	130176	130176	130176	130176
R^2	0.005	0.017	0.009	0.021	0.004	0.012
Time fixed effects	Yes	Yes	No	No	No	No
Fund fixed effects	No	Yes	No	Yes	No	No
Time x Style fixed effects	No	No	Yes	Yes	No	Yes
Family fixed effects	No	No	No	No	Yes	Yes

Note:
The dependent variable is the changes in cash holdings ($\Delta^{Cash} = Cash_t - Cash_{t-1}$). Redemptions correspond to the negative net flows lying within -50% and 0%, and zero otherwise. Subscriptions are the positive net flows lying within 0% and 200%, and zero otherwise. Hence, $Netflows_{f,t} = Redemptions_{f,t} + Subscriptions_{f,t}$. Our regression model is $\Delta^{Cash}_{f,t} = Redemptions_{f,t} + Subscriptions_{f,t} + Redemptions_{f,t} \times Team_{f,t} + Subscriptions_{f,t} \times Team_{f,t} + Team + \epsilon_{f,t}$. We include a set of fixed effects to control for unobserved confounding variation. Standard errors appear in parentheses and are clustered at the fund level. Significance levels are indicated as follows: *** denotes 1% significance level, ** denotes 5% significance level, and * denotes 10% significance level.

5 Conclusions

In this study, we have thoroughly investigated the influence of organizational structures on generating competitive outcomes in response to flow dynamics. Our findings indicate that team-managed funds exhibit a competitive edge compared to individual-managed funds when confronted with outflows. These team-managed funds demonstrate their proficiency in effectively mitigating the adverse effects of redemptions and making valuable trading decisions, showcasing their ability to handle pressure and sustain performance. Conversely, during periods of inflows, team-managed funds underperform individual-managed funds as they face challenges in expanding their portfolios and making informed investment decisions. This leads to a decline in future performance and a shift away from competitive behavior.

Furthermore, our research sheds light on the underlying mechanisms behind the competitive behavior patterns within team-managed funds. We find that these patterns are influenced by the willingness of fund shareholders to shape competitive actions by disciplining managers who deviate from their interests. This underscores the importance of monitoring team-managed funds during inflows to avoid agency issues and leverage the informed decision-making embedded within team structures. Moreover, our study uncovers important factors that contribute to the competitiveness of team-managed funds. Large, older, and diverse experienced teams exhibit higher levels of competitiveness, as they are better equipped to make informed trading decisions. However, diverse teams in terms of ethnicity and interconnectedness pose risks, as they constrain the capability of teams to generate value through decision-making. Therefore, investors need to consider the composition of teams and their impact on the ability to discipline manager behavior and drive performance.

We provide empirical evidence that strengthens the robustness of our findings, demonstrating that the competitive differences between team-managed and individual-managed funds cannot be explained by cash intensity alone. These results confirm the significance of investors' ability to discipline manager behavior and the informative advantage of team-managed funds in making valuable decisions. Our study has broader implications for both investors and regulators. It emphasizes the importance of supervising the competitive dynamics within team-managed portfolios, as these funds represent around 76% of the industry and manage more than 1.2 billion dollars in capital assets. Our reliable insights can guide investors in making informed decisions by considering different fund structures' behavior and performance implications during flow periods. Regulators, too, should exercise caution when assessing the competitive behavior of fund managers, recognizing the distinct dynamics and decision-making processes within team-managed and individual-managed structures.

Overall, our research makes a valuable contribution to the field by providing robust evidence and conclusive insights into the performance predictability and competitive behavior of team-managed funds in the active equity asset management industry. The statistical significance of our results bolsters the credibility of our findings, further supporting their practical relevance for investors and regulators alike. For example, we suggest regulators overlook how management companies may take advantage of conglomerates by placing managers in multiple portfolios at the cost of subtracting value from mutual fund shareholders. We consider further research must be done to explore why mutual fund families allocate managers in multiple portfolios and what specific benefits they obtain by adopting this strategy.

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