Salience in Mutual Funds

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Abstract

This paper explores the implications of salience theory (ST) in mutual funds. We find that mutual fund investor flows are sensitive to the salience of fund returns. The flow-ST relation is stronger among funds with limited information, such as small and young funds, and funds that spend less on advertisements. In addition, we provide evidence that fund managers are aware of the flow-ST relation and adjust their portfolio choices to attract investor flows. Finally, our analysis reveals that funds characterized by higher return salience do not achieve superior performance, and salience inadvertently redirects investments away from highly-skilled managers, impeding optimal capital allocation among mutual funds.

Keywords: Salience Theory, Mutual Fund Flows, Manager Skill, Capital Allocation

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1 Introduction

An important topic in finance research is understanding how economic agents make investment decisions. The mutual fund industry offers a valuable setting for studying this issue, as we can infer investors' preferences by observing the capital flows across funds. In an influential paper, Berk and Green (2004) develop a model assuming that investors are rational learners who chase fund past performance until the risk-adjusted return (i.e., alpha) diminishes. However, investors often behave irrationally and are subject to behavioral biases. This paper specifically focuses on one such bias introduced in the salience theory, initially proposed by Bordalo, Gennaioli, and Shleifer (2012). The salience theory posits that individuals tend to give disproportionate probability weights to the information most salient in their minds, forming biased expectations of future returns. Although many studies have explored diverse applications of salience theory, empirical evidence on how salience influences investor choices within the mutual fund industry remains limited. This paper aims to bridge this gap by applying the salience theory to mutual funds. We investigate how mutual fund investors respond to varying levels of return salience and how these responses, in turn, affect mutual fund managers' decisions, given that managers' compensation is highly related to the capital flow received.

To capture investors' perception of the salience of mutual fund performance, we follow Cosemans and Frehen (2021) and construct a fund-level salience theory (ST) value, which measures the distortion in return expectations arising from salient thinking. Essentially, the ST value captures investors' tendency to overweight probabilities of salient payoffs instead of using objective probabilities, where salient payoffs can be either positive or negative. More specifically, the ST value of a fund is defined as the difference between the expected mutual fund returns under salience weights and the expected returns under equal weights. A large positive (negative) ST value occurs when a fund's highest (lowest) past returns are salient and thus overemphasized by investors. Consequently, it can lead to salience-driven demand

and affect investor flows.

We document a positive and significant relation between mutual fund investor flows and past ST value, with no reversal within the following 12 months. Specifically, a one standard deviation increase in the ST value is associated with an increase in subsequent fund flows by 1.33% per month. The economic magnitude is substantial compared to other factors documented in the literature that investors consider. In addition, motivated by the finding of a non-linear relation between fund flows and past performance in Sirri and Tufano (1998), we use a piecewise linear regression to explore whether the sensitivity of fund flows to the ST value varies with ST levels. To this end, we sort mutual funds into terciles or quintiles and find that the flow-ST relation is more sensitive in the top and bottom ST groups. Furthermore, we categorize mutual funds into retail and institutional funds based on the share class indicators, and we find that the sensitivity of fund flows to the ST value prevails among both retail and institutional funds. However, the salience effect is slightly stronger among retail investors, which is consistent with previous finding that retail investors are less sophisticated and behave more irrationally (e.g., Barber and Odean, 2000). In addition, we separate fund flows into inflows and outflows and find that salient thinking affects both investors' purchase and redemption decisions. Nevertheless, the effect is stronger for purchase decisions.

Across different funds, we find that a fund's visibility significantly impacts investors' responses to its return salience. Without access to relevant information, salient performance of a fund, such as recent high returns, is more likely to serve as a heuristic or mental shortcut for investors' decision-making. As a result, investors tend to assign higher probability weights on salient payoffs when forming return expectations. Hence, the availability of information about a fund may significantly influence the flow-ST sensitivity. Many factors can impact information availability in a fund. Smaller or younger funds typically have shorter track records and lower visibility in the market. Similarly, funds with lower advertising budgets may not communicate as effectively or frequently with potential investors, resulting in gaps in awareness and available data. Therefore, in this paper, we explore fund size, fund age, and the advertising expenditures of a fund as potential factors. Our results reveal that investors in funds that are smaller, younger, and have lower advertisement expenditures are more sensitive to mutual fund ST values. This suggests that limited information access exacerbates investors' reliance on salient thinking.

Managers care about investor flows. Most of the mutual fund managers' compensation depends on the size of the funds they manage. As we learn about the salience-driven demand of investment in mutual funds, we further study whether mutual fund managers are taking advantage of investors' salience-chasing biases. Managers have perfect information about investors' flow and, at the same time, have the delegated right to make portfolio choices. It is plausible that managers make investment choices to influence flows rather than to manage risk or returns for investors. Through the lens of the salience behavioral bias of investors, we attempt to understand how managers make portfolio decisions to exploit the behavioral bias of investors and result in a conflict of interest of the two parties.

Using managers' holdings data, we show that fund managers are aware of the flow-ST relation and actively capitalize on it. Given that a manager's compensation is closely tied to the fund's size and flows, managers have the incentives to recognize the salience effect and promote their funds to exploit it. Our analysis of mutual funds' portfolio holdings reveals a strategic shift by managers in response to adverse outcomes. Specifically, we observe that mutual funds with significant capital withdrawals or poor performance exhibit increases in their ST values in the subsequent period. Further examination reveals that these fund managers adjust their portfolios by increasing investments in stocks with high ST values while decreasing holdings in stocks with low ST values. The behavior of fund managers suggests a tactical use of salient assets to maneuver investors' perception of future performance. By doing so, fund managers can potentially attract inflows and slow down outflows. In summary, the evidence suggests that fund managers are aware of the salience effect and strategically adjust portfolio compositions to either attract new investments or mitigate the impact of redemptions.

Finally, we investigate the consequences of the salience effect on investment returns and capital allocation efficiency across mutual funds. The distortion in return expectations resulting from investors' overemphasis on recent salient returns may not indicate solid underlying investment fundamentals or persistent future performance. In other words, examining future fund performance can help us understand whether salient thinking is more of a rational choice or a behavioral bias. To this end, we use both Fama and MacBeth (1973) and panel regression methods and find that funds with higher ST values do not deliver better performance in the subsequent period. Furthermore, we show that the ST value decreases how fund flows react to signals that more accurately reflect manager skills. The results suggest that the ST value is neither a good indicator for investors to select skilled managers nor a reliable signal for making purchase and redemption decisions over time, consistent with an interpretation of behavioral bias and a loss in capital allocation efficiency.

Our paper contributes to several strands of literature. First, this paper complements the expanding body of research on the influence of salience on decision-making. The salience theory proposed by Bordalo, Gennaioli, and Shleifer (2012) provides a theoretical framework for understanding how attention to salient information distorts decision-making processes.[1] Moreover, earlier studies apply salience to a wide range of fields and find that it helps explain decision-making in various contexts, including tax effects (Chetty, Looney, and Kroft, 2009), consumer choices (Bordalo, Gennaioli, and Shleifer, 2013b), judicial decisions (Bordalo, Gennaioli, and Shleifer, 2015), educational choices (Choi, Lou, and Mukherjee, 2017), corporate policies (Dessaint and Matray, 2017), and stock return predictability (Cosemans and Frehen, 2021; Cakici and Zaremba, 2022). Building upon existing research, our paper

[1]The authors have several papers exploring how agents' economic decisions can be distorted by salience. See, e.g., Bordalo, Gennaioli, and Shleifer (2013a) and Bordalo, Gennaioli, and Shleifer (2020).

expands the application of salience theory to delegated portfolio management (i.e., mutual funds) and offers new insights into how salience influences investor choices and fund manager strategies.

Second, our paper adds to the literature on revealed preferences of investors. A growing body of research uses mutual fund flows to infer investor preferences and links fund flows to various signals, ranging from more sophisticated ones like risk-adjusted returns (Barber, Huang, and Odean, 2016; Berk and van Binsbergen, 2016) to simpler and readily available signals such as media attention (Kaniel and Parham, 2017), sustainability ratings (Hartzmark and Sussman, 2019), Morningstar ratings (Evans and Sun, 2021), and unadjusted returns (Ben-David, Li, Rossi, and Song, 2022). Salient returns, whether upside or downside, are attention-grabbing signals that are readily available and can thus influence investor decisions. Consistent with findings of a negative relation between salience and future equity returns in both US and international markets (Cosemans and Frehen, 2021; Cakici and Zaremba, 2022), we observe that mutual funds with higher ST values are not associated with better future performance. This suggests that return salience is unlikely to be informative of manager skills. Therefore, our study adds evidence to the view that mutual fund investors have limited financial sophistication and make investment decisions based on simple signals.

Finally, this paper adds evidence to the agency problem existing in the delegated portfolio management industry and advances our understanding of the impact of investor behavior on capital allocation efficiency. Pooled investment vehicles such as mutual funds typically charge a fixed management fee based on the total assets under management, creating incentives for managers to "window dress" fund returns or holdings to attract capital inflows (e.g., Lakonishok, Shleifer, Thaler, and Vishny, 1991; Sias and Starks, 1997; Agarwal, Gay, and Ling, 2014). Consistent with this view, many studies find evidence that fund managers strategically customize their portfolio holdings to cater to various investor preferences, such as stocks from the the home nation (Luo, 2017), prospect theory (Han, Sui, and Yang, 2021), and lottery stocks (Agarwal, Jiang, and Wen, 2022). Similarly, our paper examines the equity holdings of mutual funds and documents active portfolio adjustments towards high ST stocks to attract investor flows, providing additional evidence of strategic adjustments by fund managers. This echoes the argument that salience can be strategically manipulated, as noted in Bordalo, Gennaioli, and Shleifer (2022).

The remainder of the paper is organized as follows. Section 2 introduces the data and the salience theory measure. Section 3 presents our main results. Section 4 provides additional analyses and robustness checks. Finally, Section 5 concludes.

2 Data and measure

2.1 Mutual fund sample

Our dataset comprises US mutual funds sourced from the CRSP survivor-bias-free mutual fund database, focusing specifically on domestic actively managed equity mutual funds. We exclude balanced funds, bond funds, sector funds, index funds, and ETFs.[2] The CRSP database covers open-ended mutual funds at the share class level. Although various share classes of a fund may cater to different client needs, they generally maintain identical investment portfolios but vary only in fee structures. Therefore, we aggregate all classes to the fund level for funds with multiple share classes and compute value-weighted fund returns and characteristics.

Following the literature (e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998), the

[2]Following the literature, we first select funds with one of the following Lipper classification codes: EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, or SCVE. If the Lipper classification code is missing, we pick funds with one of the following Strategic Insights objective codes: AGG, GMC, GRI, GRO, ING, or SCG. If both codes are not available, we collect funds with one of the following Wiesenberger objective codes: G, GCI, IEQ, LTG, MCG, or SCG. In addition, we exclude index funds and ETFs by checking the CRSP index fund and ETF flags and examining fund names for terms such as “Index”, “ETF”, “iShares”, “SPDR”, “S&P”, “Russell”, etc.

monthly net mutual fund flow (i.e., inflows in excess of outflows) is defined as:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \cdot (1 + r_{i,t})}{TNA_{i,t-1}}. \tag{1}$$

where $TNA_{i,t}$ is the total net assets (i.e., fund size) of fund i at the end of month t, and $r_{i,t}$ is the fund raw return over month t. The flow measure denotes the net variation in the size of the fund after accounting for the fund's return during the month. To mitigate the effect of outliers, we winsorize fund flows at both the upper and lower 1% thresholds.

2.2 Salience theory measure

Calculating the salience theory (hereafter ST) value of a fund involves assessing the prominence or salience of fund returns, and a general approach is to assign weights to fund returns based on their salience, i.e., how much they stand out or attract attention. Following the method of Cosemans and Frehen (2021), we use daily returns to construct the ST value for each mutual fund on a monthly basis in two steps.

In the first step, we quantify the salience of fund daily returns. Since we focus on domestic actively managed equity mutual funds, we assume that fund investors' choice set comprises all stocks available in the market. Consequently, investors assess mutual fund performance in the context of all other stocks. Therefore, the salience of a fund's daily return is calculated using the following salience function proposed in Bordalo, Gennaioli, and Shleifer (2012):

$$\sigma(r_{is}, \bar{r}_s) = \frac{|r_{is} - \bar{r}_s|}{|r_{is}| + |\bar{r}_s| + \theta} \tag{2}$$

where r_{is} is fund i's return on day s, $\bar{r}_s$ is the market return on that day, and θ is a positive parameter that controls the salience when $r_{is} = 0$. In essence, the measure captures the scaled distance of a fund's return from the average return in the market.

In the second step, we first sort each fund's daily returns r_{is} on their salience measure computed from equation (2), and assign ranks k_{is} ranging from 1 (most salient) to S_{it} (least salient), where S_{it} denotes the number of fund i's daily returns in month t. Assuming each daily return occurs with an equal objective probability of $\pi_{is} = 1/S_{it}$, we next calculate the salience-weighted subjective probability $\tilde{\pi}_{is}$ of a salient thinker who distorts the objective probability of fund daily returns by their salience, using the following formula:

$$\tilde{\pi}_{is} = \pi_{is} \times \omega_{is} \tag{3}$$

where ω_{is} is the salience weight defined as:

$$\omega_{is} = \frac{\delta^{k_{is}}}{\sum_{s'} \delta^{k_{is'}} \times \pi_{is'}}, \qquad \delta \in (0, 1] \tag{4}$$

The parameter δ in equation (4) captures the degree to which decision weights (i.e., subjective probabilities) are distorted by the salience effect. A rational decision-maker with $\delta = 1$ (i.e., $\omega_{is} = 1$ for $\forall s \in S$) exhibits no salience distortion as decision weights are simply equal to objective probabilities. By construction, the salience weights are normalized to sum to 1 ($\mathbb{E}[\omega_{is}] = 1$) so that the expected distortion is zero. Conversely, a salient thinker with $\delta < 1$ overweights salient states ($\omega_{is} > 1$) and underweights non-salient states ($\omega_{is} < 1$), and her tendency to focus on the most salient payoffs becomes stronger as δ approaches 0. Following the literature (e.g., Bordalo, Gennaioli, and Shleifer, 2012; Cosemans and Frehen, 2021; Cakici and Zaremba, 2022), the parameter values are set to $\theta = 0.1$ and $\delta = 0.7$, and the ST value of fund i in month t is defined as follows:

$$\begin{aligned} ST_{i,t} \equiv cov[\omega_{is,t}, r_{is,t}] &= \mathbb{E}[\omega_{is,t} \times r_{is,t}] - \mathbb{E}[\omega_{is,t}] \times \mathbb{E}[r_{is,t}] \\ &= \sum_{s=1}^{S_{it}} \underbrace{\pi_{is,t}\omega_{is,t}}_{\tilde{\pi}_{is,t}} r_{is,t} - \sum_{s=1}^{S_{it}} \pi_{is,t} r_{is,t} \\ &= \mathbb{E}^{ST}[r_{is,t}] - \bar{r}_{i,t} \end{aligned} \tag{5}$$

Thus, for a mutual fund i, $ST_{i,t}$ captures the difference between salience-weighted and equal-weighted fund daily returns in month t, which measures the distortion of investors' return expectations on the fund. A mutual fund with more salient positive (negative) daily returns would result in greater (lower) expectations about its future performance.

2.3 Summary statistics

Table 1 reports the summary statistics for all fund-month observations of the main variables used in our analysis. Our sample spans from October 1998 to September 2023 and covers 3,688 unique mutual funds. On average, mutual funds experience a monthly net flow of 0.25% with a standard deviation of 5.49%. While the ST value has an average of -0.72, the 10th percentile cutoff is -7.40 and the 90th percentile cutoff is 6.17, indicating substantial dispersion in return salience across funds. In terms of performance, the average fund delivers a net-of-fee return of 0.66% per month and yields slightly negative alphas after adjusting for risks using different risk factor models over the sample period. Specifically, the average monthly alphas are -0.10% for the CAPM, -0.07% for the Fama-French-Carhart four-factor model (FFC), and -0.03% for the Fama-French five-factor model (FF5). The median fund size in our sample is $201.50 million, while the mean is $1,311.46 million, suggesting a right-skewed distribution of fund size. Furthermore, mutual funds charge an average annual expense ratio of 1.19%, and nearly half of the funds charge either a front-end load or a rear-end load.

In addition, Table 1 reveals significant variations in idiosyncratic volatility, return extremes, and past one-year returns, which may be related to fund return salience and hence the ST value. These variables are accounted for when examining the flow-ST relation in our later analysis.

3 Main results

3.1 Salience theory and fund flows

3.1.1 Baseline results

To understand whether the salience of mutual fund performance affects investors' capital allocation decisions, we examine the sensitivity of fund flows to fund ST values in the cross-section of mutual funds using the following regression:

$$Flow_{i,t} = \alpha_0 + \beta_1 ST_{i,t-1} + \beta_2 Alpha_{i,t-1} + \beta_3 Flow_{i,t-1} + \boldsymbol{\beta}' Controls_{i,t-1} + \gamma_j + \gamma_t + \varepsilon_{i,t} \quad (6)$$

where $Flow_{i,t}$ is fund i's investor flow in month t, and $ST_{i,t-1}$ is fund i's ST value in month $t-1$, computed using equation (5). A high ST value suggests that investors tend to form upward return expectations by overweighting past salient positive returns, while a negative ST value indicates lower return expectations. The two main control variables are fund risk-adjusted performance, $Alpha_{i,t-1}$, estimated using the five-factor model proposed by Fama and French (2015, hereafter FF5), and past fund flow $Flow_{i,t-1}$. Following the literature, we also include other control variables including fund TNA, expense ratio, and an indicator variable that equals one if a fund charges a load (either front-end or back-end) and zero otherwise. We include two fixed effects in equation (6): fund style fixed effects, γ_j, and time fixed effects, γ_t.[3] The coefficient of interest is β_1, which captures the sensitivity of mutual fund flows on past salience-weighted performance.

Table 2 reports the results from the panel regression specified above. The significant positive coefficients on ST across all models indicate that biased expectations, formed from the overestimation of recent salient mutual fund returns, can drive future fund flows. To

[3]Fund styles are categorized according to the Morningstar style classifications. Based on fund holdings, Morningstar assigns each fund into one of nine (3-by-3) style categories by size and book-to-market value criteria. These style categories include small-cap value, mid-cap value, large-cap value, small-cap blend, mid-cap blend, large-cap blend, small-cap growth, mid-cap growth, and large-cap growth.

alleviate the concern that the ST value captures other factors affecting fund flows, we control for several variables in the regression, including fund performance, idiosyncratic volatility, and maximum fund return. In addition, recent studies show that investors tend to respond to simple and easily accessible signals such as Morningstar ratings (Evans and Sun, 2021; Ben-David, Li, Rossi, and Song, 2022). Therefore, we include Morningstar ratings in columns (3) and (4) as an additional control, and our findings remains unchanged. In terms of economic magnitude, a one standard deviation increase in ST is associated with a 1.33% annualized increase in fund flows across different funds within the same style category. This suggests that the salience of recent returns plays a substantial role in influencing the capital allocation decisions of mutual fund investors.

Next, we extend the horizon of subsequent fund flows up to 12 months to examine the long-term implications of salience on investor choices. Specifically, we use the average monthly fund flows within a quarter, for the subsequent first to fourth quarters, as the dependent variable and apply the same panel regression setting as in equation (6). Table 3 presents the regression results. The coefficient on ST is statistically significant in column (1), indicating that return salience in the current month can significantly influence fund flows in the subsequent quarter. Although ST generally loses its statistical significance starting from the second quarter, it suggests that the short-term relation between salience and fund flows does not reverse within the following 12 months.

3.1.2 Heterogeneous responses: piecewise regression results

The salience bias occurs when prominent information captures investor attention and distorts their decision-making processes. Therefore, it is reasonable to assume that more salient information leads to greater distortions, suggesting a nonlinear relation between salience and fund flows. To investigate potential variations in the sensitivity of mutual fund flows to the ST value, we conduct a piecewise linear regression following Sirri and Tufano (1998). Specifically, we categorize mutual funds into several groups based on their ST values and then examine the flow-ST sensitivity for each group. Table 4 presents the results for the piecewise linear regression. Columns (1) and (2) present the results of dividing mutual funds into 3 and 5 groups, respectively. The findings show that funds with either the lowest or highest ST values exhibit a positive and statistically significant relation between fund flows and ST values. This indicates that funds at the extremes of return salience are more likely to attract or discourage investors. In contrast, mutual funds in the middle ranks do not show a significant association with fund flows, suggesting that the sensitivity of fund flows to the ST value varies across different levels of return salience.

3.1.3 Retail versus institutional funds

Empirical evidence suggests that retail investors generally lack sophistication and are more prone to behavioral biases when making investment decisions (e.g., Barber and Odean, 2000). Consequently, investor flows in retail funds, designed for individual investors, are expected to be more sensitive to the salience bias. To test this hypothesis, we construct samples of both retail and institutional funds using share class type indicators from the CRSP mutual fund database and compare their respective sensitivities of fund flows to the ST value.

Table 5 outlines the regression results, with retail funds presented in the first two columns and institutional funds in the last two columns. For both retail and institutional funds, the coefficients on ST are positive and statistically significant at least at the 10% level, indicating that return salience influences fund flows for both types. This is consistent with the notion that all investors resort to mental shortcuts, also known as heuristics, to facilitate their decision-making in certain cases. Nevertheless, the flow-ST relation is slightly stronger for retail funds (0.307) than for institutional investors (0.264), suggesting that retail investors may be more influenced by return salience due to their greater susceptibility to behavioral biases.

3.2 Visibility and salience bias

The ST value of a fund arises from investors' overemphasis on recent salient returns. Therefore, information availability is expected to significantly affect the magnitude of salience bias, as investors are likely to focus more on salient performance when a fund's information is less accessible. In this subsection, we examine fund size, fund age, and fund advertising expenditures as potential factors that impact information availability in a fund. We hypothesize that smaller funds, younger funds, and funds with lower advertising expenditures will exhibit greater salience bias.

We first examine how the flow-ST sensitivity varies across different fund size groups. Figure 1 presents the monthly flow difference between funds in the top and bottom deciles based on their ST values across three distinct fund size categories: Small, Medium, and Big. Funds in the Small group are categorized as those falling in the bottom 30% of total net assets (TNA) each month, while funds in the Big group comprise the top 30% in terms of TNA. The Small group exhibits the most substantial monthly flow difference between the top and bottom decile ST funds, exceeding 0.76% per month, while the Medium and Big categories show more modest differences of 0.61% and 0.29% per month, respectively. The flow differences are statistically significant at the 1% level in all three size categories, suggesting that funds with higher ST values tend to attract significantly more fund flows, regardless of their sizes. The magnitude of the flow difference decreases monotonically from the Small to the Big group. More importantly, we construct a SMB (small-minus-big) category to capture the difference in the salience effect between the Small and Big categories and find that the salience effect is significantly stronger in the Small group. This finding suggests that fund flows are more sensitive to return salience signals in smaller funds, which is consistent with our hypothesis.

In addition to fund size, fund age can also play an important role in the availability of historical fund records. Figure 2 shows the monthly flow divergence between funds in the highest and lowest deciles sorted on their ST values, segmented by three fund age categories: Young, Medium, and Mature. The Young group consists of funds in the bottom third of age, while the Mature group includes funds in the top third. In particular, funds in the Young group exhibit the largest monthly flow difference with an approximate value of 0.60% per month, indicating that investors are most sensitive to the salience of performance in the youngest funds. In contrast, funds in the Medium and Mature groups produce smaller flow differences of 0.48% and 0.39% per month respectively, with each difference reaching statistical significance at the 1% level. Moreover, the comparison category labeled YMM (young-minus-mature) shows the difference in the salience effect between the youngest and oldest funds, with a difference of 0.21% per month that is statistically significant at the 10% level. This result indicates that investors are more likely to focus on salient returns when investing in younger funds.

Finally, some funds actively engage in marketing to enhance their visibility in the market. They provide comprehensive fund information, build brand awareness, and attract potential investors throughout the process. In line with previous studies, we use funds' 12b-1 fees as a proxy for their advertising efforts and categorize mutual funds into three categories: Low, Medium, and High. Funds with lower 12b-1 fees are presumed to spend less on advertising and investor outreach, resulting in less information available to investors. As a result, investors tend to rely more on simple signals, such as return salience, to facilitate their decision-making, which increases their susceptibility to the salience bias. Figure 3 plots the monthly flow disparity between the top and bottom ST deciles across the three 12b-1 fee categories. It shows a monotonic decrease in flow difference from the Low to the High group. Additionally, the LMH (low-minus-high) category exhibits a significantly positive flow difference, implying that investors are more responsive to to return salience in funds with lower 12b-1 fees, which provides further support for our hypothesis.

3.3 Past performance and manager portfolio choice

So far, we have documented that the bias induced by past salient performance of mutual funds strongly drives investor flows. Specifically, when funds experience salient upside returns, they tend to attract additional inflows, whereas funds with salient downside returns face increased outflows. Given that the management fee is charged as a percentage base of fund TNA, managers' compensation is strongly linked to investor flows. Thus, we are interested in whether mutual fund managers are aware of investors' tendency to overestimate salient performance and, if so, whether they tailor portfolio choices accordingly to cater to investors' preference for salience. Specifically, we consider two scenarios in which managers would have increased incentives to adjust their portfolio holdings: when a fund experiences significant outflows or when it underperforms relative to its peers. The adjustments may act as a means to enhance investors' perception of the fund's future performance. To this purpose, we obtain data on quarterly mutual fund holdings (1991q1–2018q4) from the Thomson Reuters s12 database and perform the following analysis.

3.3.1 Past performance and portfolio salience

We first consider the overall equity holdings of the mutual fund managers and compute a ST value based on the holdings for each mutual fund i in quarter q. The holdings-based ST value is defined as the value-weighted ST values of all the stocks held by fund i based on its holdings data in quarter q, which can better reflect the investment choices of managers. In contrast, the return-based ST value, calculated using more readily available returns data, can better reflect investors' perception of a fund's future performance. To test our hypothesis that fund managers make strategic portfolio adjustments in certain cases, we investigate how the holdings-based ST value changes across funds with varying past flows and performance with the following model:

$$ST\_hold_{i,q} = \alpha_0 + \beta_1 Bottom_{i,q-1} + \beta_2 ST\_hold_{i,q-1} + \boldsymbol{\beta}' Controls_{i,q-1} + \gamma_j + \gamma_q + \varepsilon_{i,q} \quad (7)$$

where the dependent variable, $ST\_hold_{i,q}$, is the holdings-based ST value of fund i in quarter q. Similarly to the construction of the ST value for an individual fund, we obtain the monthly ST value for each stock using its daily returns within the month. This process results in three ST values for each stock in quarter q, from which we choose either the maximum or the average as the stock-level ST value for that quarter. Additionally, we calculate a quarterly ST value using the stock's daily returns over the entire quarter. Therefore, we consider a total of three forms of quarterly stock-level ST measures. The independent variables include an indicator variable, $Bottom_{i,q-1}$, that equals one if fund i belongs to the bottom quintile group sorted on aggregate fund flows or returns in quarter $q-1$, one-quarter lagged ST value, fund TNA, load dummy, and expense ratio. In addition, γ_j and γ_q represent Morningstar style and quarter fixed effects, respectively.

Table 6 reports the results from the panel regression. In column (1), the coefficient on $Bottom\_flow$ is positive and statistically significant at the level 1%, suggesting that funds experiencing extreme outflows tend to increase their holdings-based ST values in the following quarter. In column (2), $Bottom\_return$ is also positively and significantly related to the subsequent holdings-based ST value, indicating that funds with poor performance in the current quarter tend to adjust their portfolios to raise the ST values in the subsequent quarter. This inference remains unchanged regardless of the specific form of stock-level ST measure we use, whether it is the maximum ST value in columns (1) and (2), the average ST value in columns (3) and (4), or the quarterly ST value in columns (5) and (6). Our mutual fund sample has an average holdings-based ST value of -0.030 per quarter when using the average stock-level ST value in columns (3) and (4). Consequently, a mutual fund in the bottom flow (return) group is associated with an increase of 0.005 (0.020) in the ST value based on subsequent holdings, representing a significant economic impact.

3.3.2 Trading on individual stocks

We have thus far presented evidence indicating that fund managers actively adjust holdings-based ST values when funds encounter significant outflows or poor returns. Next, we further examine whether changes in holdings-based ST values are associated with changes in holdings of stocks with extreme ST values. To this end, stocks are categorized into five groups based on their quarterly ST values, with stocks in the bottom quintile group defined as low ST stocks and those in the top quintile group defined as high ST stocks. Subsequently, we calculate the quarterly change in aggregate holdings of low ST stocks for each mutual fund and examine whether this change is related to the fund's past performance using a regression setting similar to that in equation (7). The regression results, as presented in Table 7, reveal significantly negative coefficients on $Bottom\_flow$ across all model specifications, indicating that funds experiencing severe outflows tend to sell low ST stocks. In addition, the negative coefficients on $Bottom\_return$ suggest that funds with the lowest returns are also inclined to decrease their holdings in low ST stocks. Similarly, we redo the analysis for changes in holdings of high ST stocks and report the results in Table 8. The results provide some evidence that funds experiencing significant outflows tend to increase their subsequent holdings in high ST stocks. More notably, the impact of past poor performance is more pronounced as the dummy variable $Bottom\_return$ carries a significantly positive coefficient across all model specifications. This indicates a stronger tendency among fund managers to shift towards high ST stocks following periods of substantial outflows or significant underperformance. In general, fund characteristics are not significantly related to changes in holdings of stocks with extreme ST values.

To summarize, the results presented in this subsection suggest that manager portfolio choice can be affected by fund past performance. Overall, the evidence points to a strategic adjustment of portfolio holdings by mutual fund managers following periods of significant capital withdrawals or underperformance.

3.4 Salience Distortion

The salience theory value can be considered a distortion in fund return expectations resulting from salient thinking. Given the observation that investors allocate more capital to funds with higher ST values, a pertinent question emerges: is this preference justified? In other words, are investors better off extrapolating mutual fund future performance by putting more weights on salient returns? To address this question, we first examine whether mutual funds with higher ST values are associated with better future performance. This analysis can shed light on the extent to which the ST value can serve as a proxy for manager skills. In addition, we investigate whether the ST value influences the flow-performance sensitivity with the assumption that rational investors would chase manager skills until alpha diminishes, as suggested by Berk and Green (2004).

3.4.1 ST value and fund future performance

The investigation into whether investor allocations to funds with higher ST values are associated with better future performance is crucial for understanding the rationality of salient thinking in mutual fund selection. To examine this question, we perform the Fama-MacBeth regression of fund future performance on the ST value, and we report the results in Table 9. In the regression, the Fama-French 5-factor alpha (FF5 alpha) is used as the fund performance measure, and it is measured over either the next month or the next quarter. Fund style dummies are also included in columns (2) and (4). In all model specifications, the coefficients on ST range from -0.081 to -0.052, indicating a negative relation between fund ST value and future performance, although these coefficients are not statistically significant. This suggests that higher ST values are not predictive of better future performance. On the other hand, the coefficients on expense ratio are negative and statistically significant across all model specifications, implying that funds with higher fund expenses tend to exhibit lower future performance.[4]

In summary, our finding suggests that making capital allocation decisions based on salient thinking (i.e., selecting funds based on their ST values) does not improve investment performance. One possible explanation is that investors' tendency to prioritize salient information can lead them to overlook high-quality mutual fund managers, resulting in sub-optimal capital allocation among managers. This challenges the rationality of utilizing salient thinking when making investment decisions.

3.4.2 Cross-sectional distraction

Our finding of an insignificant relation between a fund's ST value and its future performance suggests that the ST value may not serve as an effective proxy for manager skills. Consequently, mutual funds with high ST values might be misinterpreted by investors as highly-skilled funds, potentially leading to biased capital allocation. Given the extensive literature on the relation between mutual fund flows and performance (e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Barber, Huang, and Odean, 2016; Berk and van Binsbergen, 2016), we further investigate whether the ST value can influence the flow-performance sensitivity using the following regression:

$$\begin{aligned} Flow_{i,t} = \alpha_0 + \beta_1 ST_{i,t-1} + \beta_2 Alpha_{i,t-1} + \beta_3 ST_{i,t-1} \times Alpha_{i,t-1} \\ + \beta_4 Flow_{i,t-1} + \boldsymbol{\beta}' Controls_{i,t-1} + \gamma_j + \gamma_t + \varepsilon_{i,t} \end{aligned} \tag{8}$$

where the variable of interest is the interaction term between $ST_{i,t-1}$ and $Alpha_{i,t-1}$, and its coefficient captures the change in the flow-performance sensitivity triggered by investors' salient thinking.

Table 10 presents the results from the panel regression. When including fund style fixed

[4] We also examine the relation between fund ST value and future performance using a panel regression setting, and our inference remains unchanged. We report the results in Table A.4.

effects in column (1), the coefficient on the interaction term is negative and statistically significant at the 5% level, indicating that investors become less sensitive to funds' past performance due to the impact of salient thinking. This inference remains robust in column (2) where fund fixed effects are included to identify within-fund variations over time. Moreover, a fund's ST value may capture information related to its performance, therefore, we also compute an orthogonalized ST value to remove the correlation between the ST value and fund performance. Specifically, we regress the ST value on FF5 alpha and use the residuals from this regression as the orthogonalized ST values. We repeat our analysis and report the results in columns (3) and (4). The negative and statistically significant coefficient on the interaction term again indicates that salient thinking leads to a decreased sensitivity of fund flows to past performance.

Overall, our evidence suggests that a fund's ST value, derived from investors' salient thinking, does not serve as a valid proxy for manager skills, thereby reducing the sensitivity of investor flows to more accurate signals, such as alphas or unadjusted returns.

4 Additional analyses and robustness

4.1 Analysis on fund inflows and outflows

So far, we have documented a robust positive relation between fund flows and ST values. Now, we attempt to explore whether the ST value has asymmetric relations with fund inflows and outflows. Specifically, we separate fund flows into inflows and outflows and then perform a subsample analysis. The results are presented in Table A.5. We observe that the ST value is positively associated with both inflows and outflows. However, the coefficients in the outflows analysis exhibit only marginal significance. To sum up, the flow-ST relation exists for both inflows and outflows but is stronger for inflows.

4.2 Persistence in ST

In the previous section, we have presented evidence that the ST value of a fund is not a reliable indicator of manager skills. As an additional test, we examine the time-series persistence of fund ST values. Each month, we sort individual funds into five groups based on their ST values, and then we compute the transition probability matrix of these groups over different time horizons. The results, reported in Table A.6 in the Internet Appendix, do not suggest strong persistence. That is, the ST value is not a stable fund attribute, as past realized ST values do not strongly predict future ST values. This finding lends further support to the argument that the ST value serves as a noisy proxy for manager skills.

5 Conclusion

In this paper, we use mutual funds as a laboratory to examine the impact of return salience on investors' capital allocation decisions. Our findings confirm that mutual fund flows are positively and significantly related to the salience of fund past performance, as measured by the ST value, revealing a distinct pattern of investment decisions driven by salient thinking. In addition, the sensitivity of the flow-ST relation is more pronounced among smaller funds, younger funds, and those with lower marketing expenditures. This suggests that investors are more likely to rely on attention-grabbing signals, such as return salience, when evaluating funds with less available information. Furthermore, we provide evidence that fund managers strategically adjust portfolio holdings to increase ST values after experiencing substantial outflows or significant underperformance. Consistent with an interpretation of behavioral bias, we do not find evidence that a fund's ST value is significantly related to its future performance. Additionally, ST values tend to decrease the sensitivity of fund flows to alphas that are better proxies for manager skills, implying a potential loss in capital allocation efficiency induced by salient thinking.

In conclusion, our study sheds light on the impact of salience on decision-making in the mutual fund industry, revealing its influence on both investor behavior and fund manager strategies. This study contributes to our understanding of the determinants driving investor choices and illustrates potential negative impacts of cognitive biases on investment outcomes and capital allocation efficiency.

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Figure 1: Fund size and salience effect

This figure presents the monthly flow difference on the equal-weighted long-short portfolios that buy mutual funds in the highest decile and short those in the lowest decile. The mutual fund deciles are sorted based on salience theory values (ST). The flow difference is reported in three fund size categories, as well as a small-minus-big category. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

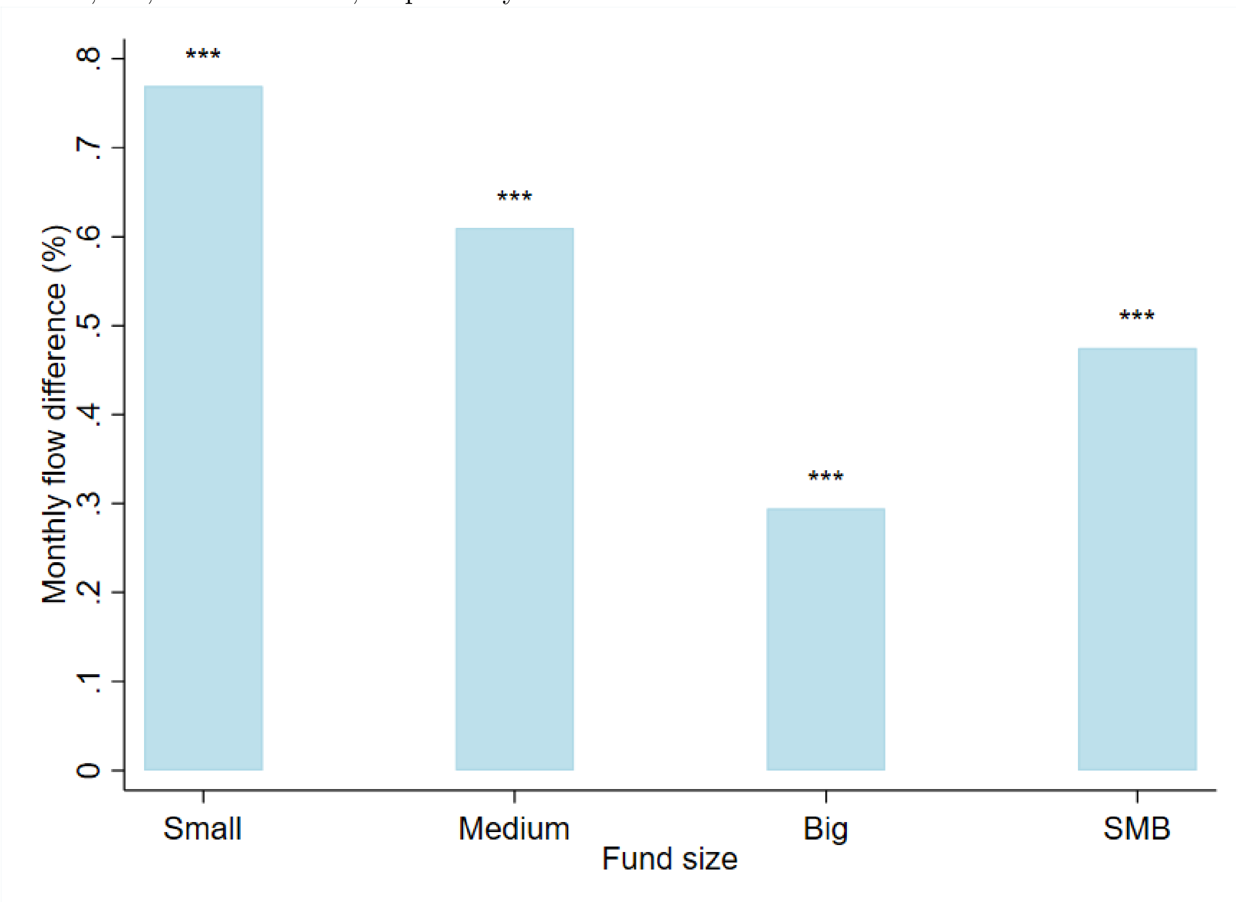

Figure 2: Fund age and salience effect

This figure presents the monthly flow difference on the equal-weighted long-short portfolios that buy mutual funds in the highest decile and short those in the lowest decile. The mutual fund deciles are sorted based on salience theory values (ST). The flow difference is reported in three fund age categories, as well as a young-minus-mature category. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

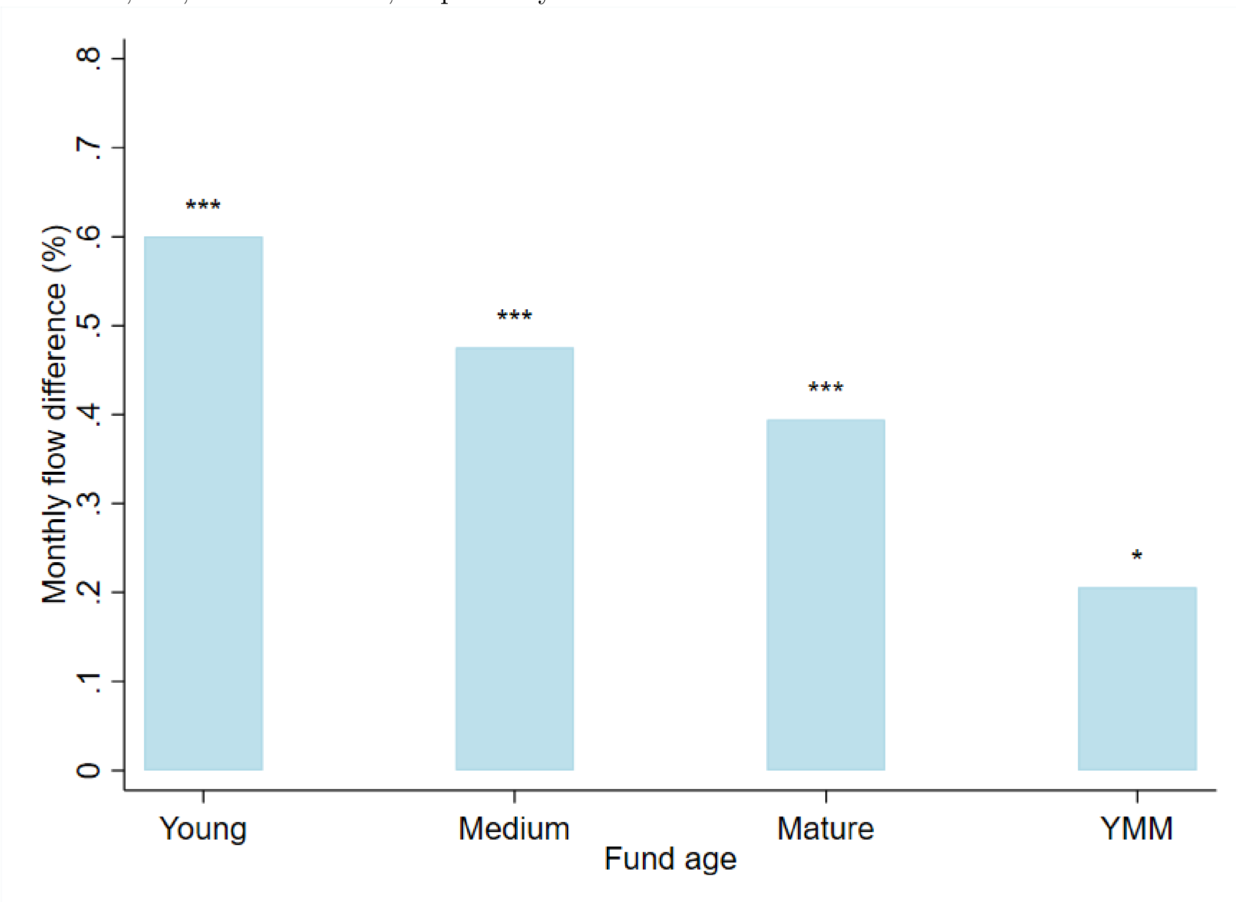

Figure 3: Fund 12b-1 fee and salience effect

This figure presents the monthly flow difference on the equal-weighted long-short portfolios that buy mutual funds in the highest decile and short those in the lowest decile. The mutual fund deciles are sorted based on salience theory values (ST). The flow difference is reported in three fund 12b-1 fee categories, as well as a low-minus-high category. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

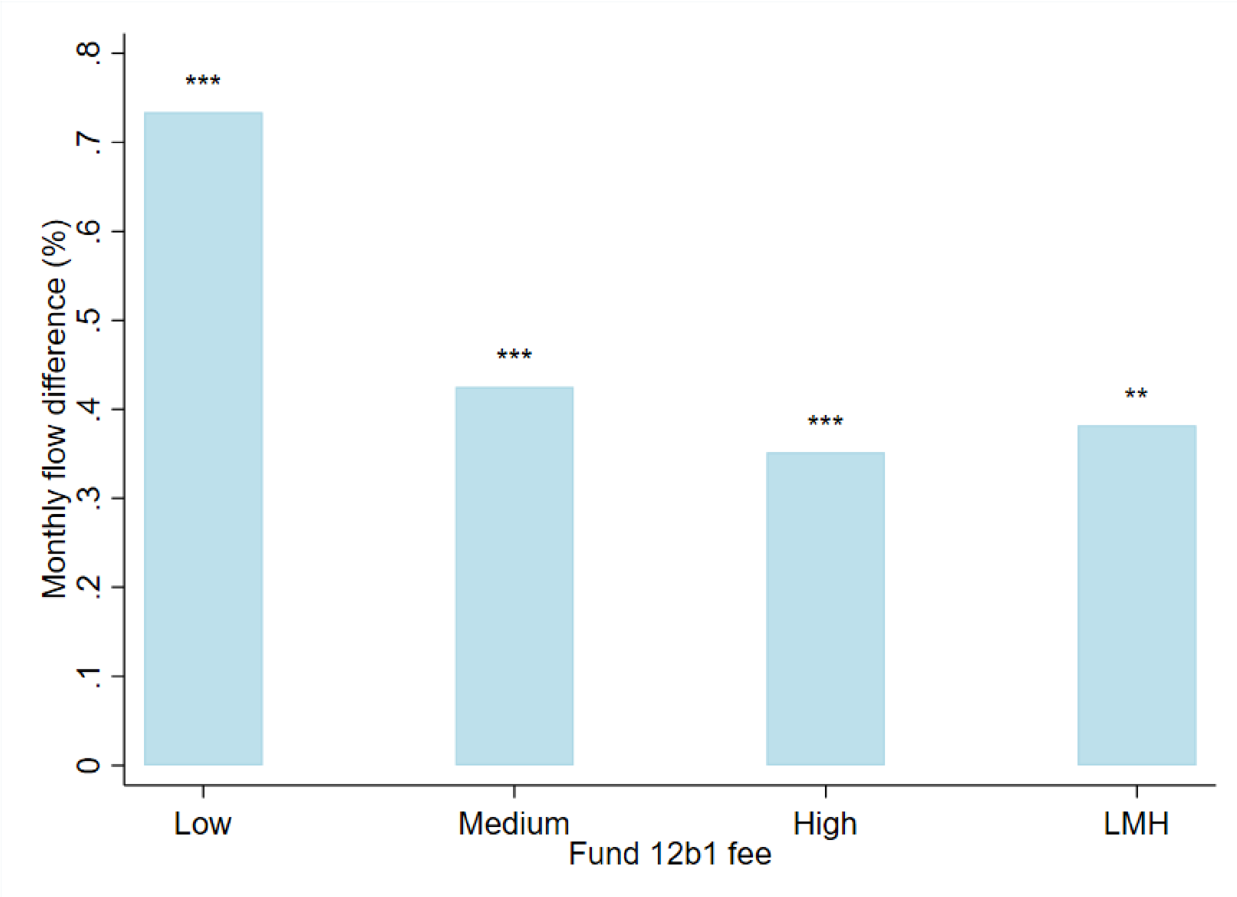

Table 1: Summary Statistics

This table provides summary statistics of fund-month observations for actively managed US equity mutual funds. Flow is monthly net fund flow in percentage. ST is monthly salience theory value calculated using fund daily returns. Return is net-of-fee monthly return. For a given fund in month t, we estimate its monthly alpha and idiosyncratic volatility (IV) based on alternative asset pricing models, including the CAPM, the Fama-French-Carhart four-factor model (FFC), and the Fama-French five-factor model (FF5), using its daily returns in month t, where we require at least 10 non-missing observations for the fund. Size is total net assets in million dollars. Expense ratio is the annual expense ratio. Load dummy equals one if the fund charges either front-end or back-end load. Max (min) return is the maximum (minimum) fund daily return in month t. Past 1Y return is fund's cumulative return over the past 12 months.

	obs	mean	std	p10	p25	p50	p75	p90
Flow (%/mo.)	526,580	0.25	5.49	-3.41	-1.60	-0.48	0.93	4.24
ST (%/mo.)	526,580	-0.72	6.02	-7.40	-3.94	-0.93	2.34	6.17
Return (%/mo.)	526,580	0.66	5.31	-6.02	-2.05	1.02	3.70	6.56
CAPM alpha (%/mo.)	526,580	-0.10	2.45	-2.58	-1.15	-0.08	0.95	2.37
FFC alpha (%/mo.)	526,580	-0.07	1.92	-1.97	-0.93	-0.08	0.78	1.84
FF5 alpha (%/mo.)	526,580	-0.03	1.91	-1.96	-0.92	-0.05	0.81	1.90
Size ($mil)	526,580	1311.46	5550.85	12.30	47.00	201.50	829.00	2631.55
Expense ratio (%/yr.)	524,436	1.19	0.94	0.64	0.90	1.14	1.44	1.78
Load dummy	524,436	0.49	0.50	0.00	0.00	0.00	1.00	1.00
CAPM IV (%/mo.)	526,580	0.39	0.29	0.14	0.20	0.31	0.48	0.70
FFC IV (%/mo.)	526,580	0.26	0.19	0.11	0.15	0.21	0.31	0.46
FF5 IV (%/mo.)	526,580	0.25	0.18	0.10	0.14	0.20	0.30	0.44
Max return (%/mo.)	526,580	2.24	1.58	1.00	1.34	1.86	2.63	3.86
Min return (%/mo.)	526,580	-2.22	1.58	-3.81	-2.73	-1.87	-1.25	-0.84
Past 1Y return (%/mo.)	505,566	7.59	20.48	-18.42	-3.18	8.46	18.30	29.95

Table 2: Salience theory and fund flows: Panel regression

This table presents coefficient estimates from the panel regression of fund flow on salience theory value (ST). In the regression, the dependent variable, fund flow, is measured over month t+1, while all independent variables are measured in month t. The independent variables include lagged fund flow, FF5 alpha, FF5 idiosyncratic volatility (FF5 IV), fund maximum return, Morningstar rating, as well as the following controls: logarithm of fund size, expense ratio, and load dummy. All regression specifications include fund style and month fixed effects. Standard errors, double-clustered at both fund and month levels, are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = Fund flow			
	(1)	(2)	(3)	(4)
ST	0.316***	0.321***	0.228***	0.238***
	(0.107)	(0.109)	(0.081)	(0.082)
Lag flow	0.304***	0.304***	0.206***	0.206***
	(0.011)	(0.011)	(0.013)	(0.013)
FF5 alpha	0.190***	0.188***	0.121***	0.119***
	(0.014)	(0.015)	(0.010)	(0.011)
FF5 IV		-0.097		0.318*
		(0.196)		(0.165)
Max return		0.025		0.030
		(0.036)		(0.022)
MS rating			0.974***	0.978***
			(0.029)	(0.029)
Controls	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	478,722	478,722	411,991	411,991
Adj. R^2	0.128	0.128	0.096	0.096

Table 3: Salience theory and fund flows beyond one-month horizon

This table presents coefficient estimates from the panel regression of fund flow on salience theory value (ST) beyond one-month horizon. The dependent variable, measured from months t+1 to t+12, represents the average monthly flow of a fund during the subsequent first, second, third, and fourth quarters, respectively. All independent variables are measured in month t. The independent variables include lagged fund flow, FF5 alpha, FF5 idiosyncratic volatility, fund maximum return, as well as the following controls: logarithm of fund size, expense ratio, and load dummy. All regression specifications include fund style and month fixed effects. Standard errors, double-clustered at both fund and month levels, are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = Average fund flow			
	1Q	2Q	3Q	4Q
	(1)	(2)	(3)	(4)
ST	0.324***	0.070	0.131	0.154*
	(0.092)	(0.091)	(0.083)	(0.080)
Lag flow	0.252***	0.167***	0.126***	0.096***
	(0.006)	(0.004)	(0.004)	(0.003)
FF5 alpha	0.175***	0.167***	0.135***	0.117***
	(0.013)	(0.014)	(0.012)	(0.013)
Controls	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	475,759	470,448	464,440	455,893
Adj. R^2	0.178	0.120	0.097	0.080

Table 4: Salience theory and fund flows: Nonlinear relation

This table presents coefficient estimates from a piecewise linear regression of fund flow on five quintiles sorted by salience theory value (ST). In the regression, the dependent variable, fund flow, is measured over month t+1, while all independent variables are measured in month t. We denote RANK as a fund's monthly fractional rank based on its percentile ST value. We define Rank1 as min(RANK, 0.2), Rank2 as min(RANK-Rank1, 0.2), and so on, up to Rank5. The independent variables include lagged fund flow, FF5 alpha, FF5 idiosyncratic volatility (FF5 IV), fund maximum return, as well as the following controls: logarithm of fund size, expense ratio, and load dummy. All regression specifications include fund style and month fixed effects. Standard errors, double-clustered at both fund and month levels, are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = Fund flow	
	(1)	(2)
Rank1	0.003**	0.005*
	(0.001)	(0.003)
Rank2	0.001	0.002
	(0.001)	(0.002)
Rank3	0.005***	0.001
	(0.001)	(0.002)
Rank4		0.002
		(0.002)
Rank5		0.007**
		(0.003)
Lag flow	0.271***	0.271***
	(0.008)	(0.008)
FF5 alpha	0.172***	0.172***
	(0.013)	(0.013)
FF5 IV	-0.068	-0.068
	(0.166)	(0.167)
Max return	0.017	0.017
	(0.033)	(0.033)
Controls	Yes	Yes
Style FE	Yes	Yes
Month FE	Yes	Yes
Observations	478,722	478,722
Adj. R^2	0.156	0.156

Table 5: Salience theory and fund flows: Retail vs. Institutional funds

This table presents coefficient estimates from the panel regression of fund flow on salience theory value (ST) for retail funds and institutional funds separately. Retail and institutional funds are identified based on fund indicators from the CRSP mutual fund database. In the regression, the dependent variable, fund flow, is measured over month t+1, while all independent variables are measured in month t. The independent variables include lagged fund flow, FF5 alpha, FF5 idiosyncratic volatility (FF5 IV), fund maximum return, as well as the following controls: logarithm of fund size, expense ratio, and load dummy. All regression specifications include fund style and month fixed effects. Standard errors, double-clustered at both fund and month levels, are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = Fund flow			
	Retail		Institutional	
	(1)	(2)	(3)	(4)
ST	0.307**	0.307**	0.326**	0.264*
	(0.128)	(0.132)	(0.141)	(0.144)
Lag flow	0.241***	0.241***	0.174***	0.174***
	(0.013)	(0.013)	(0.007)	(0.007)
FF5 alpha	0.230***	0.230***	0.206***	0.220***
	(0.016)	(0.017)	(0.022)	(0.022)
FF5 IV		0.066		0.709**
		(0.265)		(0.348)
Max return		-0.004		-0.204***
		(0.046)		(0.056)
Controls	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	401,740	401,740	301,531	301,531
Adj. R^2	0.097	0.097	0.052	0.052

Table 6: Past performance and portfolio choice

This table presents coefficient estimates from the panel regression of fund holdings-based salience theory value (ST) on past performance. ST, calculated at the fund-quarter level, represents the value-weighted salience theory value of stocks held by each fund. Three forms of quarterly stock-level ST are considered, either utilizing the maximum (columns (1) and (2)) or average (columns (3) and (4)) ST of three monthly stock values, or a quarterly (columns (5) and (6)) ST value. Each quarter, funds are sorted into quintiles based on aggregate fund flows or returns, with bottom_flow or bottom_return denoting inclusion in the lowest quintile. In the regression, the dependent variable, holdings-based ST, is measured over quarter q+1, while all independent variables are measured in quarter q. The independent variables include bottom_flow, bottom_return, lag ST, logarithm of fund size, load dummy, and expense ratio. All regression specifications include fund style and quarter fixed effects. Standard errors, double-clustered at both fund and quarter levels, are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 1991q1 to 2018q4.

	Dependent variable = Holdings-based ST					
	(1)	(2)	(3)	(4)	(5)	(6)
Bottom_flow	0.014***		0.005**		0.022***	
	(0.004)		(0.003)		(0.007)	
Bottom_return		0.061***		0.020***		0.063***
		(0.009)		(0.006)		(0.014)
Lag ST	0.516***	0.522***	0.198***	0.209***	0.193***	0.206***
	(0.026)	(0.026)	(0.042)	(0.041)	(0.041)	(0.040)
Size	-0.001*	-0.001	-0.000	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Load dummy	-0.002**	-0.002*	-0.001	-0.001	-0.002*	-0.002*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Expense ratio	0.022***	0.021***	0.009***	0.009***	0.030***	0.028***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.007)	(0.007)
Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	101,365	101,365	101,365	101,365	101,365	101,365
Adj. R^2	0.825	0.827	0.753	0.754	0.588	0.590

Table 7: Past performance and portfolio choice: Change in holdings of low ST stocks

This table presents coefficient estimates from the panel regression of change in aggregate fund holdings of low ST stocks on past performance. The dependent variable, at the fund-quarter level, measures the quarterly change in aggregate fund holdings of low ST stocks. Stocks in the lowest quintile sorted on quarterly stock-level ST are defined as low ST stocks. Three forms of quarterly stock-level ST are considered, either utilizing the maximum (columns (1) and (2)) or average (columns (3) and (4)) ST of three monthly stock values, or a quarterly (columns (5) and (6)) ST value. Each quarter, funds are sorted into quintiles based on aggregate fund flows or returns, with bottom_flow or bottom_return denoting inclusion in the lowest quintile. In the regression, the dependent variable is measured over quarter q+1, while all independent variables are measured in quarter q. The independent variables include bottom_flow, bottom_return, logarithm of fund size, load dummy, and expense ratio. All regression specifications include fund style and quarter fixed effects. Standard errors, double-clustered at both fund and quarter levels, are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 1991q1 to 2018q4.

	Dependent variable = ΔHoldings of low ST stocks					
	(1)	(2)	(3)	(4)	(5)	(6)
Bottom_flow	-0.329***		-0.398***		-0.334***	
	(0.114)		(0.111)		(0.099)	
Bottom_return		-3.265***		-3.144***		-2.878***
		(0.434)		(0.370)		(0.331)
Size	0.010	-0.013	0.007	-0.014	0.010	-0.009
	(0.017)	(0.016)	(0.017)	(0.019)	(0.018)	(0.019)
Load dummy	-0.007	-0.009	-0.014	-0.016	-0.008	-0.010
	(0.023)	(0.023)	(0.015)	(0.015)	(0.012)	(0.011)
Expense ratio	0.045	0.115	-0.028	0.038	-0.042	0.018
	(0.074)	(0.083)	(0.045)	(0.053)	(0.056)	(0.066)
Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	101,365	101,365	101,365	101,365	101,365	101,365
Adj. R^2	0.208	0.222	0.224	0.243	0.190	0.206

Table 8: Past performance and portfolio choice: Change in holdings of high ST stocks
This table presents coefficient estimates from the panel regression of change in aggregate fund holdings of high ST stocks on past performance. The dependent variable, at the fund-quarter level, measures the quarterly change in aggregate fund holdings of high ST stocks. Stocks in the highest quintile sorted on quarterly stock-level ST are defined as high ST stocks. Three forms of quarterly stock-level ST are considered, either utilizing the maximum (columns (1) and (2)) or average (columns (3) and (4)) ST of three monthly stock values, or a quarterly (columns (5) and (6)) ST value. Each quarter, funds are sorted into quintiles based on aggregate fund flows or returns, with bottom_flow or bottom_return denoting inclusion in the lowest quintile. In the regression, the dependent variable is measured over quarter q+1, while all independent variables are measured in quarter q. The independent variables include bottom_flow, bottom_return, logarithm of fund size, load dummy, and expense ratio. All regression specifications include fund style and quarter fixed effects. Standard errors, double-clustered at both fund and quarter levels, are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 1991q1 to 2018q4.

	Dependent variable = ΔHoldings of high ST stocks					
	(1)	(2)	(3)	(4)	(5)	(6)
Bottom_flow	0.100*		0.165**		0.172*	
	(0.054)		(0.079)		(0.091)	
Bottom_return		0.848***		2.531***		1.930***
		(0.197)		(0.388)		(0.278)
Size	-0.005	0.001	-0.011	0.008	-0.012	0.002
	(0.009)	(0.009)	(0.017)	(0.016)	(0.013)	(0.013)
Load dummy	0.007	0.008	-0.006	-0.005	0.003	0.004
	(0.011)	(0.011)	(0.016)	(0.010)	(0.011)	(0.011)
Expense ratio	0.060*	0.042	0.027	-0.029	0.001	-0.041
	(0.036)	(0.040)	(0.087)	(0.053)	(0.032)	(0.036)
Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	101,365	101,365	101,365	101,365	101,365	101,365
Adj. R^2	0.144	0.147	0.228	0.240	0.161	0.172

Table 9: Salience theory and mutual fund performance

This table presents coefficient estimates from the Fama-MacBeth regression of fund performance on salience theory value (ST). In this table, fund performance is measured by FF5 alpha. In the regression, the dependent variable, FF5 alpha, is measured over either next month in the first two columns or next quarter in the last two columns, while all independent variables are measured in month t. The independent variables include logarithm of fund size, load dummy, and expense ratio. Fund style dummies are included in columns (2) and (4). Standard errors, adjusted using the Newey-West method, are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = FF5 alpha			
	Next month		Next quarter	
	(1)	(2)	(3)	(4)
ST	-0.075	-0.081	-0.076	-0.052
	(0.088)	(0.068)	(0.172)	(0.157)
Size	0.012*	0.004	0.043*	0.015
	(0.006)	(0.003)	(0.023)	(0.013)
Load dummy	-0.030**	-0.015	-0.075*	-0.046
	(0.014)	(0.015)	(0.044)	(0.042)
Expense ratio	-0.036**	-0.054***	-0.184***	-0.256***
	(0.016)	(0.016)	(0.060)	(0.058)
Style FE	No	Yes	No	Yes
Observations	496,928	496,928	491,747	491,747
Adj. R^2	0.032	0.132	0.032	0.129

Table 10: Salience theory and cross-sectional distraction

This table presents coefficient estimates from the panel regression of fund flow on salience theory value (ST) and fund performance. In this table, fund performance is measured by FF5 alpha. In the regression, the dependent variable, fund flow, is measured over month t+1, while all independent variables are measured in month t. The independent variables include ST, FF5 alpha, an interaction term between ST and FF5 alpha, logarithm of fund size, load dummy, and expense ratio. Orthogonalized ST value is used in columns (3) and (4), i.e., ST is regressed on FF5 alpha and the residuals are used as the orthogonalized values. All regression specifications include month fixed effects. Fund style fixed effects are included in columns (1) and (3), and fund fixed effects are included in columns (2) and (4). Standard errors, double-clustered at both fund and month levels, are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = Fund flow			
	(1)	(2)	(3)	(4)
ST	0.247***	0.179**	0.285***	0.167**
	(0.086)	(0.082)	(0.085)	(0.081)
FF5 alpha	0.137***	0.122***	0.141***	0.125***
	(0.010)	(0.009)	(0.009)	(0.009)
ST×FF5 alpha	-0.048**	-0.035**	-0.051**	-0.035**
	(0.019)	(0.014)	(0.021)	(0.016)
Lag flow	0.328***	0.286***	0.328***	0.286***
	(0.010)	(0.010)	(0.010)	(0.010)
Size	-0.104***	-0.495***	-0.105***	-0.495***
	(0.008)	(0.027)	(0.009)	(0.027)
Load dummy	-0.112***	-0.049	-0.111***	-0.049
	(0.030)	(0.046)	(0.030)	(0.046)
Expense ratio	-0.012	0.093***	-0.013	0.092***
	(0.021)	(0.033)	(0.020)	(0.033)
Style FE	Yes	No	Yes	No
Month FE	Yes	Yes	Yes	Yes
Fund FE	No	Yes	No	Yes
Observations	451,838	494,595	451,835	494,595
Adj. R^2	0.128	0.157	0.128	0.157

Online Appendix for

Salience in Mutual Funds

Table A.1: Salience theory and fund flows: Fund fixed effects

This table presents coefficient estimates from the panel regression of fund flow on salience theory value (ST). In the regression, the dependent variable, fund flow, is measured over month t+1, while all independent variables are measured in month t. The independent variables include lagged fund flow, FF5 alpha, FF5 idiosyncratic volatility (FF5 IV), fund maximum return, Morningstar rating, as well as the following controls: logarithm of fund size, expense ratio, and load dummy. All regression specifications include fund and month fixed effects. Standard errors, double-clustered at both fund and month levels, are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = Fund flow			
	(1)	(2)	(3)	(4)
ST	0.202**	0.209**	0.198***	0.204***
	(0.103)	(0.103)	(0.072)	(0.072)
Lag flow	0.284***	0.285***	0.191***	0.191***
	(0.009)	(0.009)	(0.012)	(0.012)
FF5 alpha	0.161***	0.157***	0.108***	0.106***
	(0.012)	(0.013)	(0.009)	(0.009)
FF5 IV		0.099		0.261*
		(0.183)		(0.156)
Max return		0.068**		0.032*
		(0.029)		(0.019)
MS rating			1.148***	1.150***
			(0.036)	(0.036)
Controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	526,580	526,580	443,531	443,531
Adj. R^2	0.174	0.174	0.132	0.132

Table A.2: Salience theory and fund flows: Fama-MacBeth regression

This table presents coefficient estimates from the Fama-MacBeth regression of fund flow on salience theory value (ST). In the regression, the dependent variable, fund flow, is measured over month t+1, while all independent variables are measured in month t. The independent variables include lagged fund flow, FF5 alpha, FF5 idiosyncratic volatility (FF5 IV), fund maximum return, Morningstar rating, as well as the following controls: logarithm of fund size, expense ratio, and load dummy. Standard errors, adjusted using the Newey-West method, are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = Fund flow			
	(1)	(2)	(3)	(4)
ST	0.390***	0.348***	0.309***	0.313***
	(0.092)	(0.093)	(0.080)	(0.079)
Lag flow	0.303***	0.301***	0.217***	0.216***
	(0.012)	(0.012)	(0.008)	(0.008)
FF5 alpha	0.205***	0.220***	0.138***	0.147***
	(0.015)	(0.017)	(0.009)	(0.010)
FF5 IV		-0.257		-0.307*
		(0.191)		(0.162)
Max return		-0.105		0.028
		(0.074)		(0.038)
MS rating			0.904***	0.895***
			(0.042)	(0.042)
Controls	Yes	Yes	Yes	Yes
Observations	526,580	526,580	443,551	443,551
Adj. R^2	0.121	0.124	0.101	0.102

Table A.3: Salience theory and fund flows: Alternative rolling window

This table presents coefficient estimates from the panel regression of fund flow on salience theory value (ST). In the regression, the dependent variable, fund flow, is measured over month t+1, the independent variable ST is measured using daily returns from months t-2 to t, while all other independent variables are measured in month t. The independent variables include lagged fund flow, FF5 alpha, FF5 idiosyncratic volatility (FF5 IV), fund maximum return, Morningstar rating, as well as the following controls: logarithm of fund size, expense ratio, and load dummy. All regression specifications include fund style and month fixed effects. Standard errors, double-clustered at both fund and month levels, are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = Fund flow			
	(1)	(2)	(3)	(4)
ST	-0.062	-0.064	-0.034	-0.025
	(0.111)	(0.110)	(0.074)	(0.074)
Lag flow	0.303***	0.303***	0.206***	0.206***
	(0.011)	(0.011)	(0.013)	(0.013)
FF5 alpha	0.142***	0.142***	0.077***	0.076***
	(0.009)	(0.009)	(0.007)	(0.007)
FF5 IV		-0.173		0.278*
		(0.193)		(0.165)
Max return		0.018		0.030
		(0.033)		(0.020)
MS rating			0.969***	0.972***
			(0.028)	(0.028)
Controls	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	478,433	478,433	411,756	411,756
Adj. R^2	0.129	0.129	0.096	0.096

Table A.4: Salience theory and mutual fund performance

This table presents coefficient estimates from the panel regression of fund performance on salience theory value (ST). In this table, fund performance is measured by FF5 alpha. In the regression, the dependent variable, FF5 alpha, is measured over either next month in the first two columns or next quarter in the last two columns, while all independent variables are measured in month t. The independent variables include logarithm of fund size, load dummy, and expense ratio. Fund fixed effects are included in columns (1) and (3), and fund style fixed effects are included in columns (2) and (4). Standard errors, double-clustered at both fund and month levels, are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = FF5 alpha			
	Next month		Next quarter	
	(1)	(2)	(3)	(4)
ST	-0.171	-0.134	-0.185	-0.113
	(0.118)	(0.122)	(0.192)	(0.196)
Size	-0.073***	0.005	-0.297***	0.016
	(0.019)	(0.005)	(0.042)	(0.013)
Load dummy	-0.021	-0.017*	-0.052	-0.059**
	(0.017)	(0.010)	(0.047)	(0.030)
Expense ratio	-0.052***	-0.057***	-0.145***	-0.212***
	(0.019)	(0.010)	(0.036)	(0.019)
Fund FE	Yes	No	Yes	No
Style FE	No	Yes	No	Yes
Observations	496,917	453,819	491,739	449,275
Adj. R^2	0.008	0.003	0.047	0.009

Table A.5: Salience theory and fund flows: Inflows vs. Outflows

This table presents coefficient estimates from the panel regression of fund flow on salience theory value (ST). In the regression, fund flow is separated into inflows and outflows, which are measured over month t+1, while all independent variables are measured in month t. The independent variables include lagged fund flow, FF5 alpha, FF5 idiosyncratic volatility (FF5 IV), fund maximum return, fund minimum return, as well as the following controls: logarithm of fund size, expense ratio, and load dummy. All regression specifications include fund style and month fixed effects. Standard errors, double-clustered at both fund and month levels, are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable =			
	Inflows		Outflows	
	(1)	(2)	(3)	(4)
ST	0.304**	0.298**	0.082*	0.069*
	(0.151)	(0.138)	(0.045)	(0.039)
Lag flow	0.280***	0.280***	0.004**	0.004**
	(0.014)	(0.015)	(0.002)	(0.002)
FF5 alpha	0.175***	0.156***	0.038***	0.034***
	(0.020)	(0.019)	(0.005)	(0.005)
FF5 IV		2.300***		-0.664***
		(0.332)		(0.125)
Max return		0.083**		
		(0.037)		
Min return				0.073***
				(0.025)
Controls	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	182,279	182,279	296,443	296,443
Adj. R^2	0.158	0.159	0.045	0.048

Table A.6: Persistence in ST

This table reports the result of time-series persistence of salience theory value (ST) across individual mutual funds. Each month, we sort individual funds into five groups based on values of their ST (from the smallest to the largest). The table presents the transition probability matrix for these groups based on 1-month, 3-month, 6-month, and 12-month time windows, respectively. The rightmost column reports the percentage attrition rate for each ST group.

	Time window = 1 month					
ST group	1	2	3	4	5	Attrition
1	22.84	18.61	17.62	18.32	21.73	0.88
2	18.59	20.14	20.56	20.70	19.13	0.88
3	17.46	20.63	21.59	21.03	18.43	0.85
4	18.28	20.48	20.88	20.75	18.74	0.88
5	22.05	19.35	18.50	18.29	20.89	0.92

	Time window = 3 months					
ST group	1	2	3	4	5	Attrition
1	22.55	18.71	17.47	17.99	21.03	2.25
2	18.32	20.27	20.48	20.30	18.40	2.23
3	17.28	20.26	21.17	20.80	18.26	2.23
4	17.94	20.02	20.56	20.36	18.85	2.26
5	21.86	18.62	18.09	18.23	20.90	2.31

	Time window = 6 months					
ST group	1	2	3	4	5	Attrition
1	22.02	18.33	16.77	17.63	20.85	4.40
2	17.92	19.55	19.89	19.95	18.39	4.30
3	17.13	19.83	20.87	20.34	17.56	4.27
4	17.85	19.74	20.22	19.82	18.05	4.33
5	21.00	18.37	17.93	17.90	20.50	4.30

	Time window = 12 months					
ST group	1	2	3	4	5	Attrition
1	21.32	17.63	16.50	16.66	19.29	8.60
2	17.53	18.92	19.03	18.90	17.22	8.40
3	16.41	18.76	19.81	19.48	17.23	8.30
4	16.94	18.77	19.18	19.12	17.65	8.35
5	19.69	17.69	17.05	17.40	19.79	8.39