

Salience, Smart Money Effect, and Mutual Fund Performance Persistence

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Abstract

This study investigates the investment performance of mutual fund investors who allocate capital toward funds with salient characteristics—namely, high past returns, strong inflows, and favorable ratings—and compares their outcomes with those of investors who select funds based on high estimated alpha. Using data on active mutual fund flows in Japan and the United States, we document that investor allocations in both countries are driven more by salience than by alpha. Despite this common behavioral tendency, the performance implications differ markedly across markets. In Japan, investors who chase high past returns achieve future risk-adjusted performance that is comparable to that of investors who target high-alpha funds. In contrast, in the United States, neither return-chasing investors nor alpha-seeking investors earn superior subsequent performance. These findings suggest that return persistence is more pronounced among Japanese mutual funds, whereas alpha lacks persistence in the U.S. market, rendering alpha-based fund selection ineffective. We further demonstrate that flow-induced return effects provide a plausible mechanism underlying mutual fund performance persistence in Japan.

Keywords: Salience Bias; Smart Money Effect; Performance Persistence; Mutual Fund; Fund Flows.

JEL classification: D14, G11, G41, G53.

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1. Introduction

What information should investors rely on when selecting mutual funds? In theory, investors should consider all relevant factors influencing fund performance—whether priced or unpriced—when assessing managerial skill (Grinblatt and Titman, 1989; Pástor and Stambaugh, 2002; Barber, et al., 2016). Since a portion of fund returns can be attributed to passive exposure to well-known risk factors, an accurate assessment of fund manager ability requires controlling for these factors to isolate the component of returns attributable to active management, typically measured by risk-adjusted returns (alpha). Sophisticated investors are expected to distinguish between skill-driven returns and those that could be earned through passive investment strategies (e.g., small-cap index funds). Conversely, less sophisticated investors may lack the tools or training to make such distinctions.

However, a substantial body of literature suggests that mutual fund investors exhibit behavior that is generally considered unsophisticated. For instance, investors are attracted to funds that hold recent winners or lottery-like stocks (Solomon, et al., 2014), funds with highly positive recent returns (Akbas and Genc, 2020), funds that are heavily advertised (Jain and Wu, 2000), and those that receive media attention (Kaniel and Parham, 2017). Investors also tend to favor highly rated funds (Del Guercio and Tkac, 2008) and exhibit poor market-timing abilities (Frazzini and Lamont, 2008). These behavioral tendencies have contributed to the empirical finding that, on average, actively managed equity mutual funds yield significantly negative benchmark-adjusted returns (alphas) after accounting for fees (Jensen, 1968; Carhart, 1997; Fama and French, 2010).

Despite this, some research finds that fund flows are positively associated with future fund performance, a relationship termed the smart money effect (Zheng, 1999; Gruber, 1996). This phenomenon suggests that certain investors possess the ability to forecast short-term fund performance and reallocate capital from underperforming funds to those expected to generate superior returns, implying a level of skill in fund selection. However, alternative explanations challenge this interpretation. The price pressure hypothesis suggests that fund flows themselves may influence returns through mechanical or temporary effects unrelated to investor skill (Coval and Stafford, 2007). As a result, the existence and interpretation of the smart money effect remain subjects of ongoing academic debate.

This study investigates the behavior and performance of mutual fund investors, with particular emphasis on retail investors who exhibit a preference for top-ranked mutual funds characterized by salient features such as recent high returns, fund popularity (proxied by net capital inflows), and third-party ratings. This preference reflects a behavioral tendency known as salience bias, wherein investors rely on easily observable but potentially misleading fund attributes when making investment decisions.

Furthermore, we compare the investment outcomes of investors influenced by salience bias with those of investors who prioritize mutual funds based on risk-adjusted performance, commonly measured by alpha. A central question addressed in this study is whether sophisticated investors—those who accurately account for risk and make allocation decisions based on alpha—achieve superior returns relative to less sophisticated investors who rely on raw, unadjusted performance metrics. This question is particularly relevant given the extensive empirical evidence indicating a lack of persistence in mutual fund performance (Carhart, 1997; Berk and van Binsbergen, 2015; Fama and French, 2010). Even if investors are capable of accurately assessing managerial skills, the transitory nature of alpha suggests that sustaining risk-adjusted outperformance over time may be inherently challenging.

Ferreira et al. (2012) highlight that the relationship between fund performance and flows differs markedly across countries, indicating that U.S.-based findings may not be globally applicable. In this study, we contribute to the literature by examining the Japanese mutual fund market alongside its U.S. counterpart. The Japanese market is characterized by expanding assets and low investor financial literacy (Sekita, 2011). Although Japanese households hold substantial financial wealth, most is allocated to deposits and insurance. To encourage investment in risk assets, the Japanese government has introduced tax incentives and policy initiatives, contributing to rapid growth in investment trust assets over the past decade. These structural and behavioral contrasts with the U.S. market underscore the importance of cross-country comparison.

In this paper, we start by investigating the presence of salience bias among investors in actively managed mutual funds in Japan and the U.S. Specifically, we analyze the relationship between fund flows and three salience indicators: top 10% 12-month return, top 10% fund flow, and Morningstar 5-star rating. The findings indicate that while alpha alone positively predicts fund flows, its predictive power diminishes once salience variables are included, all of which remain consistently positive and significant. These results suggest that investors in both markets are more influenced by salient fund characteristics than by risk-adjusted performance, highlighting a reliance on easily observable signals over more sophisticated performance measures and contrasting with earlier studies that emphasized alpha as a key determinant of fund flows.

We next examine the smart money effect by comparing the performance of investors influenced by salience bias with those prioritizing risk-adjusted returns, revealing contrasting results between Japan and the U.S. In Japan, salience-driven investors—those favoring high-return funds—achieve statistically significant future performance comparable to alpha-driven investors, indicating performance persistence among historically strong funds. Conversely, in the U.S., neither salience-based nor alpha-based strategies yield superior future returns. These findings challenge the notion that behavioral biases necessarily harm investment outcomes and suggest that salience-driven behavior may be effective in Japan, whereas alpha-chasing proves ineffective

in the U.S. market.

We then examine the persistence of mutual fund performance to explain why salience-based portfolios outperform in Japan but not in the U.S. In Japan, only portfolios based on the top 10% of past raw returns exhibit statistically significant positive alphas, while those based on past alpha do not. Conversely, in the U.S., neither strategy yields significant alpha, and the overall portfolio produces negative alpha. These findings challenge the conventional view that investors identify skilled managers through past alpha and support a flow-based explanation: in Japan, investor-driven flows may temporarily influence stock prices, contributing to persistence. The absence of similar effects in the U.S. suggests that flow-induced trading has limited impact on prices and performance outcomes.

The rest of this paper is organized as follows. Chapter 2 introduces the literature review on the determinants of fund flows and the salience bias, the smart money effect, and performance persistence. Chapter 3 illustrates the analytical methodology on salience bias and the smart money effect. Chapter 4 explains the data and Chapter 5 details the empirical results. Lastly, Chapter 6 concludes.

2. Literature Review

Numerous studies have analyzed the relationship between fund flows and fund returns using data from mutual funds. This section introduces previous studies and presents the novelty of this study.

2-1. Determinants of fund flows and salience bias

Early research on mutual fund flows identifies past performance as the primary driver of investor inflows (Ippolito, 1992; Gruber, 1996; Chevalier and Ellison, 1997). Sirri and Tufano (1998) show that fund flows respond non-linearly to performance, with inflows accelerating as returns improve. Barberis and Huang (2008) and Brunnermeier, et al. (2007) attribute this pattern to investor preferences for extreme positive returns and biased expectations about their likelihood—factors that drive demand for lottery-like assets.

Recent studies have explored how fund flows respond to risk-adjusted returns (alphas) derived from factor models. Barber, et al. (2016) find that CAPM alpha is the strongest predictor of flows among asset pricing models and that more sophisticated investors consider risk-adjusted performance. Del Guercio and Tkac (2002) find that alpha loses significance when Morningstar ratings are included, highlighting investors' reliance on third-party evaluations.

In Japan, Omori and Kitamura (2022) find that investors respond to alpha but not to factor-related returns, contrasting with U.S. findings. However, their 2023 study argues that unsophisticated investors in Japan struggle to evaluate factor-adjusted performance, with extreme

fund flows—particularly from the top 1%—driving the observed relationship.

Several studies highlight the role of media and ratings in reinforcing behavioral biases. Solomon, et al. (2014) show that media coverage amplifies investor responses to past performance. Kaniel and Parham (2017) find that being ranked in the Top 10 by The Wall Street Journal leads to significantly higher inflows than lower-ranked funds. Del Guercio and Tkac (2008) show that a Morningstar rating upgrade from 4 to 5 increases flows by 25%, while downgrades, particularly from 3 to 2, result in substantial outflows.

This study focuses on salience bias, where investors overweight easily observed fund characteristics. Theoretical work by Bordalo, et al. (2013) suggests that salient payoffs increase demand for risky assets. Empirically, Cosemans and Frehen (2021) find that investors chase stocks with the most visible gains, inflating their valuations. Frydman and Wang (2020), using investor-level data from China, show that salience shocks—without new information—intensify the disposition effect by 17%.

This study defines salience bias as the tendency of investors to favor mutual funds that exhibit prominent characteristics—specifically, high recent returns, strong popularity (proxied by high fund inflows), and favorable third-party ratings. We examine the presence of salience bias among mutual fund investors in Japan and the U.S. To quantify this bias, we employ dummy variables indicating whether a fund ranks in the top decile based on recent returns or net flows, as well as Morningstar ratings. By analyzing the determinants of mutual fund flows, we assess whether investor allocations are driven by salient fund attributes or by superior risk-adjusted performance (alpha).

2-2. The smart money effect

The smart money effect is a hypothesis that investors possess the ability to select superior funds and allocate capital accordingly. This hypothesis was first tested by Gruber (1996), who demonstrated that investors tend to allocate their capital to funds that are expected to outperform in the future. One interpretation of the smart money effect is that investors can identify managers with superior investment abilities and possess fund selection skills. Despite the wide-ranging evidence suggesting that active funds do not generate added value (alpha) on average, his findings serve as a justification for investments in active funds and address the puzzling, continued growth of the active fund industry.

Zheng (1999) built upon Gruber's (1996) research and discovered that inflows into small funds contribute to risk-adjusted returns (alpha). However, Sapp and Tiwari (2004) pointed out that these results are attributable to the momentum effect in stock returns. They argued that strong-performing stocks tend to maintain their performance, leading investors to subsequently shift capital to the funds that performed the best. This momentum effect is observed as a manifestation

of the smart money effect. When accounting for the momentum factor in stock returns, they demonstrated that the abnormal returns of funds experiencing inflows disappeared.

On the other hand, Keswani and Stolin (2008) reexamined the smart money effect using data from the UK and the US, confirming its presence among both individual and institutional investors. According to their study, the performance difference between funds with positive flows and those with negative flows is statistically significant. Furthermore, their reanalysis of US data demonstrated that the smart money effect is also observed when using monthly flows instead of quarterly flows. They indicated that Sapp and Tiwari (2004) could not find a significant relationship between fund flows and subsequent fund returns in the US because of their use of quarterly fund flows.

There is another interpretation of the smart money effect. The positive relationship between fund flows and future performance is explained by the idea that inflows into funds create positive price pressure on the underlying securities of those funds. Conversely, outflows from a fund can depress stock prices, deteriorating the fund's performance. Coval and Stafford (2007) referred to this as the "Price Pressure hypothesis." According to this hypothesis, fund flow-driven buying elevates stock prices beyond the momentum effect, pushing the prices of the current securities upward and causing stock prices to deviate from their informationally efficient values.

This study investigates the risk-adjusted performance (alpha) of portfolios formed from net inflows into mutual funds characterized by high past returns, strong capital inflows, and favorable third-party ratings—attributes indicative of salience bias. Although such investment behavior is widespread, empirical evidence on whether salience-driven strategies yield positive risk-adjusted returns remains limited. Furthermore, this study compares the performance of investors influenced by salience bias with that of investors who allocate capital based on risk-adjusted performance, as measured by alpha.

2-3. Performance persistence

The persistence of mutual fund performance has been a key topic in asset pricing research. Early studies including Grinblatt and Titman (1992), Goetzmann and Ibbotson (1994), and Brown and Goetzmann (1995) documented persistence in abnormal returns, while Hendricks et al. (1993) found short-term outperformance among top-performing funds. However, Carhart (1997) demonstrated that this persistence largely disappears when controlling for momentum, with consistent performance mainly observed among underperforming funds. This conclusion has been supported by subsequent studies, including Fama and French (2010) and Berk and van Binsbergen (2015), both of whom confirmed that persistent performance in U.S. mutual funds is mostly confined to underperformers. More recent research such as Bollen and Busse (2005) and Cohen et al. (2005) reports stronger evidence of persistence using refined methodologies.

In contrast, studies outside the U.S. present different findings. Research on U.K. mutual funds suggests stronger long-term persistence among outperforming funds. Blake and Timmermann (1998) and Otten and Bams (2002) found that persistence in the U.K. is largely driven by winner funds. Keswani and Stolin (2006) further attributed this to structural factors, such as market competitiveness. Extending the analysis globally, Ferreira et al. (2019) examined mutual fund performance across 27 countries and reported statistically significant persistence in most markets, suggesting that the U.S. experience may not be representative of broader global trends.

This study examines the performance persistence of mutual funds exhibiting salient characteristics—such as high past returns, substantial inflows, and favorable ratings—as well as those with historically high alphas. By comparing results between Japan and the U.S., the analysis assesses whether investments driven by salience bias can lead to superior future performance through the persistence of past fund performance.

3. Methodology

3-1. Salience bias

In this study, we measure fund flow using the net flow rate, defined as follows:

$$Net\ Flow\ Rate_{i,t} = \frac{Net\ Flow_{i,t}}{TNA_{i,t-1}} \quad (1)$$

where $TNA_{i,t}$ is the total net assets of fund i at the end of month t . For the net flows of U.S. mutual funds, we use the "Estimated Share Class Net Flow (Monthly)" provided by Morningstar Direct, which is defined in Equation (2). By summing up these values, we calculate the net flow at the fund level.

$$Net\ Flow_{i,t} = TNA_{i,t} - (1 + R_{i,t})TNA_{i,t-1} \quad (2)$$

Here, $R_{i,t}$ is the total return of fund i at the end of month t . Similarly, we sum the TNA of the share classes to calculate the TNA at the fund level. This enables us to calculate the net flow rate at the fund level. On the other hand, since the Japanese fund dataset allows us to calculate the accurate net flow (the difference between the purchase amount and the sale amount as shown in Equation (3)), we will use the "Monthly Net Cash Flow," which is the precise net flow provided by Morningstar, to analyze the flows in the Japanese mutual fund market.

$$Net\ Flow_{i,t} = Purchase\ Amount_{i,t} - Sales\ Amount_{i,t} \quad (3)$$

Furthermore, since share class schemes do not exist in Japan, we do not perform the aggregation procedure at the fund level as we do for U.S. mutual funds.

We use the following two regression models using monthly panel data to identify salience bias.

$$\begin{aligned}
Flow_{i,t} = & \alpha + \beta_1 ALPHA_{i,t-1}^{18M} \\
& + \beta_2 Top\ 10\% Return\ Dummy_{i,t-1} + \beta_3 Top\ 10\% Flow\ Dummy_{i,t-1} \\
& + \beta_4 Morningstar\ Rating\ 5\ Dummy_{i,t-1} + Control\ Variables_{i,t-1} \\
& + (Timefixed\ Effect) + \epsilon_{i,t}
\end{aligned} \tag{4}$$

$$\begin{aligned}
Flow_{i,t} = & \alpha + \beta_1 Top\ 10\% ALPHA^{18M}\ Dummy_{i,t-1} \\
& + \beta_2 Top\ 10\% Return\ Dummy_{i,t-1} + \beta_3 Top\ 10\% Flow\ Dummy_{i,t-1} \\
& + \beta_4 Morningstar\ Rating\ 5\ Dummy_{i,t-1} + Control\ Variables_{i,t-1} \\
& + (Timefixed\ Effect) + \epsilon_{i,t}
\end{aligned} \tag{5}$$

Where *Flow* is the net flow rate as specified in Equation (1). $ALPHA^{18M}$ is a variable calculated by weighing the monthly fund alphas with exponentially decaying weights that decrease further back in time (details will be provided later). *Top 10% Return Dummy*, *Top 10% Flow Dummy*, and *Morningstar Rating 5 Dummy* are variables that represent salience bias. Specifically, *Top 10% Return Dummy* is a dummy variable that takes the value of one if a fund's total return over the past 12 months calculated at the end of each month falls within the top 10% and zero otherwise. *Top 10% Flow Dummy* is a dummy variable that takes the value of one if monthly net flow amounts fall within the top 10% for each month and zero otherwise. *Morningstar Rating 5 Dummy* is a dummy variable that takes the value of one if Morningstar Rating is 5 and zero otherwise. *Morningstar Rating* is based on the Morningstar Overall Rating for each month. Morningstar rating is evaluated over periods of 3 years, 5 years, and 10 years, with a rating awarded on a scale of 1 to 5 (with 5 being the highest rating). We use the Morningstar Overall Rating, which is the weighted average ratings over different time periods, with weights of 20% for the 3-year rating, 30% for the 5-year rating, and 50% for the 10-year rating. For U.S. mutual funds, returns and Morningstar Ratings are provided at the share class level; therefore, we construct fund-level returns and Morningstar Ratings based on the TNA-weighted averages of the share classes. *Top 10% ALPHA^{18M} Dummy* is a dummy variable that takes the value of one if $ALPHA^{18M}$ at the end of each month falls within the top 10% and zero otherwise.

The control variables, following Barber et al. (2016), include the variables calculated by weighting the monthly fund's factor returns with exponentially decaying weights that decrease the further back in time ($MKTRET^{18M}$, $SMBRET^{18M}$, $HMLRET^{18M}$, $RMWRET^{18M}$, $CMARET^{18M}$, $WMLRET^{18M}$; details of these variables will be provided later) in month $t - 1$, the natural logarithm of total net assets ($LogTNA$) in month $t - 1$, the natural logarithm of the number of days since fund inception ($LogDays$) in month $t - 1$, the annualize standard deviation of monthly fund returns over the past 12 months (*Fund Volatility*) in month $t - 1$, the No-load fund dummy (*No - load Dummy*) in month $t - 1$, the expense ratio (*Expense Ratio*) in month $t - 1$, and lagged fund flows (*Flow*) from month $t - 1$ to $t - 19$. For U.S. funds, the number

of days since fund inception (fund age) is determined by the oldest share class. The No-load dummy is a dummy variable that takes the value of 1 if the share class held by the fund is exclusively a no-load class and takes the value of 0 otherwise in the U.S. In the case of Japanese funds, it takes the value of 1 if the maximum sales load fee is 0, and 0 otherwise. The Expense Ratio, for U.S. funds, is a variable that converts the share class-based Total Expense Ratio to fund-level using total net assets as weights, while in Japan, the management fee is used.

The performance variables mentioned above, $ALPHA^{18M}$, are calculated based on the Fama and French (2015) five-factor model augmented with the momentum factor (FFC6). Specifically, following Barber, et al. (2016) and Omori and Kitamura (2022, 2023), we first conduct a time series regression for fund i at time t , with $\tau = t - 1, \dots, t - 36$ using the following equation:

$$R_{i,\tau} - R_{f,\tau} = \alpha_{i,t} + \beta_{i,t}(Mkt_{\tau} - R_{f,\tau}) + s_{i,t}SMB_{\tau} + h_{i,t}HML_{\tau} + r_{i,t}RMW_{\tau} + c_{i,t}CMA_{\tau} + w_{i,t}WML_{\tau} + \epsilon_{i,\tau} \quad (6)$$

where $R_{i,\tau}$ is the monthly fund return, $R_{f,\tau}$ is the risk-free rate, Mkt_{τ} is the market return, SMB_{τ} is the size-factor return, HML_{τ} is the value-factor return, RMW_{τ} is the profitability-factor return, CMA_{τ} is the investment-factor return, and WML_{τ} is the momentum-factor return. Regarding Japanese mutual funds, we use the TOPIX total return index for the market return, and for the risk-free rate, we use the yield of the 10-year Japanese government bond. For US mutual funds, the market return is the value-weighted return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ, and the risk-free rate is the one-month Treasury bill rate. We retrieve the Mkt and the risk-free rate for U.S. Funds and the factor returns for both Japanese and U.S. Funds from the Kenneth R. French Data Library¹.

Using the factor loading obtained from Equation (6), we calculate the factor-related return (FRR) for fund i at time t , as shown in Equation (7):

$$FRR_{i,t} = \hat{\beta}_{i,t}(Mkt_t - R_{f,t}) + \hat{s}_{i,t}SMB_t + \hat{h}_{i,t}HML_t + \hat{r}_{i,t}RMW_t + \hat{c}_{i,t}CMA_t + \hat{w}_{i,t}WML_t \quad (7)$$

Next, we calculate the alpha, which represents the FFC6-adjusted return for fund i at time t , using Equation (8):

$$Alpha_{i,t} = (R_{i,t} - R_{f,t}) - FRR_{i,t} \quad (8)$$

Furthermore, since investors are likely to reference performance not only from the most recent period but also from several previous periods, we follow the approach of Barber et al. (2016). Specifically, we empirically estimate the rate at which the flow-return connection decays by utilizing monthly fund returns. Initially, we analyze the following unrestricted model of the flow-return relationship:

$$Flow_{i,t} = \alpha + \sum_{s=1}^{18} \beta_s MAR_{i,t-s} + Control\ Variables_{i,t-1} + (Time - fixed\ Effect) + \epsilon_{i,t} \quad (9)$$

¹ https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

In this equation, MAR signifies the lagged market-adjusted return for the fund i at lag s , ranging from 1 to 18 months. The market-adjusted return (MAR) is calculated by subtracting the fund return from the market return. We set the lag length to 18 months, following Barber et al. (2016).

The control variables include the natural logarithm of total net assets, the natural logarithm of days from fund inception, the annualized standard deviation of fund returns over the past twelve months, expense ratio, No-load dummy and lagged fund flows (net flow rate) from month $t - 1$ to $t - 19$. Time fixed effects are also added to the model.

This regression framework produces a series of coefficient estimates that capture the relationship between flows in month t and the MAR lagged by s months (where $s = 1, 2, \dots, 18$). Consistent with the findings of Barber et al. (2016), the estimated coefficients over the 1- to 18-month lag horizon exhibit a monotonic decline, indicating that more recent returns exert a stronger influence on fund flows than more distant past returns.

To parsimoniously characterize the observed decay in the sensitivity of fund flows to lagged market-adjusted returns, we adopt an exponential time-decay specification, in which λ denotes the decay rate. The exponential decay model is estimated based on Equation (10). The estimated decay rates are 0.0762 for Japan and 0.1704 for the United States. Using these estimated decay parameters, we construct the 18-month decayed performance measure, $ALPHA^{18M}$, as specified in Equation (11).

$$Flow_{i,t} = \alpha + \beta_1 \sum_{s=1}^{18} e^{-\lambda(s-1)} MAR_{i,t-s} + Control\ Variables_{i,t-1} + (Time\ fixed\ Effect) + \epsilon_{i,t} \quad (10)$$

$$ALPHA_{i,t}^{18M} = \frac{\sum_{s=1}^{18} e^{-\lambda(s-1)} Alpha_{i,t-s}}{\sum_{s=1}^{18} e^{-\lambda(s-1)}} \quad (11)$$

Similarly, we apply the exponential decay function to weight each factor return calculated using Equation (7). For example, the return associated with SMB ($SMBRET^{18M}$) is calculated as follows:

$$SMBRET_{i,t}^{18M} = \frac{\sum_{s=1}^{18} e^{-\lambda(s-1)} \hat{S}_{i,t-s} SMB_{t-s}}{\sum_{s=1}^{18} e^{-\lambda(s-1)}} \quad (12)$$

In Equation (4) and (5), if the coefficients of salience variables (*Top 10% Return Dummy*, *Top 10% Flow Dummy*, *Morningstar Rating 5 Dummy*) are significantly positive, it indicates the presence of salience bias. Additionally, by comparing the model results with and without the inclusion of salience variables, we can assess whether investors react to past alpha by examining the coefficient of $ALPHA^{18M}$ and *Top 10% ALPHA^{18M} Dummy*.

3-2. The smart money effect

To examine the smart money effect, we use the "portfolio regression approach"², following the methodologies of Zheng (1999), Sapp and Tiwari (2004), and Keswani and Stolin (2008). The portfolio regression approach investigates investors' fund selection ability by estimating the performance of new money portfolios constructed based on the fund's realized net flows. The performance measures of the portfolio regression approach are the risk-adjusted return (alpha) obtained by regressing the time series of the portfolio returns against the factor returns. This study investigates the average monthly alpha estimated using the three different factor models: the Fama-French three-factor model (FF3), the Fama-French and Carhart four-factor model (FFC4) and the Fama-French five-factor model with the momentum factor (FFC6).

The construction of portfolio returns and the measurement of alpha are represented by the equations below:

$$R_{p,t} = \frac{\sum (R_{i,t} \times w_{i,t})}{\sum w_{i,t}} \quad (13)$$

$$R_{p,t} - R_{f,t} = \alpha_p + B_{1,p}(Mkt_t - R_{f,t}) + B_{2,p}SMB_t + B_{3,p}HML_t + \epsilon_{p,t} \quad (14)$$

$$R_{p,t} - R_{f,t} = \alpha_p + B_{1,p}(Mkt_t - R_{f,t}) + B_{2,p}SMB_t + B_{3,p}HML_t + B_{4,p}WML_t + \epsilon_{p,t} \quad (15)$$

$$R_{p,t} - R_{f,t} = \alpha_p + B_{1,p}(Mkt_t - R_{f,t}) + B_{2,p}SMB_t + B_{3,p}HML_t + B_{4,p}RMW_t + B_{5,p}CMA_t + B_{6,p}WML_t + \epsilon_{p,t} \quad (16)$$

Here, $R_{p,t}$ is the monthly return of the fund portfolio weighted by w , $R_{f,t}$ is the risk-free rate, Mkt_t is the market return, SMB_t is the size-factor return, HML_t is the value-factor return, RMW_t is the profitability-factor return, CMA_t is the investment-factor return, WML_t is the momentum-factor return.

In this study, we construct the portfolio using monthly flows (i.e., monthly rebalancing). Specifically, we divide the funds into those with positive net flows and negative net flows based on the monthly fund flows from the previous month and create both flow-weighted and equal-weighted portfolios for each category to calculate the monthly returns of the portfolio for the subsequent month.

In this analysis, the funds under consideration are primarily categorized into three types: all funds, funds associated with salience bias, and funds with high past alpha. We compare the performance of portfolios constructed from these categories. Funds with salience bias are defined as those that meet the following criteria at the end of each month: (1) funds that fall within the

² In addition to the portfolio regression approach, the fund regression approach is also used to examine the smart money effect. However, the portfolio regression approach has the advantage of not incorporating look-ahead bias (Zheng, 1999).

top 10% of 12-month returns (*Top 10% Return Dummy*), (2) funds that fall within the top 10% of monthly flows (*Top 10% Flow Dummy*), and (3) funds with a Morningstar rating of 5 (*Morningstar Rating 5 Dummy*). Funds with high past alpha are defined as those that rank in the top 10% based on $ALPHA^{18M}$ in Equation (11) at the end of month (*Top 10% $ALPHA^{18M}$ Dummy*). Based on the expectation that sophisticated investors are likely to select funds with historically high average alpha, we construct a portfolio composed of the top 10% alpha funds to facilitate comparison with the funds selected due to salience bias. It is important to note that the point in time for identifying these funds is set to one period prior to when flows are observed, as investors make their investment decisions based on past salience variables and performance information. For example, when measuring the returns of a portfolio based on the top 10% 12-month return dummy, we focus on funds that ranked in the top 10% for total returns over the past year as of December 31, 2019. A portfolio is constructed based on the monthly flows of these funds during January 2020, and the returns for February 2020 are then calculated. This process is repeated monthly, resulting in a series of monthly returns for the portfolio. The resulting time series of monthly portfolio returns (after deducting the risk-free rate) is then regressed against factor returns to measure the portfolio's alpha.

In this paper, we construct 6 types of portfolios for each group of funds we analyze:

1. A portfolio weighted by positive net flow amounts
2. A portfolio equally weighted by funds with positive net flows
3. A portfolio weighted by negative net flow amounts
4. A portfolio equally weighted by funds with negative net flows
5. A portfolio that takes a long position in portfolio 1 and a short position in portfolio 3
6. A portfolio that takes a long position in portfolio 2 and a short position in portfolio 4

Portfolios 1 and 2 are constructed using funds with positive net flow based on the flow-weighted and equal-weighted average of those funds. In contrast, Portfolios 3 and 4 are based on funds with negative net flow, also utilizing the flow-weighted and equal-weighted average of those funds. Unlike equal-weighted portfolios, flow-weighted portfolios emphasize funds that experience larger absolute flows. Portfolios 5 and 6 are different portfolios created by subtracting the returns of the portfolio weighted by funds with negative flow from the returns of the portfolio weighted by funds with positive flow. This represents the performance difference between the buying portfolio (with positive net flows) and the selling portfolio (with negative net flows) from the investor's perspective. In prior research, if the performance of the buying portfolio exceeds that of the selling portfolio, it is often considered to be "smart." However, Jiang and Yuksel (2017) found that the significant performance difference between the buying (positive flow) and selling

(negative flow) portfolios is primarily due to the underperformance of the selling (negative flow) portfolio, which casts doubt on the smart money hypothesis. Especially when considering whether investors can achieve higher returns in the future, the buying portfolio is considered to be more important. Based on this, this study will focus not only on the performance difference between the buying and selling portfolios but also on the performance of the buying portfolio itself.

Additionally, we conduct a comparative analysis of portfolios 1 through 4 among different groups of funds: all funds selected based on salience bias, and funds with high past alpha. We compare the following two cases:

7. A portfolio that takes a long position in a portfolio composed of funds with high past alpha and takes a short position in a portfolio composed of all funds
8. A portfolio that takes a long position in a portfolio composed of funds with high past alpha and takes a short position in a portfolio composed of funds selected based on salience bias

If the alpha of portfolios 7 and 8 are statistically significant and positive, investors selecting funds with high past alphas will demonstrate better performance than the overall average investor and those relying on salience bias.

4. Data

The data is obtained from Morningstar Direct provided by Ibbotson Associates. Regarding Japanese mutual funds, we focus on actively managed mutual funds that invest in Japanese equities and exclude DC-specific and wrap/SMA-specific funds, as their fund flow characteristics are considered to differ from those of general mutual funds. Currency selection-type funds³ that invest in Japanese equities are also excluded due to their performance being affected by foreign exchange fluctuations. Additionally, we exclude sector funds, long-short funds and option trading funds.

Regarding U.S. mutual funds, we conduct the analysis at the fund level rather than at the share class level. Specifically, we focus on share classes that correspond to A, B, C, and No-Load types⁴

³ A currency selection-type fund is an investment vehicle that not only invests in target assets but also engages in currency trading to add returns such as currency hedge premiums.

⁴ A, B, C, and No-Load share classes are common types of mutual fund share categories with different fee structures. Class A shares typically charge a front-end load. Class B shares impose a back-end load or the so-called contingent deferred sales load (CDSL). Additionally, Class B shares automatically convert to Class A shares after being held for a certain period. Class C shares generally do not charge front-end loads but impose relatively higher annual 12b-1 fees (e.g., around 1.00%). No-Load shares are sold without front- or back-end sales charges and are usually distributed directly by the investment company

as provided by Morningstar, and we construct fund-level variables as previously mentioned. Advisor share classes, institutional investor classes, and retirement share classes are excluded from the scope of this study. Advisor share classes are excluded because, in the Japanese mutual fund market, sales through independent advisors are infrequent, with the majority of sales occurring through distributors such as securities firms and banks or via direct sales by asset management companies. Additionally, they are similar to wrap/SMA-specific funds, which are also excluded from the analysis in the Japanese market. Given that the primary investors in the Japanese mutual funds examined in this research are predominantly retail investors, institutional investor classes are omitted. Additionally, retirement-related funds, including defined contribution (DC) funds, are also excluded from this analysis, thus allowing the focus to remain on the aforementioned share classes. We focus on actively managed mutual funds that invest in US equities and exclude sector funds, long-short funds and option trading funds. To minimize survivor bias, funds that have already been liquidated are also included in the sample for both U.S. and Japanese datasets.

The analysis period for the determinants of fund flows is from May 2016 to December 2024. This is because Morningstar Ratings for Japanese mutual funds are unavailable prior to April 2016. To calculate alpha and factor-related returns in equation (5), 36 months of historical return data is required. Furthermore, since the performance variables used in equation (6) are derived from past 18 months of alpha and factor-related returns using an exponential decay model, the data is obtained starting from October 2011. Following Barber et al. (2016), net flow rate is truncated below -90% and above $1,000\%$.

The total number of funds used in the analysis of the determinants of fund flows for Japanese mutual funds is 507, while for U.S. funds, it is 882. On the other hand, in the examination of the smart money effect, the analysis period is set from June 2016 to December 2024. In the portfolio regression approach, since the calculation of alpha is not conducted for each fund, funds with shorter performance histories or newly established funds are also included in the analysis, resulting in a greater total number of funds compared to the analysis of the determinants of fund flows. The number of funds included in the analysis of the portfolio regression approach varies over time due to the establishment or liquidation of funds. On a monthly basis, the average number of funds for Japanese mutual funds is approximately 418, while the total number of funds over the entire period is 578. As for US mutual funds, the average number of funds per month is approximately 750, while the total number of funds over the entire period is 893.

Table 1 presents the descriptive statistics for the variables used in the analysis of the determinants of fund flows. The negative average of the net flow rate for Japanese mutual funds is influenced by the fact that the average age of the funds in the sample is 4,726 days

(approximately 12.9 years⁵). This is because older funds are more susceptible to outflows (sales) in Japan. The requirement of 54 months of data necessary for constructing the performance variables contributes to the prevalence of these older funds. Similarly, in the U.S., the average net flow rate is also negative. This is believed to be influenced by the recent capital shift from active funds to passive funds, particularly ETFs. The average risk-adjusted return ($ALPHA^{18M}$) is nearly zero for Japan, while in the U.S., it is slightly negative (-0.15%).

5. Empirical Results

5-1. Salience bias

In this section, we first investigate whether salience bias exists among investors in actively managed mutual funds. Specifically, we aim to clarify the relationship between fund flows measured by net flow rates and the three salience variables: 1) top 10% 12-month return dummy, 2) top 10% flow dummy, and 3) Morningstar rating 5 dummy. Tables 2 and 3 present the results of the determinants of net flow rates in Japanese and U.S. markets, respectively. In Table 2, the models (1) and (4) present the results when alpha is only used as the independent variable, while (2), (3), (5), and (6) illustrate the results when salience variables are added as independent variables. In all regression models, we include as control variables each factor return of the FFC6 model based on the previous 18 months of data using an exponential decay model, the natural logarithm of total net assets, the natural logarithm of the number of days since fund inception, the annualized standard deviation of monthly fund returns, the no-load fund dummy, and the expense ratio (referred to as management fee in Japan and total expense ratio in the U.S.), all lagged by one period. Additionally, past fund flows (net flow rates) lagged from t-1 to t-19 are included.

We use different alphas in the models (1)-(3) and (4)-(6): $Alpha^{18M}$ in (1)-(3) and top 10% $Alpha^{18M}$ dummy in (4)-(6). Since the control variables include each factor return of the FFC6 model based on the previous 18 months of data using an exponential decay model, the model (1) is the similar model used in Barber et al. (2016), which analyzed what variables investors focus on in their fund selection. On the other hand, in the model (4), top 10% $Alpha^{18M}$ dummy is used instead of $Alpha^{18M}$ while keeping the control variables same. The results show that in (1) and (4), where no salience variables are included as independent variables, the coefficient of both alphas are positive and significant. This indicates that capital appears to be flowing into funds with high alpha.

However, as observed in (3) and (6), when three salience dummies are included as independent variables, the coefficients for these variables are all significant and positive, suggesting that investors are allocating their capital to the funds with these salience characteristics. Surprisingly,

⁵ It is calculated by averaging the number of days before natural logarithmic transformation.

when including the salience variables, significance of $Alpha^{18M}$ and top 10% $Alpha^{18M}$ dummy is lost. In other words, investors are investing in funds with salience features than those of high alpha.

While there is a positive correlation between $Alpha^{18M}$ and the top 10% 12-month return dummy, as well as the Morningstar rating 5 dummy, the correlation coefficients are 0.21 and 0.23, respectively. Additionally, the correlation coefficients between the Top 10% $Alpha^{18M}$ dummy and the top 10% 12-month return dummy, as well as the Morningstar rating 5 dummy, are 0.21 and 0.20, respectively, making it unlikely that multicollinearity is the cause of these results. This result suggests that investors are likely relying on these salience variables when investing in funds and indicates that they are not sophisticated investors who base their decisions on alpha. This tendency is also observed in the U.S. market as displayed in Table 3.

Prior research focusing on U.S. and Japanese active mutual funds, such as Barber et al. (2016) and Omori and Kitamura (2022, 2023), reported that funds with higher alpha experience significant inflows. However, our results suggest that both U.S. and Japanese investors select mutual funds not based on past alpha but on salience biases.

5-2. The smart money effect

We next examine the smart money effect in the Japanese and U.S. mutual fund markets using the portfolio regression approach.

Table 4 presents the alphas of the portfolios measured using the FF3, FFC4 and FFC6 model specified in equation (14), (15) and (16) for Japanese mutual funds. Panel A presents a portfolio consisting of all funds, while Panels B through D present portfolios composed of funds selected based on salience biases. Panel E shows a portfolio consisting of funds with high past alpha. Panel A indicates that none of the portfolio alphas are statistically significant. This implies that the funds traded by the overall investor base—both buys and sells—do not support the smart money effect, irrespective of future performance. In contrast, examining Panels B through E, which represent portfolios constructed based on salience biases, we find that all alphas for the Positive Flow portfolios in Panel B are positive and statistically significant. Additionally, one Positive Flow portfolio in Panel D also shows a statistically significant alpha. This suggests that investors who select funds with high recent return rankings or high Morningstar ratings can earn alpha, but Morningstar ratings are not particularly robust. Conversely, in Panel C, none of the portfolios have statistically significant alphas, indicating that investors who select funds based on high recent flow rankings do not earn alpha. In Panel E, the alphas of some Positive Flow portfolios (flow-weighted portfolios) are positive and statistically significant. This suggests that investors who invest in historically high alpha funds can achieve future alpha.

Next, Table 5 presents the comparison of alphas between funds with high past alpha and those

from all funds as well as funds selected based on salience biases for Japanese mutual funds. The portfolio in Panel A takes a long position in a portfolio consisting of funds with high past alpha while taking a short position in a portfolio consisting of all funds. The portfolios in Panels B through D take a long position in a portfolio comprising funds with high past alpha and a short position in a portfolio consisting of funds selected based on salience biases. Panel A confirms that the alphas of the flow-weighted buy-side (Positive Flow) portfolios are statistically significant and positive. This indicates that investors who allocate capital to funds with high past alphas achieve higher alphas compared to the average overall investor. A similar trend is observed in Panel C, where investors investing in funds with high past alphas attain higher alphas compared to those who select funds based on high recent flow rankings. In contrast, both Panel B and Panel D show that the alphas are not statistically significant. This suggests that investors selecting funds with high Morningstar ratings (highly rated funds) or those with high past returns achieve alphas that are comparable to those of investors choosing funds with high past alpha.

Table 6 presents the results for U.S. mutual funds, mirroring the format of Table 4. In Panel A, all Negative Flow portfolios exhibit statistically significant negative alphas, while the equal-weighted Positive-Negative portfolio shows a statistically significant positive alpha under the FF3 model. These findings align with Jiang and Yuksel (2017), who suggest that U.S. investors tend to sell funds with poor expected performance. They posit that outflows from retail funds exhibit a high degree of persistence, leading to the price pressure hypothesis, i.e., past outflows (or inflows) influence the current net asset value (NAV) by pushing it downward (or upward), resulting in the observed positive relationship.

Similar patterns are observed in Panels C and D. On the other hand, Panels B and E show no statistically significant alphas across portfolios. Overall, Positive Flow portfolios in the U.S. do not yield significant alphas, indicating that investors driven by salience biases or past alpha do not achieve superior future performance. Notably, the significantly positive alpha of the flow-weighted Positive-Negative portfolio in Panel C is primarily due to the underperformance of Negative Flow portfolios, further reinforcing the lack of effectiveness of salience-driven strategies in the U.S. market.

Table 7 presents the results for U.S. mutual funds in the same format as Table 5. Unlike in Japan, none of the portfolios have statistically significant positive alphas. In fact, there are cases where the negative flow portfolios produce significantly negative alphas. This suggests that investors who invest in funds with high past alphas do not achieve high performance compared to investors investing in funds with high raw returns and high ratings.

The results reveal contrasting patterns between Japan and the U.S. In Japan, investors exhibiting salience bias—favoring high-return funds—achieve statistically significant future alpha, comparable to those investing in high past-alpha funds, traditionally associated with sophisticated

behavior. This suggests performance persistence among historically strong funds and challenges the conventional view that behavioral biases impair investment outcomes. In contrast, in the U.S., neither salience-driven investors nor those chasing past alpha realize superior future performance, indicating a lack of alpha persistence and questioning the effectiveness of alpha-chasing investment strategy in the U.S. market.

6. Performance Persistence

Salience-based portfolios and high-alpha portfolios require performance persistence to achieve future risk-adjusted returns. This section explores the underlying reasons why salience-based portfolios achieve superior future performance in Japan, while high-alpha portfolios do not in the U.S., by analyzing the persistence of fund performance in each market.

We adopt a recursive portfolio sorting approach at the portfolio level. This method involves sorting mutual funds based on a predetermined attribute such as past performance, and rebalancing the portfolios at regular intervals (e.g., monthly). For each period, we form equally weighted portfolios and track their returns over the subsequent month. To evaluate performance, we estimate alphas by regressing portfolio returns on factor returns from each model (the FF3, FFC4, and FFC6). This methodology allows for a realistic assessment of whether an ex-ante investment strategy would have generated abnormal returns (Cuthbertson et al., 2022).

Table 8 reports the alphas of portfolios constructed using all funds, funds selected based on salience bias, and funds with high past alphas. In the Japanese market, portfolios composed of funds in the top 10% by past raw returns exhibit statistically significant positive alphas, indicating the potential for salience-driven strategies to generate future outperformance. In contrast, portfolios based on other criteria, including the top 10% by past alpha over an 18-month horizon, do not yield statistically significant alphas. This finding implies that selecting funds based on high past raw returns may be more effective in generating future alpha than selecting based on past risk-adjusted performance. In the U.S. market, the portfolio of all funds exhibits a statistically significant negative alpha. Neither salience-based portfolios nor those formed using past alpha rankings display significant alpha, suggesting that these selection strategies do not result in superior future performance on average.

The conventional explanation for performance persistence posits that some mutual fund managers possess superior skill, which retail investors can identify. Under this assumption, portfolios formed from the top 10% of funds ranked by past alpha should yield statistically significant future alphas. However, empirical results do not support this: such portfolios do not generate significant future alpha. In contrast, portfolios constructed from the top 10% of funds based on past raw returns do exhibit statistically significant positive alphas. This discrepancy suggests an alternative explanation, namely, the flow-based interpretation of persistence. Wermers

(2003) and Lou (2012) propose that flow-induced trading can significantly affect individual stock prices, temporarily moving them away from their fundamental values. These price impacts, driven by fund flows, occur even after controlling for momentum, implying that investor behavior and flow dynamics contribute meaningfully to observed performance persistence.

Tables 9 and 10 present the average Total Net Assets (TNA) and average flows of funds belonging to decile portfolios sorted by past annual raw returns and past alphas for Japanese and U.S. mutual funds. From these tables, it is evident that in Japan, funds in the top 10% decile based on past annual raw returns exhibit significantly positive flows compared to other deciles. This suggests that Japanese investors display a salience bias, actively allocating capital to funds with high past raw returns. In contrast, such a pronounced pattern is not observed in the U.S. market.

To further investigate the role of flow-induced trading in driving mutual fund performance persistence in the Japanese and U.S. markets, we conduct a double sort analysis similar to Lou (2012). Specifically, we first conduct the following regression to compute the expected flow, $E[\text{Flow Rate}]$.

$$Flow_{i,t} = \alpha + \beta_1 Annual\ Raw\ Return_{i,t-1} + \sum_{s=1}^{12} \gamma_s Flow_{i,t-s} + (Timefixed\ Effect) + \epsilon_{i,t} \quad (17)$$

Next, based on $E[\text{Flow Rate}]$ and $Alpha^{18M}$, we classify funds each month into four groups: top 10%, 10–50%, 50–90%, and bottom 10%. We then construct equally weighted portfolios of funds within each group and analyze their future performance. The portfolios are sorted first by $E[\text{Flow Rate}]$ and then by $Alpha^{18M}$, as well as in the reverse order.

The table 11 presents the FFC6-adjusted alphas of these portfolios. Our analysis reveals a clear pattern in the Japanese mutual fund market. When funds are first sorted by expected flow rates (Panel A), portfolios with higher $E[\text{Flow Rate}]$ deliver significantly positive alphas. In particular, the highest flow portfolio outperforms the lowest flow portfolio with a statistically significant positive alpha spread. This result aligns closely with the flow-based explanation proposed by Lou (2012). In contrast, this positive and significant performance pattern for high expected flow portfolios is not observed in the U.S. market within Panel A. Panel B, where funds are first sorted by $Alpha^{18M}$ and then by expected flows, further corroborates these conclusions. Even among funds with high past alpha, expected flow remains a significant predictor of future performance. Furthermore, it is shown that in both Japan and the U.S., funds with high past alpha do not exhibit statistically significant high future alpha. This suggests that the observed persistence in fund returns is more plausibly explained by flow dynamics than by manager skill per se.

In sum, the double sorting results provide strong empirical support for the flow-based

explanation of mutual fund performance persistence in Japan⁶. The alpha-based explanation, representing managerial skill, lacks sufficient explanatory power, while predictable capital flows play an important role in driving the continuation of performance. Therefore, investor behavior reflected in flow patterns should be carefully taken into account when interpreting apparent performance persistence.

7. Conclusion

This study examines mutual fund investor behavior, focusing on retail investors' tendency to favor funds with salient features—such as recent high returns, popularity, and third-party ratings—over those with superior risk-adjusted performance (alpha). This preference reflects salience bias whereby investment decisions are influenced by attributes that are easy to notice but may be misleading. Analyzing fund flows in Japan and the U.S., we find that while alpha initially predicts flows, its influence diminishes when salience measures are included, suggesting that investors in both markets rely more on salient cues than on sophisticated performance metrics.

We further assess whether salience-driven or alpha-driven investment strategies yield superior outcomes. In Japan, investors who chase top-return funds realize statistically significant positive alphas, whereas alpha-based strategies do not outperform—implying that salience-based behavior can lead to persistent outperformance. In contrast, neither strategy proves effective in the U.S., where mutual fund returns show no significant persistence. These contrasting results support a flow-based explanation of performance in Japan. Flow-induced trading may temporarily distort prices in Japan, while such effects appear muted in the more efficient U.S. market.

⁶ We consider the possibility that macro-level policy interventions—most notably the Bank of Japan's (BOJ) exchange-traded fund (ETF) purchase program—may mechanically influence fund returns and thereby confound a flow-based interpretation of performance persistence. To address this concern, we estimate regressions of excess returns over the risk-free rate and fund alphas that explicitly control for monthly BOJ ETF purchase activity (see Appendix Table A-5). The results indicate that BOJ ETF purchases are not statistically significant determinants of fund returns.

Importantly, the BOJ primarily acquires TOPIX-linked ETFs, which are market-capitalization-weighted. As a result, BOJ purchases effectively represent market-cap-weighted aggregate demand rather than investor-driven reallocations based on past performance. This mechanical demand is therefore fundamentally distinct from retail investor flows, which respond endogenously to lagged returns. This distinction is further supported by our cross-sectional evidence showing that the sensitivity to past returns differs markedly between portfolios with high and low investor flows.

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Table 1 Descriptive Statistics

Variable	Mean	SD	5th Percentile	25th Percentile	50th Percentile	75th Percentile	95th Percentile
Panel A : Japanese Mutual Funds							
Flow (%)	-0.02	17.17	-6.04	-1.73	-0.58	0.00	5.15
ALPHA ^{18M} (%)	0.00	0.44	-0.65	-0.25	-0.02	0.23	0.76
MKTRET ^{18M} (%)	0.76	0.92	-0.63	0.03	0.74	1.44	2.27
SMBRET ^{18M} (%)	0.00	0.27	-0.42	-0.08	0.00	0.06	0.50
HMLRET ^{18M} (%)	0.02	0.32	-0.51	-0.12	0.01	0.16	0.56
RMWRET ^{18M} (%)	-0.01	0.20	-0.33	-0.09	0.00	0.08	0.29
CMARET ^{18M} (%)	-0.03	0.19	-0.37	-0.08	-0.01	0.04	0.23
WMLRET ^{18M} (%)	-0.01	0.11	-0.18	-0.05	0.00	0.03	0.13
Top 10% ALPHA ^{18M}	0.10	0.30	0.00	0.00	0.00	0.00	1.00
Top 10% Return Dummy	0.10	0.30	0.00	0.00	0.00	0.00	1.00
Top 10% Flow Dummy	0.10	0.30	0.00	0.00	0.00	0.00	1.00
Morningstar Rating 5 Dummy	0.10	0.30	0.00	0.00	0.00	0.00	1.00
LogTNA	21.75	1.75	19.09	20.77	21.76	22.86	24.40
LogDays	8.10	1.06	6.07	7.55	8.45	8.86	9.13
Fund Volatility (%)	15.35	5.42	7.31	11.26	14.81	19.17	24.23
No-load Dummy	0.06	0.25	0.00	0.00	0.00	0.00	1.00
Expense Ratio (%)	1.39	0.30	0.82	1.20	1.50	1.56	1.75
Panel B : U.S. Mutual Funds							
Flow (%)	-0.67	11.31	-3.70	-1.43	-0.78	-0.26	1.79
ALPHA ^{18M} (%)	-0.15	0.50	-0.92	-0.42	-0.15	0.12	0.62
MKTRET ^{18M} (%)	0.90	1.13	-0.98	0.19	0.92	1.46	2.90
SMBRET ^{18M} (%)	-0.01	0.33	-0.52	-0.09	0.00	0.06	0.43
HMLRET ^{18M} (%)	0.04	0.37	-0.49	-0.11	0.01	0.16	0.68
RMWRET ^{18M} (%)	0.00	0.15	-0.22	-0.04	0.01	0.05	0.17
CMARET ^{18M} (%)	-0.03	0.26	-0.43	-0.08	0.00	0.08	0.30
WMLRET ^{18M} (%)	0.00	0.12	-0.19	-0.05	0.00	0.04	0.17
Top 10% ALPHA ^{18M}	0.10	0.30	0.00	0.00	0.00	0.00	1.00
Top 10% Return Dummy	0.10	0.30	0.00	0.00	0.00	0.00	1.00
Top 10% Flow Dummy	0.10	0.30	0.00	0.00	0.00	0.00	1.00
Morningstar Rating 5 Dummy	0.04	0.20	0.00	0.00	0.00	0.00	0.00
LogTNA	19.21	2.19	15.58	17.92	19.35	20.68	22.41
LogDays	9.12	0.44	8.51	8.85	9.08	9.32	9.92
Fund Volatility (%)	17.04	7.00	6.67	12.09	16.43	21.52	29.11
No-load Dummy	0.18	0.38	0.00	0.00	0.00	0.00	1.00
Expense Ratio (%)	1.19	0.45	0.60	0.98	1.18	1.35	1.88

Notes: This table reports the descriptive statistics of the variables in equation (6).

Table 2 Determinants of fund flow in the Japanese market

	(1)	(2)	(3)	(4)	(5)	(6)
ALPHA ^{18M}	0.5044*** (0.1087)	0.1486** (0.0715)	0.0853 (0.0700)			
Top 10% ALPHA ^{18M} Dummy				0.6031*** (0.1589)	0.1475 (0.1228)	0.0868 (0.1183)
Top 10% Return Dummy		1.436*** (0.3680)	1.287*** (0.3256)		1.455*** (0.3704)	1.298*** (0.3260)
Top 10% Flow Dummy			2.330*** (0.5928)			2.333*** (0.5923)
Morningstar Rating 5 Dummy		0.3783*** (0.1202)	0.3226*** (0.1085)		0.3968*** (0.1174)	0.3328*** (0.1059)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Time (Month) FE	Yes	Yes	Yes	Yes	Yes	Yes
S.E.: Clustered	Fund & Month	Fund & Month	Fund & Month	Fund & Month	Fund & Month	Fund & Month
Observations	34,175	33,852	33,852	34,175	33,852	33,852
R2	0.15885	0.16038	0.16917	0.15850	0.16033	0.16916
Within R2	0.13764	0.13871	0.14774	0.13728	0.13867	0.14772

Notes: This table reports the results of the determinants of net flow rate estimated in equation (6) in the paper. Standard errors clustered as the fund and month levels are in parentheses. The symbols ***, ** and * denote significance at the 1%, 5% and 10% levels. The analysis period is from May 2016 to December 2024. The control variables include each factor return of the FFC6 model based on the previous 18 months of data using an exponential decay model, the natural logarithm of total net assets, the natural logarithm of the number of days since fund inception, the annualized standard deviation of monthly fund returns, the no-load fund dummy, and the expense ratio (referred to as management fee in Japan and total expense ratio in the U.S.), all lagged by one period. Additionally, past fund flows (net flow rates) lagged from t-1 to t-19 are included.

Table 3 Determinants of fund flow in the U.S. market

	(1)	(2)	(3)	(4)	(5)	(6)
ALPHA ^{18M}	0.3156*** (0.1032)	0.1589* (0.0893)	0.1060 (0.0877)			
Top 10% ALPHA ^{18M} Dummy				0.4732*** (0.1345)	0.2109* (0.1149)	0.1443 (0.1092)
Top 10% Return Dummy		1.072*** (0.1454)	0.8652*** (0.1306)		1.069*** (0.1462)	0.8625*** (0.1321)
Top 10% Flow Dummy			1.510*** (0.2867)			1.513*** (0.2868)
Morningstar Rating 5 Dummy		1.083*** (0.2070)	0.7755*** (0.1648)		0.8273*** (0.1769)	0.7804*** (0.1677)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Time (Month) FE	Yes	Yes	Yes	Yes	Yes	Yes
S.E.: Clustered	Fund & Month	Fund & Month	Fund & Month	Fund & Month	Fund & Month	Fund & Month
Observations	76,762	76,629	76,629	76,762	76,629	76,629
R2	0.02976	0.03328	0.03692	0.02973	0.03325	0.03691
Within R2	0.02585	0.02923	0.03289	0.02582	0.02920	0.03288

Notes: This table reports the results of the determinants of net flow rate estimated in equation (6) in the paper. Standard errors clustered as the fund and month levels are in parentheses. The symbols ***, ** and * denote significance at the 1%, 5% and 10% levels. The analysis period is from May 2016 to December 2024. The control variables include each factor return of the FFC6 model based on the previous 18 months of data using an exponential decay model, the natural logarithm of total net assets, the natural logarithm of the number of days

since fund inception, the annualized standard deviation of monthly fund returns, the no-load fund dummy, and the expense ratio (referred to as management fee in Japan and total expense ratio in the U.S.), all lagged by one period. Additionally, past fund flows (net flow rates) lagged from $t-1$ to $t-19$ are included.

Table 4 Alpha by fund groups in the Japanese Market

	Flow-Weighted Portfolio			Equal-Weighted Portfolio		
	FF3	FFC4	FFC6	FF3	FFC4	FFC6
PanelA : All Funds						
Positive Flow	0.1528 (0.1311)	0.1270 (0.1260)	0.0886 (0.1244)	0.0398 (0.0620)	0.0238 (0.0530)	0.0071 (0.0575)
Negative Flow	-0.0330 (0.0790)	-0.0432 (0.0688)	-0.0584 (0.0711)	-0.0221 (0.0568)	-0.0300 (0.0543)	-0.0639 (0.0582)
Positive – Negative	0.1857 (0.1147)	0.1701 (0.1194)	0.1470 (0.1121)	0.0619 (0.0519)	0.0537 (0.0477)	0.0710 (0.0499)
PanelB : Top 10% Return						
Positive Flow	0.4283** (0.1875)	0.3962** (0.1818)	0.4072** (0.1838)	0.3615** (0.1600)	0.3082** (0.1328)	0.3203** (0.1531)
Negative Flow	0.2181 (0.1823)	0.1645 (0.1522)	0.1587 (0.1597)	0.2496 (0.1576)	0.1902* (0.1145)	0.1734 (0.1175)
Positive – Negative	0.2101 (0.1541)	0.2317 (0.1562)	0.2486 (0.1653)	0.1119 (0.0810)	0.1180 (0.0814)	0.1469* (0.0861)
PanelC : Top 10% Flow						
Positive Flow	0.1972 (0.1397)	0.1744 (0.1339)	0.1322 (0.1306)	0.0741 (0.0906)	0.0562 (0.0899)	0.0403 (0.1050)
Negative Flow	0.0715 (0.1548)	0.0606 (0.1451)	0.0306 (0.1390)	-0.0450 (0.0951)	-0.0499 (0.0934)	-0.0895 (0.1038)
Positive – Negative	0.1213 (0.1843)	0.1145 (0.1747)	0.1035 (0.1746)	0.1109 (0.0882)	0.1024 (0.0850)	0.1280 (0.0999)
Panel D : MorningstarRating 5						
Positive Flow	0.2994 (0.1806)	0.2621* (0.1551)	0.2581 (0.1608)	0.1509 (0.0981)	0.1218 (0.0888)	0.1222 (0.0877)
Negative Flow	0.0846 (0.1541)	0.0686 (0.1416)	0.0861 (0.1460)	0.1452 (0.0942)	0.1261 (0.0806)	0.1095 (0.0839)
Positive – Negative	0.2148 (0.1774)	0.1935 (0.1973)	0.1721 (0.2042)	0.0058 (0.0929)	-0.0043 (0.1031)	0.0127 (0.1022)
Panel E : Top 10% ALPHA ^{18M}						
Positive Flow	0.4652** (0.1874)	0.4482** (0.1925)	0.3712 (0.2334)	0.1676 (0.1350)	0.1491 (0.1320)	0.0990 (0.1360)
Negative Flow	0.2106 (0.1868)	0.1888 (0.1776)	0.1112 (0.1710)	0.0995 (0.1044)	0.0808 (0.1063)	0.0220 (0.1001)
Positive – Negative	0.2649 (0.2378)	0.2693 (0.2167)	0.2758 (0.2107)	0.0736 (0.1338)	0.0735 (0.1338)	0.0862 (0.1337)

Notes: This table reports the alpha (%) of each portfolio measured using the FF3, FFC4 and FFC6 model. Standard errors (shown in parentheses) are calculated using the Newey-West method. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Positive flow indicates when the net flow is positive, while negative flow indicates when the net flow is negative. Positive-Negative is a difference portfolios, created by subtracting the returns of the portfolio weighted by negative flow from the returns of the portfolio weighted by positive flow. The performance measurement period for the portfolios is from June 2016 to December 2024.

Table 5 Comparison of Alpha among fund groups in the Japanese Market

	Flow-Weighted Portfolio			Equal-Weighted Portfolio		
	FF3	FFC4	FFC6	FF3	FFC4	FFC6
Panel A : Top 10% ALPHA ^{18M} – All						
Positive Flow	0.3061** (0.1450)	0.3145*** (0.1187)	0.2768** (0.1253)	0.1296 (0.1092)	0.1269 (0.1010)	0.0947 (0.1036)
Negative Flow	0.2435 (0.1700)	0.2319 (0.1761)	0.1696 (0.1715)	0.1216 (0.0746)	0.1108 (0.0744)	0.0859 (0.0776)
Panel B : Top 10% ALPHA ^{18M} – Top 10% Return						
Positive Flow	0.0254 (0.2040)	0.0400 (0.2004)	-0.0505 (0.2016)	-0.1954 (0.1615)	-0.1615 (0.1499)	-0.2245 (0.1641)
Negative Flow	-0.0076 (0.1988)	0.0243 (0.1942)	-0.0475 (0.2070)	-0.1500 (0.1311)	-0.1094 (0.1128)	-0.1514 (0.1157)
Panel C : Top 10% ALPHA ^{18M} – Top 10% Flow						
Positive Flow	0.2642* (0.1383)	0.2697** (0.1233)	0.2364* (0.1265)	0.0970 (0.0956)	0.0961 (0.0940)	0.0635 (0.0952)
Negative Flow	0.1454 (0.1860)	0.1389 (0.1888)	0.0898 (0.1742)	0.1544 (0.1071)	0.1441 (0.1075)	0.1234 (0.1058)
Panel D : Top 10% ALPHA ^{18M} – Morningstar Rating 5						
Positive Flow	0.1589 (0.2037)	0.1786 (0.2001)	0.1048 (0.1961)	0.0395 (0.1163)	0.0495 (0.1143)	0.0032 (0.1122)
Negative Flow	0.1260 (0.2267)	0.1201 (0.2380)	0.0251 (0.2246)	-0.0456 (0.1097)	-0.0453 (0.1097)	-0.0874 (0.1086)

Notes: This table reports the alpha (%) of each long-short portfolio measured using the FF3, FFC4, and FFC6 model. Standard errors (shown in parentheses) are calculated using the Newey-West method. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Positive flow indicates when the net flow is positive, while negative flow indicates when the net flow is negative. The performance measurement period for the portfolios is from June 2016 to December 2024.

Table 6 Alpha by fund groups in the U.S. Market

	Flow-Weighted Portfolio			Equal-Weighted Portfolio		
	FF3	FFC4	FFC6	FF3	FFC4	FFC6
Panel A : All Funds						
Positive Flow	0.0672 (0.1398)	-0.0020 (0.1326)	0.0065 (0.1252)	-0.0466 (0.0725)	-0.0783 (0.0650)	-0.0792 (0.0626)
Negative Flow	-0.1436*** (0.0531)	-0.1292** (0.0589)	-0.1114** (0.0545)	-0.1793*** (0.0527)	-0.1716*** (0.0578)	-0.1651*** (0.0488)
Positive – Negative	0.2108 (0.1783)	0.1272 (0.1473)	0.1179 (0.1393)	0.1328* (0.0719)	0.0933 (0.0578)	0.0859 (0.0600)
Panel B : Top 10% Return						
Positive Flow	0.1948 (0.2503)	0.0736 (0.1978)	0.1113 (0.2132)	0.2366 (0.2003)	0.1126 (0.1824)	0.1414 (0.1693)
Negative Flow	0.2687 (0.1864)	0.1601 (0.1777)	0.1972 (0.1695)	0.1647 (0.1947)	0.0554 (0.1597)	0.0776 (0.1574)
Positive – Negative	-0.0739 (0.1140)	-0.0866 (0.1501)	-0.0859 (0.0723)	0.0719 (0.0790)	0.0572 (0.0791)	0.0639 (0.0872)
Panel C : Top 10% Flow						
Positive Flow	0.0345 (0.1701)	-0.0541 (0.1416)	-0.0445 (0.1460)	0.0090 (0.0769)	-0.0511 (0.0939)	-0.0412 (0.0899)
Negative Flow	-0.3627*** (0.1279)	-0.3654*** (0.1255)	-0.3209** (0.1230)	-0.0884 (0.0715)	-0.0998* (0.0564)	-0.1044* (0.0589)
Positive – Negative	0.3972** (0.1557)	0.3113* (0.1751)	0.2764* (0.1523)	0.0974 (0.0864)	0.0487 (0.0912)	0.0632 (0.0965)
Panel D : MorningstarRating 5						
Positive Flow	-0.0165 (0.1959)	-0.1178 (0.1846)	-0.0990 (0.1698)	-0.0343 (0.1396)	-0.1020 (0.1174)	-0.0840 (0.1150)
Negative Flow	-0.0104 (0.1140)	-0.0099 (0.1245)	0.0471 (0.1129)	-0.1912* (0.1085)	-0.2087* (0.1218)	-0.1723* (0.1028)
Positive – Negative	-0.0061 (0.2448)	-0.1079 (0.2138)	-0.1462 (0.2116)	0.1570 (0.1164)	0.1067 (0.1347)	0.0883 (0.1364)
Panel E : Top 10% ALPHA ^{18M}						
Positive Flow	0.0934 (0.1978)	-0.0060 (0.1859)	0.0039 (0.1867)	0.0238 (0.1319)	-0.0343 (0.1240)	-0.0357 (0.1242)
Negative Flow	-0.2528 (0.1687)	-0.2593 (0.1807)	-0.1835 (0.1628)	-0.1657 (0.1309)	-0.1811 (0.1333)	-0.1570 (0.1231)
Positive – Negative	0.3463 (0.2782)	0.2532 (0.2573)	0.1875 (0.2398)	0.1895 (0.1390)	0.1468 (0.1089)	0.1213 (0.1125)

Notes: This table reports the alpha (%) of each portfolio measured using the FF3, FFC4 and FFC6 model. Standard errors (shown in parentheses) are calculated using the Newey-West method. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Positive flow indicates when the net flow is positive, while negative flow indicates when the net flow is negative. Positive-Negative is a difference portfolios, created by subtracting the returns of the portfolio weighted by negative flow from the returns of the portfolio weighted by positive flow. The performance measurement period for the portfolios is from June 2016 to December 2024.

Table 7 Comparison of Alpha among fund groups in the U.S. Market

	Flow-Weighted Portfolio			Equal-Weighted Portfolio		
	FF3	FFC4	FFC6	FF3	FFC4	FFC6
Panel A : Top 10% ALPHA ^{18M} – All						
Positive Flow	0.0262 (0.1137)	-0.0041 (0.1414)	-0.0025 (0.1243)	0.0704 (0.0936)	0.0440 (0.0890)	0.0435 (0.0936)
Negative Flow	-0.1092 (0.1294)	-0.1301 (0.1462)	-0.0722 (0.1266)	0.0136 (0.1132)	-0.0096 (0.1164)	0.0081 (0.1100)
Panel B : Top 10% ALPHA ^{18M} – Top 10% Return						
Positive Flow	-0.1014 (0.1433)	-0.0796 (0.1671)	-0.1073 (0.1507)	-0.2127 (0.1496)	-0.1470 (0.1471)	-0.1771 (0.1280)
Negative Flow	-0.5215* (0.2908)	-0.4194 (0.2741)	-0.3807* (0.2262)	-0.3304 (0.2424)	-0.2365 (0.1823)	-0.2345 (0.1742)
Panel C : Top 10% ALPHA ^{18M} – Top 10% Flow						
Positive Flow	0.0589 (0.0953)	0.0481 (0.1203)	0.0485 (0.0997)	0.0148 (0.0716)	0.0168 (0.0861)	0.0055 (0.0766)
Negative Flow	0.1098 (0.1609)	0.1061 (0.1654)	0.1374 (0.1546)	-0.0773 (0.1182)	-0.0813 (0.1199)	-0.0526 (0.1018)
Panel D : Top 10% ALPHA ^{18M} – Morningstar Rating 5						
Positive Flow	0.1099 (0.1033)	0.1117 (0.1151)	0.1030 (0.1113)	0.0581 (0.0992)	0.0676 (0.1086)	0.0483 (0.1037)
Negative Flow	-0.2424* (0.1273)	-0.2494* (0.1341)	-0.2306* (0.1322)	0.0255 (0.0873)	0.0275 (0.0866)	0.0153 (0.0885)

Notes: This table reports the alpha (%) of each long-short portfolio measured using the FF3, FFC4 and FFC6 model. Standard errors (shown in parentheses) are calculated using the Newey-West method. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Positive flow indicates when the net flow is positive, while negative flow indicates when the net flow is negative. The performance measurement period for the portfolios is from June 2016 to December 2024.

Table 8 Alpha of Equal-Weight Portfolio by Fund Groups

	FF3	FFC4	FFC6
Panel A : Japanese Mutual Funds			
All	-0.0025 (0.0526)	-0.0129 (0.0494)	-0.0398 (0.0481)
Top 10% Return	0.3746** (0.1739)	0.3094** (0.1393)	0.3133** (0.1518)
Top 10% Flow	0.1007 (0.0871)	0.0787 (0.0800)	0.0595 (0.0862)
Morningstar Rating5	0.1088 (0.0858)	0.0852 (0.0741)	0.0792 (0.0764)
Top 10% ALPHA ^{18M}	0.1203 (0.0927)	0.0968 (0.0922)	0.0454 (0.0903)
Panel B : U.S. Mutual Funds			
All	-0.1568*** (0.0498)	-0.1572*** (0.0507)	-0.1526*** (0.0454)
Top 10% Return	0.1972 (0.1912)	0.0847 (0.1737)	0.1240 (0.1608)
Top 10% Flow	-0.0019 (0.0946)	-0.0520 (0.0860)	-0.0506 (0.0830)
Morningstar Rating5	-0.0912 (0.0888)	-0.1389* (0.0824)	-0.1084 (0.0712)
Top 10% ALPHA ^{18M}	-0.1296 (0.1213)	-0.1528 (0.1252)	-0.1118 (0.1154)

Notes: This table reports the alpha (%) of each portfolio measured using the FF3, FFC4 and FFC6 model. Standard errors (shown in parentheses) are calculated using the Newey-West method. The time-series returns of each portfolio are calculated by measuring the next month's return from investing an equal amount in funds that exhibit salience bias and have high past alphas at the end of each month. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The performance measurement period for the portfolios is from May 2016 to December 2024.

Table 9 Portfolio Attributes of Japanese Mutual Funds (Decile Breakdown)

Decile	Annual Raw Return			ALPHA ^{18M}		
	TNA (JPY Mil)	Flow Amount (JPY Mil)	Flow Rate (%)	TNA (JPY Mil)	Flow Amount (JPY Mil)	Flow Rate (%)
1 (High)	11,025	269.5	2.3	11,705	109.3	0.2
2	12,032	71.1	0.2	13,108	-31.6	-0.4
3	11,143	-22.0	-0.6	16,139	15.0	-0.4
4	11,974	-72.3	-0.8	14,285	-13.8	-0.5
5	11,376	-55.2	-0.7	14,317	-10.7	-0.5
6	13,511	-101.4	-1.0	11,858	-7.7	-0.7
7	14,025	-108.4	-1.1	11,323	-47.7	-0.8
8	12,080	-123.3	-1.3	12,239	16.6	-0.7
9	10,265	-84.9	-1.1	12,073	-35.0	-0.9
10 (Low)	8,205	-102.8	-1.2	8,137	-96.7	-1.2

Notes: This table reports the average Total Net Assets (TNA), average flow amounts, and average flow rates of funds belonging to decile portfolios sorted based on past annual raw returns and ALPHA^{18M}.

Table 10 Portfolio Attributes of US Mutual Funds (Decile Breakdown)

Decile	Annual Raw Return			ALPHA ^{18M}		
	TNA (USD Mil)	Flow Amount (USD Mil)	Flow Rate (%)	TNA (USD Mil)	Flow Amount (USD Mil)	Flow Rate (%)
1 (High)	2,339	-3.4	0.5	2,255	-8.4	-0.2
2	2,459	-11.7	-0.3	2,401	-13.5	-0.6
3	2,048	-11.6	-0.4	2,301	-14.4	-0.6
4	1,730	-11.8	-0.7	1,955	-12.1	-0.8
5	1,868	-14.1	-0.8	1,796	-11.9	-0.8
6	1,949	-15.3	-0.9	1,696	-11.3	-0.8
7	1,392	-11.8	-0.9	1,462	-10.3	-1.1
8	1,535	-13.9	-1.1	1,355	-10.9	-1.1
9	1,201	-11.5	-1.3	1,175	-10.6	-1.2
10 (Low)	741	-8.5	-1.7	824	-8.9	-1.2

Notes: This table reports the average Total Net Assets (TNA), average flow amounts, and average flow rates of funds belonging to decile portfolios sorted based on past annual raw returns and ALPHA^{18M}.

Table 11 Alpha of Portfolio Sorted by Expected Flow and Past Alpha

Panel A : First Ranked By E[Flow Rate] then by ALPHA ^{18M}										
Ranks by ALPHA ^{18M}	Japanese Mutual Funds					US Mutual Funds				
	Ranks by E[Flow Rate]					Ranks by E[Flow Rate]				
	1	2	3	4	4-1	1	2	3	4	4-1
1	-0.0392 (0.2483)	-0.1049 (0.1110)	0.0558 (0.1401)	0.1655 (0.1827)	0.2047 (0.3221)	-0.3887 (0.2421)	-0.1290 (0.1089)	0.0556 (0.1163)	0.1373 (0.1706)	0.5260 (0.3478)
2	-0.1772* (0.0995)	-0.1306** (0.0553)	0.0023 (0.0751)	0.2664** (0.1032)	0.4436** (0.1832)	-0.3646** (0.1433)	-0.2040** (0.0836)	-0.0504 (0.0762)	0.0270 (0.1380)	0.3916 (0.2425)
3	-0.1493 (0.1100)	-0.0981 (0.0634)	-0.0129 (0.0666)	0.1821* (0.0957)	0.3314** (0.1653)	-0.4489** (0.1769)	-0.2689*** (0.1020)	-0.1303* (0.0736)	0.0075 (0.1457)	0.4563 (0.2837)
4	-0.1777 (0.2268)	-0.2154* (0.1179)	0.0307 (0.0955)	0.5766** (0.2736)	0.7543** (0.3673)	-0.5227* (0.2656)	-0.2012 (0.1240)	0.0440 (0.1188)	0.1233 (0.1962)	0.6460 (0.4594)
4-1	-0.1385 (0.3418)	-0.1105 (0.1339)	-0.0251 (0.1594)	0.4111 (0.2998)		-0.1340 (0.3208)	-0.0722 (0.1713)	-0.0116 (0.1697)	-0.0140 (0.1499)	
Panel B : First Ranked By ALPHA ^{18M} then by E[Flow Rate]										
Ranks by E[Flow Rate]	Japanese Mutual Funds					US Mutual Funds				
	Ranks by ALPHA ^{18M}					Ranks by ALPHA ^{18M}				
	1	2	3	4	4-1	1	2	3	4	4-1
1	-0.1879 (0.1737)	-0.1394 (0.1113)	-0.1650 (0.0998)	-0.0664 (0.1744)	0.1216 (0.2473)	-0.4035** (0.1959)	-0.3044* (0.1560)	-0.3777** (0.1680)	-0.6000** (0.3010)	-0.1966 (0.3014)
2	-0.1821* (0.1028)	-0.1098** (0.0522)	-0.1076* (0.0643)	-0.0722 (0.1084)	0.1099 (0.1308)	-0.2312* (0.1269)	-0.1995** (0.0833)	-0.2358** (0.0905)	-0.1955 (0.1355)	0.0356 (0.2147)
3	-0.0286 (0.1258)	0.0020 (0.0758)	-0.0098 (0.0676)	0.0560 (0.1001)	0.0847 (0.1365)	-0.0800 (0.1052)	-0.0656 (0.0739)	-0.1188 (0.0790)	0.0509 (0.1402)	0.1309 (0.1744)
4	0.1278 (0.1674)	0.1107 (0.1249)	0.1705 (0.1061)	0.4572** (0.1866)	0.3294 (0.2475)	0.0630 (0.1567)	0.0380 (0.1183)	0.0250 (0.1325)	0.0336 (0.2036)	-0.0294 (0.2304)
4-1	0.3157 (0.2808)	0.2501 (0.1856)	0.3356** (0.1531)	0.5235** (0.2517)		0.4665 (0.2918)	0.3424 (0.2489)	0.4027 (0.2882)	0.6336 (0.4496)	

Notes: This table reports the alpha (%) of each portfolio measured using the FFC6 model. Standard errors (shown in parentheses) are calculated using the Newey-West method. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Portfolios are formed monthly by classifying funds into four groups based on their expected flow (E[Flow Rate]) and ALPHA^{18M}: top 10%, 10–50%, 50–90%, and bottom 10%. Panel A shows the performance of portfolios sorted first by expected flow (E[Flow Rate]) and then by ALPHA^{18M}, while Panel B reports the performance of portfolios sorted in the reverse order—first by ALPHA^{18M} and then by expected flow(E[Flow Rate]).

Appendix

The smart money effect (using quarterly flows)

In this section, we examine the smart money effect using quarterly flows following Zheng (1999) and Sapp and Tiwari (2004). Specifically, we divide the funds into those with positive net flows and negative net flows based on the cumulative fund flows from the preceding quarter and create both flow-weighted and equal-weighted portfolios for each category to calculate the monthly returns of the portfolio for the subsequent quarter. Funds with salience bias and funds with high past alpha are identified at the end of each quarter. For example, when measuring the returns of a portfolio based on the top 10% 12-month return dummy, we focus on funds that ranked in the top 10% for total returns over the past year as of December 31, 2019. A weighted average portfolio is constructed based on the cumulative flows of these funds from January to March 2020. This process is repeated quarterly, with the monthly returns of the portfolio calculated for the period from April to June 2020. The resulting time series of monthly portfolio returns (after deducting the risk-free rate) is then regressed against factor returns to measure the portfolio's alpha. The analysis period, following the process that uses quarterly flows as described above, spans from October 2016 to December 2024.

Table A-1 presents the alphas of the portfolios measured using the FF3, FFC4 and FFC6 model specified in equation (14), (15) and (16) in the paper for Japanese mutual funds. Panel A presents a portfolio consisting of all funds, while Panels B through D present portfolios composed of funds selected based on salience biases. Panel E shows a portfolio consisting of funds with high past alpha. We find results approximately similar to those using monthly flows, but for example, in Panel D, which focuses on funds with a Morningstar Rating 5, the smart money effect is more prominently observed. In Panel A-2, we also find results generally similar to those using monthly flows; however, in the case of the negative flow portfolio in Panel B, some alphas are significantly negative, which is a notable difference.

Table A-3 presents the results for U.S. mutual funds in the same format as Table A-1. We find results approximately similar to those using monthly flows, but for example, in Panel A, when using quarterly flows, the alphas of the Positive-Negative portfolios are not statistically significant. On the other hand, in Panel B, there are cases where the alphas of the Positive-Negative portfolios are statistically significant, and this is not due to the low alpha of the Negative portfolio. Table A-4 presents results that are largely consistent with those obtained using monthly flows.

Table A-1 Alpha by fund groups in the Japanese Market (using quarterly flows)

	Flow-Weighted Portfolio			Equal-Weighted Portfolio		
	FF3	FFC4	FFC6	FF3	FFC4	FFC6
Panel A : All Funds						
Positive Flow	-0.0068 (0.1255)	-0.0206 (0.1173)	-0.0501 (0.1258)	0.0384 (0.0701)	0.0308 (0.0686)	0.0106 (0.0728)
Negative Flow	-0.0524 (0.0731)	-0.0603 (0.0775)	-0.0633 (0.0635)	-0.0119 (0.0550)	-0.0164 (0.0551)	-0.0394 (0.0532)
Positive – Negative	0.0456 (0.1199)	0.0398 (0.1244)	0.0132 (0.1329)	0.0503 (0.0578)	0.0472 (0.0574)	0.0500 (0.0610)
Panel B : Top 10% Return						
Positive Flow	0.2767 (0.1780)	0.2512 (0.1593)	0.2583 (0.1653)	0.3631** (0.1705)	0.3315** (0.1434)	0.3454** (0.1474)
Negative Flow	0.2610 (0.1832)	0.2374 (0.1759)	0.2385 (0.1858)	0.3362** (0.1581)	0.3021** (0.1302)	0.3061** (0.1319)
Positive – Negative	0.0157 (0.1668)	0.0138 (0.1697)	0.0199 (0.1834)	0.0269 (0.1012)	0.0295 (0.1030)	0.0393 (0.1139)
Panel C : Top 10% Flow						
Positive Flow	0.1098 (0.1264)	0.0956 (0.1165)	0.0906 (0.1183)	0.0980 (0.0933)	0.0852 (0.0845)	0.0807 (0.0844)
Negative Flow	0.1665 (0.1474)	0.1604 (0.1317)	0.1481 (0.1541)	0.0755 (0.1102)	0.0707 (0.1103)	0.0571 (0.1135)
Positive – Negative	-0.0567 (0.1416)	-0.0649 (0.1374)	-0.0574 (0.1476)	0.0225 (0.0989)	0.0145 (0.0971)	0.0236 (0.0975)
Panel D : MorningstarRating 5						
Positive Flow	0.4215** (0.1802)	0.3970** (0.1617)	0.4049** (0.1585)	0.2190* (0.1283)	0.1992* (0.1078)	0.1882 (0.1154)
Negative Flow	-0.0742 (0.1239)	-0.0833 (0.1252)	-0.0732 (0.1329)	0.0863 (0.0703)	0.0784 (0.0635)	0.0712 (0.0670)
Positive – Negative	0.4957*** (0.1603)	0.4803*** (0.1766)	0.4781** (0.1838)	0.1326 (0.1060)	0.1208 (0.1069)	0.1170 (0.1090)
Panel E : Top 10% ALPHA ^{18M}						
Positive Flow	0.3730* (0.1922)	0.3514* (0.1780)	0.3514** (0.1746)	0.2280* (0.1370)	0.2180 (0.1318)	0.2090 (0.1334)
Negative Flow	-0.0461 (0.1684)	-0.0550 (0.1719)	-0.0698 (0.1607)	0.0302 (0.0906)	0.0247 (0.0965)	-0.0196 (0.0881)
Positive – Negative	0.4190* (0.2224)	0.4064* (0.2160)	0.4212* (0.2207)	0.1978* (0.1167)	0.1933* (0.1139)	0.2286** (0.1128)

Notes: This table reports the alpha (%) of each portfolio measured using the FF3, FFC4 and FFC6 model. Standard errors (shown in parentheses) are calculated using the Newey-West method. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Positive flow indicates when the net flow is positive, while negative flow indicates when the net flow is negative. Positive-Negative is a difference portfolios, created by subtracting the returns of the portfolio weighted by negative flow from the returns of the portfolio weighted by positive flow. The performance measurement period for the portfolios is from October 2016 to December 2024.

Table A-2 Comparison of Alpha among fund groups in the Japanese Market (using quarterly flows)

	Flow-Weighted Portfolio			Equal-Weighted Portfolio		
	FF3	FFC4	FFC6	FF3	FFC4	FFC6
Panel A : Top 10% ALPHA ^{18M} – All						
Positive Flow	0.3797** (0.1678)	0.3720** (0.1618)	0.4015** (0.1699)	0.1895 (0.1165)	0.1872* (0.1111)	0.1984* (0.1181)
Negative Flow	0.0064 (0.1453)	0.0053 (0.1536)	-0.0066 (0.1468)	0.0420 (0.0697)	0.0411 (0.0693)	0.0198 (0.0662)
Panel B : Top 10% ALPHA ^{18M} – Top 10% Return						
Positive Flow	0.0963 (0.1900)	0.1002 (0.1891)	0.0931 (0.2079)	-0.1351 (0.1400)	-0.1135 (0.1260)	-0.1364 (0.1426)
Negative Flow	-0.3071 (0.2145)	-0.2924 (0.2139)	-0.3083 (0.2272)	-0.3060** (0.1456)	-0.2773** (0.1209)	-0.3257** (0.1252)
Panel C : Top 10% ALPHA ^{18M} – Top 10% Flow						
Positive Flow	0.2631* (0.1332)	0.2558** (0.1203)	0.2608** (0.1220)	0.1300 (0.0998)	0.1328 (0.0894)	0.1283 (0.0970)
Negative Flow	-0.2126 (0.2013)	-0.2155 (0.1874)	-0.2179 (0.1790)	-0.0454 (0.1060)	-0.0460 (0.1107)	-0.0767 (0.1140)
Panel D : Top 10% ALPHA ^{18M} – Morningstar Rating 5						
Positive Flow	-0.0486 (0.1372)	-0.0456 (0.1356)	-0.0535 (0.1381)	0.0091 (0.1297)	0.0188 (0.1255)	0.0208 (0.1300)
Negative Flow	0.0281 (0.1421)	0.0283 (0.1240)	0.0034 (0.1210)	-0.0561 (0.0773)	-0.0536 (0.0779)	-0.0909 (0.0709)

Notes: This table reports the alpha (%) of each long-short portfolio measured using the FF3, FFC4 and FFC6 model. Standard errors (shown in parentheses) are calculated using the Newey-West method. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Positive flow indicates when the net flow is positive, while negative flow indicates when the net flow is negative. The performance measurement period for the portfolios is from October 2016 to December 2024.

Table A-3 Comparison of Alpha among fund groups in the U.S. Market (using quarterly flows)

	Flow-Weighted Portfolio			Equal-Weighted Portfolio		
	FF3	FFC4	FFC6	FF3	FFC4	FFC6
Panel A : All Funds						
Positive Flow	-0.1072 (0.1035)	-0.1601 (0.0987)	-0.1067 (0.0904)	-0.1522** (0.0750)	-0.1850*** (0.0664)	-0.1715*** (0.0637)
Negative Flow	-0.1009* (0.0508)	-0.0831* (0.0492)	-0.0685 (0.0466)	-0.1460*** (0.0544)	-0.1400** (0.0544)	-0.1374*** (0.0486)
Positive – Negative	-0.0063 (0.1037)	-0.0770 (0.0942)	-0.0381 (0.0840)	-0.0062 (0.0641)	-0.0450 (0.0545)	-0.0341 (0.0520)
Panel B : Top 10% Return						
Positive Flow	0.1374 (0.2062)	0.0377 (0.2057)	0.1230 (0.1824)	0.0781 (0.1926)	-0.0212 (0.1789)	0.0458 (0.1564)
Negative Flow	-0.1026 (0.1476)	-0.1881 (0.1346)	-0.1797 (0.1301)	-0.0590 (0.1795)	-0.1371 (0.1504)	-0.1105 (0.1438)
Positive – Negative	0.2400* (0.1266)	0.2257 (0.1404)	0.3026** (0.1252)	0.1371 (0.0878)	0.1160 (0.0884)	0.1564** (0.0781)
Panel C : Top 10% Flow						
Positive Flow	-0.0393 (0.1206)	-0.1122 (0.1105)	-0.0530 (0.0990)	-0.0384 (0.0897)	-0.0840 (0.0860)	-0.0612 (0.0767)
Negative Flow	-0.1431 (0.1362)	-0.1605 (0.1359)	-0.1491 (0.1330)	-0.0702 (0.0774)	-0.0813 (0.0806)	-0.0859 (0.0812)
Positive – Negative	0.1038 (0.1677)	0.0484 (0.1609)	0.0961 (0.1497)	0.0319 (0.0886)	-0.0027 (0.0844)	0.0248 (0.0753)
Panel D : Morningstar Rating 5						
Positive Flow	-0.1671 (0.1305)	-0.2252 (0.1468)	-0.1317 (0.1418)	-0.2060* (0.1115)	-0.2474** (0.1110)	-0.1874* (0.1024)
Negative Flow	0.0510 (0.1826)	0.0511 (0.1511)	0.0537 (0.1489)	-0.2509* (0.1308)	-0.2618* (0.1467)	-0.2472** (0.1165)
Positive – Negative	-0.2181 (0.1712)	-0.2763 (0.1838)	-0.1855 (0.1756)	0.0449 (0.1217)	0.0143 (0.1244)	0.0597 (0.1246)
Panel E : Top 10% ALPHA ^{18M}						
Positive Flow	-0.1594 (0.1695)	-0.2099 (0.1885)	-0.1423 (0.1699)	-0.2256 (0.1525)	-0.2545 (0.1574)	-0.1986 (0.1454)
Negative Flow	-0.1988 (0.1841)	-0.1681 (0.1686)	-0.1204 (0.1831)	-0.2137 (0.1396)	-0.2031 (0.1395)	-0.1769 (0.1428)
Positive – Negative	0.0394 (0.1845)	-0.0417 (0.1855)	-0.0219 (0.1722)	-0.0119 (0.1092)	-0.0514 (0.1095)	-0.0217 (0.1078)

Notes: This table reports the alpha (%) of each long-short portfolio measured using the FF3, FFC4 and FFC6 model. Standard errors (shown in parentheses) are calculated using the Newey-West method. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Positive flow indicates when the net flow is positive, while negative flow indicates when the net flow is negative. The performance measurement period for the portfolios is from October 2016 to December 2024.

Table A-4 Comparison of Alpha among fund groups in the U.S. Market (using quarterly flows)

	Flow-Weighted Portfolio			Equal-Weighted Portfolio		
	FF3	FFC4	FFC6	FF3	FFC4	FFC6
Panel A : Top 10% ALPHA ^{18M} – All						
Positive Flow	-0.0522 (0.1053)	-0.0497 (0.1124)	-0.0356 (0.1098)	-0.0734 (0.1331)	-0.0695 (0.1353)	-0.0271 (0.1040)
Negative Flow	-0.0979 (0.1532)	-0.0850 (0.1642)	-0.0518 (0.1569)	-0.0678 (0.1331)	-0.0631 (0.1186)	-0.0394 (0.1375)
Panel B : Top 10% ALPHA ^{18M} – Top 10% Return						
Positive Flow	-0.2968 (0.2058)	-0.2475 (0.1963)	-0.2653 (0.1954)	-0.3037 (0.2199)	-0.2333 (0.1929)	-0.2444 (0.1842)
Negative Flow	-0.0961 (0.2429)	0.0199 (0.2121)	0.0593 (0.1968)	-0.1547 (0.2316)	-0.0659 (0.2178)	-0.0663 (0.2028)
Panel C : Top 10% ALPHA ^{18M} – Top 10% Flow						
Positive Flow	-0.1201 (0.1234)	-0.0977 (0.1183)	-0.0893 (0.1182)	-0.1873 (0.1437)	-0.1705 (0.1414)	-0.1374 (0.1227)
Negative Flow	-0.0557 (0.1883)	-0.0076 (0.1897)	0.0287 (0.1860)	-0.1435 (0.1155)	-0.1218 (0.1240)	-0.0909 (0.1140)
Panel D : Top 10% ALPHA ^{18M} – Morningstar Rating 5						
Positive Flow	0.0077 (0.1257)	0.0154 (0.1264)	-0.0106 (0.1293)	-0.0196 (0.1298)	-0.0071 (0.1278)	-0.0112 (0.1200)
Negative Flow	-0.2497* (0.1381)	-0.2192 (0.1395)	-0.1741 (0.1303)	0.0372 (0.0984)	0.0587 (0.1025)	0.0703 (0.1048)

Notes: This table reports the alpha (%) of each long-short portfolio measured using the FF3, FFC4 and FFC6 model. Standard errors (shown in parentheses) are calculated using the Newey-West method. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Positive flow indicates when the net flow is positive, while negative flow indicates when the net flow is negative. The performance measurement period for the portfolios is from October 2016 to December 2024.

BOJ ETF purchase and mutual fund performance

Table A-5 presents regressions of risk-free-rate excess returns and FFC6-adjusted alphas for Japanese actively managed equity mutual funds. All specifications include fund fixed effects and three measures of Bank of Japan (BOJ) ETF purchase activity: (i) the natural logarithm of monthly BOJ ETF purchases, (ii) monthly BOJ ETF purchases scaled by aggregate equity market capitalization, and (iii) an indicator variable equal to one when monthly BOJ ETF purchases fall within the top decile of the sample (“Extreme BOJ Purchase”). When excess returns over the risk-free rate are used as the dependent variable, FFC6 factor returns are additionally included as control variables. Across all specifications, the estimated coefficients on the BOJ purchase variables are economically small and statistically insignificant, indicating that BOJ ETF purchases do not have a detectable effect on fund returns or alphas.

Table A-5 BOJ ETF Purchase and Mutual Fund Performance

Dependent Variable :	Rf Excess Return			FFC6 Alpha		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(BOJ Purchase)	0.0005 (0.0032)			-0.0027 (0.0039)		
BOJ Purchase Rate		-0.9332 (0.8657)			-0.7259 (0.7937)	
Extreme BOJ Purchase Dummy			-0.3488** (0.1692)			-0.2618 (0.1811)
FFC6 Factor Return	Yes	Yes	Yes	No	No	No
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
S.E.: Clustered	Fund & Month	Fund & Month	Fund & Month	Fund & Month	Fund & Month	Fund & Month
Observations	43,557	43,557	43,557	37,600	37,600	37,600
R2	0.79412	0.79434	0.79462	0.01990	0.02087	0.02176
Within R2	0.79333	0.79356	0.79383	0.00037	0.00136	0.00227

Notes: This table reports the results of the determinants of Rf Excess Return and FFC6-adjusted alpha. Standard errors clustered as the fund and month levels are in parentheses. The symbols ***, ** and * denote significance at the 1%, 5% and 10% levels. The analysis period is from May 2016 to December 2024.